INTERNATIONAL JOURNAL OF CLIMATOLOGY
Int. J. Climatol. **36**: 563–575 (2016)
Published online 5 May 2015 in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/joc.4365

RMetS
Royal Meteorological Society

Spatiotemporal Patterns of Agricultural Drought in Sri Lanka: 1881–2010

Thushara Gunda,[a*] George M. Hornberger[a,b] and Jonathan M. Gilligan[b]

[a] *Vanderbilt Institute for Energy and Environment, Department of Civil and Environmental Engineering, Vanderbilt University, Nashville, TN, USA*
[b] *Vanderbilt Institute for Energy and Environment, Department of Earth and Environmental Sciences, Vanderbilt University, Nashville, TN, USA*

ABSTRACT: A spatiotemporal analysis of two well-known agricultural drought indices, the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index at a 9-month scale (SPI-9), is presented for Sri Lanka. The analysis was conducted based on monthly precipitation and temperature data from January 1881 to December 2010 using 13 stations distributed across the three climatic zones of the country. Principal component analysis shows that the first two principal components of PDSI and SPI-9 are spatially comparable and could physically represent the two main monsoons. A wavelet analysis of these principal components' scores for both indices indicates a stronger association between the Northeastern monsoon and El-Niño in recent decades. Correlation analysis with agricultural metrics suggests that different indices might be appropriate for each of the climatic zones in Sri Lanka. PDSI correlated best with the intermediate zone districts; SPI-9 correlated best with the dry zone districts; but neither index correlated well with the wet zone districts.

KEY WORDS Sri Lanka; drought; PDSI; SPI; PCA; wavelets

Received 21 August 2014; Revised 3 April 2015; Accepted 8 April 2015

1. Introduction

Drought is a creeping natural hazard, with no clear beginning or end (Patel *et al.*, 2007). It is a complex phenomenon with global impacts (Keyantash and Dracup, 2002); between 1980 and 2008, annual damages from drought were approximately $25 billion worldwide (UNISDR, 2014). The socioeconomic impacts of drought in South Asia, in particular, are only expected to increase due to increased rainfall variability and increased temperatures, both of which can adversely affect agricultural productivity (World Bank, 2014). Sri Lanka provides an interesting case study for drought within South Asia due to its geographic isolation and large agricultural sector; approximately 28% of the population and 65% of land is engaged in agricultural activities in the country (DCS, 2001, Socioeconomics & Planning Centre, 2012).

Drought is the most frequent natural disaster in this island nation, where it greatly affects crop production and livelihoods (Chithranayana, 2008). Over half of agricultural crop damage in Sri Lanka is due to drought (DesInventar, 2012). In 2003–2004, drought in two consecutive seasons affected nearly 1.5 million people, most of whom were subsistence farmers (World Food Programme, 2007). Drought also affects public health, hydropower generation, and other sectors of the Sri Lankan economy: protracted drought in 2001–2002 caused a 1% drop in the nation's gross domestic product growth rate (Lyon *et al.*, 2009). Climate change is expected to increase the frequency and severity of drought in the country (Eriyagama *et al.*, 2010).

Thus far, studies in Sri Lanka have predominantly focused on characterizing specific years of anomalous rainfall (Jayamaha, 1975); spatiotemporal patterns of rainfall (Suppiah and Yoshino, 1984a, 1984b); and relationships among rainfall, rice production, and Southern Oscillation Index and other El Niño indices (Suppiah, 1996, 1997, Kane, 1998, Zubair, 2002, Malmgren *et al.*, 2003, Zubair *et al.*, 2005, Wickramagamage, 2009). Chithranayana (2008) developed a monthly Moisture Availability Index to identify regions of Sri Lanka that are vulnerable to drought. Lyon *et al.* (2009) studied the relationship between the Standardized Precipitation Index (SPI) and drought relief payments in the country and found the strongest correlation with a 9-month cumulative drought index. Fernando (2010) found a significant difference in total rice production and yield between drought and non-drought years. Bandara *et al.* (2010) found good correlation between a weighted-average SPI and the Palmer Drought Severity Index (PDSI) for Idamelanda from 1960 to 2000. Ekanayake and Perera (2014) characterized SPI at a 3-month scale for the Anuradhapura district and identified 46 drought occurrences between 1951 and 2007. However, these studies have only characterized restricted time periods of drought and none of them have assessed spatiotemporal patterns of drought.

This article is one of the first to assess the spatiotemporal patterns of agricultural drought in Sri Lanka. We assess agricultural drought using two well-known indices: the

* Correspondence to: T. Gunda, Vanderbilt Institute for Energy and Environment, Department of Civil and Environmental Engineering, Vanderbilt University, PMB 407702, 2301 Vanderbilt Place, Nashville, TN 37240-7702, USA. E-mail: thushara.gunda@vanderbilt.edu

PDSI and Standardized Precipitation Index at a 9-month scale (SPI-9). This study is part of a larger, multidisciplinary research project investigating environmental and social influences on climate change adaptation in Sri Lanka (NSF-EAR 1204685). We selected PDSI and SPI-9 because both indices are being used by Sri Lankan government agencies; SPI is widely used for local meteorological drought analysis and our research partners at the National Building Research Organization are evaluating PDSI as an indicator of agricultural drought. We analyze differences in the spatiotemporal patterns of PDSI and SPI-9 and consider whether such differences lead to a preferred drought monitoring tool for the country. SPI is computationally simple and only requires precipitation data; it can be analysed at multiple timescales and is gaining wider acceptance as a drought monitoring tool in Asia (Patel *et al.*, 2007). Unlike SPI, PDSI accounts for the influence of temperature on water shortages by incorporating evapotranspiration processes (Karl, 1983). Drought indices, such as PDSI and SPI-9, can facilitate reporting of drought conditions and development of drought management strategies (including contingency planning) (United Nations, 2009). Bandara *et al.* (2010) considered PDSI at a discrete location in Sri Lanka, but as far as we know, none have investigated the spatial distribution of PDSI across the whole country. Thus, the research objectives of this study are:

- to evaluate spatial and temporal patterns of agricultural drought in Sri Lanka from 1881 to 2010;
- to evaluate the utility of PDSI and SPI-9 as agricultural drought monitoring tools for Sri Lanka.

Spatiotemporal patterns of drought have been studied by coupling principal component analysis (PCA) with spectral analysis of the principal component (PC) scores (Eder *et al.*, 1987) or by coupling wavelets with PCA of significant periods of variance (Elsanabary *et al.*, 2014). We use a combination of these two approaches by first conducting PCA on the data (per Eder *et al.*, 1987) and then applying wavelets instead of spectral analysis to the PCs (per Elsanabary *et al.*, 2014). Specifically, spatial patterns are identified by PCA and temporal patterns are identified by wavelet analysis of the scores of the retained PCs of the PDSI and SPI-9 time series. Our analysis shows similar spatiotemporal patterns of drought for both indices. An assessment of the utility of PDSI and SPI-9 as agricultural drought monitoring tools using correlation analysis suggests that different indices might be appropriate for each of the climatic zones in Sri Lanka. PDSI correlated best with the intermediate zone districts, SPI-9 correlated best with the dry zone districts, but neither index correlated well with the wet zone districts.

2. Methods

2.1. Site description

Sri Lanka is an island country located in the northern Indian Ocean, southeast of India. Rainfall patterns in Sri Lanka are categorized into four periods: the northeast monsoon (NEM) spans December–February, the first intermonsoon (FIM) spans March–April, the southwest monsoon (SWM) spans May–September, and the second intermonsoon (SIM) spans October–November (Suppiah, 1996; Malmgren *et al.*, 2003; Zubair *et al.*, 2008). Spatial variability in rainfall, arising from cyclonic and orographic influences (Zubair *et al.*, 2008), creates three climatic zones in the country: the wet zone, the intermediate zone, and the dry zone (Thambyahpillay, 1954; Wickramagamage, 2009). These zones are demarcated based on hydrology, relative meteorology, soils, and vegetation (Zubair, 2002). The wet zone receives most of its rain during the SWM and SIM and experiences more than 2500 mm of rainfall annually (Suppiah, 1996; Zubair, 2002). The dry zone predominantly receives rainfall during the SIM and NEM, the latter of which is weaker than the SWM. So the dry zone receives less than 1750 mm annually, 70% of which is received during the NEM, giving rise to semi-arid conditions in the zone the rest of the year (Amarasinghe *et al.*, 1999; Zubair, 2002). The intermediate zone is a transition zone and experiences conditions intermediate between the wet and dry zones.

