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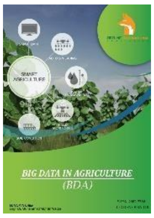

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RESEARCH ARTICLE

DROUGHT RISK ANALYSIS USING SPI FOR EFFECTIVE AGRICULTURAL PROJECTS' AND WATER RESOURCE MANAGEMENT OVER VICTORIA STATE, AUSTRALIA

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ABSTRACT

Drought is a gradual and persistent hazard resulting from below-average precipitation, which poses a threat to various economic sectors and human life as a whole. This external and insurable risk predominantly affects agriculture and water resource management projects, causing a ripple effect across related sectors and operations. The objective of this study was to analyse drought risk in the Victoria State of Australia using the Standardized Precipitation Index (SPI) to monitor and characterize drought occurrences, with the aim of safeguarding and enhancing agricultural and water resource management initiatives. The SPI methodology was employed, computing four temporal scales (SPI-3, 6, 12, and 24) for assessing both agricultural and hydrological drought. The findings indicate a consistent pattern across most stations, revealing significant declines in SPI values on various time scales, suggesting an escalation in drought severity in the near future. Although there is some optimism for agriculture and related projects in the region, caution is warranted due to the decreasing trends observed in SPI-3 and 6. On the other hand, SPI-12 and 24 clearly demonstrate that severe droughts have already affected all stations, with the potential for even more severe episodes in the future. Consequently, it is imperative for the government and relevant stakeholders to exercise extreme caution in water usage, as irresponsible or excessive consumption could have adverse effects on water-intensive projects and activities in the area.

KEYWORDS

Drought risk, SPI, Agricultural projects, water resource management, Victoria State, Australia

1. INTRODUCTION

Drought is a period when an area or region receives less rain than usual. Inadequate precipitation, whether rain or snow, can result in decreased soil moisture or groundwater, reduced stream flow, crop damage, and a general water shortage (Requena, et al., 2013). This phenomenon is further defined as a normal recurring event that affects the livelihoods of millions of people worldwide, particularly the 200 million people who live in all parts of the world (Beguería et al., 2010). Climate variability, which includes excessive and volatile seasonal rainfall, floods, and cyclones, puts farming at risk across most of southern Africa, but especially in marginal rainfed agricultural areas with low and erratic precipitation (Morán-Tejeda et al., 2013). The latter condition is expressed in crop and livestock production that is relatively poor and highly unpredictable (Ennajeh et al., 2010). A severe drought, or a series of droughts, can be a disaster-triggering agent, exacerbating social and economic problems and jeopardizing a society's overall livelihood security (Bauman, Goemans, Pritchett, & McFadden, 2013). These issues are more serious in areas where populations are the least diverse and almost everyone is reliant on one or the other (Ennajeh et al., 2010).

Extended drought or unusually high rainfall or flooding periods in these regions can devastate already marginal production levels, putting subsistence agriculture at risk. Australia's climate has always been unpredictable, particularly when it comes to droughts (Udmale et al., 2014). Droughts have a major effect on agricultural yields which can lead to a rise in retail food prices. The recent drought has been related to exceptionally large and long-term price rises, which have harmed agricultural projects and development (Parvez, 2019). Drought is likely to increase globally in the coming decades as a result of climate change. Regional forecasts suggest that changes in rainfall patterns and rising temperatures which increase the severity of the drought are adversely affecting South East Australia. By 2070, the drought in eastern Australia may be 40 percent longer and conditions in a high-emission scenario will become worse (Parvez, 2019). This process can begin with the recent drought events (Cao,et al., 2013). More average temperatures have certainly exacerbated their impact due in part to human-made climate change. Additional changes, such as increased storm severity, also have negative consequences (Udmale et al., 2014). For Australian consumers, this would mean higher average food prices, as well as an increase in the frequency and intensity of price increases (DaMatta and Cochicho Ramalho, 2006). Unless strong action is taken to reduce global pollution, price shocks similar to those experienced by Australian consumers during the current extreme drought which start to occur every two to four years, rather than once every decade, for foods such as fresh fruit and vegetables that are primarily supplied by local producers (Haddad et al, 2009).

1.2 Drought impact and agricultural vulnerability in Victoria, Australia

Historically, Victoria has experienced several significant drought events, with notable impacts on its agricultural output. Agroup of researchers in 2014 provide a comprehensive analysis of drought patterns in Australia, emphasizing the increasing frequency and intensity of these events in recent decades (Udmale et al., 2014). This trend is corroborated by studies in 2010 who link these patterns to broader climatic shifts (Beguería et al., 2010). The historical data reveal a clear correlation between drought

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periods and reduced agricultural productivity in Victoria, with severe implications for both crop and livestock production. Recent studies indicate a worsening trend in drought severity in Victoria, with direct consequences for the agricultural sector. A Research in 2013 highlights a decrease in soil moisture and groundwater levels, adversely affecting crop yields and livestock health (Morán-Tejeda et al., 2013). The impact is not uniform across the state, with certain regions experiencing more acute effects (Ennajeh et al., 2010). These findings are critical in understanding the current state of agricultural vulnerability in Victoria, where water scarcity has become a limiting factor in agricultural productivity.

The economic implications of drought in this area extend beyond the immediate impact on agricultural output. The ripple effects of reduced agricultural productivity, including increased food prices and disrupted supply chains (Bauman et al., 2013). This economic strain is felt most acutely by rural communities, where agriculture forms the backbone of the local economy. The social ramifications are equally significant, with drought contributing to increased rates of rural depopulation (Haddad et al., 2009). These studies showed the broader economic and social challenges posed by drought in Victoria, highlighting the need for comprehensive strategies to mitigate its impacts.

1.3 Standardized Precipitation Index (SPI) as a tool for drought analysis

The SPI, that has been introduced in 1993, calculates drought severity based on precipitation data for selected time scales (McKee et al., 1993). This index normalizes precipitation data, allowing for the comparison of drought conditions across different regions and climates. A researcher elaborated on the SPI calculation, emphasizing its ability to capture both short-term and long-term drought impacts (Guttman, 1999). The flexibility of SPI in representing various drought types, from meteorological to hydrological, is one of its key strengths (Lloyd-Hughes and Saunders, 2002). The application of SPI in drought analysis has been extensive. Studies have demonstrated the utility of SPI in monitoring drought conditions, providing early warning systems for agricultural and water resource management (Hayes et al., 1999). More recent research; has applied SPI in diverse climatic regions, showcasing its adaptability and reliability in different environmental settings (Wu et al., 2007). These studies highlight the role of SPI in informing drought mitigation strategies and policymaking. While SPI is widely regarded as an effective tool for drought analysis, it is not without limitations. Its reliance on precipitation data alone, can overlook other factors contributing to drought, such as temperature and evapotranspiration (Wilhite et al., 2000). Furthermore, the effectiveness of SPI in predicting long-term hydrological impacts can be limited, necessitating the integration of SPI with other indices for comprehensive drought assessment (Vicente-Serrano et al., 2010). Recent advancements in SPI methodology have focused on integrating temperature and evapotranspiration data (Vicente-Serrano et al., 2010). These modifications aim to enhance the accuracy of SPI in reflecting the multifaceted nature of drought. Additionally, the integration of SPI with remote sensing and GIS technologies, represents a significant leap forward, offering more spatially detailed and timely drought assessments (Mishra and Singh, 2010).

2. Materials and Methods

The Standardized Precipitation Index (SPI) is a widely used index for describing meteorological drought over a wide range of timescales. The SPI is closely related to soil moisture on short timescales, but it can also be related to groundwater and reservoir storage on longer timescales (Manatsa et al., 2008). The SPI can be used to compare climates in different regions. It quantifies observed precipitation as a standardized deviation from a probability distribution function chosen to model the raw precipitation data. Raw precipitation data are typically fitted to a gamma or Pearson Type III distribution before being transformed to a normal distribution (Manatsa et al., 2008).

The number of standard deviations by which the observed anomaly deviates from the long-term mean is represented by the SPI values. Using monthly input data, the SPI can be generated for periods ranging from one to 36 months. The SPI has been accepted by the operational community as the standard index for quantifying and monitoring meteorological drought that should be accessible worldwide (Manatsa et al., 2008).

2.1 Normality test

Normality tests are used in statistics to assess if a data set is well-modelled by a normal distribution and to compute the likelihood that a random variable underlying the data set is normally distributed. The tests are a type of model selection, and they can be interpreted in a number of ways, depending on how one interprets probability. A normality test was used in this analysis to see whether the sample data came from a normally distributed population. A normally distributed sample population is needed for a number of statistical tests, including the student's t-test and one-way and two-way ANOVA. This was done in order to select relevant statistics for further analysis of the datasets.

2.2 Data stationarity test

Time series analysis relies heavily on the concept of stationarity. Stationarity refers to the fact that the statistical properties of a time series (or, more specifically, the process that generates it) do not change over time (Poirier et al., 1986). This concept is important because it underpins many useful analytical tools, statistical tests, and models. This test determines whether or not a series is stationary (Szablowski et al, 1997). There are two approaches: stationarity tests, such as the KPSS test, which consider as the null hypothesis H0 that the series is stationary, and unit root tests, such as the Dickey-Fuller test and its augmented version, the augmented Dickey-Fuller test (ADF), or the Phillips-Perron test (PP), which consider as the null hypothesis H0 that the series does not possess a unit root and thus is not stationary (Castro-Kuriss et al,. 2010).

2.3 Mann kendall's test

A non-parametric Mann Kendall trend test was used in this paper. Mann-Kendall (MK) analysis is used to determine whether there is a monotonic upward or downward trend in the variable of interest over time. A monotonic upward (downward) trend indicates that the variable consistently increases (decreases) over time, but the trend may or may not be linear (Pal and Al-Tabbaa, 2011). The MK test can be used in place of a parametric linear regression analysis, which can be used to determine whether the slope of the estimated linear regression line is greater than zero. The regression analysis requires that the residuals from the fitted regression line be normally distributed; this assumption is not required by the MK test, which is a non-parametric (distribution-free) test (Morán-Tejeda et al., 2013).

