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Multi-Scale Spatiotemporal Drought Assessment in Sri Lanka Using the Standardized Precipitation Index (SPI) and Probabilistic Modeling

J. W. E. W. De Silva[1,*] **and S. P. Abeysundara**[2]

[1]Department of Computing, SLIIT Kandy Uni, Pallekele, Sri Lanka

[2]Department of Statistics and Computer Science,
University of Peradeniya, Sri Lanka

*Corresponding author: erandiwathsalas@gmail.com

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ABSTRACT

Drought is a pre-existing threat to agriculture, water, and socio-economic stability of Sri Lanka. The research evaluates the spatiotemporal variability of droughts with reference to five geographically distinct areas characterized by different climates, such as China Bay, Colombo, Nuwara Eliya, Puttalam, and Kurunegala using the Standardized Precipitation Index (SPI) at several time scales (1 to 24 months) between the years 2010 and 2023. The monthly precipitation data were modeled using Gamma, Exponential, and Normal distributions. The most appropriate model for each region was identified based on the Akaike Information Criterion (AIC). Findings indicate that the regions in the Dry Zone especially China Bay and Puttalam are most affected and high by frequent severe short-term drought whereas Kurunegala has the most vulnerability to long-term drought. The paper also discovers that the choice of probability distribution is important for deriving SPI at various time scales. These results are an indication of the regional differences in the drought risk and the necessity of the customized early warning systems, agricultural plans, and strategies of water management. This multiscale, probabilistic method can provide a very solid design of enhancing drought resilience in Sri Lanka.

Keywords: Drought, spatiotemporal Variability, Standardized Precipitation Index, probability distribution, Akaike Information Criterion

1 Introduction

Drought is one of the multifaceted and recurring natural hazards that have extreme impacts on water resources, agriculture, the ecosystems, and the socio-economic stability. As opposed to the sudden onset disasters, droughts are very slow, and therefore they are quite difficult to predict and prevent. Sri Lanka is an island country located in South Asia which is extremely susceptible to drought occurrences owing to the sheer efficiency of relying on rainfall as monsoons and the existence of different climatic areas- Dry Climatic, Wet Climatic, and Intermediate, Panigrahi and Vidyarthi (1993). The incidences and mixture of droughts experienced in Sri Lanka have been growing in intensity and frequency over several decades, which has produced unswerving impressions on food security, livelihoods, and a balance on environmental sustainability.

The two main monsoons which come to the country Southwest (Yala) monsoon and Northeast (Maha) monsoon provide uneven distribution of rainfall and the Dry Zone is most prone to droughts,Wickramagamage (2016) According to the recent researches, droughts are observed in the Dry Zone in 57 percent of examined years, whereas in the Wet Zone, and the droughts occur in 49 percent, and 47 percent of the years in the Intermediate Zone, Abeysingha and Rajapaksha (2020). Also, the decadal changes in precipitation and reduced strength of moisture transport have been attributed to the growing menace of droughts occurring in the Yala season. Such tendencies point toward the importance of developed and effective drought monitoring and control techniques, especially considering the central place of agriculture in the economy and labor market of Sri Lanka, Lin and Shelton (2020).

The SPI was compiled by McKee et al. (1993) and is useful in measuring the deficit of precipitation at several periods, hence it serves well to determine the occurrence of both the short-term and long-term droughts. Its effectiveness and flexibility have attributed to its application in many climatic conditions, even in Sri Lanka Samaraweera et al. (2024) Nevertheless, past research tends to concentrate on short periods or narrow geographical areas, so it does not provide much insight into the large geographical scale of spatiotemporal dynamics of droughts in Sri Lanka. Moreover, inter-connection between the local drought situations and international climatic events such as ENSO is not much studied under Sri Lankan context. This research paper fills these information gaps by providing an in-depth analysis of drought pattern on the five selected regions and checking the regional differences as well as exploring on any possible climatic relationships, Zubair (2002).

Extensive research has been conducted on the properties of the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI) with respect to the spatiotemporal characteristics of drought. In Sri Lanka, it has been discovered that the Dry Zone is the most vulnerable area, where frequent incidents of moderate and severe droughts occur, Shelton et al. (2022). Notable trends in time, especially in the Yala crop period, have been established with a considerable level of weather stations revealing rising occurrences of drought. Likewise, changes in drought site variability during the decadal period have been attributed to alterations in large-scale atmospheric circulation, including the slacked downwind circulation patterns and moisture divergence, Bayissa et al. (2022).

A close correlation has also been examined between droughts and vegetation. Studies have revealed that 40% of vegetation in the Dry Zone responds with drought signal in a range of 1-4 months of the event. These findings imply short-term to long-term drought impacts on agroecosystems, indicating the necessity to have adaptive management solutions, Somasundaram et al. (2024). Moreover, the agricultural-based drought indices have been formed to look at the spatial distribution of drought patterns in Sri Lanka in which they have had considerable effects in the Yala season notably in the large rice-producing districts, Alahacoon and Amarnath (2022).

The SPI has been in significant extent applied in study of intensity and frequency of droughts in various continents, Zhang et al. (2012). As an example, the increasing trend in China has been observed in studies conducted in China because of a reduced precipitation rate and changing weather conditions, Wagan et al. (2015). On the same note, studies in India and Afghanistan have demonstrated that SPI can be applied in drought risk assessment and planning of water resources, a fact which indicates the applicability of SPI under a variety of climates, Patel et al. (2007).

With the application of SPI, this analysis extensively analyzes the patterns of drought in different time scales, temporal and spatial orientation with the view of deriving trends in its occurrence, intensity, as well as geographical susceptibilities. It investigates climatic conditions that affect drought processes and uses sophisticated statistical techniques, as well as probability distribution matching, and trend analyses, to calculate the best mitigation measures. To investigate how the findings can strengthen early warning systems, provide guidance about the water resource management policies, and aid in climate resilience planning, it was considered that the outcomes may apply to Sri Lanka and other parts of the world prone to droughts, Sellathurai et al. (2021).

2 Methodology

2.1 Source of data

The precipitation data of five of the most popular meteorology stations located in different climatic zones in Sri Lanka (reached through regional meteorology offices of the Sri Lanka Department of Meteorology) were provided and will be used to represent monthly precipitation data starting in 2010 to 2023.

2.2 Sampling Scheme

This study has used all the meteorological regions of Sri Lanka that represent the different climatic regions of Sri Lanka as the target population because Sri Lanka has three different climatic zones Dry, Wet and Intermediate. The purposive sampling scheme was utilized to quantify the spatial diversity as regards the droughts condition, using five meteorological stations, namely China Bay, Colombo, Nuwara Eliya, Puttalam, and Kurunegala. The selection of these stations was to be in diverse geographical locations and climate such as along the coasts, central highlands, and the transition areas. The measurements were done using monthly precipitation data between the year 2010 and 2023 in each station. The Study variable was monthly rainfall, as calculated Monthly Standardized Precipitation Index (SPI) with various timescales (1-, 3-, 6-, 12-, 18- and 24-months). The meteorological and agricultural drought conditions indicate the short time scales (1-3 months) whereas the change in soil moisture and stream flow are observed in the intermediate time scales (6-12 months). Larger intervals (18-24 months) are the hydrological drought and long-term water resource sustainability. Several properties of this multi-scalar approach allow the evaluation of cumulative precipitation deviations at different durations, as well as connecting various elements of the water cycle with the effects of drought associated with them. Operations involved cleansing data, fitting probability distributions (Gamma, Exponential, and Normal) to the precipitation data and choosing the best fitting model among the three stations with regards to Akaike Information Criterion (AIC). This has been done through these steps providing a strong evaluation of space and time variability of drought over the selected areas.