2.2. Drought indices

The PDSI is calculated by conducting a physical water balance of precipitation, evapotranspiration, recharge, and runoff (Palmer, 1965). Details of the calculations, assumptions, and associated limitations can be found in Palmer (1965), Alley (1984), Briffa *et al.* (1994), and Ntale and Gan (2003). While PDSI was established as an indicator of meteorological drought, it has also been used to assess agricultural drought (Rohli *et al.*, 2008). The dimensionless values of PDSI range from −4 to 4, with negative numbers representing dry spells (Hu and Willson, 2000). A drought period begins when the index value reaches −1 and ends the first month when the moisture conditions begin an uninterrupted rise that ultimately erases the water deficit (Keyantash and Dracup, 2002). Because antecedent conditions are accounted for as a part of the PDSI calculations, the temporal scale of the PDSI is ambiguous; Guttman (1998) and Heim (2002) identified the time scale of PDSI to be about 9 months. The data requirements for this index are monthly precipitation and temperature data, as well as the available water capacity (AWC) of a soil reservoir conceptualized in the water balance model.

PDSI values for Sri Lanka were calculated using a MATLAB PDSI tool (Jacobi *et al.*, 2013). Potential evapotranspiration values were estimated using the Thornthwaite method and the entire period of record was used for calibration of the PDSI values (Karl, 1986). PDSI calculations on a time interval require boundary conditions to be imposed at the beginning and end. Those conditions bias results at times close to the beginning and end; but sufficiently far from the boundaries, results are insensitive to the boundary conditions (Guttman, 1991). We calculated PDSI on data from January 1875 to December 2013, obtaining stable values for 1881–2010.

The SPI is calculated by fitting all of the historical precipitation data at a meteorological station to a gamma distribution, which is then transformed to a Gaussian distribution (McKee *et al.*, 1993). The SPI values are standardized precipitation anomalies: the number of standard deviations by which the precipitation total for a time interval (e.g. 1-month, 3-month, or 9-month) differs from the long-term mean of that interval. At short timescales (e.g. 1-month), SPI is considered as a meteorological drought indictor; when SPI captures long-term anomalies of precipitation (e.g. 3-month and 9-month), it is considered as an agricultural drought indicator (Patel *et al.*, 2007). Sri Lankans often capture rainfall during the NEM and use it for agricultural production in the SWM; therefore, a SPI scale longer than 6 months is needed to adequately capture this interplay between the two monsoon seasons. To be consistent with the approximate time scale of PDSI, SPI at a 9-month scale was selected for this initial analysis. Moreover, Lyon *et al.* (2009) observed that 9-month timescales for drought indices produced the greatest correlation with agricultural drought, as measured by relief payment to farmers. SPI-9 values for each month incorporate precipitation information for the preceding 8 months. For example, SPI-9 for January 2009 requires precipitation values from May 2008 to January 2009.

SPI values range from −2 to 2. Similar to PDSI, SPI is dimensionless with negative numbers representing dry spells. SPI considers a drought period to begin when the index value reaches −1 and to end when the index value reaches 0 (Morid *et al.*, 2006). SPI-9 values were

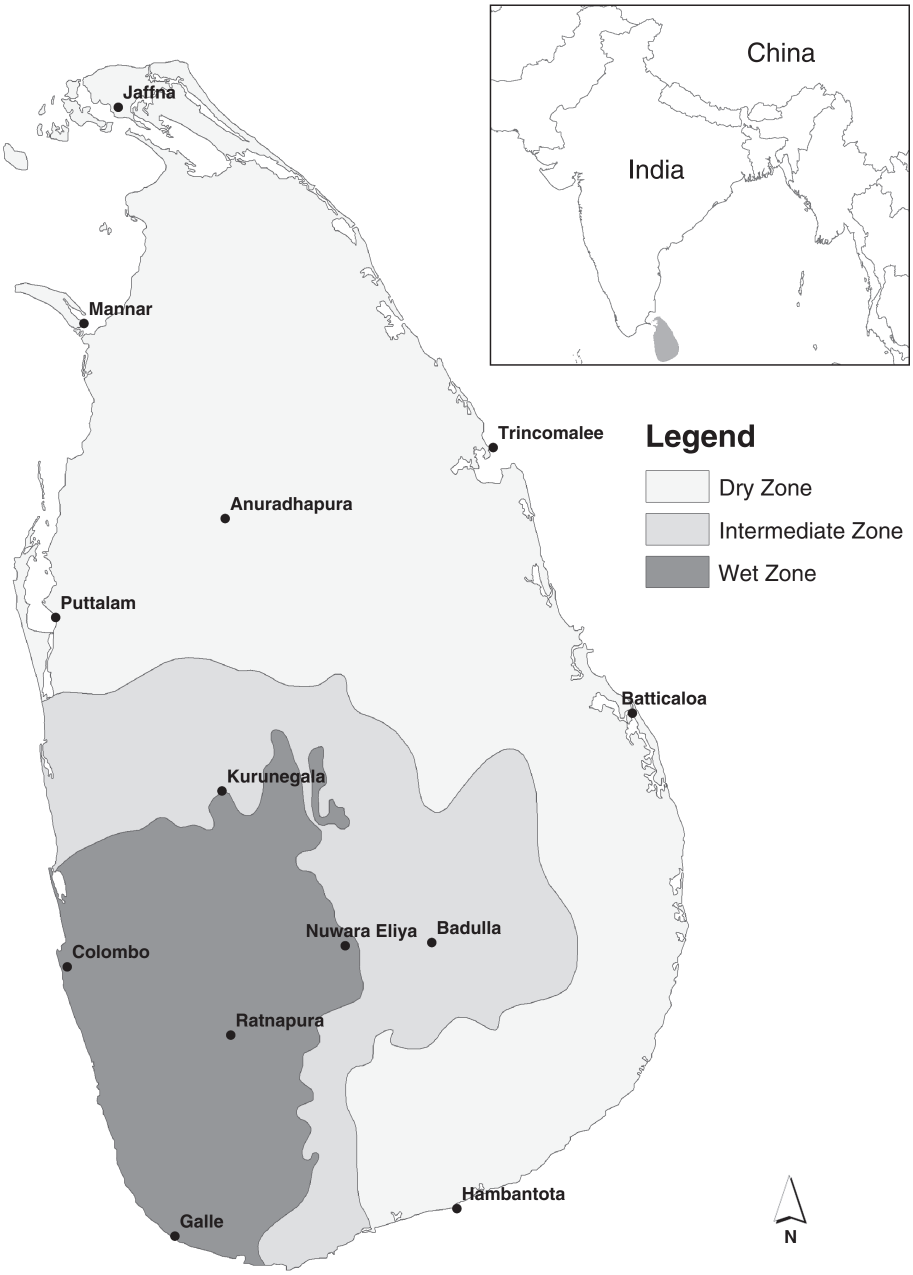


Figure 1. Meteorological stations.

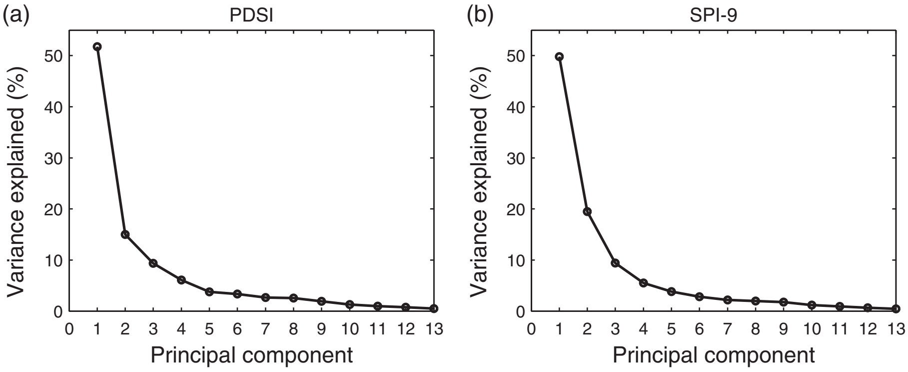


Figure 2. Scree plots for PDSI and SPI-9. Both plots show an elbow at PC 2.

calculated using a MATLAB SPI tool (Lee, 2009). To be consistent with the PDSI calculations, the same date range (January 1875 to December 2013) was also used for the SPI tool.

