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Dry spells risk characterisation and determination of Southern oscillation index influence on precipitation patterns over Victoria State, Australia

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ABSTRACT

A dry spell is defined as the consecutive number of days with precipitation less than a specified threshold value of a standardised precipitation index (SPI). A cumulative effect of these dry spells amount to drought events and thereby negatively affect socio-economic activities in the communities. The current study aimed at determining the influence of El Niño-Southern Oscillation (ENSO) aided by Southern Oscillation Index (SOI) in order to make easy prediction given clear SOI cyclicity of anything from 3 to 7 years. The study used SPI to define dry spells and was also used a conceptual framework to quantify dry spells. A spectral analysis was also applied to SPI-1 time series datasets to determine return levels to provide government and all relevant authorities with behavioural characteristics of dry spells in the area for proactive mitigation strategies. Main results of this study ENSO having no direct influence over all the selected station's precipitation. All the stations showed an average of 12 months or 1 year return level. This implies that after every 1 year, the study area is highly likely to experience dry spells which could lead to detrimental effects of the most important amenities of the study area. This phenomenon provides authorities with relevant information to plan proactively as dry spells may amount or graduate to drought events and thereby adversely affect water consuming activities in the area.

Introduction

El Niño - Southern Oscillation (ENSO) is an irregular regular variation in the temperature of the winds and the surface of the sea in the tropical Eastern Pacific which affects the tropics and the subtropics (Rajagopalan, Lall, & Cane, 1997). The temperature warming stage is referred to as El Niño or La Niña (Straus & Shukla, 2002). In combination with the change of the sea temperature, the Southern Oscillation is the accompanying atmospheric component: El Niño is accompanied by a high air pressure on the western Pacific and La Niña tropical air surface (Straus & Shukla, 2002). The two periods last several months and usually occur with varying intensities every couple of years (Borlace, Cai, & Santoso, 2013).

The two phases relate to the traffic of walkers discovered in the early 20th century by Gilbert Walker (Letson, Podestá, Messina, & Ferreyra, 2001). The pressure gradient force of the Walker circulation is caused by a high-pression region in the eastern Pacific and a low-pressure system in Indonesia (Fasullo & Webster, 2002). Deep sea waters are reduced or eliminated from the weakening or reversal of the circulation of walkers (including trade winds), which creates El Niño by increasing the surface of the oceans to above average temperatures (Fasullo & Webster, 2002). La Nina is caused by a very strong Walker circulation, which induces greater upwelling and colder ocean temperatures. Increased precipitation occurs along the Gulf coast and Southeast during the El Nina period of ENSO due to a higher than average and more southerly polar jet stream (Lin, Liou, & Huang, 2015). During El Nina events in late winter and early spring, Hawaii should predict drier-than-average weather (Romero-Centeno, Zavala-Hidalgo, Gallegos, & O'Brien, 2003).

Methods and materials

Data quality control: Stationarity test

When non-stationary time series data is used in forecasting models, the effects are inaccurate and spurious, resulting in poor interpretation and forecasting (Von Sachs & Neumann, 2000). The problem can be solved by converting the time series data so that it becomes stationary (Gregoriou & Kontonikas, 2006). ADF and KPSS are fast stationary statistical checks that will help a researcher understand the data he or she is working with. The bulk of mathematical forecasting methods are based on the premise that time series are roughly stationary. A stationary series is reasonably simple to forecast essentially assume that its statistical properties will be the same in the future as they were in the past (Sabavala & Morrison, 1981). The first step in transforming non-stationary data into stationary data (trend removal) so that mathematical forecasting techniques can be applied is to evaluate time series trends (Ajewole, Adejuwon, & Jemilohun, 2020). Having the data stationary, choosing the correct model, and assessing model accuracy are the three basic phases in creating a high-quality forecasting time series model (Vezzoli, Mercogliano, & Pecora, 2013).

Correlational analysis

Correlation analysis is a mathematical technique for determining the intensity of a relationship between two quantitative variables (Manatsa, Chingombe, & Matarira, 2008). A high correlation indicates that two or more variables have a close relationship, while a low correlation indicates that the variables are barely related. In other words, it is the process of measuring the intensity of the relationship using statistical data that is available (Manatsa et al., 2008). This methodology is inextricably linked to linear regression analysis, which is a statistical method for modelling the relationship between a dependent variable, known as the answer, and one or more explanatory or independent variables (Manatsa et al., 2008). The aim of this paper is to provide a general overview of correlation analysis as a tool for evaluating ENSO influences on precipitation patterns in the study area.