2.3 Development of the design of the study

Rainfall data from five meteorological stations were collected for the period 2010 to 2023 to analyze drought conditions. Among the various techniques available for drought monitoring (WMO and GWP, 2016), this study employed the Standardized Precipitation Index (SPI),McKee et al. (1993) , SPI is a widely used and straightforward index that relies solely on long-term precipitation data, ideally over a minimum of 30 years, to assess drought severity for meteorological, hydrological, and agricultural applications. In this study, SPI was calculated at multiple time scales –1-month, 3–month, 6–month, 12–month, 18–month, and 24–month intervals to capture short- to long-term drought conditions. The Gamma distribution was used to fit the precipitation data, and the resulting SPI values were compared against standard SPI classification thresholds to determine drought or wetness categories. Drought frequency was then estimated by identifying periods where SPI < 0, Xia et al. (2017). To enhance accuracy, SPI was also calculated for the best-fitting probability distribution model. All statistical analyses and computations were conducted using R software.

Standardized Precipitation Index (SPI)

The precipitation Standardized Precipitation Index (SPI) is one of the most common instruments that defines meteorological drought on different time scales. It is specifically appreciable because of its flexibility that enables assessment of droughts on both short-term and time scales closely connected with soil moisture conditions and long-term scales which are linked to the ground water level and reservoir storage. The SPI is one of the strengths since it can also be used in any region due to the difference in climatic conditions; hence, a strong comparative index of drought. The process of computing SPI has several steps as shown below:

Steps in SPI Calculation

Step 1: Aggregation of Precipitation

On a selected interval of time (e.g. 3-month interval), precipitation is added together to produce a moving total. This step brings out cumulative values on the initial monthly values in a way that fits distribution.

Step 2: Fitting a Probability Distribution

Fitted probability distribution is usually a gamma distribution as this works well when modeling positive skewed and non-negative data such as precipitation. In this study, however, the monthly precipitation data were rigorously tested using the Gamma, Exponential, and Normal distributions. The most appropriate model for each region and timescale was determined using the Akaike Information Criterion (AIC). The probability density function (PDF) of the gamma distribution is given by:

$$f(x;\alpha,\beta) = \frac{x^{\alpha-1}e^{-\frac{x}{\beta}}}{\beta^{\alpha}\Gamma(\alpha)}, \quad x > 0 \tag{1}$$

where:
- x is the precipitation amount,

- α is the shape parameter,

- β is the scale parameter, and

- $\Gamma(\alpha)$ is the gamma function.

Step 3: Estimation of Cumulative Probability

Then the non-exceedance probability $G(x)$ of the fitted gamma distribution is calculated as a cumulative distribution function (CDF) of the fitted gamma distribution: the probability that a specific precipitation value is equal or smaller than x.

Adjustment for Zero Precipitation

Since gamma distribution has no value at zero, a modification is done. Edited data is used to calculate the probability of zero precipitation q and it is added to the CDF as shown below:

$$H(x) = q + (1 - q) \times G(x) \tag{2}$$

where, $H(x)$ is the adjusted cumulative probability and q is the proportion of zero-precipitation observations.

Step 4: Standardization (Z-Transformation)

Lastly the cumulative probability adjusted, $H(x)$, is converted to a value of a standard normal with the inverse of standard normal distribution:

$$SPI = \phi^{(-1)}(H(x)) \tag{3}$$

where, $\phi^{(-1)}$ is the inverse standard normal cumulative distribution function.

The approach guarantees that drought severity can be compared regionally and between climates, presenting a common drought assessment methodology. The same is measured by many researchers using gamma distribution but this study has used the Akaike Information Criterion (AIC) when choosing the best fitted probability distribution to use in the precipitation data. The AIC score was used to estimate the best probability distribution. The selected distribution was further used to estimate the SPI to have an accurate evaluation of the drought conditions based on the characteristics of the data.

3 Results and Discussion

In this current study, short-term drought variability was examined in five Sri Lankan stations based on the 1-month Standardized Precipitation Index (SPI) for the period 2010-2023 (Figure 1). This was characterized by significant

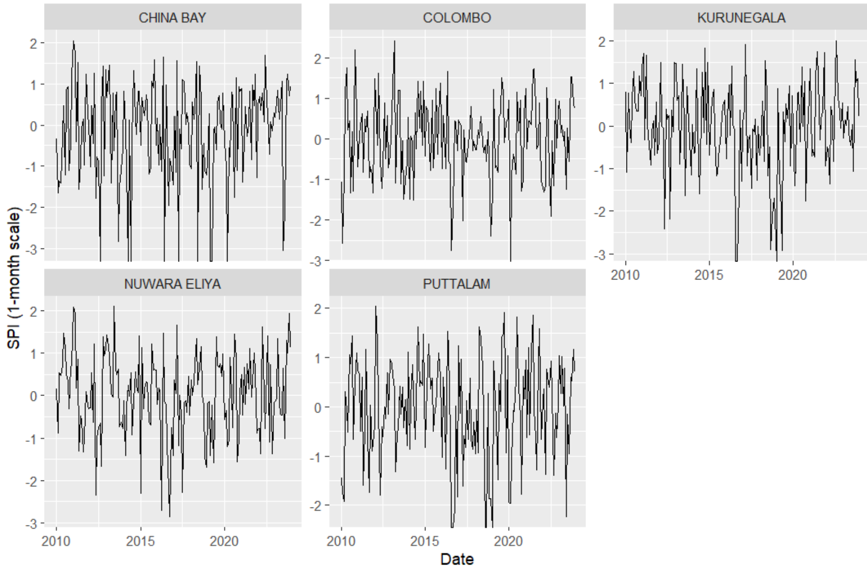

Figure 1: Trends of 1-month SPI (2010–2023) in five Sri Lankan stations

spatial and temporal variability with dry zone station, such as China Bay and Puttalam recording frequent and severe droughts (SPI < -2) whereas wet zone locations, such as Colombo, had relatively steady conditions. Kurunegala and Nuwara Eliya were characterized by occasional droughts as this is the effect of the seasonal and topography factors.

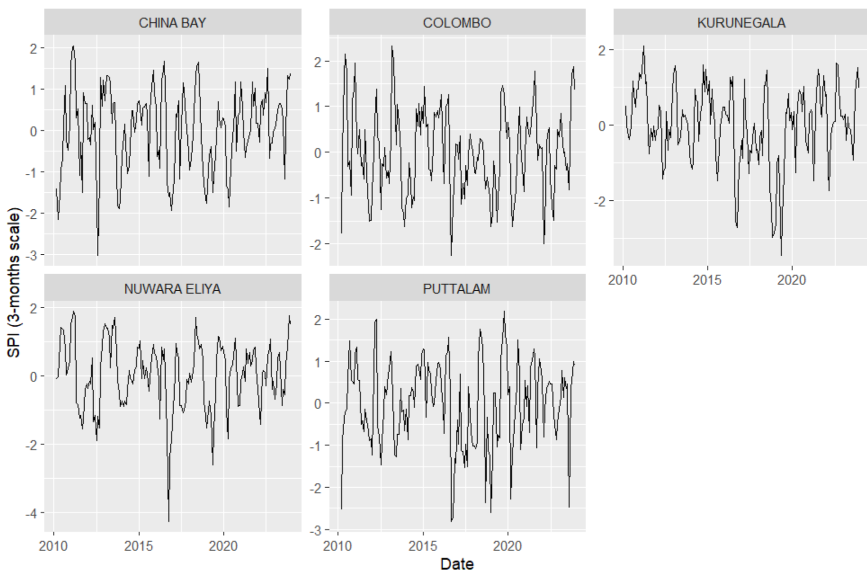

Figure 2: Trends of 3-months SPI (2010–2023) in five Sri Lankan stations

As illustrated in Figure 2, the stations with dry zones include China Bay and Puttalam, which experience severe and frequent droughts especially in 2014

2016 and 2020 with the SPI values generally declining to less than -2. Although it falls in the wet zone, Colombo also has moderate droughts that are observed occasionally, though in the Kurunegala and Nuwara Eliya the dry spells are less significant but also characterized by periodic occurrences.

