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Agricultural drought characterization for sugarcane management in Thailand

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Abstract

One of the main factors affecting sugarcane production in Thailand is drought hazard due to reliance on rainfed irrigation. Sugarcane agricultural drought was studied over four regions of dense cane areas from 1990 to 2020 to help inform appropriate policies and practices for mitigating future damages. The research aimed to assess agricultural drought variability of 15 locations throughout the mainland Thailand during the three decades. Actual evapotranspiration (ETa) was used as an indicator and then transformed into the standardized ETa index (SEaI12) over a 12-month timescale, as the sugarcane crop cycle in Thailand is approximately 12 months. For the last decade, the SEaI12 series of each location was correlated with sugarcane yield, sweetness (CCS), and Nino 3.4 resulting in very good, poor, and fair, respectively. All SEaI12 time series were quantified for drought event time series using the run theory. The severity of drought was characterized by duration and deficit, and since they were closely related, only duration was explored. All evaluation processes from ETa to SEaI12 to drought characteristics were cautiously performed in detail. Drought characterizations were demonstrated in two conditions: (i) spatial distribution of the longest drought from each location; (ii) comparison of distribution and frequency of droughts among the three decades. The highest value of the longest drought is located at the highest latitude and decreases towards the lower latitudes. Among the three decades, the 1990s, an El Nino dominated decade, showed highest accumulated drought and frequency values and the 2000s, a La Nina dominated decade, gave the lowest values.

Keywords: Drought hazard, Sugarcane, Standardized actual evapotranspiration index, El Nino, Theory of runs

1. Introduction

Thailand is known for its sugar production from sugarcane and export since the nineteenth century. Interestingly, in 1850 sugar, not rice, was its major export [1]. At present, sugarcane and sugar businesses involve more than one million personals [2] and fifty-seven sugar factories [3] in Thailand. Top five countries involve in the sugar and sugarcane businesses namely India, Brazil, China, Thailand and Pakistan, their rankings can change annually depending on several factors. The key factor governing sugarcane and sugar production is weather conditions the country of concerned, which are always varied.

Thailand is one of the most drought prone countries in southeast Asia [4, 5]. Impact of droughts on Thailand costed USD 440 million, 220 million, and 3,300 million in 1997/1998, 2004/2005, and 2015-2017, respectively [6, 7]. Since these periods were marked by El Nino events, this study hypothesized that El Nino Southern Oscillation (ENSO) indices can indicate drought situations in Thailand. Droughts damaging national rice productions have been studied extensively [7, 8] but not much for other crops. The two most important economic crops are rice for lowland areas and sugarcane for upland areas [9]. Generally, drought impacts can deteriorate both yield and sweetness [10]. Drought impacts on sugarcane crop in Thailand has always been great [11], as a result there is a need to study and understand so that mitigation and policy planning can be informed.

Among many hydroclimatic drought indices in literature, the two most popular ones namely the standardized precipitation index (SPI) and the standardized precipitation evapotranspiration index (SPEI) have been the most researched in Thailand and other countries [6, 12]. These indices are mainly appropriate for meteorological drought studies, they were used for other drought type studies. The SPI requires only precipitation data to quantify while SPEI uses precipitation and potential evapotranspiration (ETp). Most studies claim that SPEI is better than SPI and the reason is that SPEI is determined by not only precipitation but also evapotranspiration. Homdee et al. [13] found that when replacing ETp by actual ET (ETa), SPEI detects more droughts when compared to official records for the Chi basin in northeast Thailand. According to [13], the paper concludes '[thus], the use of [ETa] may be a useful parameter for better understanding drought trends in that kind of basin'. ETa is the true value of ET which has two components evaporation and transpiration.

The main hydrological components are precipitation, actual evapotranspiration (ETa), runoff, and infiltration. Precipitation produces runoff, infiltration, and ETa at different proportions depending on edaphic, land-use, and meteorological factors for each region. The feature of precipitation and ETa relationship varies from region to region. While precipitation indicates meteorological drought, ETa then indicates agricultural drought. The use of solely ETa as an indicator for drought index was rare. Łabędzki and Kanecka-Geszke [14] initiated standardized drought index based on ETa to study sugar beet drought management in Poland. Their ETa

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estimation involved soil condition, meteorological condition, water stress coefficient, crop coefficient, and water balance simulation. This lengthy procedure unpopularized the use of ETa as a drought indicator.

The Bouchet hypothesis now allows ETa to be estimated from only meteorological data by a complementary relationship method. Kim and Rhee [15] used the method to determine ETa and ETa deficit. An ETa deficit is when the ETa value is less than a fixed value of environmentally wet ET. They used ETa deficit to evaluate standardized ETa deficit index with the structure of SPI but instead of using nonexceedance cumulative distribution as SPI they used exceedance one. This means that they evaluated an equivalent standardized ETa index. With the timescale of 9 months, the index was compared to SPI9 and SPEI9 with good agreement. The index was also comparable to vegetation health index on CONUS [15].

To our knowledge, only these two abovementioned studies used solely ETa to identify agricultural drought conditions by multiscale standardized index structure. None of them moved further to quantifying drought events and their characteristics in terms of drought deficit volume, duration, and frequency. Understanding agricultural drought characteristics is key to sugarcane drought mitigation and management. This study's overall goal was therefore to characterize agricultural drought over the main part of Thailand for sugarcane drought management for three decades i.e. the decades of severe drought, moderate drought, and wet conditions. To accomplish this goal, the study set out to (i) determine and use ETa as an indicator to create a suitable drought index; (ii) correlate the drought index with sugarcane yield and sweetness (commercial cane sugar, CCS) for 15 locations in 4 regions of mainland Thailand and with an index of ENSO; (iii) quantify drought event time series for 3 decades from 1990 to 2020; and (iv) analyze and illustrate drought characteristics of mainland Thailand. The findings of the study would help to facilitate supplementary water management for sugarcane cultivation in the future.

2. Materials and methods

2.1 Sugarcane cultivation and climate variability in Thailand

Sugarcane cropping areas in Thailand cluster around 57 sugar factories that scatter in the mainland between 99.0 °E to 105.5 °E and 12.0 °N to 18.0 °N. The areas cover 4 regions i.e. North, Central, Northeast, and East. Fifteen locations were chosen in this study, four from each region except three from the East, the smallest region (Figure 1).

