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Drought Characteristics and Drought-Induced Effects on Vegetation in Sri Lanka

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Abstract: Understanding the spatiotemporal characteristics of drought and its impacts on vegetation is a timely prerequisite to ensuring agricultural, environmental, and socioeconomic sustainability in Sri Lanka. We investigated the drought characteristics (duration, severity, frequency, and intensity) from 1990 to 2020 by using the Standardized Precipitation Evapotranspiration Index (SPEI) at various timescales and the cumulative and lagged effects on vegetation between 2000 and 2020 across the climatic zones of Sri Lanka (Dry, Wet, and Intermediate). SPEI indexes at 1-, 3-, 6-, 12-, and 24-month scales were used to analyze the drought characteristics. Frequent droughts (~13%) were common in all zones, with a concentration in the Dry zone during the last decade. Drought occurrences mostly ranged from moderate to severe in all zones, with extreme events more common in the Dry zone. This research used SPEI and the Standardized Normalized Difference Vegetation Index (SNDVI) at 0 to 24-month scales to analyze the cumulative and lagged effects of drought on vegetation. Cumulated drought effects and vegetation had maximum correlation coefficient values concentrated in the −0.41–0.98 range in Sri Lanka. Cumulated drought effects affected 40% of Dry and 16% of Intermediate zone vegetation within 1–4 months. The maximum correlation between the lagged drought effect and vegetation SNDVI showed coefficient values from −0.31–0.94 across all zones, and the high correlation areas were primarily distributed in Dry and Intermediate zones. Over 60% of the Dry and Intermediate zones had a lagged drought impact within 0 to 1 month, while 52% of the Wet zone experienced it over 11 months. The resulting dominant shorter timescale responses indicate a higher sensitivity of vegetation to drought in Sri Lanka. The findings of this study provide important insights into possible spatiotemporal changes of droughts and their possible impact on vegetation across climate zones.

Keywords: drought; SPEI; vegetation; cumulative effect; lagged effect; Google Earth Engine

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1. Introduction

Drought is a climate-related natural disaster that poses a significant threat to agricultural, environmental, and socioeconomic sustainability [1–3]. Drought is a complex phenomenon since climatic conditions are spatially and temporally varied, thus resulting in region-specific cumulative effects [4,5]. Climatic differences highly affect the spatiotemporal variation of drought severity worldwide [6], and evapotranspiration further prompts them [7–9]. The degree of water deficit plays a crucial role in defining the prevailing form of drought. Hence, droughts are generally classified into different drought categories: meteorological, agricultural, hydrological and socioeconomic droughts [10,11]. Vegetation is a principal component of terrestrial ecosystems [12]. Drought intensification can seriously threaten vegetation growth and productivity by causing systematic and abrupt changes in the ecosystem structure and services [13,14]. Drought also has complex environmental consequences, and that impact can last longer even after a severe drought [1]. Therefore, understanding the drought and the sensitivity and tolerance of vegetation to drought can help with effective ecosystem conservation measures [15]. Precisely quantifying the drought events is crucial to effectively delineating their characteristics and assessing their impacts. Due to their complex characteristics, many drought indices, such as the Standardized Precipitation Index (SPI) [16], Palmer Drought Severity Index (PSDI) [17], Rainfall Anomaly Index [18], and the Standardized Precipitation Evapotranspiration Index (SPEI) [10,19] have been widely used to track droughts globally because one single drought index does not provide detailed information about drought. Among these indices, the SPI is one of the most widely used multiscale drought indices that only use precipitation to calculate drought. Most studies used only the precipitation-based SPI index to monitor drought characteristics without considering the effect of evapotranspiration [20–23]. The PSDI is the most widely used regional drought index, based on a soil water balance principle. However, the PDSI is fixed on temporal scale, is not well suited for spatiotemporal comparability, and fits well for water deficiencies over long time intervals [17,24]. Climate change makes dry regions drier and wet regions wetter, including Sri Lanka [25]. In dry regions, rising temperatures cause water to evaporate more quickly, increasing the risk of drought or prolonging drought periods. However, it should be noted that a drought index based solely on precipitation may be insufficient to monitor droughts. Thus, temperature and evapotranspiration must be included and regarded as significant factors of multiscale drought variability. The SPEI is a comprehensive drought index based on an analysis of the advantages and disadvantages of the SPI and the PDSI by representing the combined effect of precipitation and potential evapotranspiration to calculate multiscale drought and is one of the well-established drought metrics worldwide [26–28]. SPEI may be a helpful drought indicator, given that it accounts for the impact of rising temperatures on water demand. Several studies indicate that vegetation is predominantly influenced by the temporal effects of droughts: current drought conditions and earlier droughts [29]. Numerous studies have investigated the relationship between vegetation and concurrent drought conditions using correlation analysis, which has been widely applied globally [30]. Recently, analyzing this relationship using correlation coefficients at a multi-temporal scale has become the main research focus [29,31–33]. Thus, understanding both the cumulative and lagged effects can provide a clearer insight into how drought affects vegetation growth and vegetation sensitivity and tolerance to multiscale drought.

Drought is one of the most severe natural disasters in Sri Lanka, having a wide-ranging impact on livelihood, agriculture, economy, and the environment [34–37]. Drought accounted for over 50% of crop damage between 1974 and 2013 [34]. A severe drought in 2014 affected the livelihoods of over one million people, and 58 percent of the country faced severe water shortages to cultivate crops during the dry season [35]. Recently, the Climate Risk Index for 2019 ranked Sri Lanka as the second most impacted country in the world regarding the percentage of the population affected by various natural disasters [38]. Being an agricultural-based country, it is essential to analyze the drought occurrence and its cumulative and lagged effects on vegetation in both spatial and temporal contexts. Such a study would help in decision-making for sustainable agricultural planning. For instance, rice, one of the main crops in Sri Lanka, is highly susceptible to precipitation variations. In contrast, other crops such as tea, coconut, and rubber are also dependent on precipitation during different growing periods. Sri Lanka is experiencing drought due to the significant effect of climate change, including apparent spatial and seasonal differences in precipitation and temperature and intensified water variability and scarcity [25,39–42]. Efforts to utilize various drought indices to identify and analyze drought in Sri Lanka have increased in recent years [42–46]. However, most studies are limited to exploring the drought using the SPI and Palmer Drought Severity Index [47] with location-specific data. However, the SPEI index and the combined effect of precipitation and potential evapotranspiration have not yet been widely used [42]. Those studies do not adequately capture the spatial and temporal distribution of droughts across the country, as they rely on location-specific data, and most of them did not document detailed spatial-temporal drought trends. One study investigated only the factors that drive variations in agricultural vegetation responses to drought; the spatiotemporal impact and responses remained unknown. In order to understand drought and mitigate its social and economic impacts at the regional levels, precise information on drought and its effects on vegetation is vital. Detailed information for understanding the variability in drought patterns across Sri Lanka at the climatic zone level is currently insufficient. Further, drought duration, severity, frequency, and intensity have yet to be well studied and documented at the climate zone level. Furthermore, the cumulated and lagged effects of drought on vegetation across Sri Lanka have not yet been investigated. There is an urgent need for information on drought patterns and vegetation response to effectively manage agricultural planning and drought mitigation, and improve agricultural drought prevention in the country. Considering these existing knowledge gaps, this study aimed explicitly at the satellite-based monitoring of drought duration, frequency, and intensity to reveal drought-induced lagged and cumulated effects on vegetation at various timescales at climatic zone levels in Sri Lanka for the first time.

This study focused on bridging the research gap on drought variability and provided essential information on changes in drought patterns and lag and cumulative impacts on vegetation, allowing us to reveal anticipated future drought changes and effects (1) to compute the SPEI over a range of time scales using precipitation and evapotranspiration data for the temporal period 1990–2020; (2) to conduct spatiotemporal analysis of drought characteristics by measuring drought intensity, frequency, and severity; and (3) to explore the spatiotemporal patterns of cumulative and time-lag effects of drought on vegetation dynamics in climatic zones using lagged and accumulated SPEI and long-term Standardized Normalized Difference Vegetation Index (SNDVI). These results provide a scientific foundation for drought monitoring and help prioritize adaptive measures to reduce and mitigate the impact of drought.

2. Materials and Methods

2.1. Study Area

Sri Lanka is an agricultural country located in the Indian Ocean, covering a 65,610 km^2 area. Sri Lanka has a typical tropical monsoonal climate with four seasons: (1) the north-east monsoon (DJF—December to February), (2) the first inter-monsoon season (MA—March to April), (3) the south-west monsoon (MJJAS—May to September), and (4) the second inter-monsoon (ON—October to November) [48]. The annual average precipitation varies from 900 mm at the southeastern lowlands to over 5000 mm over the southwestern slopes of the central highlands. Sri Lanka is divided into three major climatic zones based on the spatial variation of long-term annual mean precipitations and major land use categories: (1) Dry (<1750 mm), (2) Wet (>2500 mm), and (3) Intermediate zones (1750–2500 mm) [49]. Figure 1 presents the climatic zone boundaries. The annual average temperature varies from 18 to 27.5 °C over central highlands and lowlands, respectively [48].