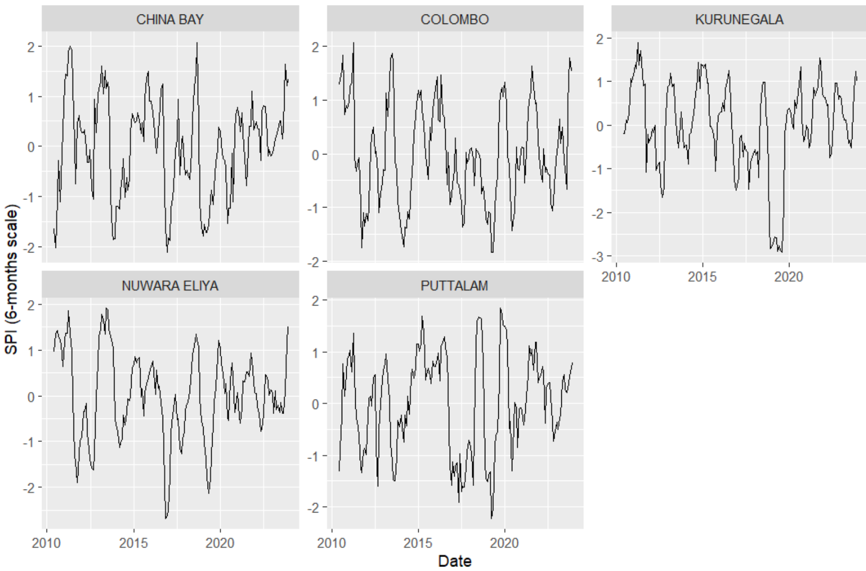

Figure 3: Trends of 6-months SPI (2010–2023) in five Sri Lankan stations

Figure 3 demonstrates that seasonal variability is evident in all stations and the values of SPI varying in the range of +2.5 and about –2.5. Relatively high frequency of wet-dry periods is reported in China Bay and Colombo where the extreme drought situation (SPI < -2) is uncommon. Kurunegala is characterized by an evident and prolonged period of dryness in 2020, when the SPI dropped below -2.5 and indicated an eminent shortage of precipitation over the years. Nuwara Eliya shows stable variation in SPI indicating its climatic sensitivity even though average rainfall is high.

All stations exhibit considerable interannual variability in SPI values, indicating alternating wet and dry periods (Figure 4). Kurunegala stands out with more frequent and intense drought conditions, as seen with SPI values occasionally dropping below -2.5, particularly around 2020. In contrast, Nuwara Eliya and Colombo exhibit a more balanced fluctuation, with fewer extreme drought events. China Bay and Puttalam show distinct cycles of wet and dry conditions, but extreme values are less pronounced compared to Kurunegala.

The 18-month SPI plots highlight long-term precipitation trends across five stations in Sri Lanka, revealing notable spatial and temporal variability. Kurunegala and Puttalam appear particularly vulnerable to Long-duration droughts, with significant dry spells observed around 2020 and 2018–2019, respectively. Colombo experiences extended wet periods, with SPI values occa-

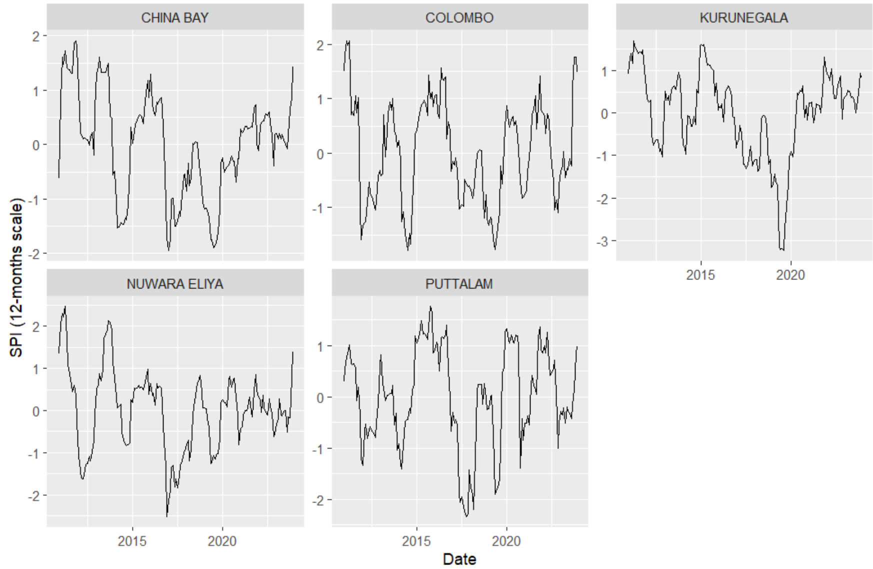

Figure 4: Trends of 12-months SPI (2010–2023) in five Sri Lankan stations

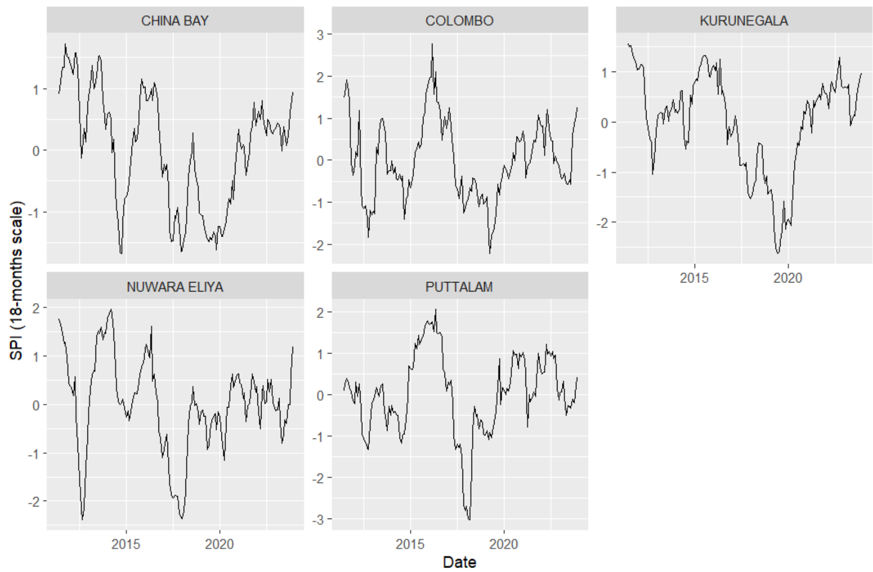

Figure 5: Trends of 18-months SPI (2010–2023) in five Sri Lankan stations

sionally exceeding +2, while dry conditions remain moderate. China Bay and Nuwara Eliya show regular fluctuations, indicating sensitivity to long-term moisture changes, though extreme droughts are less common (Figure 5). Figure 6 shows that Kurunegala once again emerges as particularly Vulnerable to dry conditions, with a marked and extended negative SPI trend around 2019–2020, dropping below -2, signifying a severe long-term drought. Puttalam also shows a long dry period during the same time, which means it is likely to be

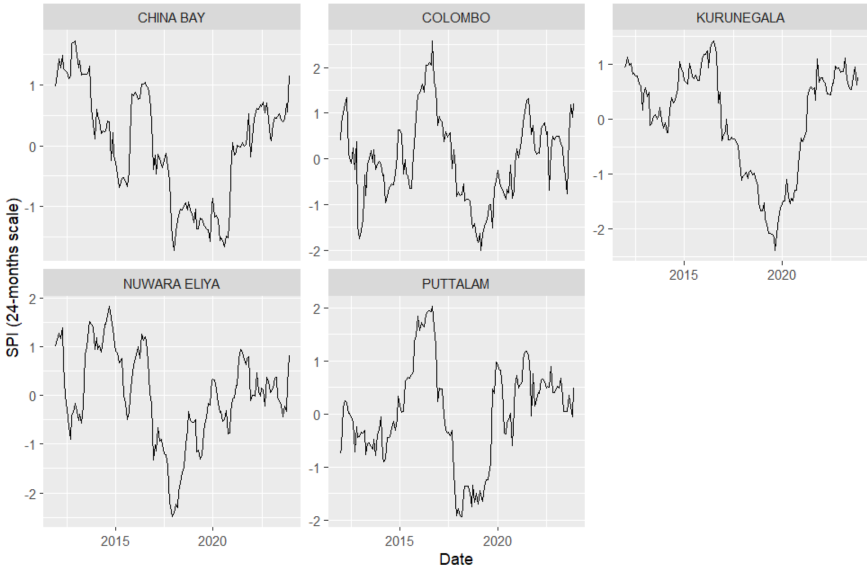

Figure 6: Trends of 24-months SPI (2010–2023) in five Sri Lankan stations

affected by a lack of rain over an extended time. In contrast, Colombo and Nuwara Eliya experience more frequent transitions between wet and dry conditions, though the extremes are less significant.

