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Standard precipitation index to track drought and assess impact of rainfall on watertables in irrigation areas

S. Khan · H. F. Gabriel · T. Rana

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Abstract The Standard Precipitation Index (SPI) is employed to track drought and assess the impact of rainfall on shallow groundwater levels in three selected irrigation areas of the Murray-Darling Basin in Australia. The continuous SPI method can provide better means of quantifying rainfall variability and correlating it with changes of shallow watertable levels since it is based on continuous statistical functions comparing rainfall variability over the entire rainfall record. Drought analysis in the Australian irrigation areas using SPI indicates that the recent 2000–2006 drought is not the worst drought that has occurred in the recorded history, however if the current low rainfall pattern continues, it would be one of the most prolonged drought. The shallow groundwater fluctuations in the Murrumbidgee Irrigation Area show a very strong correlation with winter rainfall variation. The shallow piezometric levels in the Coleambally Irrigation Area show a weaker degree of correlation with the SPI due to local and regional groundwater dynamics and changes in rice water use. The groundwater levels in the Murray Irrigation Area show least correlation with the SPI, which may be attributed to improved irrigation management practices and complex nature of the groundwater recharge and discharge processes in this area. The overall results however show that the SPI correlates well with fluctuations in shallow ground water table in irrigation areas, and can also capture major drought patterns in Australia. The correlation of SPI with groundwater levels can be adopted for environmental reporting and used as a

S. Khan (✉) · H. F. Gabriel
International Centre of Water for Food Security, Charles Sturt University, Building 24,
Wagga Wagga Campus, Wagga Wagga, NSW 2678, Australia
e-mail: skhan@csu.edu.au

S. Khan · H. F. Gabriel · T. Rana
Commonwealth Scientific and Industrial Research Organization (CSIRO), Charles Sturt University,
Wagga Wagga, NSW 2678, Australia

S. Khan
UNESCO IHP-HELP, Paris, France

H. F. Gabriel
NIT, National University of Sciences and Technology (NUST), Risalpur Campus, Risalpur Cantt,
Pakistan

method of relating climatic impacts on watertables. Differences in piezometric response between years with similar winter and yearly SPI values can be attributed to improvement in irrigators' management practices.

Keywords Australia · Drought · Murray-darling basin · Rainfall variability · Standard Precipitation Index (SPI) · Regression · Watertable

Introduction

Rainfall is one of the key factors affecting the sustainability of irrigation areas in terms of dictating the need for supplemental irrigation to meet crop water demand and determining drainage requirements to avoid shallow watertable conditions and secondary soil salinisation. The variability of rainfall in the upper catchments of rivers determines the water available in storage reservoirs that can be available for irrigation to meet crop water use requirements. In irrigation regions the volume of rainfall over and above crop water requirements and soil storage capacity enters the groundwater and contributes to rising water tables and secondary salinisation.

Quantifying rainfall variability has been an area of great interest for many researchers studying the droughts in Australia (Foley 1957; Gibbs and Maher 1967; Opoku-Ankomah and Cordery 1993; Smith et al. 1993; White and O'Meagher 1995). While the effects of low rainfall and associated drought are dramatic and immediately obvious, the effects of high rainfall are much less noticeable except in extreme cases, and even then the effects can often go unnoticed for many years. In Australia, concerns about the contribution of rainfall to the development of shallow water table condition over the irrigation areas arose in the early 1930's in the Riverine Plains in the New South Wales. During the winter of 1931, major waterlogging problems appeared on the horticultural farms of the Murrumbidgee Irrigation Area when 92 mm rainfall fell during June (Butler 1971) and perched watertable rose to the ground surface in many places. Later investigations showed presence of 'blue' clay layers at 3 m depth, which allow very slow vertical drainage. The limiting vertical drainage capacity combined with overall shallow piezometric levels rendered areas of the Riverine Plains at high risk of waterlogging and salinisation if winter rainfalls were above the average. Lately, during the period 2000–2006, shallow watertables in irrigation areas dropped due to lower water allocations, improved irrigation practices and below average rainfall.

There is a need to differentiate and quantify the influence of rainfall on water tables from the management impacts, to ascertain whether reductions in shallow watertable areas under the irrigation areas are a result of dry climatic conditions or improved land and water management practices or both. In order to understand the impact of rainfall on water tables it is necessary to understand its seasonal variability. In this paper the Standard Precipitation Index (SPI) is employed to track drought and assess the impact of rainfall on water tables in the three irrigation areas of the Murray-Darling Basin in Australia.

Standard precipitation index

Standard Precipitation Index is a state-of-the-art method for assessing climatic variability and was developed by McKee et al. (1993, 1995). The SPI is based on statistical techniques, which can quantify the degree of wetness by comparing three, six, 12 or 24-monthly rainfall totals with the historical rainfall period over the history. For example, a six monthly SPI for August 2006 will compare the March 2006 to August 2006 rainfall totals with historic totals for the March to August period. The SPI requires different interpretations according to its time scale. For example, the 1-month SPI reflects short-term conditions, and its application can be related closely to soil moisture; the 3-month SPI provides a seasonal estimation of precipitation; the 6- and 9-month SPI indicates medium term trends in precipitation patterns; and the 12-month SPI reflects the long-term precipitation patterns, usually tied to stream flows, reservoir levels, and even groundwater levels (NDMC 2007).

Inconsistent conclusions could be obtained if different time lengths of precipitation record are involved in the SPI calculation. The longer the length of record used in the SPI calculation, the more reliable the SPI values will be, especially for long-time-scale SPI values (Wu et al. 2005). The use of robust data is desirable in the analysis of the climatic responses of hydrologic processes because of disparities in station records including inhomogeneity and inconsistency of observations in space and time (Ropelewski and Halpert 1986). Conceptually, the SPI is similar to the impartial z-score, which has zero mean and unit standard deviation (Edwards and McKee 1997), and provides a measure of the precipitation frequency distribution (Kim et al. 2006).

McKee et al. (1993, 1995) fitted a gamma distribution to the precipitation histogram for calculating SPI. Using an equiprobable transformation, the cumulative density function (CDF) of the gamma distribution was then transformed to the CDF of the standard normal distribution. The transformed standard deviate is the SPI for the given precipitation total (Kim et al. 2006).

The SPI is computed by dividing the difference between the normalised seasonal precipitation and its long-term seasonal mean by the standard deviation (Bhuiyan et al. 2006):

$$SPI = \frac{X_{ij} - X_{im}}{\sigma} \quad (1)$$

where, X_{ij} is the seasonal precipitation at the i^{th} raingauge station and j^{th} observation, X_{im} the long-term seasonal mean and σ is its standard deviation.

