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Analysis of groundwater drought building on the standardised precipitation index approach

J. P. Bloomfield[1] **and B. P. Marchant**[2]

[1]British Geological Survey, Maclean Building, Crowmarsh Gifford, Wallingford, Oxfordshire, OX10 8BB, UK
[2]British Geological Survey, Environmental Science Centre, Keyworth, Nottingham, NG12 5GG, UK

Correspondence to: J. P. Bloomfield (jpb@bgs.ac.uk)

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Abstract. A new index for standardising groundwater level time series and characterising groundwater droughts, the Standardised Groundwater level Index (SGI), is described. The SGI builds on the Standardised Precipitation Index (SPI) to account for differences in the form and characteristics of groundwater level and precipitation time series. The SGI is estimated using a non-parametric normal scores transform of groundwater level data for each calendar month. These monthly estimates are then merged to form a continuous index. The SGI has been calculated for 14 relatively long, up to 103 yr, groundwater level hydrographs from a variety of aquifers and compared with SPI for the same sites. The relationship between SGI and SPI is site specific and the SPI accumulation period which leads to the strongest correlation between SGI and SPI, q_{max}, varies between sites. However, there is a consistent positive linear correlation between a measure of the range of significant autocorrelation in the SGI series, m_{max}, and q_{max} across all sites. Given this correlation between SGI m_{max} and SPI q_{max}, and given that periods of low values of SGI can be shown to coincide with previously independently documented droughts, SGI is taken to be a robust and meaningful index of groundwater drought. The maximum length of groundwater droughts defined by SGI is an increasing function of m_{max}, meaning that relatively long groundwater droughts are generally more prevalent at sites where SGI has a relatively long autocorrelation range. Based on correlations between m_{max}, average unsaturated zone thickness and aquifer hydraulic diffusivity, the source of autocorrelation in SGI is inferred to be dependent on dominant aquifer flow and storage characteristics. For fractured aquifers, such as the Cretaceous Chalk, autocorrelation in SGI is inferred to be primarily related to autocorrelation in the recharge time series, while in granular aquifers, such as the Permo–Triassic sandstones, autocorrelation in SGI is inferred to be primarily a function of intrinsic saturated flow and storage properties of aquifer. These results highlight the need to take into account the hydrogeological context of groundwater monitoring sites when designing and interpreting data from groundwater drought monitoring networks.

1 Introduction

Drought is a costly natural hazard affecting socio-economic activity and agricultural livelihoods as well as adversely impacting public health, and threatening the sustainability of many natural environments (Calow et al., 1999; Wilhite, 2000; Fink et al., 2004; Sheffield and Wood, 2008; Mishra and Singh, 2010). Droughts typically develop slowly and can last from months to a few years (Santos, 1983; Lloyd-Hughes and Saunders, 2002; Tallaksen and van Lanen, 2004; Tallaksen et al., 2009; van Lanen et al., 2013). As highlighted in a recent review of drought concepts by Mishra and Singh (2010), groundwater droughts can impact adversely on water resources such as public water supply or water for industry and agricultural irrigation, as well as effecting groundwater discharge to groundwater-dependent surface waters and ecosystems. During the early stages of a drought, as deficits are developing in surface water and unsaturated zone stores, groundwater sources can provide relatively resilient water supplies and will sustain surface flows through groundwater baseflow (Hughes et al., 2012). Conversely, groundwater may be highly susceptible to relatively persistent or

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prolonged droughts, because, compared with surface water resources, groundwater storage may take significantly longer to be replenished and recover as a drought begins to break.

A number of studies have sought to develop a better understanding of groundwater droughts in the context of meteorological drivers and, in particular, how droughts propagate through hydrological systems (Eltahir and Yeh, 1999; Peters, 2003; Peters et al., 2003, 2005, 2006; Tallaksen et al., 2006, 2009; Leblanc et al., 2009; van Lanen et al., 2013). These studies have usually focussed on the catchment scale and have brought process understanding to bear on the evolution of groundwater droughts. Other studies related to groundwater drought have emphasised monitoring, characterisation of longer-term trends and the development of drought warning systems (Chang and Teoh, 1995; Bhuiyan et al., 2006; Mendicino et al., 2008; Fiorillo and Guadagno, 2010, 2012). A common feature of many of these latter studies is the need to develop relatively simple but consistent measures or indices of the status of groundwater drought: indices that can be applied between different observation sites, in different aquifers, as well as that enable groundwater drought to be compared with other hydro-meteorological aspects of drought. Despite the previous work, there are still no commonly accepted indices to quantify groundwater droughts, so making it difficult to incorporate groundwater drought phenomena into wider drought assessments. To address this issue we present a new groundwater level index for use in groundwater drought monitoring and analysis. The new index builds on the SPI methodology, taking into account known shortcomings of the SPI approach when applied to hydrometric data.

Context for development of the SGI

Many drought indices have been developed in recent decades in attempts to enable aspects of drought severity, duration and/or spatial extent to be characterised and compared in a consistent manner (Mishra and Singh, 2010). These include indices focussed on meteorological, hydrological, agricultural and other dimensions of drought. One of the most widely used indices of meteorological drought is the SPI, (McKee et al., 1993; Edwards and McKee, 1997; Hayes et al., 2011). The SPI consists of a normalised index obtained by fitting a gamma distribution to long-term precipitation records, where fitting is done for each calendar month to account for seasonal differences. The monthly fitted distributions are then transformed to a standard normal distribution and the estimated standardised values combined to produce the SPI time series. There are a number of strengths to the SPI approach: (i) it only uses one relatively commonly available parameter (i.e. precipitation); (ii) it can be estimated for a variety of timescales (by calculating using precipitation data for a range of accumulation periods); (iii) it is relatively simple compared with other widely used indices such as the Palmer Drought Severity Index, PDSI (Palmer, 1965); and (iv) it is spatially constant, again unlike the PDSI. A number of potential disadvantages related to SPI have also been recognised, including: (i) the assumption that suitable probability distributions can be found to model the observed precipitation time series (Guttmann, 1999; Wu et al., 2007; Angelidis et al., 2012); (ii) the requirement for a long precipitation time series (Guttmann, 1999); (iii) the need for time series of consistent length where multiple sites are being evaluated and compared (Wu et al., 2005); and (iv) in regional analyses where the aim is to identify areas that may be more drought prone than others, extreme droughts measured by SPI will tend to occur with the same frequency at all locations as the timescale of analyses increases (Lloyd-Hughes and Saunders, 2002).

Despite these limitations, SPI has been used widely to characterise meteorological drought and has recently been recommended by the WMO as an index of choice to characterise meteorological droughts (WMO, 2012). Because of the perceived advantages of the SPI approach to drought characterisation, and as suggested by McKee et al. (1993) that it "could be applied in a similar manner to precipitation, snowpack, stream flow reservoir storage, soil moisture and ground water", the SPI methodology has also been applied in some modified or derived form to a variety of other hydrological time series to characterise aspects of hydrological droughts. Related SPI-like normalisation procedures have been applied to a variety of observed and/or modelled time series, for example, reservoir storage (Vincente-Serrano and Lopez-Moreno, 2005), runoff (Vincente-Serrano and Lopez-Moreno, 2005; Shukla and Wood, 2008; Lopez-Moreno et al., 2009; Vidal et al., 2010), soil moisture (Sheffield and Wood, 2008; Sheffield et al., 2009; Vidal et al., 2010, 2012), spring discharge (Fiorillo and Guadagno, 2010, 2012), groundwater detention (Mendicino et al., 2008) and pre- and post-monsoon groundwater levels (Bhuiyan et al., 2006). Most recently the SPI-like normalisation approach has been extended to include atmospheric water demand, i.e. the Standardised Precipitation-Evapotranspiration Index, SPEI (Vincente-Serrano et al., 2010; McEvoy et al., 2012).

If an appropriate normalisation procedure can be applied, groundwater levels at observation boreholes are a useful measure of the quantitative status of groundwater resources during a drought. In this paper, issues that have been previously identified related to the application of SPI-like normalisation methods to other hydrometric time series are explicitly addressed in the context of groundwater level data; furthermore, a methodology, building on the SPI approach, is presented that enables monthly groundwater level time series to be used as the basis for estimating a new Standardised Groundwater level Index (SGI). SGI is calculated for groundwater level hydrographs from 14 sites across the United Kingdom (UK), where sites have been selected from a range of aquifer types and to exhibit a range of hydrograph characteristics. The relationship between groundwater droughts, defined by SGI, and meteorological droughts, defined by SPI, at the study sites is investigated and quantified using correlation analysis. In particular, the relationships between "memory" in groundwater levels, as expressed by the autocorrelation structure of the SGI time series, and features of the associated SPI time series, specifically the correlation with precipitation accumulation periods or timescales, is explored. Groundwater droughts at the study sites are then identified and described and the influence of some possible hydrogeological explanatory factors on SGI is investigated. The paper is concluded with a critical assessment of the application of an SPI-like approach to groundwater drought characterisation and a brief discussion SGI in the context of existing and related hydrological drought indices.