Table 1: Comparison of AIC values for fitted probability distributions across selected rainfall stations

Distribution \ Station	**China Bay**	**Colombo**	**Kurunegala**	**Nuwara Eliya**	**Puttalam**
Normal Distribution	2193.123	2207.198	2137.259	2044.992	2029.629
Exponential Distribution	1636.913	2131.510	2025.346	1994.641	1833.786
Gamma Distribution	1996.927	2133.448	2027.001	2022.111	1852.743

Using the AIC, the exponential distribution was identified as the most suitable model for the monthly precipitation data across all stations (Table 1). Based on this fitted distribution, the SPI was calculated to assess short-term rainfall variability. The resulting SPI values were then plotted to visualize temporal patterns and drought conditions at each station.

SPI for the fitted distribution

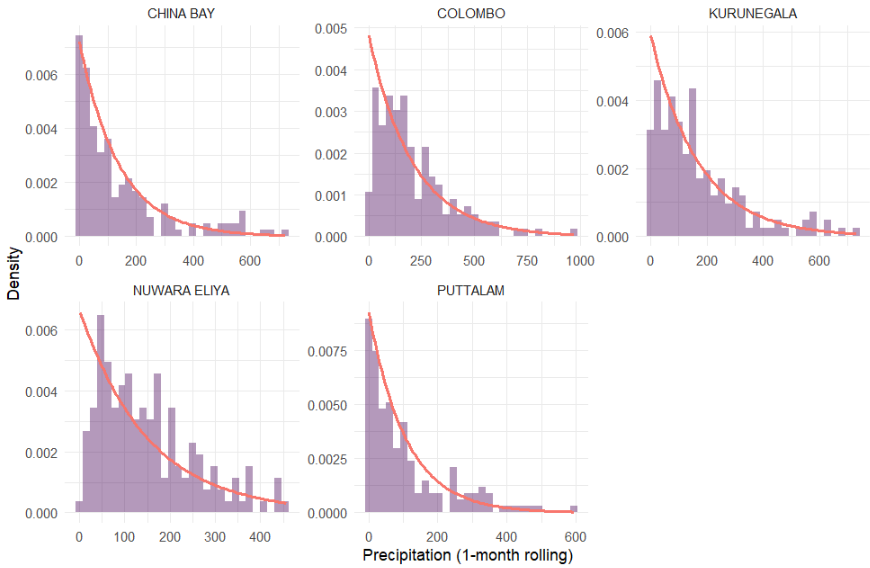

Figure 7: 1-month rolling precipitation with fitted exponential distributions.

As shown in the Figure 7, the exponential distribution has an excellent visual fit at all places, and particularly at the quick depletion in the frequency with power of precipitation levels. This implies that precipitation in these parts of the world is skewed towards the positive side with less extreme and small rainfall events being abundant in the 1-month rolling precipitation. According to this analysis, exponential distribution was found out to be the best fitting distribution of the 1-month accumulated precipitation data.

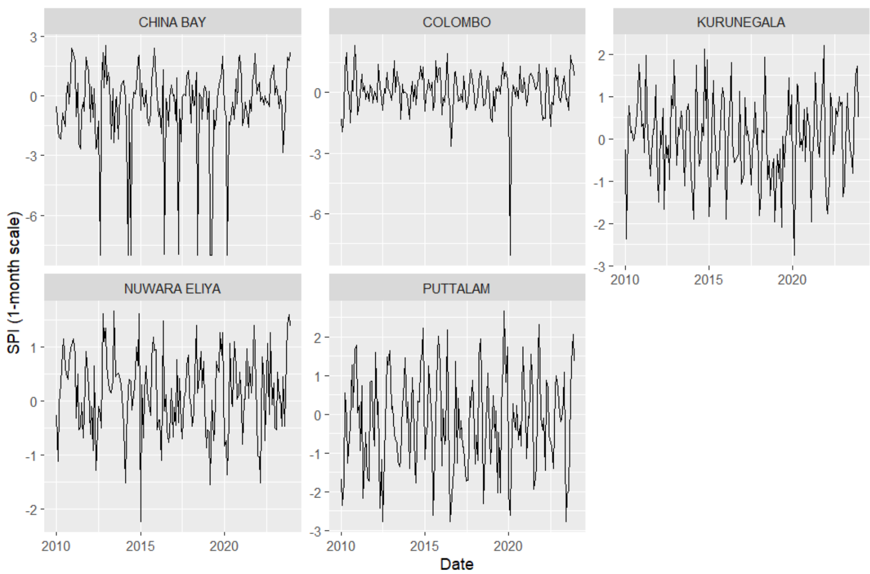

Figure 8: SPI (1-month scale) for five stations using a fitted distribution.

The fitting distribution approach of the graph above produces SPI values at stations that are less extreme and exhibit greater stability. Figure 8 also provides high readability as composing the dates is well marked and it is easier to read the relationship between time and the variability pattern of precipitation. In general, though Gamma-based SPI covers more extreme cases, fitted distributions offer smooth and possibly more reliable descriptions.

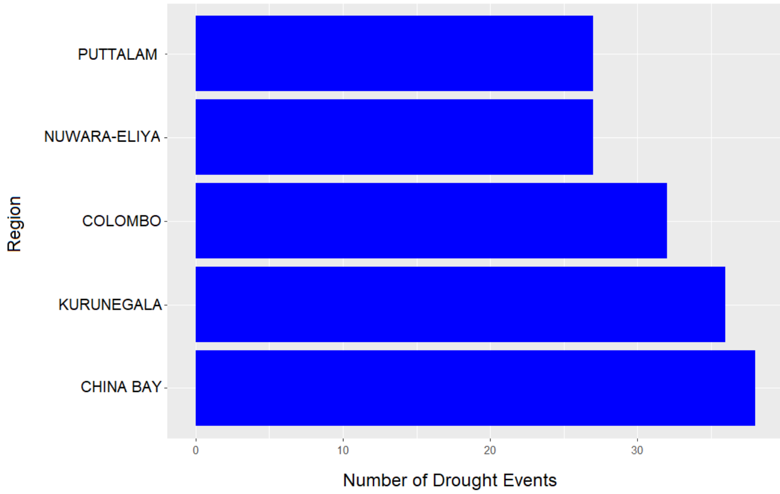

Figure 9: Events of droughts by region considering SPI (1-month scale) analysis.

Figure 9 illustrates the frequency of drought events across different regions, derived using the Standardized Precipitation Index (SPI). The horizontal bars represent the number of drought occurrences in each region, highlighting the regions most affected by drought. For instance, China Bay consistently experiences the highest number of drought events (around 35), followed by Kurunegala and Colombo. Meanwhile, Puttalam and Nuwara Eliya show relatively lower but still notable drought frequencies.

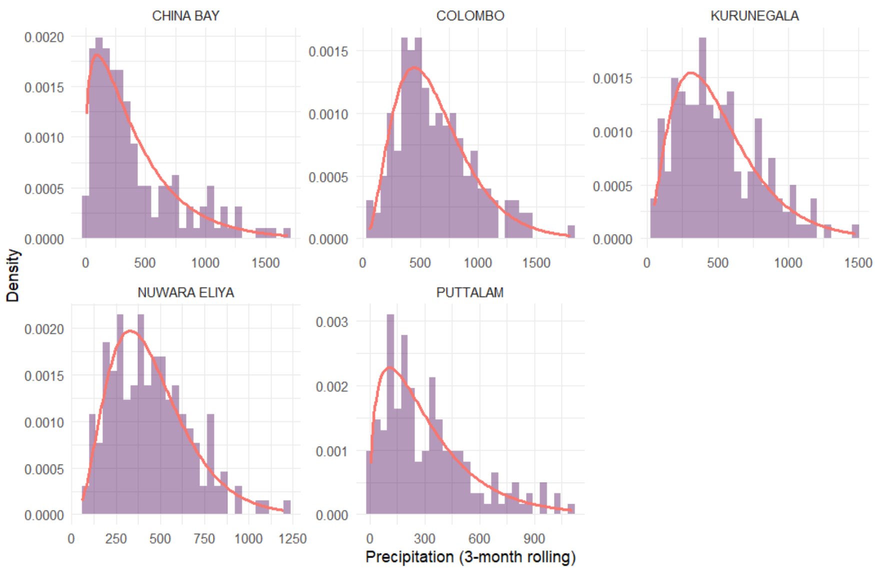

Figure 10: 3-month rolling precipitation with fitted Gamma distributions.