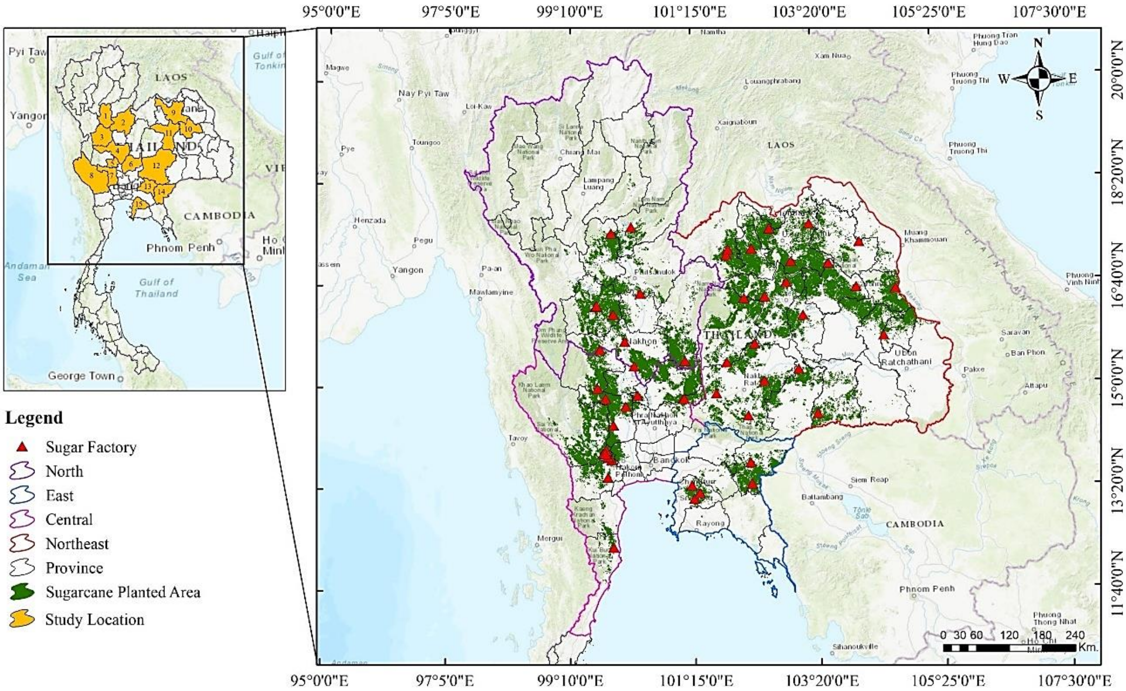


Figure 1 Clusters of sugarcane areas surrounding millers (Δ) with 15 study locations.

Sugarcane in Thailand typically is a one-year crop that is planted during October to March and harvested during milling operation period usually from November to April [16]. After harvested, a cane stubble grows into a new plant called ratoon, some regions produce several generations of ratoon. Sugarcane grows in four stages, gemination (1 month), stalk elongation (3 months), grand growth (6 months), and maturity (2 months). For the case of ratooning, gemination stage is replaced by sprouting of similar duration. Sugarcane in Thailand is easy to grow and care for but to obtain higher yield and sweetness it needs to be carefully treated. On average the life cycle of sugarcane is from January to December, therefore germination period is during January, stalk elongation is during February to April, grand growth is during May to October, finally maturity is in November and December.

More than ninety percent of sugarcane farms are subjected to rainfed condition. The rainfall pattern, in mainland Thailand, matches well with the growth stages of sugarcane. Once the rainy season ends in October the weather cools down from November to February keeping ample soil moisture helping with germination and sprouting [9]. During stalk elongation stage from February to April rainfall and temperature increase gradually which is beneficial to sugarcane crops. The third stage is grand growth, the highest water needed period [17], covering May to October which is the whole rainy season. From November onward, rainfall and temperature gradually decrease which benefits sugarcane to increase sucrose accumulation during maturity stage. Although general rainfall patterns match well with the water requirement of sugarcane, the amount and pattern of rainfall vary from year to year. It is thus crucial to understand climate variability, or drought, related to sugarcane cultivation.

Rainfall in mainland Thailand depends on the position of a low-pressure band called the intertropical convergence zone (ITCZ) which is the result of interaction between the sun, land, ocean, and atmosphere. The ITCZ band moves to the mainland from the South in May passing through the North in July and back again in late July and moving down south until October. Therefore, the rainy season spans from May to October yet a short drought spell occurs in July. The rainy season in mainland Thailand can be separated into the first and second rainy season. The first one is from May to early July and the second one from late July to October. The strength of the ITCZ indicates the amount of rain from both wet monsoon and tropical cyclone. It varies temporally and spatially causing rainfall variation in mainland Thailand. The ITCZ strength can be sensed by ENSO index which is the anomaly different of the sea surface temperature or the air pressure between equatorial east and west Pacific Ocean. The ENSO phenomenon is expressed by several indices, e.g. SOI, ONI, and Nino 3.4. The Nino 3.4 was used in this study for its popularity and simplicity [18].

From 2010 to 2020, the sugarcane yields and CCSs from 15 locations fluctuated around a mean of 63.68 t/ha (Table 1) and 12.02% (Table 2), respectively. At Suphanburi for example, when comparing between 2010, a La Nina year of -5.86, and 2019, an El Nino year of 5.76, it was found that the sugarcane yields were 76.81 and 37.88 t/ha (Table 1) and the CCSs were 10.94% and 11.39% (Table 2), respectively. It was clear that climatic variation strongly influenced yields but not CCSs, therefore the yield variation was explored more closely in this study. Understanding the relationship behaviors of climate with sugarcane yield helps to stabilize high sugarcane yield by informing the right policy and tactical water and crop management.

Table 1 Sugarcane yield (t/ha) from 15 locations from 2010 to 2020 with Nino 3.4.

Region	Province	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Avg.
North	(1) Sukhothai	74.69	76.19	73.25	69.94	69.94	57.19	61.75	74.38	69.06	47.19	42.13	65.06
	(2) Phitsanulok	75.94	76.56	72.38	69.00	69.63	55.69	61.25	75.00	69.38	45.31	40.69	64.62
	(3) Kamphaengphet	77.00	76.81	72.38	69.81	69.81	59.75	60.31	74.19	67.75	44.75	42.38	64.99
	(4) Nakhonsawan	78.94	78.06	72.19	69.44	69.44	55.06	58.44	73.94	66.50	43.69	39.06	64.07
Central	(5) Chainat	76.56	77.31	72.63	73.25	69.63	57.00	60.13	75.00	64.31	38.00	37.25	63.73
	(6) Lopburi	76.13	79.94	74.19	73.13	68.63	55.50	58.63	74.06	65.69	38.25	37.56	63.79
	(7) Suphan Buri	76.81	76.44	72.56	71.63	68.19	61.31	60.13	74.56	64.25	37.88	37.56	63.76
	(8) Kanchanaburi	76.56	77.44	71.38	71.13	67.94	56.69	60.00	74.44	64.44	44.56	44.19	64.43
Northeast	(9) Udonthani	69.38	69.69	68.63	69.69	70.31	55.25	58.13	73.25	68.94	46.44	50.44	63.65
	(10) Kalasin	70.38	69.88	68.44	69.88	69.88	58.75	58.75	72.63	72.06	51.44	47.06	64.47
	(11) Khon Kaen	70.06	68.81	70.44	70.69	69.63	56.75	57.63	72.94	67.81	46.13	48.88	63.62
	(12) Nakhon Ratchasima	70.13	71.69	68.00	70.13	68.88	56.38	56.56	73.31	65.38	43.19	50.25	63.08
East	(13) Prachin Buri	68.75	67.94	66.56	66.94	63.06	61.50	57.19	69.69	63.06	46.50	52.94	62.19
	(14) Sakaeo	68.06	67.00	67.94	67.81	69.88	58.69	57.50	70.00	63.06	48.88	54.13	63.00
	(15) Chonburi	68.13	64.94	64.25	64.50	69.56	53.13	55.13	70.13	62.69	42.38	53.31	60.74
Nino 3.4		-5.86	-10.37	-1.67	-3.86	1.38	17.49	3.97	-2.42	0.17	5.75	-4.35	

Table 2 Sugarcane CCSs (%) from 15 locations from 2010 to 2020 with Nino 3.4.

