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State-space prediction of spring discharge in a karst catchment in southwest China

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ABSTRACT

Southwest China represents one of the largest continuous karst regions in the world. It is estimated that around 1.7 million people are heavily dependent on water derived from karst springs in southwest China. However, there is a limited amount of water supply in this region. Moreover, there is not enough information on temporal patterns of spring discharge in the area. In this context, it is essential to accurately predict spring discharge, as well as understand karst hydrological processes in a thorough manner, so that water shortages in this area could be predicted and managed efficiently. The objectives of this study were to determine the primary factors that govern spring discharge patterns and to develop a state-space model to predict spring discharge. Spring discharge, precipitation (PT), relative humidity (RD), water temperature (WD), and electrical conductivity (EC) were the variables analyzed in the present work, and they were monitored at two different locations (referred to as karst springs A and B, respectively, in this paper) in a karst catchment area in southwest China from May to November 2015. Results showed that a state-space model using any combinations of variables outperformed a classical linear regression, a back-propagation artificial neural network model, and a least square support vector machine in modeling spring discharge time series for karst spring A. The best state-space model was obtained by using PT and RD, which accounted for 99.9% of the total variation in spring discharge. This model was then applied to an independent data set obtained from karst spring B, and it provided accurate spring discharge estimates. Therefore, state-space modeling was a useful tool for predicting spring discharge in karst regions in southwest China, and this modeling procedure may help researchers to obtain accurate results in other karst regions.

1. Introduction

It is estimated that karst regions comprise between 7% and 12% of the earth's continental surface, and that almost 25% of the world's population depends largely on drinking water derived from karst aquifers (Ford and Williams, 2013; Hartmann et al., 2014). The hydrogeological characteristics of a karst complex include a porous rock matrix, fissures, fractures, and a network of solution conduits embedded in karst aquifers (Jukić and Denić-Jukić, 2015; Martin et al., 2016). In addition, karst aquifers can be described as double-porosity (matrix vs conduits) hydraulic media (Li et al., 2016a).

With respect to runoff on karst terrain, it has been stated that surface runoff may vary considerably as a function of how fissured and fractured the terrain or rock matrix is (Tague and Grant, 2004). For example, in a karst landscape with no soil cover, most of the water derived from rainfall may reach groundwater systems or the network of conduits through fissures and fractures, so that only a relatively small amount of surface runoff may be present in a karst system at a specific period of time (Peng and Wang, 2012). It is also important to mention that the presence of open conduits (one of the characteristics of karst aquifers) provides low resistance pathways for groundwater flow and usually short-circuits the fracture permeability of the aquifer (White, 2002). Also, almost all of the groundwater in karst catchment areas may eventually flow through an extensive network of groundwater conduits to a

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discharge point at a spring (Barfield et al., 2004; Malagò et al., 2016). Therefore, spring discharge can reflect the fluctuation of groundwater level, as well as the variability of groundwater storage in a catchment (Hu et al., 2008).

Southwest China is located in a humid climate zone. It is one of the largest continuous karst regions in the world, and the small karst springs present in this area have been used as the only source of potable water for around 1.7 million people who live in this region (Jiang et al., 2014; Li et al., 2016b). Owing to inadequate land use and severe soil erosion, rocky desertification processes are very noticeable in this region (Bai et al., 2013). As a direct consequence of rocky desertification, severe drought has occurred more frequently in southwest China, and several karst springs have dried up (Jiang et al., 2014; Liu et al., 2015). In this context, it is very important for researchers to understand the factors that govern the dynamics of spring discharge to prevent severe drought or rocky desertification. Moreover, it is essential to develop appropriate management plans for tackling the problem of water shortages, as well as managing water resources in a more effective and sustainable fashion.

Spring discharge is a physical consequence of rainfall, and thus it represents a phenomenon that is highly susceptible to climate changes (Hao et al., 2006; Huo et al., 2016). The relationship between spring discharge and precipitation has previously been analyzed (Barfield et al., 2004; Hartmann et al., 2012; de Rooij et al., 2013; Jukić and Denić-Jukić, 2015; Li et al., 2016a). For instance, Chen et al. (2004) suggested that precipitation correlated significantly with spring levels in a carbonate rock aquifer in Canada. Hao et al. (2006) showed that a continuous decrease in spring discharges in semi-arid regions in China might be largely attributed to a decline in regional precipitation over the last two decades. In addition, time series of air temperature and relative humidity could determine the time variability of evapotranspiration processes, thereby exerting considerable influence on the temporal variation patterns of spring discharge (Jukić and Denić-Jukić, 2011, 2015). Both temperature and electrical conductivity of spring water were observed to be closely related to spring discharge (Desmarais and Rojstaczer, 2002; Ravbar et al., 2011). For example, Birk et al. (2004) showed that localized spring discharge in a karst aquifer can be characterized by simultaneously analyzing the electrical conductivity and temperature of spring water.