A return period, also known as a recurrence interval or repeat interval, is the average time or estimated time between events such as earthquakes, floods, landslides, or river discharge flows. We examined the drought return period using suitably fitted probability distributions in this paper. It is a statistical measurement that is typically based on historical data over a long period of time and is used for risk analysis. Examples include deciding whether a project should be allowed to proceed in a risk zone or designing structures to withstand events with a specific return period (Pal and Al-Tabbaa, 2011).

3. Results and Discussions

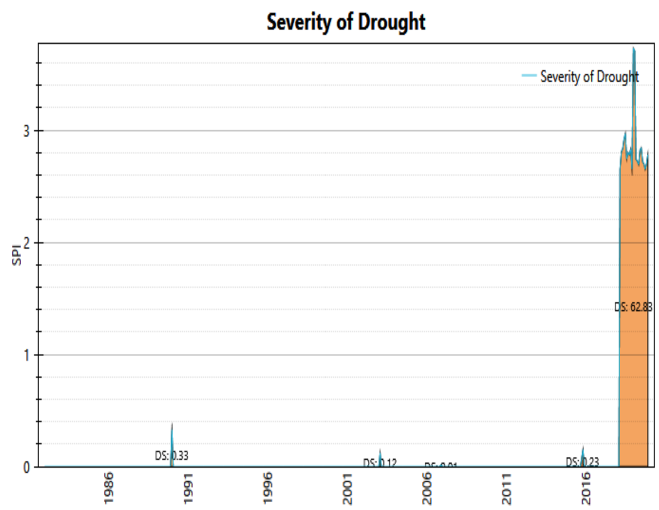
Tables 1, 2 and 3 show descriptive statistics, normality, and stationarity test respectively of the study area's precipitation. The top five stations in the study area seem to receive relatively high precipitation ranging from 57 to 72 mm shown by their means. The same stations depict high levels of variability in the precipitation where South Gippsland and East Gippsland have the highest levels of variability shown by the computed standard deviations in table 1. Prior to any time-series data analysis, it is important to test for normality, table 2 shows the results of this test which showed all stations' precipitation datasets not normal as Shapiro-Wilk and all other normality tests criteria p-values were significantly lower than the significance level of 0.05 as shown in table 2. To avoid spurious regressions and other analysis tests, a stationarity test was conducted as shown in table 3 aided by the Dickey-Fuller test criterion on all stations' precipitation datasets. The results of this test showed all stations' datasets stationarity as all tests criteria's p-values were lower than the specified significance level of 0.05 as computed by XLSTAT computer software programme.

Table 1: Precipitation descriptive statistics					
Station	**No of Obs.**	**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

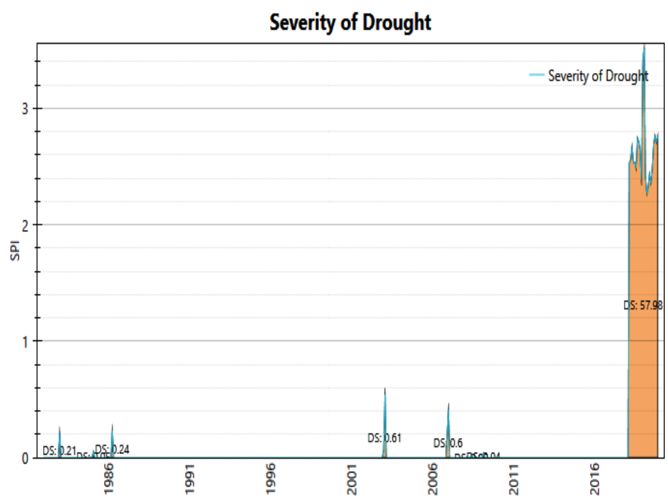
Table 2: Precipitation normality test				
Station	**Shapiro-Wilk**	**Anderson-Darling**	**Lilliefors**	**Jarque-Bera**
South Gippsland	0.000	0.006	0.008	0.012
East Gippsland	<0.0001	<0.0001	<0.0001	<0.0001
Colac-Otway	<0.0001	0.002	0.008	0.004
Glenelg	<0.0001	0.002	0.008	0.004
Murrindindi	<0.0001	<0.0001	0.001	0.000
Hindimash	<0.0001	<0.0001	<0.0001	<0.0001
Loddon	<0.0001	<0.0001	<0.0001	<0.0001
Mildura	<0.0001	<0.0001	<0.0001	<0.0001

Table 3: 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

Standardised Precipitation Index (SPI) was computed on four temporal scales, SPI-3,6,12 and 24 to assess two categories of drought namely: Agricultural and hydrological linked with SPI-3, 6 and 12, 24, respectively. Figures, 1,2 3 and 4 show the plots of drought severities in the four specified temporal scales. On SPI-3, all stations experienced severe drought event in 2019 as shown in figure 1. This implies that there is still hope for these areas to support agricultural activities without much drought stress. However, on the last temporal scales, all stations experience multiple stresses of drought which affect water resources in dams, rivers and other reservoirs and thereby affecting water resources and other agricultural projects in the area. The three last temporal scales are plugged with several spikes of drought severities as shown from figures 2 to 4, where 2019 was the most severe drought event in the area. Hydrological drought seems to be more frequent that agricultural drought with more spikes of severities across all candidate stations. This implies that cation must be exercised in the usage of water resources in the area to sustain water related projects.



South Gippsland



East Gippsland

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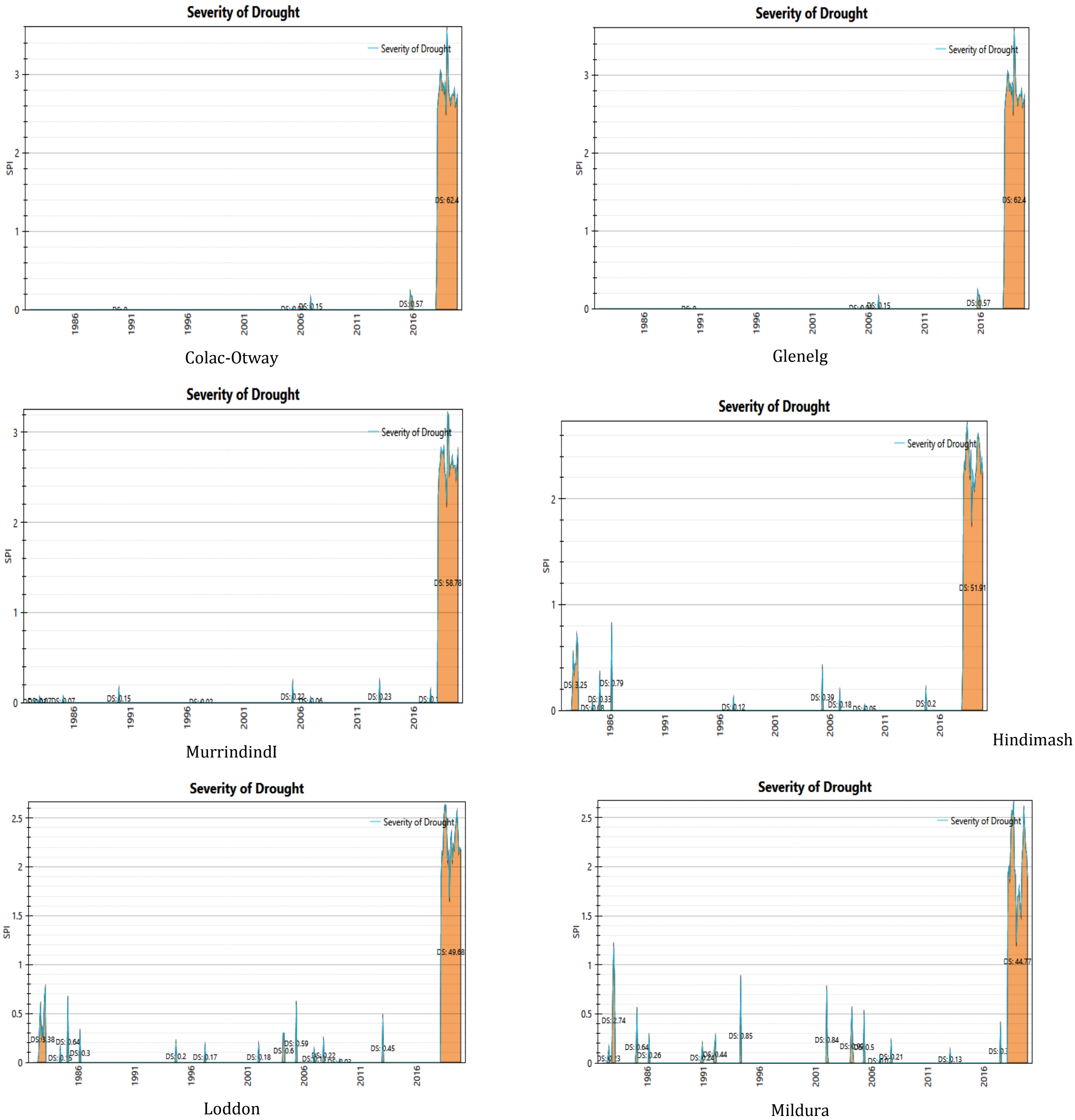
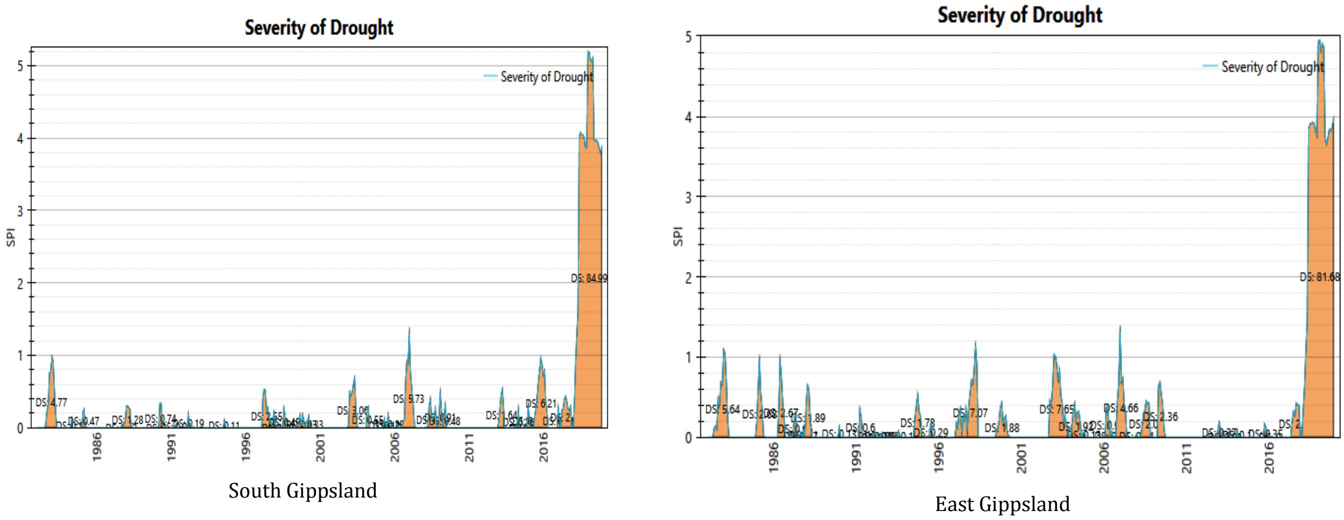