Spectral Analysis

Periodic behaviour can be seen in a variety of time series. Periodic behaviour can be extremely complex (Von Sachs & Neumann, 2000). The technique of spectral analysis allows us to discover underlying periodicities. We must first transform data from the time domain to the frequency domain before we can perform spectral analysis (Mossaad & Wu, 1984). The spectral analysis was used in this paper to determine the return periods of the dry spells risk for the study area in order to make informed decisions.

Results and discussions

Figure 1 depicts graphs of all stations' precipitation from 1982 to 2019. This is to visualise the datasets and determine outliers existent in the datasets across all candidate stations. In this figure 1, it can be noted that there are three clear such outliers all from the East Gippsland. After the removal of all outliers by SPSS software, all precipitation datasets from all the candidate stations were tested for stationarity as shown in table 1. All p-values were significant with values less than the specified significance level of 5% across all stations, implying that further analysis could be carried out without results being spurious.

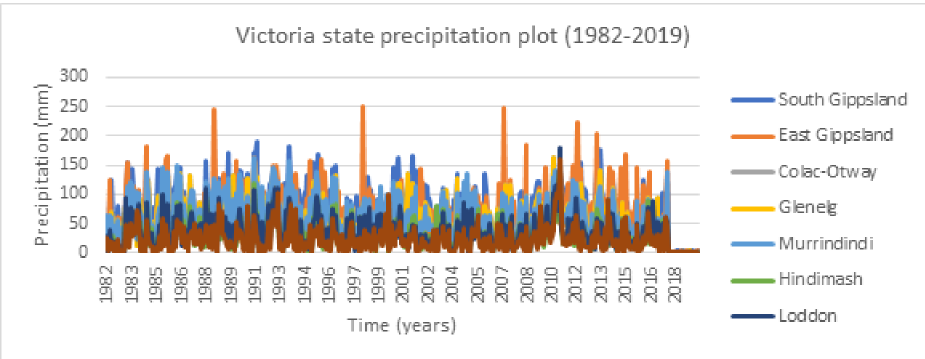


Figure 1: Graph of precipitation of Victorian state of Australia

Table 1: Precipitation's Dickey-Fuller test (ADF (stationary)

Station	Tau (Observed value)	Tau (Critical value)	p-value (one-tailed)	alpha
South Gippsland	-6.674	-3.389	< 0.0001	0.05
East Gippsland	-5.674	-3.389	< 0.0001	0.05
Colac-Otway	-6.357	-3.389	< 0.0001	0.05
Glenelg	-6.357	-3.389	< 0.0001	0.05
Murrindindi	-6.698	-3.389	< 0.0001	0.05
Hindimash	-7.328	-3.389	< 0.0001	0.05
Loddon	-6.307	-3.389	< 0.0001	0.05
Mildura	-6.260	-3.389	< 0.0001	0.05

Figure 2 and table 2 show a graph of Southern oscillation index and descriptive statistics for Precipitation and Southern Oscillation Index (SOI) respectively. From the graph of SOI, clear cycles can be seen, and these are approximately 7 to 10 years. Table 2 shows the top five stations receiving relatively high precipitation that ranges from to 57.7 to 73.2mm. However, these five stations exhibit relatively high variability as depicted by the calculated standard deviations. The SOI seems to vary homogeneously with the last three stations with the standard deviation of around 22.

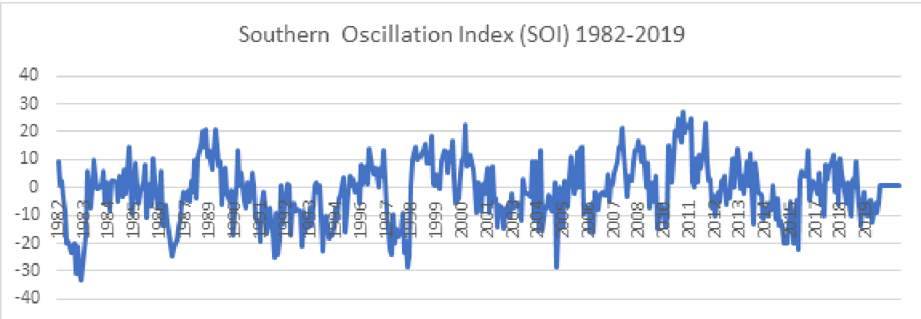


Figure 2: Graph of the Southern Oscillation Index time series

Table 2: Descriptive statistics for Precipitation and Southern oscillation index

Station	Observations	Minimum	Maximum	Mean	Std. deviation
South Gippsland	456	0.370	188.750	72.310	39.308
East Gippsland	456	0.410	249.840	64.853	40.932
Colac-Otway	456	0.140	162.830	57.744	32.558
Glenelg	456	0.140	162.830	57.744	32.558
Murrindindi	456	0.210	161.630	60.033	35.827
Hindimash	456	0.070	147.060	31.332	23.448
Loddon	456	0.090	178.040	34.030	26.061
Mildura	456	0.010	158.800	22.941	22.061
SOI	456	-33.300	27.100	-1.605	10.843

