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Analysis of Spatial and Temporal Patterns of Meteorological Drought Exposure and Its Impact on Economic Crops, Nakhon Ratchasima Province, Thailand

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Abstract

Background and Objectives: Drought is one of the most complex influencing factors among all-natural disasters. It is a complex phenomenon because of the unpredictable start and end of its period, the length of the event, as well as the nonspecific spatial extent or geography and uncertain frequency and intensity. Meanwhile, meteorological drought is usually defined based on the degree of dryness and the duration of the dry period. Nakhon Ratchasima province is a drought-prone area since the annual rainfall between 1975 and 2022 was mostly lower than the average annual rainfall in the same period, with a value of 1,223.59 mm for about 24 years. Therefore, this study aims to examine spatial and temporal patterns of meteorological drought exposure and its impact on economic crops in Nakhon Ratchasima province. The objectives of the study were (1) to classify and map meteorological drought frequency, intensity and exposure and (2) to analyze spatial and temporal patterns of meteorological drought exposure and its impact on economic crops. Herein

Methodology: The research methodology comprised four main steps after the Standardized Precipitation Index calculation in 4 periods, including 3m7 (May to July), 3m10 (August to October), 6m10 (May to October), and 12m (January to December): (1) meteorological drought frequency index extraction and classification, (2) meteorological drought intensity index extraction and classification, (3) meteorological drought exposure index extraction and classification, and (4) spatial and temporal patterns analysis of meteorological drought exposure and its impact on economic crops: rice, cassava, sugarcane and corn. Herein, three meteorological drought indices, meteorological drought frequency, meteorological drought intensity, and meteorological drought exposure, were calculated based on a long-term rainfall record (1975-2022) from 37 stations. In the meantime, spatial and temporal patterns of meteorological drought exposure at district and sub-district levels using zonal analysis with majority operation.

Main Results: The most dominant class of meteorological drought exposure classification of the 4 periods (3m7, 3m10, 6m10 and 12m) was a moderate, moderate, moderate, and low covered area of about 33.22%, 35.26%, 42.11% and 35.69%, respectively. The spatial distribution of the meteorological drought exposure classification of the 4 periods displayed a completely different pattern. Still, the meteorological drought exposure severity classification of the 4 periods showed a strong positive linear relationship among them. The correlation coefficient values varied from 0.8100 to 0.8966. These results imply the similarity of meteorological drought exposure patterns among 4 periods. Besides, the majority severity classification of the meteorological drought exposure in the 6m10 period exhibited the highest impacts at district and sub-district levels, with 16 districts and 138 sub-districts. Based on the spatial pattern changes of meteorological drought exposure severity levels among 3-periods (3m7, 3m10 and 6m10), covering the economic crop calendar, the severity classification of the meteorological drought exposure in the 6m10 period exposed the highest meteorological drought compared with other periods (3m7 and 3m10). In the meantime, the potential impact areas of meteorological drought exposure in the 6m10 period (May to October) at moderate, high, and very high severity levels on rice in 2023 was about 3,939.40 sq. km 64.65% of the total area of rice, cassava about 2,918.67 sq. km 75.74% of the total area of cassava, sugarcane, about 1,423.47 sq. km or 69.48% of the total area of sugarcane, and corn, about 441.33 sq. km or 56.38% of the total area of corn. Furthermore, based on Pearson bivariate correlation analysis, the most dominant meteorological drought exposure index that impacts crop yield is the meteorological drought exposure index in the 3m7 period (May to July). This index displayed a negative linear relationship with the average rice, cassava and corn yield between 2011 and 2022. On the contrary, the meteorological drought exposure index showed no linear relationship with sugarcane since a multi-cropping system of about three years is applied for sugarcane by farmers.

Conclusions: Spatial and temporal patterns analysis of meteorological drought exposure were successfully conducted based on a standardized precipitation index for quantifying the severity of drought and its impact on economic crops in different periods (3m7, 3m10, 6m10 and 12m). The presented research workflow can be used as a guideline for the relevant government agencies, such as the Department of Agricultural Extension and the Department of Disaster Prevention and Mitigation, to monitor meteorological drought for mitigation of the potential impact of drought on economic crops in the future. In addition, early warning systems of meteorological drought at the regional level are recommended to be implemented by the Thai Meteorological Department.

Keywords: Meteorological drought exposure; Spatial and temporal patterns of meteorological drought; Impact of drought on crops

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Introduction

Drought is one of the most complex influencing factors among all-natural disasters. However, it is the least understood by humans and difficult to detect (Wilhite, 2000; Lawal *et al.,* 2021). Wilhite *et al.* (2006) defined drought as a severe moisture deficit below expected levels that restricts some activity. It does not have straightforward entry, duration and termination points compared to floods, fires and storms. There are random properties of drought that do not lend themselves to standard analysis (Gordon, 1992). Park *et al.* (2016) stated that drought is a slow-developing event, and it is hard to define its spatial extent and temporal starting and ending point. Its severity typically depends on duration, intensity, spatial extent, and local socioeconomic conditions (Son *et al.,* 2012). No single indicator can fully explain the complexity and diversity of drought because it usually has multiple factors as a cause. Wilhite & Glantz (1985) categorized the definitions into four basic approaches to measuring drought: meteorological, hydrological, agricultural, and socioeconomic.

Meteorological drought is usually defined based on the degree of dryness (compared to some "normal" or average amount) and the duration of the dry period. Definitions of meteorological drought must be considered region-specific since the atmospheric conditions resulting in precipitation deficiencies are highly variable from region to region. This approach deals with the way to measure drought as a physical phenomenon for monitoring drought. (National Drought Mitigation Center, University of Nebraska, 2024). Currently, the U.S. Drought Monitor System was implemented jointly by the National Drought Mitigation Center at the University of Nebraska-Lincoln, the National Oceanic and Atmospheric Administration and the US Department of Agriculture. (U.S. Drought Monitor, 2025). So, meteorological drought, which reflects phenomena quickly, is chosen to examine drought spatial and temporal patterns in four different periods: 3m7 (May to July), 3m10 (August to October), 6m10 (May to October), as a short-term period and 12m (January to December) as a long-term period using the Standardized Precipitation Index (SPI) in Nakhon Ratchasima province based on rainfall records from 1975 to 2022. The expected results will provide spatiotemporal meteorological drought exposure in the area in a specific period instead of in situ reports by government officers. Besides, the applied method can be further used by the relevant government agencies to monitor and mitigate drought in the area.

The SPI was developed by McKee *et al.* (1993) at Colorado State University, United States and was first presented at the 8th Conference on Applied Climatology, held in January 1993. The basis of the index is that it builds upon the relationships of drought to frequency, duration and timescales (Svoboda *et al.,* 2016). WMO (2012) recommended SPI as the main meteorological drought index that countries should use to monitor and follow drought conditions. Many researchers applied SPI to determine meteorological drought conditions in many countries, such as Patel *et al.,* 2007; Nosrati & Zareiee, 2011; Wichitarapongsakun *et al.,* 2016; Zhou & Liu, 2016; Wambua *et al.,* 2018; Yilmaz, B. 2018; Caloiero & Veltri, 2019; Kornkosa *et al.,* 2021; Promping & Tingsanchali. 2021; Mehr *et al.,* 2020; Pandhumas *et al.,* 2020; Karimi *et al.,* 2022; Mohammed *et al.,* 2022; Pande *et al.,* 2022; Omar *et al.,* 2023; He *et al.,* 2023; Nimisha & Arunkumar, 2023.

Nakhon Ratchasima province is Thailand's largest province, located in the middle of the country and far from the coastal zone. The influence of rain from the Indian Ocean and typhoons from the Pacific Ocean leads to less rainfall in the area. According to rainfall records between 1975 and 2022 from 37 stations in Nakhon Ratchasima province and its surroundings, it was found that the annual rainfall between 1975 and 2022 was lower than the average annual rainfall in the same period, with a value of 1,223.59 mm for about 24 years. This finding indicates that Nakhon Ratchasima province is a drought-prone area. Along with the recent report of USDA Foreign Agricultural Service by Prasertsri (2020), the severe drought in Thailand in 2020 caused losses in agricultural production estimated at approximately 26 billion Thai Baht (US $840 million), mainly due to reduced MY2019/20 off-season rice production. The drought is also expected to affect off-season field crops, fruit trees, and freshwater fish farming production, but to a much lesser degree than rice.