Figure 1: SPI-3 drought severities in Victoria State: Australia



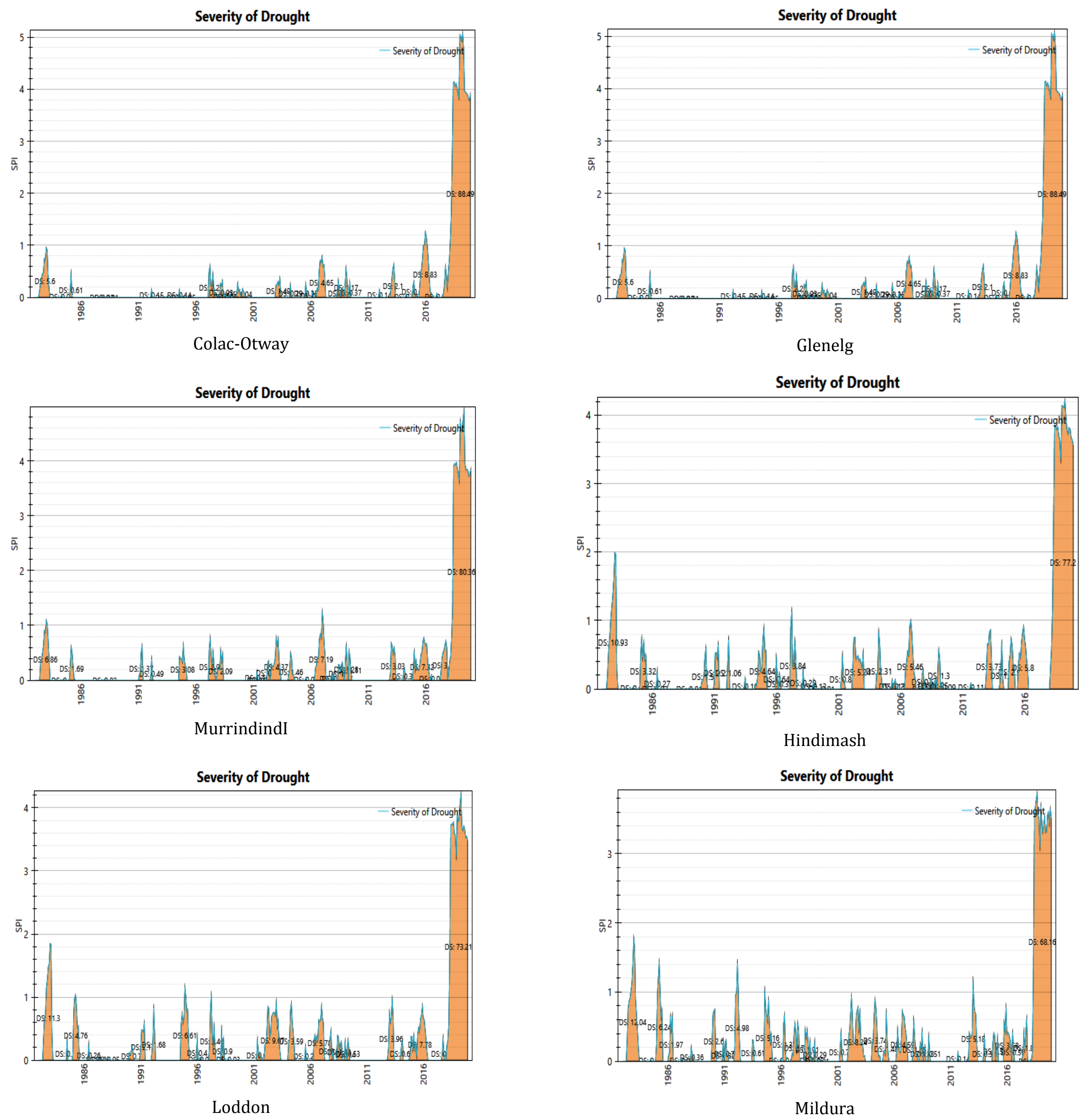
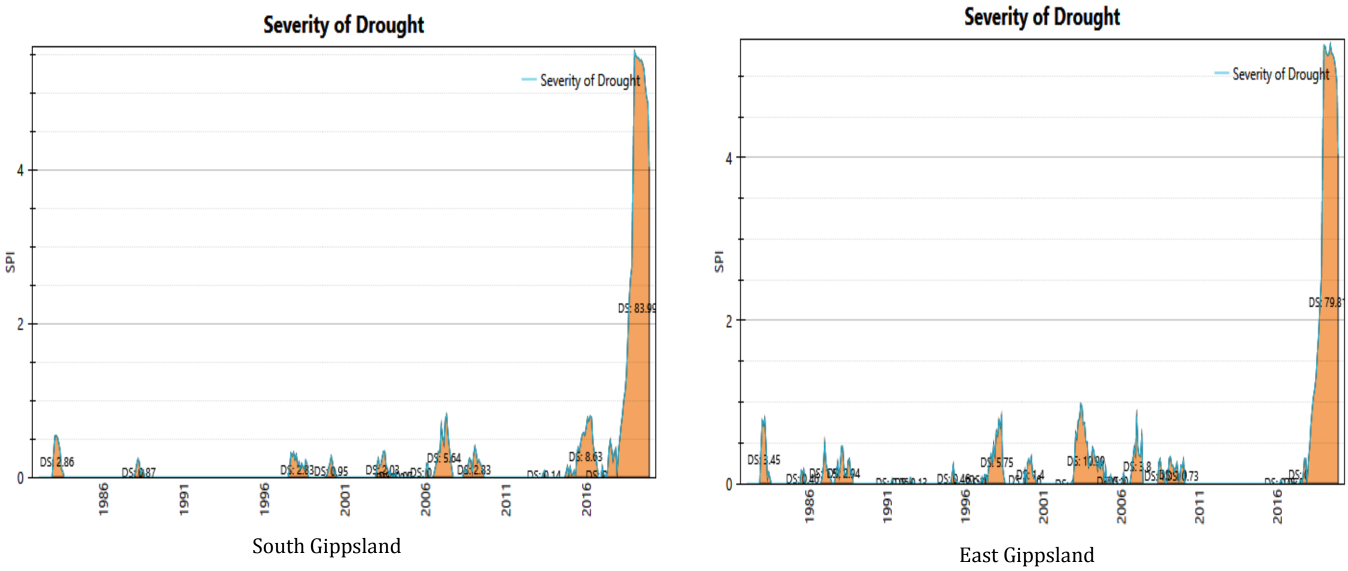
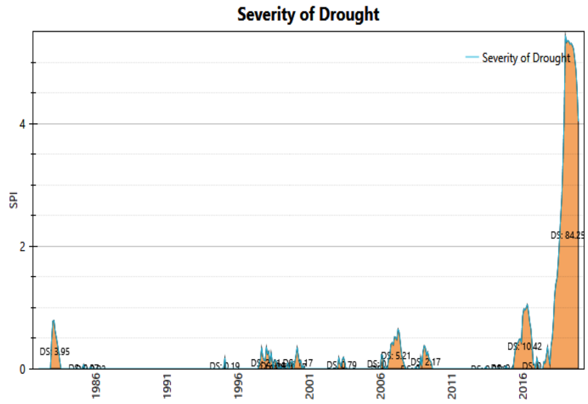
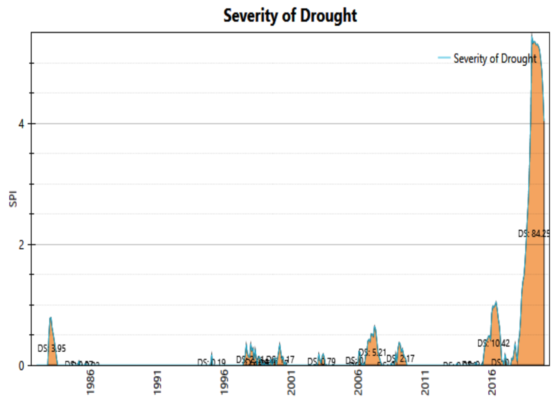