Post analysis of the descriptive statistics of precipitation datasets of all stations and SOI, A non-parametric correlation test (Spearman's test) was applied to test for any correlation presents amongst stations and SOI, to check if SOI has any influence over precipitation patterns of the study area. Table 2 show a correlation matrix of precipitation of all stations and SOI. It can be seen that most stations correlated strongly positive with one another except with SOI where correlation coefficients are all weak. None of the stations' precipitation datasets correlated significantly with SOI. This phenomenon clearly indicates that SOI has no special influence on the precipitation patterns of the study area. This result is in line with literature where not all stations' precipitation is influenced by SOI.

Table 3: Spearman's correlation matrix: SOI vs Precipitation

Station	South Gippsland	East Gippsland	Colac-Otway	Glenelg	Murrindindi	Hindimash	Loddon	Mildura	SOI
South Gippsland	1.00	0.53	0.86	0.86	0.81	0.65	0.63	0.46	0.15
East Gippsland	0.53	1.00	0.48	0.48	0.59	0.40	0.53	0.48	0.18
Colac-Otway	0.86	0.48	1.00	1.00	0.86	0.80	0.75	0.57	0.12
Glenelg	0.86	0.48	1.00	1.00	0.86	0.80	0.75	0.57	0.12
Murrindindi	0.81	0.59	0.86	0.86	1.00	0.82	0.90	0.72	0.21
Hindimash	0.65	0.40	0.80	0.80	0.82	1.00	0.89	0.80	0.17
Loddon	0.63	0.53	0.75	0.75	0.90	0.89	1.00	0.85	0.22
Mildura	0.46	0.48	0.57	0.57	0.72	0.80	0.85	1.00	0.25
SOI	0.15	0.18	0.12	0.12	0.21	0.17	0.22	0.25	1.00

Values in bold are different from 0 with a significance level alpha=0.05

Table 4: Spearman's correlation matrix: SOI vs SPI-1

Station	South Gippsland	East Gippsland	Colac-Otway	Glenelg	Murrindindi	Hindimash	Loddon	Mildura	SOI
South Gippsland	1	0.579	0.844	0.844	0.772	0.573	0.587	0.421	0.130
East Gippsland	0.579	1	0.517	0.517	0.606	0.435	0.536	0.467	0.111
Colac-Otway	0.844	0.517	1	1.000	0.834	0.747	0.730	0.552	0.119
Glenelg	0.844	0.517	1.000	1	0.834	0.747	0.730	0.552	0.119
Murrindindi	0.772	0.606	0.834	0.834	1	0.802	0.896	0.722	0.092
Hindimash	0.573	0.435	0.747	0.747	0.802	1	0.890	0.816	0.080
Loddon	0.587	0.536	0.730	0.730	0.896	0.890	1	0.849	0.079
Mildura	0.421	0.467	0.552	0.552	0.722	0.816	0.849	1	0.062
SOI	0.130	0.111	0.119	0.119	0.092	0.080	0.079	0.062	1

Values in bold are different from 0 with a significance level alpha=0.05

Having determined that SOI has no influence on all stations' precipitation, Standardised Precipitation Indices (SPI) were computed on SPI-1 temporal scale to characterise dry spells in the study area. Table 5 shows the results of descriptive statistics of dry spells' duration in Victoria state computed from a Drought Monitoring and Prediction software (DMAP). From this table, it can be seen that all the stations experience relatively the same amount of dry spells on average. This behaviour is confirmed by the non-parametric Kruskal-Wallis test in table 6 with a non-significant p-value of 0.978 > 0.05.

Table 5: Summary descriptive statistics of dry spells' duration in Victoria state

Station	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
Colac-Otway	4	94	28.000	730.000	60.181	79.484
East Gippsland	0	98	28.000	730.000	63.959	79.536
Glenelg	4	94	28.000	730.000	60.181	79.484
Hindimash	4	94	28.000	761.000	66.330	86.283
Loddon	1	97	28.000	730.000	64.856	84.482
Mildura	0	98	28.000	730.000	64.224	77.964
Murrindindi	6	92	28.000	730.000	63.489	86.767
South Gippsland	4	94	28.000	730.000	58.585	79.109

Table 6: Kruskal-Wallis test / Two-tailed test: Durations

K (Observed value)	1.627
K (Critical value)	14.067
DF	7
p-value (one-tailed)	0.978
alpha	0.05

An approximation has been used to compute the p-value.