Region	Province	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
North	(1) Sukhothai	10.94	11.91	11.26	12.11	12.35	11.87	11.87	12.45	12.13	12.84	12.84
	(2) Phitsanulok	10.84	11.51	10.58	11.52	11.70	11.54	11.54	12.11	12.16	12.08	12.01
	(3) Kamphaengphet	11.41	11.66	10.97	11.64	11.58	11.76	11.76	11.96	11.55	12.25	12.07
	(4) Nakhonsawan	11.02	11.62	10.90	12.34	11.85	11.21	11.21	11.68	12.03	12.20	12.16
Central	(5) Chainat	10.99	11.84	10.74	11.89	10.96	11.06	11.16	11.60			
	(6) Lopburi	12.01	12.03	11.59	12.75	12.05	11.87	11.87	12.21	12.47	12.26	12.35
	(7) Suphan Buri	10.94	11.61	10.55	11.77	11.04	11.07	11.07	11.24	11.36	11.39	11.49
	(8) Kanchanaburi	10.98	11.40	10.77	11.75	11.45	11.05	11.05	11.31	11.33	11.43	12.13
Northeast	(9) Udonthani	12.57	12.6	12.43	13.17	12.84	12.82	12.82	13.21	13.52	13.86	13.78
	(10) Kalasin	13.22	13.11	13.44	13.97	13.84	13.69	13.69	13.82			
	(11) Khon Kaen	12.44	12.48	12.69	12.75	12.72	12.22	12.22	13.42	13.47	12.98	13.70
	(12) Nakhon Ratchasima	12.18	11.99	11.98	12.57	12.22	12.26	12.26	12.82	13.06	12.87	13.46
East	(13) Prachin Buri	11.06	11.31	11.26	12.25	11.69	11.19	11.19	11.96			
	(14) Sakaeo	11.84	12.11	13.31	12.94	11.83	11.57	11.57	12.41	13.02	13.23	13.41
	(15) Chonburi	10.68	10.91	10.24	11.91	11.63	11.00	11.00	11.74	12.37	12.32	12.43
Nino 3.4		-5.86	-10.37	-1.67	-3.86	1.38	17.49	3.97	-2.42	0.17	5.75	-4.35

2.2 Standardized actual evapotranspiration index

Three types of ET are always referred to in the literature namely, potential, reference, and actual evapotranspiration [19]. Whereas potential ET (ETp) implies the highest possible value, and reference ET (ETo) helps for calculating crop water uses, however only actual ET (ETa) is the exact amount of water loss from soil and vegetation to the atmosphere which is a true value. We therefore opted to use ETa in our study.

Even though actual evapotranspiration (ETa) is one of the most proper agricultural drought indicators, it has not been popularly used because of the difficulty and complexity in monitoring and computing the value. The Bouchet hypothesis allows ETa calculation to be less complicated by requiring only atmospheric data and was applied successfully in Thailand [20]. The ETa evaluation procedure was later computerized in R-programming package which is much easier to perform [19]. Detailed examples of using R-package for ETa computation are in [21].

The ETa by itself cannot be statistically used for multiscale drought measurement and comparison. It must be transformed to a standardized index. The daily meteorological data from the 15 locations were retrieved from the Thai Meteorological Department databases and used to generate monthly ETa for three decades from January 1990 to December 2020. Since the life cycle of sugarcane in Thailand is approximately 12 months, therefore, the time series of standardized actual evapotranspiration indices of 12-month timescale (SEaI12) were to be evaluated for all locations.

Following the standardized precipitation index (SPI) structure, the SEaI12 can be determined with these steps. (i) Preparing first a 12-month timescale ETa (ETa12) time series from monthly ETa time series using backward moving total e.g., the first value is from January 1990 + February + March + … + November + December being that of December 1990, then February 1990 + March + April + … + December 1990 + January 1991 being that of January 1991, and so on. (ii) Each location set of ETa12 is fitted by the most appropriate theoretical distribution function (tcdf). (iii) The tcdfs of the time series are transformed into standardized normal distribution which are standardized index series. The second step is based on the hypothesis that any variable set should belong to a distribution function, but this is not the case of ETa because it was triggered by at least three phenomena i.e., energy limitation, transition, and water limitation. This study therefore proposed to use empirical function, ecdf, instead of theoretical function, tcdf, as suggested by [22]. The empirical formulae are several and the values from all of them are closed together except at extreme points. To represent probability values of ETa we chose to use Weibull formula due to its simplicity and high accuracy [23].

To obtain empirical cumulative distribution function, Fs, the monthly ETa of 12-month timescale (ETa12) data are sorted in ascending order using Weibull ecdf,

$$Fs = m/(n+1) \quad (1)$$

where m is the order of the data and n is the number of the data. The Fs can be transformed to normal cdf, Fn, by

$$Fn = (Fs-\mu)/\sigma \quad (2)$$

where μ is mean and σ is standard deviation of the Fs. From the pair of sorted ETa12 and Fn, Fn was matched to the time series of ETa12, which is the standardized actual evapotranspiration time series of 12-month timescale, SEaI12. The transformation process was performed by using two functions in Excel i.e., MATCH and INDEX.

The SEaI12 needs to be assessed as agricultural drought index for sugarcane management by correlating with yield, CCS, and Nino 3.4 time series using Pearson correlation coefficient, r. The time series of SEaI12, sugarcane yield, CCS, and Nino 3.4 (Tables 1 and 2) between 2010 and 2020 for the 15 locations were used for evaluating r-values. The r-value approaching 1 or -1 is considered the best correlation.

2.3 Agricultural drought quantification by SEaI12

The SEaI12 time series can be used to quantify agricultural drought events by using the theory of runs [24]. A monthly SEaI12 time series with three thresholds R_0, R_1, and R_2 (Figure 2) is shown as an example for identifying drought events. The values of the thresholds were obtained from SPI classification of McKee [23], which R_1 and R_2 are the upper and lower bounds of moderate drought, respectively, and R_0 is the midpoint of mild drought. The three steps of manipulation are as follows.

- The primary step is to separate drought consequences using threshold R_1 (= -1.0 in this study and other references e.g., [12, 25]). Five events a, b, c, d, and e have their parts below R_1 therefore they demonstrate droughts.
- The second step is to eliminate minor droughts by considering a one-month drought such as a- and d-event. The one-month drought event that is above R_2 (= -1.5 in this study) is considered minor thus to be eliminated such as a- but not d-event.
- The final step is to merge two events which are separated by a one-month drought that is below the threshold R_0 (= -0.5). The events b and c are separated by the one-month event f while that of d and e are separated by the event g. Since f is below R_0 whereas g is above R_0 therefore the events b and c are merged but not d and e.

The SEaI12 time series in Figure 2 has three drought events i.e., b+c, d, and e. Once drought event time series have been identified from SEaI12, drought characteristics can then be quantified.

