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Developing a Combined Drought Index to Monitor Agricultural Drought in Sri Lanka

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Abstract: Developing an agricultural drought monitoring index through integrating multiple input variables into a single index is vital to facilitate the decision-making process. This study aims to develop an agricultural drought index (agCDI) to monitor and characterize the spatial and temporal patterns of drought in Sri Lanka. Long-term (1982 to 2020) remote sensing and model-based agroclimatic input parameters—normalized difference vegetation index (NDVI), land surface temperature (LST), 3-month precipitation z-score (stdPCP), and evaporative demand drought index (EDDI)—were used to develop agCDI. The principal component analysis (PCA) approach was employed to qualitatively determine the grid-based percentage contribution of each input parameter. The agCDI was apparently evaluated using an independent dataset, including the crop yield for the major crop growing districts and observed streamflow-based surface runoff index (SRI) for the two main crop growing seasons locally, called Yala (April to September) and Maha (October to March), using 20-years of data (from 2000 to 2020). The results illustrate the good performance of agCDI, in terms of predominantly capturing and characterizing the historic drought conditions in the main agricultural producing districts both during the Yala and Maha seasons. There is a relatively higher chance of the occurrence of moderate to extreme droughts in the Yala season, compared to the Maha season. The result further depicts that relatively good correlation coefficient values (> 0.6) were obtained when agCDI was evaluated using a rice crop yield in the selected districts. Although the agCDI correlated well with SRI in some of the stations (>0.6), its performance was somehow underestimated in some of the stations, perhaps due to the time lag of the streamflow response to drought. In general, agCDI showed its good performance in capturing the spatial and temporal patterns of the historic drought and, hence, the model can be used to develop agricultural drought monitoring and an early warning system to mitigate the adverse impacts of drought in Sri Lanka.

Keywords: agricultural drought monitoring; aggregate drought indicator; evaluation of drought index; data mining approach; Sri Lanka

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1. Introduction

Drought is a recurring natural hazard in Sri Lanka that triggers water shortage that consequently has a diversified impact on agricultural production and other sectors [1]. When severe to extreme drought events occur, Sri Lanka suffers economic losses and damages, including crop failure, lack of clean and adequate quantity of drinking water, inadequate hydropower generation, and disease outbreaks [2]. The primary cause of drought is a persistent precipitation deficit or failure of monsoon rainfall that potentially prompts the subsequent decline in soil moisture, groundwater, and other surface water storage and flows accessible for agriculture, domestic, and other uses [3,4]. Previous studies have illustrated the frequent occurrence of drought in Sri Lanka [5–7]. For example, Nianthi [5] reported that the frequency of occurrence of extreme drought in Sri Lanka is once every ten years, even though local to regional droughts occur once every 3 to 4 years. Although there are several contributing factors to the occurrences and severity of drought, the failure of the monsoons and effects of El Niño–Southern Oscillation are the primary causes that prompt droughts in Sri Lanka. For example, the failure of monsoons led to the 2007 drought in parts of Sri Lanka, and El Niño–Southern Oscillation events were connected to the 1982-1983 drought event, where more than one million people were affected [8]. Rainfed agriculture is the first sector vulnerable to drought, and its failure often significantly influences the agrarian economy, the livelihood of the community, and the household level income [9].

According to a World Bank report, the agricultural sector employed approximately 24% of the total labor force in Sri Lanka in 2020, even though its contribution to the gross domestic product (GDP) has been declining since 1974 [10]. Water resources, including the drinking water supply, are also vulnerable to drought and climate change and sensitive to the seasonal variability of the rainfall [11]. There were significant agricultural losses in 1988, 2001, and 2004 largely attributed to the occurrence of severe drought events [12]. Drought-related impacts surpass other natural disasters (e.g., floods, landslides, etc.) and have accounted for the highest percentage (~52%) of the agricultural losses from 1974 to 2013 [2]. In terms of the total number of populations affected by the historical drought events, more than one million farmers were affected by drought in 2013 [2] and 2016-2017 [1,13]. This highlights the need for the development of drought-resilient farming systems to mitigate its adverse impacts on socioeconomic sectors through developing effective drought monitoring and early warning systems.

Wilhite and Glantz [14] categorized drought into four types, including meteorological, agricultural, hydrological, and socioeconomic droughts, although their definitions vary per discipline. Meteorological drought measures the degree of dryness due to persistent deficits of rainfall, in comparison to the threshold value. Agricultural drought, on the other hand, measures the deficits of soil moisture and evapotranspiration, largely due to the shortage of rainfall, while hydrological drought characterizes the effects of precipitation shortfalls on the groundwater, streamflow, reservoir, and lake levels. Socioeconomic drought is linked to drought impacts on the socioeconomic sectors. These droughts can be characterized using the drought monitoring indices. There have been significant efforts made to develop drought monitoring systems at the local to global spatial scales using drought indices [15–18]. The effectiveness of these drought indices, however, depends largely on the availability of input data at reasonable spatial and temporal scales, beyond the difference in the conceptual frameworks. Most of the drought indices use a single input variable, traditionally obtained from local gauging stations, to characterize the different aspects of drought. Despite the good quality and accuracy of the station's data, the lack of capturing the continuous drought condition across space, due to their sparse locations, limits the wide application to characterize drought at a larger spatial scale, particularly in developing countries [19]. Therefore, remote sensing products are extensively applied to bridge these gaps and to monitor drought at a finer spatial resolution covering larger extents [20]. Some of the remote sensing products even blend station-based observations to enhance the data quality and accuracy. In addition to meteorological observations, the remote sensing-based approaches make other key parameters paramount to monitoring droughts available, such as the vegetation health, soil moisture, and water levels [21]. The potential application of remote sensing products has been highlighted in water resource management, particularly in data-scarce regions in developing countries [22,23].

In Sri Lanka, there are several drought monitoring studies that have been conducted to characterize meteorological and agricultural droughts using the most common and widely used drought indices. For example, Alahacoon et al. [1] attempted to monitor meteorological and agricultural droughts using the standardized precipitation index (SPI), rainfall anomaly index (RAI), and vegetation health index (VHI) drought indices. There were also other studies conducted to monitor meteorological drought [4,13,24–28], agricultural drought [1,29–32], hydrological drought [25], and socioeconomic drought [33]. However, there is still limited effort to evaluate the impacts of drought on the agricultural sector using the integrated drought approaches by combining several hydroclimatic and agricultural input variables.

Since droughts are evaluated based on the local impacts, the broad spectrum of drought in a given sector cannot be fully captured using a single index that uses largely single input variables [34]. This prompted the great attention of researchers towards developing the combined drought index using several biophysical input variables under a "convergence of evidence" framework [35]. Thus far, few attempts have been made to monitor drought by developing the combined drought index, and the effectiveness of the index has been reported to monitor drought in real-time across the US and Canada [36–38], East Africa [39,40], the Middle East and North Africa regions [34], and India [41]. Different approaches, such as regression tree, PCA, and expert opinion and judgment, were used to quantify the percentage contributions of the input variables. Such drought monitoring approaches have never been used to develop a combined drought index in Sri Lanka, as per the knowledge of the authors. Therefore, this study aimed to develop a combined drought index to monitor agricultural drought in Sri Lanka using the remote sensing-based input variables, including CHIRPS rainfall, NDVI, LST, and EDDI. An objective approach was followed to estimate the grid-based percentage contributions of each input variable in the process of developing the combined drought indicators. The method followed in this study can be applied to other study regions to develop a drought monitoring tool that can be used to characterize the severity of the historic drought conditions.