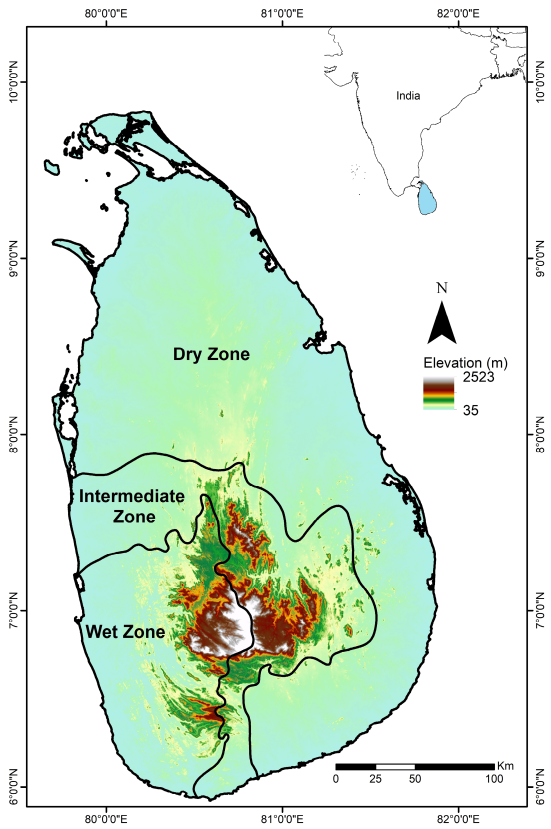

Figure 1. Climatic zones of Sri Lanka.

2.2. Data

Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) Precipitation, European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5) for temperature, wind, pressure, and radiation flux, and Famine Early Warning Systems Network (FEWS NET) Land Data Assimilation System (FLDAS) radiation flux from 1990–2020 were used to calculate SPEI. Terra-MODIS (Terra Moderate Resolution Imaging Spectroradiometer) Normalized Difference Vegetation Index (NDVI) data were used to calculate vegetation from January 2000 to May 2020. These datasets were obtained and analyzed in the Google Earth Engine (GEE) platform, and the information on the GEE datasets is summarized in Table 1.

Table 1. Datasets used.

Data	Variable	Resolution		GEE Asset Address
		Spatial	Temporal	
CHIRPS V2.0	Precipitation (mm)	0.05°	1 day	UCSB-CHG/CHIRPS/DAILY
ECMWF ERA5	Minimum temperature at 2 m height	0.10°	1 month	ECMWF/ERA5_LAND/MONTHLY
	Maximum temperature at 2 m height	0.10°	1 month	ECMWF/ERA5_LAND/MONTHLY
	Mean temperature at 2 m height	0.10°	1 month	ECMWF/ERA5_LAND/MONTHLY
	Dewpoint temperature at 2 m height	0.10°	1 month	ECMWF/ERA5_LAND/MONTHLY
	U component of wind (ms^{-1})	0.10°	1 month	ECMWF/ERA5_LAND/MONTHLY
	V component of wind (ms^{-1})	0.10°	1 month	ECMWF/ERA5_LAND/MONTHLY
	surface pressure (Pa)	0.10°	1 month	ECMWF/ERA5_LAND/MONTHLY
FLDAS V1	Downward longwave radiation flux ($W\ m^{-2}$)	0.10°	1 month	NASA/FLDAS/NOAH01/C/GL/M/V001
MOD13Q1 V6.1	Normalized Difference Vegetation Index	250 m	16 days	MODIS/061/MOD13Q1

2.3. Method

Figure 2 shows the detailed overview of the methodological flow used for the study.

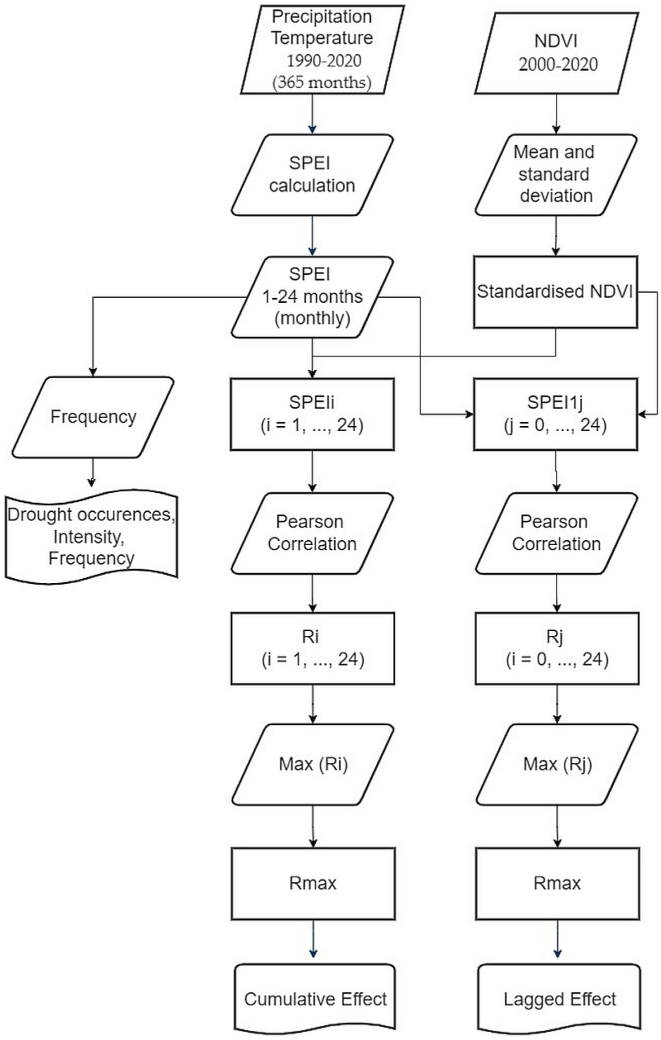

Figure 2. Methodological flowchart of the study.

2.3.1. Precipitation Trend

The Mann–Kendall (MK) test [50] and Sen's slope [51] estimator test were used to calculate the precipitation trends to analyze Sri Lanka from 1990 to 2020. The MK trend test is a non-parametric statistical test method. It has the advantage that the measured values do not need to follow a normal distribution and are unaffected by missing values and outliers. MK statistical test was employed to indicate an increasing or decreasing trend in meteorological time series in each season (DJF, MA, MJJAS, and ON) in various decadal periods (1990–1999, 2000–2009, 2010–2020) based on CHIRPS precipitation data.

Sen's estimator was used to estimate the magnitude of the trend within decadal precipitation. In the case of a linear trend in a time series, the exact Sen's slope is computed using the Theil–Sen median method, which is usually used in combination with the MK test. Further, areas belonging to positive and negative trends were calculated.

2.3.2. Standardized Precipitation Evapotranspiration Index (SPEI)

SPEI [10] is one of the most widely used drought indexes and is a multi-scalar drought metric (i.e., monthly, seasonally, and annually) that mainly considers the precipitation and potential evapotranspiration climatic data. Incorporating precipitation and temperature climate variables allows us to better capture the duration, severity, and intensity of drought over a period. Furthermore, it can be calculated on various time scales in order to capture the response of agricultural, hydrological, and other environmental systems to climate variability. The shorter time scales better capture the rapid variations in precipitation and

PET and are suitable for monitoring a short-term drought. The larger time scales better capture the anomalies accumulated over past climate conditions. Therefore, we calculated the SPEI at different time scales (1 to 24 months) from 1990 to 2020.

The main steps for calculating SPEI are calculating Penman–Monteith evapotranspiration, the monthly accumulated climatic water balance, standardized F(x) values, and the SPEI [10]. The reference evapotranspiration (ET_o) was calculated using the Penman–Monteith method [52]. The monthly minimum, maximum, mean and dewpoint temperatures, U and V components of wind, surface pressure, and downward longwave radiation flux (Table 1) were used to calculate monthly ET_o in Penman–Monteith method.

The monthly accumulated climatic water balance is determined by the difference between precipitation and reference evapotranspiration for the month i:

$$\mathrm{D_i = p_i - ET_{oi}} \tag{1}$$

This provides a simple measure of the excess or shortage of water for the month analyzed. The D is then normalized as a log-logistic probability distribution. This is a well-established fitting method globally [10,53–56]. The probability density function of a three-parameter log-logistic distributed variable is expressed as:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1} + \left[1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right]^{-2} \tag{2}$$

where α, β, and γ are variable, scale, shape, and origin parameters, respectively, for D values in the range ($\gamma > D < \infty$). Thus, the probability distribution function of D can be expressed by

$$F(x) = \left[1+\left(\frac{\alpha}{x-\gamma}\right)^{\beta}\right]^{-1} \tag{3}$$

where parameters α, β, and γ derive from a probability-weighted moments calculation. p is the probability of exceeding a determined value of D. $p = 1 - F(x)$, where $p \leq 0.5$; if $p > 0.5$, then $p = F(x)$.