Table 7 shows descriptive statistics of dry spells' severities in the study area computed at threshold of below zero aided by DMAP. Visually all stations have similar mean severities and variability as computed by standard deviations. However, a further test to confirm this observation was carried out as shown in table 8, the results disconfirmed the observed visual similarity where a two-tailed test Kruskal-Wallis had a significant p-value of 0.008< 5%. Although the candidate stations revealed similar behavioural patterns in terms of dry spells duration, there is a significant difference in the amount of severities each receives as shown by the test in table 8.

Table 7: Summary descriptive statistics of dry spells' severities in Victoria state

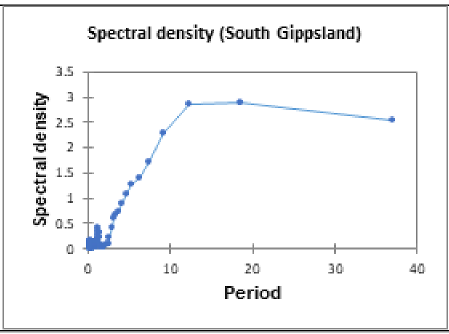
Variable	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
Colac-Otway	4	94	0.000	76.900	1.651	7.901
East Gippsland	0	98	0.002	71.338	1.632	7.177
Glenelg	4	94	0.000	76.900	1.651	7.901
Hindimash	4	94	0.028	61.703	1.851	6.382
Loddon	1	97	0.018	59.863	1.829	6.121
Mildura	0	98	0.005	53.032	1.855	5.368
Murrindindi	6	92	0.000	73.148	1.740	7.619
South Gippsland	4	94	0.026	77.088	1.686	7.914

Table 8: Kruskal-Wallis test / Two-tailed test: Severities

K (Observed value)	19.025
K (Critical value)	14.067
DF	7
p-value (two-tailed)	0.008
alpha	0.05

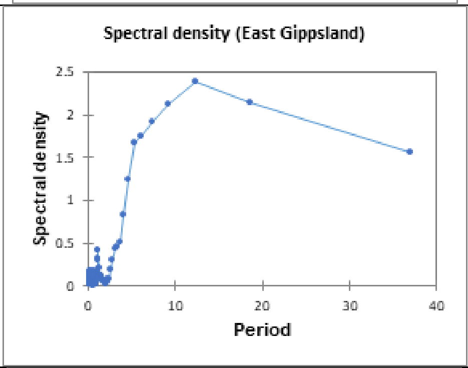
An approximation has been used to compute the p-value

Having observed similarities and differences of the stations on two drought parameters namely duration and severity, XLSTAT computer software was used to fit suitable probability distributions on all SPI-1's (dry spells). Figure 3 shows the spectral densities for each station's SPI-1 and fitted probability distribution's parameters. The determined parameters were used to compute the return level or periodicities of each station's dry spell in the study area. All the stations showed an average of 12 months or 1 year return level. This implies that after every 1 year, the study area is highly likely to experience dry spells which could lead to detrimental effects of the most important amenities of the study area.



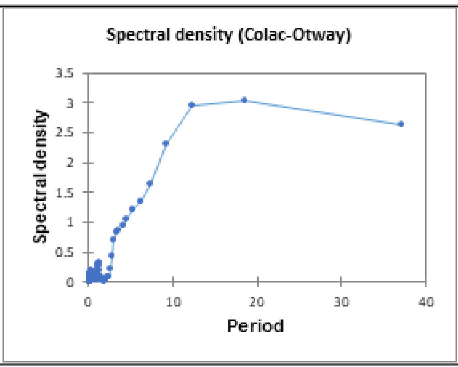
Statistic	Value	p-value
Fisher's kappa	23.577	< 0.0001
Bartlett's Kolmogorov-Smirnov	0.506	< 0.0001

Spectral density peak: 12.36 months



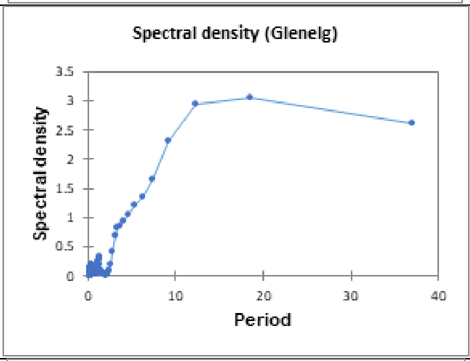
Statistic	Value	p-value
Fisher's kappa	18.490	< 0.0001
Bartlett's Kolmogorov-Smirnov	0.437	< 0.0001