2. Materials and Methods

2.1. Description of the Study Area

Sri Lanka is an island country located at the southern tip of the Indian sub-continent at a geographic coordinate of 7°00 N and 81°00E. It covers a boundary area of 65,610 sq km, and the elevation ranges between 0 m (Indian Ocean) to 2524 m (Pidurutalagala peak in the central massif). According to the Department of Meteorology of Sri Lanka, there are four rainfall seasons, including northeast monsoon (NEM, December–February), first inter-monsoon (FIM; March–April), southwest monsoon (SWM; May–September), and the second inter-monsoon (SIM; October–November). The rainfall originates mainly from monsoonal, conventional, and weather systems formed in the Bay of Bengal (i.e., low-level atmospheric disturbances and depressions) and is spatially variable, due to orographic influences [42]. Figure 1 shows the three climatic zones in Sri Lanka (wet, intermediate, and dry zones), delineated based on hydroclimatic variables, mainly rainfall and other biophysical characteristics. The wet zone receives relatively high mean annual precipitation (>2500 mm) during the SWM and SIM seasons, as compared to the dry zone (less than 1750 mm during the SIM and NEM and the intermediate zone between 1750 and 2500 mm). The temperature reaches a maximum during summer months, with the highest values ranging between 32 °C and 35 °C in April and May, while the lowest temperature ranges between 18 °C and 24 °C in January [43]. The temperature further declines to the range of 9 °C and 21 °C in the central highlands throughout the year. Maha (October to March) and Yala (April to the end of September) are the two main crop-growing seasons [1,44,45]. Maha growing season covers the two consecutive rainfall seasons, SMI and NEM, while the Yala season combines FIM and SWM seasons [46]. The dry zone receives only FIM rainfall from mid-March to early May, since SWM rainfall is not onset in the dry zone. In addition, the dry zone receives only a small amount of rain for two months during the Yala season; thus, there is no significant agricultural production during this season, and supplementary irrigation is required to boost crop cultivation. Rice is the primary food crop grown in Sri Lanka. The per capita arable land is decreasing, due to the increase in population, despite agricultural land being the dominant land use (50%) in Sri Lanka [45].

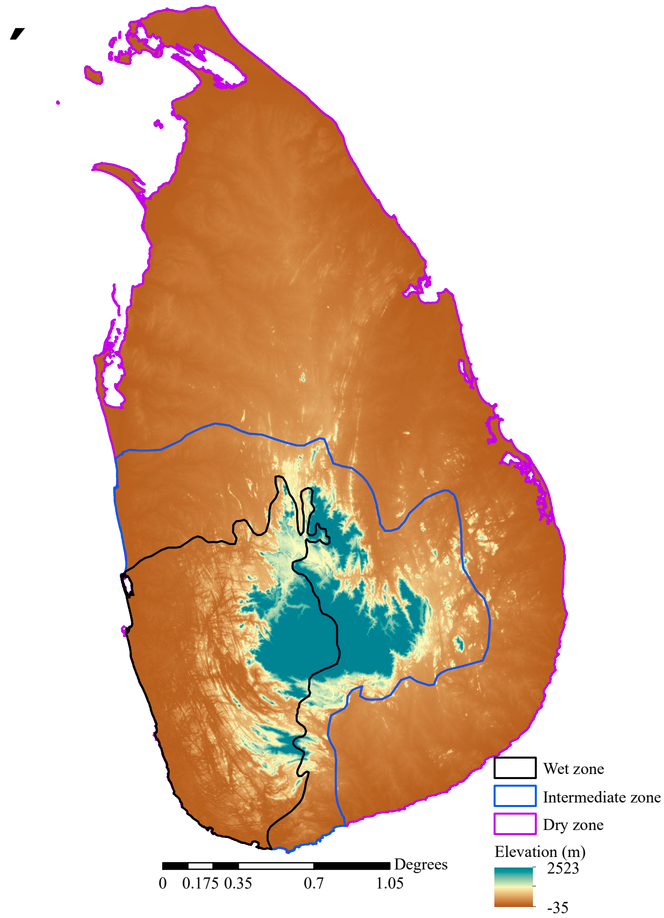

Figure 1. Topography and climatic zones of Sri Lanka.

2.2. Data Used

Table 1 shows the summary of input variables used in this study. These input variables represent the different components of the water budget and are viable for drought monitoring and evaluation. A detailed description of each input variable is presented in the subsequent subsections.

Table 1. Input variables used to monitor agricultural and water supply droughts and their spatial and temporal resolutions.

Sno	Input Variables	Resolution		Data Length	Source
		Spatial	Temporal		
1	CHIRPS or other satellite or observed rainfall (SPI- at various time scales)	5 km	daily	1982-present	University of California, Santa Barbara
2	Normalized difference vegetation index (NDVI)	4 km	weekly	1982-present	NOAA STAR
3	Land surface temperature (LST)	4 km	weekly	1982-present	NOAA STAR
4	Evaporative demand drought Index (EDDI)	12.5 km	Monthly	1982-present	NOAA

2.2.1. Precipitation

CHIRPS is a blended product developed by the U.S. Geological Survey (USGS) and the Climate Hazards Group at the University of California, Santa Barbara (UCSB). It combines precipitation climatology and quasi-global geostationary TIR satellite observations from the Climate Prediction Center (CPC) and the National Climate Forecast System, version 2 (CFSv2) [47]. Good performance and skillful application of this product have been validated in Sri Lanka [48,49], as well as in other parts of the world [50–54]. The long-term gridded data were acquired from the Climate Hazards Center data portal from 1982 to 2020, at 5 km $\times$ 5 km pixel size.

2.2.2. Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST)

Gridded smoothed weekly time series of NDVI and LST were acquired from National Oceanic and Atmospheric Administration (NOAA) Satellite Applications and Research (STAR) from 1982 to 2020. The data are a blended product of Visible Infrared Imaging Radiometer Suite (VIIRS, 2013–present) and Advanced Very High-Resolution Radiometer (AVHRR, 1982–2012), freely accessible from the NOAA data portal. The spatial resolution of the data is 4 km $\times$ 4 km, and the time series data were extracted for Sri Lanka from the global product. These products are widely applied to monitor the vegetation condition in response to changing weather and climate [55].

2.2.3. Evaporative Demand Drought Index (EDDI)

The EDDI is a drought index that characterizes the anomalous atmospheric evaporative demand across space and time [56]. EDDI can be applied to monitor agricultural and hydrologic droughts. It provides near-real-time information on the persistence of water stress and excess relevance for the preparedness of natural hazards. Penman–Monteith FAO56 was used to estimate the reference evapotranspiration during EDDI computation. Its input parameters, including temperature, humidity, wind speed, and incoming solar radiation, were extracted from North American Land Data Assimilation System (NLDAS-2). The spatial and temporal resolutions of EDDI are presented in Table 1.

2.2.4. Agricultural Land Use

The land use shapefile, which shows the distributions and extents of the different land use classes in Sri Lanka, was acquired from the Natural Resource Management Center, Department of Agriculture, Peradeniya. Figure 2 shows mainly the agricultural land use classes. Forest, grassland, bare area, urban, and rocks were aggregated into the "other land use" class, while open water and wetlands were grouped into water bodies. The percentage area coverage of each land use type is shown in Table 2. Woody perennial crops are the dominant agricultural land use (17%), widely distributed in different districts. Paddy crop is cultivated mainly in the dry zone, while perennial crops dominate in the wet and intermediate zones. The land use map masks the non-agricultural pixels, while developing the drought model and presenting the result.

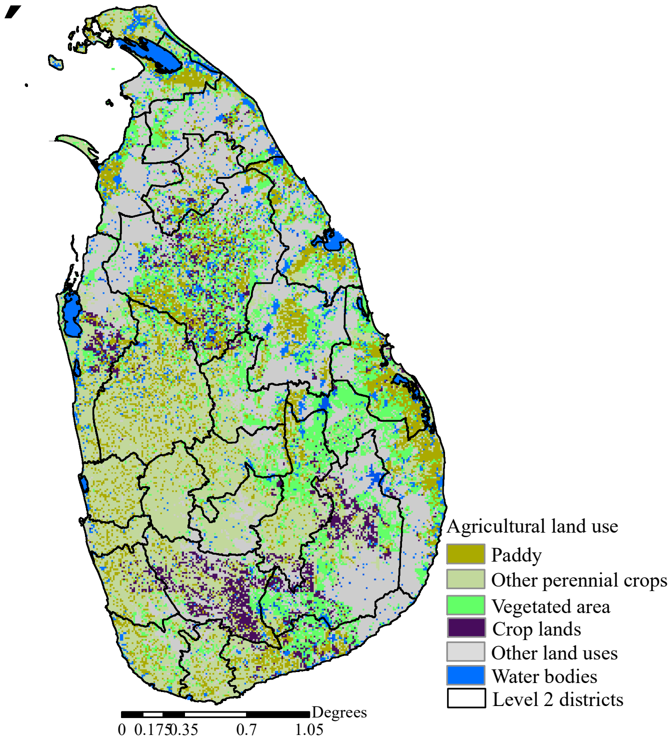

Figure 2. The spatial distribution of the agricultural land use in Sri Lanka.