The gamma distribution effectively models the positively skewed nature of the precipitation data, capturing both the peak and the long right tail across all sites. While multiple distributions were evaluated, the exponential distribution was initially considered; however, the gamma distribution provided a significantly better fit for the 3-month rolling data. Its flexibility in modeling skewed, continuous data makes it more suitable for representing medium-term aggregated precipitation patterns (Figure 10).

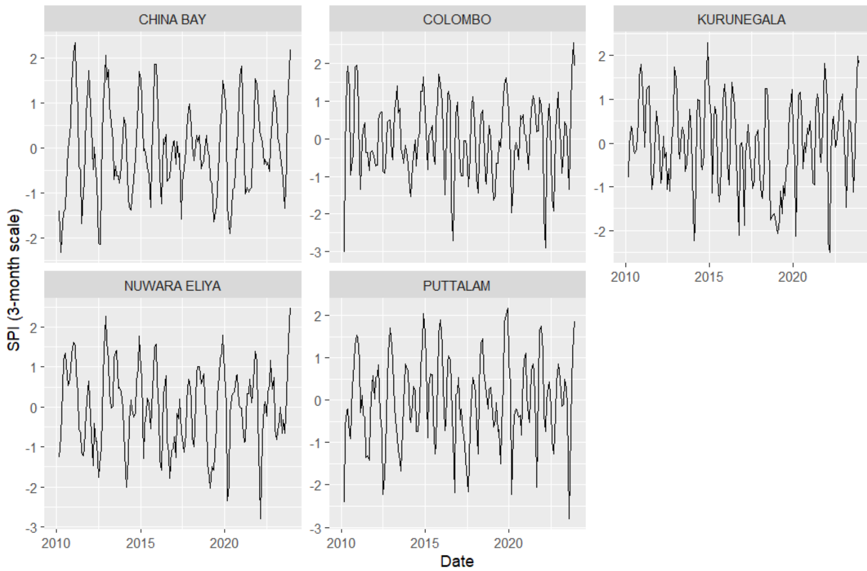

Figure 11: SPI (3-month scale) for five stations using a fitted distribution.

Figure 11 displays the SPI graphs for the 3-month precipitation time scale were generated using both the standard Gamma distribution and a fitted distribution approach. The analysis revealed that the fitted distribution for the 3-month precipitation data is also a Gamma distribution. Consequently, both graphs display similar patterns across all stations. This similarity confirms that the Gamma distribution is well-suited for modeling 3-month precipitation and reinforces the reliability of SPI values calculated using this method According to Figure 12, Puttalam and Colombo have had regular occurrence of drought events, whereas, drought risks are also high in China Bay and Kurunegala . Nuwara Eliya also experiences a high rate of droughts to a certain degree. These findings highlight the susceptibility of these regions to drought necessitating the need to ensure drought management and resilience initiatives that are specific to the requirements of the region.

Regarding the model selection based on the AIC, the gamma distribution was found as the most appropriate model to be considered in the case of the 6-month summarized precipitation records in all the locations, as shown in Figure 13. Using gamma distribution is effective, and it describes the data as positively skewed with a single peak, and the density decreases progressively as the precipitation increases. It implies that values of precipitation for

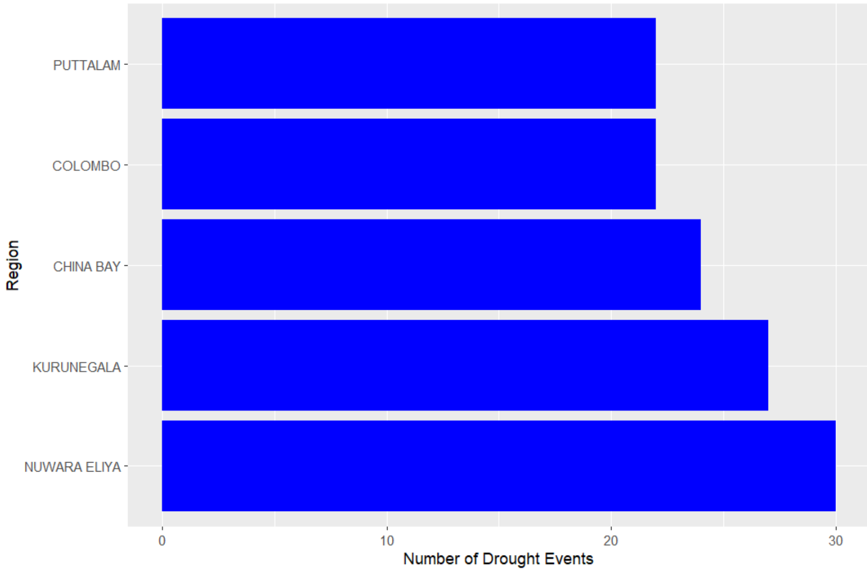

Figure 12: Events of droughts by region considering SPI (3-month scale) analysis.

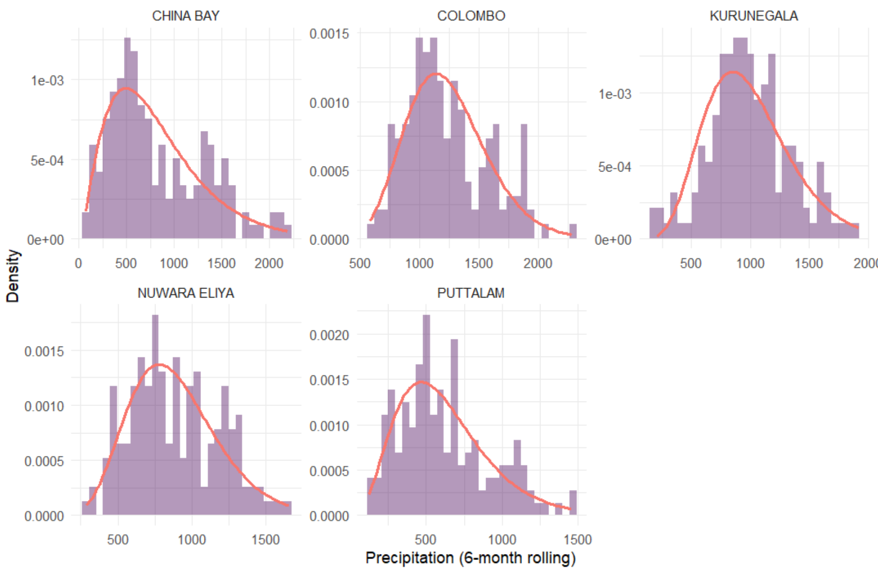

Figure 13: 6-months rolling precipitation with fitted Gamma distributions.

6 months are non-stationary and non-normally, right-skewed distributed, and the gamma model freely approximates the observed distribution and provides it with appropriate accuracy.

For the six-month time scale, the fitted distribution was identified as the gamma distribution. As a result, Figure 14 derived from the raw precipitation data and those generated using the fitted gamma distribution are virtually identical.