Therefore, this study aims to examine spatial and temporal patterns of meteorological drought exposure and its impact on economic crops in Nakhon Ratchasima province. The specific objectives of the study are (1) to classify and map meteorological drought frequency, intensity and exposure and (2) to analyze spatial and temporal patterns of meteorological drought exposure and its impact on economic crops.

Methodology

1. Study Area

1.1 Location

The study area is Nakhon Ratchasima province, situated in the Khorat plateau between longitudes 101 degrees 10.8 minutes east and 103 degrees 0.77 minutes east and between latitude 14 degrees 7.2 minutes north and 1 degree 48.6 minutes north (Office of Agricultural Economics, 2010). Nakhon Ratchasima province covers an area of about 20,729 sq. km and has 288 sub-districts in 32 districts (Figure 1).

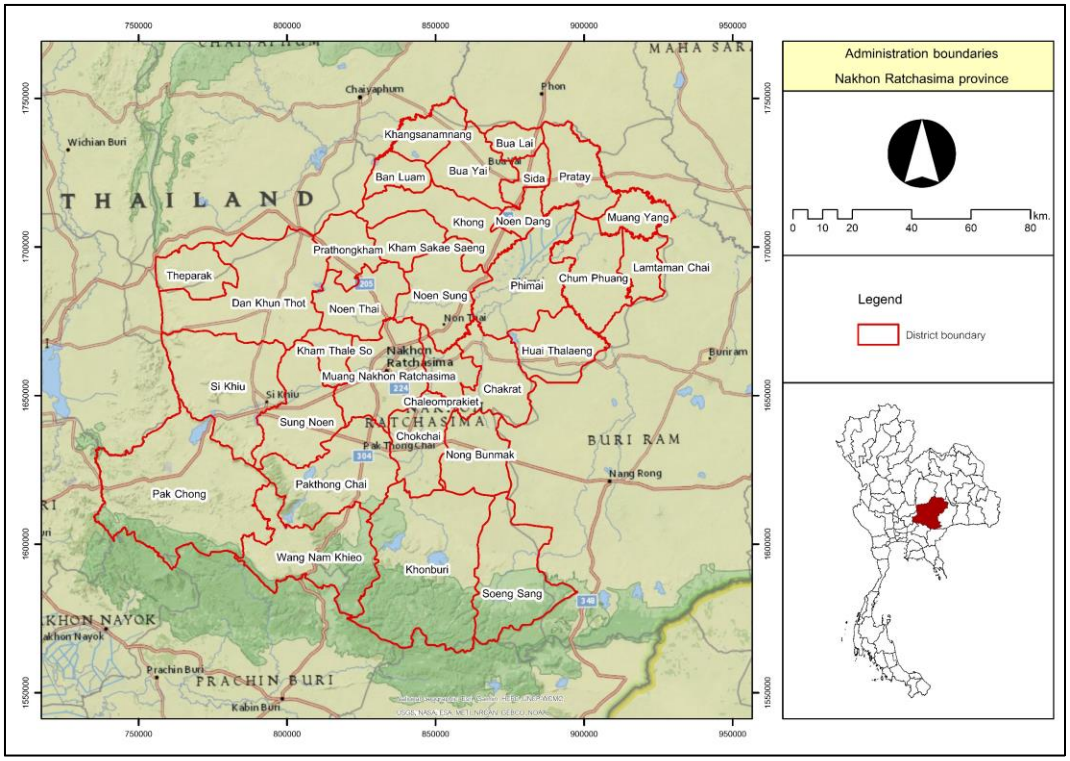


Figure 1 Location and administration boundaries of the study area

1.2 Topography

According to STRM DEM data, elevation in the study area varies between 86 m and 1,352 m above mean sea level. Meanwhile, prominent landforms, which are classified based on the percent of slope (LDD, 2009), include (a) flat or almost flat (19.63%), (b) slightly undulating (46.03%), (c) undulating (23.78%), (d) rolling (4.74%), (e) hilly (3.80%), and (f) steep (2.02%). The dominant landforms are slightly undulating to undulating.

1.3 Climate

There are three seasons in Nakhon Ratchasima: hot season (mid-February to mid-May), rainy season (mid-May to mid-October) and cool, dry season (mid-October to mid-February). In the study area, the annual mean temperature is 27.7 degrees Celsius, the annual mean maximum temperature is 33.2 degrees Celsius, and the annual mean minimum temperature is 23.2 degrees Celsius. The annual rainfall is 1,120 mm, and the annual rainy day is 116 days (Climate Data, 2023).

2. Data

The required input data for spatial and temporal patterns of meteorological drought exposure and its impact on economic crops are (1) long-term rainfall records from 37 meteorological stations in the study area and its surroundings between 1975 and 2022, (2) land use data in 2023 from the Land Development Department, and (3) administrative boundary at district and sub-district levels of Nakhon Ratchasima province.

3. Methodology

The workflow of the research methodology, composed of four main steps after SPI calculation, including meteorological drought frequency classification, meteorological drought intensity classification, meteorological drought exposure classification, and spatial and temporal patterns of meteorological drought exposure and its impact on economic crops, is displayed in Figure 2.

3.1 Meteorological drought frequency classification

Step 1. Monthly rainfall data records between 1975 and 2022 from 37 stations were used to calculate SPI (McKee *et al.,* 1993) by SPI Generator software developed by the National Drought Mitigation Center - UNL. McKee *et al.* (1993) developed the SPI to quantify the precipitation deficit for multiple periods, which reflected the impact of precipitation deficiency on the availability of the different water suppliers. The basis of the index is built upon the relationships of drought to frequency, duration and periods (Svoboda *et al.,* 2016). In this study, 4 periods of SPI: 3m7 (May to July), 3m10 (August to October), 6m10 (May to October), as a short-term period and 12m (January to December) as a long-term period, which covers crop calendar of economic crops in the study area, in-season rice, cassava, sugarcane and corn, were calculated for MDF classification. Mathematically, SPI for period i is calculated as:

$$SPI_i = (X_i - X_{mean})/\sigma \quad (1)$$

where, X_i is standardized rainfall of station for period i; X_{mean} and σ is the long-term mean and standard deviation of standardized rainfall for the same period.

Step 2. The classified SPI values of 4 periods, 3m7, 3m10, 6m10, and 12m, were categorized into four drought severity levels: near normal drought (NND), moderate drought (MD), severe drought (SD) and extreme drought (ED) as suggested by McKee *et al.* (1993). See Table 1. In the meantime, the probability of drought occurrence of four drought severity (NND, MD, SD, and ED) of each period at each meteorological station was calculated by taking the ratio of drought occurrences in each period to the total drought occurrences in the same period and drought category (Sönmez *et al*., 2005).