Figure 2: SPI-6 drought severities in Victoria State: Australia

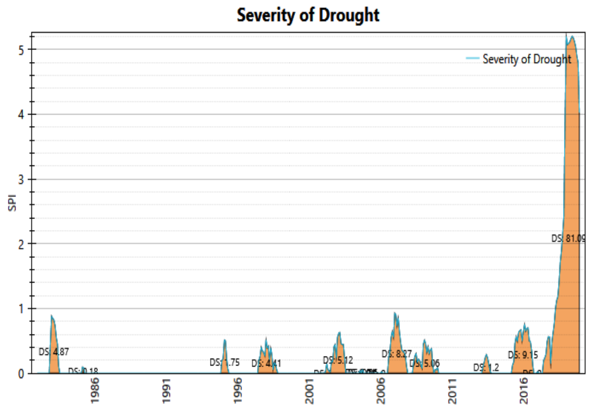




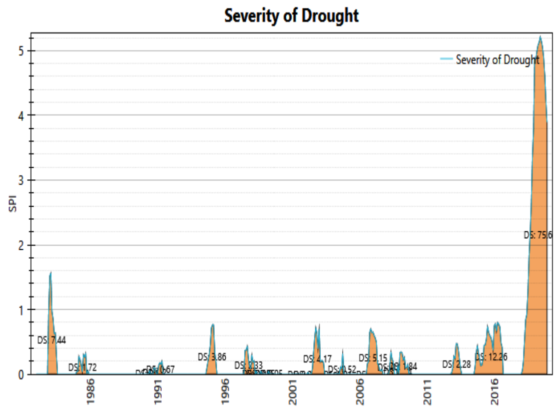
Colac-Otway



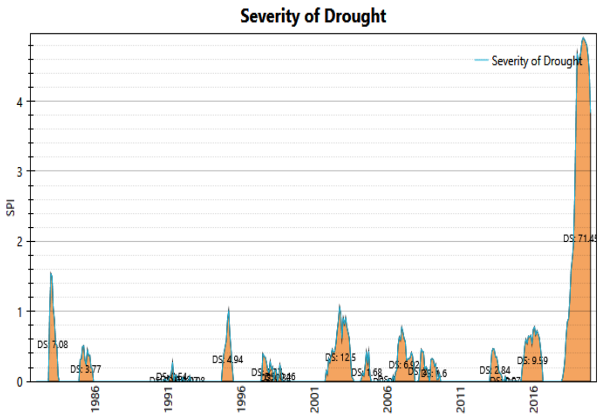
Glenelg



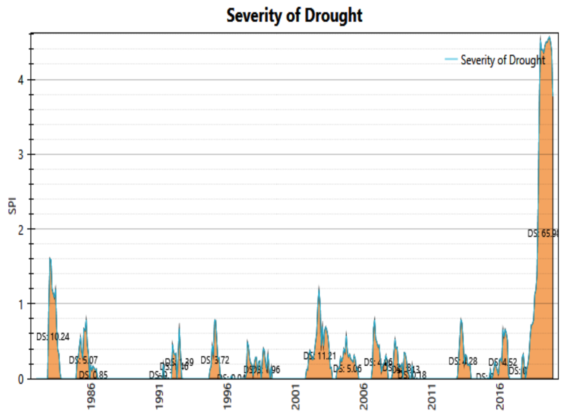
MurrindindI



Hindimash

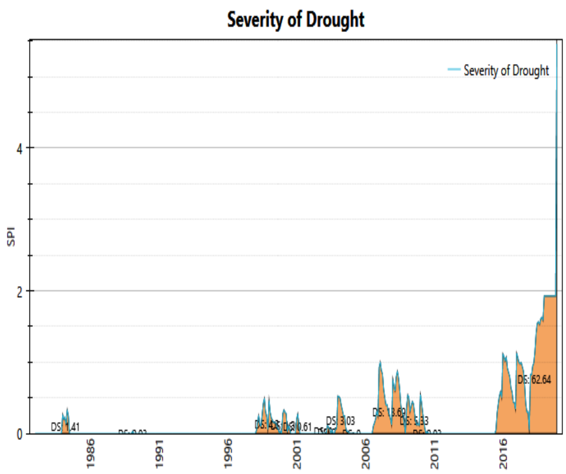


Loddon

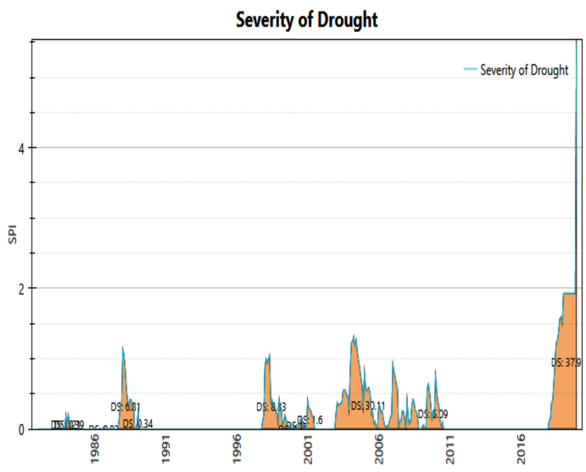


Mildura

Figure 3: SPI-12 drought severities in Victoria State: Australia



South Gippsland



East Gippsland

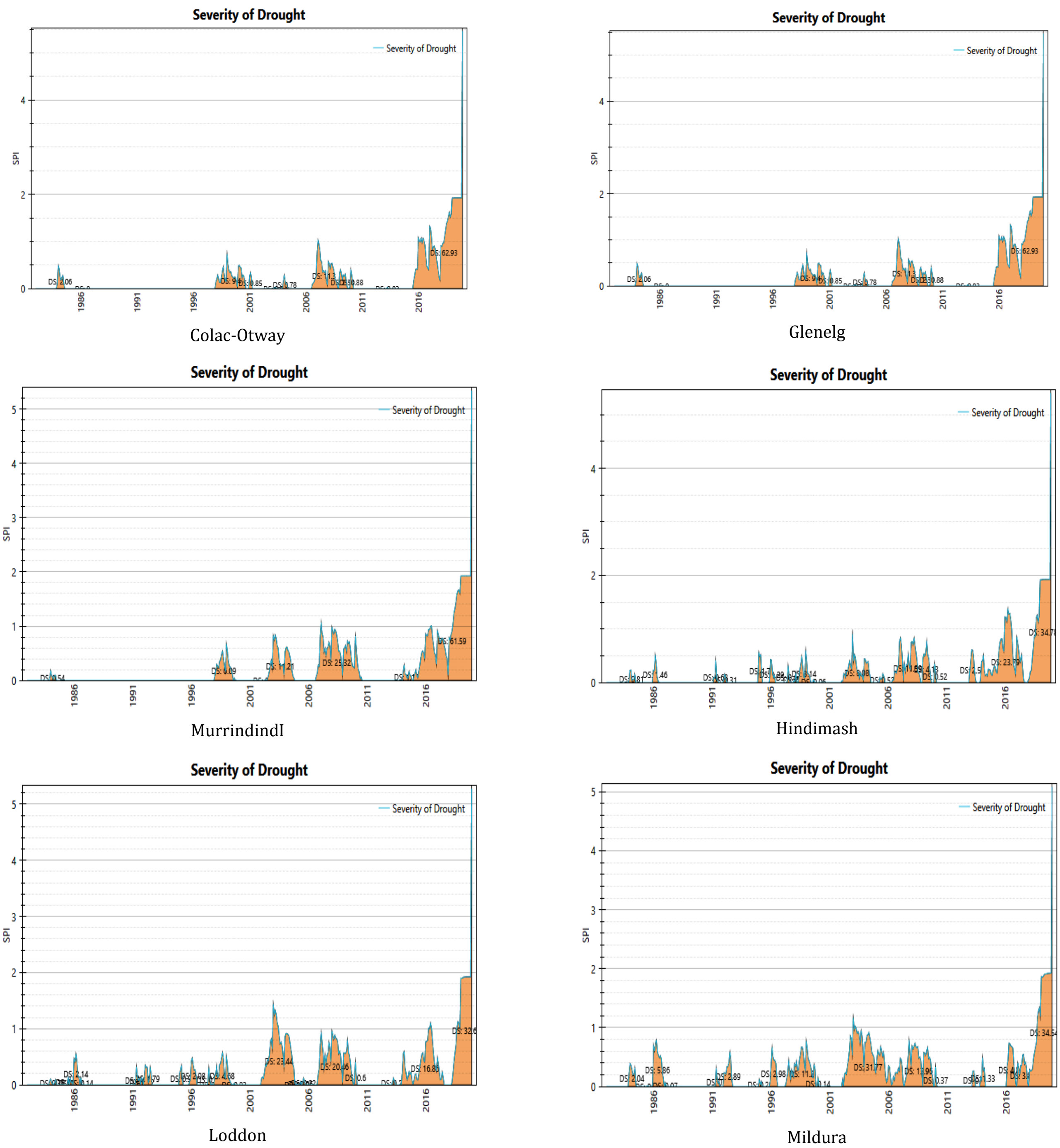
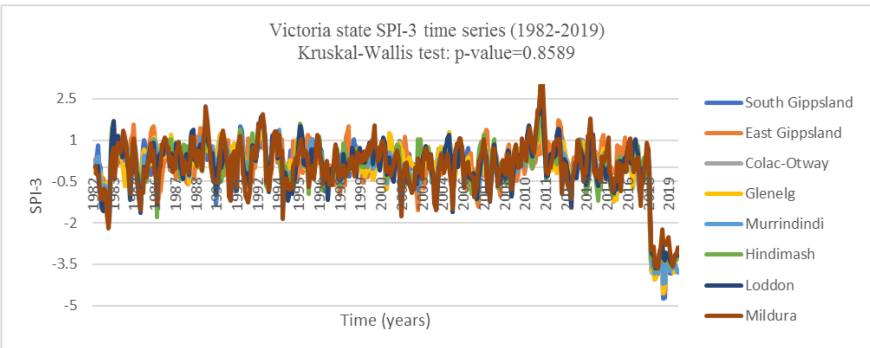


Figure 4: SPI-24 drought severities in Victoria State: Australia

Figures 5,6,7 and 8 depicts plots of all computed temporal scales of drought subjected to nonparametric Mann Kendalls' trend (MK) and Kruskal-Wallis tests. MK was applied on the time series to determine if there was any monotonic decreasing or increasing trends in the computed time scales. SPI-3 and 6 corresponding to agricultural drought, all stations depicted decreasing tends in SPI-3 all their MK p-value <0.05 except East Gippsland station. A decrease in SPI-3 means an increase in drought severities. Although, the determined drought severities shown non-existent trends in figures 1 to 4, the SPI-3 reveals a threatening behaviour of SPI-3 over years to come across all stations except East Gippsland. A two-tailed non-parametric Kruskal-Wallis test indicated that all the stations came from the same population meaning that they had similar behavioural characteristics.