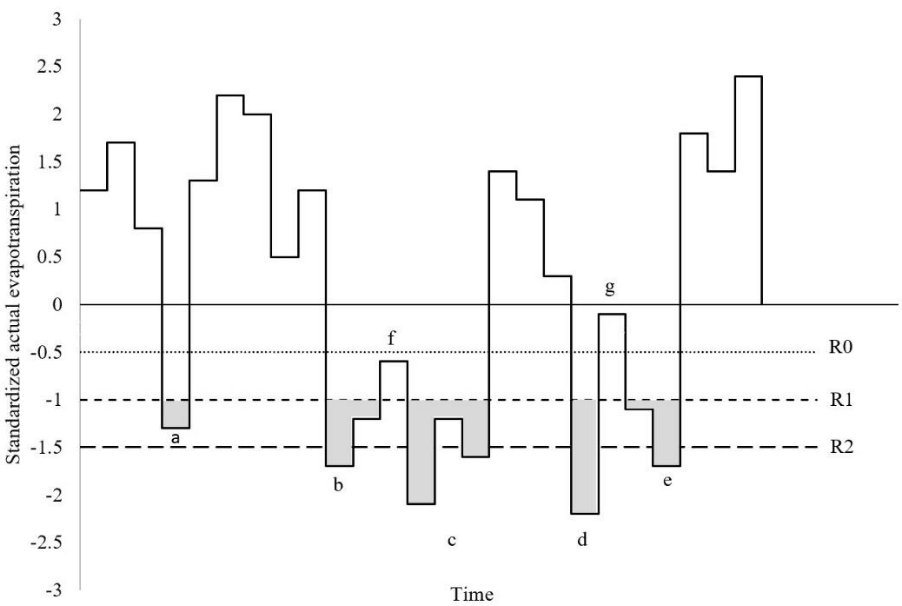


Figure 2 Example of discrete SEaI12 time series with the thresholds R_0, R_1, and R_2.

A drought event can be characterized by its onset, termination, duration, severity, and deficit. The duration is a period between onset and termination inclusively. The severity is the sum of SEaI12 during a drought event. The deficit is the sum of SEaI12 value below a threshold. The five drought characteristics were evaluated from the SEaI12 time series of 15 locations from January 1990 to December 2020. The frequency of drought is the number of drought events per decade from 1990s to 2010s.

2.4 Agricultural drought characterization

The two main characteristics, deficit and duration, of an agricultural drought event, duration can be expressed in a physical meaning usually in the number of months, while deficit, a portion of severity, is only a relative term [26]. Sugarcane farmers in Thailand usually notify drought as a length of time for their drought management. On the study of drought impacting the physiology of Thai sugarcane, Tippayawat et al. [10] considered only drought duration. Duration is therefore an appropriate parameter to be used for characterizing drought for sugarcane management in Thailand. The relationship between duration and deficit can be determined from all drought events to provide for conversion.

Typical climate condition in mainland Thailand is wet for half a year from May to October and dry for another half year from November to April. It can be a wetter or drier year, however. During the year, Thai farmers use farm ponds or some other facilities to mitigate drought spells [8]. The design, operation, and maintenance of farm ponds are important and need accurate drought information.

This study presents historical drought characterization in two conditions, (i) the longest drought during the whole study period of each location, and (ii) total duration and frequency of drought for each location during each decade. The drought frequency in the drought literature is differently defined. This study follows that of Moccia et al. [27] defining that drought frequency is the number of drought events in a specified period which is a decade herein.

3. Results and discussions

3.1 Actual evapotranspiration of the study area

Actual evapotranspiration (ETa) is a significant component of the hydrological cycle implying net water available on agricultural lands. High volume of ETa of a specific land area indicates plenty of water has been used by plants in the area. ETa is not subjected only to soil water availability, but also to plant water useability [28]. The main water supply to the earth's surface is precipitation, therefore ETa varies with the amount of rainfall. Their relationship is nonlinear because the driving mechanism of ETa changes with the amount of water availability [29]. When higher rainfall occurs even though very wet soil, ETa may decline due to cloudiness and limited sunshine. Figure 3 shows monthly rainfall and ETa relationship from the fifteen locations during 1990 to 2020. Since the rate of change of monthly ETa with respect to rainfall varies exponentially and decay, with integration and manipulation, the represent equation is

$$\text{ETa} = a+b(1-\exp(-cr)) \tag{3}$$

where a, b, and c are constants, and r is monthly rainfall in mm. The values of a, b, and c are 20, 150, and 0.006, respectively which give the R^2 value of 0.83. During rainless months, the ETa values vary from 5 mm up to 95 mm, due to variation of water stored in earth surface. The highest value of ETa is about 165 mm at 375 mm of rainfall (Figure 3).

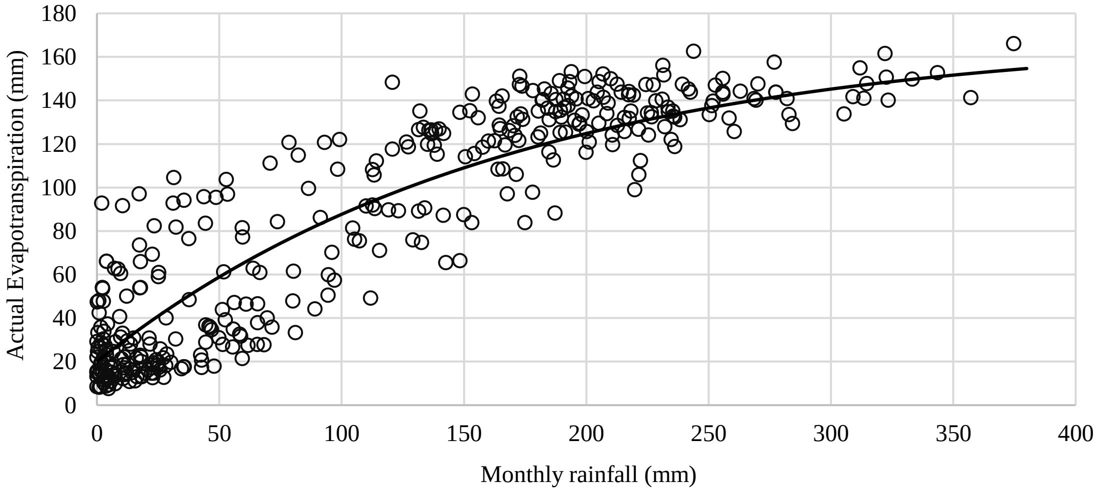
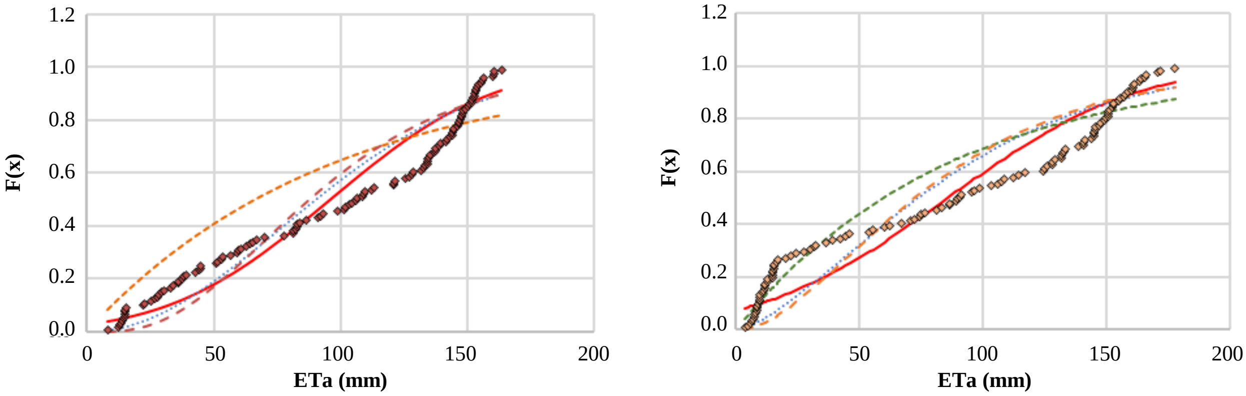


Figure 3 Monthly rainfall and ETa relationship of fifteen locations during 1990 to 2020.