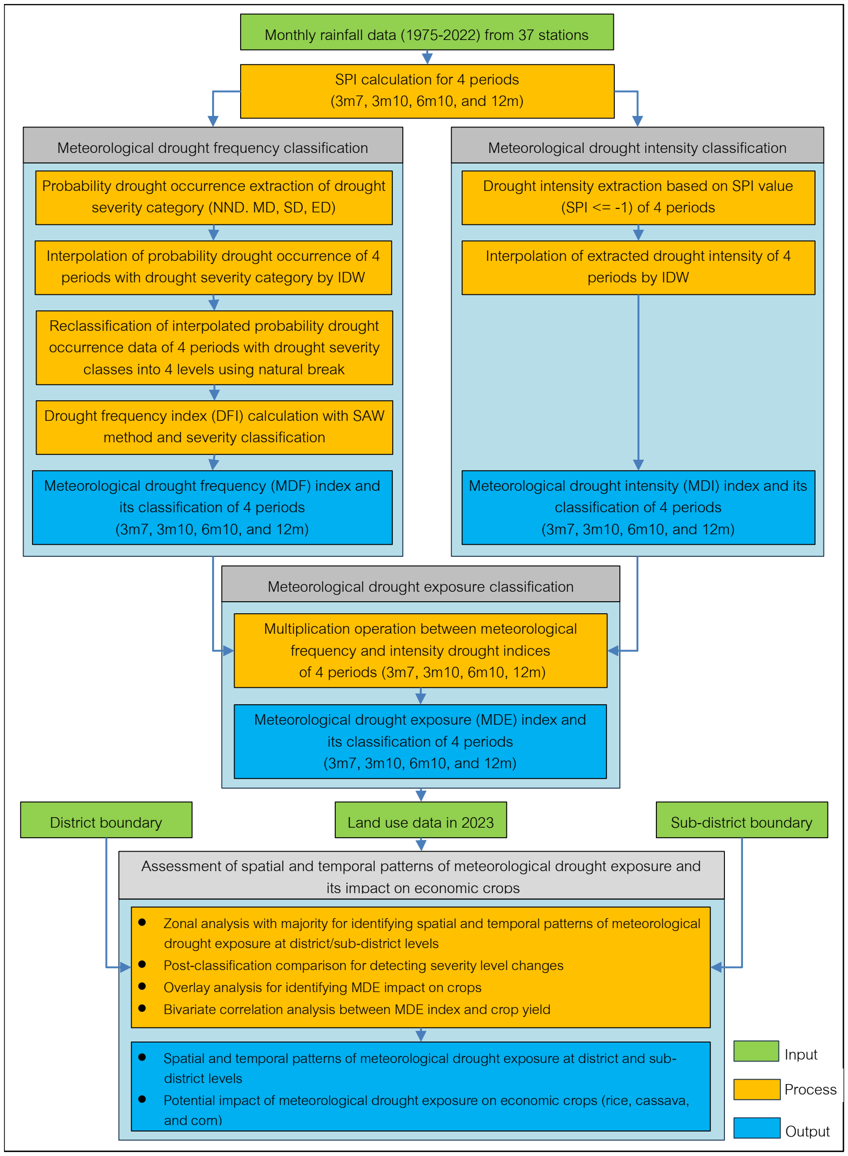


Figure 2 Workflow of research methodology

Table 1 Drought classification based on SPI and its weight

Drought severity category	SPI value	Probability of occurrence (%)	Weight
Near-normal drought (NND)	0 to -0.99	34.1	1
Moderate drought (MD)	-1.00 to -1.49	9.2	2
Severe drought (SD)	-1.50 to -1.99	4.4	3
Extreme drought (ED)	-2.00 and less	2.3	4

Source : McKee *et al.*, 1993

Step 3. The probability of drought occurrence of each period with four drought severity (NND, MD, SD, and ED) at each meteorological station of 37 stations were interpolated separately to create continuous surface data using the IDW method as suggested by Tadesse *et al.* (2010). The output data are the drought occurrence probability of 4 periods for each drought severity category.

Step 4. The interpolated probability of drought occurrence of each period for each drought severity class (NND, MD, SD, and ED) was reclassified into four levels: low, moderate, high, and very high, using the natural break method and assigned rating of each level with a value of 1, 2, 3, and 4, respectively.

Step 5. The MDF index of each period with drought severity category was separately integrated using Simple Additive Weighting (SAW) (Kaliszewski & Podkopaev, 2016) in accordance with assigned weight and rate:

$$MDFI_{Met} = (NND_r \times NND_w) + (MD_r \times MD_w) + (SD_r \times SD_w) + (ED_r \times ED_w) \qquad (2)$$

Where $MDFI_{Met}$ is the meteorological drought frequency index of a specific period,
NND_r is the rating of near-normal drought (NND) occurrence,
NND_w is the weight of near-normal drought (NND) occurrence,
MD_r is rating of moderate drought (MD) occurrence,
MD_w is the weight of moderate drought (MD) occurrence,
SD_r is the rating of severe drought (SD) occurrence,
SD_w is the weight of severe drought (SD) occurrence,
ED_r is the rating of extreme drought (ED) occurrence,
ED_w is the weight of extreme drought (ED) occurrence,

After that, the MDF index of each period was reclassified into five severity scales: very low, low, moderate, high and very high, using the natural break method.

3.2 Meteorological drought intensity classification

Step 1. The meteorological drought intensity of each period at each meteorological station was extracted based on SPI values less than or equal to -1 (Sehgal & Dhakar, 2016).

Step 2. The extracted MDI of each period at each meteorological station of 37 stations was interpolated separately to create the MDI index using the IDW method suggested by Tadesse *et al.* (2010).

After that, the MDI index of each period was reclassified into five severity scales: very low, low, moderate, high and very high, using the natural break method.

3.3 Meteorological drought exposure classification

The MDE index is created by combining the MDF and MDI indices of 4 periods using a multiplication operation. Later, each period of the MDE index was reclassified into five severity scales: very low, low, moderate, high and very high, using the natural break method.

3.4 Spatial and temporal patterns of meteorological drought exposure and its impact on economic crops

Step 1. The MDE classification was used to assess spatial and temporal patterns of MDE in 4 periods at district and sub-district levels using zonal analysis with majority operation under a GIS environment.

Step 2. The spatial pattern changes of MDE severity levels of 3m7, 3m10 and 6m10 periods, which cover the economic crop calendar, were examined to detect from-to change with increasing, decreasing and unchanging severity levels among periods using a post-classification comparison algorithm (Jensen, 2015).

Step 3. The potential impact areas of MDE of 4 periods on economic crops (rice, cassava, sugarcane, and corn) were assessed based on land use data in 2023 of LDD using overlay analysis under a GIS environment.

Step 4. Pearson bivariate correlation analysis was applied to characterize the linear relationship between the MDE index of 4 periods and economic crop yields between 2011 and 2023 of the Nakhon Ratchasima Provincial Agriculture and Cooperatives Office. Herein, the centroid of each sub-district polygon was created to extract the MDE index value, and they were used to analyze the correlation with the average yield of each economic crop. Their values were normalized using Equation 3 since these values have different units (Malczewski, 2000).

$$X' = \frac{(\mathrm{X}\text{-}\mathrm{X_{min}})}{(\mathrm{X_{max}}\text{-}\mathrm{X_{min}})} \qquad (3)$$

Where X' is the normalized value; X is the original value; $\mathrm{X_{min}}$ is the minimum value, and $\mathrm{X_{max}}$ is the maximum value.

Results

<u>*1. Meteorological drought occurrence probability of 4 periods of SPI*</u>

Results of meteorological drought occurrence probability of 4 periods of 4 drought severity categories (NND, MD, SD and ED) with rating scores are summarized in Table 2. Classification of meteorological drought occurrence probability with four levels (low, moderate, high, and very high) of 4 periods under the drought severity category (NND, MD, SD, and ED) is reported in Table 3. The calculated meteorological drought occurrence probability relies on the rainfall records between 1975 and 2022 from 37 stations.

2. Meteorological drought frequency classification

The result of the meteorological drought frequency (MDF) index of 4 periods, which was created separately by integrating four drought occurrence probability classifications (NDD, MD, SD, and ED) with its rating and weight using SAW operation, is displayed in Figure 3(a) to Figure 3(d). The classification of MDF with five severity levels is presented in Figure 3(e) to Figure 3(h). The percentage of MDF classification of 4 periods is reported in Table 4.

3. Meteorological drought intensity classification

The results of the meteorological drought intensity (MDI) index of 4 periods are displayed in Figures 4(a) to 4(d). Meanwhile, the classification of MDI with five severity levels is presented in Figures 4(e) to 4(h). The area of MDI classification of 4 periods is reported in Table 5.

4. Meteorological drought exposure classification

The result of the meteorological drought exposure (MDE) index and its classification of 4 periods is displayed in Figure 5. The area of MDE classification of 4 periods is reported in Table 6.