Since the SPI is equal to the z-value of the normal distribution, McKee et al. (1993, 1995) proposed a seven-category classification for the SPI: extremely wet (z>2.0), very wet (1.5 to 1.99), moderately wet (1.0 to 1.49), near normal (−0.99 to 0.99), moderately dry (−1.49 to 1.0), severely dry (−1.99 to 1.5), and extremely dry (<−2.0) (Table 1). The expected time in each drought category was based on an analysis of a large number of rainfall stations across Colorado, USA. The percent of time in moderate, severe and extreme drought correspond to those expected from a normal distribution of the SPI (Paulo et al. 2005).

Recent research has shown that the SPI has many advantages over other indices such as the Palmer Drought Severity Index (PDSI) and is relatively simple, spatially consistent, and temporally flexible, thus allowing observation of water deficits at different scales (Ji and Peters 2003; Guttman 1998)). The SPI does not require information about land surface conditions and is solely a function of the precipitation amount (Kim et al. 2006). Since the SPI is more reliable for detecting emerging drought, it is becoming an increasingly important tool for: assessing moisture condition and initiating drought response actions at state, regional and local level (Wilhite et al. 2000); planning for drought; monitoring drought; drought risk and impact analysis; and mitigating drought by putting a drought plan together for water conservation. Our motivation is to provide an application of the SPI for selected irrigation areas in Australia, which have a history of worst droughts. This information may be useful for drought planning efforts in Australia.

Table 1 SPI and its corresponding cumulative distribution and moisture categories (McKee et al. 1993, 1995)

Standard Precipitation Index	Cumulative Density Function	Moisture category
−3.0	0.001	Extreme dry (ED)
−2.5	0.006	
−2.0	0.023	
−1.5	0.067	Severe dry (SD)
−1.0	0.159	Moderate dry (MD)
−0.5	0.309	Incipient dry (ID)
0.0	0.500	Incipient wet (IW)
0.5	0.691	
1.0	0.841	
1.5	0.933	Moderate wet (MW)
2.0	0.977	Severe wet (SW)
2.5	0.994	Extreme wet (EW)
3.0	0.999	

Previous studies to quantify rainfall variability

In the recent times Australia has been facing a very prolonged drought, which promoted the then Australian Prime Minister to foreshadow the possibility of zero water allocation to agriculture in 2007/08. Tools and methods are hence increasingly being sought to analyse the droughts and develop mitigation plans. Khan and Short (2001) used the SPI to analyse how it relates with known years of drought in the Murray-Darling Basin. It was determined that persistently negative 12- and 24-monthly SPI were the best indicators of drought conditions. In a similar vein, Khan et al. (2002) divided the historic rainfall amounts before and after 1950 to show an increase in the average annual rainfall and an increase in the variability of that rainfall at sites along the Murrumbidgee River. The study also showed that the average availability of water in the Murrumbidgee River increased after the 1950's and allowed policy-makers to over-allocate surface and groundwater resources (Khan et al. 2002).

Wu et al. (2001) evaluated the SPI, China-Z Index (CZI) and the statistical Z-Score on 1-, 3-, 6-, 9- and 12-month time scales using monthly precipitation totals for four locations in China from January 1951 to December 1998 representing humid and arid climates, and cases of drought and flood. The CZI and Z-Score provided results similar to the SPI for all time scales, and that the calculations of the CZI and Z-Score was relatively easily compared with the SPI, possibly offering better tools to monitor moisture conditions.

Lloyd-Hughes and Saunders (2002) analysed the incidence of 20th century European drought, based on the monthly SPIs calculated on a 0.5° grid over the European region 35–70° N and 35° E–10° W at time scales of 3, 6, 9, 12, 18, and 24 months for the period 1901–1999. Their approach provided, for a given location or region, the time series of drought strength, the number, the mean duration, and the maximum duration of droughts of a given intensity, and the trend in drought incidence.

Bonaccorso et al. (2003) carried out an analysis of drought in Sicily from 1926 to 1996. Drought occurrence was estimated by means of the SPI. To study long-term drought variability, a Principal Component Analysis (PCA) was also applied to the SPI field. A combination of SPI and PCA was also used by Bordi et al. (2004) for studying the time–space covariability of dry and wet periods during the last 50 years in eastern China.

Min et al. (2003) showed that the occurrence of droughts over central eastern China, Manchuria, and the north coast of Japan was highly correlated with those in Korea. However, the time scales of occurrence of droughts over the three regions were different: droughts in eastern China represented in-phase variations with those in Korea with a time interval of 5–8 years; those in Manchuria occurred with a time interval of 15 years; and those in Japan had no coincident variations.

Quiring and Papakryiakou (2003) carried out a comparative performance analysis to determine the most appropriate index for monitoring agricultural drought and predicting spring wheat yield on the Canadian prairies. A series of curvilinear regression-based crop yield models were generated for each of the 43 crop districts (20 in Saskatchewan, 12 in Manitoba, and 11 in Alberta) based on four commonly used measures of agricultural drought (SPI, PDSI, Palmer's *Z*-index, and NOAA Drought Index). The significant variations in model performance between the four agricultural drought indices underscored the necessity of carrying out a performance evaluation prior to selecting the most appropriate agricultural drought index for a particular application.

Wu et al. (2004) developed an agricultural drought risk-assessment model for Nebraska, USA, for corn and soybeans on the basis of variables derived from the SPI and crop-specific drought index using multivariate techniques. The model can be used to assess real-time agricultural drought risk for specific crops at critical times before and during the growing season by retaining previous and adding current, weather information as the crops pass through the various growth stages.

Data mining techniques have also been used to find associations between drought and several oceanic and climatic indices (Tadesse et al. 2004) that could help users in making knowledgeable decisions before the drought actually occurs. The drought episodes were determined based on the SPI and PDSI. Associations were observed between drought episodes in Nebraska, USA and oceanic and atmospheric indices such as the Southern Oscillation Index and the Pacific Decadal Oscillation Index.

Likewise Paulo et al. (2005) showed that SPI and Markov chain stochastic models can be used to monitor droughts and to produce early warning in combination with other indicators for several sites of Alentejo, a drought prone region of southern Portugal.

Finally, research conducted in the Murrumbidgee Irrigation Area, Australia show that across the entire area, groundwater recharge from rainfall and irrigation cause changes in discrete layers of shallow groundwater with different chemical compositions for 30 m from the top of the watertable. After an irrigation event, the salinity of the groundwater quickly decreases, but during the drying phase, it increases due to the capillary uptake of freshwater by the crops. The salt crystals are left behind and, as a result, the quality of the groundwater deteriorates (Northey et al. 2005).