2.3. Data

Monthly precipitation and temperature data were obtained from the Meteorological Department of Sri Lanka for 13 stations with long-term records (Table S1, Supporting Information). Although there are only 13 stations used in this study, the stations are well-distributed across the three climatic zones (Figure 1) and adequately capture the climatic spatial variability in the country (Figures S1 and S2). Approximately 13% of the temperature and 14% of the precipitation data were missing. Guttman (1991) showed that temperature anomalies of up to 1.7 °C result in only minor effects on PDSI values. Because the monthly temperature values at each station had a variance less than 1 °C, missing temperature values at each station were estimated with the corresponding station's average monthly temperature value. This method produced comparable values (i.e. less than 1 °C difference) to those estimated by Thevakaran and Sonnadara (2013) using the between-stations technique for missing monthly temperature values at Jaffna. Missing precipitation values were computed using the modified normal ratio method, which uses regression-weighted precipitation data from three stations selected based on correlation coefficients (per Young, 1992). In Sri Lanka, the correlation coefficients generally followed climatic zones.

To determine the AWC of soils near each of the meteorological stations, the soil type was first identified using De Alwis and Panabokke (1972)'s soil map for the country. Only two stations in the dry zone had published AWC values (Mapa and Pathmarajah, 1995). For the remaining stations, AWC estimates from similar soil types elsewhere in the world (Hong *et al.*, 2013) were used since soil water contents are strongly correlated with soil textures (Minasny *et al.*, 1999).

2.4. Spatial analysis

PCA is a common method used to identify spatial patterns in climatic data (Santos *et al.*, 2010). By reducing dimensionality, PCA emphasizes relationships among variables (i.e. stations) and observations (i.e. monthly drought indices). Using linear combinations, data for k variables can be used to produce k PCs to account for the variation in the original data for the same time period. The PCs are, by definition, orthogonal and uncorrelated to each other. The coefficients of the linear combinations are weights of the original variables in the PCs and are called loadings (Jolliffe, 2002). The dataset of PC scores, which contains transformed data points from the original axis system to the axis system of the PCs, is the same length as the original dataset.

The original dataset consists of monthly values for 130 years, or 1560 data points for each of the 13 stations. Since PC loadings can be influenced by uneven distribution of data (Karl *et al.*, 1982), the PDSI and SPI-9 values at each station were weighted by the corresponding station's Thiessen polygon area prior to PCA (Drosdowsky, 1993; Chung and Nigam, 1999; Wrublack *et al.*, 2013). From this dataset of 13×1560, a 13×13 covariance matrix was constructed to identify specific regions with high variance relative to the rest of the field (Overland and Preisendorfer, 1982; Eder *et al.*, 1987). Scree plot analysis was used to decide on the number of PCs to retain (Jolliffe, 2002). Monthly contributions for the retained PC scores were calculated by summing the PC scores for each month and dividing by the total variance at each station. Communalities, or the proportion of variance attributable to each station, were also calculated by summing the squared loadings of the retained PCs following the methodology in Eder *et al.* (1987). All of the PC analysis was conducted in MATLAB.

To facilitate interpretation, an orthogonal rotation was also implemented on the retained PCs. The Varimax rotation preserves the orthogonality of the PCs but maximizes the sum of the variances of the squared loadings, which can result in a spatial clustering of the variables (Drosdowsky, 1993). The goal is to produce more physically explainable patterns by more clearly identifying a factor with a (relatively) small number of variables, which provides a clearer division between the components (Santos *et al.*, 2010). Following the methods outlined in Jolliffe (2002), PCs were rotated using MATLAB commands. To visualize the spatial patterns in loadings, the coefficients of both

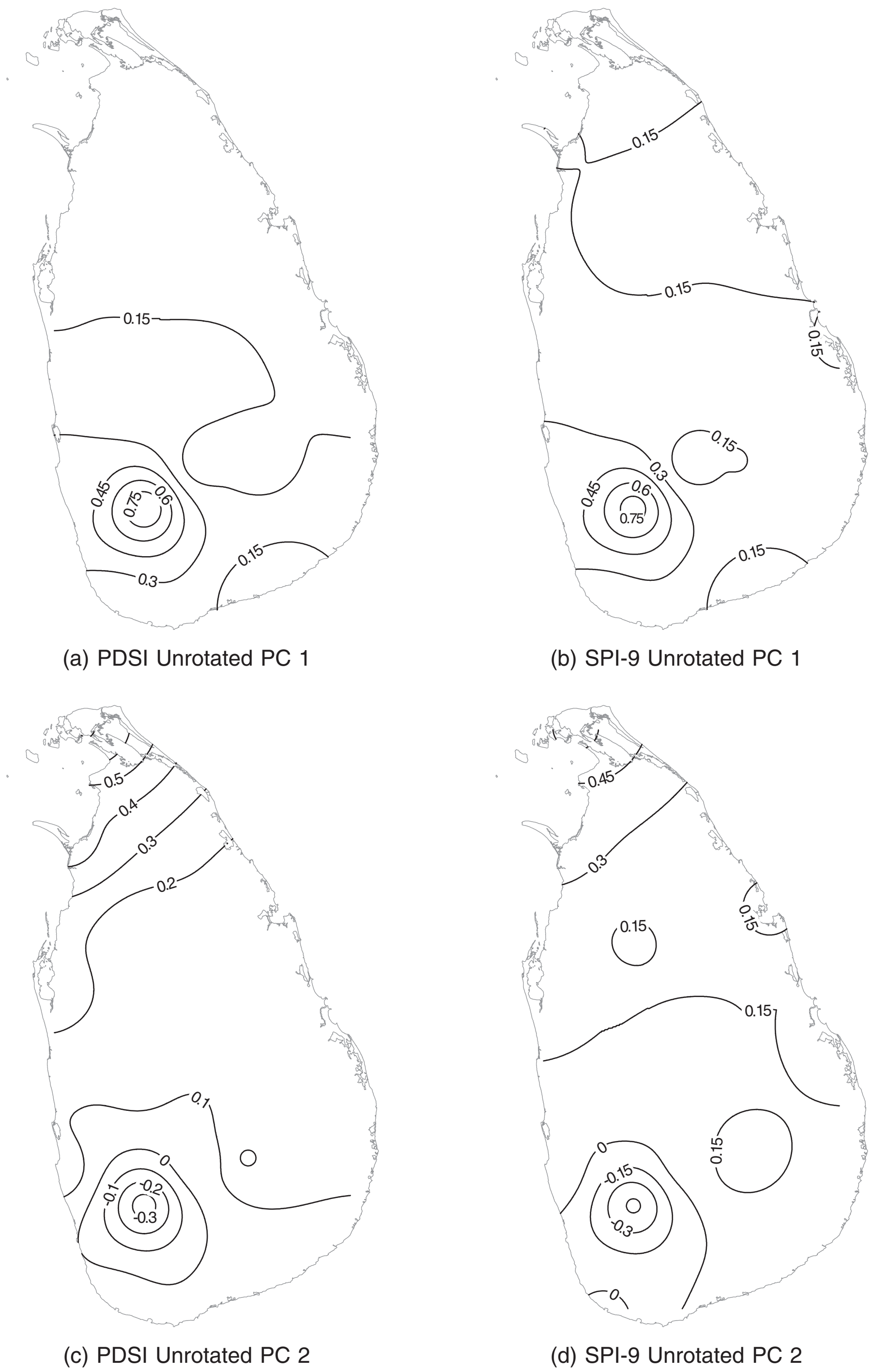


Figure 3. Unrotated principal components of PDSI and SPI-9. Both PC 1s show a general trend from the north to the southwest while both PC 2s show a general trend from the southwest to the north.

unrotated and rotated PCs (RPCs) were interpolated using the inverse distance weighted technique in ArcMap 10.2.

2.5. Temporal analysis

Wavelet analysis has been used in an array of geophysical studies to assess the Southern Oscillation, cold fronts, rainfall patterns, and dispersion of ocean waves (Torrence and Compo, 1998). Wavelets allow decomposition of a time series into time-frequency space so that dominant modes of variability can be explored over time. The Morelet wavelet, which is a plane wave modulated by a Gaussian window, was chosen for this analysis because it provides reasonable localization of both time and frequency (Grinsted *et al.*, 2004). Because we are working with a finite-length time series, errors occur at the beginning and end of the wavelet power spectra; outside the cone of influence (COI) is the region of the wavelet spectrum where these edge effects are important. Therefore, information outside the COI should be considered with caution.

Table 1. Monthly contributions (as percentage of total variance) to principal component scores. February and March contribute the most to PC 1 of PDSI but the remaining PCs have relatively little variability in monthly contributions.

Month	PDSI		SPI-9	
	PC 1	PC 2	PC 1	PC 2
January	56.0	14.8	48.9	21.7
February	59.8	14.3	49.4	21.0
March	59.0	15.9	50.2	21.1
April	54.7	14.6	49.2	21.3
May	50.6	16.3	50.9	20.2
June	47.4	16.2	51.5	18.8
July	49.0	15.4	53.5	16.6
August	47.8	15.4	55.0	16.0
September	48.1	15.7	52.8	16.1
October	45.8	13.1	47.0	19.0
November	47.4	13.3	44.3	20.6
December	51.5	13.7	44.6	21.9

Table 2. Communalities, proportion of variance attributable to each station. Stations with the highest contributions to PC loadings are distributed across the climatic zones.