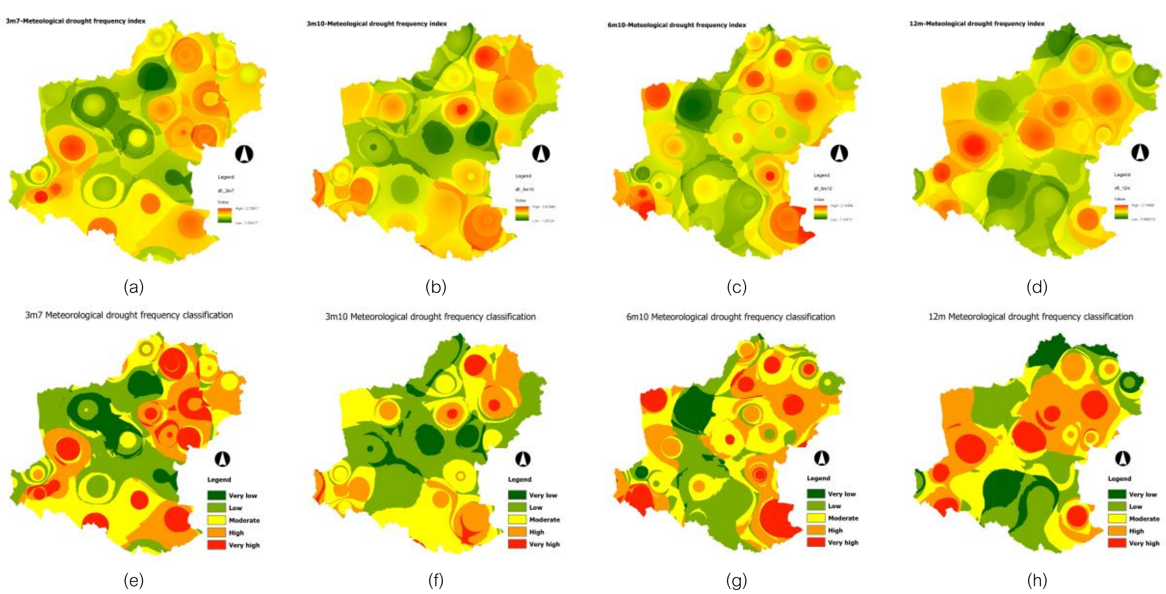


Figure 3 Spatial distribution of meteorological drought frequency index and its classification: (a) 3m7, (b) 3m10, (c) 6m10, (d) 12m, (e) 3m7, (f) 3m10, (g) 6m10, and (h) 12m, respectively.

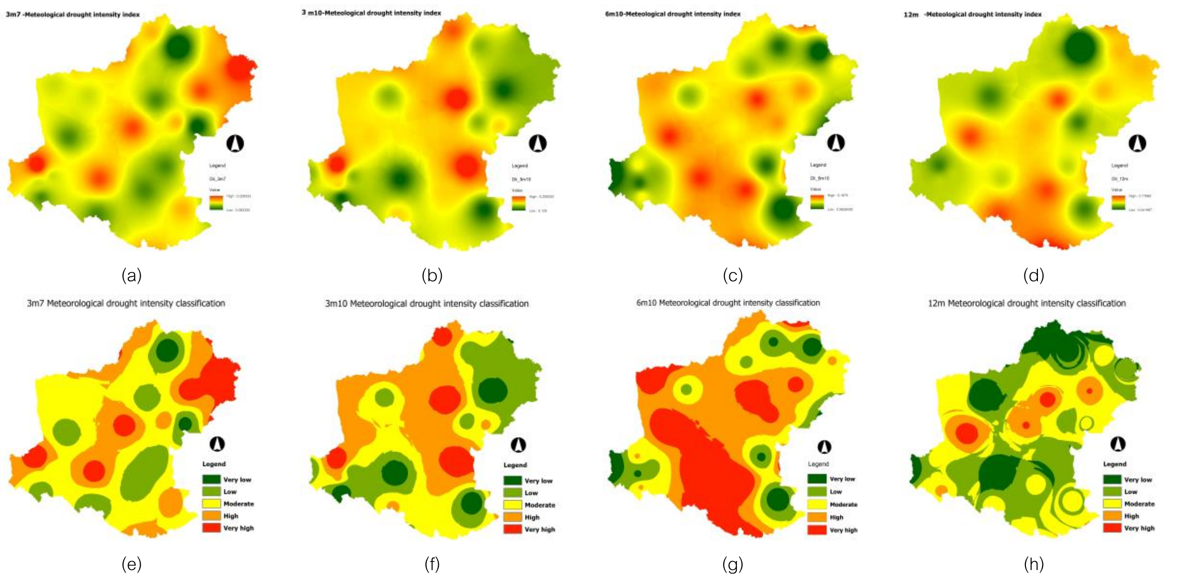


Figure 4 Spatial distribution of meteorological drought intensity index and its classification: (a) 3m7, (b) 3m10, (c) 6m10, (d) 12m, (e) 3m7, (f) 3m10, (g) 6m10, and (h) 12m, respectively.

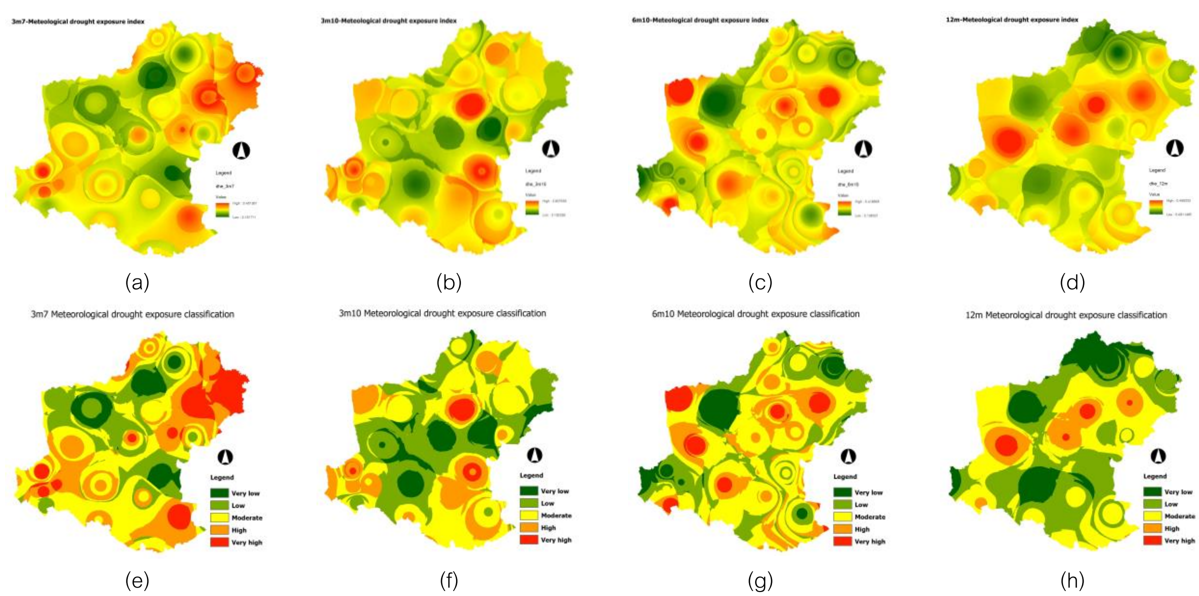


Figure 5 Spatial distribution of meteorological exposure index and its classification of 4 periods: (a) 3m7 (May - July), (b) 3m10 (August- October), (c) 6m10 (May - October), (d) 12m (January - December), (e) 3m7 (May - July), (f) 3m10 (August- October), (g) 6m10 (May - October) and (h) 12m (January - December), respectively.