Finally, the SPEI can be calculated as follows [10]:

$$SPEI = W - \frac{C_0 + C_1W + C_2W^2}{1 + d_1W + d_2W^2 + d_3W^3} \tag{4}$$

where $W = \sqrt{-2\ln(p)}$, where $p \leq 0.5$; if $p > 0.5$, then $W = \sqrt{-2\ln(1-p)}$ and SPEI is multiplied by -1. The constants are $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$ [10].

The SPEI was calculated each month of the year at various time scales (1–24 months) to monitor drought and capture its effect on vegetation. Few studies have investigated the potential meteorological (1-month timescale), agricultural (3–6-month timescale), and hydrological (12-month timescale) droughts [10,11], and the drought categories are defined in the following Table 2.

Table 2. Classification ranges used for the SPEI drought index [57,58].

Range of SPEI	Category of Drought
$-1.0 <$ SPEI ≤ -0.50	Mild
$-1.5 <$ SPEI ≤ -1.0	Moderate
$-2.0 <$ SPEI ≤ -1.5	Severe
SPEI ≤ -2.00	Extreme

2.3.3. Calculation of Drought Intensity and Frequency

SPEI index was more sensitive to the spatial and temporal characterization of drought assessment. We assessed drought intensity and frequency using SPEI values generated at a 1-month time scale.

The value of SPEI, consecutively lower than normal conditions (SPEI ≤ -1), was recorded as drought incidences, and drought duration was defined as the period during which the drought indices are continuously negative [59]. Drought severity is computed as the absolute sum of all drought indices during a drought event.

The drought intensity is calculated by dividing the severity by the drought duration, and the formula is given by

$$I = \frac{\sum_{n=1}^{T} SPEI_n}{T} \quad (5)$$

where I—drought intensity, $\mathrm{SPEI_n}$—the value of SPEI below the threshold, set to be less than or equal to -1 in this study, meaning the drought level is greater than moderate drought, T—the duration of the drought process

Drought frequency is used to assess the vulnerability of drought, and the formula is given by

$$F = \frac{\mathrm{n}}{\mathrm{N}} \times 100\% \quad (6)$$

where F—the frequency of drought, n—the number of drought events during the period, and N—the total months for the time series.

2.3.4. Calculation of Cumulative and Lagged Effects of Drought

NDVI is a measure of vegetation health and dynamics. The NDVI values were obtained from MOD13Q1 product with 250 m spatial resolution and 16-day temporal resolution. The monthly maximum was selected as the monthly NDVI value. For comparison, the NDVI composites were aggregated according to the spatial resolution of the SPEI. The spatially aggregated NDVI composites were standardized in order to remove the seasonal changes prior to the comparison with the SPEI. The monthly time series of each pixel was then standardized using their long-term monthly mean and standard deviation, as shown in the following equation, where i is the month and j is the year.

$$SNDVI_{i,j} = \frac{NDVI_{i,j} - Mean(NDVI_i)}{Standard\ deviation(NDVI_i)} \quad (7)$$

Pearson's correlation was used to analyze the correlation between the variables. The distribution of land cover types was obtained from the MODIS land cover type products (MCD12Q1) in 2020 with a 500 m spatial resolution. Urban and water land cover pixels were excluded from the analysis.

The cumulative effect of drought on vegetative growth is the impact of the accumulated effect of water deficit on subsequent growth. The cumulative effects of drought on vegetation growth were calculated using Pearson correlation coefficients. Due to the association between vegetative growth activity and drought being substantially reliant on the drought time scale at the global level [6,60], the correlation between the SNDVI and the SPEI was calculated at various time scales ranging from 1 to 24 months to determine the response time of vegetation to the accumulated drought over that specific period (Equation (8)) [29,32]. Given the significant seasonality of vegetation in the country, correlations were obtained separately for each individual month (R_1, R_2. . ., R_{24}). The higher coefficient R indicates that the response time is more sensitive and vice versa [33]. Thus, the highest absolute correlation coefficient value (Rmax) was considered as the cumulative effect by indicating that the growth of vegetation was consistently affected by the cumulative drought conditions over the previous i months. The corresponding month scale (i) with the Rmax was considered as the cumulative time effect of drought on vegetation. For example, if the correlation coefficient between

SNDVI and SPEI for the previous 3 months was the largest, then a cumulative time scale of 3 months indicates that 3 months of cumulative drought conditions had the greatest impact on current vegetation.

$$R_i = corr(SNDVI, SPEI_i),\ 1 \le i \le 24 \tag{8}$$

where R_i is the Pearson correlation coefficient between the SNDVI and the SPEI with a cumulative effect of i months, and i is the total number of cumulative months, ranging from 1–24.

The lag effect of drought on vegetative growth is the impact of a prior drought episode on current growth. In contrast to the cumulative effects, the lag effects used only a 1-month timescale, SPEI. We identified the lag effect between SPEI and SNDVI using Pearson correlation coefficients with a lag of 0 to 24 months. Then, the timescale with the highest absolute correlation value (Rmax) was identified as the ideal lagged month.

$$R_j = corr(SNDVI, SPEI_j),\ 0 \le j \le 24 \tag{9}$$

where R_j is the Pearson correlation coefficient between the SNDVI and lagged j months SPEI (The value of $j = 0$ indicates no time lag, and 24 indicates a maximum time lag of 24 months); for example, a 1-month lag was the resulting correlation between the monthly SNDVI from 2000 to 2020 and the monthly SPEI from December 1999 to November 2020.

3. Results

3.1. Precipitation Trends

Annual and quarterly precipitation trends from 1990 to 2020 and significant trends (p-value $\le$ 0.05) are shown in Figure 3. Areas with significant positive and negative trends were calculated. During 1990–1999, 27.77% of the country showed significant positive trends in the DJF season (Table 3). During the DJF season, the whole of Sri Lanka experienced a negative precipitation trend over the last two decades. During 2000–2010, 100% of the country showed a negative trend, which was not significant ($p > 0.05$), the magnitude of the trend varied between -25.0 to 2.7 year^{-1}, and 96.63% of Sri Lanka showed significant negative trends in last decade, with the highest magnitude was -48.0 year^{-1} (Figure 3).

Conversely, during the MA season in 2010–2020, there was a notable increase in the significant positive trend area, rising to 84.85% compared to the earlier decade. This increase was followed by a negative trend in the last decade, affecting an area of 83.35%. From 2010 to 2020, most of the country was severely affected by precipitation reductions with high magnitudes during December–April. The ON season showed significant positive trends during the first two decades, and 35% of the area showed a non-significant negative trend. During the MJJAS season, we experienced both positive and negative trends.

Table 3. Percentage of areas showing positive and negative precipitation trends in Sri Lanka.

Season	DJF		MA		MJJAS		ON	
Decade	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
1990–1999	27.77	0.00	2.08	0.00	8.37	0.04	0.58	0.00
2000–2009	0.00	12.70	84.85	0.00	4.33	11.32	16.15	0.00
2010–2020	0.00	96.63	0.00	83.35	29.64	0.00	4.83	0.12