Table 2. Area coverage of the land use classes shown in Figure 2.

Land Use Type	Area Coverage (%)
Paddy	13
Crop lands	5
Vegetated area	16
Perennial agriculture—rubber	4
Perennial agriculture—tea	3
Perennial agriculture—coconut	6
Woody perennial crops	17
Other land uses	28
Water bodies	7

2.2.5. Crop Yield

Crop yield data were acquired from the Department of Census and Statistics of Sri Lanka and used to evaluate the agricultural drought index. The crop yields are at level 2 administration districts spatial scale and are accessible for cereal crops, vegetable, and paddy crops from 2000 to 2020. However, the rice crop yield is used in this study for selected five districts responsible for more than half of the country's annual rice production. The crop yield data are at seasonal temporal scale for each district; hence, the data for Yala and Maha seasons were used in this study.

2.2.6. Streamflow Data

The streamflow data were acquired from the Irrigation Department of Sri Lanka for stations mainly located in the wet and intermediate zones. The data are at the daily time step and for a total of 20 gauging stations. However, the data of ten stations are used in this study from 2000 to 2020, based on the availability of continuous historical time series of records.

2.3. Method

This method is designed to develop a combined drought index to monitor agricultural drought across Sri Lanka. Four remote sensing-based input variables, including NDVI, LST, precipitation, and EDDI, were used in this study. These input variables were selected due to their usefulness and broader application to monitoring agricultural drought and due to the availability of long-term data, as per the recommendation of previous studies [57–59]. The inconsistency in the spatial resolution of the input variables was treated using inverse distance weight (IDW) methods, and coarser spatial resolution input variables (e.g., EDDI) were resampled to 4km. Except for EDDI, all other input variables are available at a weekly time step on a global scale. Thus, the monthly EDDI, currently available in the public domain for the study country, was used to represent each week within the month. Next, each input variable, except EDDI, was standardized to avoid any impacts on the units of measurement and to enhance the spatial comparison of each parameter [38]. Three-month aggregate period of precipitation, recommended for agricultural drought monitoring, was considered to derive the time series z-score values (stdPCP). Then, we applied the principal component analysis (PCA) to compute the percentage contribution of each input variable.

Although PCA is widely applied in the atmospheric and hydrologic sciences to reduce the dimensionality of observational data, it has also become popular in drought studies to integrate several hydro-climatic variables into a single drought index [38]. It follows an objective approach to quantify the percentage contribution of each input variable for each week and grid point. The number of PCs corresponds to the number of input variables, and PCs cannot be combined to accommodate the total variability in the data [38]. However, the first principal axis accommodated the immense variability of the data (>75%) and was used to develop the percentage contributions of each input variable [39,41]. The eigenvalues of the first PC were estimated using the PCA approach and then squared to quantify the percentage contribution of each input variable [40]. Figure 3 illustrates the steps to develop PCA-based agriculture drought monitoring (agCDI) for Sri Lanka. There are six main steps, including:

1. Standardize all the input variables based on long-term weekly mean and standardization values.
2. Estimate the eigenvectors/eigenvalues used to transform each variable into separate orthogonal principal components (PCs).
3. Determine the percentage contributions (weight) of each input variable in PC1 (a total of 52 grid-based maps of the percentage contribution of each input variable were developed and used as a weight to combine the input variables into a single combined drought index).
4. Compute the weighted sum of the input variables using Equation (1) and generate the time series CDI maps, then normalize to minimize the higher degree of variability if it exists in some weeks.
5. Assess the spatial and temporal patterns of drought.
6. Evaluate the agricultural drought maps using independent datasets, including crop yield and streamflow-based SRI.

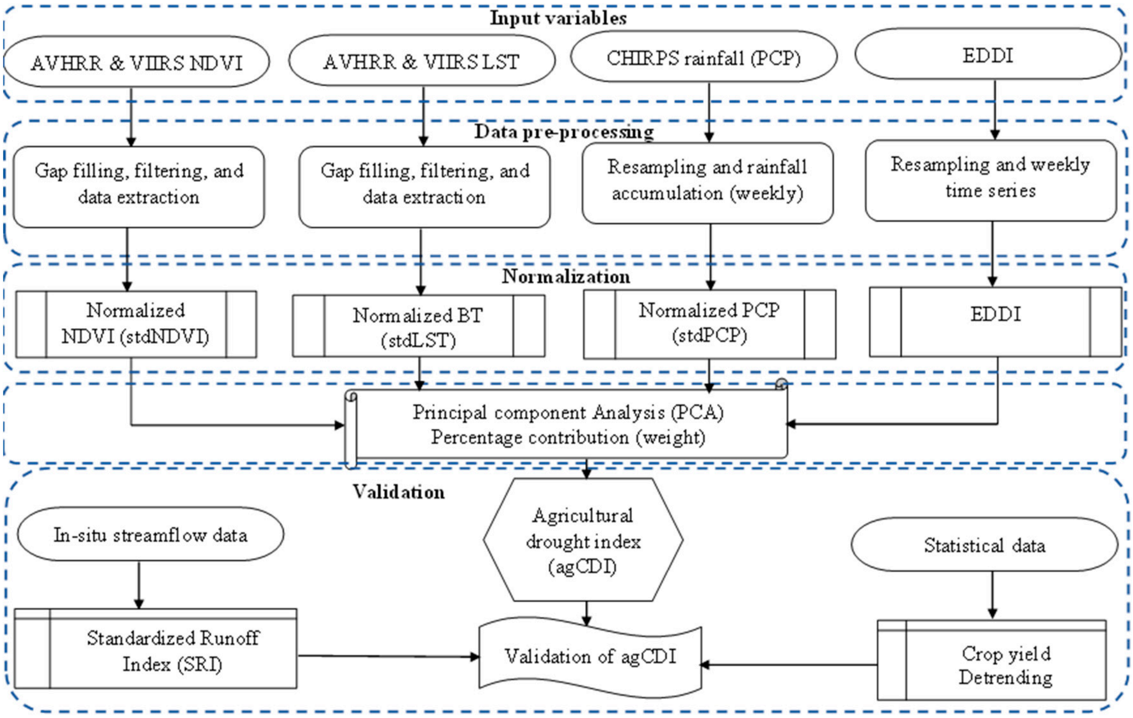

Figure 3. Summary of the method used in this study.

Equation (1) shows the mathematical representations of the agricultural drought indices, respectively.

$$agCDI_{Z,I} = \omega_{pcp,i} * stdPCP_{z,i} + \omega_{BT,i} * stdLST_{z,i} + \omega_{NDVI,i} * stdNDVI_{z,i} + \omega_{EDDI,i} * EDDI_{z,i} \quad (1)$$

where z and I represent the data length (1982–2020) and weeks (52 weeks), respectively; $agCDI_{Z,I}$ is weekly agricultural combined drought index value for a particular year $\omega_{pcp,i}$, $\omega_{BT,i}$, $\omega_{NDVI,i}$, *and* $\omega_{EDDI,i}$are the percentage contribution of the anomaly values of precipitation, LST, NDVI, and EDDI, respectively.

stdPCP is standardized precipitation; stdLST is standardized land surface temperature; stdNDVI is standardized NDVI; and EDDI is the anomaly of the atmospheric evaporation demand.