Table 2 Drought occurrence probability of 4 periods and its rating by each drought severity category

	Drought occurrence probability				Rating
	3m7 (May-June)	3m10 (July-Oct)	6m10 (May-Oct)	12m (Jan-Dec)	
Severity level	Near normal drought (NND)				
Low	0.25 - 0.3235	0.2292 - 0.2937	0.25 - 0.3201	0.2774 - 0.3509	1
Moderate	0.3235 - 0.3578	0.2937 - 0.3297	0.3201 - 0.3507	0.3509 - 0.3843	2
High	0.3578 - 0.3961	0.3297 - 0.3607	0.3507 - 0.3893	0.3843 - 0.4244	3
Very high	0.3961 - 0.5	0.3607 - 0.4375	0.3893 - 0.4792	0.4244 - 0.5208	4
Severity Level	Moderate drought (MD)				
Low	0.0208 - 0.06	0.0417 - 0.0768	0.0208 - 0.0556	0.0208 - 0.0515	1
Moderate	0.06 - 0.0801	0.0768 - 0.0919	0.0556 - 0.0757	0.0515 - 0.0698	2
High	0.0801 - 0.1027	0.0919 - 0.1099	0.0757 - 0.0939	0.0698 - 0.0881	3
Very high	0.1027 - 0.1458	0.1099 - 0.1458	0.0939 - 0.1458	0.0881 - 0.1294	4
Severity Level	Severe drought (SD)				
Low	0 - 0.0324	0 - 0.0234	0 - 0.0261	0.0208 - 0.0355	1
Moderate	0.0324 - 0.0495	0.0234 - 0.0365	0.0261 - 0.0376	0.0355 - 0.0478	2
High	0.0495 - 0.0721	0.0365 - 0.0468	0.0376 - 0.0497	0.0478 - 0.0625	3
Very high	0.0721 - 0.125	0.0468 - 0.0656	0.0497 - 0.0833	0.0625 - 0.0833	4
Severity Level	Extreme drought (ED)				
Low	0 - 0.0169	0 - 0.0184	0 - 0.0176	0 - 0.0179	1
Moderate	0.0169 - 0.0284	0.0184 - 0.0304	0.0176 - 0.0294	0.0179 - 0.0299	2
High	0.0284 - 0.0417	0.0304 - 0.0429	0.0294 - 0.043	0.0299 - 0.0426	3
Very high	0.0417 - 0.0625	0.0429 - 0.0625	0.043 - 0.0722	0.0426 - 0.0625	4

5. Spatial and temporal patterns of meteorological drought exposure

The spatial and temporal patterns of the MDE severity of 4 periods at district and sub-district levels, using zonal analysis with a majority, are displayed in Figure 6. The number of district and sub-district levels with severity levels of MDE in 4 periods are reported in Table 7.

Furthermore, the spatial pattern changes of MDE severity levels among 3 periods (3m7, 3m10 and 6m10), covering the economic crop calendar, are displayed in Figure 7. Meanwhile, the area of from-to-change among MDE severity of the 3 periods is reported in Table 8 and displayed in Figure 8.

6. Potential impact areas of meteorological drought exposure on economic crops

The potential impact area of MDE in different periods on economic crops in 2023, rice, cassava, sugarcane and corn, using overlay analysis are reported in Table 9. The result of the potential impact area of MDE on crops relies on land use data in 2023.

Table 3 Area of meteorological drought occurrence probability under drought severity category in 4 periods

	Area of meteorological drought occurrence probability (%)			
	3m7 (May-June)	3m10 (July-Oct)	6m10 (May-Oct)	12m (Jan-Dec)
Level	Near normal drought (NND)			
Low	15.6	9.41	31.06	20.36
Moderate	37.23	33.05	32.65	33.39
High	39.45	40.35	26.35	42.36
Very high	7.72	17.19	9.94	3.89
Total	100	100	100	100
Level	Moderate drought (MD)			
Low	7.47	9.85	9.45	36.13
Moderate	28.94	44.79	30.89	36.89
High	50.86	38.63	37.91	17
Very high	12.73	6.73	21.74	9.98
Total	100	100	100	100
Level	Severe drought (SD)			
Low	33.5	4.4	13.07	28.3
Moderate	40.69	16.82	26.57	40.67
High	20.2	60.07	40.5	23.51
Very high	5.61	18.7	19.87	7.52
Total	100	100	100	100
Level	Extreme drought (ED)			
Low	7.79	9.56	11.81	15.76
Moderate	52.44	58.73	50.14	36.75
High	38.04	24	31.92	43.55
Very high	1.73	7.72	6.14	3.94
Total	100	100	100	100

Table 4 Percentage of meteorological drought frequency classification of 4 periods

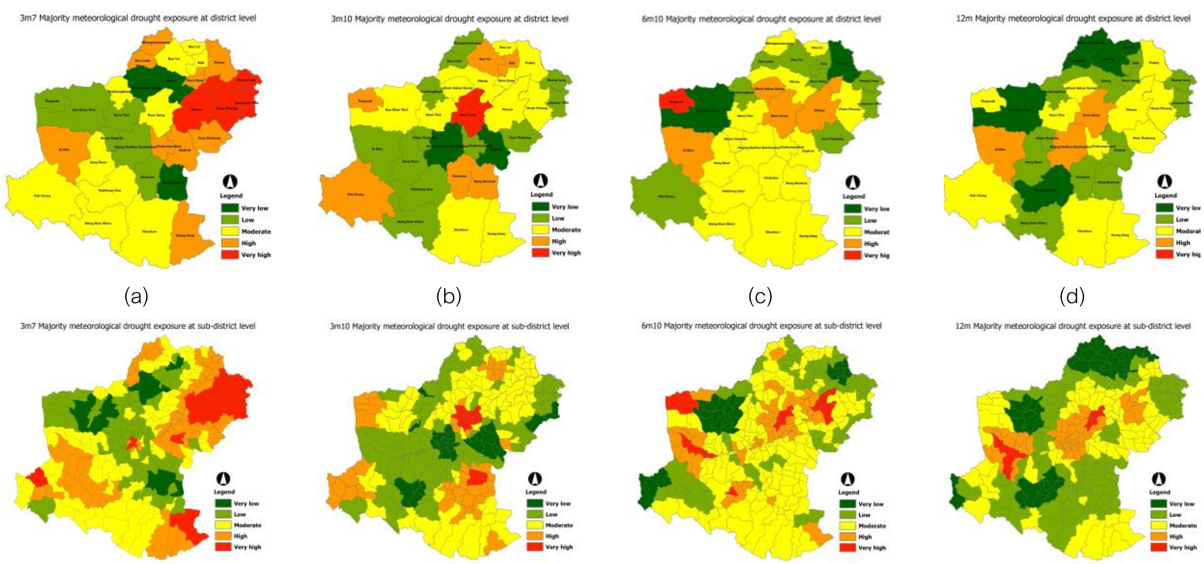
Severity level	Area of meteorological drought frequency (%)			
	3m7 (May-June)	3m10 (July-Oct)	6m10 (May-Oct)	12m (Jan-Dec)
Very low	9.51	7.8	6.16	11.72
Low	27.04	37.62	25.06	25.15
Moderate	24.87	33.2	28.59	22.51
High	24.68	18.38	28.27	29.11
Very high	13.9	3	11.92	11.51
Total	100	100	100	100

Table 5 Area of meteorological drought intensity classification of 4 periods

Level	Classification of meteorological drought intensity (%)			
	3m7 (May-Jun)	3m10 (Jul-Oct)	6m10 (May-Oct)	12m (Jan-Dec)
Very low	1.96	6.03	3.96	15.83
Low	17.48	25.19	11.16	35.69
Moderate	43.54	28.63	23.71	35.56
High	26.26	32.55	32.98	10.71
Very high	10.76	7.6	28.19	2.21
Total	100	100	100	100

Table 6 Area of meteorological drought exposure classification of 4 periods

Severity level	Classification of meteorological drought exposure (%)			
	3m7 (May-June)	3m10 (July-Oct)	6m10 (May-Oct)	12m (Jan-Dec)
Very low	7.77	11.07	8.56	15.83
Low	20.96	33.25	24.23	35.69
Moderate	33.22	35.26	42.11	35.56
High	26.78	17.87	18.86	10.71
Very high	11.26	2.55	6.24	2.21
Total	100	100	100	100



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 6 Spatial and temporal patterns of majority drought exposure severity of 4 periods at the district level and sub-district level: (a) 3m7 (May - July), (b) 3m10 (August- October), (c) 6m10 (May - October), (d) 12m (January – December), € 3m7 (May – July), (f) 3m10 (August- October), (g) 6m10 (May – October) and (h) 12m (January - December), respectively.