The above studies show the possibility of using precipitation indices such as the SPI for seasonal water/irrigation management in several countries around the globe. The knowledge-based for Australia is rather limited. This study therefore aims to assess the impact of rainfall variability on shallow water tables in selected irrigation areas in Australia, to provide a management tool to farmers and irrigation companies.

Description of study area

The Murray-Darling Basin, which crosses four state boundaries in south-eastern Australia namely New South Wales, Victoria, South Australia, and Queensland, is characterized by its extensive irrigation schemes. It is one of Australia's largest drainage basins. It is comprised of the three longest rivers in Australia. These are the Murray River, which is 2,530 km long, the Darling River, which is 2,740 km long, and the Murrumbidgee River which is 1,690 km long (DEH 2005). Twenty-one smaller rivers and hundreds of other tributaries are also located within the Basin (Crabb 1997).

By covering 1,061,469 km^2, the Murray-Darling Basin makes up 14% of Australia's landmass (Crabb 1997). Globally it ranks 21st in drainage basin area (DEH 2005). This drainage basin, however, is characterized by very low water runoff. In fact, 86% of the Basin contributes no runoff to the rivers except during times of flood (Crabb 1997). Since the majority of Australia receives between 0 to 500 mm of rain each year and the south-eastern Australia falls within this majority, water availability has historically been inconsistent within the Murray-Darling Basin (BOM 2006). Since the 1950's, however, south-eastern Australia has shown a major climate shift leading to rainfall variability which has resulted in more frequent extremes in high and low rainfall events (Khan et al. 2002).

The lack of runoff and extreme variability of rainfall greatly affect the flow of the rivers in the Basin. For example, in the town of Menindee, between 1885 and 1960, the Darling River stopped flowing on 48 separate occasions and between 1902 and 1903, it had no water for 364 consecutive days (Crabb 1997).

These periods of drought and lack of river flows caused the Australian federal government to form the River Murray Agreement with the State governments of New South Wales, Victoria, and South Australia in 1915. This agreement created plans for permanent flows of water for irrigation and navigation (Khan et al. 2002). It allowed for the creation of locks and weirs along the Murray and Murrumbidgee Rivers. Also, reservoirs, such as the Burrinjuck Dam on the Murrumbidgee River, were created and irrigation areas were developed. These areas quickly became vital to the economy. They provide water for the 51,672 farms that make up 80% of the entire Murray-Darling Basin (Crabb 1997). The production of the crops in the area depends greatly on the reliability of water. As a result, the irrigation areas and rainfall amounts affect the rice, wheat, barley, cotton, oil seeds, grapes, citrus fruits, and a large variety of other cereals and beans (Crabb 1997).

The Murrumbidgee Irrigation Area (MIA) and the Coleambally Irrigation Area (CIA) are two irrigation areas that were developed along the Murrumbidgee River. This river flows west from the Snowy Mountains where it receives most of its source water. Near the town of Balranald, on the border between New South Wales and Victoria, it joins up with the Murray River. Together, the MIA and the CIA have a total of 10,000 km of irrigation channels. Their irrigation industry provides 25% of New South Wales' fruits and vegetables, 42% of its grapes, and 50% of all of Australia's rice. In total, agriculture in these two irrigation areas contributes \$1.9 billion annually to the Australian economy (NRM 2004).

Methodology

SPI data collection

In order to perform SPI analysis on the sites in the Murray-Darling Basin, it was necessary to determine which sites would be valuable. After overlaying the gauge locations on the irrigation areas, it was determined that Coleambally, Deniliquin, Finley, Griffith, Leeton, Moulamein, and Narrandera would be the main sites of focus (Fig. 1). These are mainly concentrated on the Murrumbidgee River and the Murray River and they give the best spread of upstream and downstream sites for investigation. Other sites throughout the

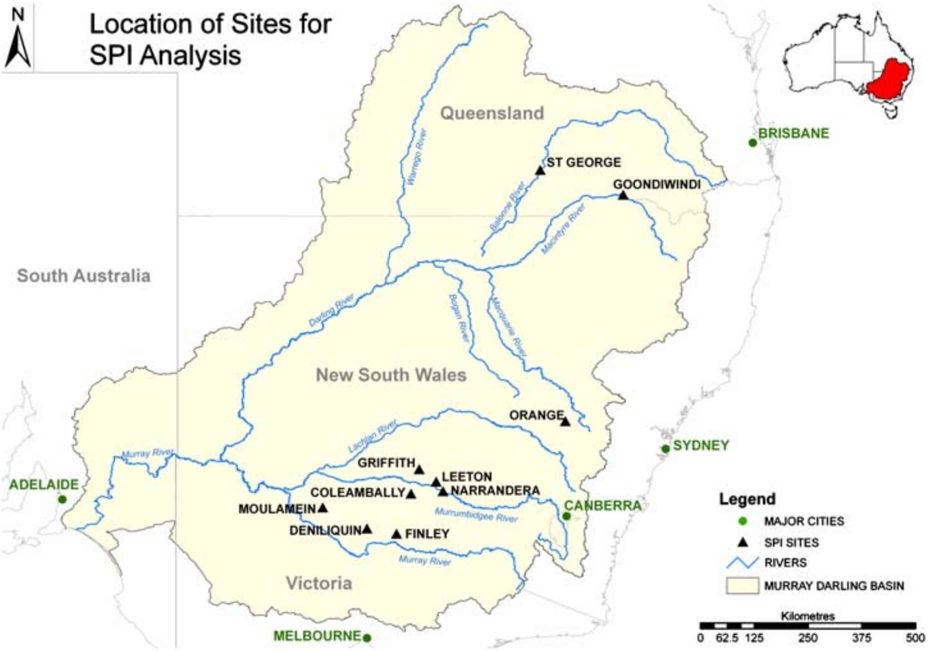


Fig. 1 Location of sites for SPI analysis

Murray-Darling Basin were examined to gain a spatial comparison of rainfall conditions. The continuous daily meteorological data was retrieved from the websites of Australian Bureau of Meteorology (www.bom.gov.au/silo/) and Department of Natural Resources and Water (http://www.nrw.qld.gov.au/silo/). The evapotranspiration data from these sites were also used to make comparisons on the amount of water provided by rainfall and the amount of water required by the crops at the different sites.

Groundwater data collection

Over 3,000 piezometers were used to collect data on the watertable behaviour in the Murray-Darling Basin. The groundwater data was used to create a comparison with the SPI analysis. In theory, over the course of a dry year with a negative SPI value, the average piezometric level should decrease. This means that the watertable would get deeper because less water is available to recharge it. To test this hypothesis, September SPI values (three, six, 12 and 24 monthly) were plotted against the change in spatial average piezometric value in the Coleambally, Murrumbidgee and Murray Irrigation Areas.

