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Quantifying the place of karst aquifers in the groundwater to surface water continuum: A time series analysis study of storm behavior in Pennsylvania water resources

Ellen K. Herman [a,*], Laura Toran [b], William B. White [c]

[a] Department of Geology, Bucknell University, 224 O'Leary Center, Lewisburg, PA 17837, United States
[b] Department of Geology, Temple University, Philadelphia, PA 19122, United States
[c] Department of Geosciences and Materials Research Institute, The Pennsylvania State University, University Park, PA 16802, United States

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SUMMARY

Though karst aquifers have commonly been identified, with respect to their behavior, as intermediate between ground and surface water, their putative location between these end members is generally descriptive rather than quantitative. Autocorrelation and spectral analysis of data from four karst springs, three wells, and eight stream gauges in Pennsylvania illustrate that specific karst water resources exhibit widely varying inertia with lag times that overlap those of groundwater and surface water. When analyzed in the frequency domain, the same data reveal distinctive patterns for each type of water resource.

The four springs display characteristic lag times ranging from 5 to 25 days, compared to 1–10 days for streams and 11–46 days for wells. Physically, karst waters may behave as a mix of porous media, fracture, and open-channel flow, but in temporal terms the balance of this mix results in a range of system behaviors with characteristic periodicities evident in the karst aquifers. In the frequency domain, karst aquifers manifested slow flow paths as a gradual fall-off at lower frequency and quick flow paths as a flattening at high-frequency.

Our comparison of water resources across different time periods revealed that the period considered can have strong effects on results. One spring displayed characteristic lag times of 12 and 25 days for two different time spans. To directly compare water resources over relatively short time scales, precipitation inputs must be similar and data sets must cover the same period; otherwise, substantial differences in lag times can be due to data collection and input differences rather than system characteristics. This limitation is less when the same data are analyzed in the frequency domain.

Introduction

Many investigators have considered how a karst aquifer alters a storm signal between recharge and spring (Brown, 1973; Dreiss, 1982, 1983, 1989a,b; Mangin, 1984; de Vera, 1984; Padilla and Pulido-Bosch, 1995; Eisenlohr et al., 1997a,b; Halihan et al., 1998; Halihan and Wicks, 1998; Larocque et al., 1998; Bouchaou et al., 2002; Amraoui et al., 2003; Denic-Jukic and Jukic, 2003; Rahnemaei et al., 2005). The storm signal in turn has been used to deduce source waters and aquifer structure (e.g., Smart, 1988; Desmarais and Rojstaczer, 2002; Birk et al., 2004). The time-invariant transfer function is appealing for storm signal interpretation because of its simplicity and its method of combining all storms across the monitored time series into a single signal. Non-linear time variant analysis, such as wavelet transforms, further defines rainfall–runoff relationships in karst springs and may enable better prediction of input–output relations where non-stationary behavior occurs (Lambrakis et al., 2000; Beaudeau et al., 2001; Labat et al., 2000, 2001, 2002; Majone et al., 2004; Dryden et al., 2005). However, in comparing systems with substantially different signal magnitudes, time-invariant transfer functions based on autocorrelation remain very useful.

Mangin (1984) first applied the calculation of autocorrelation to karst springs in the Pyrenees, characterizing their inertia to assess the time a signal persisted in the system. Additional studies have employed similar techniques with some adding cross-correlation between precipitation and other variables such as discharge and turbidity (de Vera, 1984; Jemcov et al., 1998–1999; Bouchaou et al., 2002; Amraoui et al., 2003; Denic-Jukic and Jukic, 2003; Massei et al., 2006). In the groundwater literature, autocorrelation and cross-correlation are only rarely employed to describe storm responses in wells, largely due to high inertia evident in most wells (Lee and Lee, 2000; Rademacher et al., 2002); these techniques are, however, implemented in groundwater settings with higher frequency variations like coastal aquifers and wells subject to earth

* Corresponding author. Tel.: +1 570 577 3088; fax: +011 570 577 3031.
E-mail address: ekh008@bucknell.edu (E.K. Herman).

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tides (Shih et al., 1999; Shih and Lin, 2002; Marechal et al., 2002). In surface water study, autocorrelation has been used for several decades to characterize catchments responding to storms, and has recently been used by climate scientists attempting to separate trends from autocorrelation in long-term stream flow signals (e.g., Yue et al., 2002; Potts et al., 2003; Labat et al., 2004; Coulibaly and Burn, 2005; Kallache et al., 2005; Pagano and Garen, 2005).

This study focuses on autocorrelation of high-frequency flow and stage data from karst springs, wells, and streams in Pennsylvania. Multiple sites with different characteristics were examined to discover where the karst springs fit in among the groundwater wells and surface streams in terms of inertia. The wells selected were screened in clastic rocks, and the surface streams selected, while sometimes fed by karst spring systems, are not sinking and rising streams. These selections were made to insure that the behavior of neither the wells nor the streams was controlled by karst flow regimes. The consistent assumption among hydrogeologists is that streams pass storm signals very quickly, but signals in wells, if present, persist across long periods. We examine this assumption and consider if karst springs fit in the middle, as often described (White, 1988; Ford and Williams, 1989; White, 2002; Lee and Lee, 2000; Pinault et al., 2001; Denic-Jukic and Jukic, 2003; Quinn et al., 2006).