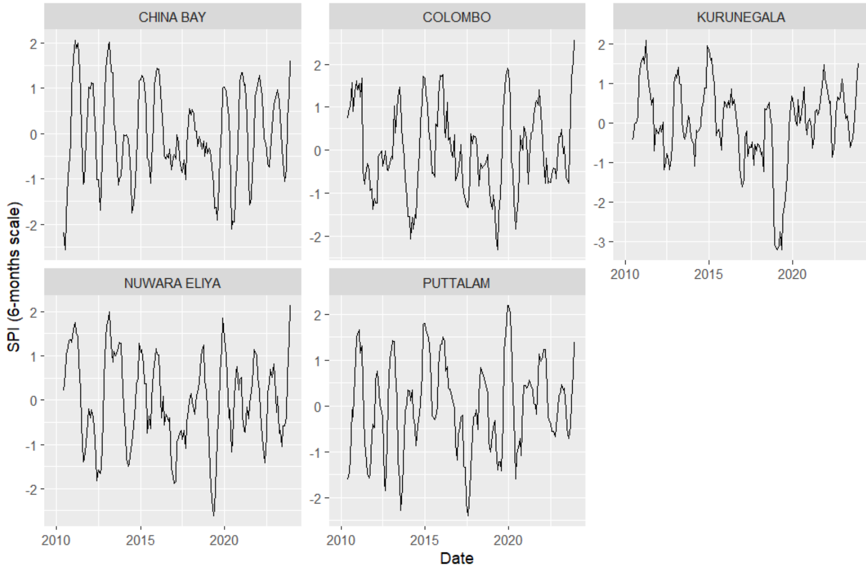

Figure 14: SPI (6-month scale) for five stations using a fitted distribution.

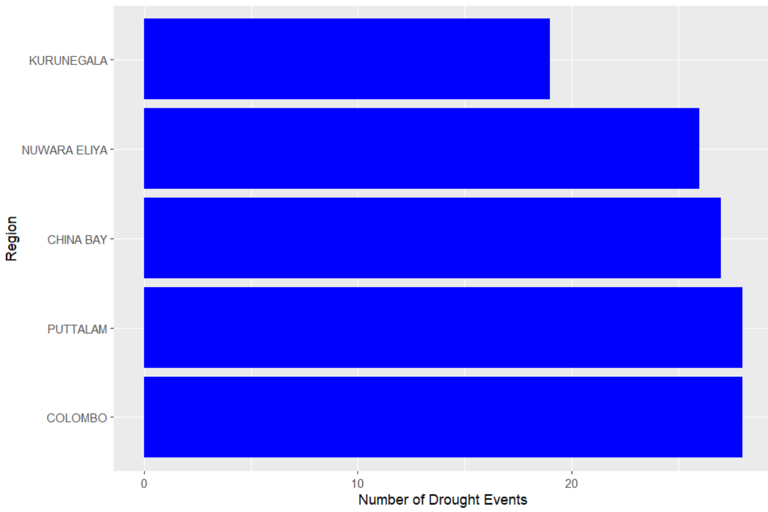

Figure 15: Events of droughts by region considering SPI (6-month scale) analysis.

According to the heights of the bars in Figure 15, Kurunegala, Nuwara Eliya, and China Bay consistently experience a high number of drought events, while Puttalam and Colombo also face significant drought risks.

Figure 16 shows that China Bay exhibits moderate variability, while Nuwara Eliya and Kurunegala exhibit more consistent precipitation with narrower spreads. Colombo's data is slightly skewed, suggesting deviations from a perfect normal distribution. Puttalam displays a pronounced peak, indicating mod-

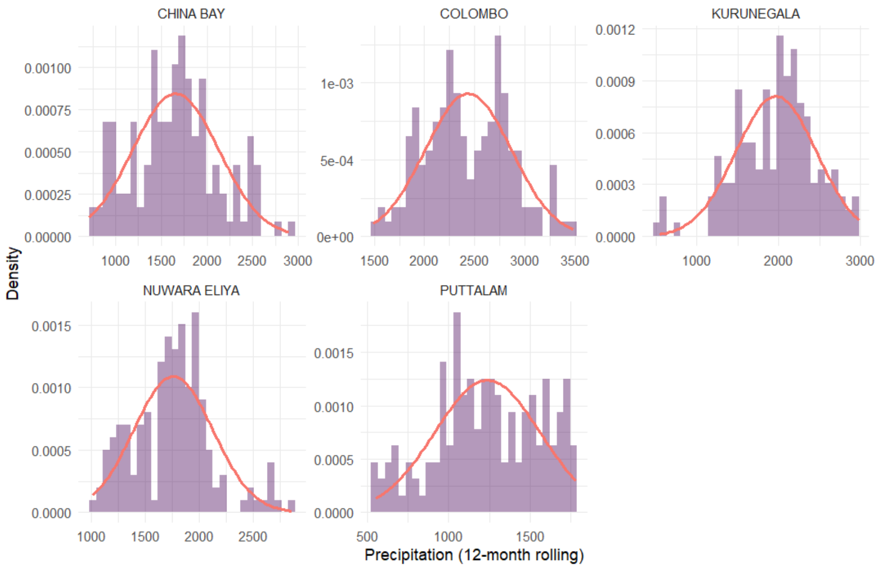

Figure 16: 12-month rolling precipitation with fitted Normal distributions.

erate variability. The AIC method ensured the best-fit model, though alternative distributions may better capture skewness in some regions.

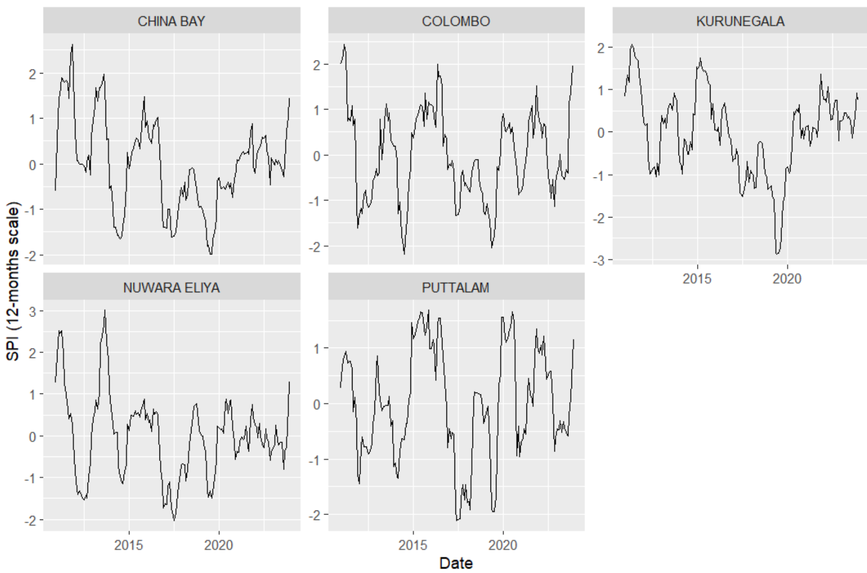

Figure 17: SPI (12-month scale) for five stations using a fitted distribution.

For the 12-month time scale, Figure 17 was developed using both the Gamma distribution and a fitted distribution approach. In this case, the fitted distribution was identified as the Normal distribution. While both methods capture general precipitation trends, the SPI values derived from the Normal distribution show a more symmetric and moderate variation compared to those from the Gamma distribution, which tend to exhibit skewness and more extreme values. This difference highlights the impact of distribution choice on SPI interpretation, especially over longer time scales, where the Normal distribution may provide a more balanced representation of long-term precipitation variability.