Results and discussions

Drought analysis

The negative values of the SPI show that recently the sites in the Murray-Darling Basin are experiencing drought conditions. As can be seen from Fig. 2, the Griffith 12-monthly SPI analysis shows that the recent drought began in 2001 and experienced the same intensity as

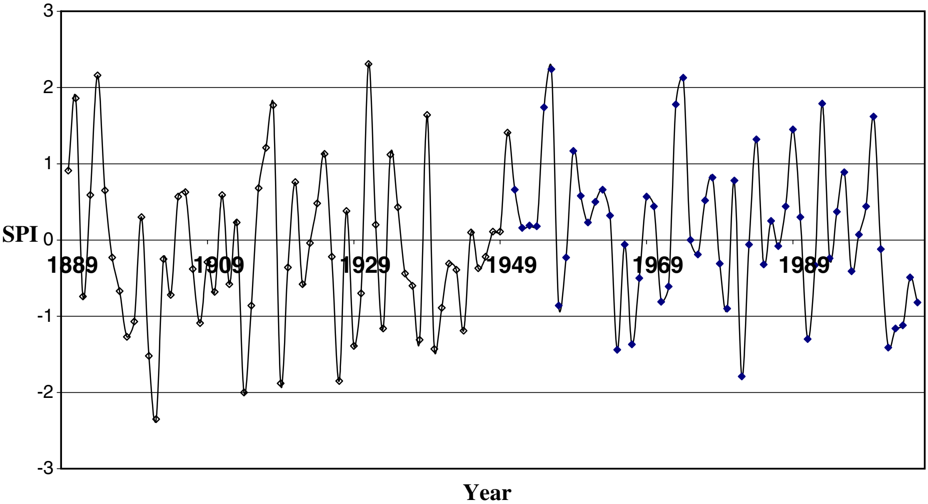


Fig. 2 12-monthly September SPI for Griffith (1890–2006)

many droughts throughout history such as the ones that occurred in 1991, 1965, 1940, 1929, and 1898. It is not nearly as intense as the droughts that occurred in 1982, 1914 and 1902. It is, however, a much more prolonged drought than the previous droughts. As can be observed from this figure, the more intense historical droughts would have very low rainfall for 1 or 2 years followed by 1 or 2 years of above average rain. The recent drought has not been followed by years of above average rainfall. Instead, Griffith continues to have below average rainfall conditions.

Other locations show similar trends, but are not quite as dramatic as Griffith. The Coleambally station, Fig. 3, for example, shows that drought conditions beginning in 2002 were followed by about average rainfall levels in 2005 and then the low rainfall levels began again. Also, Moulamein, Fig. 4, which is further inland received rainfall much below

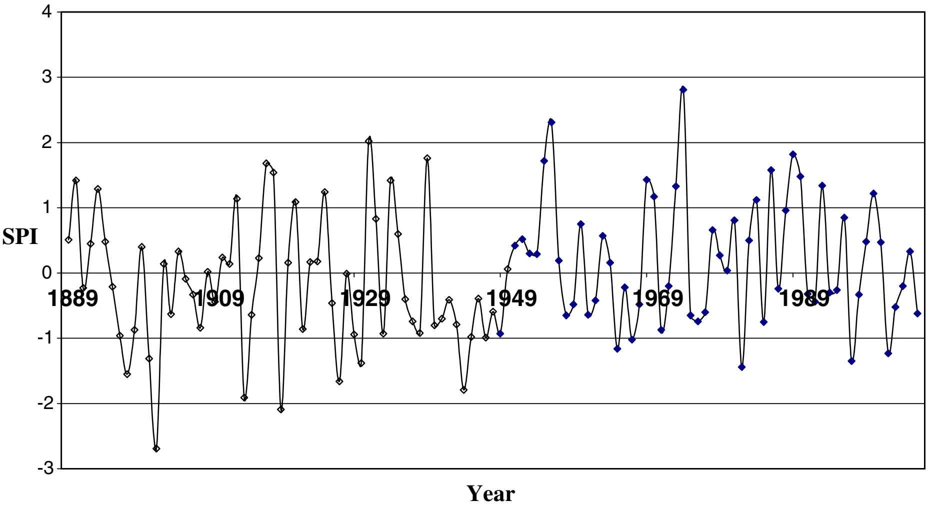


Fig. 3 12-monthly September SPI for Coleambally (1890–2006)

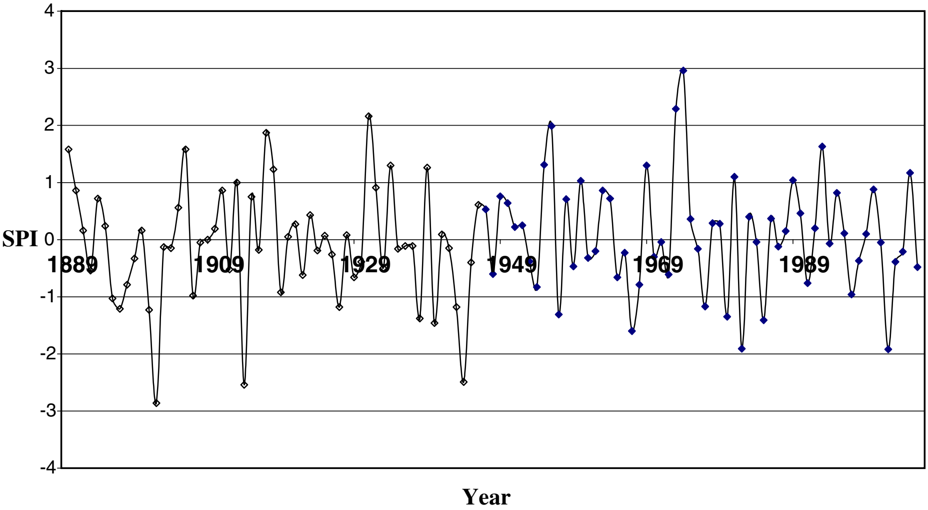


Fig. 4 12-monthly September SPI for Moulamein (1890–2006)

average than the other sites in 2002, but this was followed by a "moderately wet" year in 2005. Overall, the SPI demonstrate that the Murray-Darling Basin is experiencing a drought since 2000 because none of the sites have recorded real above average rainfall levels (SPI values above 1.5) in the past 6 years.

In general, this analysis shows that the 2000–2006 drought is not the worst drought that has occurred in recorded history for the area, however if the current low rainfall pattern continues, it would be one of the most prolonged droughts in the recorded history.

With the rainfall data for all the sites, it was also possible to compare different regions of the Murray-Darling Basin to determine the spatial differences in drought conditions. By comparing the most severe years of drought for each site, it was also possible to compare drought intensity overtime and to contrast it with the other sites. In Fig. 5, the September 24-monthly SPI values were compared with different droughts. The current SPI values are shown in black. Each site shows that the 2000–2006 drought is not the most intense drought in history. Different areas throughout the Murray-Darling Basin are facing different levels of drought intensity. Drought planning efforts and actions must acknowledge this reality.