This study fitted and compared four theoretical cumulative distribution functions (CDFs) i.e. normal, Weibull, gamma, and exponential distributions to each of the empirical CDFs of ETa for all locations. Figure 4 shows, for example, the graphic comparisons for (a) Khon Kaen and (b) Kampaengpet which are two of the 15 locations. These two graphs, and others that are not shown herein, demonstrate that neither of the theoretical CDFs fitted the empirical results. The Kolmogorov Smirnov goodness of fit tests for all locations show poor chances of fitting, as the p-values are in the range of less than 0.0001 to 0.176 which are very small. We concluded that the possibility of any theoretical CDF to be the parental CDF of ETa is also very small. The empirical CDFs in Figure 4 show four distinct portions depending on availability of water in soil [29], one each at extreme dry and wet conditions and one each for moderately-dry and -wet transitions.



(a) Khon Kaen (b) Kamphaengphet

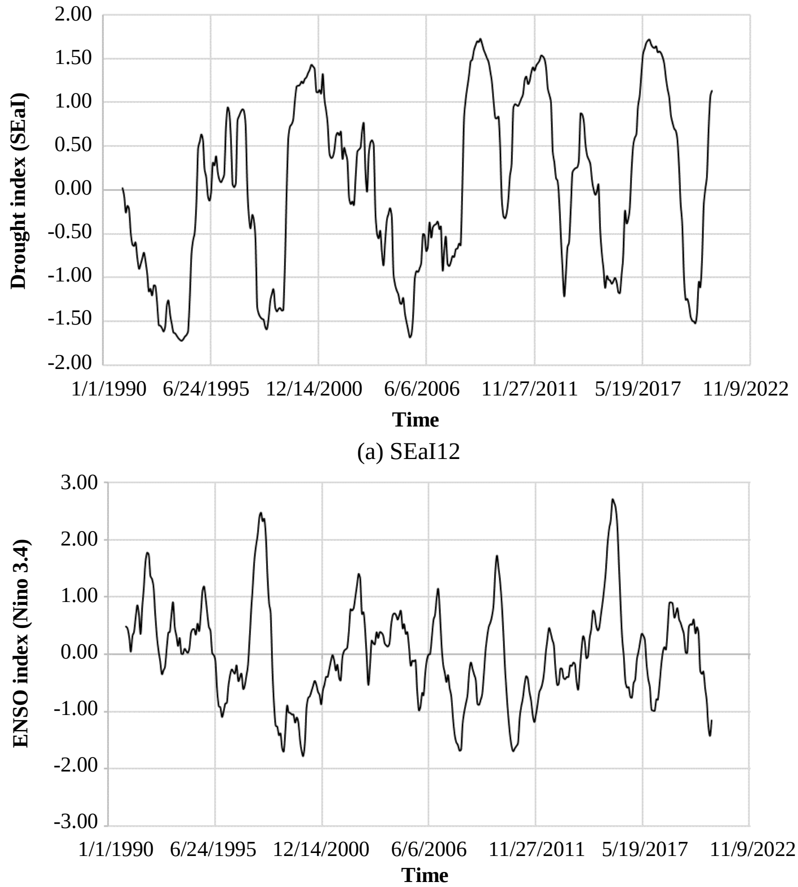
Figure 4 Comparison among four theoretical CDFs to fit with each of empirical CDFs (diamond), i.e., normal (dotted line), Weibull (small dash), exponential (large dash), and gamma (solid line). (a) Khon Kaen and (b) Kamphaengphet.

3.2 Correlations of SEaI12 index with sugarcane yield, CCS and Nino 3.4

3.2.1 SEaI12 and Nino3.4 time series during 1990-2020

The monthly standardized actual evapotranspiration (SEaI12) indices for 12-month timescale of all 15 locations have been calculated as time series from 1990 to 2020 (not shown). The monthly SEaI12 time series for Khon Kaen location were plotted as an example together with Nino 3.4 time series in Figure 5. Khon Kaen was chosen as it was our most familiar location.

Nino 3.4 is one of the ENSO indices showing variation of the atmosphere and ocean interaction in the Pacific Ocean which is calculated from the sea surface temperature anomalies between 5°N-5°S and 170°W-120°W. The positive values above 0.5°C is El Nino phenomenon and negative values below minus 0.5°C is La Nina. These two phenomena indicate meteorological anomalies in most of the regions around the globe with opposite effects. The El Nino however relates to less-than-normal precipitation in Thailand which is the primary cause of drought. Figure 5 shows the SEaI12 time series for Khon Kaen location with Nino 3.4. Figure 5(b) shows two large El Nino indices, 1997/1998 and 2015/2016, during the study period of 1990 to 2020 which were the two largest El Nino indices since 1950 [18].



(b) Nino 3.4

Figure 5 Example illustration of two time series (a) SEaI12 for Khon Kaen (b) Nino 3.4

3.2.2 Pearson correlations of SEaI12 with yield, CCS, and Nino 3.4

Higher yield and CCS are important economic return for Thai sugarcane farmers because both weight (or yield) and CCS are significant components for sugarcane pricing [16]. Evapotranspiration is one of the main factors affecting sugarcane production [30], therefore the Pearson correlation coefficients of SEaI12 with both yield and CCS were to be examined. The annual values of SEaI12 together with sugarcane yield, CCS, and Nino 3.4 between 2010 to 2020 were determined for each of the 15 locations and only Khon Kaen values are presented in Table 3 as an example. The change of technology advancement affecting sugarcane yield in Thailand was minimal in the last decade [9], therefore those of the 2010s decade were used for their correlation analyses.

Table 3 The values of annual SEaI12, sugarcane yields and CCS for Khon Kaen with annual Nino 3.4 from 2010 to 2020.

Year	SEaI	Yield (t/ha)	CCS (%)	Nino 3.4
2010	3.44	70.06	12.44	-5.86
2011	14.16	68.81	12.48	-10.37
2012	14.27	70.44	12.69	-1.67
2013	-4.57	70.69	12.75	-3.86
2014	5.01	69.63	12.72	1.38
2015	-8.39	56.75	12.22	17.49
2016	-6.59	57.63	12.22	3.97
2017	16.11	72.94	13.42	-2.42
2018	16.02	67.81	13.47	0.17
2019	-6.08	46.13	12.98	5.75
2020	-4.51	48.88	13.70	-4.35

The annual time series of SEaI12 were correlated to that of yield, CCS, and Nino 3.4 from 2010 to 2020 in Table 4 as good, poor, and moderate, respectively. The SEaI12 index is therefore an excellent indicator for sugarcane yield but not for CCS in Thailand. The Nino 3.4 is only a fair index to predict SEaI12. The positive correlation between SEaI12 with yield indicates that they vary in the same direction i.e., the year of high SEaI12 produces high sugarcane yield. While negative correlation between SEaI12 and Nino 3.4 means they relate in opposite directions, that is El Nino climate causing negative SEaI12 and La Nina causing positive. The correlation of SEaI12 with CCS is in random fashion which is meaningless. This is consistent with the findings of Watanabe et al. [30] using pot experiments of sugarcane in Thailand and found that droughts can affect sugarcane yield but not CCS.

Table 4 The Pearson coefficient, r, values of SEaI12 with yield and CCS of sugarcane together with Nino 3.4 from 2010 to 2020.