Methods

A time series data set can be separated into three components, overall trend, noise, and autocorrelation. Autocorrelation defines the dependence of a data point on prior points. Many climate-oriented hydrologists are interested in removing the autocorrelation of time series to examine the trend in climatic data over time; conversely, the autocorrelation portion of the series, once the trend is removed, reveals important information about the system itself in terms of temporal behavior. Mangin (1984) first popularized the autocorrelation approach of Box and Jenkins (1976) as a measure of system inertia in karst, defining autocorrelation as follows:

$$r_k = \frac{\sum_{i=1}^{n-k}(x_i - \bar{x})(x_{i+k} - \bar{x})}{\sum_{i=1}^{n}(x_{i+k} - \bar{x})^2} \tag{1}$$

where r_k is the autocorrelation coefficient at any point in the series, k is a point in the series, x is the data series with the trend removed, and $\bar{x}$ is the arithmetic mean of the series (Padilla and Pulido-Bosch, 1995; Eisenlohr et al., 1997b; Larocque et al. 1998; Amraoui et al., 2003). The slope of the autocorrelation function illustrates whether individual data points have long-term effects on the entire data series. Because individual rainfall measurements have little to no effect on the preceding and subsequent measurements, the autocorrelation function drops off quickly indicating that precipitation has low inertia. A karst spring with high storage would be expected to manifest an autocorrelation function with a low slope as an individual measurement of water level should be closely related to subsequent and previous measurements. For the purposes of this study, we take the characteristic lag time as the lag at which the correlation coefficient, r_k, is equal to 0.2, allowing comparison of different systems (Mangin, 1984). A system with persistent storage where individual measurements are closely related to other measurements will have a longer characteristic lag indicating greater inertia. Below 0.2, the autocorrelation coefficient r_k is essentially identical to the autocorrelation of noise (Mangin, 1984). There are additional ways of selecting lag time or characterizing the autocorrelation function (e.g., Massei et al., 2006).

Another common way of examining the autocorrelation function involves transforming the correlogram of a time series (the function r_k over a series of time lags) into the frequency domain as the following spectral density function (S_f):

$$S_f = 2\left[1 + 2\sum_{k=1}^{m} D_k r_k \cos(2\pi f k)\right] \tag{2}$$

$$D_k = \frac{1}{2}\left(1 + \cos\pi\frac{k}{m}\right) \tag{3}$$

where f is a given frequency and D_k is the Tukey filter (Larocque et al. 1998; Amraoui et al., 2003). The fast Fourier transform (FFT) of the raw data series may also be analyzed in similar fashion; however, the FFT of the autocorrelation function (r_k) highlights periodic behavior in the data series (Lee et al., 2005; Massei et al., 2006).

Other researchers have used the regulation time (T_{reg}) of the system to determine the duration of the impulse response or the length of time the input signal persists in the system by marking when the spectral density of the autocorrelation function approaches zero. There is ambiguity in the calculation of T_{reg} in the literature. Some calculate T_{reg} by determining the frequency where the maximum spectral density is reduced by half and inverting that frequency to yield T_{reg} (Larocque et al., 1998). Others use the inverse of a break frequency where spectral density drops off to another specified value (Lee and Lee, 2000; Bouchaou et al., 2002).

For the purposes of this study, we employ a different approach to analyzing the frequency spectrum that preserves more of the information in the signal. Rather than identifying a frequency and corresponding period where S_f crosses an arbitrary boundary, we examine the spectrum of each autocorrelation function in log–log space to describe the frequency where the power function has breaks in slope revealing different behavior modes.

The time lag and frequency analysis both provide measures of memory in the system. However, the frequency analysis is less sensitive to the sampling interval and correlation between distant events (Larocque et al., 1998) and can reveal basic information about the physical characteristics of a system (Molenat et al., 1999).

Site selection and data description

Springs

Four springs in Pennsylvania were monitored for inclusion in this study, Arch Spring in Blair County, Nolte Spring in Lancaster County, and Tippery Spring and Near Tippery Spring in Huntingdon County (Fig. 1). Instruments were installed at Nolte spring from the fall of 2002 through the fall of 2004; at Arch spring from winter of 2002 to spring of 2005; and at Tippery and Near Tippery from summer of 2004 to winter of 2005. These sites were selected for their varying baseflow discharges (from 0.04 to 0.5 m^3/s) and drainage areas (from 3 to 25 km^2). Key characteristics of each site including drainage basin area, baseflow, periods analyzed, and recording intervals are presented in Table 1a. Portions of the monitoring record at the springs were not used in this study either because the data had substantial gaps or irregularities that could not be corrected.

Each site was equipped with monitoring equipment designed to capture long-term data sets. A Global Water 8-channel logger recorded specific conductance, stage, and temperature at sub-hourly intervals; a sample data set is presented in Fig. 2. Complete data sets for all water resources are included in the supplementary material. A stormwater sampler was also in place at each site, but those data are not presented here. Site visits spaced up to one month apart confirmed logged conductivity, stage, and temperature values. Hourly precipitation data for the spring areas are available from the National Oceanic and Atmospheric Administration's (NOAA) National Climatic Data Center (NCDC) webpage (www.ncdc.noaa.gov).