Table 7 Number of district and sub-district levels with different severity levels of meteorological drought exposure in 4 periods

Severity level of meteorological drought exposure	Number of district and sub-district							
	3m7 (May-June)		3m10 (July-Oct)		6m10 (May-Oct)		12m (Jan-Dec)	
	District	Sub-district	District	Sub-district	District	Sub-district	District	Sub-district
Very low	3	27	2	37	2	25	1	49
Low	6	79	12	104	9	62	2	101
Moderate	10	81	11	91	16	138	14	83
High	9	70	6	45	4	50	13	49
Very high	4	31	1	11	1	13	2	6
Total	32	288	32	288	32	288	32	288

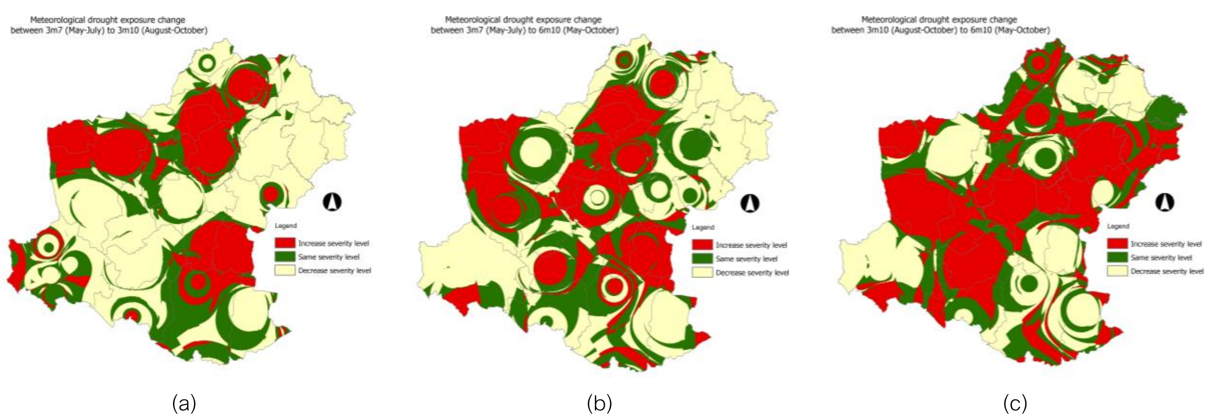


Figure 7 Spatial pattern change of severity of meteorological drought exposure: (a) between 3m7 and 3m 10 period, (b) between 3m7 and 6m10 period and (c) between 3m10 and 6m10 period

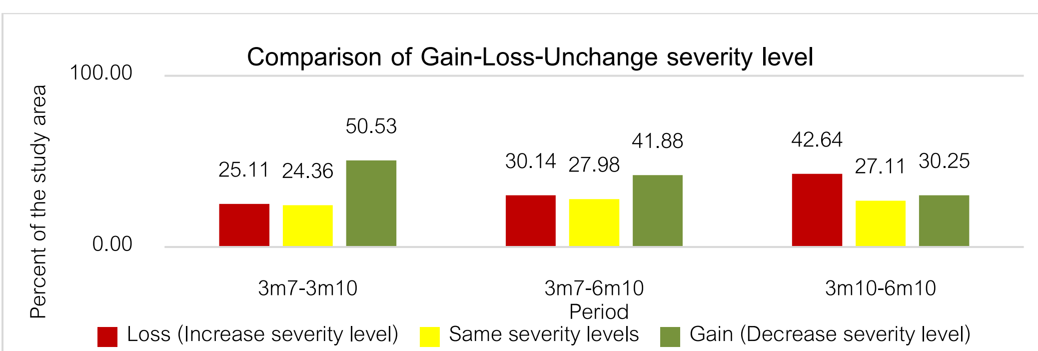


Figure 8 Spatial pattern change of severity level of meteorological drought exposure

Table 8 Changed area of the severity level of meteorological drought exposure

MDE Change: 3m7-3m10	Severity level of 3M10 level					
Severity level of 3m7 period	Very low	Low	Moderate	High	Very high	Total
Very low	0.28%	1.34%	3.56%	1.76%	0.82%	7.77%
Low	1.61%	7.63%	5.75%	5.92%	0.05%	20.96%
Moderate	3.56%	12.33%	11.59%	4.38%	1.37%	33.22%
High	4.58%	8.33%	9.01%	4.71%	0.15%	26.78%
Very high	1.05%	3.62%	5.34%	1.10%	0.15%	11.26%
Total	11.07%	33.25%	35.26%	17.87%	2.55%	100.00%
MDE Change: 3m7-6m10	Severity level of 6M10					
Severity level of 3m7	Very low	Low	Moderate	High	Very high	Total
Very low	2.43%	0.61%	3.47%	1.26%	0.00%	7.77%
Low	1.97%	3.56%	9.88%	3.37%	2.18%	20.96%
Moderate	1.14%	9.66%	14.62%	6.51%	1.29%	33.22%
High	1.62%	6.30%	11.15%	6.16%	1.56%	26.78%
Very high	1.41%	4.10%	2.98%	1.56%	1.22%	11.26%
Total	8.56%	24.23%	42.11%	18.86%	6.24%	100.00%
MDE Change: 3m10-6m10	Severity level of 6M10					
Severity level of 3m10	Very low	Low	Moderate	High	Very high	Total
Very low	0.45%	1.70%	5.78%	2.40%	0.74%	11.07%
Low	2.13%	9.74%	13.53%	6.26%	1.59%	33.25%
Moderate	4.23%	8.19%	14.17%	7.30%	1.37%	35.26%
High	1.60%	4.30%	7.83%	2.17%	1.97%	17.87%
Very high	0.16%	0.30%	0.80%	0.72%	0.57%	2.55%
Total	8.56%	24.23%	42.11%	18.86%	6.24%	100.00%

Meanwhile, a Pearson bivariate correlation analysis between the MDE index and the normalized average yield of four economic crops: in-season rice, cassava, sugarcane and corn between 2011 and 2023 at the sub-district level (288 points) is reported in Table 10. The result of correlation analysis relies on the geometric location of the centroid in each sub-district, which is used to extract the MDE index value and crop statistic data at the sub-district level from the Nakhon Ratchasima Provincial Agriculture and Cooperatives Office.

Table 9 The potential impact areas of meteorological drought exposure on economic crops in 2023.

Economic crop	Severity level of drought exposure	SPI periods			
		3m7 (May-June)	3m10 (July-Oct)	6m10 (May-Oct)	12m (Jan-Dec)
Rice	Very low	9.64%	8.04%	9.22%	19.50%
	Low	24.96%	33.33%	26.12%	**32.96%**
	Moderate	**26.82%**	**42.30%**	**42.09%**	30.90%
	High	23.37%	11.84%	17.06%	14.46%
	Very high	15.21%	4.50%	5.50%	2.18%
	Total	100.00%	100.00%	100.00%	100.00%
Cassava	Very low	14.38%	6.94%	8.53%	13.54%
	Low	**29.75%**	**40.51%**	15.73%	**44.18%**
	Moderate	27.82%	28.43%	**55.09%**	28.26%
	High	17.23%	21.47%	14.18%	11.36%
	Very high	10.82%	2.66%	6.47%	2.66%
	Total	100.00%	100.00%	100.00%	100.00%
Sugarcane	Very low	9.24%	10.63%	3.88%	15.18%
	Low	18.98%	**49.89%**	26.64%	**42.64%**
	Moderate	**33.89%**	26.91%	**49.63%**	33.00%
	High	28.23%	11.80%	14.57%	7.30%
	Very high	9.66%	0.77%	5.28%	1.88%
	Total	100.00%	100.00%	100.00%	100.00%
Corn	Very low	9.85%	1.24%	20.09%	11.13%
	Low	26.70%	**45.52%**	23.53%	38.49%
	Moderate	**42.84%**	24.54%	**38.81%**	**40.47%**
	High	15.19%	28.59%	10.16%	8.12%
	Very high	5.42%	0.11%	7.41%	1.80%
	Total	100.00%	100.00%	100.00%	100.00%

Table 10 Correlation analysis between meteorological drought exposure (MDE) index of 4 periods and average yield (from 2011 to 2023) of rice, cassava, sugarcane, and corn

	MDE index of 3m7	MDE index of 3m10	MDE index of 6m10	MDE index of 12m
Average in-season rice yield	-.121*	-.104	.163**	-.033
Average cassava yield	-.169**	-.017	.087	-.192**
Average sugarcane yield	.026	-.143*	.081	-.132*
Average corn yield	-.290**	-.098	-.068	-.029

Note **. Correlation is significant at the 0.01 level (2-tailed) and *. Correlation is significant at the 0.05 level (2-tailed).