Region	Province	Pearson coefficient, r		
		SEaI-yield	SEaI-CCS	SEaI-Nino3.4
North	(1) Sukhothai	0.491	-0.397	-0.370
	(2) Phitsanulok	0.774	-0.123	-0.468
	(3) Kamphaengphet	0.806	-0.517	-0.523
	(4) Nakhonsawan	0.798	-0.102	-0.561
Central	(5) Chainat	0.517	0.407	-0.502
	(6) Lopburi	0.804	0.004	-0.509
	(7) Suphan Buri	0.837	-0.019	-0.505
	(8) Kanchanaburi	0.850	-0.268	-0.465
Northeast	(9) Udonthani	0.574	-0.097	-0.310
	(10) Kalasin	0.642	-0.108	-0.358
	(11) Khon Kaen	0.706	0.307	-0.529
	(12) Nakhon Ratchasima	0.778	-0.212	-0.553
East	(13) Prachin Buri	0.857	0.303	-0.549
	(14) Sakaeo	0.825	0.175	-0.552
	(15) Chonburi	0.764	-0.289	-0.595

The correlation r-values of SEaI12 with yield above 0.7 are 11 out of 15 locations (Table 4). The three lowest r-values, i.e. Sukhothai, Chainat, and Udonthani with 0.49, 0.52, and 0.57 values, respectively, are the northern-most of the North, the Central, and the Northeast, respectively. However, these three areas are equipped with large scale irrigation projects, i.e. Sukhothai has the largest Groundwater Irrigation Project, Chainat is at the upstream of the Great Chao Prya Irrigation Project, and Udonthani has the Huay Luang Irrigation Project. Large scale irrigations can modulate the values of SEaI12 by adding more water on the land that can increase ETa, then the index. Most of irrigation water goes to rice paddies not much to the upland crops, therefore the sugarcane yield does not increase by much. The r-values of SEaI12 with Nino 3.4 below -0.5 are 10 out of 15 locations (Table 4). To this end, the SEaI12 index is proven to be an effective characterization of the agricultural drought for assessing the sugarcane yield in Thailand. In addition, Nino 3.4 is a fair indicator of SEaI12 for mainland Thailand.

3.3 Agricultural drought characterization of mainland Thailand

The SEaI12 time series was determined for all 15 locations from January 1990 to December 2020. The time series was used for specifying drought events and their features. Table 5 shows an example of agricultural drought characteristics for Khon Kaen during the three decades. The main characteristics are duration and deficit which are usually related.

Table 5 Example of drought characteristics of Khon Kaen location.

Event	Onset	Termination	Duration (month)	Severity	Deficit	Frequency per decade
1	1/5/1992	1/6/1994	26	38.33	12.33	2
2	1/11/1997	1/3/1999	17	23.59	6.59	
3	1/11/2004	1/11/2005	13	17.57	4.57	1
4	1/9/2015	1/4/2016	8	8.60	0.60	2
5	1/8/2019	1/5/2020	10	13.35	3.35	

For agricultural drought studied herein, we related deficit and duration from 15 locations during 1990 to 2020 and found linear relationship with R^2 of 0.91 (Figure 6). We decided therefore to assess only duration, instead of both, drought deficit can also be evaluated by a simple linear regression as,

$$s = 0.4694d - 1.1377 \quad (4)$$

where s = deficit and d = duration (month).

We illustrated the drought characterizations in two conditions, (i) spatial distribution of longest drought for the whole studied period; (ii) drought variations among the three decades.

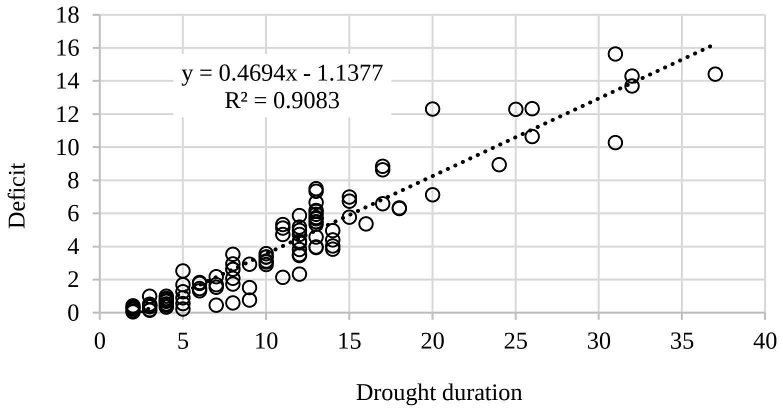


Figure 6 Drought duration and deficit relationship from 15 locations during 1990 to 2020.

3.3.1 Longest drought characterization

The longest drought duration values for each location are shown in Table 6 with their onsets, terminations, and deficit values. They are also mapped in Figure 7. The longest duration can be used as a guide for assessment of water supplementary infrastructure. All longest values in Table 6 indicate that the droughts in mainland Thailand are multiyear with the shortest of 14 months at Chonburi, southern-most (latitude 13.13°N) eastern region, and the largest 37 months at Sukhothai, northern-most (17.01°N) in northern region. The regional longest averages for the North, Central, Northeast, and East are 31.5, 23.5, 23.0, and 17.7, respectively, which indicates that the northern region has the largest water deficit while the eastern region has the least. The central and northeast regions are relatively moderate. Interestingly, the northern region is located at highest latitude while the eastern lies at lowest latitude. The longest drought durations of all regions occurred during the 1990s, except for the central region with one in 1990s, one in 2000s, and two in 2010s (Table 6). The agricultural drought phenomenon is relatively uniform over the mainland of Thailand except for the central region that is equipped with large irrigation projects.

Table 6 Maximum duration values with onset, termination, and deficit values.

Region	Province	Max Duration month/event	Onset	Termination	Deficit
North	(1) Sukhothai	37	1/6/1991	1/6/1994	14.41
	(2) Phitsanulok	32	1/11/1991	1/7/1994	14.29
	(3) Kamphaengphet	26	1/5/1992	1/6/1994	10.65
	(4) Nakhonsawan	31	1/11/1991	1/5/1994	15.64
Central	(5) Chainat	25	1/12/2014	1/12/2016	12.29
	(6) Lopburi	31	1/11/1991	1/5/1994	10.28
	(7) Suphan Buri	18	1/6/2019	1/10/2020	6.33
	(8) Kanchanaburi	20	1/3/2004	1/10/2005	12.31
Northeast	(9) Udonthani	32	1/11/1991	1/6/1994	13.70
	(10) Kalasin	17	1/12/1997	1/4/1999	8.85
	(11) Khon Kaen	26	1/5/1992	1/6/1994	12.33
	(12) Nakhon Ratchasima	17	1/11/1997	1/3/1999	8.62
East	(13) Prachin Buri	15	1/8/1997	1/10/1998	6.73
	(14) Sakaeo	24	1/5/1992	1/4/1994	8.94
	(15) Chonburi	14	1/12/1990	1/1/1992	4.03

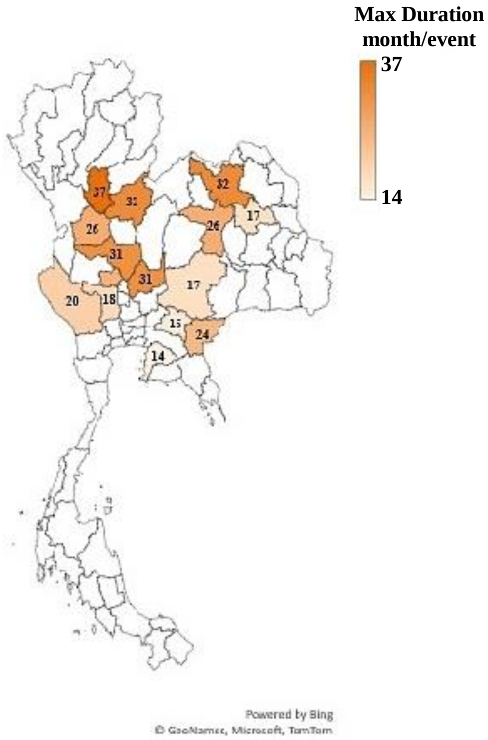


Figure 7 Longest drought durations of fifteen locations.