Parameter	South Gippsland	East Gippsland	Colac-Otway	Glenelg	Murrindindi	Hindimash	Loddon	Mildura
S :	-20080	-5922	-20232	-20232	-22203	-15059	-13517	-9012
Z :	6.2168	1.8332	6.2639	6.2639	6.8741	4.6622	4.1848	2.79
p-value	5.07E-10	**0.066766**	3.7E-10	3.7E-10	6.2E-12	3.1E-06	2.8E-05	0.005272

Figure 5: Victoria state SPI-3 plots and Mann Kendall's trend test

Figure 6 shows graphs of SPI-6 from 1982 to 2019. Upon the application of Kruskal-Wallis test, it was observed that all stations exhibited similar drought characteristics with a p-value=0.04677 > 0.05. However, all stations are experiencing significantly decreasing trends proven by MK with significant p-values computed by XLSTAT software. This is an indication that drought events in the area are yet to be more severe in the near future.

Parameter	South Gippsland	East Gippsland	Colac-Otway	Glenelg	Murrindindi	Hindimash	Loddon	Mildura
S :	-24523	-6753	-23936	-23936	-26639	-18326	-14753	-9271
Z :	7.6682	2.1114	7.4847	7.4847	8.3299	5.7304	4.6131	2.8988
p-value	1.74E-14	0.034737	7.17E-14	7.17E-14	8.09E-17	1.00E-08	3.97E-06	0.003746

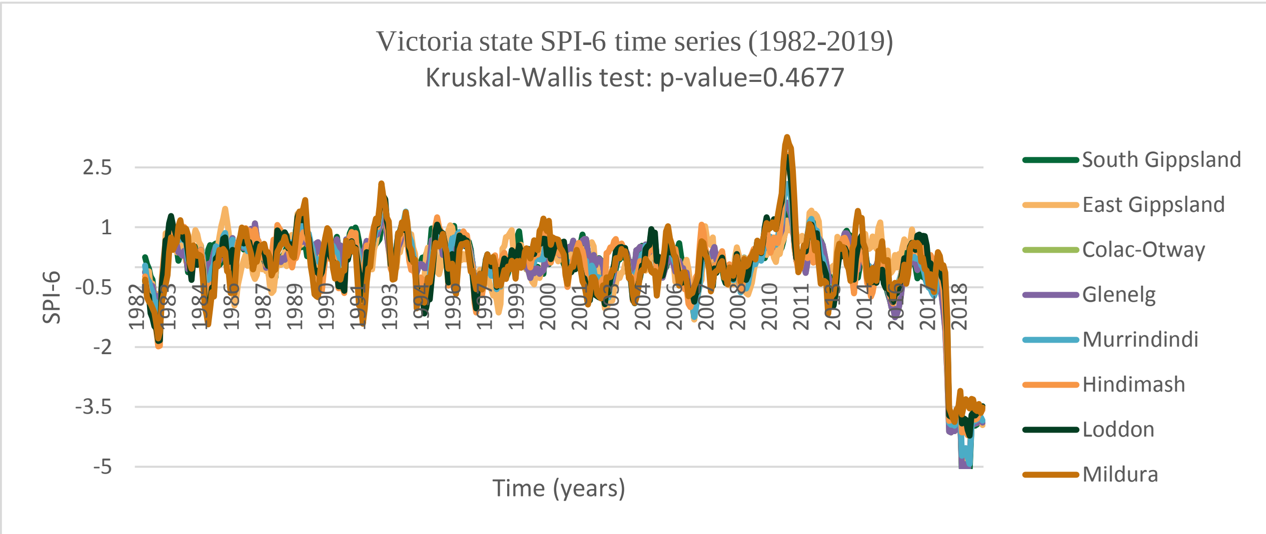


Figure 6: Victoria state SPI-6 plots and Mann Kendall's trend test

Parameter	South Gippsland	East Gippsland	Colac-Otway	Glenelg	Murrindindi	Hindimash	Loddon	Mildura
S :	-26489	-7523	-27323	-27323	-32703	-26683	-19245	-12705
Z :	8.4509	2.3999	8.717	8.717	10.433	8.5128	6.1397	4.0532
p-value	2.89E-17	0.016401	2.86E-18	2.86E-18	1.74E-25	1.70E-17	8.27E-10	5.05E-05

On SPI-12 and 24, a two tailed Kruskal-Wallis test revealed that all stations different as p-value was less than the specified significance level of 0.05. However, all stations experienced decreasing SPI-12 and 24, which implies that more pressure is yet to be felt by all water users and projects in the area. MK trend test shows the negative Sen's slopes with all significant p-values <0.05 across SPI-12 and 24 stations.

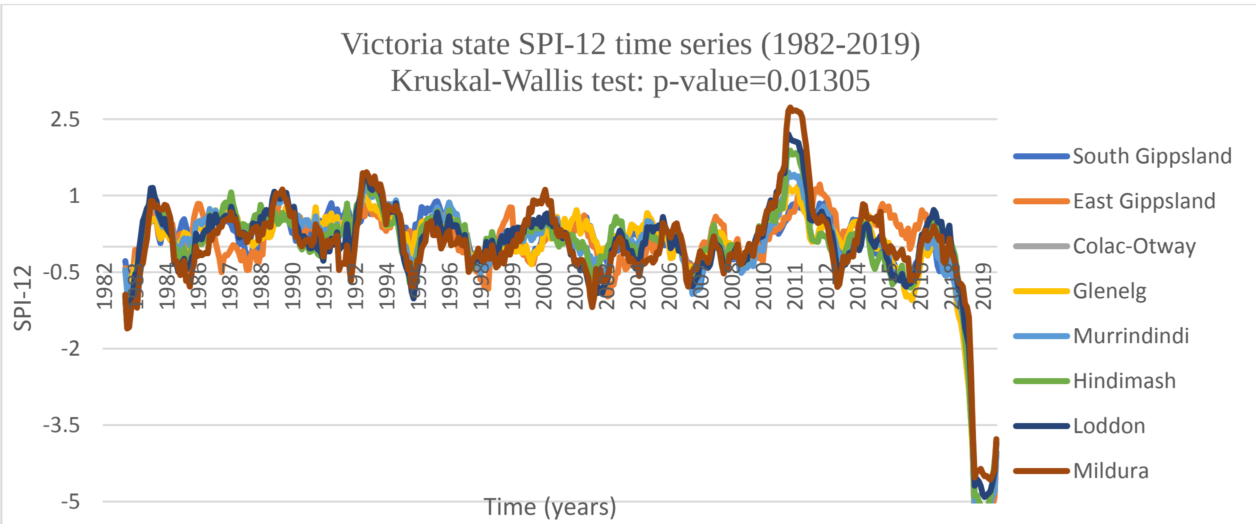
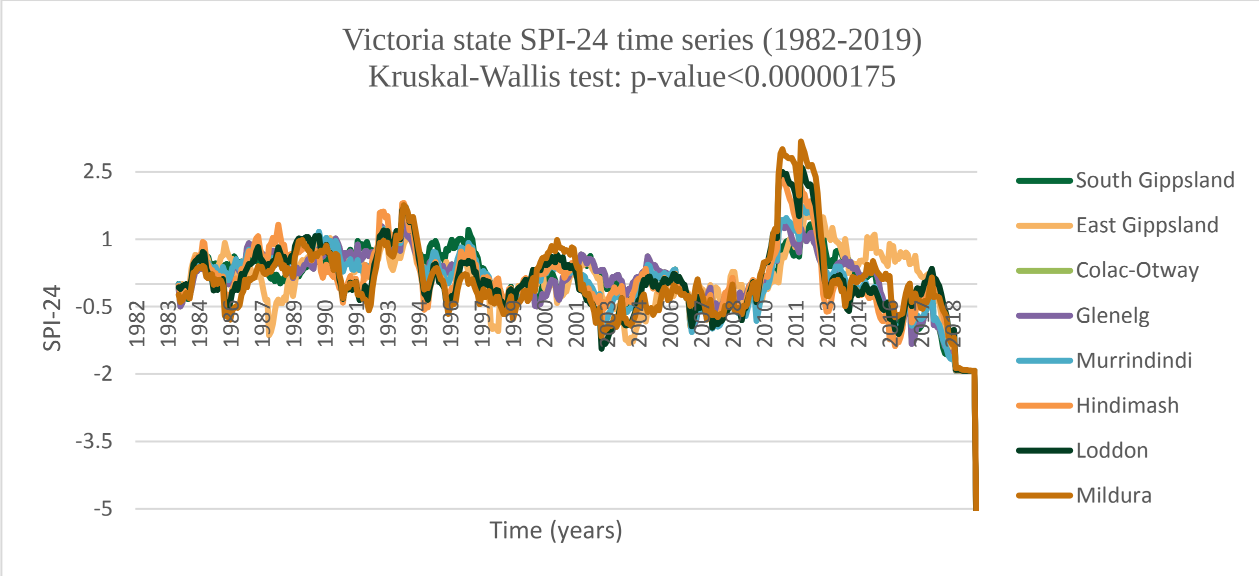