Climate Zone	Stations	PDSI	SPI-9
Wet	Colombo	0.12	0.14
	Galle	0.03	0.03
	Nuwara Eliya	0.01	0.01
	Ratnapura	0.87	0.88
Intermediate	Badulla	0.06	0.09
	Kurunegala	0.04	0.05
Dry	Anuradhapura	0.02	0.03
	Batticaloa	0.04	0.06
	Hambantota	0.00	0.01
	Jaffna	0.51	0.43
	Mannar	0.20	0.15
	Puttalam	0.08	0.11
	Trincomalee	0.02	0.03

The MATLAB code provided by Grinsted *et al.* (2004) was used to generate continuous wavelet transforms (CWTs) of the scores of retained PCs from the spatial analysis. The normality of the score time series was confirmed using Q-Q plots and the Shapiro-Wilk test. For each score, monthly means of PDSI and SPI-9 were removed from the records to define an anomaly time series that focuses on long-term forcings. For each of the CWTs, there were 1560 data points and 98 scales (ranging from 0.17 to 45.2 years). Significance levels at 95% of the observed spectra were determined relative to a background spectrum of red noise, commonly modelled with a first order autoregressive (AR1) process for geophysical phenomena (Torrence and Compo, 1998; Grinsted *et al.*, 2004).

Zubair *et al.* (2005) showed that variations in the Niño 3.4 dataset explained some of the variability in seasonal agricultural production. The relationship between the scores and monthly anomalies of Niño 3.4 (Rayner *et al.*, 2003) was assessed using crosswavelet transforms (XWTs) and wavelet coherences (WTCs). XWTs expose the common power between two CWTs and the relative phase in time-frequency space. WTCs show localized correlation coefficients in time-frequency space, and thus, can expose areas of significant coherence between two CWTs even though the common power is low (Grinsted *et al.*, 2004).

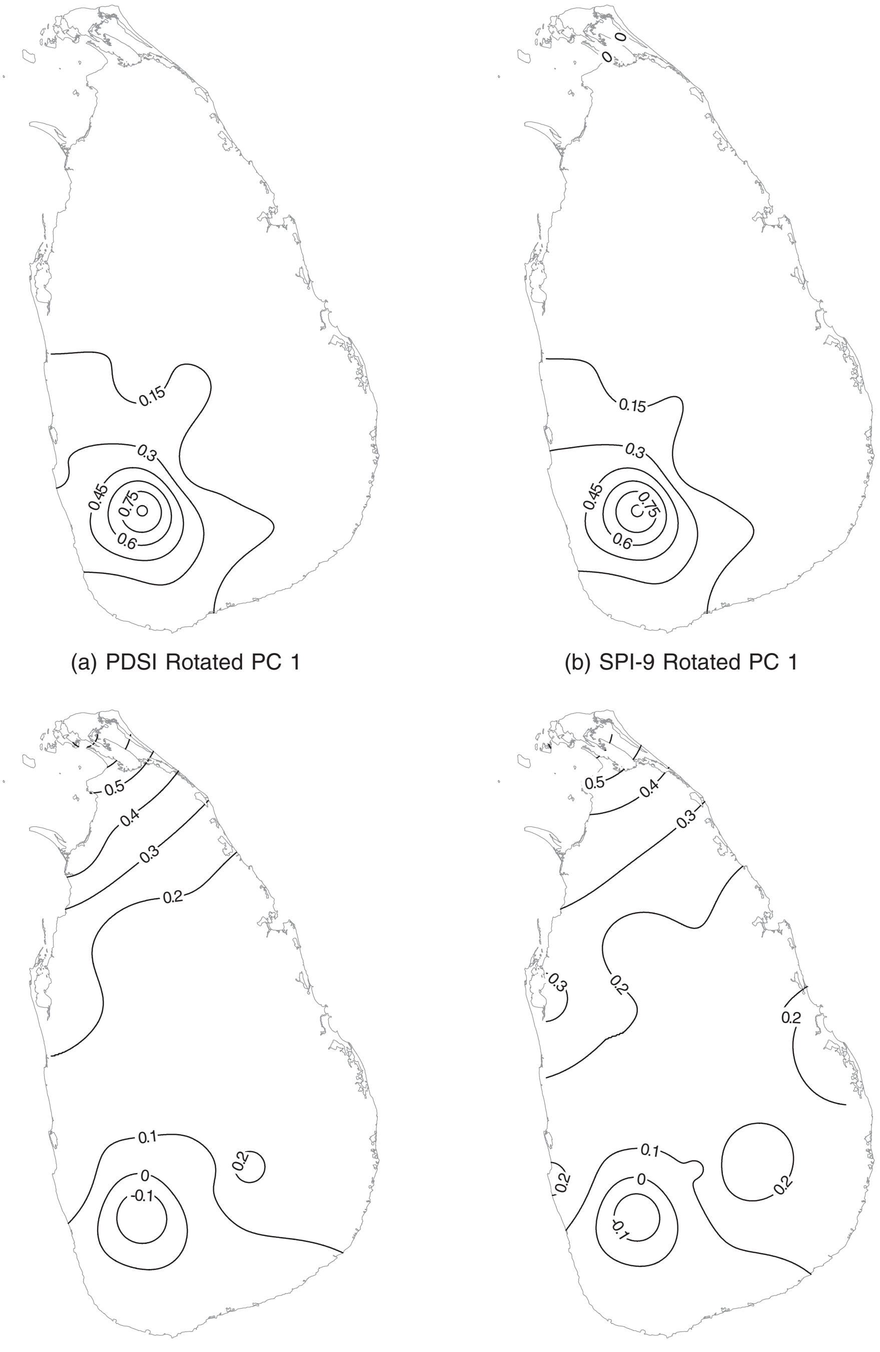
2.6. Correlation analysis

Monthly impacts of drought on agricultural activity from 1974 to 2010 for 11 metrics were obtained at the district-level from the disaster management information system, DesInventar (DesInventar, 2014). These metrics include demographic, crop, and economic parameters such as the number of Grama Niladharis (GNs; i.e. lowest administrative division) affected by drought, loss of paddy (i.e. unmilled rice), and relief payments (Table S2). The usefulness of PDSI and SPI-9 as agricultural drought monitoring tools was evaluated using correlation analysis (Haldar and Mahadevan, 2000) between drought index time series and the corresponding district's agricultural metrics from DesInventar. We calculated correlations between the two drought indices and the 33 metrics for which we had sufficient data (at least 10 months of recorded drought in the district and an absence of significant autocorrelation in the metric; see Table S3). Linear trend analysis was then conducted on PDSI and SPI-9 time series at selected stations, for which correlations with DesInventar metrics were statistically significant at $P < 0.05$ (Haldar and Mahadevan, 2000). Both PDSI and SPI-9 time series showed serial correlation (data not shown), which affects the accuracy of estimated trends (Yue *et al.*, 2002). Therefore, linear trend analysis was conducted on individual monthly time series at each station. The nonparametric Mann-Kendall test was used to assess the significance of trends at $\alpha = 0.05$ (Hirsch *et al.*, 1982).

3. Results

3.1. Spatial patterns

The scree plots of PDSI and SPI-9 PCs show an elbow at the 2nd PC for both indices (Figure 2). Thus, the first two PCs of PDSI and SPI-9, which explain 67% and 69% of the total variance, respectively, were retained for further analysis (Table S4). The unrotated PC 1 of both indices shows little variance and is flat or in phase (i.e. all parts of the island experience drought conditions together) while the unrotated PC 2s are out of phase (Figure 3). The unrotated PC 1s both show a general trend from the north to the southwest. In contrast, the unrotated PC 2s both show a general trend from the southwest to the north. February and March months contribute the most to PC 1 of PDSI but the remaining PCs have relatively little variability in monthly contributions (i.e. fraction of the total variance explained by the PC attributable to each month; Table 1). The station communalities indicate that the stations with the highest contributions are distributed across climate zones (Table 2). The RPCs clarify visually the similarities between the two PC 1s and the two PC 2s (Figure 4).



(a) PDSI Rotated PC 1

(b) SPI-9 Rotated PC 1

(c) PDSI Rotated PC 2

(d) SPI-9 Rotated PC 2

Figure 4. Rotated principal components of PDSI and SPI-9. The rotated components clarify visually the similarities between the two PC 1s and the two PC 2s.