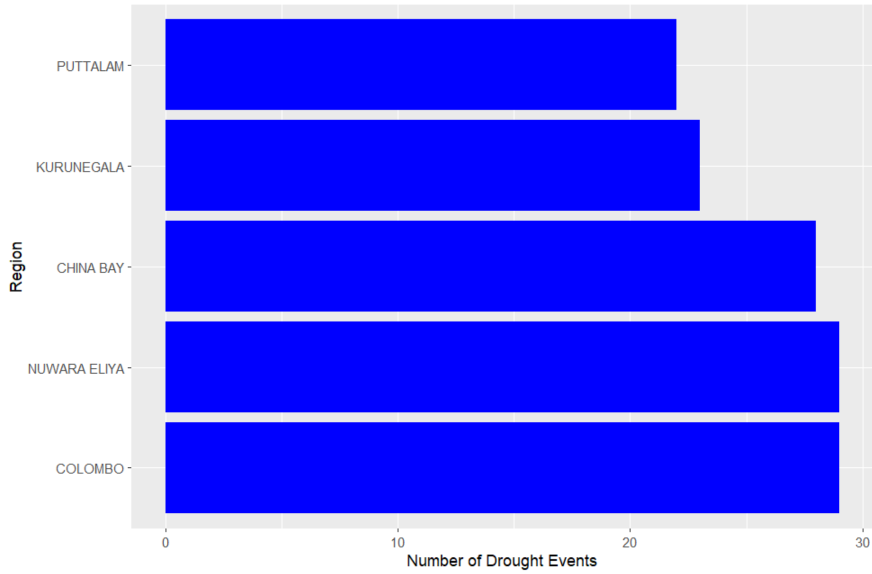

Figure 18: Events of droughts by region considering SPI (12-month scale) analysis.

Figure 18 shows that Puttalam and Kurunegala often experience droughts, and China Bay is also at considerable risk. Nuwara Eliya and Colombo also display a relatively high frequency of drought events. These findings highlight the susceptibility of these areas to drought, underscoring the need for targeted drought management and resilience strategies specific to each region.

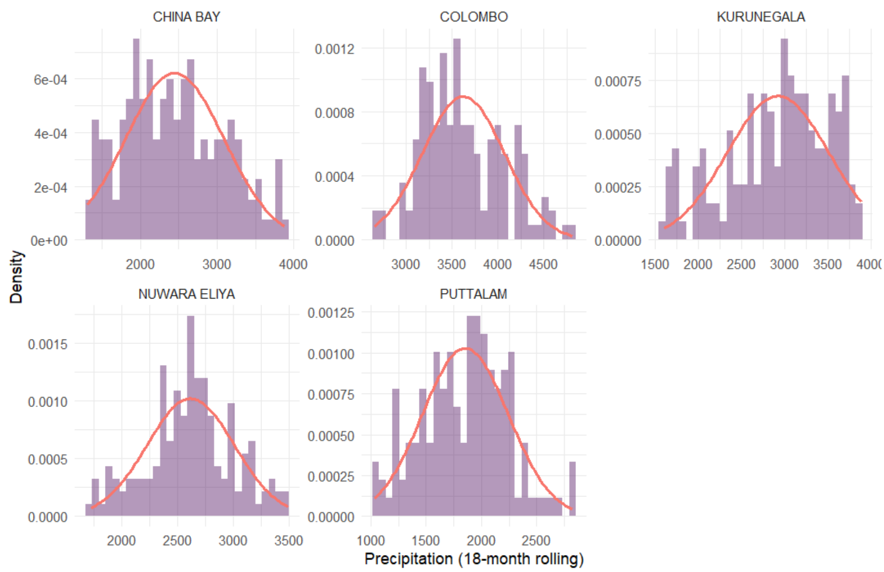

Figure 19: 18-month rolling precipitation with fitted Normal distributions.

Based on the AIC criteria, the normal distribution was the best fit. This suggests that over longer periods, precipitation data becomes more stable and normally distributed, making the normal model suitable for analysis (Figure 19).

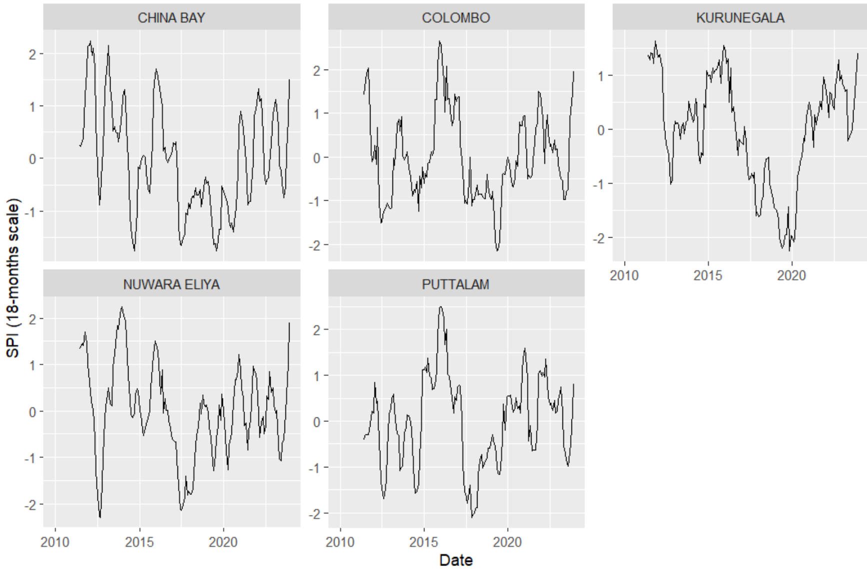

Figure 20: SPI (18-month scale) for five stations using a fitted distribution.

For the 18-month time scale, SPI was calculated using both the Gamma distribution and a fitted distribution, which in this case was also the Normal distribution, as shown in Figure 20. Like the 12-month scale, the SPI values from the Normal distribution display smoother and more symmetric patterns, while the Gamma-based SPI shows slightly more skewed and extreme values. This indicates that over extended time scales, the Normal distribution may offer a more stable and balanced representation of long-term precipitation trends, though both methods reflect similar overall patterns.

Figure 21 highlights the prevalence of drought events in various regions. Colombo emerges as particularly drought-prone, while Nuwara Eliya also faces significant drought risks. Additionally, China Bay, Kurunegala, and Puttalam show a relatively high frequency of drought occurrences. These observations point to the vulnerability of these regions to drought, stressing the need for region-specific drought management and resilience strategies. China Bay's precipitation shows a broad spread with moderate density, while Kurunegala's distribution is tighter, suggesting more consistent rainfall. Puttalam exhibits a pronounced peak, indicating lower variability (Figure 22). The AIC value was used to select the best-fit normal distribution, ensuring a balance between model accuracy and simplicity. While the normal distribution fits reasonably well for most locations, slight deviations in some areas suggest that alternative distributions could be explored for improved precision.

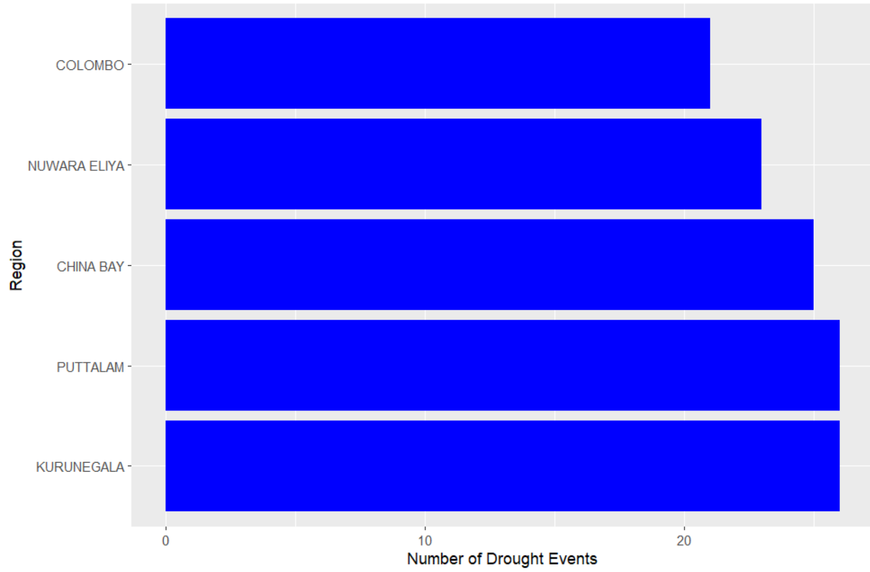

Figure 21: Events of droughts by region considering SPI (18-month scale) analysis.