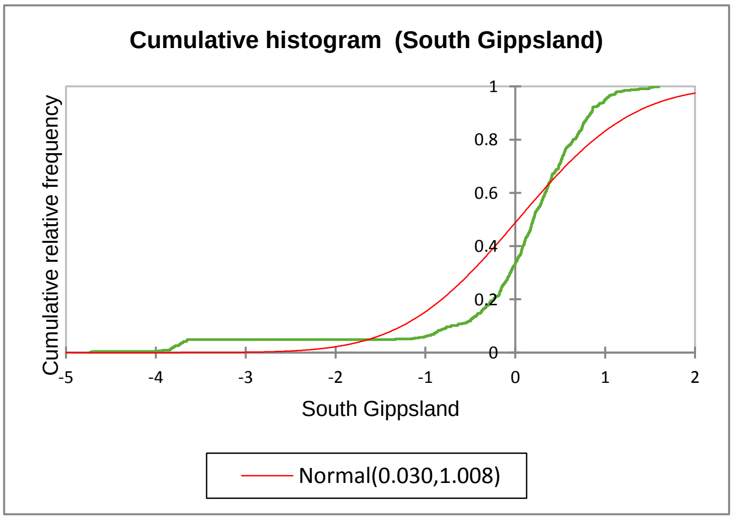
Figure 7: Victoria state SPI-12 plots and Mann Kendall's trend test



Parameter	South Gippsland	East Gippsland	Colac-Otway	Glenelg	Murrindindi	Hindimash	Loddon	Mildura
S :	-29275	-9635	-29803	-29803	-38200	-33808	-24572	-15818
Z :	9.7303	3.2022	9.9059	9.9059	12.697	11.237	8.1671	5.2573
p-value	2.24E-22	0.001364	3.93E-23	3.93E-23	6.15E-37	2.68E-29	3.16E-16	1.46E-07

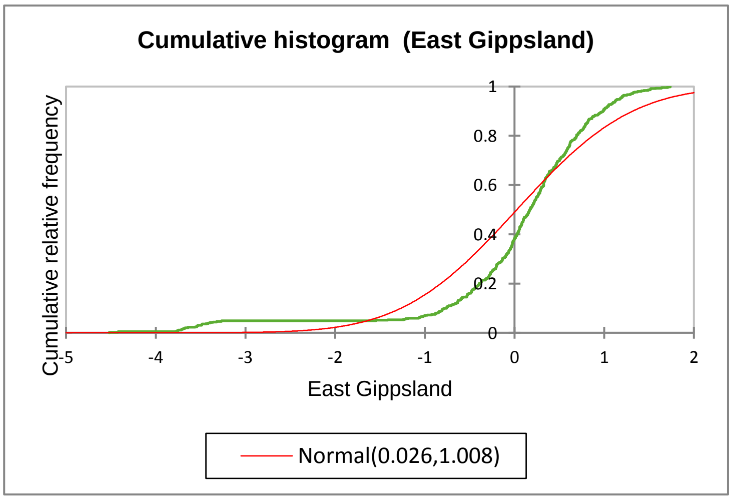
Figure 8: Victoria state SPI-24 plots and Mann Kendall's trend test

Given that all the datasets tested non-normal, all SPI time series datasets were fitted to their suitable probability distributions. Figures 9 and 10 show the fitted probability distributions and parameters which were used to compute SPI-3 and 24 corresponding to Agricultural and hydrological droughts episodes. All the stations on SPI-3 revealed a return levels of approximately 7 months on average. On the other hand, SPI-24 showed average return level of approximately 80 months. Although this is quite a long time for a return, given the significant decreasing trend patterns of these scales SPI-12 and 24, a caution must be exercised in the use of water in the study area.



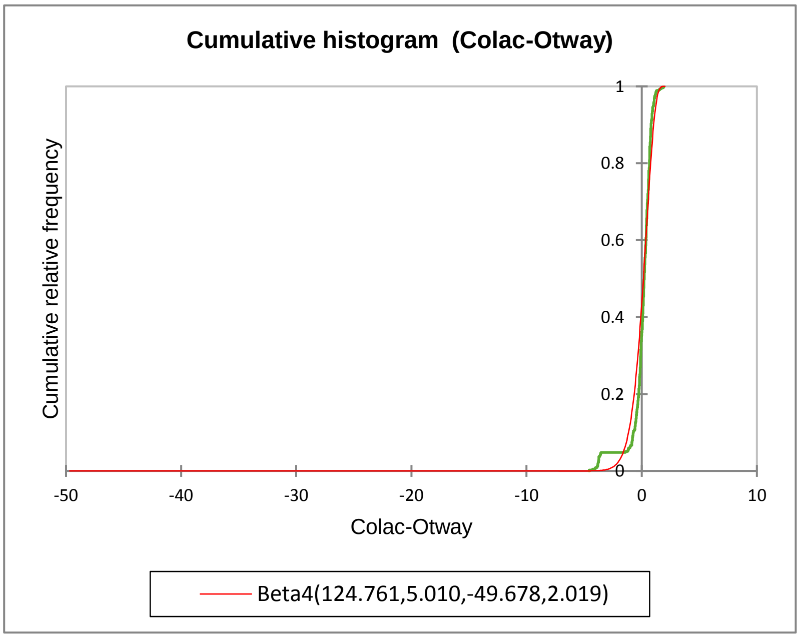
Parameter	Value	Standard error
μ	0.030	0.047
sigma	1.008	0.033

Return period (months)=6.7



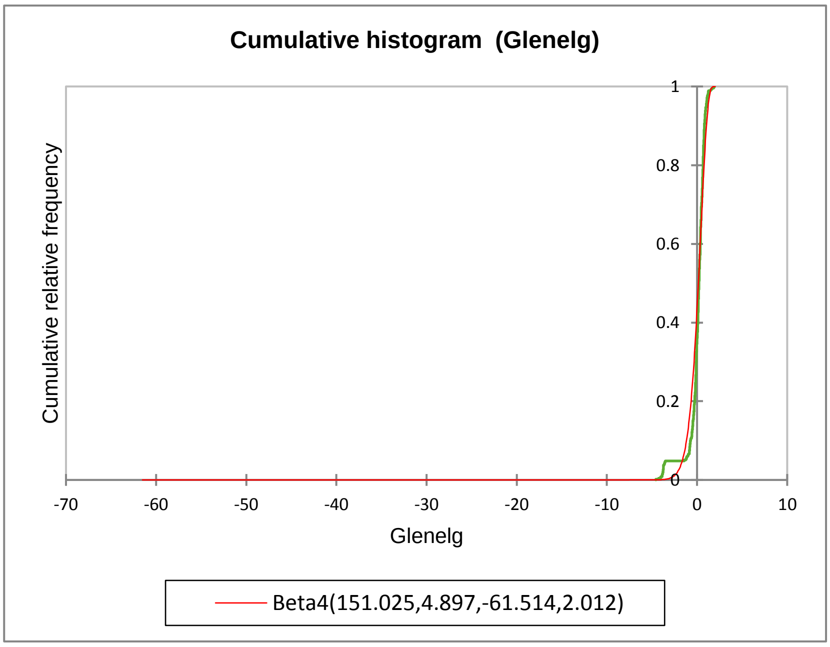
Parameter	Value	Standard error
μ	0.026	0.047
sigma	1.008	0.034

Return period (months)= 6.7



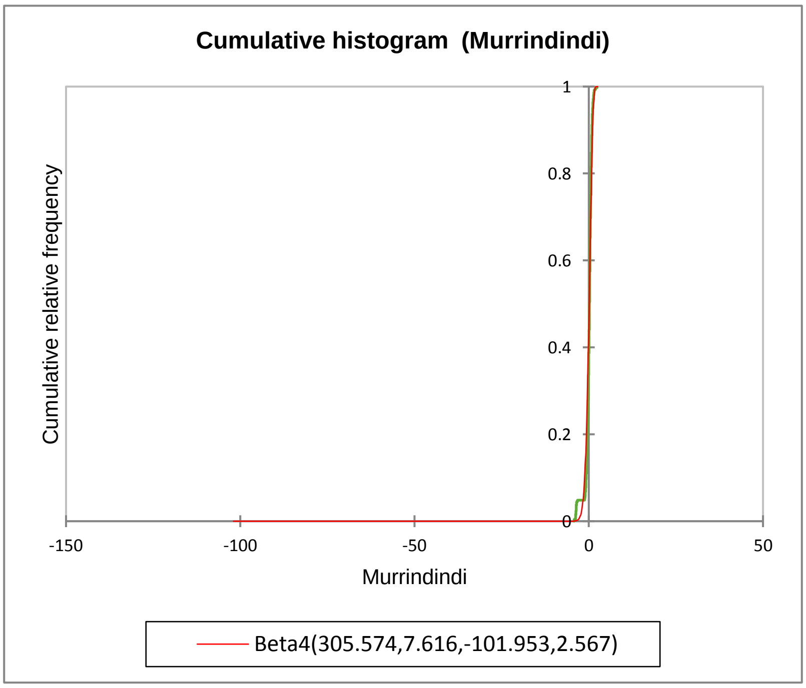
Parameter	Value	Standard error
alpha	124.761	3.749
beta	5.010	0.005
c	-49.678	0.206
d	2.019	0.074