2 Study sites and data

Groundwater level hydrographs from 14 sites across the UK have been used in the study. The sites are part of the UKs long-term observation borehole network (Marsh and Hannaford, 2008) and consist of a broad range of unconfined consolidated aquifer types (Bloomfield et al., 2009). The sites include those located on the Lincolnshire Limestone, a fractured limestone aquifer (Allen et al., 1997); the Chalk aquifer, a dual porosity, dual permeability carbonate aquifer with local karstic development (Bloomfield, 1996; Maurice et al., 2006); and the Permo–Triassic Sandstone and Lower Greensand aquifers (Allen et al., 1997; Bloomfield et al., 2001) where intergranular flow predominates. Figure 1 shows the location of the observation boreholes in relation to the major aquifers in the UK, and summary information about the sites and groundwater hydrographs is given in Table 1. All groundwater levels in Table 1 and subsequent figures are reported as metres above mean sea level. Note, the UK has no nationally important unconsolidated aquifers. Consequently, there are no long-term high-quality groundwater level monitoring records for such aquifers in the UK. The methodology presented in the following sections, however, is applicable to groundwater level time series from any aquifer type or setting.

Monthly groundwater level data for the study sites has been taken from the UK National Groundwater Level Archive (National Groundwater Level Archive, 2013). The monthly groundwater level records range in length from 29 to 103 yr. Figure 2 is a plot of the monthly groundwater level hydrographs for the 14 sites, where all hydrographs are drawn to the same scale. Precipitation data has been derived from two sources. From 1961 to the end of 2005, precipitation data is taken from the Centre for Ecology and Hydrology's CERF 1 km gridded precipitation data set (Keller et al., 2005; Dore et al., 2012). CERF gridded precipitation data is generated from rain gauge data held in the UK Met Office national precipitation monitoring network. A triangular planes methodology is used to produce a daily 1 km^2 grid based on a weighted average (inverse distance) of the three nearest rain gauges. Daily rainfall is then summed to give monthly gridded rainfall. Pre-1961 monthly precipitation data has been taken from the Meteorological Office Integrated Data Archive System, MIDAS (UK Meteorological Office, 2013). MIDAS has been searched for the closest rain gauge to the observation borehole of interest that has a relatively long and continuous time series that coincides with the period of groundwater level observations prior 1961. The equidistant quantile matching technique of Li et al. (2010) has then been applied to these records to remove bias associated with spatial differences and to maintain any nonstationarity in rainfall that might have occurred over time. The pre- and post-1961 rainfall records are combined to give a continuous precipitation record at each site. An example of a precipitation time series is given in Fig. 3. It shows one month of accumulated precipitation for Dalton Holme for the period of 1977 to end of 2005, plotted with the corresponding monthly groundwater level. Average annual precipitation varies between sites from 580 to 1100 mm (Table 1).

When normalised drought histories are compared quantitatively between sites, the normalisation should be applied to records of consistent length to avoid biases in the estimated indices. Where such quantitative analysis has been undertaken in the present study, the last 29 yr of monthly records

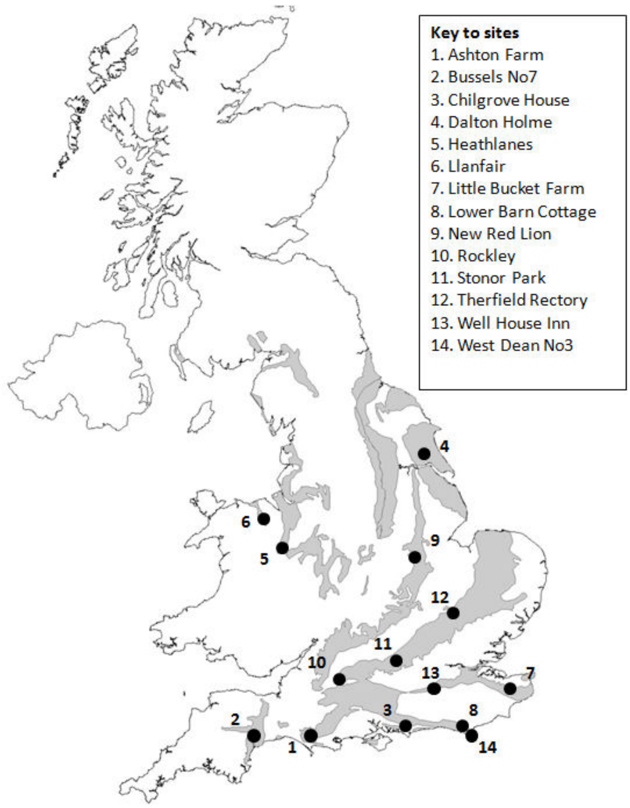

Fig. 1. Location of the observation boreholes in relation to the major aquifers in the UK.

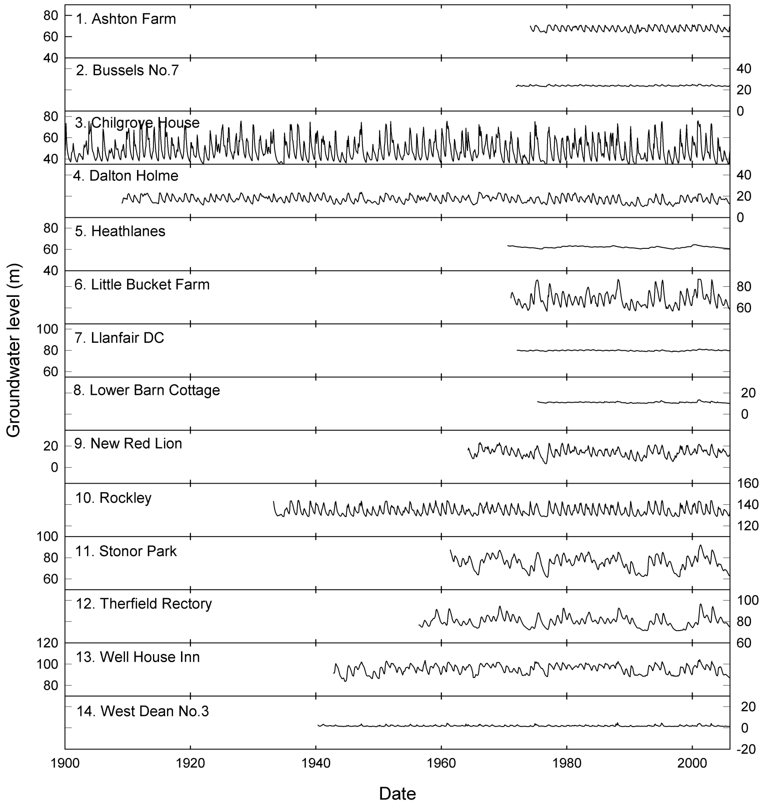

Fig. 2. Groundwater level hydrographs for the 14 study sites. Plots are for sites listed in Table 1 in alphabetical order from top to bottom.

common to all 14 sites, from the start of 1997 to the end of 2005, have been used.

3 Statistical methods

3.1 Development of a new Standardised Groundwater level Index (SGI)

The SPI was proposed by McKee et al. (1993) as an objective precipitation-based measure of the severity and duration of meteorological droughts. McKee et al. (1993) suggested that meteorological drought status could be described by a normally distributed index. The index was fitted to a time series of the recorded precipitation at a site for accumulation periods of 3, 6, 12, 24 and 48 months. The calculation of the SPI requires three steps. First a gamma distribution is fitted to the time series of accumulated precipitation observed at a particular site. The precipitation time series is denoted z_i for $i = 1, 2, \ldots, n$, where i is the number of months since the start of the time series and n is the total number of observations. For each $i = 1, 2, \ldots, n$, McKee et al. (1993) then used the fitted distribution to determine p_i, the probability that a value drawn at random from the fitted distribution was less than or equal to z_i. Finally, McKee et al. (1993) applied the inverse normal cumulative distribution function (with mean zero and variance one) to these p_i to yield a length n time series of SPI values denoted here as $\mathrm{SPI}_q(i)$, where q is the number of months over which rainfall is accumulated. The resulting SPI is a continuous variable, however, McKee et al. (1993) also arbitrarily defined drought intensity according to the SPI where they denoted $\mathrm{SPI} \leq -2$ corresponding to extreme drought, $-1.5 \geq \mathrm{SPI} > -2$ corresponding to severe drought, $-1.0 \geq \mathrm{SPI} > -1.5$ corresponding to moderate drought, $0 \geq \mathrm{SPI} > -1$ corresponding to minor drought and $\mathrm{SPI} > 0$ corresponding to no drought.

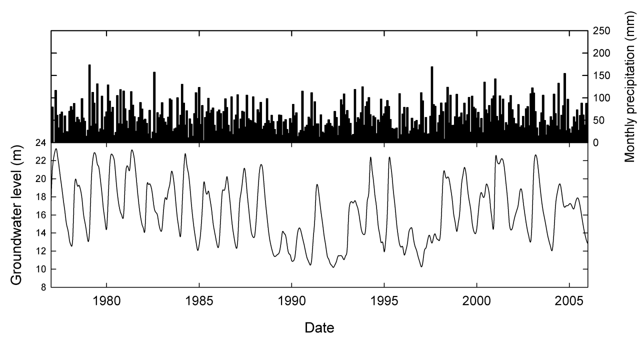

Fig. 3. Histogram showing monthly precipitation totals (one month aggregation) and corresponding monthly groundwater level hydrograph for Dalton Holme for the period of 1977 to end of 2005.

Table 1. Summary information for the 14 groundwater level hydrographs and associated rainfall data for each site.