The re-distributed percentages of variance corresponding to the RPCs are 50.9% and 15.9% for PDSI RPC 1 and 2, respectively and for SPI-9 RPC 1 and 2 are 46.8% and 22.5%, respectively.

3.2. Temporal patterns

The confidence bands in the CWTs highlight the 1980s in the 4–6 year period range for PDSI Score 1 and in the 1–8 year period range for PDSI Score 2 (Figure 5). The confidence bands also highlight the 1980s but in the 1–2 and 4–6 period range for SPI-9 Score 1 and in the 1–4 year range for SPI-9 Score 2 (Figure 6). While some of these regions could be spurious correlations, there is generally high power between 2 and 16 years in the CWTs for all four of the retained PC scores. The CWT of the Niño 3.4 dataset also shows significant power in the 2–4 year range in the 1880–1920 as well as from 1960 to 2010, which is consistent with observations by Torrence and Compo (1998). There also appears to be a lengthening of frequency in the Niño 3.4 time series from 1970 to 1990 (Figure 7). The XWTs show significant common power between all of the scores and Niño 3.4

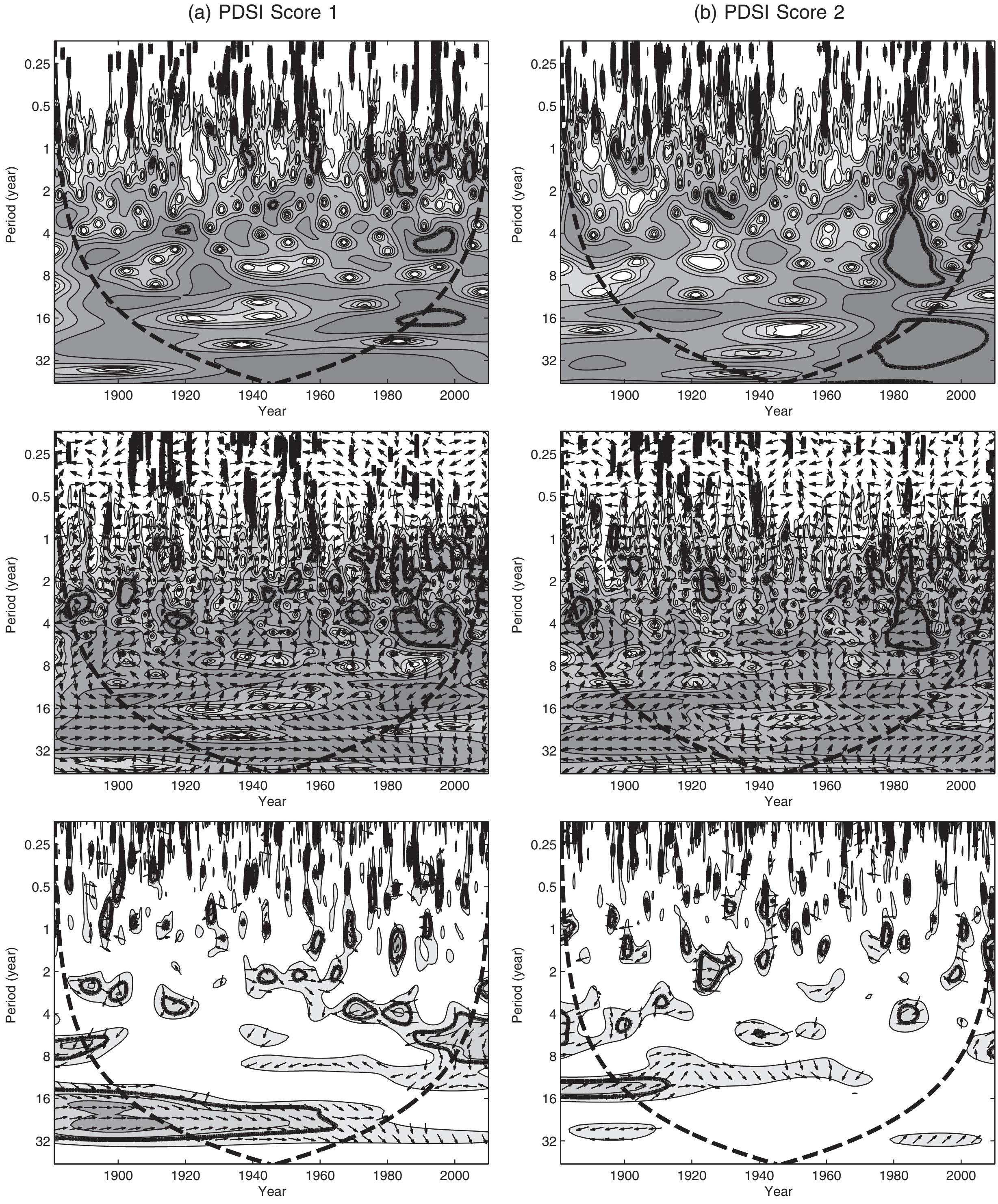


Figure 5. Wavelets of PDSI scores: Row 1 = continuous wavelet transforms, Row 2 = crosswavelets (XWTs), Row 3 = wavelet coherences (WTCs). XWTs and WTCs were constructed using Niño 3.4 data. Areas with dark shading have high power. Significant regions are indicated by black lines and the cone of influence by a dashed line.

from 1980 to 2000. During this time period, the first score of each index shows a consistent anti-phase relationship (i.e. left-pointed arrows) with Niño 3.4 data during the 4–6 period range. The second score of PDSI also shows an anti-relationship with Niño 3.4 data in the 1980s during the 4–6 period range while the second score of SPI-9 does not show any clear relationships with the Niño 3.4 data. In general, however, the phase relationships varied greatly in the XWTs. Greater areas stand out as being significant in the WTCs compared to the XWTs. The WTCs of each index's Score 1 and PDSI Score 2 again show the anti-phase relationship with the Niño 3.4 data during 1980–1990 in the 4–6 period and varying phase relationships in the other regions.