Spectral density peak: 12.36 months



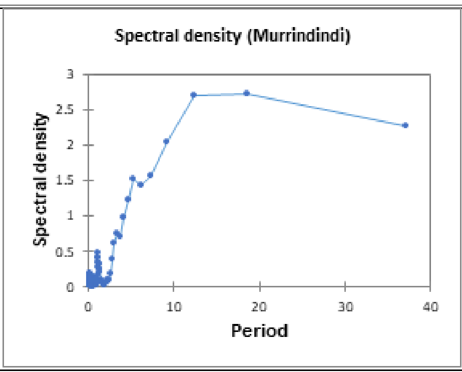
Statistic	Value	p-value
Fisher's kappa	26.629	< 0.0001
Bartlett's Kolmogorov-Smirnov	0.523	< 0.0001

Spectral density peak: 18.5 months



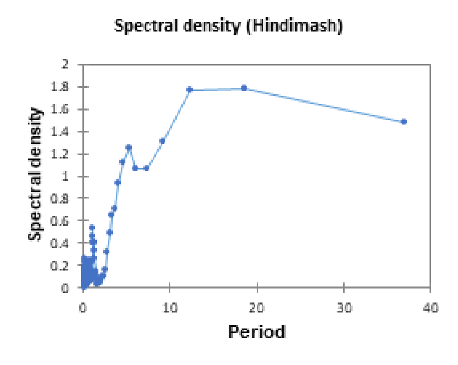
Statistic	Value	p-value
Fisher's kappa	26.629	< 0.0001
Bartlett's Kolmogorov-Smirnov	0.523	< 0.0001

Spectral density peak: 18.5 months



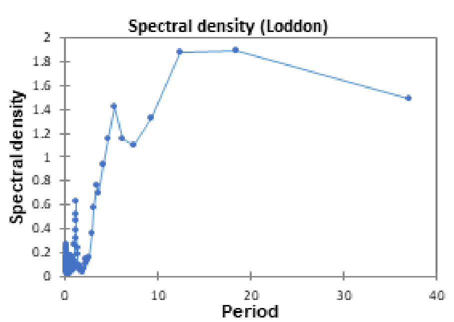
Statistic	Value	p-value
Fisher's kappa	22.699	< 0.0001
Bartlett's Kolmogorov-Smirnov	0.494	< 0.0001

Spectral density peak: 12.36 months



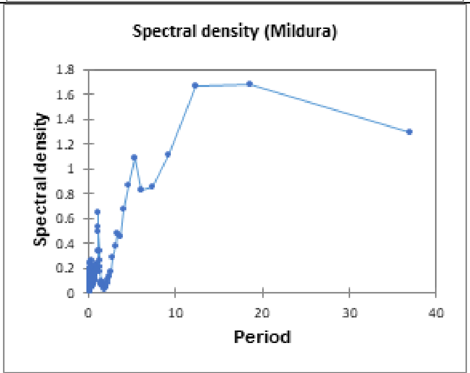
Statistic	Value	p-value
Fisher's kappa	15.562	< 0.0001
Bartlett's Kolmogorov-Smirnov	0.365	< 0.0001

Spectral density peak: 12.36 months



Statistic	Value	p-value
Fisher's kappa	17.258	< 0.0001
Bartlett's Kolmogorov-Smirnov	0.383	< 0.0001

Spectral density peak: 12.36 months



Statistic	Value	p-value
Fisher's kappa	16.218	< 0.0001
Bartlett's Kolmogorov-Smirnov	0.303	< 0.0001

Spectral density peak: 12.36 months

Figure 3: Spectral density graphs depicting peak periods/circles

Conclusion and recommendations

In conclusion, El Niño–Southern Oscillation (ENSO) which is the periodic variation in winds and sea surface temperature over the tropical eastern Pacific Ocean, affecting the climate of much of the tropics and subtropics does not always have influence on all areas' precipitation. From the current study results a non-parametric correlation test (Spearman) results ENSO having no direct influence over all the selected station's precipitation. The determined parameters from suitably fitted probability distributions were used to compute the return level or periodicities of each station's dry spell in the study area. All the stations showed an average of 12 months or 1 year return level. This implies that after every 1 year, the study area is highly likely to experience dry spells which could lead to detrimental effects of the most important amenities of the study area. This phenomenon provides authorities with relevant information to plan proactively as dry spells may amount or graduate to drought events and thereby adversely affect water consuming activities in the area.

Conflict of interest

The author declares that there was no conflict of interest.

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