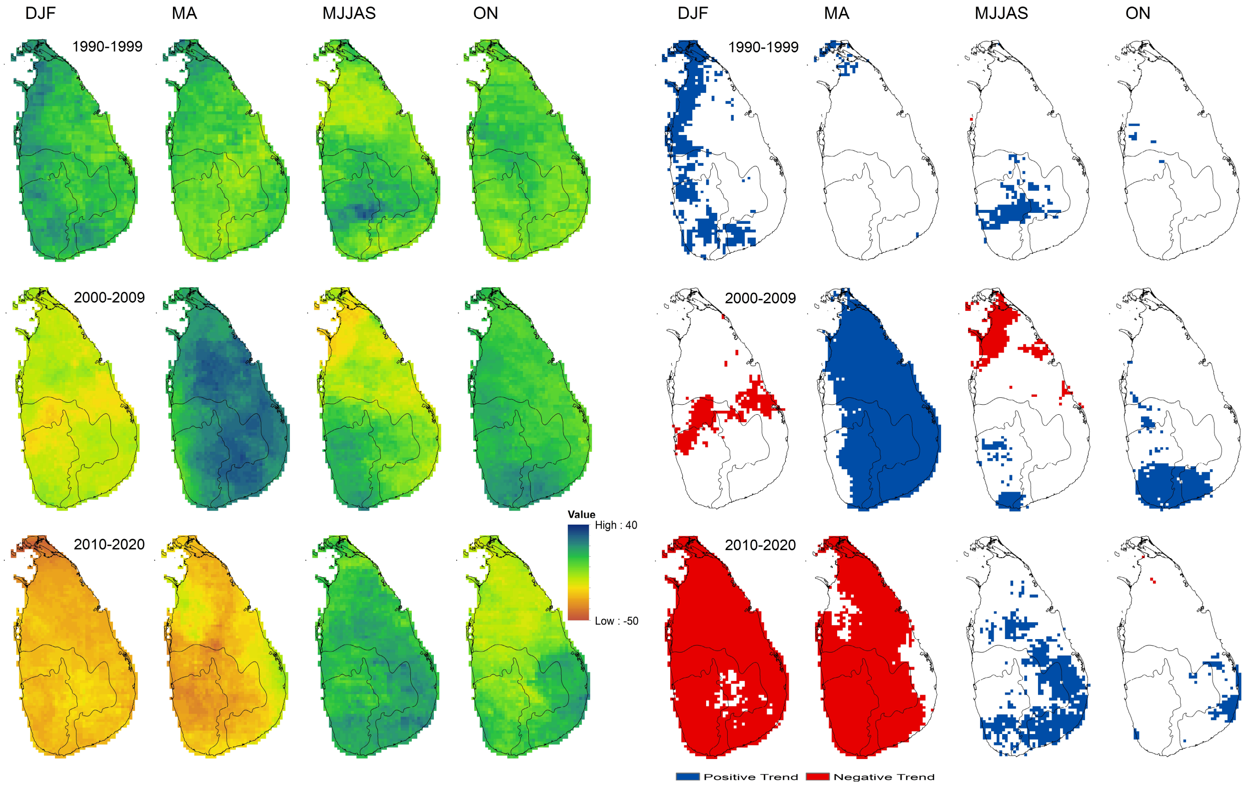

Figure 3. MK trend coefficient of precipitation on climatic seasons (DJF, MA, MJJAS, and ON) and significant trends (p-value ≤ 0.05).

3.2. SPEI Time Series-Based Drought

Figure 4 shows the 3-, 6-, 12-, and 24-month timescale mean SPEI values for the Dry, Wet, and Intermediate zones of Sri Lanka from 1990 to 2020, respectively. The SPEI with different timescales is relevant for agricultural drought (3–6-month timescale) and hydrological drought (12–24-month timescale) [10,11,61,62]. In this study, SPEI time scales 3 and 6 enable the precise detection of drought events that threaten agriculture, as most of the agricultural crops in Sri Lanka require 3–6 months for full growth, whereas 12- and 24-month time scales represent hydrological droughts. The results illustrated that severe dryness conditions have frequently occurred since 1990 across Sri Lanka (Figure 4). Drought occurrences were found in various zones in the years 1990–1992, 1994, 1996, 1998, 1999, 2000, 2001, 2002, 2004, 2005, 2005, 2009, 2011, 2012, 2013, 2014, 2016, 2017, 2018, 2019, and 2020, respectively, as reported in various studies [34,35]. With SPEI 6, 12, and 24, it can be recognized that the country had been stricken by agricultural and hydrological drought, and the years 1990,1992, 1997–1998, 2002, 2009, 2012, 2014, and 2016–2017 were recorded as dry periods. Over the last three decades, extreme dry conditions (SPEI ≤ -2) followed by wet conditions were recorded by SPEI3, SPEI6, SPEI12, and SPEI24 during 1992, 1994, 1997,1998, 2002, 2004, 2009 (Dry zone), and 2016. This finding highly corresponds with the strong El Niño periods [63].

A closer investigation of SPEI illustrates the spatial and chronological variability of both short-term and long-term droughts among three climate zones. During the study period, drought occurred only in some zones of the country. For instance, SPEI 3 and 6 detected a drought condition only in the Dry zone in 1990, 1993, 1999, and 2009. This is an indication of the high vulnerability of the Dry zone to agricultural drought. This is further evidenced by the lowest SPEI values obtained than other zones at a 3-month timescale. Similarly, highly intensified hydrological droughts in 2002 and 2012 mainly occurred in the Wet zone, where most of the hydropower stations are located. This is consistent with the reported severe drought impact on hydropower generation in Sri Lanka [37].

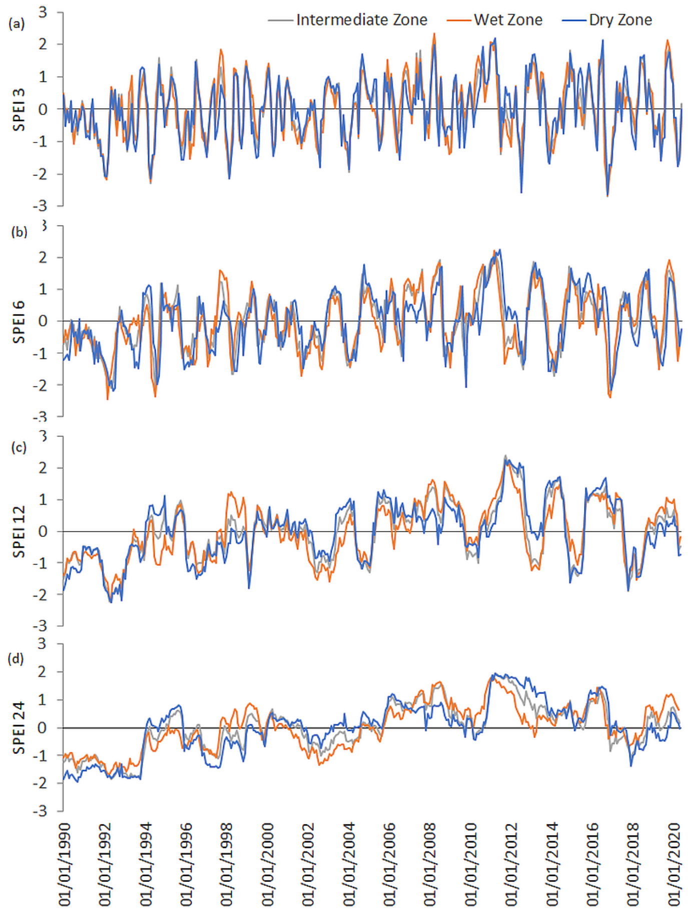

Figure 4. SPEI for 3-, 6-, 12-, and 24-month scales for different climatic zones (Dry, Wet, and Intermediate) in Sri Lanka.

SPEI well captured the above-mentioned drought years and the wet conditions with heavy precipitation and flooding, including the years 2010, 2011, 2013, and 2015. The years 2013 and 2014 are significant from a meteorological perspective, as they showed a transition between regular drought and a non-drought period.

3.3. Drought Intensity and Frequency

All drought incidents at selected SPEI time scales were recorded and classified based on their intensity during the study period for each climatic zone (Table S1). Two or more consequent months with negative SPEI are considered a drought event. The findings showed that all types of droughts happen often in Sri Lanka. October 2016 was exceptionally dry across the country, with negative peaks of −2.70, −2.66, and −2.63 in the Intermediate, Wet, and Dry zones, respectively, according to SPEI 3. However, under SPEI 6 in the Wet zone, April 1992 was an extremely dry year, with a negative peak of −2.43. In June 1992, the Dry zone recorded an exceptional dry peak of −2.19. In the Intermediate zone, December 2016 was an extremely dry year, with a negative peak of −2.21.

Based on the 1-month timescale SPEI values from 1990–2020 over Sri Lanka, drought hotspots (meteorological) were identified by calculating the frequency of moderate drought and higher for each decade and the entire study period (Figure 5). The results showed that from 1990 to 2020, the frequency of moderate drought and above was between 0.27% and 13.10%. During 1990–1999, the drought frequency was mainly low to medium range in all zones. During 2000–2009, the frequency of droughts in most parts of the Wet, Intermediate, and Dry zones increased compared to the previous decade. However, from 2010 to 2020, the frequency of droughts in the Dry zone increased significantly, except in the northern parts, and they primarily occurred in the north-central part of the country. According to the results of drought frequency for the entire study period of 1990–2020, we found that the drought hotspots were mainly concentrated throughout the country except in a few places in the north and east. This indicates that drought frequency is gradually aggravated in the Dry zone, and the drought trend in Sri Lanka shifting from south to north.