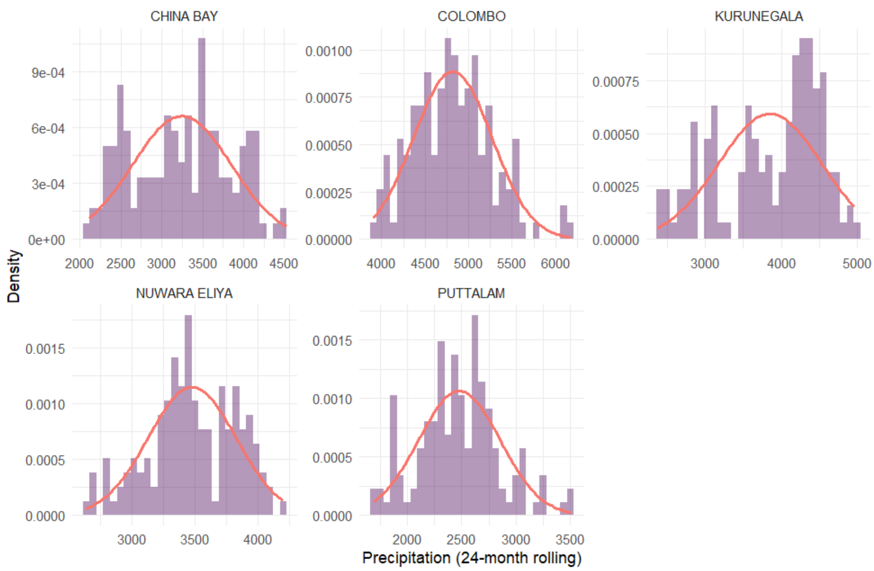

Figure 22: 24-months rolling precipitation with fitted Normal distributions.

The 24-month SPI was computed with the Gamma distribution and with the Normal distribution, which was the best-fitting distribution according to the AIC. As shown in Figure 23, Since this time scale is long, the two methods yielded very similar patterns in the values of SPI observed in the measured stations. However, the SPI based on the Normal distribution maintains a more symmetric and smoothed variation, while the Gamma-based SPI still reflects slight skewness. This suggests that for long-term precipitation analysis, the

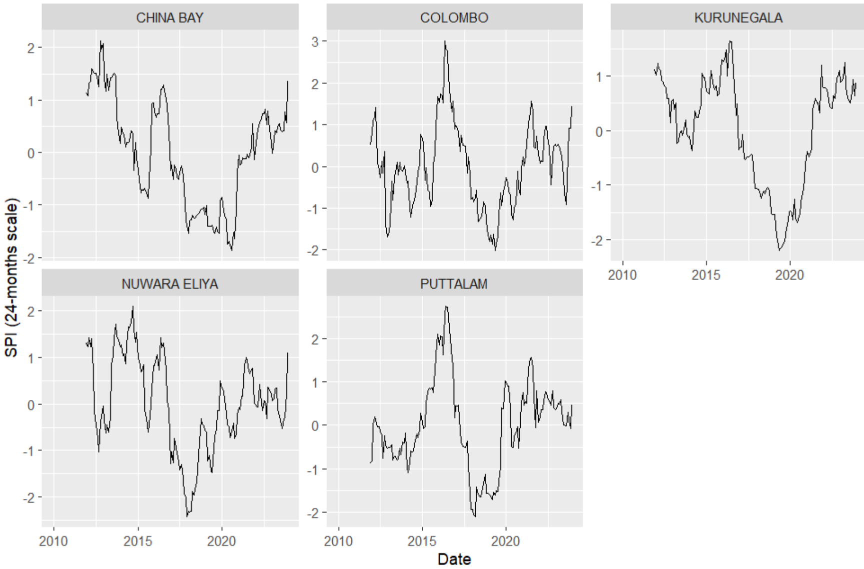

Figure 23: SPI (24-month scale) for five stations using a fitted distribution.

Normal distribution provides a reliable and consistent approach for SPI calculation, offering clear representation of prolonged wet and dry periods.

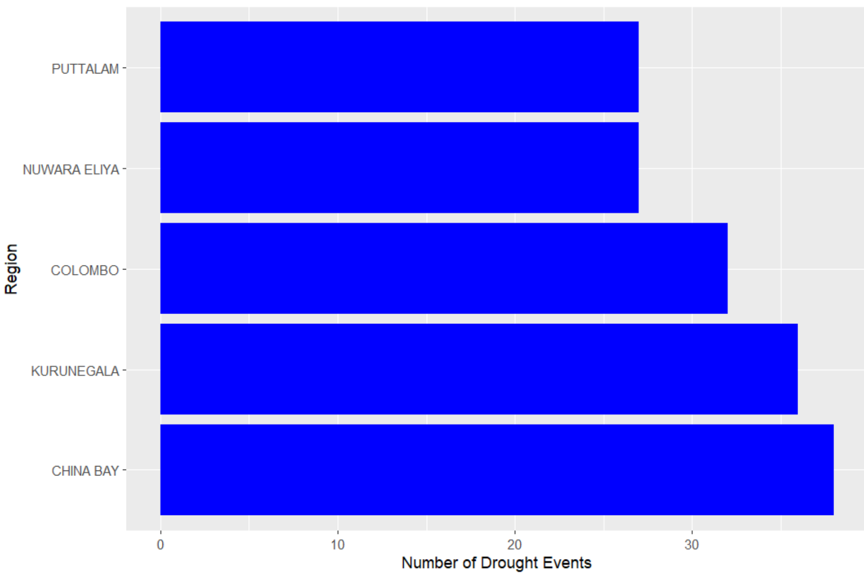

Figure 24: Events of droughts by region considering SPI (24-month scale) analysis.

Figure 24 shows that China Bay has recorded the highest drought events when compared to other regions studied and Kurunegala and Colombo have recorded droughts frequently. On the contrary, although the frequency of occurrence of drought in Puttalam and Nuwara Eliya is relatively lower, the experiences cannot be overlooked and require additional focus.

4 Conclusion

The proposed study was able to provide a detailed account of the variability of the drought in five climatically different parts of Sri Lanka namely, China Bay, Colombo, Nuwara Eliya, Puttalam, and Kurunegala over the period 2010 to 2023 and through different time scales (1-24 months), through the Standardized Precipitation Index (SPI). The choice of the regions itself was strategic because it allows covering the main climate areas of Sri Lanka: Dry, Wet, and Intermediate Zones. Their incorporation guarantees a wide geographical area coverage indicating the differences in elevation, topography, and exposure to monsoon systems that would allow the comprehensive comprehension of drought processes in the country.

The SPI was adopted to act as the main analytical instrument since it has demonstrated its flexibility in reflecting both short- term and long-term drought conditions. It normalizes deficits in precipitation and can be compared between regions and seasons on an objective basis. Also, its flexibility regarding numerous probability distributions, which are proved by the Akaike Information Criterion (AIC), makes this procedure a powerful tool to monitor droughts in different climatic conditions. The flexibility of the SPI in timescale also comes in handy in coordinating the impact of droughts with envisaged agricultural, hydrological, and ecological processes.

The analysis has found that the regions in Dry Zone, especially China Bay and Puttalam had the maximum number of periodicities of drought occurrences in the short-term domain. Kurunegala, which was in the intermediate zone also proved to be highly vulnerable and reported long lasting and intense drought. The Wet Zone (Colombo) and the highland regions (Nuwara Eliya) had the least number of extreme droughts and still had a large vulnerability in times where there were long dry periods.

These results are critical to the farming industry in Sri Lanka. The SPI trends which can be used to determine the drought prone periods and regions can be used to have important information in crop planning, timing of irrigation and management of drought risks. Some such areas might include China Bay or Kurunegala requiring improved crop types resistant to drought and investment in irrigations systems, so they use less water. In the meantime, the outcomes of the longer paths of SPI can be used in formulating strategic planning on the policy of reservoir management and long-term yearly agricultural policy decision-making.

To conclude, using SPI-based drought synthesis in ways combined with regional climatic specificities provides a potent instrument towards generating contextual and data-reliant agricultural adaptation policies. Based on such findings, it is possible to create early warning systems, customize crop calendars, and improve water resources management to make the agricultural system in Sri Lanka much more resilient to the rising threats of drought caused by the effects of climate variability.

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