2.4. Spatial and Temporal Assessment of Drought

The time series of agCDI were extracted at level 2 administration boundaries of Sri Lanka to analyze the temporal patterns of drought at the district level and to compare with district level detrended crop yield. McKee et. al. [60] drought classification category (Table 3) was used to identify the drought severity classes of the agCDI. Bayissa et al. [39] developed the threshold of the combined drought index and reported similar severity classes as McKee et al. [60]. Thus, in this study, we used the drought severity classes in Table 3 to categorize agCDI into different severity classes. The spatial patterns of drought were also assessed in agricultural-dominated land use in Sri Lanka. The frequency of occurrence of mild, moderate, severe, and extreme drought was computed using the time series of agCDI at each grid location. The percentage of the number of occurrences of each drought category (i.e., mild, moderate, severe, and extreme), with respect to the total data length, was used to quantify the frequency of the occurrence of each drought category. These drought characteristics measure the severity and persistence of the agricultural and water supply droughts.

Table 3. Drought category based on McKee et al. [60].

SPI Values	Drought Category
−2.00 and less	Extreme drought
−1.50 to −1.99	Severe drought
−1.00 to −1.49	Moderate drought
0 to −0.99	Near normal or mild drought
Above 0	No drought

2.5. Evaluation of agCDI

The agCDI was evaluated using two independent datasets (i.e., crop yield and streamflow-based SRI) for selected districts and hydrological boundaries. According to the Department of Census and Statistics (DCS) of Sri Lanka, Ampara, Polonnaruwa, Kurunegala, Anuradhapura, and Hambantota (Figure 3) districts are the central rice-producing districts in the country. More than 50% of the annual rice production occurs in these five districts. Hence, agCDI was evaluated using these five districts' rice crop yield data for the Yala and Maha seasons. The crop yield data were detrended first to eliminate the impacts of improvement in agricultural management practices on the crop yield. Detrending removes the upward linear increase in the crop yield, due to improvements in farming practices, and accounts only for weather-related changes in crop yield [40,61]. The average seasonal values of agCDI were extracted at these five districts and compared with the corresponding detrended crop yield to explore any temporal association between these variables.

Similarly, we use the streamflow data of selected stations located mainly in the wet and intermediate zones to generate the time series of SRI. These stations were selected based on the availability of continuous flow data from 2000 to 2020. Then, the hydrological boundary of each flow gauging station was delineated and used to extract the seasonal time series of agCDI. The locations and extents of the hydrological boundaries are shown in Figure 4. The name of each hydrological boundary corresponds to the name of the corresponding gauging station. The Pearson correlation coefficient was used to measure the strength of the statistical relationship between agCDI and detrended crop yield and SRI.

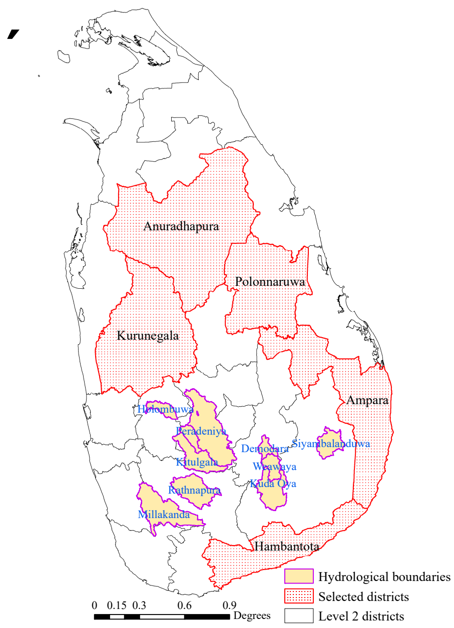

Figure 4. Location of the selected five districts (red boundaries) used for crop yield-based evaluation of the agCDI. In addition, the locations and extents of the hydrological boundaries (yellow background) are shown and labeled using the names of the river gauging stations.

3. Results and Discussions

3.1. Identifying the Historical Drought Years

The grid-based percentage contributions of each of the input variables were computed for each week, and a total of 208 maps were generated. However, the resulting figures for the selected weeks in the Maha and Yala cultivation seasons are shown in Appendix A (Figures A1 and A2). The results illustrate relatively higher contributions of stdNDVI and stdLST, as compared to stdPCP and EDDI. The latter variable contributions are higher in some pocket areas across the study area. In addition, the stdPCP contribution was higher, as compared to other variables in some weeks. Overall, the contribution of EDDI was relatively lower than the other input variables, perhaps due to its coarser spatiotemporal resolution, which impeded the capture of the variability of the evaporative demand across space. The objective-based approach of determining the percentage contribution of the input variables has an advantage over the expert judgment-based approach, which is susceptible to subjectivity and lacks capturing the spatial variability of the weights.

The weekly percentage contribution of each input variable has been utilized to generate the time series of the agricultural drought index (agCDI). Then, agCDI was used to identify the historical drought events in the past 38 years. The number of weeks with severe to extreme drought intensities each year was identified and compared to stipulate the historic drought years. Therefore, 1983, 1984, 1986, 1992, 1994, 2000, 2011, and 2016 were identified as the historical drought years, since a relatively large number of weeks were identified with severe to extreme drought conditions, as compared to the other years (Figure 5). The highest number of weeks of intense drought intensities were observed in 1994, and it covered a vast agricultural area across Sri Lanka. Similarly, a higher number of weeks of severe drought events were observed in 1983 and 1984, mainly in the southwest and central parts, where perennial agriculture (i.e., rubber, coconut, and tea) and other crops were dominantly growing and located relatively in the higher rainfall zones (wet and intermediate zones). Similar spatial patterns of the drought events were observed in 1986 and 1992, as of 1983 and 1984. Conversely, a smaller number of drought events were detected relatively in 2000, 2006, and 2009, except in pocket areas in the central, eastern, and northern parts, where there were more than 20 weeks of severe drought intensities indicated. The prevalence of severe to extreme drought was observed mainly in the dry zone in 2016. Predominantly, rainfed and irrigation-based crop production is taking place in the dry zone, particularly in the northern, north-central, eastern, and south-eastern parts of it. The historic drought years identified in this study are in line with the drought years indicated in previous studies. For example, Abeysingha and Rajapaksha [13] detected some of the drought years, such as 1982–1983, 1986–1987, 2000–2001, and 2016–2017, on their weather stations-based meteorological (SPI) drought assessment in the study period from 1970 to 2017. Ekanayake, and Perera [62] also identified the occurrence of severe drought events in 1986, 1992, 1995, and other years using SPI in the Anuradhapura districts in Sri Lanka. The 2012 and 2016 drought years were spotted in the study by Alahacoon and Ranagalage [62]. Therefore, agCDI has shown its capability to identify the historic drought years in Sri Lanka.

A similar analysis of the frequency of occurrence of drought or the number of weeks under severe and extreme drought conditions was carried out for the Yala and Maha crop growing seasons in Sri Lanka. According to the department of agriculture of Sri Lanka, rice is one of the popular crops that is grown widely, with average cultivation areas of ~748,027 ha in the Maha and 368,906 ha in Yala seasons, with an annual total of 1,116,933 ha, accounting for 34% of the total cultivated area of the island. Out of 25 administrative districts of the country, Ampara, Anuradhapura, Polonnaruwa, Kurunegala, and Hambanthota are the top rice crop growing districts in Sri Lanka. The historical drought years were also identified in both the Yala and Maha seasons (Figure 6). Relatively more severe drought events were captured in both seasons, except 2016, where more weeks under drought conditions were observed in the Maha season.