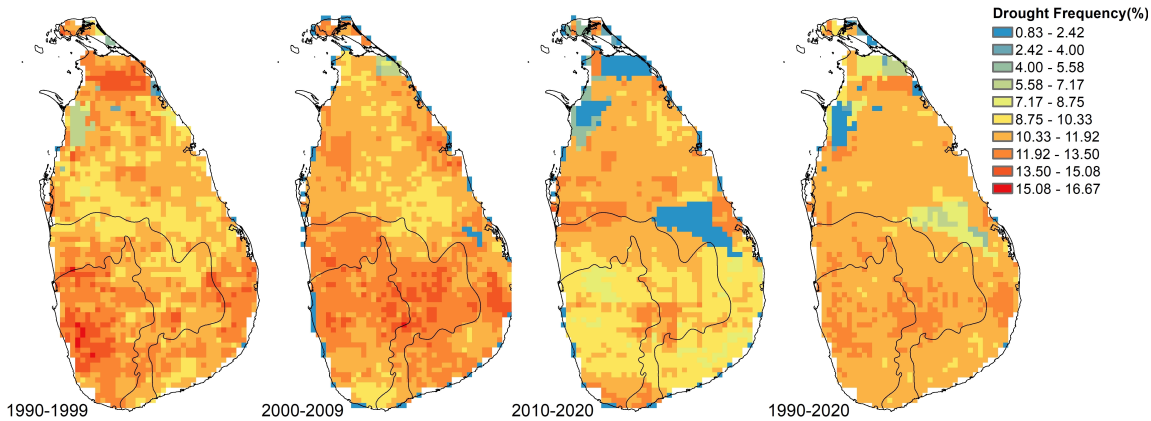

Figure 5. Spatial distribution of the drought frequency per decade during 1990–1999, 2000–2009, 2010–2020, and entire period of 1990–2020 in Sri Lanka.

Figure 6 shows the categories of the detected drought incidents on various timescales (1, 3, 6, 12, and 24 months). The results clearly show that drought incidents were frequent in all zones throughout the study period of 365 months. At the 1-month timescale, Wet, Dry, and Intermediate zones experienced drought at 40.82%, 57.26%, and 46.85% of study months, respectively. The results revealed that the drought occurrences in the Wet and Intermediate zones were more moderate to severe in all timescales. However, extreme dry incidents were more common across the Dry zone. It is explicit that drought incidents in the Dry zone were generally dry extreme on the SPEI 1-, 6- and 12-month scales.

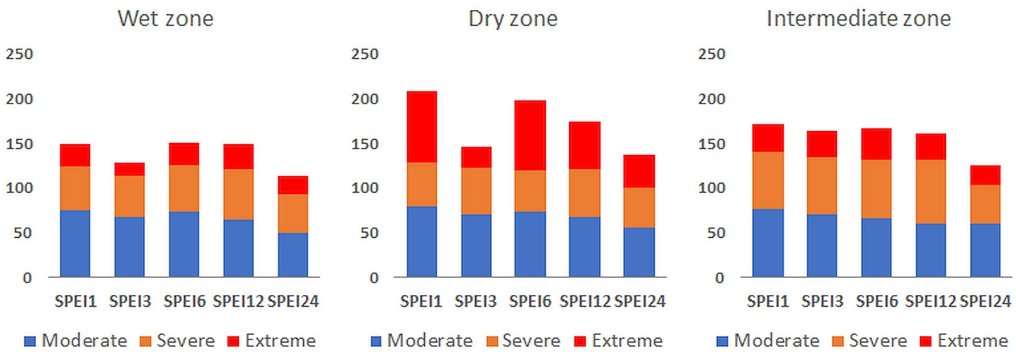

Figure 6. The number of moderate, severe, and extreme drought months detected under SPEI 1-, 3-, 6-, 12-, and 24-month timescale for each climatic zone (total number of SPEI 1 month is 365).

3.4. Cumulative Effects of Drought on Vegetation

We obtained the cumulative effect of drought on vegetation from the highest correlation coefficient value (Rmax) between SNDVI and SPEI on 1- to 24-month timescales from 2000 to 2020, and the corresponding timescale was considered the cumulative effect period of drought on vegetation. The spatial distribution of the highest cumulative effect (R_{max}) of drought on vegetation and its corresponding cumulative duration in months are shown in Figure 7a; a total of 92.92% of the Dry zone SNDVI and cumulated SPEI were positively correlated. Overall, 77.95% of vegetation areas in the Dry zone were significantly ($p < 0.05$) affected. Similarly, the Intermediate zone showed a positive relationship of 85.02%. A total of 73.85% of the total vegetated area in the Intermediate zone showed a significant correlation. In the Wet zone, 68.25% showed a positive correlation, and 31.75% of areas were negatively correlated. Positive correlations were primarily found in the Dry and Intermediate zones, and negative correlations were broadly scattered across the Wet zone.

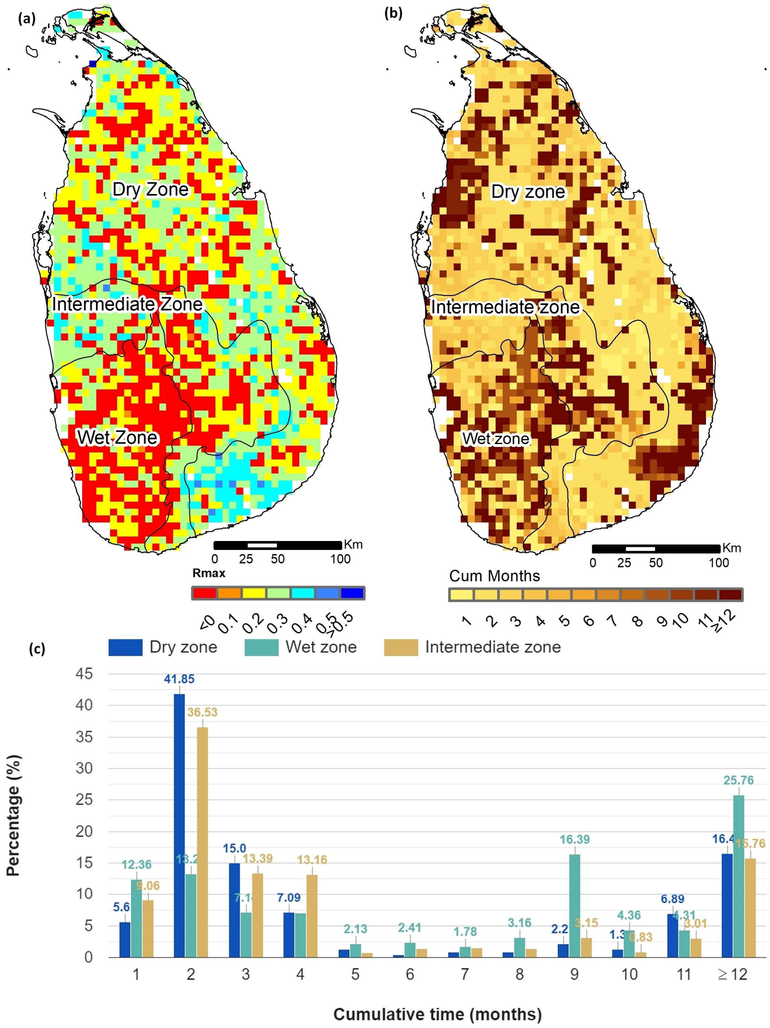

Figure 7. Distribution of the cumulative effects of drought on vegetation in climatic zones; (**a**) Spatial distribution of Rmax of SNDVI and cumulative SPEI (1–24 months); (**b**) Spatial distribution of accumulated drought months corresponding to Rmax; and (**c**) temporal variations in the percentage of area.

The months of accumulated effects indicate drought tolerance, while short accumulation reflects low tolerance [31]. Drought tolerance differed significantly among climate zones across the country (Figure 7b). Most of the Dry zone vegetated areas (69.55%) respond faster to cumulated drought (1–4 months). Similarly, 39.71% of the Intermediate zone is widely affected by short-term accumulated droughts of 1–4 months.

Two months of accumulated SPEI most extensively affected 41.85% and 36.53% of areas, mainly in the Dry and Intermediate zones, respectively (Figure 7c). In contrast, long-term accumulated drought occurred in the Wet zone. More than half of the wet zone (54%) vegetation response time is considerably longer (>8 months) for cumulative droughts, suggesting that vegetation in the Wet zone is more tolerable for long-term cumulative drought and tended to respond to SPEI on a higher time scale. The high correlation coefficient values of the SPEI and vegetation SNDVI were concentrated in the range of −0.41–0.98.

3.5. Lagged Effects of Drought on Vegetation

Overall, 78.53% of vegetated areas in the Dry zone were positively affected by lagged drought (Figure 8a). In total, 95.29% of the vegetation showed a significant effect. Vegetated areas in Wet and Intermediate zones showed a positive correlation between 60.39% and 68.19% with lagged SPEI, respectively. Higher positive correlations were found in the northeastern part of the Dry zone. SNDVI was largely negatively affected by the lagged SPEI in 39.61% of the Wet zone.