Discussion

1. *Meteorological drought occurrence probability of 4 periods of SPI*

As a result, in Tables 2 and 3, under the near normal drought category with SPI value from 0.00 to -0.99, the dominant probability of high-level drought occurrence occurs in 3m7, 3m10, and 12m periods, except 6m10 period with moderate levels. Meanwhile, the dominant probability of drought occurrence with moderate level occurs in 3m10 and 12m periods under the moderate drought category with SPI value from -1.00 to -1.49. Still, the dominant probability of drought occurrence with high level occurs in 3m7 and 6m10 periods. In the meantime, under the near severe drought category with SPI value from -1.50 to -1.99, the dominant probability of drought occurrence with moderate level occurs in 3m7 and 12m periods, and the dominant probability of drought occurrence with high level occurs in 3m10 and 6m10 periods. Meanwhile, the dominant probability of drought occurrence with moderate level occurs in 3m7, 3m10 and 6m10 periods under the extreme drought category with SPI value from -2.00 and less. Still, the dominant probability of drought occurrence with high level occurs in a 12m period. Besides, the distribution of the four probability of drought occurrence classes shows a completely different pattern among the 4 periods. These findings indicate variation in rainfall from 37 stations, which are used to calculate SPI, as mentioned by Sönmez *et al*., 2005.

2. *Meteorological drought frequency classification*

As a result, in Table 4, the top three dominant severity levels of MDF occurring in 4 periods are low, moderate, and high. Areas of three severity levels of MDF in 4 periods cover an area of 76.59%, 89.2%, 81.92%, and 76.77%, respectively. The spatial distribution of very high drought frequency in 3m7 and 6m10 periods (Figure 3e and Figure 3g) randomly scatters in the study area. Meanwhile, the spatial distribution of very high drought frequency in the 3m10 period (Figure 3f) occurs in the northern part. In the meantime, the spatial distribution of very high drought frequency in the 12m period (Figure 3h) is situated in the northeastern and southwestern parts.

The spatial distribution of the MDF index and its severity in the 4 periods (Figure 3) shows different allocated patterns. However, using spatial correlation analysis, the correlation coefficient (R) value, varying from -1 to 1, shows a strong positive linear relationship among MDF severity levels of the 4 periods, as classified by Cohen (1988). The R values among MDF severity levels of the 4 periods vary from 0.8220 to 0.8896 (Table 11). These findings indicate the significance of the period for SPI calculation, as mentioned by Sönmez *et al.,* 2005.

3. *Meteorological drought intensity classification*

As a result, in Table 5, the top three dominant severity levels of MDI in the 3m7 and 3m10 periods are low, moderate and high and cover an area of 87.28% and 86.37% of the study area, respectively. In the meantime, the top three dominant severity levels of MDI in the 6m10 period are moderate, high and very high and cover an area of 84.88% of the study area. Meanwhile, the top three dominant severity levels of MDI in the 12m period are very low, low and moderate and cover an area of 87.08% of the study area.

The spatial distribution of very high drought intensity in the 3m7 period (Figure 4e) is in the northeastern and southwestern parts. Meanwhile, the spatial distribution of very high drought intensity in the 3m10 period (Figure 4f) occurs in the northern and southern parts. In the meantime, the spatial distribution of very high drought intensity in the 6m10 period (Figure 4g) occurs in the southern part. Meanwhile, the spatial distribution of very high drought intensity in the 12m period (Figure 4h) marginally occurs in the southwestern part.

Like MDF classification, the spatial distribution of the MDI index and its classification of the 4 periods (Figure 4) shows a completely different pattern. However, the R values using spatial correlation analysis among MDI severity levels of the 4 periods show a strong positive linear relationship (Cohen, 1988), as reported in Table 12.

Table 11 Correlation matrix of meteorological drought frequency (MDF) severity levels of the 4 periods

MDF-Period	Correlation coefficient			
	MDF-12m	MDF-3m10	MDF-3m7	MDF-6m10
MDF-12m	1	0.8220	0.8413	0.8896
MDF-3m10	0.8220	1	0.8694	0.8735
MDF-3m7	0.8413	0.8694	1	0.8530
MDF-6m10	0.8896	0.8735	0.853	1

Table 12 Correlation matrix of meteorological drought intensity (MDI) severity levels of the 4 periods.

MDI-period	Correlation coefficient			
	MDI-12m	MDI-3m10	MDI-3m7	MDI-6m10
MDI-12m	1.0000	0.8099	0.7917	0.8283
MDI-3m10	0.8099	1.0000	0.7627	0.8522
MDI-3m7	0.7917	0.7627	1.0000	0.8265
MDI-6m10	0.8283	0.8522	0.8265	1.0000

4. Meteorological drought exposure classification

As a result in Table 6, the top three dominant severity levels of MDE in 3m7, 3m10 and 6m10 periods are low, moderate and high and cover an area of 80.96%, 86.38%, and 85.20% of the study area, respectively. In the meantime, the top three dominant severity levels of MDE in the 12m period are very low, low and moderate and cover an area of 87.08% of the study area.

The spatial distribution of a high and very high drought exposure in the 3m7 period (Figure 5e) is situated in the northeastern, southern and western parts. Meanwhile, the spatial distribution of high and very high drought exposure in the 3m10 period (Figure 5f) occurs in the northern and southern parts. In the meantime, the spatial distribution of a high and very high drought exposure in the 6m10 period (Figure 5g) occurs in the western and central parts. Meanwhile, the spatial distribution of a high and very high drought exposure in the 12m period (Figure 5h) marginally occurs in the western and central parts.

The spatial patterns of MDE classification in 4 periods (Figure 5) display a completely different pattern. However, the R values using spatial correlation analysis among MDE severity of the 4 periods show a strong positive linear relationship (Cohen,1988), with values varying from 0.8100 to 0.8966 (Table 13). These results imply the similarity of MDE patterns among 4 periods.

Table 13 Correlation matrix among meteorological drought exposure (MDE) severity levels of the 4 periods.

MDE-period	MDE-12m	MDE-3m10	MDE-3m7	MDE-6m10
MDE-12m	1.0000	0.8100	0.8454	0.8966
MDE-3m10	0.8100	1.0000	0.7941	0.8218
MDE-3m7	0.8454	0.7941	1.0000	0.8318
MDE-6m10	0.8966	0.8218	0.8318	1.0000

5. Spatial and temporal patterns of meteorological drought exposure

As a result, in Table 7, the majority severity level of MDE at district and sub-district levels from May to June (3m7) is moderate, with 10 districts and 81 sub-districts. On the contrary, the majority severity level of MDE at district and sub-district levels from June to October (3m10) is low, with 12 districts and 104 sub-districts. However, the majority severity level of MDE at district and sub-district levels from May to October (6m10) is moderate, with 16 districts and 138 sub-districts. In the meantime, the majority severity level of MDE from January to December (12m) in the district is moderate, with 14 districts. Still, the majority severity level of MDE in the same period at the sub-district level is low, with 101 sub-districts. The spatial and temporal patterns of MDE are displaced in 4 periods. These findings are consistent with the previous studies of Sönmez *et al*., 2005; Wattanakij *et al*., 2006; Patel *et al*.,2007; Nosrati & Zareiee, 2011; Sehgal & Dhakar, 2016; Caloiero & Veltri, 2019; Mehr *et al*., 2020; Kornkosa *et al*., 2021; Omar *et al*., 2023. The MDE in the 6m10 period exhibits the highest meteorological drought exposure in the study area. Additionally, MDE at a very high and very high severity level repeatedly occurs at district and sub-district levels in four periods and should be intensively monitored for meteorological drought by relevant government agencies such as the Department of Agricultural Extension and the Department of Disaster Prevention and Mitigation for mitigating potential impact of drought on economic crops in these areas.