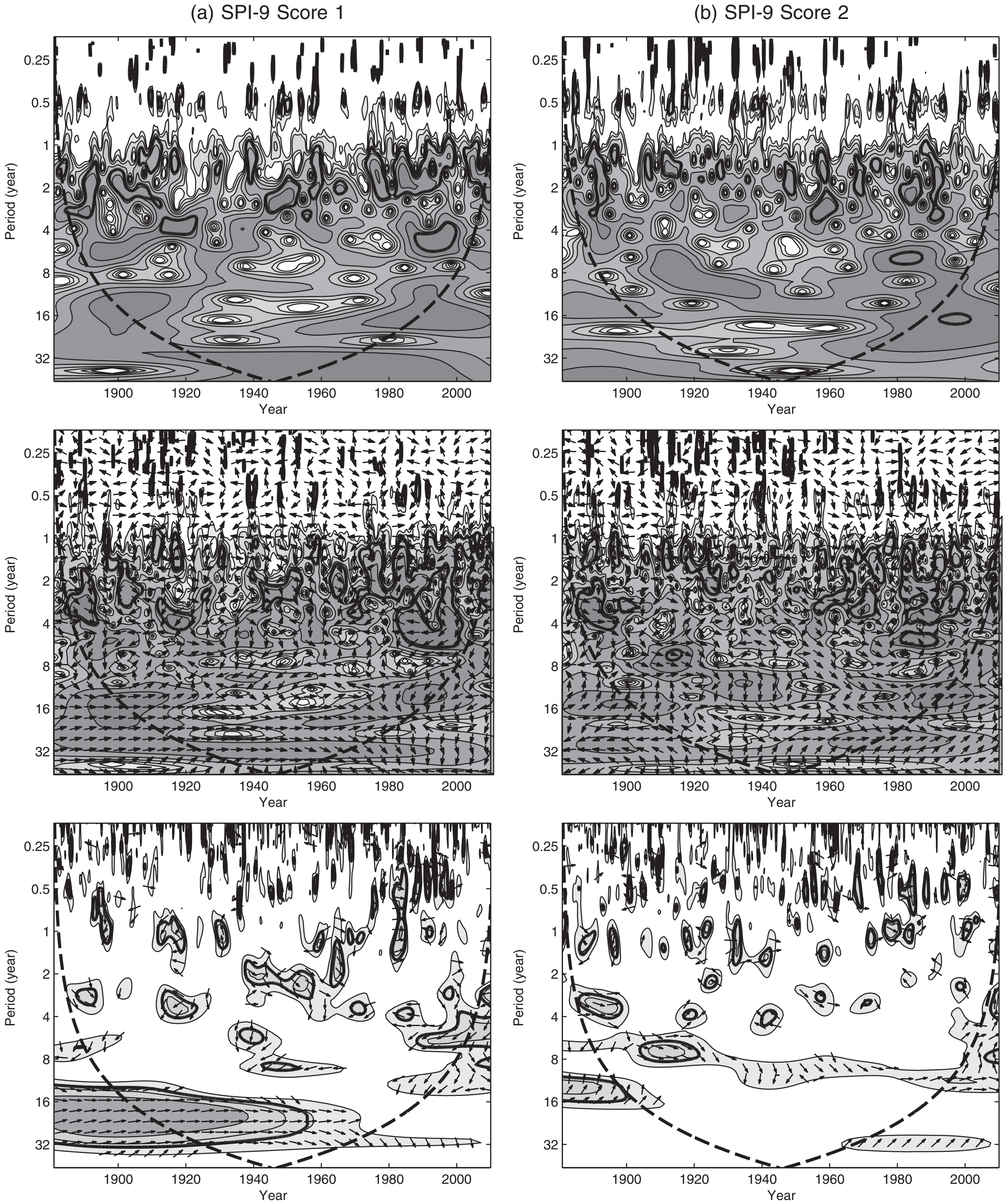


Figure 6. Wavelets of SPI-9 scores: Row 1 = continuous wavelet transforms, Row 2 = crosswavelets (XWTs), Row 3 = wavelet coherences (WTCs). XWTs and WTCs were constructed using Niño 3.4 data. Areas with dark shading have high power. Significant regions are indicated by black lines and the cone of influence by a dashed line.

3.3. Correlations with agricultural metrics

Economic and demographic metrics related to agriculture rather than crop-specific metrics showed significant correlations with drought indices (Table 3). These correlations with the drought indices varied depending on the climatic zone. The intermediate zone stations of Badulla and Kurunegala both significantly correlated with PDSI while the dry zone stations of Anuradhapura, Puttalam, and Trincomalee significantly correlated with SPI-9; none of the wet zone districts had significant correlations with either of the drought indices. The correlation results indicate that there is a counterintuitive, inverse relationship between drought and the number of families affected by

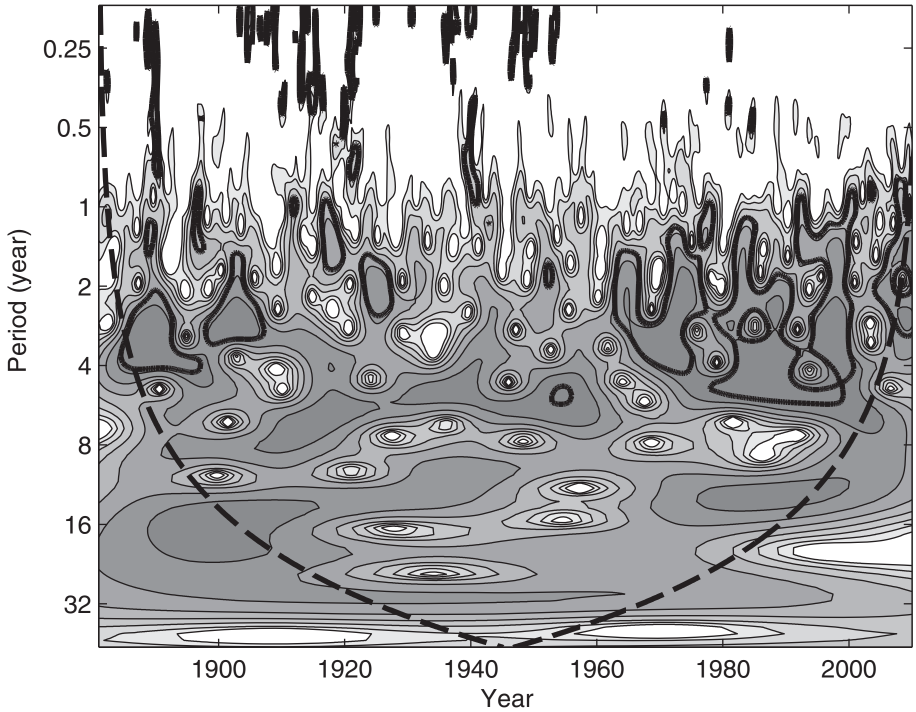


Figure 7. Continuous wavelet transform of Niño 3.4. Areas with dark shading have high power. Significant regions are indicated by black lines and the cone of influence by a dashed line.

Table 3. Significant correlations ($\alpha = 0.05$) with DesInventar agricultural metrics.

	District	Metric	*R* value	*P* value
PDSI	Badulla	Number of families affected	−0.37	0.03
	Kurunegala	Loss for paddy (rupees)	0.27	0.01
		Loss for other farm (rupees)	0.24	0.02
SPI-9	Anuradhapura	Payment for relief (loss of other crop in rupees)	0.33	0.02
		Loss for other farm (rupees)	0.33	0.02
	Puttalam	Payment for relief (livelihood option)	−0.36	0.02
	Trincomalee	Number of Grama Niladhari divisions affected	0.45	0.01

drought in Badulla and relief payments for livelihood in Puttalam (Table 3). Linear trend analysis for PDSI shows that Badulla is experiencing drier conditions from December to July (Table 4). Kurunegala is also experiencing drier conditions during 5 months of the year. Of the dry zone stations with significant correlations, significant trends were only observed at Anuradhapura; monthly SPI-9 values are decreasing from December to August at Anuradhapura (Table 4).

4. Discussion

Selection of a drought index as a monitoring tool is dependent on both the quantity of climate data and the ability of the index to consistently detect spatial and temporal variations of a drought event (Morid *et al.*, 2006). Both indices show similar spatial patterns for drought in Sri Lanka, with in phase PC 1s and out of phase PC 2s. Although, all of the months show similar contributions to PC loadings, PCs 1 and 2 could be physically interpreted as the NEM and SWM. The in phase PC 1s indicate that drought (and consequently non-drought) conditions are experienced uniformly across the island. This is consistent with the NEM, which brings rainfall to the entire island. The out of phase PC 2s indicate that drought conditions experienced in the southwest portion of the island are opposite those of the conditions experienced elsewhere on the island. This is consistent with the SWM, which brings rainfall to the southwest of the island but not elsewhere. Temporal analysis of the PC scores showed high power in the 4–6 year period range, consistent with the dominant modes of oscillations observed for rainfall (Suppiah and Yoshino, 1984b). The XWTs and WTCs showed a consistent anti-phase lag relationship between PC Score 1s and Niño 3.4 data during 1980–2000 in the 4–6 period range. This indicates a weakening of NEM during El Niño years in recent decades, which is consistent with findings by Zubair and Ropelewski (2006) and Zubair *et al.* (2008).

While determination that one particular index is better overall than another index can rarely be made (Heim, 2002), our study suggests that different indices might be appropriate for each of the climatic zones in Sri Lanka:

Table 4. Significant monthly linear trends ($\alpha = 0.05$) with R values in parentheses. All trends are decreasing.

Stations	January	February	March	April	May	June	July	August	September	October	November	December
Badulla	PDSI (0.28)	PDSI (0.25)	PDSI (0.24)	PDSI (0.22)	PDSI (0.29)	PDSI (0.36)	PDSI (0.27)					PDSI (0.24)
Kurunegala	PDSI (0.27)							PDSI (0.23)	PDSI (0.19)	PDSI (0.20)		PDSI (0.22)
Anuradhapura	SPI-9 (0.23)	SPI-9 (0.22)	SPI-9 (0.20)	SPI-9 (0.20)	SPI-9 (0.20)	SPI-9 (0.22)	SPI-9 (0.22)	SPI-9 (0.22)				SPI-9 (0.23)

PDSI for the intermediate zone stations and SPI-9 for the dry zone stations. Neither the PDSI nor SPI-9 correlated with the wet zone stations. Agricultural metrics showed strong correlations with PDSI values of Badulla and Kurunegala as well as SPI-9 values of Anuradhapura, Puttalam, and Trincomalee. Rice planting decisions are typically made during the months of March and September for the minor and major rice cultivation seasons, respectively (Zubair *et al.*, 2008). Weather during these months could have large impacts on farming decisions. Coupled with results from the monthly linear trend analysis, our results show that Anuradhapura and Badulla have been experiencing drier conditions during the March planting month while Kurunegala has been experiencing drier conditions during the September planting month; since the stations all have different climates, explanations for the increasing drying conditions are limited (Malmgren *et al.*, 2003). PDSI and SPI-9 for the wet zone stations of Nuwara Eliya or Ratnapura did not correlate with any of the district-level agricultural metrics, possibly due to the limited recorded drought information in DesInventar at these locations (20 and 22 months, respectively). The remaining two wet zone stations, Colombo and Galle, had less than 10 months of recorded drought information and were thus excluded from the correlation analysis. Especially given the negative correlations between the drought indices and some of the DesInventar metrics, additional research is needed to verify the validity of using correlations with DesInventar metrics and to identify alternative agricultural metrics to select appropriate drought indices for the wet zone. Although there are some issues, the correlation analysis with the DesInventar drought metrics was a first step towards determining an adequate agricultural drought monitoring tool for Sri Lanka.