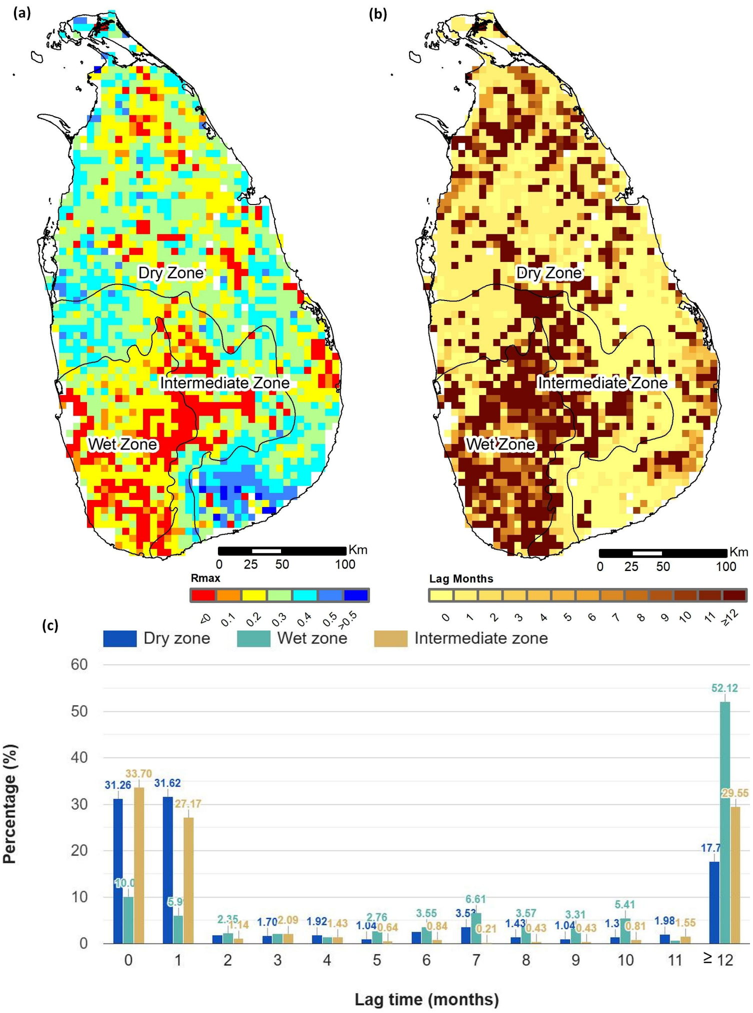

Figure 8. Distribution of the lag effects of drought on vegetation in climatic zones; (**a**) Spatial distribution of Rmax of SNDVI and cumulative SPEI (1–24 months); (**b**) Spatial distribution of lagged drought months corresponding to Rmax; and (**c**) temporal variations in the percentage of area.

The months of lagged effects reflect vegetation sensitivity to drought. The shorter lagged month indicates the stronger sensitivity of vegetation. The results revealed that lagged drought mainly occurred within 0–1 month and primarily affected the vegetation in the country (Figure 8b).

Over 60% of the area in both Dry and Intermediate zones was extensively affected by the 0–1-month lag effects of drought (Figure 8c). These indicate that vegetation in the Dry and Intermediate zones was mostly vulnerable to short-term drought of 0–1 month. In contrast, around 52% of Wet zone vegetation was more sensitive to prolonged drought, with most of the area having a lagged effect of more than 11 months. Similarly, a drought that lasted over 11 months substantially impacted a considerable amount of the Intermediate and Dry zone areas. The time lags of 2–11 months have very little influence on vegetated areas across the country. The maximum correlation coefficient values of the SPEI1 and vegetation SNDVI were concentrated in the range of −0.31–0.94.

4. Discussion

4.1. Spatial and Temporal Distribution of Drought

The spatial distribution pattern of drought frequencies varies over decadal periods from 1990 to 2020. However, the findings revealed that during the last 30 years, all parts of all three climate zones have witnessed increasing drought frequencies and the spread of high-frequency event areas. Furthermore, from 2010 to 2020, the highest drought frequencies were mainly concentrated in the Dry zone (Figures 4–6). It is important to note that those highly intensified droughts took place in all three zones during the first and last decades of the study years. The Dry zone experienced more intensified short and long temporal droughts than other zones. The MJJAS seasonal precipitation experienced a decreasing trend almost over the entire country, and DJF showed a reduction in the Dry zone between 1981 and 2010 [64]. These dry weather tendencies may result in a higher number of drought events across Sri Lanka. The Dry and Intermediate zones are important parts of the main agricultural areas of the country, and therefore, frequent drought effects on agriculture, particularly rainfed cultivation, will be severe. This has far-reaching consequences for irrigation and domestic and industrial water supply in these zones. Specifically, this will further aggravate the already existing water deficit in the Dry zone during the Yala crop season (March–September). Furthermore, from 2010 to 2020, the highest drought frequencies were mainly concentrated in the Dry zone (Figures 4–6). However, land use change may have an effect on the spatiotemporal variation of drought occurrences. Sri Lanka underwent a large deforestation in 2012, and a large area of the Dry zone forests was cleared for agriculture [65]. Studies in Amazonia show that deforestation can cause drying conditions [66]. In this study, the short- and long-term drought events identified by the SPEI show a strong association with historically reported drought events [34,35,44].

The most severe drought event recorded in Sri Lanka in the period 2016–2017 in all SPEI time scales. This drought affected more than 1.2 million people across 19 out of 25 districts. This drought impacted the main Maha harvest with a 45 percent reduction in the production of paddy crops [67]. The economic losses caused by this event made the country listed second in the global Climate Risk Index of that year [38]. Assessing the occurrence of drought during crop seasons is crucial for efficient drought management. Two crop seasons, referred to as "Yala" and "Maha," can be distinguished in Sri Lanka based on the tropical monsoons. The Yala season is from April to September, while the Maha season is from October to the following year March [68]. To better understand the significance of drought's impact on agriculture, the variations of drought occurrences during the Yala and Maha seasons were compared. Figure 9 shows that drought frequency is generally higher during the Yala than Maha in all zones. The Dry zone usually experiences more droughts during Yala, followed by the Intermediate zone. These two zones are the highest agricultural production zones in the country. The precipitation trends in the MJJAS season were shown to be decreasing over Sri Lanka between 1981 and 2010 [64]. These drying tendencies during the Yala season could potentially lead to an increase in drought occurrence. Effective drought management and decision-making are crucial for the country.

The El Niño events may have accelerated the intensity of droughts in Sri Lanka over the last four decades [69]. These El Niño events appeared to correlate with the increase in drought intensities in all zones in 1992, 1994, 1997, 1998, 2002, 2004, 2009, and 2016 (Figure 4). The most severe El Niño event in this region includes the drought in 2016–2017 (Figure 4). The SPEI3-based drought classification in this study found that September–October and March–April (during the El Niño periods) were the driest months, which corresponds with the conclusions of existing studies showing the post-El Niño effect of reduced first inter-monsoon seasonal precipitation [70]. Monitoring drought is crucial for effective decision-making and policy development, especially in a country like Sri Lanka, which is vulnerable to climate variability. Conducting proper drought monitoring can help policymakers and planners understand important information on drought occurrence, severity, and spatial distribution. This can indeed minimize the impact of drought and reduce the potential socioeconomic and environmental damage to the country.

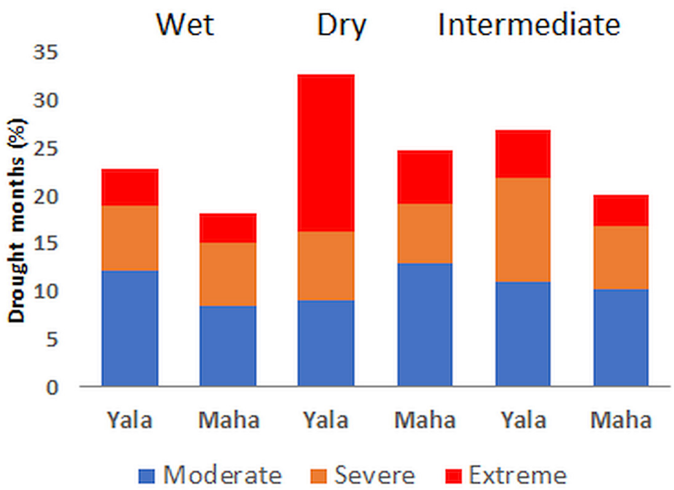

Figure 9. The number of drought months detected for Yala and Maha growing seasons under SPEI 1-month timescale for each climatic zone.

Comparison Between SPEI and SPI over the Study Area

In this study, we identified droughts based on the SPEI index, a variant of SPI. Previous studies have demonstrated the robustness of SPEI in identifying and characterizing droughts across diverse regions of the world [1,71–73]. In Sri Lanka, SPI is also a more commonly used index [43,44] than SPEI. Due to its topography and climate variability, variation in drought classification is expected. An assessment of agreement between SPEI and SPI enabled us to understand the role of precipitation and potential evapotranspiration in determining the spatial and temporal patterns of droughts in Sri Lanka.