Correlation between rainfall variability and shallow watertable fluctuations

The continuous nature of SPI was compared with the shallow piezometric (derived from continuous data sets) level changes in the following irrigation areas:

- Murrumbidgee Irrigation Area: Griffith and Leeton locations
- Murray Irrigation Area: Wakool Region, Deniboota Region, Denimein Region, Berriquin Region
- Coleambally Irrigation Area: Divided into four sub-regions i.e. North, Centre, South and West CIA (Fig. 6)

Different periods were compared due to varying lengths of the groundwater data, as discussed below.

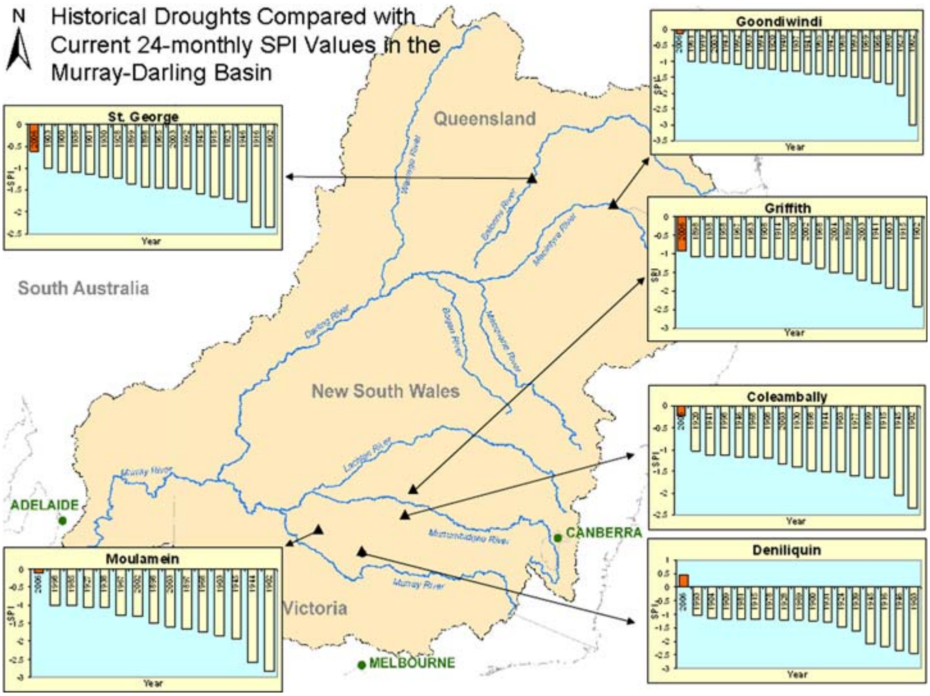


Fig. 5 Historical droughts compared with recent 24-monthly September SPI values in the Murray-Darling Basin

Piezometric fluctuations in the Murrumbidgee Irrigation Area

Figure 7a shows shallow piezometric (0–15 m deep, 505 data points) fluctuations with winter SPI six monthly (April to September) and annual values (12 monthly October to September) for the 1996 to 1999 period in the Griffith region. The results show that the changes in SPI values coincided with the changes in the shallow piezometric levels. Figure 7b shows the shallow piezometric (0–15 m deep, 422 data points) changes with winter SPI (six monthly March to August SPI) and annual (12 monthly July to August) for the 1996 to 1999 period in the Leeton region. The results indicate that similar to the Griffith area changes in SPI value are related with corresponding changes in the shallow piezometric levels.

The overall results show that fluctuations in shallow groundwater levels are related with SPI values in the Murrumbidgee Irrigation Area.

Piezometric fluctuations in the Murray Irrigation Area

Figure 8a shows the shallow piezometric (0–15 m deep, 51 data points) changes with winter SPI for Moulamein six monthly (March to August) and annual values (12 monthly July to August) for the 1996 to 1999 period in the Wakool region. The results indicate that smaller and lower values of SPI are related with the falling groundwater levels during 1997 to 1998. However for 1989 to 1992 period, similar groundwater level changes are associated with widely varying SPI values. The rising water tables with low SPI values indicate groundwater changes caused by poor water management practices or groundwater discharge from other areas. This aspect needs to be further confirmed through groundwater modelling studies.

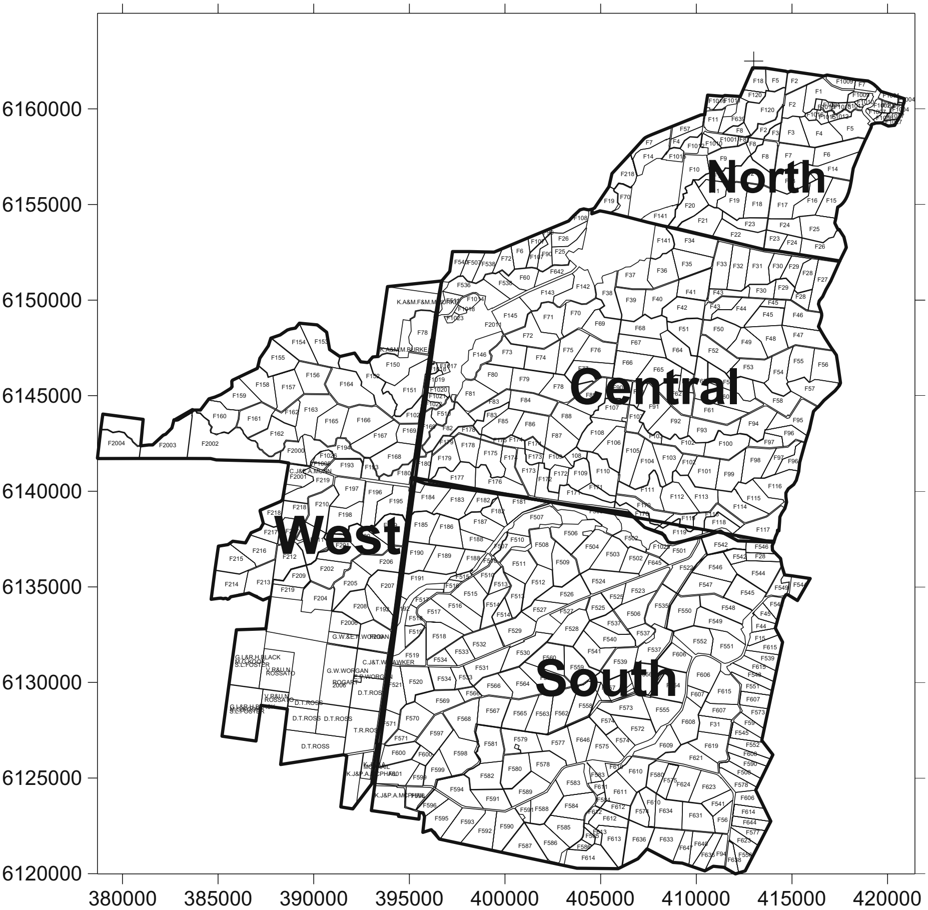


Fig. 6 Subdivision of the Coleambally Irrigation Area for detailed watertable response analysis