Although SPI is computationally simple and only needs precipitation data, the index does not account for the influence of temperature on water shortages. Alternatively, PDSI is constructed using a physical water balance model that incorporates evapotranspiration processes into the calculations but lack of data for parameters (such as site-specific AWC values) in Sri Lanka introduces uncertainties in the results (Karl, 1983). Furthermore, PDSI values can vary depending on the evapotranspiration equation used in the calculations (Sheffield *et al.*, 2012). While PDSI values were similar at the regional and global level for both the Thornthwaite and Penman-Monteith evapotranspiration equations (van der Schrier *et al.*, 2011), local comparisons of these estimates have not been conducted for Sri Lanka to date. These local comparisons of evapotranspiration models at multiple timescales (i.e. daily and monthly) are the focus of ongoing work in our research group. Further research is also needed to identify a drought index (such as SPI at different timescales or the Standardized Precipitation Evapotranspiration Index; Vicente-Serrano *et al.*, 2010) for the wet zone and for the dry zone districts of Batticaloa, Hambantota, Jaffna, and Mannar.

Sri Lanka's economy is closely tied with the agricultural sector (FAO, 2012). Therefore, continuing to study drought indices will assist national understanding of drought in the country, development of a drought monitoring system, and associated drought management strategies (GWP, 2014). Particular attention should be given to robust indices that reflect expected climate change impacts such as increasing temperatures (Eriyagama *et al.*, 2010) and strengthening of El Niño phenomena (Dai *et al.*, 1998).

Acknowledgements

We thank David Furbish and the anonymous reviewers for their guidance on this work. This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE-0909667 and by WSC program Grant No. NSF-EAR 1204685.

Supporting Information

The following supporting information is available as part of the online article:

Figure S1. Location map of 30 and 13 stations used to compare the effect of the number of stations on spatial patterns.

Figure S2. Comparison results from spatial patterns derived with 30 stations *vs* 13 stations.

Table S1. Summary of meteorological stations.

Table S2. DesInventar metrics.

Table S3. Regression analyses conducted.

Table S4. Principal component variances.

References

Alley WM. 1984. The Palmer Drought Severity Index: limitations and assumptions. *J. Clim. Appl. Meteorol.* **23**: 1100–1109, doi: 10.1175/1520-045.

Amarasinghe UA, Mutuwatta L, Sakthivadivel R. 1999. Water scarcity variations within a country: a case study of Sri Lanka, International Water Management Institute. Research Report No. 32, International Water Management Institute, Colombo.

Bandara HRS, Yahiya Z, Zubair L. 2010. Assessment of rain water harvesting potential – a case study for Idamelanda. In *Proceedings from the International Conference on Sustainable Built Environment*, Kandy, Sri Lanka, 13–14 December 2010.

Briffa KR, Jones PD, Hulme M. 1994. Summer moisture variability across Europe, 1892–1991: an analysis based on the Palmer Drought Severity Index. *Int. J. Climatol.* **14**(5): 475–506, doi: 10.1002/joc.3370140502.

Chithranayana D. 2008. Identification of drought prone agro-ecological regions in Sri Lanka. *J. Natl. Sci. Found Sri Lanka* **36**(2): 117–123.

Chung C, Nigam S. 1999. Weighting of geophysical data in principal component analysis. *J. Geophys. Res.* **104**(D14): 925–928.

Dai A, Trenberth KE, Karl R. 1998. Global variations in droughts and wet spells: 1900–1995. *Geophys. Res. Lett.* **25**(17): 3367–3370.

Department of Census and Statistics of Sri Lanka (DCS). 2001. Census of population and housing: Number and percentage of agricultural and fishery workers and nonagricultural and fishery workers by district. http://www.statistics.gov.lk/PopHouSat/PDF/Population/p9p22%20Number%20and%20percentage%20of%20agricultural%20and%20fishery%20workers%20and%20nonagricultural.pdf (accessed 1 March 2014).

De Alwis K, Panabokke CR. 1972. *Handbook of the Soils of Sri Lanka*. Soil Science Society of Ceylon: Colombo, 98 pp.

DesInventar. 2012. Sri Lanka National Report on Disaster Risk, Poverty, and Human Development Relationship: Chapter 3 – Disaster event & impact profile. United Nations Development Programme Regional Centre, Bangkok. http://www.desinventar.lk/des_html/disaster_profile/disaster_profile.pdf (accessed 15 June 2014).

DesInventar. 2014. Disaster information management system in Sri Lanka from 1974 to date. Joint effort of the Disaster Management Centre and United Nations Development Programme in Sri Lanka. http://www.desinventar.lk/ (accessed 15 May 2014).

Drosdowsky W. 1993. An analysis of Australian seasonal rainfall anomalies: 1950–1987. I: spatial patterns. *Int. J. Climatol.* **13**: 1–30.

Eder BK, Davis JM, Monahan JF. 1987. Spatial and temporal analysis of the Palmer Drought Severity Index over the south-eastern United States. *J. Climatol.* **7**(1): 31–56, doi: 10.1002/joc.3370070105.

Ekanayake E, Perera K. 2014. Analysis of drought severity and duration using copulas in Anuradhapura, Sri Lanka. *Br. J. Environ. Clim. Change* **4**(3): 312–327, doi: 10.9734/BJECC/2014/14482.

Elsanabary MH, Gan TY, Mwale D. 2014. Application of wavelet empirical orthogonal function analysis to investigate the nonstationary character of Ethiopian rainfall and its teleconnection to nonstationary global sea surface temperature variations for 1900–1998. *Int. J. Climatol.* **34**(6): 1798–1813, doi: 10.1002/joc.3802.

Eriyagama N, Vladimir S, Chandrapala L, Fernando K. 2010. Impacts of climate change on water resources and agriculture in Sri Lanka: a review and preliminary vulnerability mapping, International Water Management Institute (IWMI). Research Report No. 135, International Water Management Institute, Colombo.

Food and Agriculture Organization of the United States (FAO). 2012. FAOSTAT: Top production – rice, paddy. http://faostat.fao.org/site/339/default.aspx (accessed 28 June 2014).

Fernando DN. 2010. *Predicting and Monitoring Drought in the Humid Tropics: A Case Study on Sri Lanka*, PhD thesis, Rutgers, the State University of New Jersey, New Brunswick, 165 pp.

Grinsted A, Moore JC, Jevrejeva S. 2004. Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlinear Process. Geophys.* **11**: 561–566.

Guttman NB. 1991. A sensitivity analysis of the Palmer Hydrologic Drought Index. *Water Resour. Bull.* **27**: 797–807.

Guttman NB. 1998. Comparing the Palmer Drought Index and the Standardized Precipitation Index. *J. Am. Water Resour. Assoc.* **34**: 113–121.

Global Water Partnership (GWP). 2014. Drought Monitoring System for South Asia: Summary Report of the Need Assessment Survey on the Development of South Asian Drought Monitoring System (SA DMS), Compiled by Global Water Partnership, South Asia with support from the WMO/GWP Integrated Drought Management Programme (IDMP). http://www.droughtmanagement.info/literature/GWP_SA_Summary_Report_Need_Assessment_Survey_2014.pdf (accessed 13 August 2014).

Haldar A, Mahadevan S. 2000. *Probability, Reliability, and Statistical Methods in Engineering Design*. John Wiley & Sons: New York, NY, 304 pp.

Heim RR Jr. 2002. A review of twentieth-century drought indices used in the United States. *Bull. Am. Meteorol. Soc.* **83**(August): 1149–1165.

Hirsch RM, Slack J, Smith RA. 1982. Techniques of trend analysis for monthly water quality data. *Water Resour. Res.* **18**(1): 107–121.

Hong SY, Minasny B, Han KH, Kim Y, Lee K. 2013. Predicting and mapping soil available water capacity in Korea. *PeerJ* **1**: e71, doi: 10.7717/peerj.71.

Hu Q, Willson GD. 2000. Effects of temperature anomalies on the Palmer Drought Severity Index in the central United States. *Int. J. Climatol.* **20**(15): 1899–1911.

Jacobi J, Perrone D, Duncan LL, Hornberger G. 2013. A tool for calculating the Palmer drought indices. *Water Resour. Res.* **49**(9): 6086–6089, doi: 10.1002/wrcr.20342.