3.3.2 Drought variations among the three decades

Spatial accumulative durations over each decade are shown in Table 7 together with frequencies. Due to multiyear drought covering all parts of the country, a decade period was used as a temporal unit for frequency analysis. Mean duration values for all locations are 41.33, 12.47, and 20.73 months and mean frequency values are 3.4, 1.4, and 2.1 events/decade, for 1990s, 2000s, and 2010s, respectively. On average, the droughts during the decades of 1990s, 2000s, and 2010s were the most severe, the least, and the moderate which were agreeable with the Nino 3.4 distribution that being strong El Nino (decadal net value of Nino 3.4 being 6.85), strong La Nina (-5.38), and moderate El Nino (6.09), respectively (Figure 5(b)). The El Nino value of 6.09 for the 2010s decade, despite high, was considered moderate because its extreme El Nino during 2015/2016 was the result of central Pacific domination which is not as strong as the eastern Pacific one. This phenomenon was also observed in Central Vietnam [24].

Table 7 and Figure 8 show duration variations among regions of the three decades. The North illustrated very large values of duration during strong El Nino decade (1990s), very low values during La Nina (2000s), and moderate duration for moderate El Nino (2010s). The Central region showed a strange pattern that Chainat and Kanchanaburi both have low duration values in the strong El Nino and high duration in strong La Nina period. The Northeast and the East regions showed common patterns where the high values of duration were in the strong El Nino period and low values were in the strong La Nina period.

Table 7 shows reasonable results on frequency such that of all three decades the number of droughts is 1 to 4 events per decade. Almost all locations had 2 to 4 events in the strong El Nino period, 1 to 2 events for the strong La Nina decade, and 2 events during the moderate El Nino decade.

Table 7 Drought durations and frequencies of 15 locations in the decades of 1990s, 2000s, and 2010s.

Region	Province	Duration (month)			Frequency (event/decade)		
		1990s	2000s	2010s	1990s	2000s	2010s
North	(1) Sukhothai	51	3	23	3	1	2
	(2) Phitsanulok	50	2	23	4	1	2
	(3) Kamphaengphet	44	4	27	4	2	2
	(4) Nakhonsawan	46	5	25	4	1	2
Central	(5) Chainat	14	24	37	2	2	2
	(6) Lopburi	46	15	16	3	1	2
	(7) Suphan Buri	42	1	21	4	1	2
	(8) Kanchanaburi	26	31	20	4	3	2
Northeast	(9) Udonthani	45	23	8	2	2	3
	(10) Kalasin	44	14	16	4	2	2
	(11) Khon Kaen	43	13	18	2	1	2
	(12) Nakhon Ratchasima	35	13	25	4	1	2
East	(13) Prachin Buri	48	13	13	4	1	1
	(14) Sakaeo	41	13	19	3	1	2
	(15) Chonburi	45	13	18	4	1	3
	mean	**41.33**	**12.47**	**20.60**	**3.40**	**1.40**	**2.07**

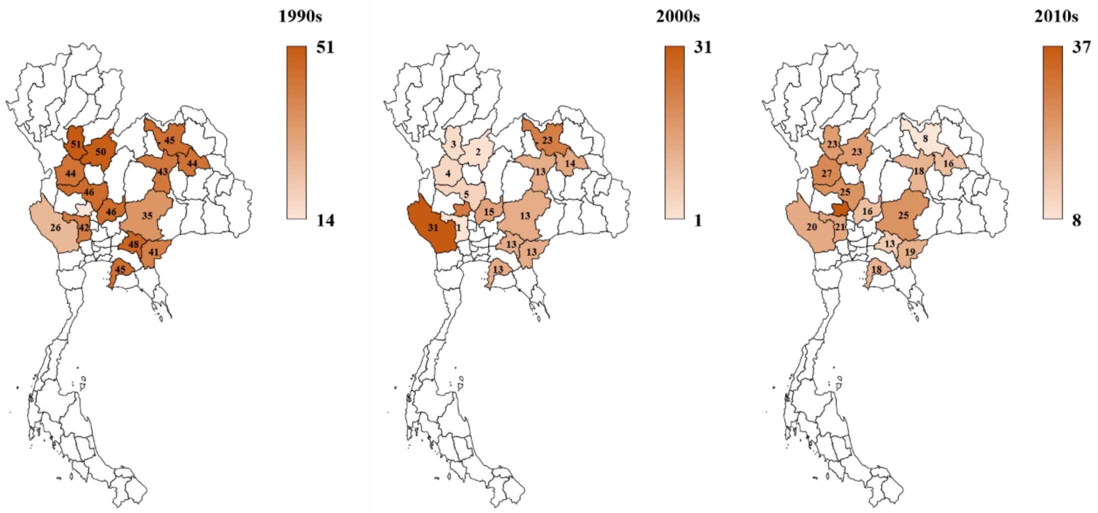


Figure 8 Drought durations covering sugarcane cultivation area, (a) 1990s, (b) 2000s, and (c) 2010s.

Sugarcane in Thailand is a one-year crop on average from the beginning of the year to the end. Traditionally, farming areas in Thailand have a farm pond or at least a shallow well that is reasonable proportional to farm size. These ponds can modulate drought impacts especially for a long-standing crop like sugarcane by providing appropriate deficit irrigation [17]. There are bad, good, and normal years which farmers will face. Even within a single year, a few drought and wet periods can occur alternately, therefore farm ponds together with drought characterization knowledge can help to buffer sugarcane drought impact. In bad years the northern farmers will experience very serious drought while those in other regions will experience minder events. Those in two locations, Chainat and Kanchanaburi, in the central region will likely be the least affected. In good years, all areas are in good shape, especially in the north. In a normal year, all areas are similarly moderate, and it is a year to put more effort into sugarcane farms to raise their productivity. The findings suggest that farm ponds in the North should be larger than those in other regions for the same soil texture of sugarcane farming areas. The details of farm pond design for crop supplementary in Thailand is in Prabnakorn [8] which suggests that a nominal size is about 3000 m^3/ha.