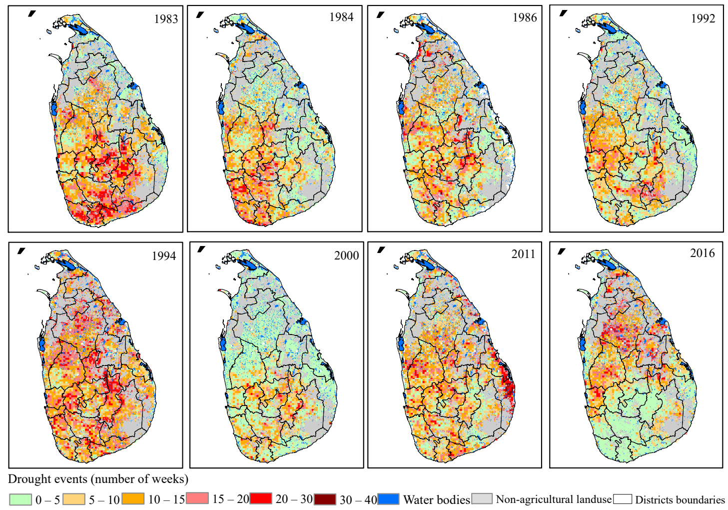

Figure 5. Historical drought years identified based on the number of severe to extreme drought weeks in each year.

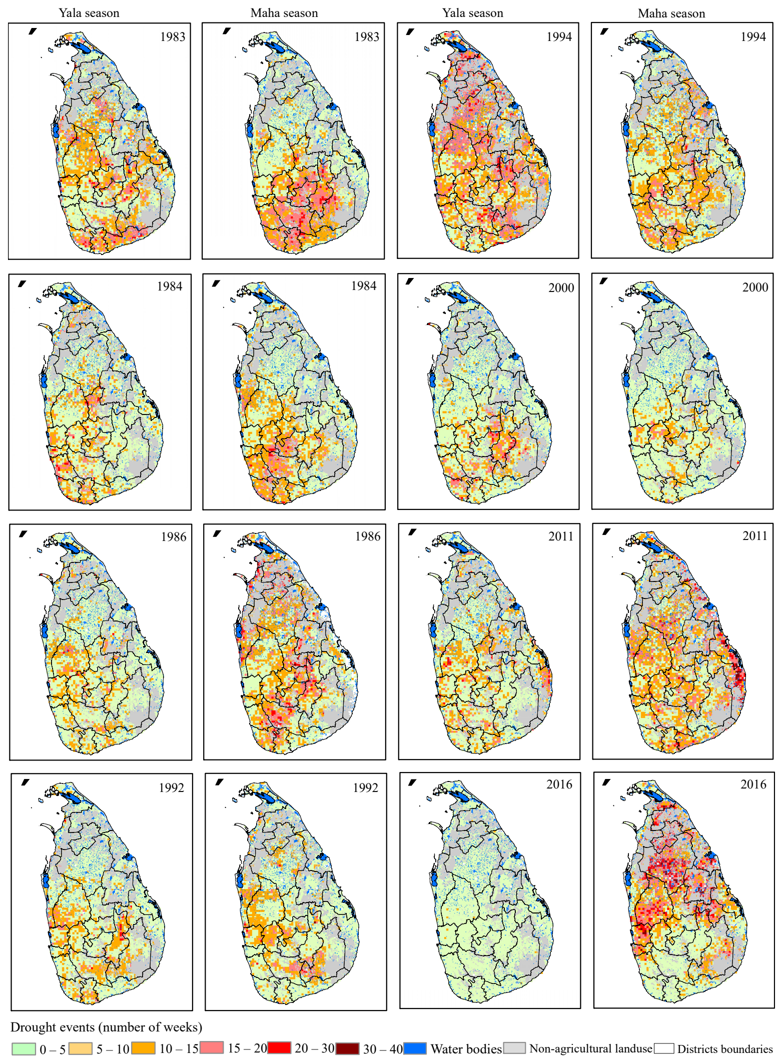

Figure 6. Historical drought years identified based on the number of weeks with severe to extreme drought conditions in Yala and Maha crop growing seasons.

3.2. Frequency of Occurrence of Drought

Figure 7 illustrates the frequency of the occurrence of mild, moderate, severe, and extreme droughts in Yala and Maha, as well as the annual time scales in the agricultural-dominated areas in Sri Lanka. The occurrence of these drought categories in the study period (1982–2020) was taken into consideration to generate the maps. The frequency of the occurrence of drought in this section refers to the ratio of the number of weeks under each drought category to the total number of weeks of the corresponding seasons within the analysis period. Different legend categories were used for each drought type for better visualization of the spatial distribution of the frequency of the occurrence of drought. The results, in general, illustrate the frequent occurrence of mild droughts, as compared to the other drought categories, in the majority of the agricultural lands. There is a more than 30% chance of the occurrence of mild drought in the annual time scale, while the seasonal analysis demonstrated relatively more prevalent mild drought conditions in the Maha season, as compared to the Yala season. On the other hand, there is somewhat more of a chance of the occurrence of moderate drought (>10%) in the Yala season, compared to the Maha season. The result on an annual time scale further depicts relatively more frequent moderate drought (>8%) in some of the major rice-growing districts, such as Anuradhapura and Hambantota. Moderate drought occurred more frequently next to the mild droughts across majorities of the districts. Severe droughts occurred (2–4%) across the different crop growing districts at an annual time scale, although more than 4% frequent severe droughts have been observed in some pocket areas in central crop growing districts. Relatively more frequent severe droughts have occurred in the Yala season, as compared to the Maha season, in the majority of the districts. Similarly, extreme droughts occurred across a majority of the regions, with a frequency of occurrence of 2%. A higher frequency (>2%) of extreme droughts occurred mainly in the southern region (wet and intermediate zones) and some pocket areas in the dry zone, where agricultural practices are prevalent (eastern part). The frequency of an extreme drought above 3% is often considered significant, since the probability of the occurrence of extreme events is once in a while in a given analysis period [63]. The comparison of the seasonal frequency of the occurrence of severe to extreme drought intensities indicated relatively more frequent severe droughts in the Yala season, as compared to the Maha season, across the agricultural lands. Abeysingha and Rajapaksha [13] indicated more drought events during the Yala season, compared to the Maha season, on their SPI-based spatiotemporal drought assessment across Sri Lanka—the finding somehow supports the results of this study.

Figure 8 presents the frequency of the occurrence of moderate to extreme drought conditions in the dry, intermediate, and wet zones in Sri Lanka. The average areal values of the frequency of occurrences of moderate to extreme drought were generated for each zone. This analysis somehow infers the drought-prone zone in Sri Lanka. The result shows relatively more frequent droughts occur in the dry zone during the Yala season (16%), while a bit less frequent droughts occur in the wet zone. In addition, relatively more severe droughts occur during the Yala seasons in all three zones.