Figure 8b shows the shallow piezometric (0–15 m deep, 77 data points) changes with winter SPI for Finely six monthly (April to September) and annual values (12 monthly October to September) for the 1996 to 1999 period in the Deniboota region. The results indicate that smaller and lower values of SPI are related with the falling groundwater levels during 1991, 1992, 1997 and 1998. For other years the shallow piezometric levels rise with increasing SPI, the greatest rise is in 1993 and 1994 for which SPI values are highest in the record.

Figure 8c shows the shallow piezometric (0–15 m deep, 38 data points) changes with winter SPI for six monthly (March to August) and annual values (12 monthly July to August) for the 1996 to 1999 period in the Denimein region. The results indicate that the years with lower/higher values of SPI and falling/rising groundwater levels are the same as for Finely above.

Figure 8d shows the shallow piezometric (0–15 m deep,) changes with winter SPI for six monthly (March to August) and annual values (12 monthly July to August) for the 1996 to 1999 period in the Berriquin region. The results show that positive or negative values of SPI coincide with a rise or fall in the piezometric levels, respectively. However a change in the magnitude of the SPI value does not always produce a corresponding change in the

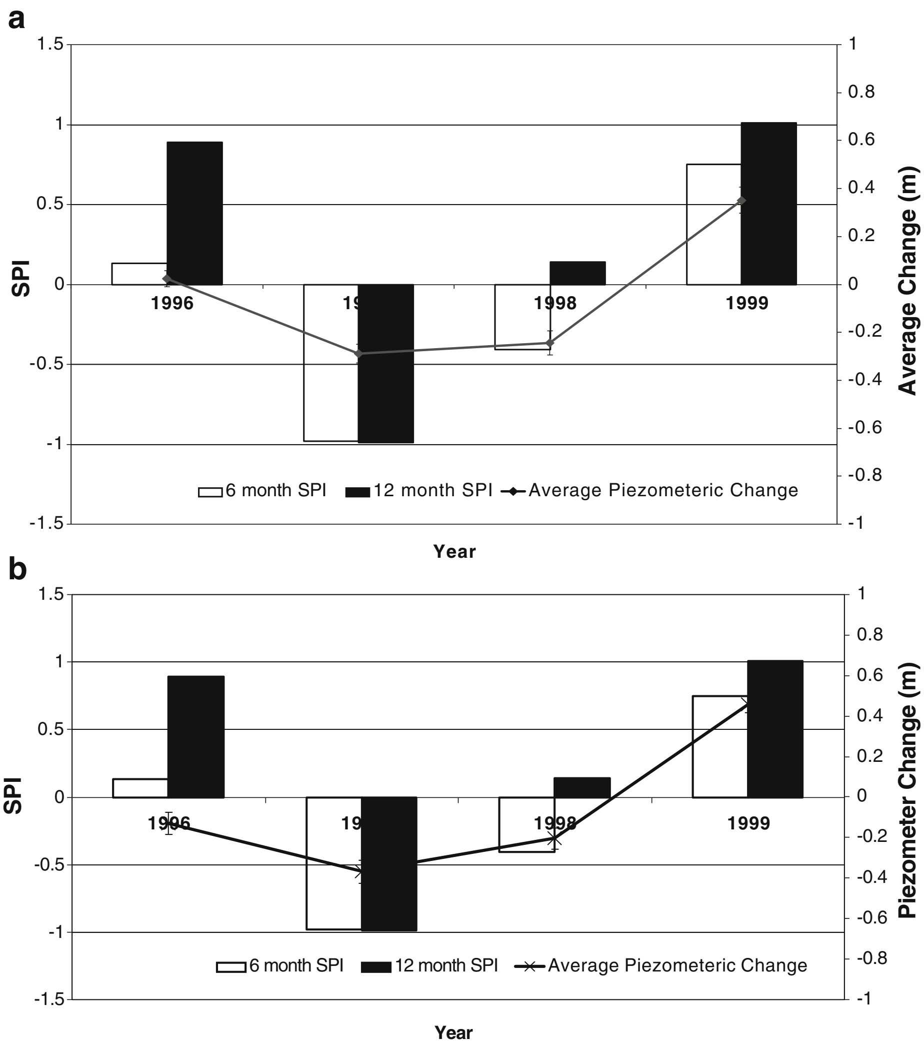
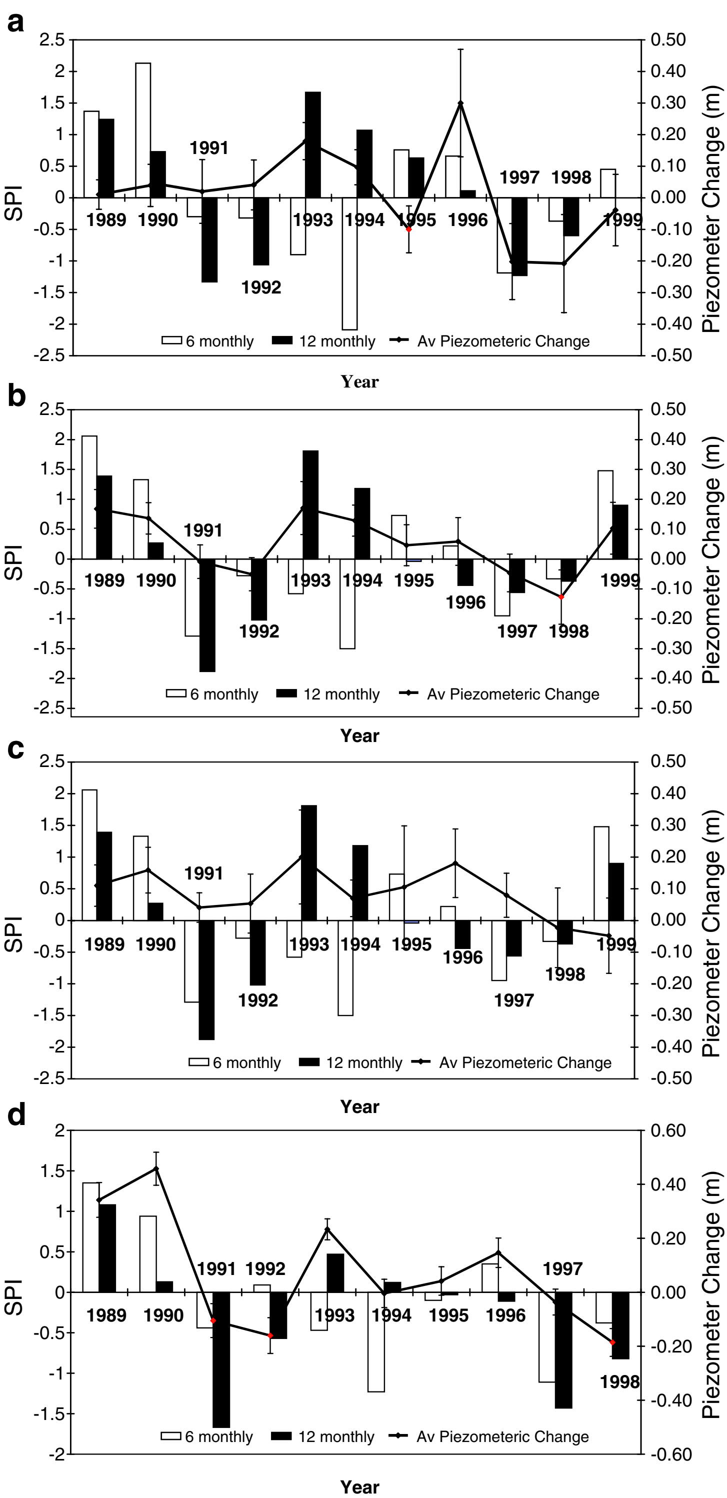