Site	Aquifer (type)	Start of record	End of record	Mean annual precipitation (mm)	Well depth relative to soil surface (m)	Groundwater level (m a.s.l.)			Mean thickness unsaturated zone (m)	Transmissivity ($m^2\ day^{-1}$)	Storage coefficient	$\log_{10}$ hydraulic diffusivity
						Min.	Max.	Mean				
1. Ashton Farm	Chalk (fractured)	1 Mar 1974	1 Jan 2006	1010	11.70	63.13	71.46	67.55	4.57	210	0.003	4.85
2. Bussels No. 7	Permo–Trias Sandstone (granular)	1 Dec 1971	1 Jan 2006	800	91.44	22.91	25.28	23.89	3.07	95	0.10	2.98
3. Chilgrove House	Chalk (fractured)	1 Jan 1900	0 Jan 2006	950	62.03	33.46	76.24	48.89	28.28	500	0.002	5.40
4. Dalton Holme	Chalk (fractured)	1 Feb 1909	1 Jan 2006	740	28.50	10.19	23.76	17.15	17.38	1260	0.007	5.24
5. Heathlanes	Permo–Trias Sandstone (granular)	1 Aug 1970	1 Jan 2006	660	8.74	60.25	64.45	62.01	6.60	200	0.100	3.30
6. Little Bucket Farm	Chalk (fractured)	1 Jan 1973	1 Jan 2006	820	31.33	56.77	86.94	68.35	18.94	720	0.003	5.38
7. Llanfair DC	Permo–Trias Sandstone (granular)	1 Feb 1972	1 Jan 2006	820	121.90	78.67	81.18	79.83	3.23	130	0.10	3.11
8. Lower Barn Cottage	Lower Greensand (granular)	1 Apr 1977	1 Jan 2006	840	8.25	10.14	13.49	11.06	6.95	1000	0.02	4.70
9. New Red Lion	Lincolnshire Limestone (fractured)	1 Sep 1964	1 Jan 2006	610	50.00	3.37	23.35	14.08	19.39	2750	0.05	4.74
10. Rockley	Chalk (fractured)	1 Mar 1935	1 Jan 2006	810	17.60	128.65	143.87	134.52	12.06	620	0.006	5.01
11. Stonor Park	Chalk (fractured)	1 Jun 1961	1 Jan 2006	800	87.50	61.55	92.05	75.51	45.91	820	0.004	5.31
12. Therfield Rectory	Chalk (fractured)	1 Jun 1956	1 Jan 2006	580	83.23	71.50	96.53	80.37	74.55	670	0.004	5.22
13. Well Hose Inn	Chalk (fractured)	1 Nov 1942	1 Jan 2006	820	50.60	83.54	104.19	95.36	37.00	720	0.003	5.38
14. West Dean No. 3	Chalk (fractured)	1 May 1940	1 Jan 2006	810	24.99	1.06	4.85	1.84	11.65	500	0.002	5.40

Groundwater level is a continuous variable and there is no need to accumulate it over a specified time period, however, like many other hydrological time series the distributions of monthly observed groundwater levels may not conform to a gamma distribution. In addition to the gamma distribution, a range of other distributions (including those related to the gamma distribution) have been used to normalise hydrological time series, for example, Pearson Type III (Guttmann, 1999), beta distributions (Sheffield et al., 2004; Sheffield and Wood, 2008), the log-logistic distribution (Vincente-Serrano et al., 2010; McEvoy et al., 2012), and log-normal and normal distributions (Angelidis et al., 2012). However, groundwater level time series appear to be particularly irregular in the form of their distribution of monthly groundwater levels. For example, Fig. 4 (left panels) shows four histograms of observed groundwater levels for particular calendar months at four of the study sites – (a) Chilgrove House in November, (c) New Red Lion in April, (e) Therfield Rectory in May and (g) West Dean No. 3 in June. The four histograms differ in the sign and magnitude of their skewness. Therefore, distribution functions or alternative normalisation procedures which can represent more general behaviour than the gamma distribution are required to model variations in the form of monthly distributions of groundwater levels.

We initially fitted normal, log-normal, gamma and extreme-value distributions to the monthly groundwater levels at each site by maximum likelihood (MATLAB, 2012). These distributions were selected because they can accommodate all magnitudes of non-negative skewness from zero to severe. Negative skewness was accommodated by applying a shift $z_i^* = c - z_i$ for constant c to the data prior to fitting the distribution. Figure 4 (left panels) shows the best-fitting distribution functions according to the Akaike information criterion (Akaike, 1973) for the four example histograms and the corresponding plots on the right show the resulting SGI. The best-fitting distribution function is different in each case. For Chilgrove House in November it is the gamma distribution. For New Red Lion in April it is the negatively skewed extreme value distribution and for Therfield Rectory in May and West Dean No. 3 in June it is the log-normal and extreme value distributions respectively. Figure 4 (right panels) shows that the quality of the computed SGIs also appears to vary in regards to how well the estimated values of SGI correspond to the normal distribution of zero mean and standard deviation of one. The quality of the estimated values of SGI for all months at all 14 sites have been estimated by applying the Kolmogorv–Smirnov test for normality (Everitt, 2002). The results are highly variable, with one distribution of SGI, for Chilgrove House in November, failing the Kolmogorov-Smirnov (K-S) test at the $p = 0.05$ level. Given the variation in the degree to which these SGI estimated from parametric models conform to the normal distribution it is doubtful whether they can be objectively compared.

An alternative approach to fitting standardised distributions is to use some form of non-parametric fitting. This approach has previously been applied, for example by Osti et al. (2008) who used a plotting position method to estimate a standardised precipitation, and Vidal et al. (2010) who used a non-parametric kernel density fitting routine to estimate a normalised soil wetness index. Here we apply the normal scores transform (Everitt, 2002). This is a non-parametric normalisation of data that assigns a value to observations, in this case monthly groundwater levels, based on their rank within a data set, in this case groundwater levels for a given month from a given hydrograph (note, this normalisation routine is equally applicable to timescales larger than one month). The normal scores transform is undertaken by applying the inverse normal cumulative distribution function to n equally spaced p_i values ranging from $1/(2n)$ to $1 - 1/(2n)$. The values that result are the SGI values. They are then re-ordered such that the largest SGI value is assigned to the i for which p_i is largest, the second largest SGI value is assigned to the i for which p_i is second largest and so on. The SGI distribution which results from this transform will always pass the K-S normality test.

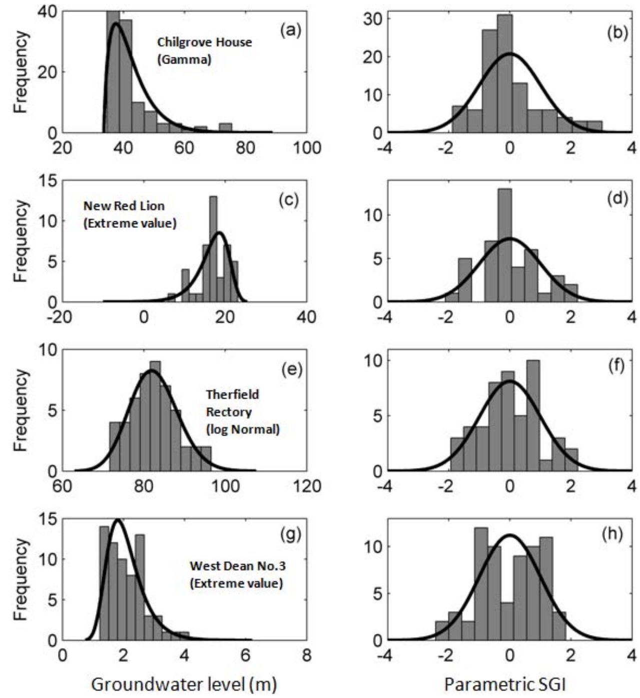

Fig. 4. Examples of histograms of groundwater levels and best fitting parametric distributions **(a, c, e, g)**, and corresponding histograms of normalised values and standardised normal distribution for groundwater level data **(b, d, f, h)** for Chilgrove House in November, New Red Lion in April, Therfield Rectory in May, and West Dean No. 3 in June.

In some statistical applications it is undesirable to use a normal scores transform because the model is overfitted. This means that the model matches the particular intricacies of the existing observed data to a degree that will not be achieved on independently gathered observations of the same property.

This could mean that the uncertainty of a prediction of the property at a time when it was not measured is underestimated. However, we wish to use the normal scores data to describe existing observations rather than to predict values. Therefore, we need not be concerned by overfitting even if it is present for some of the normal scores transforms.

In summary, for each of the 14 study sites, normalised indices are estimated from the groundwater level data for each calendar month using the normal scores transform. These normalised indices are then merged to form a continuous SGI. At each site, SPI is estimated with accumulation periods of $1, 2, \ldots, 24$ months. To ensure consistency between groundwater and precipitation indices SPIs are also estimated using the normal scores transform applied to accumulated precipitation data for each calendar month.

3.2 Methods used to analyse SGI, correlations with SPI and hydrogeological factors influencing the drought indices

In order to quantify groundwater droughts using the SGI, we are interested in characterising the autocorrelation in SGI time series taken to be an intrinsic characteristic of the SGI for a given site. Autocorrelation can be quantified using a correlogram (Diggle, 1990). If we denote the mean SGI for the borehole by $\overline{\mathrm{SGI}}$ then the k th sample autocovariance coefficient is defined to be

$$g_k = \frac{1}{n}\sum_{i=k+1}^{n}\left\{\mathrm{SGI}(i) - \overline{\mathrm{SGI}}\right\}\left\{\mathrm{SGI}(i-k) - \overline{\mathrm{SGI}}\right\} \quad (1)$$

and the k th sample autocorrelation coefficient is

$$r_k = \frac{g_k}{g_0}. \quad (2)$$

The correlogram is a plot of r_k against k. If there is no correlation between the SGI(i) observed k months apart and if the SGI values are normally distributed then r_k is approximately normally distributed with mean zero and variance $1/n$. Therefore, values of r_k with magnitude greater than $2/\sqrt{n}$ suggest significant correlation at approximately the 5 % level. We define the range of significant temporal correlation of a SGI time series to be the largest m, $m_{\max}$, for which $r_k > 2/\sqrt{n}$ for all $k \leq m$. The threshold on the autocorrelation coefficients which signifies significant correlation will vary according to the length of the time series. Since we wish to use a common threshold for all of our SGI series to enable comparison between sites, we have selected 0.11 as the SGI autocorrelation threshold, t_{SGI}, since this is the significant threshold ($p = 0.05$) for our shortest SGI time series (for Lower Barn Cottage with a record length of 29 yr). We note that the choice of the significant autocorrelation threshold is subjective and is based on the criteria that it should be (i) common and applicable to all sites; (ii) that it should be sufficiently large to avoid being influenced by noise in autocorrelation at low thresholds; and (iii) that it should capture long, significant correlations. The effect of changing the threshold on $m_{\max}$ was explored and it was found, for example, that raising the threshold to 0.15 led to slightly lower values of $m_{\max}$, while thresholds below 0.11 were unduly influenced by noise in the correlograms.