Jayamaha G. 1975. An analysis of droughts in Sri Lanka. *Proc. Indian Natl. Sci. Acad. USA* **42A**(2): 133–148.

Jolliffe IE. 2002. *Principal Component Analysis*, 2nd edn. Springer: New York, NY, 502 pp.

Kane RP. 1998. ENSO relationship to the rainfall of Sri Lanka. *Int. J. Climatol.* **18**(8): 859–871.

Karl TR. 1983. Some spatial characteristics of drought duration in the United States. *J. Clim. Appl. Meteorol.* **22**(8): 1356–1366.

Karl TR. 1986. The sensitivity of the Palmer Drought Severity Index and Palmer's Z-Index to their calibration coefficients including potential evapotranspiration. *J. Clim. Appl. Meteorol.* **25**: 77–86.

Karl TR, Koscielny AJ, Diaz HF. 1982. Potential errors in the application of principal component (eigenvector) analysis to geophysical data. *J. Appl. Meteorol.* **21**: 1183–1186.

Keyantash J, Dracup J. 2002. The quantification of drought: an evaluation of drought indices. *Bull. Am. Meteorol. Soc.* **83**(August): 1167–1180.

Lee T. 2009. MATLAB function file: SPI. http://www.mathworks.com/matlabcentral/fileexchange/26018-standardized-precipitation-index (accessed 20 February 2014).

Lyon B, Zubair L, Ralapanawe V, Yahiya Z. 2009. Finescale evaluation of drought in a tropical setting: case study in Sri Lanka. *J. Appl. Meteorol. Climatol.* **48**(1): 77–88, doi: 10.1175/2008JAMC1767.1.

Malmgren BA, Hulugalla R, Hayashi Y, Mikami T. 2003. Precipitation trends in Sri Lanka since the 1870s and relationships to El Nino-Southern Oscillation. *Int. J. Climatol.* **23**(10): 1235–1252, doi: 10.1002/joc.921.

Mapa R, Pathmarajah S. 1995. Contrasts in the physical properties of three soils of an Alfisol catena in Sri Lanka. *Soil Use Manag.* **11**(2): 90–93, doi: 10.1111/j.1475- 2743.1995.tb00502.x.

McKee TB, Doesken NJ, Kleist J. 1993. The relationship of drought frequency and duration to time scales. In *Eighth Conference on Applied Climatology*, American Meteorological Society, Anaheim, CA, 17–23 January 1993, 179–186.

Minasny B, McBratney AB, Bristow KL. 1999. Comparison of different approaches to the development of pedotransfer functions for water-retention curves. *Geoderma* **93**: 225–253.

Morid S, Smakhtin V, Moghaddasi M. 2006. Comparison of seven meteorological indices for drought monitoring in Iran. *Int. J. Climatol.* **26**(7): 971–985, doi: 10.1002/joc.1264.

Ntale HK, Gan TY. 2003. Drought indices and their application to East Africa. *Int. J. Climatol.* **23**: 1335–1357, doi: 10.1002/joc.931.

Overland JE, Preisendorfer RW. 1982. A significance test for principal components applied to a cyclone climatology. *Mon. Weather Rev.* **110**(1): 1–4.

Palmer WC. 1965. Meteorological Drought, US Department of Commerce, Research Paper No. 45, U.S. Government Printing Office, Washington, DC.

Patel NR, Chopra P, Dadhwal VK. 2007. Analyzing spatial patterns of meteorological drought using Standardized Precipitation Index. *Meteorol. Appl.* **336**(October): 329–336, doi: 10.1002/met.33.

Rayner NA, Parker D, Horton E, Folland C, Alexander L, Rowell D, Kent E, Kaplan A. 2003. Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *J. Geophys. Res.* **108**(D14): 4407, doi: 10.1029/2002JD002670.

Rohli R, Wilkerson J, Vines N. 2008. Hydroclimatological characteristics and atmospheric circulation anomalies associated with the Gulf of Mexico hypoxic zone. *Phys. Geogr.* **29**(5): 404–423.

Santos JF, Pulido-Calvo I, Portela MM. 2010. Spatial and temporal variability of droughts in Portugal. *Water Resour. Res.* **46**(3): W03503, doi: 10.1029/2009WR008071.

Sheffield J, Wood EF, Roderick ML. 2012. Little change in global drought over the past 60 years. *Nature* **491**(7424): 435–438, doi: 10.1038/nature11575.

Socioeconomics & Planning Centre. 2012. *Pocket Book of Agricultural Statistics*. Department of Agriculture: Peradeniya, Sri Lanka.

Suppiah R. 1996. Spatial and temporal variations in the relationships between the southern oscillation phenomenon and the rainfall of Sri Lanka. *Int. J. Climatol.* **16**(12): 1391–1407.

Suppiah R. 1997. Extremes of the southern oscillation phenomenon and the rainfall of Sri Lanka. *Int. J. Climatol.* **17**: 87–101.

Suppiah R, Yoshino MM. 1984a. Rainfall variations of Sri Lanka, part 1: spatial and temporal patterns. *Arch. Meteorol. Geophys. Bioclimatol.* **34**: 329–340.
Suppiah R, Yoshino MM. 1984b. Rainfall variations of Sri Lanka, part 2: regional fluctuations. *Arch. Meteorol. Geophys. Bioclimatol.* **35**: 81–92.
Thambyahpillay G. 1954. The rainfall rhythm of Ceylon. *Univ. Ceylon Rev.* **12**(4): 224–274.
Thevakaran A, Sonnadara DUJ. 2013. Reconstruction of missing monthly temperature observations in Jaffna, Sri Lanka. *J. Natl. Sci. Found Sri* **41**(1): 21–28.
Torrence C, Compo GP. 1998. A Practical Guide to Wavelet Analysis. *Bull. Am. Meteorol. Soc.* **79**(1): 61–78.
United Nations Office for Disaster Risk Reduction (UNISDR). 2014. Disaster Statistics: Drought. http://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Nino34/ (accessed on 1 July 2014).
United Nations. 2009. United Nations Conference on Sustainable Development, Rio+20, 17th Session of the Commission on Sustainable Development: Drought. http://sustainabledevelopment.un.org/index.php?menu=1246 (accessed 15 July 2014).
van der Schrier G, Jones PD, Briffa KR. 2011. The sensitivity of the PDSI to the Thornthwaite and Penman-Monteith parameterizations for potential evapotranspiration. *J. Geophys. Res.* **116**(D3): D03, doi: 10.1029/2010JD015001, 106.
Vicente-Serrano SM, Beguería S, López-Moreno JI. 2010. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *J. Clim.* **23**: 1696–1718, doi: 10.1175/2009JCLI2909.1.
Wickramagamage P. 2009. Seasonality and spatial pattern of rainfall of Sri Lanka: exploratory factor analysis. *Int. J. Climatol.* **30**(8): 1235–1245, doi: 10.1002/joc.1977.
World Bank. 2014. South Asia & Climate Change: A Development and Environmental Issue. http://go.worldbank.org/0XAV4BYO60 (accessed on 1 July 2014).
World Food Programme. 2007. Sri Lanka Food Security Assessment based on the Integrated Food Security and Humanitarian Phase Classification Approach, April, 61 pp.
Wrublack SC, Mercante E, Vilas Boas MA. 2013. Water quality parameters associated with soil use and occupation features by Thiessen polygons. *Food Agric. Environ.* **11**(2): 846–853.
Young KC. 1992. A three-way model for interpolating for monthly precipitation values. *Mon. Weather Rev.* **120**: 2561–2569.
Yue S, Pilon P, Phinney B, Cavadias G. 2002. The influence of autocorrelation on the ability to detect trend in hydrological series. *Hydrol. Process.* **16**(9): 1807–1829, doi: 10.1002/hyp.1095.
Zubair L. 2002. El Nino-southern oscillation influences on the Mahaweli streamflow in Sri Lanka. *Int. J. Climatol.* **22**(2): 249–260, doi: 10.1002/joc.714.
Zubair L, Ropelewski CF. 2006. The strengthening relationship between ENSO and northeast monsoon rainfall over Sri Lanka and southern India. *J. Clim.* **19**(8): 1567–1575, doi: 10.1175/JCLI3670.1.
Zubair L, Perera R, Yahiya Z. 2005. Was the 2002/03 Maha's bumper paddy harvest due to El Niño? *J. Instit. Eng. Sri Lanka* **38**(4): 63–70.
Zubair L, Siriwardhana M, Chandimala J, Yahiya Z. 2008. Predictability of Sri Lankan rainfall based on ENSO. *Int. J. Climatol.* **101**(June): 91–101, doi: 10.1002/joc.1514.