Fig. 7 **a** Comparison of spatial average change in September piezometer levels and six-monthly and 12-monthly August SPI for Griffith. **b** Correlation between spatial average change in September piezometer levels in Leeton and six-monthly August SPI for Griffith

piezometric levels. For example 1989 and 1990 have positive SPI values, 1990 SPI (0.9 to 0.1) is lower than 1989 (1.4 to 1.1) however the increase in piezometric levels in 1990 is approximately 0.1 m more than the 1989.

The overall results support the hypothesis that SPI influences shallow groundwater table fluctuations.

Fig. 8 **a** Comparison of six-monthly and 12-monthly August SPI for Moulamein and spatial average piezometric change in Wakool. **b** Comparison of six-monthly and 12-monthly August SPI for Deniliquin and spatial average piezometric change in Deniboota. **c** Comparison of six-monthly and 12-monthly August SPI for Deniliquin and spatial average piezometric change in Denimein. **d** Comparison of spatial average piezometric change in Berriquin and six-monthly and 12-monthly August SPI for Finley ▶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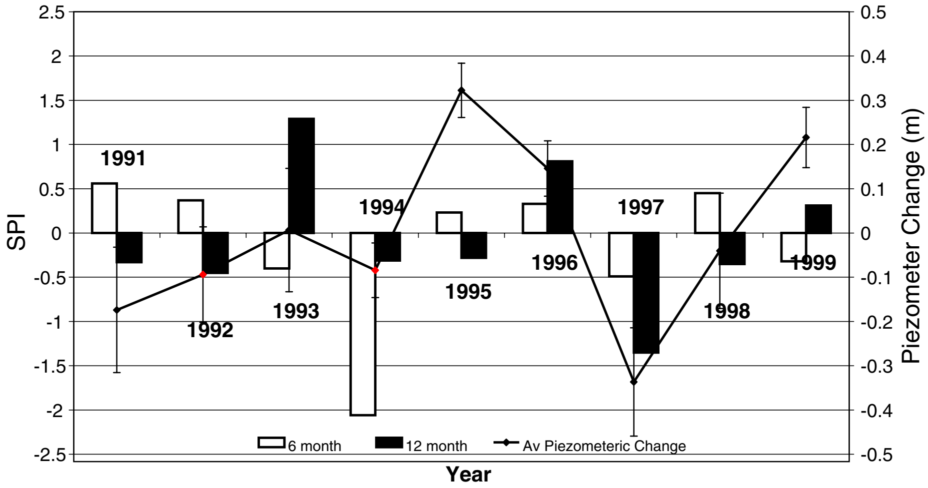

Fig. 9 Comparison of spatial average piezometric change and six-monthly and 12-monthly August SPI for Coleambally

Piezometric fluctuations in the Coleambally irrigation area

Figure 9 shows the comparison of the annual piezometric change in the Shepparton formation (August, six and 12 monthly SPI) for the CIA. In general the piezometric level changes are influenced by climatic conditions with piezometric levels declining in lower rainfall winter years of 1991, 1992, 1994, 1997 and 1998. However the 1995, 1996 and 1999 piezometric rises do not correspond with relatively smaller SPI values (<0.1). The unexpected watertable rise for these years can be explained by the excess water usage figures shown in Table 2 (Tiwari 1999).

Further comparisons of piezometric response and SPI were made by subdividing the piezometric data in four sub-regions i.e. North, Centre, South and West CIA (Fig. 5).

For CIA the analysis shows some anomalies, firstly the area with the deepest groundwater, Northern CIA, have the best regression results as compared to the other three regions. There are two plausible explanations for this result. Rainfall has a greater influence on the watertable because of different soil characteristics that allow faster movement of the rainfall into the aquifers. This is likely because Northern CIA is the area closest to the Murrumbidgee River, and it used to have many prior stream structures running through it. The other explanation is that because of the better aquifer connectivity the Northern CIA is greatly influenced by irrigation tubewell bores to the North-West bock. Thus in years of higher SPI (more rainfall) less pumping occurs in neighbouring bore

Table 2 Excess water usage on rice crops (Tiwari 1999)

Year	Number of farms	% area of all rice farms
1994/95	65	20
1995/96	28	9
1996/97	18	6
1997/98	37	11

Table 3 Summary of regression analysis of SPI and shallow watertable fluctuations in the selected three irrigation areas

Irrigation district	R^2	Regression coefficient	Intercept
Murrumbidgee			
Griffith (0–2 m)	0.9126	0.4661	0.0148
Leeton (0–2 m)	0.8298	0.4647	0.0315
Coleambally			
North (0–3 m)	0.476	0.4157	−0.0978
West (0–2 m)	0.0556	0.0789	−0.0381
Central (0–2 m)	0.3614	0.1874	−0.0225
South (0–2 m)	0.2038	0.1359	−0.0042
Murray			
Deniboota (0–2 m)	0.2786	0.1665	0.0089
Denimein (2–5 m)	0.1867	0.072	0.0182
Wakool (2–5 m)	0.0366	0.0223	0.0307
Berriquin (0–2 m)	0.2659	0.1669	−0.0343

blocks, reducing the gradient of flow between the aquifers, causing a rise in the watertable in the North (Khan et al. 2008a).