In addition, linear correlation coefficients have also been calculated to quantify relationships between SGI and SPI, and between $m_{\max}$ and possible explanatory variables. These explanatory variables, including unsaturated zone thickness, aquifer transmissivity (T), storage coefficients (S) and hydraulic diffusivity (T/S) have been estimated for each site and are listed in Table 1. Note that no pumping test data is available for any of the study sites, so T and S values are estimates based on mean values derived from pumping tests for a given region and aquifer combination as reported by Allen et al. (1997). An exception is that unconfined storage coefficients for sites on the Permo–Triassic sandstone aquifer are estimated to be 0.1 (also after Allen et al., 1997). This is because, as Allen et al. (1997) note, estimates of S from short-term pumping tests on this aquifer typically significantly underestimate long-term storage and a value of 0.1 for S has been taken as the optimal value for long-term storage.

4 Results

4.1 Estimated SGI and SPI

Estimated monthly SGI for each of the 14 study sites are given in Fig. 5. In the present study SPI has been estimated for $q = 1, 2, \ldots, 24$ months. However, SPI is usually only calculated and reported for selected accumulation periods. So for simplicity and to illustrate how SPI varies with q at one of the study sites, Fig. 6 shows SPI for Dalton Holme for $q = 1, 3, 6, 12$ and 24 months. Figure 6 also includes the SGI time series for Dalton Holme for comparison with the SPI time series.

Compared with the raw groundwater level data (Fig. 2), the SGI data does not contain a strong seasonal component and, unlike the groundwater level time series, the SGI time series (Fig. 5) shows many similar broadscale structures across all the sites. For example, all sites show generally low values of SGI in the early 1990s, with SGI increasing in the mid-1990s and then decreasing again in the late 1990s. There are, however, differences in the short-range variation in SGI between sites. For example, the SGI for Ashton Farm, Chilgrove House and West Dean No. 3 appear to be considerably noisier than Therfield Rectory, Stonor Park or Llanfair DC. This reflects differences in the structure of the SGI autocorrelation between the sites. Figure 7 (middle panels) shows plots of SGI autocorrelation as a function of lag in months (solid lines) for three example sites, Ashton Farm, Dalton Holme and Llanfair DC, with contrasting autocorrelation. Using the SGI autocorrelation threshold, t_{SGI}, of 0.11

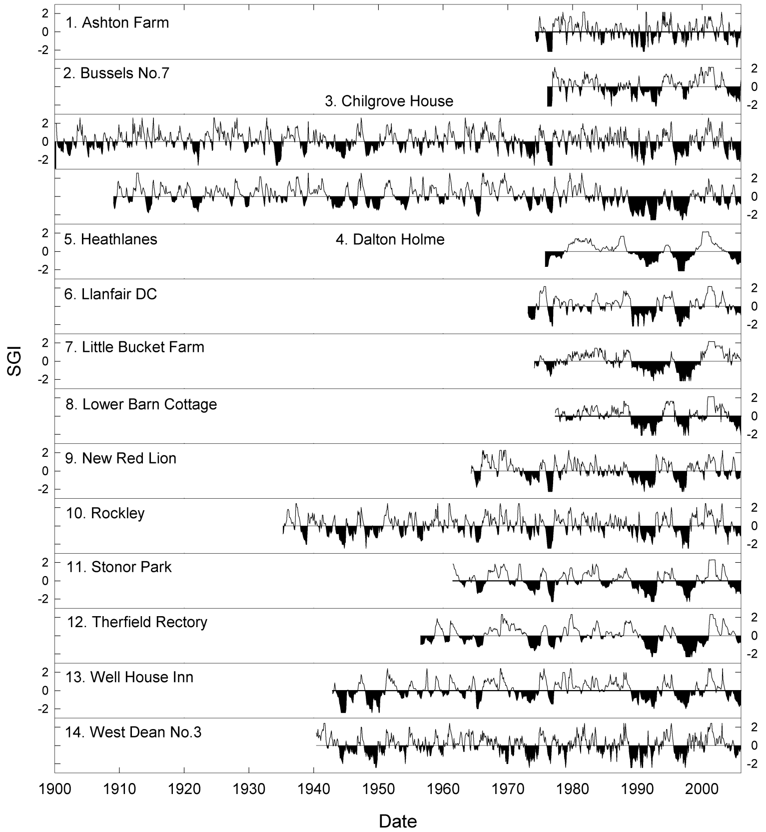

Fig. 5. Calculated time series of SGI for the 14 sites. Plots are for sites listed in Table 1 in alphabetical order from top to bottom. Episodes of groundwater drought are shown in black and denoted by negative values of SGI.

(the dashed line in the figure), the SGI autocorrelation range ($m_{\max}$) for each of the sites has been estimated and is given in Table 2. Table 2 shows that significant temporal autocorrelation in SGI, $m_{\max}$, varies between sites, from as little as 5 months at Ashton Farm up to 32 months at Llanfair DC.

As has been noted by McKee et al. (1993) and in previous studies (e.g. Vincente-Serrano and Lopez-Moreno, 2005), the degree of noise or short-range variation in SPI varies as a function of the precipitation accumulation period. This is also seen in the present study. For example, the SPI for Dalton Holme is relatively noisy for $q = 1$ compared with SGI (Fig. 6), and Fig. 7a–c show the very short autocorrelation range for SPI ($q = 1$) at the three example sites. However, SPI becomes smoother and less noisy and long-range correlations become more prominent as precipitation accumulation periods increase (Fig. 6).

4.2 Correlation between SGI and SPI

The cross-correlation between SGI and SPI for SPI accumulation periods of $q = 1, 2, \ldots, 24$ has been computed and is shown for three representative sites in Fig. 7g–i. At each site a maximum correlation can be identified and is denoted by an X in these plots. A corresponding accumulation period, shown by the vertical arrow below each of the cross-correlation curves, can also be identified in these plots. Previous studies of drought propagation have distinguished four components in the propagation of drought: pooling, attenuation, lag and lengthening (Chagnon Jr., 1987; Peters, 2003; Peters et al., 2003; van Loon and van Lanen, 2012; van Loon, 2013). Here we are interested in understanding the full spectrum of behaviour of lag correlation between SPI and SGI. So for all sites the cross-correlation between SGI and SPI has been estimated for SPI accumulation periods of $q = 1, 2, \ldots, 24$ months and for lags between SGI and SPI of one month increments up to 24 months. (Note that the lag in the bottom panels of Fig. 7 is the temporal shift between the SPI and SGI time series, whereas the lag referred to in the discussion of the SGI and SPI correlograms, in the upper and middle panels of Fig. 7, is the time separating two observations in each series.) The resulting cross-correlations are presented in the form of a heat map, Fig. 8, where dark blue tones denote weaker correlations and dark red tones denote stronger correlations, and where the maximum correlation is marked by the black square.

Figure 8 illustrates the strong site specific relationship of correlations between the SPI precipitation accumulation period, q, and lags between SGI and SPI. Generally the

Table 2. Value of the maximum cross-correlation between SPI and SGI, SGI autocorrelation range (m_{max}), the accumulation period associated with maximum cross-correlation between SPI and SGI (q_{max}), the lag associated with maximum cross-correlation between SPI and SGI (lag_{max}), and maximum and median drought duration at each site. Values in parentheses are based on a 29 yr record from 1977 to end of 2005 and are used in Fig. 12.