The spatiotemporal variability of the SPEI and SPI was analyzed by comparing the spatial and temporal distribution of the values of the SPEI and SPI indices. The SPEI and the SPI time series were calculated for each month of the year at 1-, 3-, 6-, and 12-month timescales from 1990–2020. A Pearson correlation coefficient (R) was then calculated from monthly images for monthly correlations; all the values of each individual month from 1990–2020 were used. For instance, the R between the SPEI and SPI indices for the month of January was calculated from all January images between 1990 and 2020. Figure 10 shows their spatial distribution, and Figure 11 shows the area covered with high correlation ($R \geq 0.7$) in each zone.

Overall, there was a very high correlation between the spatial pattern of the monthly series of SPEI1 and SPI1 in most of the months across the entire country from 1990 to 2020 (Figure 10). It was slightly lower from May to September but only in certain Dry zone areas. Only in June and August, specifically a few areas in the Southeast and Northwest parts of the Dry zone where precipitation is minimal, revealed a negative correlation. It was observed that the values of SPEI and SPI are varied from −0.13 to 3.99. The 3-month time scale of SPEI and SPI revealed identical patterns of high positive values, except for a few parts of the Dry and Intermediate zones from July to September. On the contrary, the 6- and 12-month SPI and SPEI had a high association throughout the year. All Dry, Wet, and Intermediate zones had very high values in all months (Table 3).

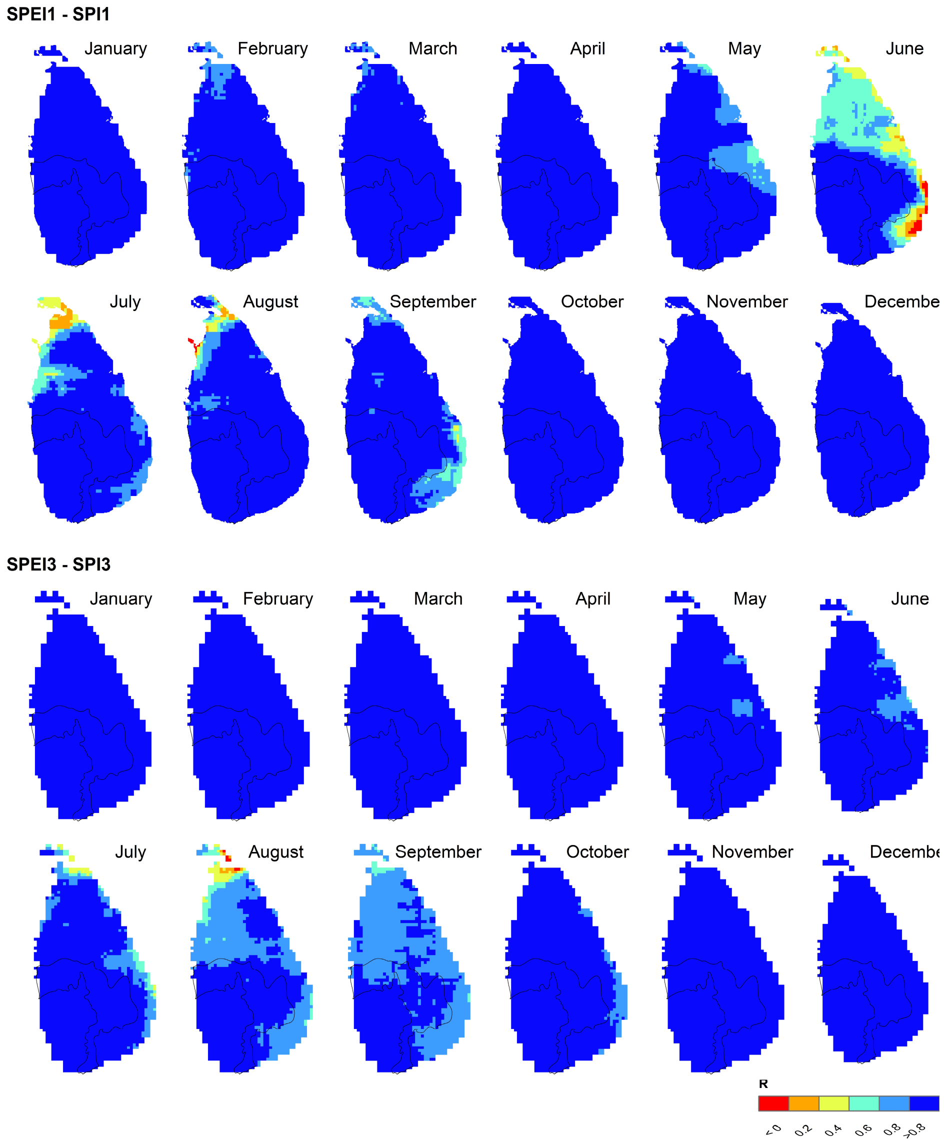

Figure 10. Spatial pattern of the Pearson correlation coefficient (R) between the SPEI and SPI 1 and 3-month time scale series over 1990–2020.

The spatiotemporal behavior of droughts in Sri Lanka is highly variable across the country [42,44]. The findings of this study revealed that both precipitation shortages and increases in PET with different spatio-temporal characteristics can cause droughts in Sri Lanka. The identified spatial and temporal correlation differences between SPEI and SPI patterns further confirmed this. The SPEI demonstrated strong spatial and temporal consistency with the SPI in most of the year, indicating that the SPEI responds primarily to changes in precipitation at 1- and 3-month scales, except dry months from June to September, mainly in the Dry zone. This shows an increase in the PET's influence on drought severity, particularly in the driest areas, although their impact is spatially variable. These findings demonstrate the SPEI's sensitivity to variations in PET during dry periods and are consistent with previous findings [7]. This result shows that temperature anomalies can play a key role in the Dry and Intermediate zones, especially in dry periods, when precipitation is generally deficient. These findings proved that SPEI is better suited for a more comprehensive understanding of drought severity in Sri Lanka, as reported in various studies conducted across the semiarid regions [28,59,74,75].

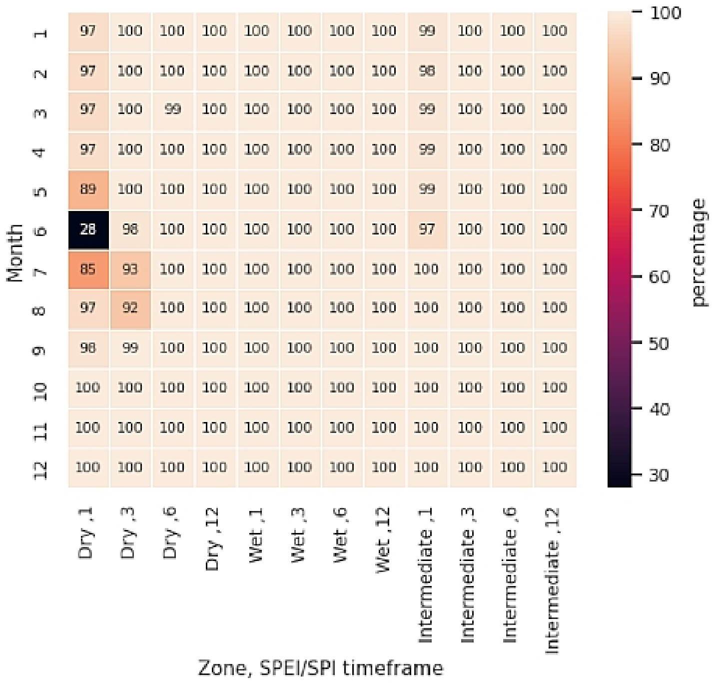

Figure 11. Percentage of areas with high correlation between SPEI and SPI for various timeframes.

4.2. Impact of Drought on Vegetation

Some studies have also shown that the association between SPEI and vegetation is more robust under dry conditions [75]. A similar result is obtained in the Dry and Intermediate zones with high cumulative and lagged effects correlations. In Sri Lanka, the most impactful lagged months of shorter time scales (1–2 months) show that most vegetation activities are vulnerable to dynamic fluctuations in dry and wet climatic conditions. Overall, lagged impacts of drought on vegetation in the Dry and Intermediate zones occurred mainly in the short-term (one month) and long terms (12–24 months) in the Wet zone; specifically, the forest areas in all zones show a very low negative correlation between SPEI1 and SNDVI and a longer lag time, which indicates that they react much slower to short-term drought. In addition, in wet regions with excessive moisture content, the effect of short-term drought on NDVI changes is almost non-significant, and the impact on vegetation can be minimal under long-term water surplus conditions [22]. The lagged effect only accounts for how the current vegetation is influenced by a past drought at a particular point in time, ignoring the ongoing dynamic conditions that impact vegetation growth following the drought event [76].