The regression and correlation analysis of SPI and shallow watertable fluctuations were performed in irrigation areas to test our hypothesis. Regression analyses (Table 3) show that the most strongly correlated region is the MIA as there is a very strong linear relationship (R^2=0.91 and 0.83) between the winter rainfall SPI and shallow piezometric levels (0–2 m depth) (156 continuous data points) changes in Griffith and Leeton area respectively. The regression coefficient for both Leeton and Griffith is approximately 0.5, indicating that for every unit increase of SPI there is a half as much increase in the watertable. For example, if SPI is 0.2 for August 1999 (six-monthly August) then the change in watertable depth from September 1998 to August 1999, will show an increase of approximately 0.1 m. As the watertable depth increments increase the regression coefficient decreases, illustrating that the climatic impacts are greatest when watertable is shallow (below 2 m).

The piezometric levels in the Murray Valley show a weaker correlation with the SPI, due to impacts of management practices and complex nature of the groundwater recharge and discharge zones in this area (Khan et al. 2008b).

Correlation analysis of SPI and piezometric fluctuations

Correlation analysis was carried out to determine whether SPI time series moves together with the piezometric time series, that is, whether the two series are auto correlated such that:

Table 4 Overall correlation of spatial average piezometric level changes with three, six, 12, 24-monthly August SPI in the Coleambally Irrigation Area from 1990 to 1999

SPI	Central	West	North	South
3-monthly	0.429	0.230	0.372	0.678
6-monthly	0.628	0.310	0.590	0.461
12-monthly	0.660	0.109	0.597	0.087
24-monthly	0.318	−0.434	−0.003	0.277

Table 5 August SPI for Finley and correlation with spatial average piezometric change from 1985 to 1999 for Murray Valley

SPI	Berriquin	Denimein	Deniboota	Wakool
3-monthly	0.31	−0.09	0.06	−0.01
6-monthly	0.68	0.42	0.69	0.33
12-monthly	0.7	0.55	0.9	0.41
24-monthly	0.74	0.47	0.86	0.27

the large values of SPI are associated with large fluctuations of piezometric data (positive correlation), or whether small values of one set are associated with large values of the other (negative correlation), or whether the values in both sets are uncorrelated (correlation near zero). The correlation coefficient was determined by using equation (2):

$$\rho_{XY} = \frac{\mathrm{cov}(X, Y)}{\sigma_X \sigma_Y} \tag{2}$$

where is the correlation of the variables X and Y i.e. SPI and piezometric fluctuations, and are the standard deviation of variables X and Y, and cov (X, Y) is the covariance between the variables X and Y.

For the four regions of the CIA the six- and 12-monthly August SPI (Table 4) shows good correlation with the piezometric fluctuations i.e. rising watertables are associated with the rising SPI values and vice versa. The least correlated regions are North and West CIA. Weaker correlation in North CIA is due to the influence of generally higher rice water use in the area and the influence of deep pumping bores to the north-west of the area on groundwater dynamics (Khan et al. 2000, 2008a).

The four regions of the Murray Valley have piezometric fluctuations that are highly correlated to the six, 12 and 24 monthly SPI values (Table 5). The three-monthly SPI shows very low correlation with the piezometric change. Of the four regions, Wakool series are the least correlated, followed by Denimein. The weaker correlation is due to the complex nature of the recharge and discharge systems within the Murray Irrigation area. Lateral flow dynamics have a much greater influence on piezometric fluctuations in the Murray region as compared to the MIA and CIA regions that show a greater response to precipitation and irrigation variables (Khan et al. 2008a, b).

Results of the correlation analysis for the MIA (Table 6) show that both the Leeton and Griffith piezometric levels and six-monthly SPI values are highly correlated.

The regression and correlation analysis thus show that SPI values and groundwater table levels in irrigation areas have a strong positive relationship, in general, however exceptions are possible due to local and regional groundwater dynamics and changes in irrigation water use. The overall results support the hypothesis that lower SPI values during drought periods are associated with falling groundwater table.

Table 6 August SPI for Leeton and Griffith with spatial average piezometric change from 1995 to 1999 for Murrumbidgee Irrigation Area

SPI	Leeton	Griffith
3-monthly	0.6	0.67
6-monthly	0.93	0.96
12-monthly	0.75	0.82
24-monthly	0.6	0.8

Conclusions

In irrigation areas with shallow watertable the rainfall variability is a very sensitive variable impacting the overall sustainability of the area. Standard Precipitation Index is based on continuous statistical functions and can therefore capture rainfall variability on a continuous basis over the entire rainfall record. The SPI was applied to analyse the drought spells and their impact on shallow watertable fluctuations using data from about 3,000 piezometers in three major irrigation areas in the Murray-Darling Basin, Australia. This empirical application of SPI showed that: low (high) SPI values can successfully capture dry (wet) periods; and the SPI can identify historical droughts over the century scale. It also confirmed that the Murray-Darling Basin was experiencing a prolonged dry period since 2000 because none of the four irrigation areas studied have recorded real above average rainfall levels in the past 6 years to 2006 (SPI values above 1.5); and different irrigation areas throughout the Murray-Darling Basin were facing varying levels of drought intensity. In general, the analysis show that the 2000–2006 drought is not the worst drought that has occurred in recorded history for the area, however if the current low rainfall pattern continues, it would be one of the most prolonged droughts in the recorded history.

The fluctuations in the piezometric levels in the selected irrigation areas show a strong positive relationship with the rainfall variability, confirming that the shallow watertable fluctuations were influenced by SPI. Regression and correlation analyses also show that shallow watertable levels were influenced by SPI vales and the two series were positively correlated such that rising watertable correspond with the rising SPI values and vice versa. However exceptions to this generic conclusion are possible due to local and regional groundwater dynamics and differences in irrigation management. Somewhat weaker correlation between the two time series for some irrigation areas, however, do support the generic conclusion when interpreted in terms of the regional groundwater dynamics and irrigation management practices. For instance, the piezometric levels in the Murray Irrigation Area show only weaker correlation with the rainfall variability as measured by SPI. Other factors come into play, suggesting that shallow groundwater levels are also influenced by water management practices, changes in cropping patterns, irrigation water delivery, and groundwater recharge and discharge zones. These impacts need to be ascertained and separated by detailed groundwater modelling studies. The overall results suggest that shallow water table are influenced by rainfall such that drought has impacts on groundwater levels and have implications for sustainable agriculture in terms of crop choices, salinity management, and drought assistance schemes. The findings may be useful for irrigators, irrigation companies, extension service, and regional authorities.

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