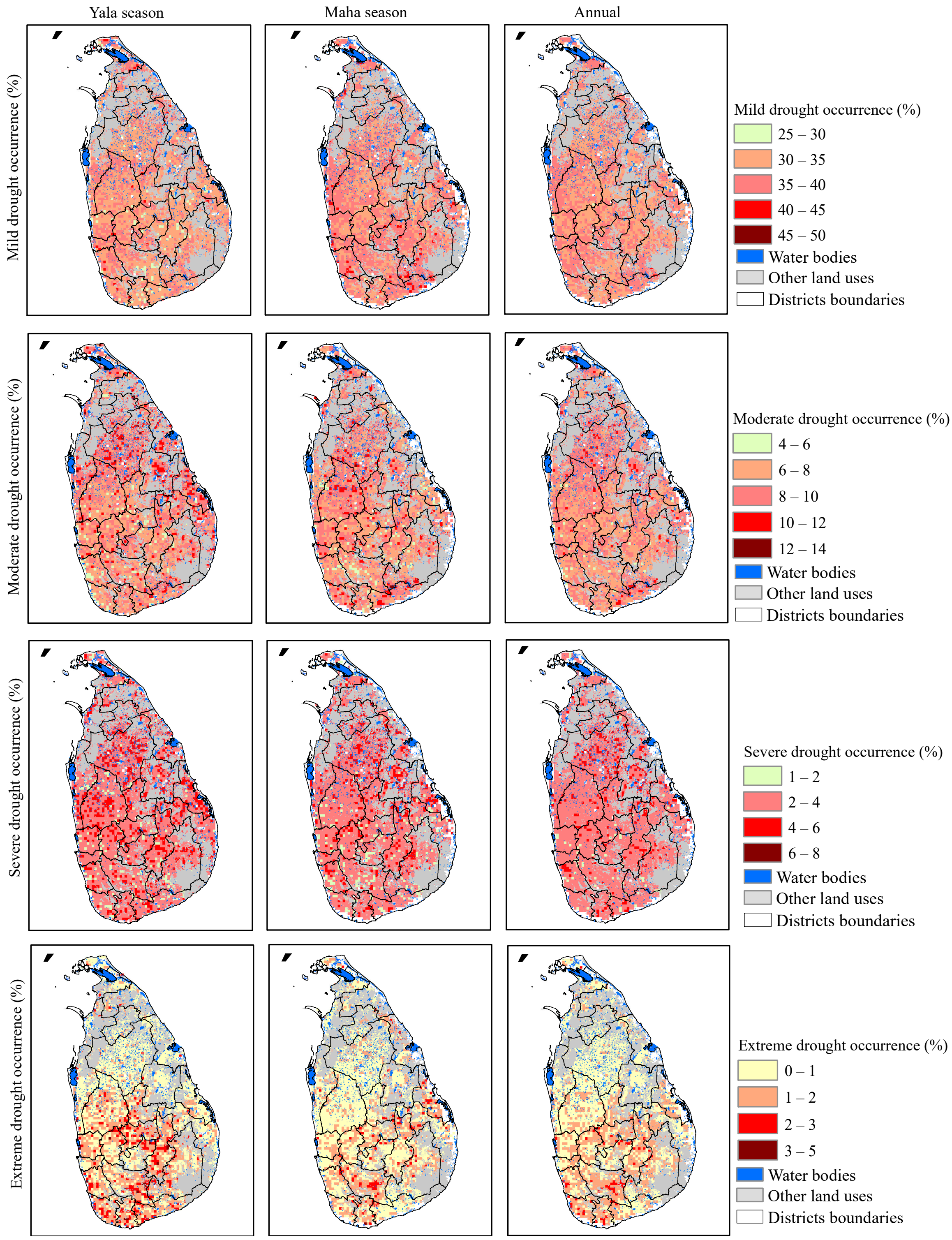

Figure 7. Frequency of occurrence of mild, moderate, severe, and extreme droughts in Yala, Maha and annual.

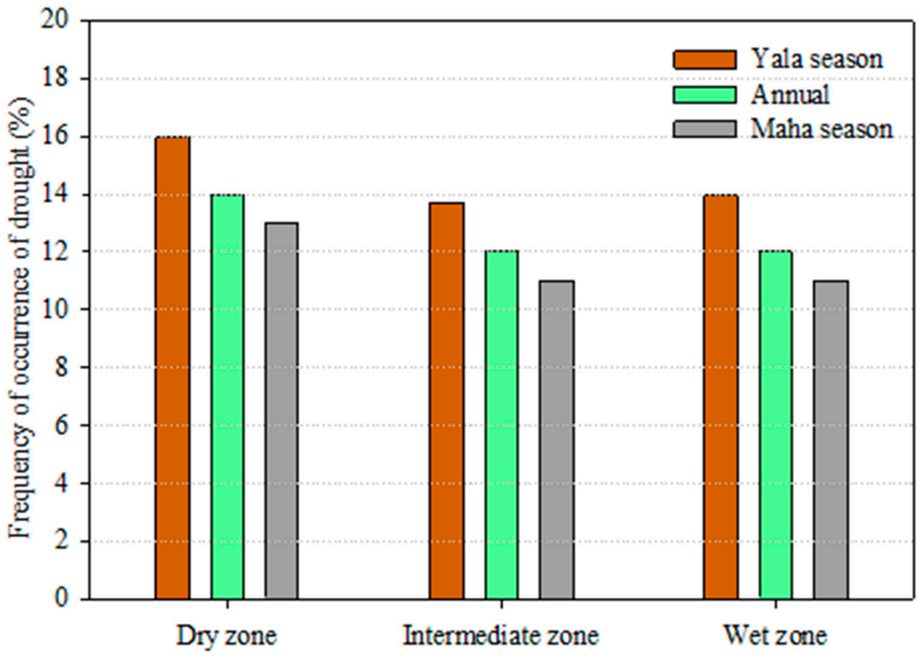

Figure 8. Frequency of occurrence of moderate to extreme drought conditions in dry, intermediate, and wet zones Yala and Maha seasons and annual time scale.

3.3. Spatial Patterns of Drought

The spatial patterns and severity of the selected historical drought events are presented in Figure 9 for the Yala and Maha seasons. The result illustrated prevalent severe drought conditions in most parts during the Yala season, except for the normal conditions in some pocket areas. The vast area had experienced abnormally drier conditions in 1983, 1994, and 2011. The drought in these years lingered in the Maha season, with relatively less severity, except in 2011, which indicated severe drought in November and December. On the other hand, the 2016 drought progressively developed in the Yala season and intensified in the Maha season. Most of the crop-producing districts were struck by moderate to extreme drought conditions in these years. Rajendram [6] reported the occurrence of extreme drought conditions in 1983 and 2016 on the drought analysis, based on SPI, using long-term (1881–2020) observed rainfall data. At the same time, the occurrence of severe drought in the other years (2011–2012 and 1994) was demonstrated by the Disaster Management Center of Sri Lanka [64].

Moreover, Chithranayana and Punyawardena [44] attempted to identify the drought-prone regions using the moisture availability index (MAI) and presented the relatively higher drought vulnerability of districts ascribed in the dry and intermediate zones—which corresponds with the findings of this study. The wet zone is relatively less at risk of drought, although it had experienced moderate to extreme drought conditions in some pocket areas in most of the drought events. Some of the severe drought events were linked to the occurrence of El Niño years. For example, El Niño events in 1982–1983 and 2015–2016 might have triggered the droughts in 1983–1984 and 2016. However, a detailed analysis is required to explore the connection between drought and El Niño occurrences in Sri Lanka. According to Zubair et al. [65], the rise in the Indian Ocean Sea temperature instigated warmer temperatures than usually expected during El Niño event, and this situation exacerbated the drier condition in 2016.