Return period (months)=8.0



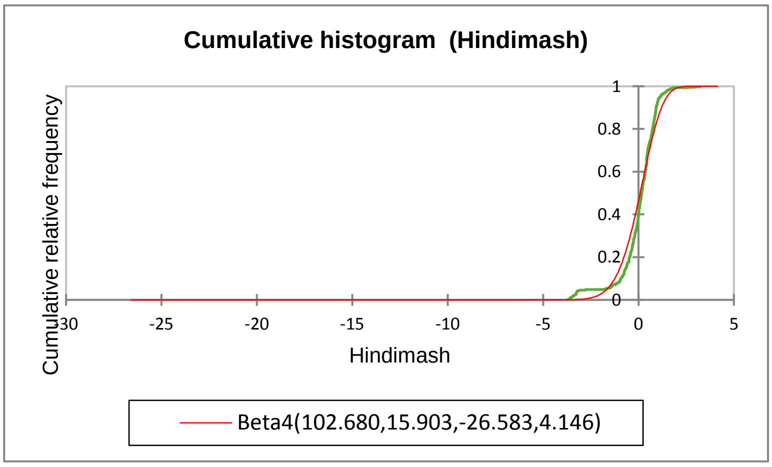
Parameter	Value	Standard error
alpha	151.025	4.842
beta	4.897	0.005
c	-61.514	0.232
d	2.012	0.077

Return period (months)=7.8



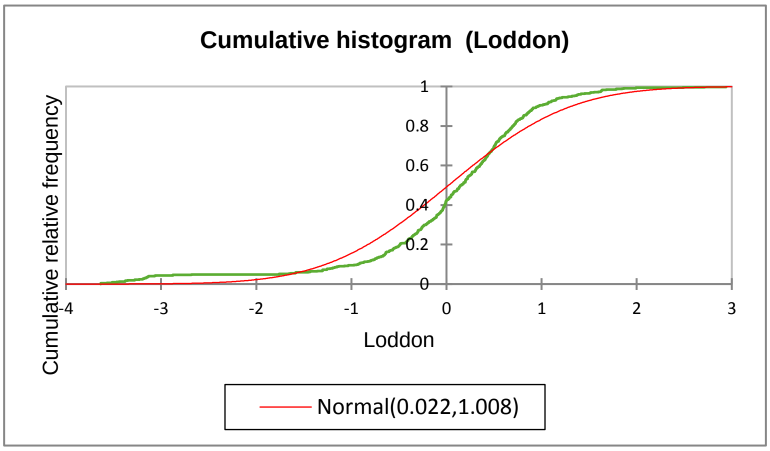
Parameter	Value	Standard error
alpha	305.574	4.837
beta	7.616	0.006
c	-101.953	0.271
d	2.567	0.059

Return period (months)=7.6



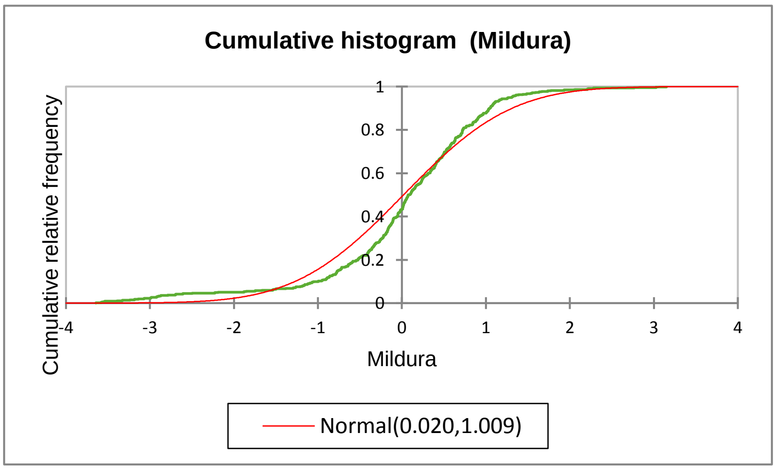
Parameter	Value	Standard error
alpha	102.680	0.945
beta	15.903	0.009
c	-26.583	0.116
d	4.146	0.062

Return period (months)=6.9



Parameter	Value	Standard error
μ	0.022	0.047
sigma	1.008	0.034

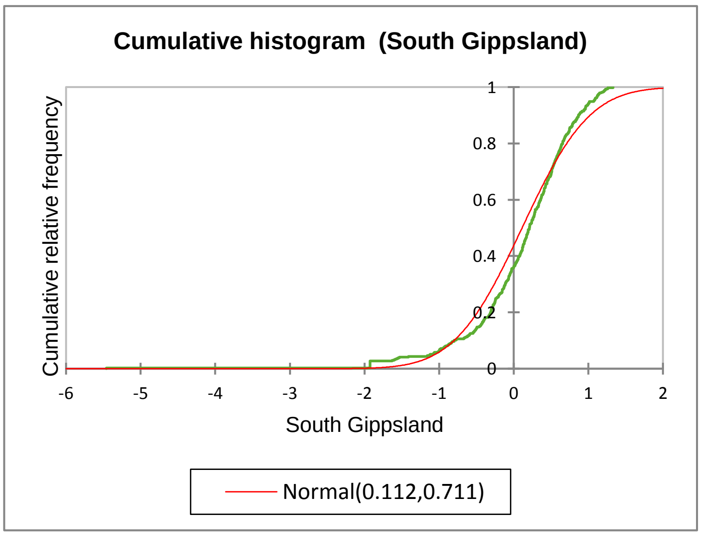
Return period (months)= 6.7



Parameter	Value	Standard error
μ	0.020	0.047
sigma	1.009	0.033

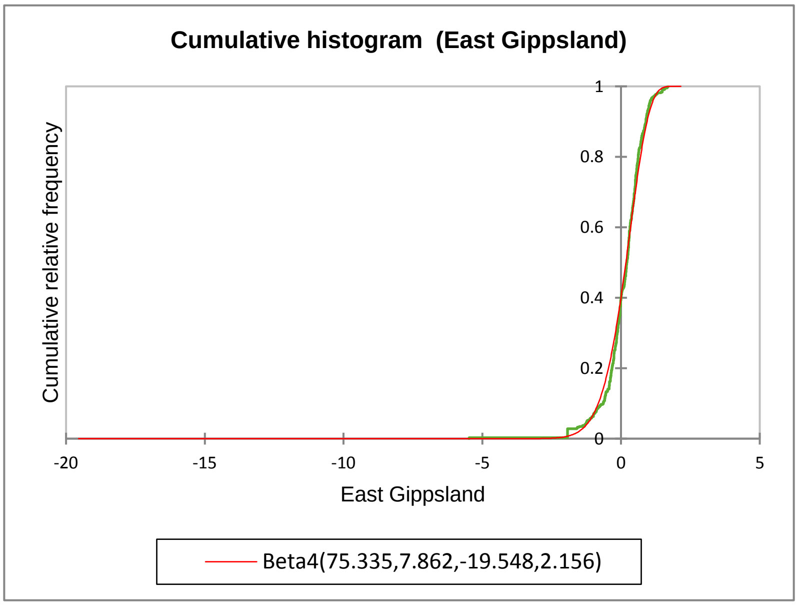
Return period (months)= 6.7

Figure 9: Victoria state SPI-3 probability distribution fitting



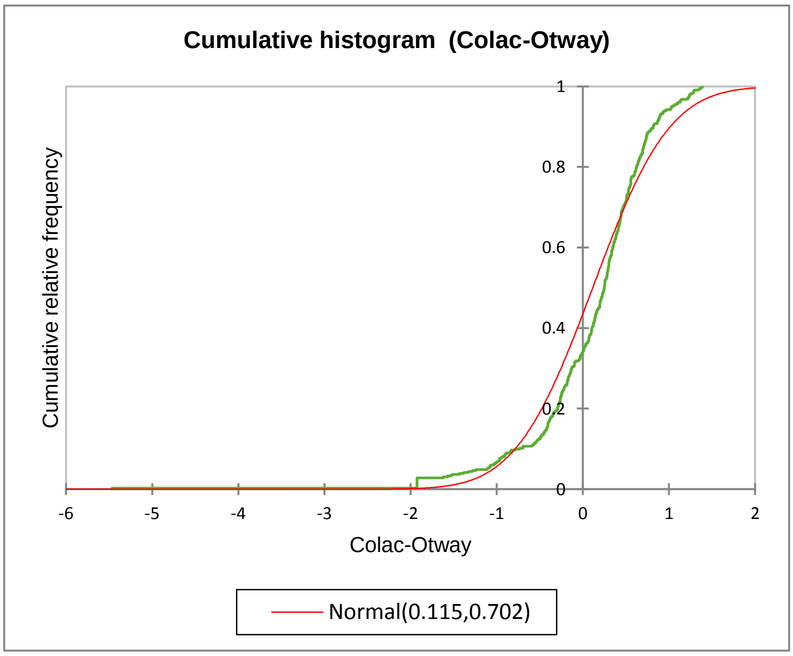
Parameter	Value	Standard error
μ	0.112	0.034
sigma	0.711	0.024