Heterogeneity in controlling factors, together with the combined effects of such factors, can cause high temporal variability in spring discharge. In this context, the ratio of maximum to minimum spring discharge can range from 10 to 1000 in southwest China (Hao et al., 2006), so that estimating spring discharge time series may well be a non-trivial task in this region. Hence, the relationship between spring discharge and the factors controlling the discharge should be quantified for accurately understanding karst hydrological processes.

With respect to modeling techniques, multiple linear regression (MLR) and back-propagation artificial neural network (BP-ANN) have been applied to model spring discharge (Barfield et al., 2004; Chen et al., 2004; Hao et al., 2006; Hu et al., 2008; Zeng et al., 2016). Least square support vector machine (LSSVM), based on kernel methods, has been effectively used in hydrological modeling, and this modeling technique may be useful for estimating spring discharge in karst regions (Kisi, 2012, 2015; Kisi and Parmar, 2016). However, MLR, BP-ANN, and LSSVM models have not accounted for temporal and/or spatial relationships between spring discharge and its influencing factors, which could lead to misinterpretation of results (Nielsen and Alemi, 1989).

State-space models, using the Kalman filter method, have been effectively used as a tool for identifying temporal/spatial relationships between spring discharge and its controlling factors, and these models could be deployed to quantify localized variation in spring discharge (Wendroth et al., 2011; Schwen et al., 2013; Aquino et al., 2015). This methodology was first proposed by Kalman (1960) and Kalman and Bucy (1961) to filter noisy electrical data, and it was then extended to analyze soil properties (e.g., soil water content) by Morkoc et al. (1985).

A temporal or spatial process of a variable is related to the same or other variables at a previous location in a state-space model (Shumway and Stoffer, 1982; Nielsen and Wendroth, 2003). That is, the magnitude of a variable compared to its value at a previous measurement time or a nearby location is taken into consideration in state-space models (Schwen et al., 2013). Even if the temporal/spatial density of observations differed among variables, state-space models could still provide an adequate representation of the temporal/spatial process of a specific variable, the confidence of estimation, and the magnitude of measurement and model errors (Nielsen and Wendroth, 2003; Wendroth et al., 2006). MLR, BP-ANN, and LSSVM models usually assume that observations are independent of one another in space and time, and that underlying processes that were not taken into consideration could not significantly change any response patterns (Nielsen and Alemi, 1989; Yang and Wendroth, 2014).

Unlike MLR, BP-ANN, and LSSVM, state-space models can account for temporal/spatial dependence inherent in observations, and they can also identify correlation between two variables in temporal/spatial point-to-point processes, resulting in greater accuracy (Timm et al., 2003; Wendroth et al., 2003). Also, state-space models have been widely and effectively applied in analyzing vegetation yield (Wendroth et al., 1992; Li et al., 2001; Timm et al., 2003; Wendroth et al., 2003; Jia et al., 2011), soil physical properties (Morkoc et al., 1985; Wendroth et al., 1999; Wendroth et al., 2006; Timm et al., 2011; Aquino et al., 2015; Duan et al., 2016), and soil chemical properties (Li et al., 2010; Wendroth et al., 2011; Schwen et al., 2013; She et al., 2014; Yang and Wendroth, 2014). However, to the best of our knowledge, very few, if any, studies have assessed the performance of state-space models in analyzing spring discharge time series in karst regions.

The objectives of this study were: (1) to investigate temporal relationships between spring discharge and its controlling factors, such as precipitation, relative humidity, water temperature, and electrical conductivity in two different karst spring areas (referred to as "A" and "B" in this work) in southwest China, (2) to compare the performance of state-space models with that of other approaches (i.e., MLR, BP-ANN, and LSSSVM models) in estimating spring discharge in karst spring A; and (3) to use state-space modeling to predict spring discharge time series in karst spring B.

2. Study site and data collection

2.1. Study site

The current study was conducted in the Guzhou catchment area in Huanjiang County (24°44′–25°33 N, 107°51′–108°43′E), Guangxi province, southwest China (Fig. 1). The local climate is characterized as subtropical monsoonal, with annual mean precipitation of 1638 mm, 80% of which occurs in the wet season from May to October. The annual mean temperature is around 15.1 °C with hot summer and cold winter. The catchment has a drainage area of 1.87 km^2, with elevation ranging from 350 to 825 m above sea level. This catchment is characterized by a typical peak-cluster depression system that is mostly composed of a flat depression at the center, surrounded by a series of hillslopes (Wang et al., 2004). The greater gradient occurs in the upslope area, while the lower gradient occurs at the foot of the hillslopes. The underlying bedrock in the catchment area is composed of pure and thick lime-