Site	Maximum cross-correlation	m_{max} (months)	q_{max} (months)	lag_{max} (months)	Maximum drought duration (months)	Median drought duration (months)
1. Ashton Farm	0.72	5 (5)	6	0	12 (12)	3.5 (4)
2. Bussels No. 7	0.83	19 (20)	9	0	41 (41)	3 (3)
3. Chilgrove House	0.74	9 (11)	6	0	31 (32)	3 (2)
4. Dalton Holme	0.76	12 (50)	10	0	65 (54)	5 (4)
5. Heathlanes	0.74	24 (24)	28	0	64 (69)	2.5 (2.5)
6. Little Bucket Farm	0.87	11 (15)	10	1	47 (47)	4 (4)
7. Llanfair DC	0.79	32 (33)	25	0	72 (73)	3 (4)
8. Lower Barn Cottage	0.81	18 (18)	15	0	59 (59)	2 (2)
9. New Red Lion	0.83	20 (17)	8	0	53 (53)	3 (2.5)
10. Rockley	0.74	8 (19)	7	0	32 (32)	4 (3.5)
11. Stonor park	0.79	15 (20)	21	1	48 (48)	6 (4.5)
12. Therfield Rectory	0.77	20 (21)	21	2	61 (62)	9 (7)
13. Well Hose Inn	0.78	14 (26)	12	0	49 (50)	10 (3.5)
14. West Dean No. 3	0.70	12 (15)	7	0	23 (25)	2 (2)

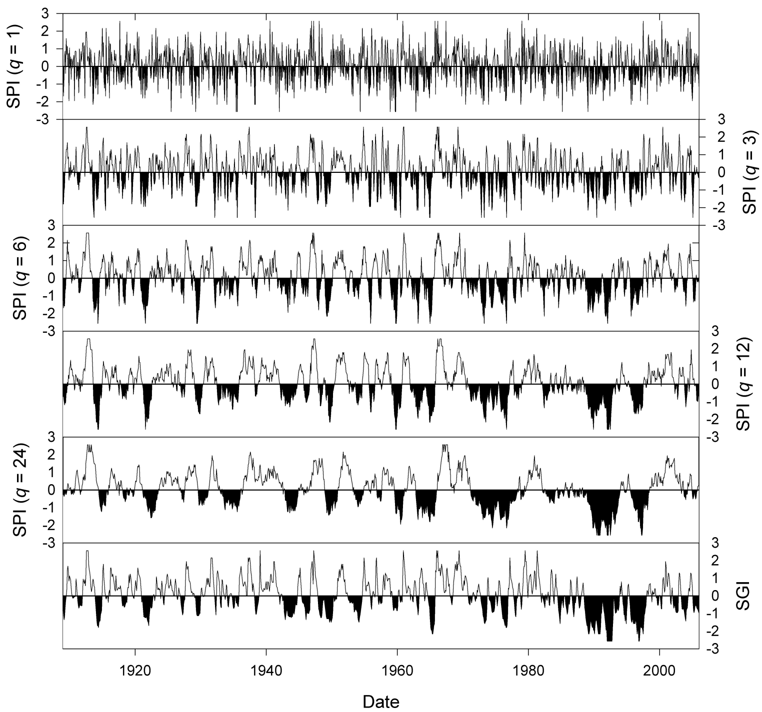

Fig. 6. SPI for Dalton Holme for accumulation periods $q = 1$, 3, 6, 12 and 24 (top five panels) and corresponding SGI (bottom panel). Episodes of drought are shown in black and are denoted by negative values of SGI and SPI.

maximum correlation is associated with lag zero between SGI and SPI. The exceptions to this being at Little Bucket Farm, Therfield Rectory and Stonor where the maximum correlation is associated with lags of 1, 1, and 2 months, respectively. Table 2 lists the values of the maximum cross-correlation between SGI and SPI, as well as the associated accumulation period, q_{max}, and lag between SGI and SPI. The maximum cross-correlation coefficients between SGI and SPI are typically in the range of 0.7 to 0.87, Table 2, with the highest coefficient of 0.87 associated with the

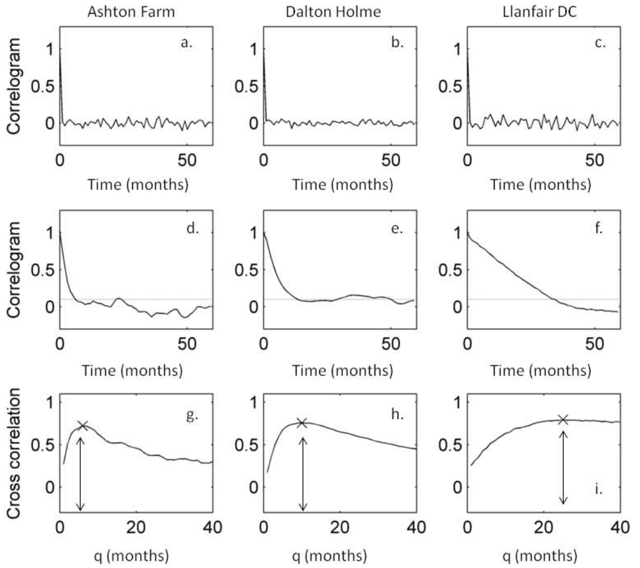

Fig. 7. (a)–(c) SPI correlograms for Ashton Farm (left panels), Dalton Holme (centre panels) and Llanfair (right panels), **(d)–(f)** SGI correlograms for the corresponding sites, where the dashed line is the SGI autocorrelation threshold, t_{SGI}, and **(g)–(i)** plots of cross-correlation between SGI and SPI as a function of SPI accumulation period in months for the corresponding sites. The maximum correlation between SGI and SPI is denoted by a cross on the curve and an associated value of q can be identified, denoted by the vertical arrows below the curves.

site at Little Bucket Farm and the lowest coefficients of 0.7 associated with the site at West Dean No. 3 – both sites being on the Chalk aquifer. Despite the site specific nature of correlations between SPI precipitation accumulation period and lags between SGI and SPI, plots of SGI as a function of SPI q_{max} show that for all sites there is a linear relationship between the two drought indices (Fig. 9).

When q_{max} is plotted against m_{max} (Fig. 10), there is an approximate one-to-one relationship with a correlation coefficient of 0.79 that is significant for $p < 0.001$. Figure 10 shows that although the SPI accumulation period associated with the maximum cross-correlations, q_{max}, and the SGI autocorrelation range, m_{max}, both vary between sites they broadly increase in the same order for the study sites. Possible relationships between m_{max} and other drought and hydrological characteristics are presented and discussed in Sects. 4.4 and 4.5.

4.3 Groundwater droughts as defined by SGI

When a new drought index is developed it is often compared against reported droughts in an attempt to qualitatively "validate" the new index. However, this is not a trivial task since most reported droughts are described in terms of their impacts, using a particular type or class of drought index, which is representative of only a certain hydrological domain that may or may not be an appropriate comparator. A number of previous studies have documented major drought episodes in the UK including studies of hydrological impacts (Cole and Marsh, 2006; Marsh et al., 2007; Lloyd-Hughes et al., 2010) and societal impacts (Taylor et al., 2009). Of these, Marsh et al. (2007) is the most pertinent with respect to the present study in that Marsh et al. (2007) identified major drought episodes on the basis of inspection of long river flow, groundwater level, and ranked rainfall deficiency time series and explicitly identified those episodes with a significant groundwater component. Marsh et al. (2007) identified seven episodes of major droughts in England and Wales during the period covered by the groundwater level records investigated in the present study. They noted that all the droughts had large geographical footprints extending over much of England and Wales and in some cases affecting the whole of the UK, but that regional variations in drought intensities are present within and between the major drought events. Of these major droughts, they estimated that all but one had sustained and/or severe impacts on groundwater levels. Marsh et al. (2007) also noted that a number of the droughts were characterised by transitions from initial surface water stress to lowered groundwater heads at the national and regional scales. Table 3 (after Marsh et al., 2007 and National River Flow Archive, 2013) summarises the major droughts in England from 1900 to the end of 2005, the period covered by the groundwater level records used in the present study, and includes a brief commentary after Marsh et al. (2007) on the individual drought characteristics.

Figure 11 is a re-presentation of the SGI data from Fig. 5 as three heat maps, where non-drought periods, $SGI > 0$, are shown in grey, and drought periods, $SGI < 0$, are shown in shades of yellow through to red with decreasing SGI (i.e. with increasing drought intensity). Given that record length can influence SGI estimates (Lloyd-Hughes and Saunders, 2002) Fig. 11a and b show SGI estimated using the entire record for each site as well as SGI estimated just for the last common 29 yr period (Fig. 11c). Although there are small differences between SGI estimated using the whole record and the more limited 29 yr records, both sets of SGI estimates consistently show the development of similar patterns in groundwater drought across the sites and the following is a description of the full SGI drought records. Figure 11 is consistent with the observations of Marsh et al. (2007) that the UK has experienced a number of major groundwater droughts. In particular, the droughts of 1976, 1990 to 1992, and 1995 to 1997 are clearly expressed by the SGI records at the majority of sites. Groundwater droughts prior to the early 1970s are less easy to discern as there are fewer records, however, the following specific observations can be made:

- there is some evidence from the Chilgrove House record for short drought episodes between 1900 and 1910 as part of the 1890–1910 "Long Drought";

Table 3. Summary of the major droughts in England from 1900 to 2006 (after Marsh et al., 2007 and National River Flow Archive, 2013).