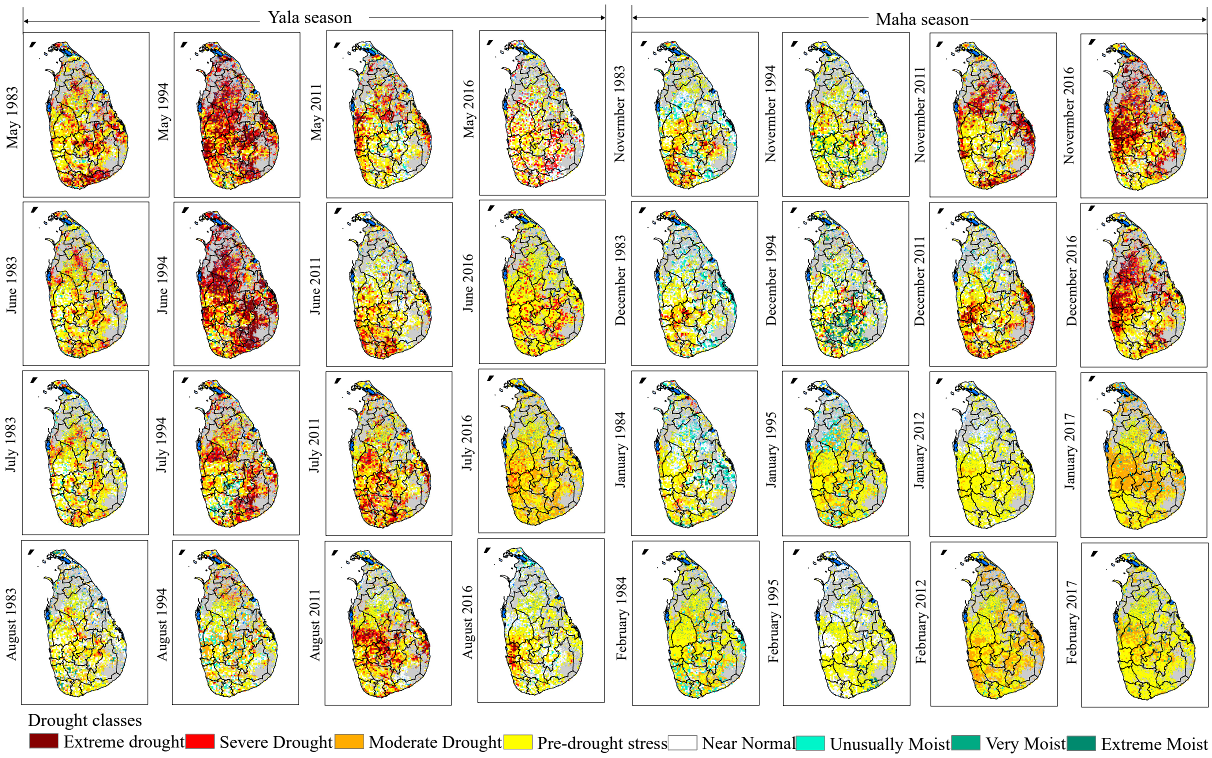

Figure 9. Spatial patterns and severity of selected historic drought years (i.e., 1983, 1994, 2011, and 2016) in Yala and Maha seasons.

3.4. Evaluation of Drought with Crop Yield and SRI

An attempt has been made to evaluate the agCDI using the district-level crop yield data. The results obtained at selected major crop growing districts have been presented in this section for the Yala and Maha seasons. Figure 10 presents the resulting time series plots in the Yala and Maha seasons. In general, there is a good agreement between the agCDI and detrended crop yield in the five selected districts, with correlation coefficient values ranging between 0.61 to 0.77 and 0.68 to 0.81 in the Yala and Maha seasons, respectively. The agCDI was able to capture the patterns of the crop yield anomalies, except for some discrepancies in some of the drought events. Relatively higher correlation coefficient values were observed in the Ampara (0.77) and Hambantota (0.81) districts in the Yala and Maha seasons, respectively. Conversely, relatively lower correlation values have been noted in Kurunegala (0.61) and Anuradhapura (0.68) in the Yala and Maha seasons. An anticipated significant crop yield reduction was largely observed in the Ampara and Hambantota districts in the Yala season, due to the 2016 drought, while the drought impact intensified largely in these districts during the Maha season, as substantiated by the crop yield reduction. The failure of the rainfall, due to El Niño and the non-formation of usual low-level atmospheric disturbances and/or depressions in the Bay of Bengal, was the principal cause that triggered the 2016 drought. Paddy cultivation was severely affected because of the dry spell in this drought event. According to WFP (2016), 63% of the paddy cultivation was affected in the 2016 Maha season, with a persistently worsening impact on the main agricultural harvest in the next Yala season in 2017 [66]. The result may further improve with the availability of maps that show the specific location of the rice cultivation farmlands. The statistical significance of the correlation coefficient values was tested at a 95% confidence interval. The result indicated there is a positive relationship between the agCDI and detrended crop yield, with alpha values less than 0.05.

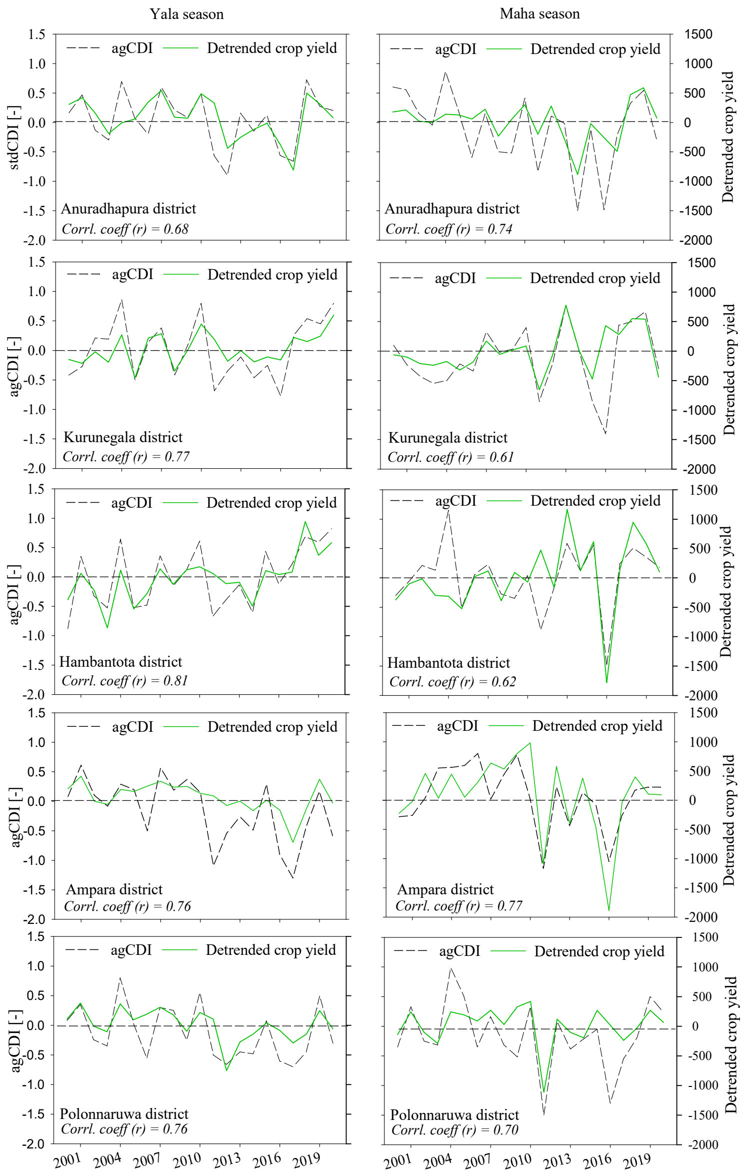

Figure 10. Evaluation of agCDI with detrended crop yield for the selected crop growing districts for the Yala and Maha seasons.

The correlation coefficient values between agCDI and paddy crop yield may further improve with the availability of locations and extents of the paddy cultivation land in each district. In the wet zone, perennial agricultural crops, such as tea, coconut, and rubbers, are the predominant agricultural land use, and the drought tolerance of these crops might also be contributed to largely less correlation in the southwestern part, where southwest monsoon rains are highly effective, as per the general rainfall climatology of the island (result not shown). In addition, the paddy cultivation in districts in the wet zone covers relatively less area, as compared to Dry Intermediate zones.

Additional effort has been made to validate the agCDI using another independent dataset, which is streamflow-based SRI. The number of stations used was selected based on the availability of the observed data with reasonable missing values. The hydrological boundary draining to each gauging station was delineated and used to extract the areal average time series values of agCDI for the Yala and Maha seasons. The spider plot in Figure 11 illustrates the correlation coefficient values between agCDI and SRI of each sample station. The result, in general, showed relatively lower correlation coefficient values, as compared to the crop yield, except for the Kude Oya station, where a relatively higher value of correlation coefficient (0.77) was observed. Since the streamflow is a response to the catchment process, there might be some lag time to respond to drought. Future studies that consider the time lag relationship and different aggregate periods of some of the input variables may improve the results in this section.