4. Conclusions

The characterization of agricultural drought in mainland Thailand for sugarcane water management was done based solely on an indicator, actual evapotranspiration (ETa), which was calculated from meteorological data for 15 locations in four regions during three decades from 1990 to 2020. This study derived the standardized ETa index of 12-month timescale (SEaI12) then applied the theory of runs to quantify drought events. Both SEaI12 and theory of runs were carefully performed in detail to accomplish high accuracy. The correlation coefficients of SEaI12 with sugarcane yield, CCS, and Nino 3.4 were very good, poor, and fair, respectively, therefore CCS was not further explored. Of the three drought characteristics i.e. duration, deficit, and frequency, the deficit variable was excluded due to the closed duration-deficit relationship. The drought characterizations were performed in two conditions, (i) the spatial distribution of the longest droughts, (ii) comparisons of the frequencies and spatial distributions of durations among the three decades which were extreme El Nino, La Nina, and moderate El Nino climates, respectively. For the first condition, we learned that the longest durations mostly occurred in the extreme El Nino decade except two in moderate El Nino decade and one in La Nina decade. The strength of the drought maxima was highest in the northern-most and decreasing toward the South. The second condition revealed that (i) the northern region illustrated longest duration during the extreme El Nino decade then shortest duration during the La Nina decade, (ii) the central region showed contradictory duration pattern, (iii) the Northeast and the East demonstrated a uniform pattern of high durations in El Nino decade and low in La Nina decade, and (iv) the drought frequencies were 2-4, 2-3, and 1-2 events/decade for the extreme El Nino, moderate El Nino, and La Nina decade, respectively. The overall results suggest that larger supplementary water storages are needed for higher latitude regions. The 3000 m^3/ha storage was suggested in literature for other crops [8], and this can be a starting point for further research on sugarcane farming development.

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6. References

[1] Doner RF, Ramsay A. Growing into trouble: institutions and politics in the Thai sugar industry. J East Asian Stud. 2004;4(1):97-138.
[2] Manivong P, Bourgois E. Thai sugarcane sector and sustainability. Bangkok: FairAgora Asia; 2017.
[3] Khumla N, Sakuanrungsirikul S, Punpee P, Hamarn T, Chaisan T, Soulard L, et al. Sugarcane breeding, germplasm development and supporting genetics research in Thailand. Sugar Tech. 2022;24(1):193-209.
[4] Ha TV, Uereyen S, Kuenzer C. Agricultural drought conditions over mainland Southeast Asia: spatiotemporal characteristics revealed from MODIS-based vegetation time-series. Int J Appl Earth Obs Geoinf. 2023;121:103378.

[5] Tanguy M, Eastman M, Magee E, Barker LJ, Chitson T, Ekkawatpanit C, et al. Indicator-to-impact links to help improve agricultural drought preparedness in Thailand. Nat Hazards Earth Syst Sci. 2023;23(7):2419-41.

[6] Khadka D, Babel MS, Shrestha S, Virdis SGP, Collins M. Multivariate and multi-temporal analysis of meteorological drought in the northeast of Thailand. Weather Clim Extrem. 2021;34:100399.

[7] Pandey S, Bhandari H, Ding S, Prapertchob P, Sharan R, Naik D, et al. Coping with drought in rice farming in Asia: insights from a cross-country comparative study. Agric Econ. 2007;37:213-24.

[8] Prabnakorn S, Ruangpan L, Tangdamrongsub N, Suryadi FX, de Fraiture C. Improving flood and drought management in agricultural river basins: an application to the Mun River Basin in Thailand. Water Policy. 2021;23(5):1153-69.

[9] Wongkhunkaew P, Konyai S, Sriboonlue V. National yield reference for sugarcane management: Thailand case study. Asia Pac J Sci Technol. 2024;29(5):1-9.

[10] Tippayawat A, Jogloy S, Vorasoot N, Songsri P, Kimbeng CA, Jifon JL, et al. Differential physiological responses to different drought durations among a diverse set of sugarcane genotypes. Agronomy. 2023;13(10):2594.

[11] Bloomberg News. Drought to cut sugar output by almost 20%. Bangkok Post [Internet]. 2023 Sep 7 [cited 2024 Sep 15]. Available from: https://www.bangkokpost.com/business/general/2643205/drought-to-cut-sugar-output-by-almost-20-.

[12] Liu C, Yang C, Yang Q, Wang J. Spatiotemporal drought analysis by the standardized precipitation index (SPI) and standardized precipitation evapotranspiration index (SPEI) in Sichuan Province, China. Sci Rep. 2021;11(1):1280.

[13] Homdee T, Pongput K, Kanae S. A comparative performance analysis of three standardized climatic drought indices in the Chi River basin, Thailand. Agric Nat Resour. 2016;50(3):211-9.

[14] Łabędzki L, Kanecka-Geszke E. Standardized evapotranspiration as an agricultural drought index. Irrig Drain. 2009;58(5):607-16.

[15] Kim D, Rhee J. A drought index based on actual evapotranspiration from the Bouchet hypothesis. Geophys Res Lett. 2016;43(19):10277-85.

[16] Jarumaneeroj P, Laosareewatthanakul N, Akkerman R. A multi-objective approach to sugarcane harvest planning in Thailand: balancing output maximization, grower equity, and supply chain efficiency. Comput Ind Eng. 2021;154:107129.

[17] Dingre SK, Gorantiwar SD. Soil moisture based deficit irrigation management for sugarcane (*Saccharum officinarum* L.) in semiarid environment. Agric Water Manag. 2021;245:106549.

[18] Li M, Yang Y, Wang P, Ji D, Liao H. Impacts of strong El Niño on summertime near-surface ozone over China. Atmos Ocean Sci Lett. 2022;15(4):100193.

[19] Guo D, Westra S, Maier HR. An R package for modelling actual, potential and reference evapotranspiration. Environ Model Softw. 2016;78:216-24.

[20] Ohba K, Ponsana P. Evapotranspiration in the Northeast District of Thailand as estimated by Morton method. J Agric Meteorol. 1987;42(4):329-36.

[21] Chaibandit K, Srison W, Muangthong S. Assessment actual evapotranspiration with R program. E3S Web Conf. 2020;187:06001.

[22] AghaKouchak A. A baseline probabilistic drought forecasting framework using standardized soil moisture index: application to the 2012 United States drought. Hydrol Earth Syst Sci. 2014;18:2485-92.

[23] Makkonen L, Pajari M, Tikanmaki M. Discussion on "Plotting positions for fitting distributions and extreme value analysis". Canadian J Civ Eng. 2013;40(9):927-9.

[24] Wu R, Zhang J, Bao Y, Guo E. Run theory and copula-based drought risk analysis for Songnen grassland in Northeastern China. Sustainability. 2019;11(21):6032.

[25] McKee TB, Doesken NJ, Kleist J. The relationship of drought frequency and duration to time scales. The 8th Conference on Applied Climatology; 1993 Jan 17-22; Anaheim, United States. p. 179-84.

[26] Van Loon AF. Hydrological drought explained. WIREs Water. 2015;2(4):359-92.

[27] Moccia B, Mineo C, Ridolfi E, Russo F, Napolitano F. SPI-based drought classification in Italy: influence of different probability distribution functions. Water. 2022;14(22):3668.

[28] Dong J, Akbar R, Short Gianotti DJ, Feldman AF, Crow WT, Entekhabi D. Can surface soil moisture information identify evapotranspiration regime transitions?. Geophys Res Lett. 2022;49(7):e2021GL097697.

[29] Hsu H, Dirmeyer PA. Soil moisture-evaporation coupling shifts into new gears under increasing CO_2. Nat Commun. 2023;14(1):1162.

[30] Watanabe K, Thienyaem T, Poniyom K, Saensupo S, Sriroth K, Jaiphong T. Effects of fertilizer application depth on the above- and belowground growth of sugarcane under different water regimes and machinery performance. Sugar Tech. 2023;25(5):1092-101.