Period	Drought characteristics
1890 to 1910	Known as the "Long drought". A major drought with major and sustained groundwater impacts including more intense phases in 1902 and 1905
1921 to 1922	Severe drought across East Anglia and SE England, but only episodic in NW England
1933 to 1934	Intense drought across southern England. Major surface water impacts in 1933 with groundwater impacts in 1934
1959	Three season drought that was most severe in eastern, central and NE England, but only modest groundwater impacts
1976	Benchmark drought in UK. Severe impacts on river flow and groundwater across UK
1990 to 1992	Major drought leading to exceptionally low groundwater levels in summer 1992, with probably lowest for at least 90 yr
1995 to 1997	Long duration drought with intense episodes. Initial surface water stress followed by very depressed groundwater levels particularly associated with hot summer in 1995

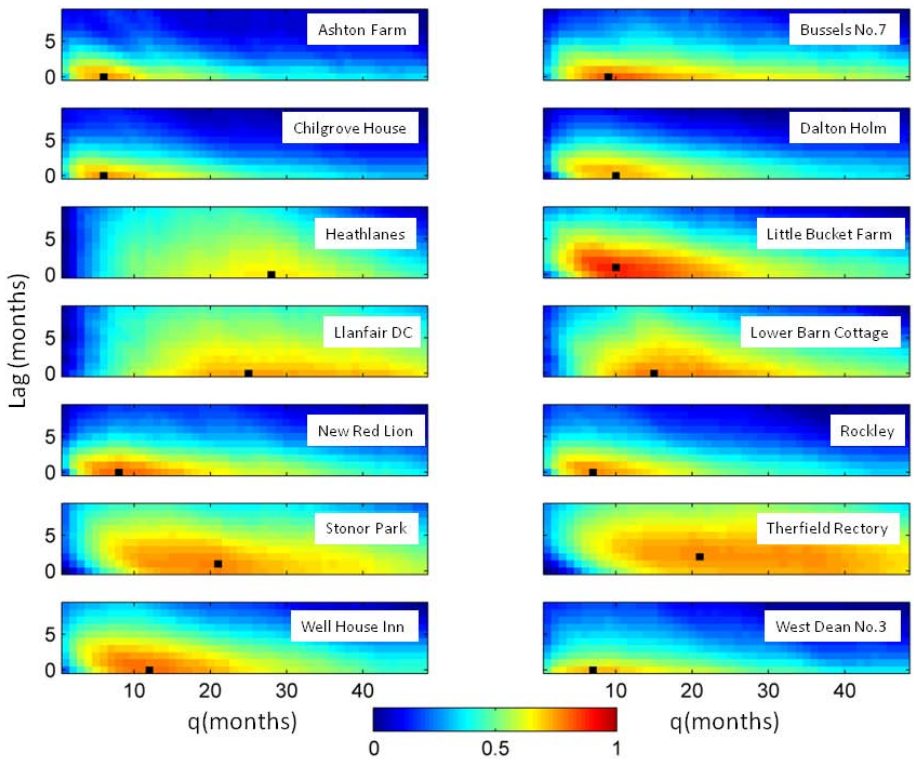

Fig. 8. Heat map of showing the variation in cross-correlation co-efficient between SGI and SPI as a function of SPI precipitation accumulation period, q, and lag between SGI and SPI time series. The maximum correlation for each accumulation period is highlighted (black cell).

– the 1921–1922 drought episodes appear in the SGI records at both Chilgrove House, and Dalton Holme;

– the 1933–1934 drought episode appears prominently in the SGI records at Chilgrove House, but is absent from the record at Dalton Holme suggesting that it may have been less significant in the northern part of the region;

– there is no evidence in the SGI data to support a significant groundwater component to the 1959 drought episode, however, this is consistent with the observation of Marsh et al. (2007) that this drought had modest groundwater impact; and, in addition, the SGI records indicate that groundwater drought conditions not previously identified by Marsh et al. (2007) were

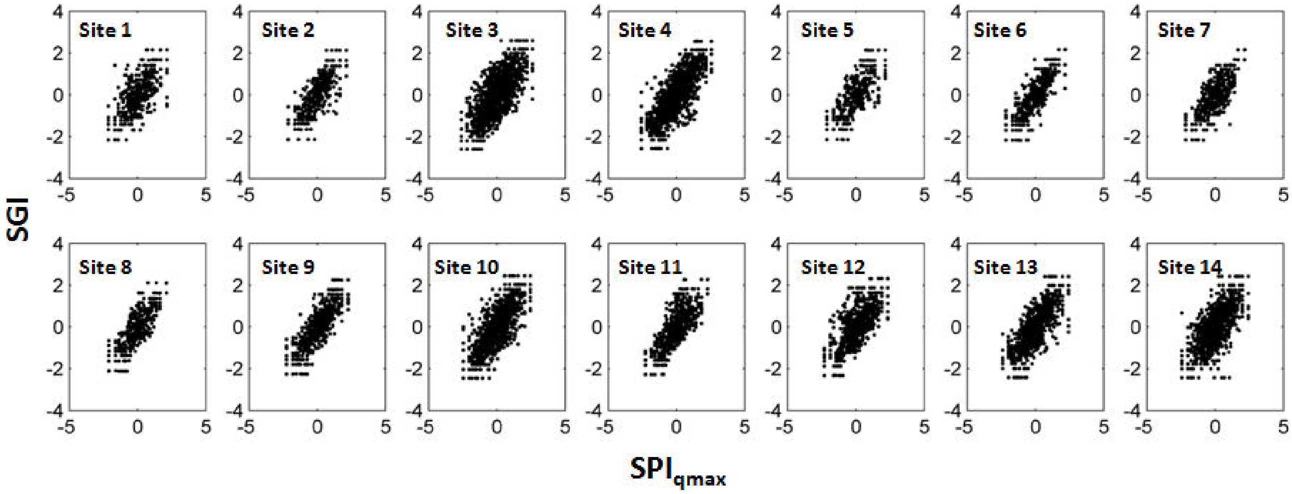

Fig. 9. SGI as a function of SPI $q_{\max}$ for each site. The plots are for sites listed in Table 1 in alphabetical order from top left to bottom right.

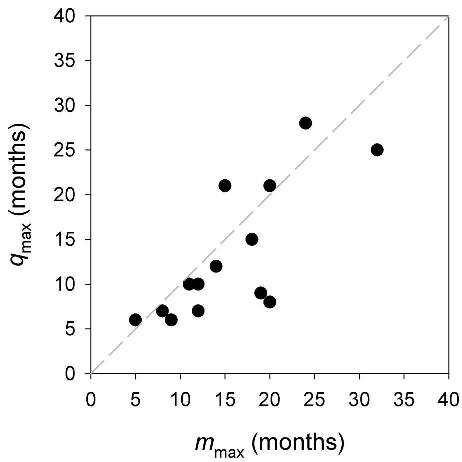

Fig. 10. Plot of the SPI precipitation accumulation period, $q_{\max}$, against autocorrelation range, $m_{\max}$, associated with the maximum cross-correlation between SGI and SPI for all study sites. A 1 : 1 line is shown for reference. Note the sites at Dalton Holme and Little Bucket Farm have identical positions in this plot.

experienced at a number of sites during the mid-1960s the mid- and late 1940s.

Based on these observations, SGI appears to record groundwater drought response to hydro-meteorological droughts previously documented by Marsh et al. (2007) as well as adding apparent refinements to the drought history. Figure 11 is also consistent with the assertion of Marsh et al. (2007) that many of the hydrometric droughts in England and Wales have a wide geographic impact. Sites at the geographical extent of the study area, such as Dalton Holme in the northeast, Llanfair DC in the northwest, Bussels No. 7 in the southwest, and Little Bucket Farm in the southeast, all record drought events in the form of anomalously low SGI values for the droughts of 1976, 1990 to 1992 and 1995 to 1997.

In summary, based on the good correlations between SGI and SPI and the consistency between documented groundwater droughts and the SGI time series, it is inferred that SGI is a robust index of groundwater drought.

Given the potential significance of SGI autocorrelation for groundwater droughts, we are interested in investigating generic hydrogeological controls on $m_{\max}$ and characterising the relationship between $m_{\max}$ and features of the drought record, such as drought duration. Marsh et al. (2007) have previously noted that all the major droughts that they described had large geographical footprints. So in the following sections we assume that, as a first-order approximation, the broad meteorological drought history of the study sites is spatially homogeneous. This assumption means that any comparative differences in drought characteristics between sites would need to be explained in terms of intrinsic differences in the SGI time series, rather than differences in the drought climatology. The assumption is supported by the findings of recent studies of the spatial coherence of hydrological droughts in the UK (Hannaford et al., 2011; Fleig et al., 2011) that indicate that the current study sites fall within a homogeneous drought region ("region 4" of Hannaford et al., 2011, and "region GB3" of Fleig et al., 2011).

4.4 The relationship between $m_{\max}$ and drought duration

SGI autocorrelation range, $m_{\max}$, varies significantly between sites (Table 2), but given that one of the purposes of developing a groundwater drought index is to compare standardised measures of drought between sites, what are the implications, if any, of this observation? For example, it may be expected that the autocorrelation structure of SGI will influence the length of groundwater droughts recorded

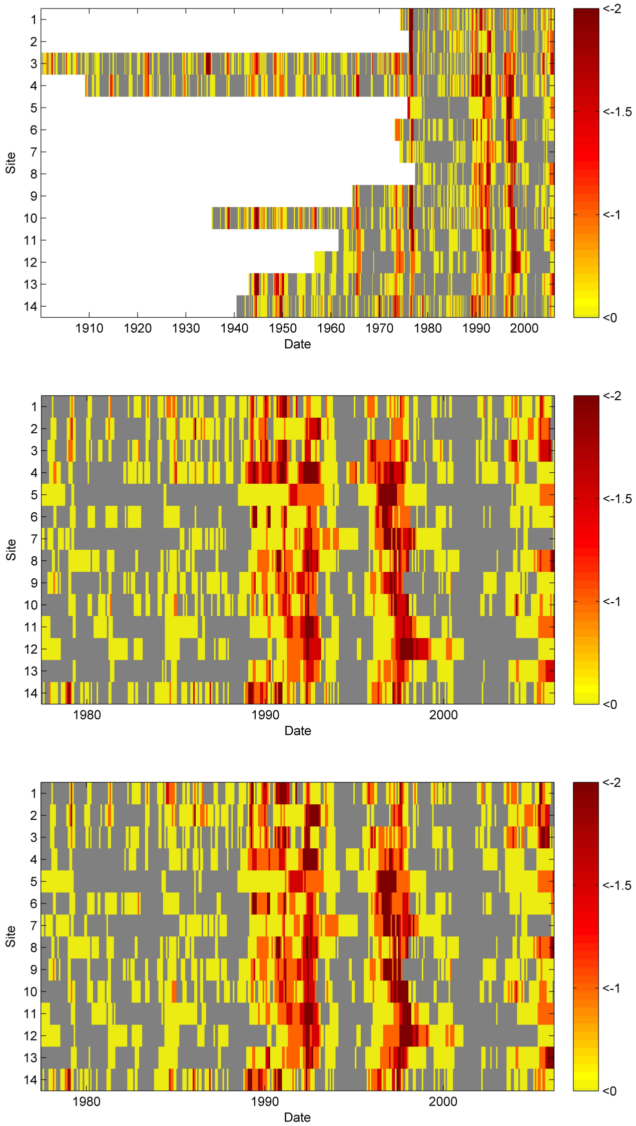

Fig. 11. (a) Monthly values of SGI for the 14 sites as heat map using for the full records, **(b)** SGI estimated using the full records, but just showing the last 29 yr of the records, and **(c)** SGI estimated only using the last 29 yr of the records. Sites are listed in Table 1 in alphabetical order from top to bottom. SGI is colour coded from 0 to −2, periods of positive SGI equating to non-drought conditions are in grey.