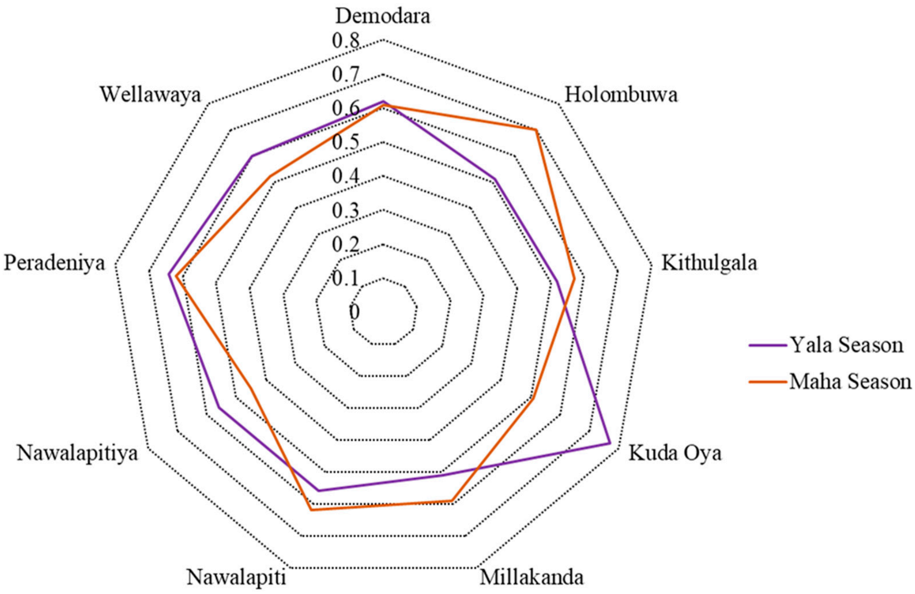

Figure 11. Evaluation of agCDI with SRI largely in the southwest parts of the districts for Yala and Maha seasons.

4. Conclusions

The agricultural drought index (agCDI) developed in this study is generally able to capture and characterize the spatial patterns of the historical drought conditions in Sri Lanka. The study presented the occurrences of moderate to extreme droughts in most agricultural lands across Sri Lanka. In addition, 1983, 1994, 2011, and 2016 were identified as some of the recent historic drought years, with severe drought conditions prevalent in the majority parts of the island. Some of the drought years followed the occurrence of El Niño and the non-formation of usual low-level atmospheric disturbances and depressions in the Bay of Bengal. In addition, the comparison of the seasonal frequency of the occurrence of severe to extreme drought intensities indicated relatively more frequent severe drought in the Yala season, as compared to the Maha season, across the agricultural lands. Therefore, the agCDI can be used to characterize and identify the spatial pattern of the agricultural drought in Sir Lanka.

The evaluation of the seasonal agCDI with the detrended crop yield data illustrated a strong linkage in the major rice growing districts during the Yala and Maha seasons. A correlation coefficient value of greater than 0.65 was observed in the majority of the selected districts, providing fair evidence for the utilization of agCDI in developing agricultural yield prediction models and decision-making processes by local governmental and non-governmental organizations. In addition, agCDI can be used to develop a drought forecasting framework to enhance the preparedness for future droughts and to mitigate its adverse impacts in the agricultural and other important socioeconomic sectors of Sri Lanka.

The potential usefulness of agCDI can be further improved using the additional input variables representing water balance components, such as groundwater, soil moisture, etc., although the input variables considered in this study somehow explain the different water balance components. In addition, comparing the outcome of this study using other data mining approaches, such as random forest, regression tree, etc., may provide better insights towards developing a robust drought monitoring system in future studies.

Author Contributions: The first author Y.B. analyzed the results and prepared the first draft of the manuscript. Y.B. and R.S. framed the research. All the authors including Y.B., R.S., G.J., A.B., A.S., S.A., R.P. and K.D.W.N. contributed to the interpretation of the results and review and provided insightful inputs at several stages of the manuscript. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement: Not applicable.

Data Availability Statement: Data used in this study can be shared without violating any data sharing policy of the corresponding organizations.

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

Appendix A

Percentage contribution (weight) of each input variable for the selected weeks in the Maha and Yala seasons.

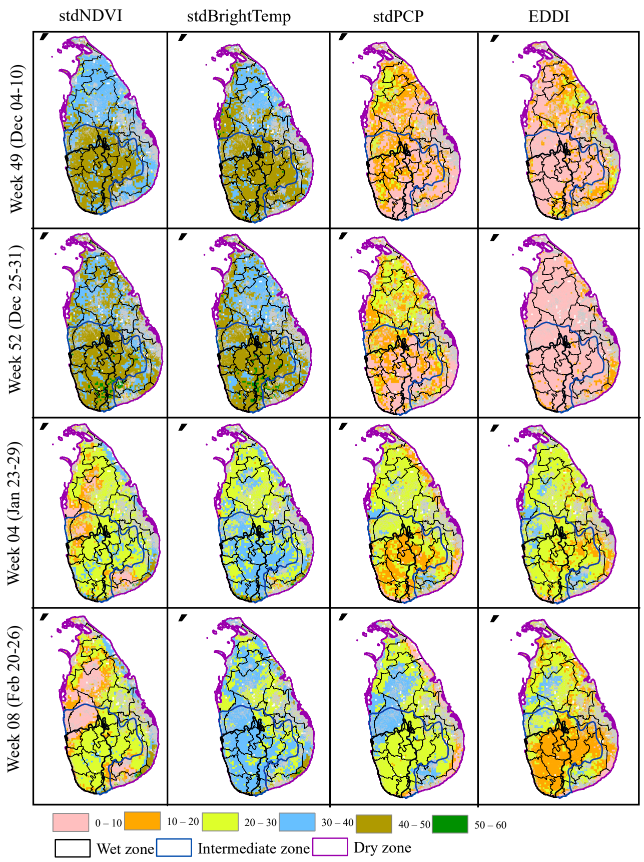

Figure A1. Maha season.

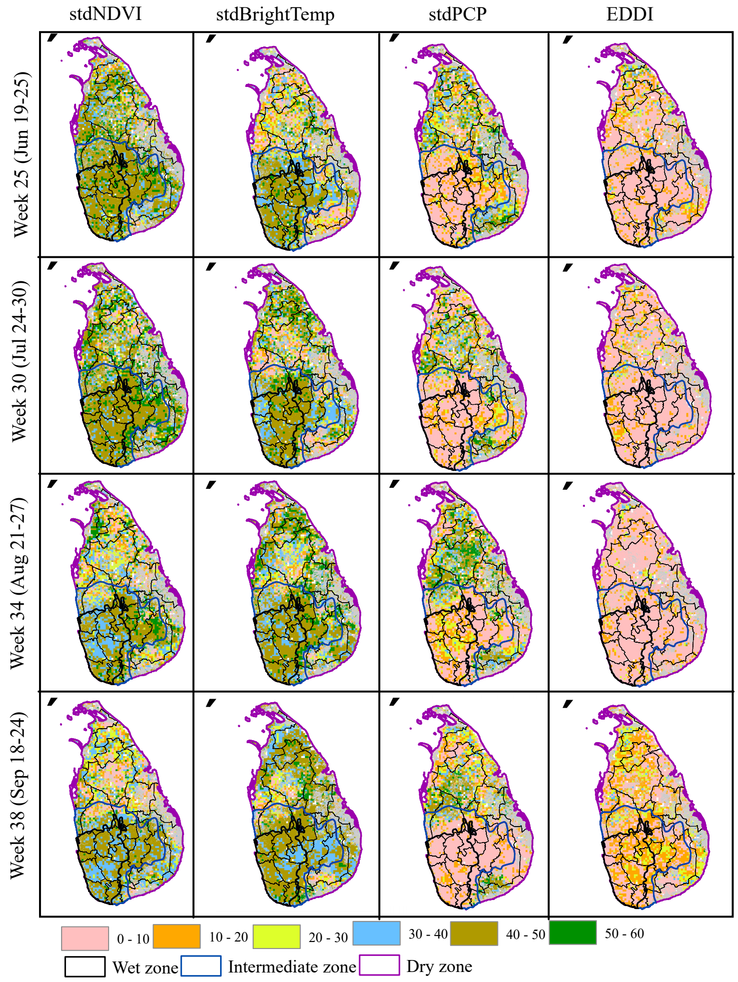

Figure A2. Yala season.

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