Return period (months)=16.9



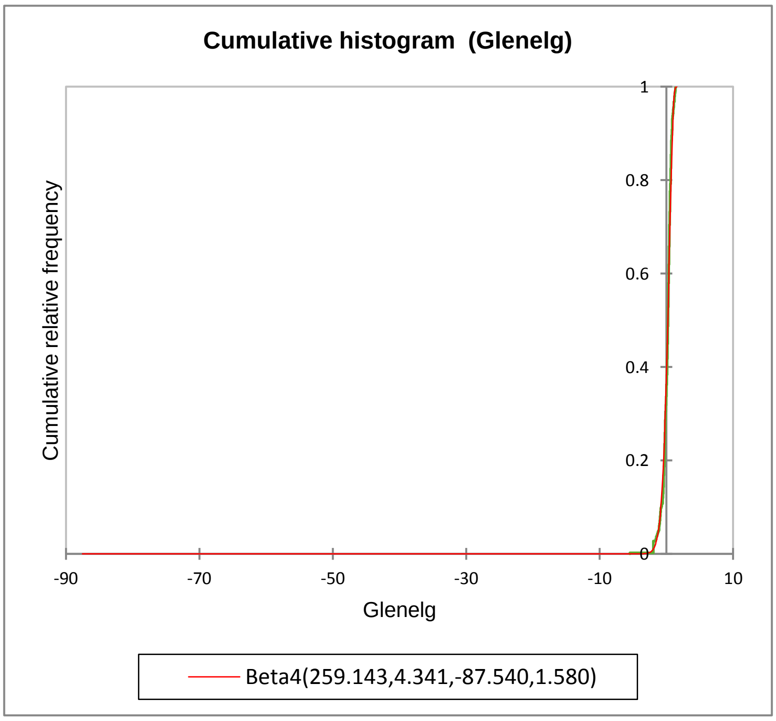
Parameter	Value	Standard error
alpha	75.335	1.058
beta	7.862	0.007
c	-19.548	0.104
d	2.156	0.046

Return period (months)=14.8



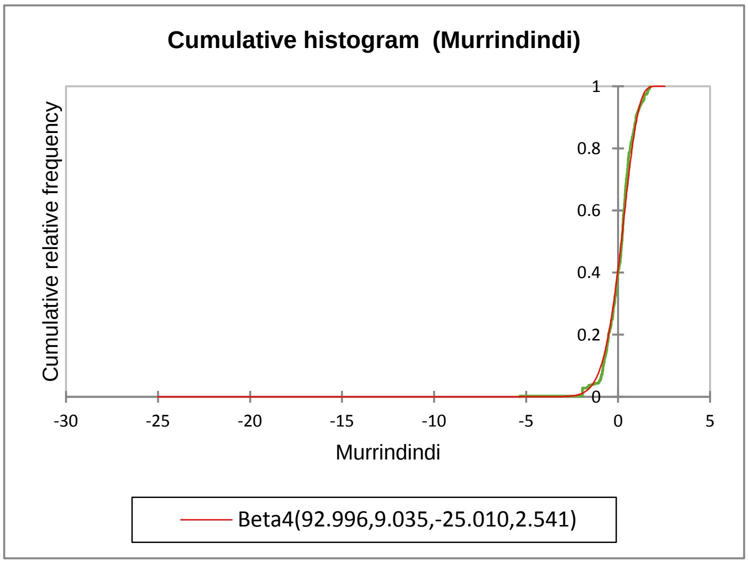
Parameter	Value	Standard error
μ	0.115	0.034
sigma	0.702	0.024

Return period (months)=16.9



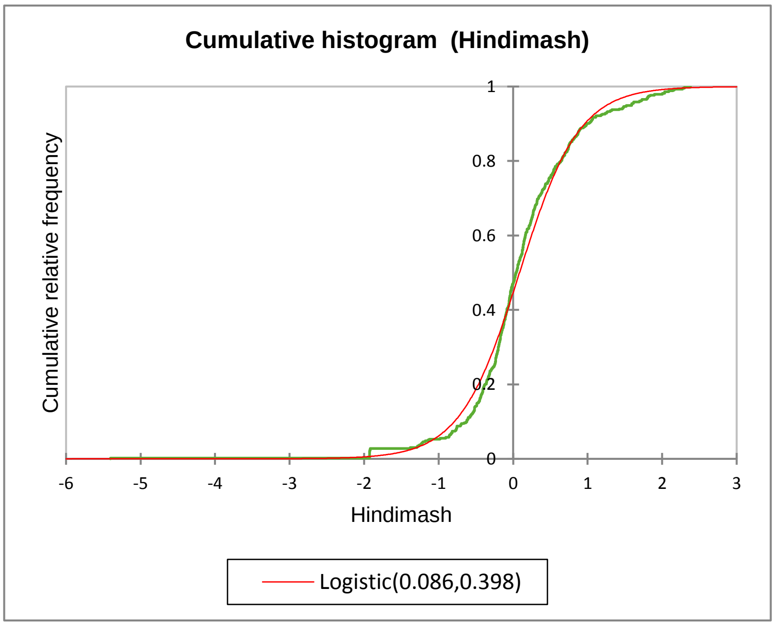
Parameter	Value	Standard error
alpha	259.143	7.812
beta	4.341	0.005
c	-87.540	0.260
d	1.580	0.056

Return period (months)=13.9



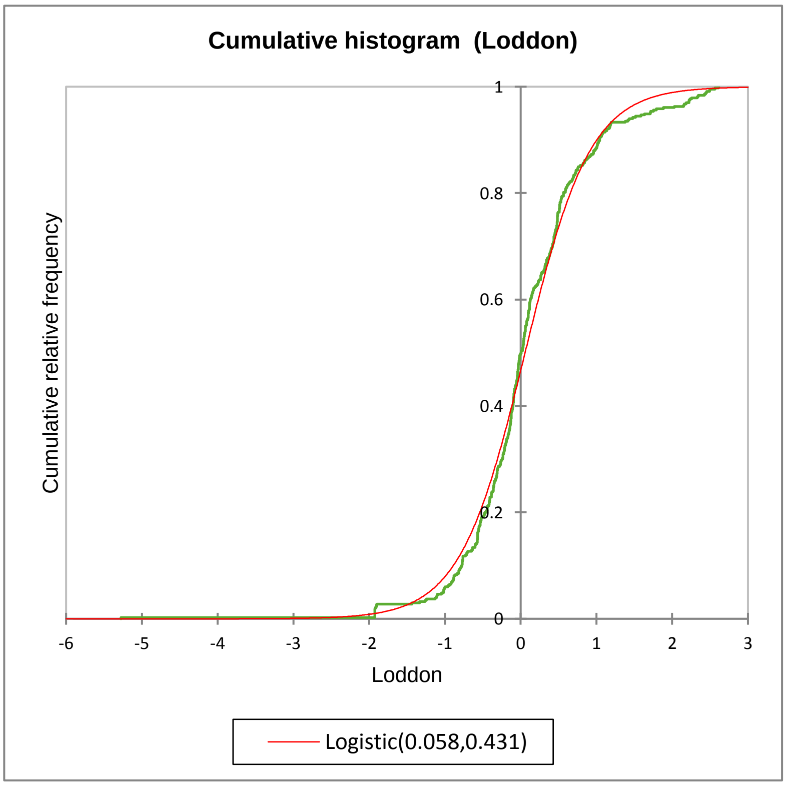
Parameter	Value	Standard error
alpha	92.996	1.205
beta	9.035	0.007
c	-25.010	0.120
d	2.541	0.051

Return period (months)=11.1



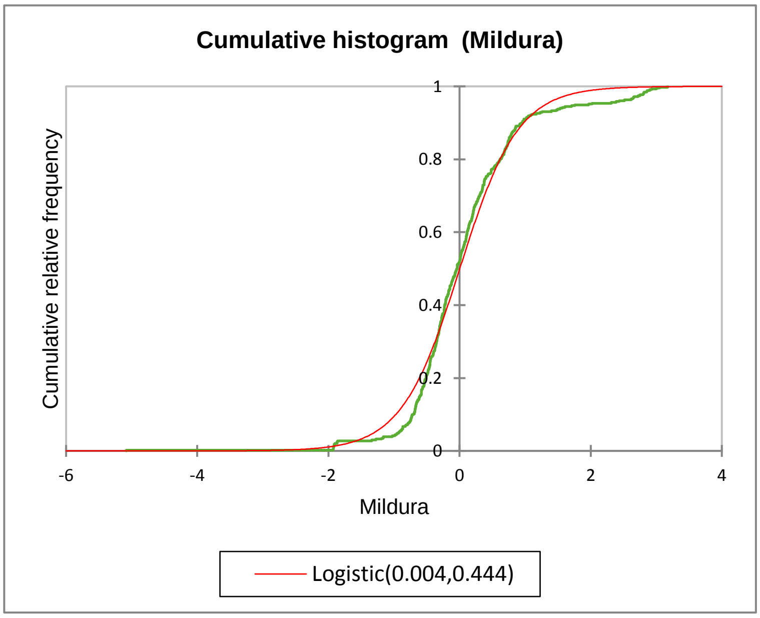
Parameter	Value	Standard error
µ	0.086	0.035
s	0.398	0.017

Return period (months)=333.3



Parameter	Value	Standard error
µ	0.058	0.034
s	0.431	0.018

Return period (months)=142.8



Parameter	Value	Standard error
μ	0.004	0.034
s	0.444	0.018

Return period (months)=84.2

Figure 10: Victoria state SPI-24 probability distribution fitting

4. Conclusion and Recommendations

In conclusion, the drought risk analysis in the areas for the protection and improvement in the use of water in the study has resulted in showing all stations behaving similarly on lower temporal scales. However, at higher time scales SPI-12 and 24 all candidate stations revealed homogenous behaviour with significantly decreasing values of SPI. a decrease in SPI implies a potential in increase in severe drought events in the near future. The study shows that there hope for Agriculture and related projects in the area though this has to be with caution given the decreasing trends in SPI-3 and 6. On SPI-12 and 24, it is clear that all stations have been experiencing severe droughts and are yet to experience even more severe episodes, this means that the government and all relevant stakeholders must use water with extreme caution as poor or reckless use may lead negative effects on high water consuming projects and activities in the area.

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