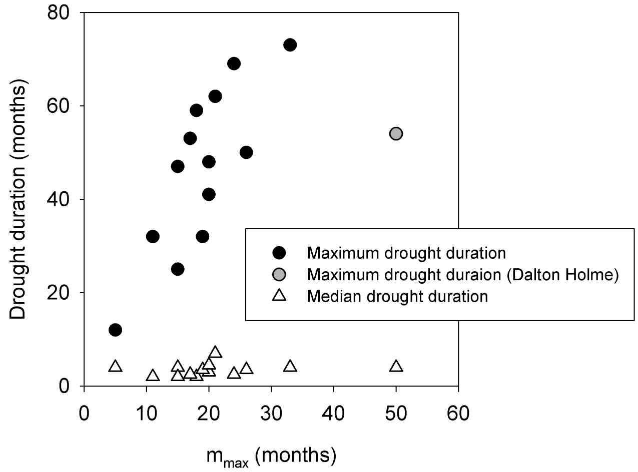

Fig. 12. Maximum and median drought durations, based on the 29 yr record from 1977 to 2006, as a function of m_{max}. The maximum drought duration at Dalton Holme is an outlier and is plotted separately.

at a given site, where sites with relatively long SGI autocorrelations might experience a limited number of relatively long droughts and sites with relatively short significant SGI autocorrelations may experience more numerous but briefer episodes of groundwater drought. How does m_{max} influence temporal patterns of groundwater drought at a site?

To investigate the effect of autocorrelation in SGI on groundwater drought, we assume, as described above, that as a first-order approximation the broad meteorological drought history of the study sites is spatially homogeneous and investigate how drought duration defined by SGI varies between sites as a function of m_{max}. Lloyd-Hughes and Saunders (2002), Wu et al. (2005) and Vidal et al. (2010, 2012) and have all emphasised the importance of consistent record lengths when making quantitative comparisons of drought characteristics based on drought indices for different sites. Consequently, using the common 29 yr SGI time series presented in Fig. 11c, simple measures of drought duration (i.e. median and maximum duration) have been estimated for each site. Here drought duration is taken to be a period where monthly SGI is continuously negative at a site, similar to the SPI classification of McKee et al. (1993).

Median and maximum drought durations are given in Table 2 (durations in parenthesis are for the common 29 yr period). Median durations range from 2 months at Chigrove House to 7 months at Thirfield Rectory, and maximum durations range from 12 months at Ashton Farm to 73 months at Llanfair DC. Figure 12 shows that based on the common 29 yr SGI record, the median drought duration appears to be insensitive to m_{max} (correlation coefficient 0.12). However, as postulated, maximum drought duration is positively linearly correlated with m_{max} with a correlation coefficient 0.81 (if the anomalous m_{max} for Dalton Holme is excluded). When the 29 yr 1977–2005 Dalton Holme record is analysed the autocorrelation estimated appears to be anomalously long, 50 months. This is due to the temporal proximity of two deep, prolonged drought episodes in that region (i.e. the 1989–1992 and the 1996–1997 droughts, combined with the relatively short record length of 29 yr). It should be noted though that although the converse is true, that sites with short m_{max} generally have shorter maximum drought durations, such sites may still respond to and record major drought episodes. For example, Ashton Farm and Chilgrove House, which have two of the shortest $m_{\max}$ (5 and 11 months respectively, based on the 29 yr record), both had low values of SGI during the 1990–1992 drought event (Fig. 11c), though these were interspersed by months with positive, non-drought, values of SGI.

4.5 Evidence for hydrogeological controls on $m_{\max}$

In order to use SGI to characterise groundwater droughts, and given the apparent association between drought duration and $m_{\max}$, it would be helpful to understand the potential hydrogeological controls on SGI autocorrelation. Tallaksen and van Lanen (2004) describe possible sources of persistence in droughts and emphasise the important role of recharge processes and groundwater storage in generating autocorrelation or memory in groundwater level time series. Here two basic potential sources of autocorrelation in SGI have been investigated. The first potential source of autocorrelation in SGI is that it arises primarily from autocorrelation in the recharge signal. Precipitation has relatively short significant autocorrelation, as reflected in the comparative SGI and SPI autocorrelation plots (Fig. 7, top panels). When the precipitation signal passes through the unsaturated zone, higher frequency components of the signal may be degraded or filtered out so that when recharge occurs at the groundwater table the recharge signal may have a longer autocorrelation. The second possible cause of autocorrelation in SGI may be associated with saturated storage and drainage processes in the aquifer. It can be postulated that aquifers that are relatively transmissive and/or have relatively low storage may dissipate pulses of recharge more quickly than those with relatively low transmissivity and/or high storage and, as may be expected, exhibit relatively short SGI autocorrelations and vice versa.

To investigate these potential causes of SGI autocorrelation a simple approach has been adopted that uses readily available information to explore relationships between $m_{\max}$ and two different possible explanatory variables. Estimates of mean unsaturated zone thickness, U, is taken as a surrogate for the potential influence of recharge-related process on $m_{\max}$. In addition, estimates of aquifer properties transmissivity (T) and storativity (S) have been used to estimate hydraulic diffusivity, D (T/S), at each site, where D is taken to be a surrogate for the potential influence of intrinsic saturated aquifer properties on $m_{\max}$. Plots of U and $\log D$ against $m_{\max}$ are given in Fig. 13a and b, respectively. Based on values estimated using the full record, $m_{\max}$, U and D are taken to be intrinsic characteristics of each groundwater hydrographs and the aquifer at each site and are therefore best described using the full records despite their disparate lengths.

For a number of sites, predominantly fractured aquifers such as the Chalk and Lincolnshire Limestone aquifers, there is a positive relationship between mean unsaturated zone thickness and $m_{\max}$, although no such relationship appears to hold for the granular aquifers, the Permo–Triassic sandstones

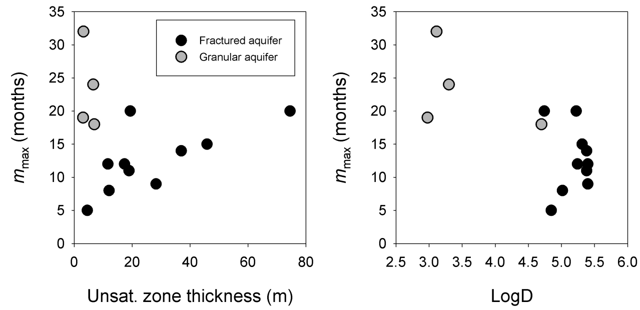

Fig. 13. $m_{\max}$ as a function of **(a)** unsaturated zone thickness and **(b)** log-hydraulic diffusivity (logD).

and the Lower Greensand aquifers (Fig. 13a). This appears to support the hypothesis that, at many of the Chalk and Lincolnshire Limestone sites at least, the origin of relatively long SGI autocorrelation is associated with the recharge process, whether it is by piston flow, by-pass flow or some combination of recharge mechanisms (Price et al., 1993). Given that unsaturated zone thickness is a positive function of distance to streams (assuming a hydraulic connection between the aquifer and stream), the observation is also consistent with the findings of Peters et al. (2005). On the basis of a spatial analysis of modelled groundwater drought in the Pang, UK, a catchment underlain by the Chalk aquifer, Peters et al. (2005) concluded that short droughts are relatively more sever near streams, as they are damped further away, whereas long periods of below average recharge have relatively more effect near the groundwater divide. However, it is not clear why the Permo–Triassic sandstone sites, each with relatively shallow unsaturated zones (all less than 10 m), exhibit such long SGI autocorrelations. Another factor must be influencing the SGI autocorrelations at these sites. We have hypothesised that a second possible cause of autocorrelation in SGI may be associated with saturated storage and drainage processes in aquifers. Correlation coefficients between m_{max} and $\log D$, $\log T$ and $\log S$ are -0.82, 0.76 and -0.57, respectively, while the correlation coefficient between $\log S$ and $\log T$ is low at -0.37. A plot of log-hydraulic diffusivity, $\log D$ against $m_{\max}$ (Fig. 13b) shows that, as would be expected, for all aquifers $\log D$ is negatively linearly related to $m_{\max}$, and that this relationship is particularly pronounced for the granular aquifers. These observations appear to support the second hypothesis that, at least for granular aquifers, longer SGI autocorrelations are associated with aquifers where the hydraulic diffusivity is relatively low.

In summary, it is inferred from Fig. 13 that autocorrelation in SGI and hence groundwater drought phenomena are a site and aquifer dependent consequence of autocorrelation in groundwater recharge and/or of the effect of intrinsic aquifer characteristics on saturated flow and storage. These results highlight the need to take into account the hydrogeological context of groundwater monitoring sites when designing and interpreting data from groundwater level drought monitoring networks.