Most of the country showed a positive correlation between SPEI and SNDVI. The highest correlations were found in the Dry zone. SPEI2 showed the highest correlation with SNDVI throughout the year in Dry and Intermediate, major agricultural zones with short-term crops. This also implies that SPEI accumulation in the previous 2 months had the most significant impact on vegetation. Therefore, the routine agricultural practices in the agricultural lands (plowed land between crop seasons) may also influence these results. The Wet zone showed the highest correlation between SPEI9 and SNDVI. In contrast to the other areas, SPEI was negatively correlated with vegetation in a large portion of forested areas in the Wet and Dry zones, where the cumulative effect was more than 6 months. Generally, water balance plays a key role in affecting the response of vegetation to drought in the Wet zone [77], which has adequate soil moisture content throughout the year. Temperature is the main limiting factor for vegetation growth in high-altitude areas. Thus, the Wet zone forest is less affected by the cumulative effect of drought. This result is consistent with the results of earlier studies [6,32] regarding the cumulative effect of drought on Wet zones, which respond to drought on a long-term scale, whereas agricultural land and Dry zones respond on a short-term scale. A positive correlation in agricultural lands indicates that short–term drought may lead to a decline in vegetation, primarily seasonal crops with relatively short periods. Negatively correlated agricultural lands can possibly be managed by irrigational water supply. We observed that a considerable area across the Dry zone had a cumulative drought effect spanning over 9 months. That vegetation probably has developed a certain degree of adaptation to prolonged drought over time [78]. Several studies have emphasized the strong influence of climate factors, such as temperature, precipitation, and soil moisture on vegetation growth [13,79]. These climatic influences account for the variations in observed cumulative effects at different-month scales.

Vegetation growth can be affected by drought conditions and can also be used as an indicator of drought conditions [13,14]. Given their strong correlation, numerous studies have investigated the relationship between SPEI and NDVI and found that drought is a major factor in vegetation growth [80]. The impact of a water deficit on vegetation growth over time is referred to as the cumulative effect. This metric can be used to assess the drought tolerance of vegetation. The time-lag effect shows how the growth of vegetation is impacted by a past drought event, hence demonstrating the sensitivity of vegetation to drought. Understanding the timing of vegetation response to drought is crucial for improving our understanding of the mechanisms underlying vegetation climate interactions and for creating practical strategies to conserve vegetation, as vegetation growth is often driven by past drought events [15]. Regular droughts cause issues like degraded ecosystems, severe crop damage, and decreased agriculture productivity in Sri Lanka. Agriculture plays a major role in the economy of Sri Lanka. Droughts between 1974 and 2013 have severely affected crops, resulting in over half of the total crop damage during this period [36]. This study reveals that most of the vegetation in the Dry and Intermediate zones had a short-term (1–4 months) cumulative and 0- to 1-month lagged effect. This indicates that the crop can be affected by drought in both the early and mature stages. This condition can have a severe impact on the country's economy. Further, from the figures of the annual gross domestic product (GDP) growth percentage of Sri Lanka [75], it is evident that the droughts are closely linked to a decrease in the GDP growth (1991–1992, 1994, 1996, 1998–1999, 2001, 2009, 2013, 2018–2019) due to drought impact on agricultural production (Figure 12). However, a very sharp decline in 2020 was observed due to both the COVID-19 pandemic situation and drought. The findings of this study have significant implications for agriculture and environmental sustainability in Sri Lanka by providing a crucial context for agricultural and drought management and planning and helping prioritize adaptive measures to reduce and mitigate the socioeconomic impacts of drought. Further, the adopted approach can be applied to similar study areas in tropical regions to monitor drought as well as global areas to quantify the impact on vegetation. In order to ensure sustainable agriculture, this can be done by altering crop patterns and durations, adopting drought-tolerant crops, making minor adjustments to the crop growing season, etc.

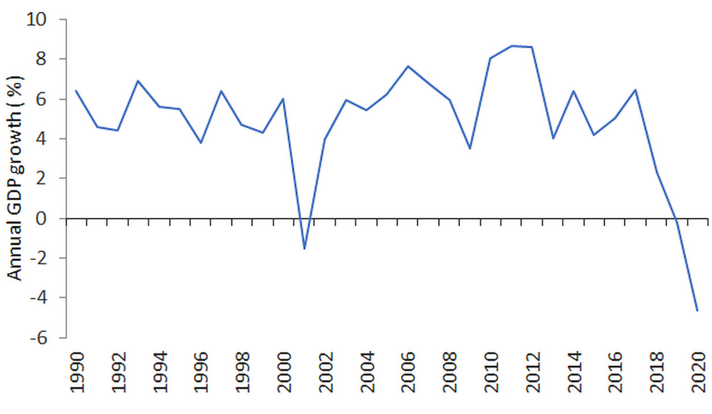

Figure 12. Annual gross domestic product (GDP) growth rate of Sri Lanka.

4.3. Limitations and Prospects

The outcomes of this study include the drought analysis and its impact on vegetation, which will serve as a base for building efficient local drought prevention and adaptation strategies. However, it is important to consider the uncertainties in this study. We used datasets with varying resolutions, which were resampled to a 5 km resolution. This process may introduce some deviations in the correlation analysis. This study compared the effect of a single drought event on vegetation productivity, ignoring the impact of drought intensification and recurring droughts [81]. Presenting the correlation between two variables, SPEI and SNDVI oversimplify the interaction between the cumulative and lagged effects as the relationship between vegetation growth and drought (SPEI). As a result, in future studies, various drought and vegetation indices should be used to model the vegetation and the drought in order to quantify better and analyze the cumulative and lagged effects of a specific drought event over a short period. This allows for a more comprehensive understanding of drought and how vegetation responds to it. This study ignores the influence of other factors on vegetation growth. Further research is necessary to investigate the impact of additional factors on vegetation growth. Variations in cumulative and lagged effects of different vegetation types in this study area need further investigation.

5. Conclusions

Sri Lanka has experienced recurrent droughts, notably in recent decades. This study analyzed the spatiotemporal patterns of drought characteristics such as duration, severity, and intensity across different climatic zones. The SPEI index at various timescales was used to analyze, with indications of a 1-month timescale for meteorological drought, 3- and 6-month timescales for agricultural drought, and 6- and 24-month timescales for hydrological drought from 1990–2020. For the first time, we also analyzed the effect of the drought on vegetation in climate zones of Sri Lanka to clarify the possible contribution of SPEI accumulation and lag to vegetation growth between 2000–2020. The key findings of this study are as follows:

- Based on drought frequency, we found drought events mainly occurred all across the country and meteorological drought occurred highly (13%). All zones experienced high drought occurrences during the study period, and the spatial and temporal occurrence in the Dry zone was greater than that in other zones during the past decade, which indicates that drought occurrence is gradually intensified in the Dry zone, and the drought trend in Sri Lanka is shifting from south to north.
- According to SPEI1, the Wet, Dry, and Intermediate zones experienced drought in 40.82%, 57.26%, and 46.85% of study months, respectively, and these recorded drought events were more in moderate to severe categories. Drought incidences were more common across the Dry zone with the highest extreme months. This shows that the Dry zone was mainly concentrated meteorological drought hotspots.
- Significant cumulative drought impact on vegetation found across the country with notable regional variations. The Dry and Intermediate zones mostly experienced cumulative effects in 1–4 months with a short tolerance. The longest duration of cumulative effects was identified in the Wet zone (9–24 months), primarily in the forest areas.
- Vegetation in Sri Lanka was significantly affected by lagged drought. Over 60% of the Dry and Intermediate zones were more sensitive to sort lagged drought impact within 0–1 month, whereas the Wet zone exhibited the strongest tolerance (more than 11 months).

This study demonstrates that the SPEI index can efficiently monitor drought at climatic zonal levels. This study is important because it captures drought intensity, frequency, and the cumulative and lagged effects on vegetation at the climatic zone level at a relatively coarse resolution for the first time. This information is crucial for drought management, prevention, and mitigation activities for sustainable agriculture.

This study only evaluates the impacts of SPEI on vegetation. These results should be analyzed with other aspects, such as climate change, which would help estimate vegetation drought tolerance under climate change scenarios. This study can also extend to various crop types for a comprehensive analysis. Therefore, to get a clear idea of the range of precipitation variation, effects from other kinds of climate variability, such as seasonal El Niño/southern oscillation (ENSO), need to be analyzed. Further research is necessary to investigate the impact of additional factors, such as soil moisture, etc. on vegetation growth for a reliable result.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/cli12110172/s1, Table S1: The recorded drought incidents and their categories during the study period for each climatic zones in Sri Lanka.

Author Contributions: Conceptualization, D.S.; methodology, D.S.; software, D.S.; validation, D.S.; formal analysis, D.S.; investigation, D.S.; data curation, D.S.; writing—original draft preparation, D.S.; writing—review and editing, D.S., J.Z., Y.Z., Y.N., Z.Z. and L.Y.; visualization, D.S.; funding acquisition, J.Z. and L.Y. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data presented in this study are available on request.

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Conflicts of Interest: The authors declare no conflicts of interest.

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