For the spatial pattern changes of MDE severity levels covering the economic crop calendar in 3m7, 6m10, and 6m10, as reported in Table 8 and Figure 8, areas of increasing severity levels (very low change to low, moderate, high, and very high; low change to moderate, high, and very high; moderate change into high, and very high; high change into very high) from 3m7 period to 3m10 period cover an area of about 25.11% of the study area. In the meantime, areas of decreasing severity levels (low change to very low, moderate change to very low and low; high change to very low, low, and moderate; very high change to very low, low, moderate, and high) in the same period covers an area of about 50.53% of the study area. Meanwhile, areas of unchanging severity levels in the same period cover an area of about 24.36% of the study area. This finding indicates that the severity of MDE from May to July (3m7) on economic crops is higher than from August to October (3m10).

Meanwhile, for spatial pattern changes of MDE severity level between 3m7 and 6m10 as reported in Table 8 and Figure 8, areas of increasing severity levels (very low change to low, moderate, high, and very high; low change to moderate, high, and very high; moderate change into high, and very high; high change into very high) from 3m7 period to 6m10 period cover an area of about 30.14% of the study area. In the meantime, areas of decreasing severity levels (low change to very low, moderate change to very low and low; high change to very low, low, and moderate; very high change to very low, low, moderate, and high) in the same period covers an area of about 41.88% of the study area. Meanwhile, areas of unchanging severity levels in the same period cover an area of about 27.98% of the study area. This finding shows that the severity of MDE from May to October (6m10) on economic crops is higher than from May to July (3m7).

In the meantime, for spatial pattern changes of MDE severity level between 3m10 and 6m10 as reported in Table 8 and Figure 8, areas of increasing severity levels (very low change to low, moderate, high, and very high; low change to moderate, high, and very high; moderate change into high, and very high; high change into very high) from 3m10 period to 6m10 period cover an area of about 42.64% of the study area. In contrast, in the same period, areas of decreasing severity levels (low change to very low, moderate change to very low and low; high change to very low, low, and moderate; very high change to very low, low, moderate, and high) covers an area of about 30.25% of the study area. Meanwhile, areas of unchanging severity levels cover an area of about 27.11% of the study area. This finding indicates that the severity of MDE on economic crops from May to October (6m10) is higher than from August to October (3m10).

Based on the spatial pattern changes of MDE severity levels among 3-periods (3m7, 3m10 and 6m10), as discussed above, the severity classification of the MDE in the 6m10 period exposes the highest meteorological drought in the study area.

6. Potential impact areas of meteorological drought exposure on economic crops

As a result, in Table 9, the dominant MDE severity in the 3m7 period displays moderate for rice, sugarcane and corn, but it displays low for cassava. Meanwhile, the dominant MDE severity in the 3m10 period displays moderate for in-season rice, but it displays low for cassava, sugarcane and corn. In the meantime, the dominant MDE severity in the 6m10 period displays moderate for in-season rice, cassava, sugarcane, and corn. Meanwhile, the dominant MDE severity in the 12m period displays low for in-season rice, cassava, and sugarcane, but it displays moderate for corn.

Besides, the potential impact areas of covering rice cultivation period (3m7, 3m10, and 6m10) at moderate, high, and very high severity levels cover an area of 3,984.59 sq. km, 3,572.73 sq. km and 3,939.40 sq. km or 65.40%, 58.64%, and 64.65% of the total area of rice in 2023 (6,092.73 sq. km), respectively. Meanwhile, the potential impact areas of cassava covering its cultivation period (3m7, 3m10, and 6m10) at moderate, high, and very high severity levels cover an area of 2,152.89 sq. km, 2,025.09 sq. km, and 2,918.67 sq. km or 55.87%, 52.56%, and 75.74% of the total area of cassava in 2023 (3,853.65 sq. km), respectively. In the meantime, the potential impact areas of sugarcane covering its cultivation period (3m7, 3m10, 6m10, and 12m) at moderate, high, and very high severity levels cover an area of 1,470.86 sq. km, 809.00 sq. km, 1,423.47 sq. km and 864.22 sq. km or 71.78%, 39.48%, 69.48%, and 42.18% of the total area of sugarcane in 2023 (2,048.75 sq. km), respectively. Meanwhile, the potential impact areas of corn covering its cultivation period (3m7, 3m10, and 6m10) at moderate, high, and very high severity levels cover an area of 496.68 sq. km, 416.73 sq. km and 441.33 sq. km or 63.45%, 53.24%, and 56.38% of the total area of corn in 2023 (783.10 sq. km), respectively. These findings provide basic information on potential impact areas of moderate, high, and very high severity levels of meteorological drought exposure on economic crops in 2023 based on land use data of LDD. See details in Table 9.

In addition, as a result of Pearson bivariate correlation analysis, in Table 10, the most dominant MDE index that impacts crop yield is the MDE index in the 3m7 period (May to July). This index shows a negative linear relationship with in-season rice, cassava and corn yields. This finding indicates the potential impact of MDE on in-season rice, cassava and corn yields since the sowing period of these crops mainly occurs from May to July. In contrast, the MDE index shows no linear relationship with sugarcane since a multi-cropping system of about three years is applied for sugarcane by farmers. Meanwhile, the MDE index in the 3m10 period (August to October) shows a negative linear relationship with sugarcane, while the MDE index in the 6m10 period (May to October) shows a negative linear relationship with in-season rice. Likewise, the MDE index in the 12m period (January to December) shows a negative linear relationship with cassava and sugarcane. These findings imply the potential impact of MDE on crops in different periods.

Conclusions

The rainfall data records between 1975 and 2022 were first used to generate a standardized precipitation index of 4 periods: 3m7, 3m10, 6m10, and 12m, and applied to generate three meteorological drought indices: frequency, intensity and exposure for analyzing spatial and temporal patterns of meteorological drought exposure and its impact on economic crops. The most dominant severity class of meteorological drought exposure of the 4 periods was a moderate, moderate, moderate, and low covered area of about 33.22%, 35.26%, 42.11% and 35.69%, respectively. The spatial distribution of the meteorological drought exposure classification of the 4 periods displayed a completely different pattern. Still, the correlation coefficient values among their classifications showed a strong positive linear relationship, with values from 0.8100 to 0.8966. The majority severity classification of the meteorological drought exposure in the 6m10 period exhibited the highest impacts at district and sub-district levels, with 16 districts and 138 sub-districts.

Similarly, based on spatial pattern change detection among 3 periods (3m7, 3m10 and 6m10), the severity classification of the meteorological drought exposure in the 6m10 period exposed the highest meteorological drought. The potential impact areas of meteorological drought exposure in the 6m10 period (May to October) at moderate, high, and very high severity levels on rice in 2023, about 3,939.40 sq. km 64.65% of the total area of rice, cassava about 2,918.67 sq. km 75.74% of the total area of cassava, sugarcane, about 1,423.47 sq. km or 69.48% of the total area of sugarcane, and corn, about 441.33 sq. km or 56.38% of the total area of corn. Furthermore, the most dominant meteorological drought exposure index that impacts crop yield was the meteorological drought exposure index in the 3m7 period (May to July). This index displayed a negative linear relationship with the average rice, cassava and corn yield between 2011 and 2022.

In conclusion, spatial and temporal patterns of meteorological drought exposure were successfully conducted based on standardized precipitation index of rainfall data for quantifying the severity of drought and impact in this study. The research workflow of the current study can be used as a guideline for monitoring and mitigating meteorological drought in the future by the relevant government agencies, such as the Department of Agricultural Extension and the Department of Disaster Prevention and Mitigation. In addition, early warning systems of meteorological drought at the regional level are recommended to be implemented by the Thai Meteorological Department.

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