5 Discussion

5.1 Critical assessment of application of SPI-like approachs to groundwater level time series

The SPI approach has a couple of features that make it particularly useful as an index of meteorological drought. It can be calculated for a variety of timescales (accumulation periods), and estimated SPI values are comparable in time and space (Lopez-Moreno et al., 2009; Mishra and Singh, 2010). However, it also has two main weaknesses, as explicitly identified by Mishra and Singh (2010). SPI values can be significantly dissimilar for different lengths of observation record due to differences in the shape and scale parameters of the fitted gamma (or other) distribution for different length records (Wu et al., 2005). In addition, values of SPI are sensitive to the form of the probability distribution that is fitted to the observed data as part of the normalisation process (Mishra and Singh, 2010; Angelidis et al., 2012).

The SGI is a normalised drought index for groundwater levels and uses an SPI-like method. Weaknesses inherent in the SPI approach may also affect SGI unless appropriate steps are taken. The issue of distribution fitting has been obviated when developing the SGI by adopting a non-parametric approach to normalisation of the groundwater level time series (i.e. the normal scores transform). As has been noted, using the normal scores transform results in a distribution of values of SGI that are always normal. The technique is robust when applied to historic time series, although additional measures to check and account for any overfitting would be necessary should the technique be applied to predict values of SGI. Because the non-parametric normal scores transform is used to normalise the groundwater level time series when estimating SGI, the length of record is not an issue in the same way that it is for SPI estimates (as a gamma or other distribution is not being fitted and the issue of discrepancies between fitted parameter for records of different lengths does not arise). However, since SGI is a normalised drought index, as with any normalised drought index, the values of SGI will reflect the period and length of the time series that is being normalised, in this case groundwater levels, for example Fig. 11b and c, and quantitative comparison of SGI estimates between sites should be undertaken based on similar length records (WMO, 2012).

Because groundwater level is a continuous variable, SGI cannot be calculated for a range of timescales in a manner similar to SPI. However, should discrete estimated recharge data (observed or modelled) be available then the SGI methodology could be applied over a range of timescales using accumulated recharge. Alternatively, differencing successive monthly groundwater level observations would produce a change in groundwater level time series that would also enable the SGI methodology to be applied over a range of timescales. Mendicino et al. (2008) used monthly "groundwater detention", an output from a distributed water balance model, as the basis for an SPI-like index of groundwater drought. This could have been accumulated over a range of timescales, but in that particular study it was only considered over a one month accumulation period.

However, the most significant issue related to the application of an SPI-like approach to groundwater level time series is that SPI is designed to produce a drought index that has values that are comparable in space (i.e. values that are unaffected by geographical differences). As with studies of other hydrological time series, such as soil moisture and stream flow (e.g. Vincente-Serrano and Lopez-Moreno, 2005; Shukla and Wood, 2008; Sheffield et al., 2009; Vidal et al., 2010), groundwater levels and the derived SGI can be strongly influenced by location. Groundwater level and SGI time series reflect not just the meteorological drought driver, but are also influenced by local and site specific recharge processes and by regional to site-specific saturated flow processes that are not simply spatially correlated. It is these recharge and saturated flow processes that result in the autocorrelation structures seen in the SGI time series (Fig. 7). As noted by van Lanen (2005) "drought characteristics derived from groundwater levels ... have spatial effects". Consequently, any interpretation or analysis of the resulting SGI needs to reflect an appreciation of the hydrogeological context of the observation boreholes. However, it has been shown that if the autocorrelation structure of the SGI is taken into account, SGI can be shown to scale linearly with SPI (Fig. 9), and a measure of significant SGI autocorrelation, $m_{\max}$, is a useful parameter that can be related to drought characteristics such as drought duration (Fig. 12) and physically meaningful catchment characteristics (Fig. 13).

5.2 Comparison of SGI with existing groundwater and related hydrological indices

The SGI uses a normalisation approach to produce a continuous drought index. Such drought indices are measures relative to a mean hydrological baseline, in the case of the SGI a mean monthly groundwater level. In contrast, threshold level approaches produce measures of drought based on absolute values (for groundwater levels mean depth below or height above the threshold) that define drought events.

Peters et al. (2003, 2005) introduced the concept of a threshold for groundwater droughts and used it to characterise modelled groundwater level drought return periods. Lopez-Moreno et al. (2009) noted that such a threshold approach when applied to river discharge enables the identification of periods of low flow, but typically does not take account of seasonal flows and can lead to the classification of naturally low summer flows as periods of low flow. A similar situation may also pertain to groundwater levels, particularly in flashy, seasonal aquifers where groundwater levels oscillate on an annual basis between high and low groundwater level stands. The threshold approach enables the identification (deficit, duration and intensity) and characterisation (e.g. return period analysis) of discrete drought episodes, and variable threshold approaches have been developed to address the issue of seasonality in hydrometric rime series (Wanders et al., 2010). Fendekova and Fendek (2012) used a threshold approach to characterise drought in baseflow of a groundwater dominated catchment but avoided the issue of seasonality by analysing the average yearly baseflow.

However, an important difference between the threshold and normalisation approaches is that the threshold approach does not provide a continuous index of drought that is amenable to analysis using techniques that provide insights into temporal structure of the drought records, such as the characterisation of autocorrelation structure (or application of other techniques that require continuous series, such as spectral or wavelet analysis). Consequently, given the significance of memory, or autocorrelation, in groundwater systems, the SGI provides an important complementary technique to the threshold approach of Peters et al. (2003, 2005) to investigate and characterise groundwater droughts.

A number of previous groundwater related studies have produced drought indices based on a normalisation process. Bhuiyan et al. (2006) applied the SPI methodology to 20 yr of twice-yearly (pre- and post-monsoon) groundwater level data from 541 wells across Rajasthan, India. Using a qualitative GIS-based analysis, they investigated the spatio-temporal dynamics of drought in the study region and compared SPI-based on pre- and post-monsoon groundwater levels, SPI, and an index of vegetation health, but were unable to demonstrate any quantitative correlations between the drought indices. Mendicino et al. (2008) applied an SPI-like normalisation to modelled monthly "groundwater detention" to estimate a Groundwater Resource Index (GRI) for a series of catchments in southern Italy. Using cross-spectral techniques they compared the GRI with SPI and found significant sensitivity in the GRI drought index to the lithological characteristics of the analysed catchment or region. Based on 80 yr of monthly karstic spring discharge for three springs in southern Italy, Fiorillo and Guadagno (2010, 2012) investigated the relationship between meteorological droughts defined by SPI and an index calculated using the SPI methodology as applied to the karstic spring discharge times series. They used cross correlation plots to showed that SPI for precipitation based on an accumulation period of 12 months was most highly correlated with SPI for the spring discharge time series, and inferred that the karst system only responded to relatively long meteorological droughts due to the large storage of the karst system.

The present study has formalised the normalisation methodologies developed in these pervious groundwater-related studies, and has extended the joint analysis of hydrogeological and meteorological drought indices and SPI by building on the correlation analysis of Fiorillo and Guadagno (2012). Unlike Fiorillo and Guadagno (2012) who investigated the cross correlation between an SPI-like drought index for spring flows and SPI for a limited number of SPI accumulation periods ($q = 3, 6, 9, 12, 24$ and 48) and for a lag of one month between the two drought indices, the present study has introduced a more comprehensive cross correlation analysis between SPI and SGI including a wide range of precipitation accumulation periods from one to 48 months and lags between the two drought indices up to ten months (Fig. 8). The benefit of such an approach for analysing groundwater related drought time series is that it acknowledges that potentially there may be strong site specific responses in groundwater levels to meteorological droughts and it enables these site specific responses to be characterised more fully. Extensive cross correlation plots such as in Fig. 8 could be used to investigate the relationship between any hydrological drought index and SPI where it is thought that site or location specific factors may be influencing the hydrological index.

The Standardised Precipitation-Evapotranspiration Index, SPEI (Vincente-Serrano et al., 2010; McEvoy et al., 2012), has recently been developed to include atmospheric water demand by normalising the monthly (or weekly) difference between precipitation and potential evapotranspiration (PET). The SPEI represents a simple water balance and uses both precipitation and temperature as drivers of drought. A major driver for groundwater drought in the UK is accumulated deficits in autumn and winter recharge (Marsh et al., 2007). However, it is not clear to what extent long-term changes in temperature over the UK (Jenkins et al., 2008) may have had on groundwater recharge. Consequently, a future comparison of SGI with both SPI and SPEI may provide some helpful insights into the potential role of changing temperature on groundwater recharge and hence groundwater levels.

6 Conclusions

- Building on the SPI methodology, groundwater level data can be normalised to produce a Standardised Groundwater level Index (SGI) if the SPI methodology is modified to take into account the form and nature of groundwater level time series.
- Given correlations established between SGI and SPI and good agreement of SGI time series with previously independently documented droughts, SGI provides a robust quantification of groundwater drought.
- Correlations between SGI and SPI are associated with a range of SPI accumulations periods that are a function of SGI autocorrelation. In addition, groundwater drought durations defined by SGI time series are also a function of SGI autocorrelation.

- Autocorrelation in SGI appears to be a site and aquifer dependent function of autocorrelation in groundwater recharge signal and of the effects of intrinsic aquifer properties on saturated groundwater flow and storage.
- Since SGI can be strongly influenced by location reflecting influences from local and site specific recharge processes and regional to site-specific saturated flow processes that are not simply spatially correlated. Consequently, interpretation or analysis of the resulting SGI needs to reflect an appreciation of the hydrogeological context of the observation boreholes.

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