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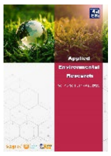

Research Article

Spatial and Temporal Pattern Assessment of Agricultural Drought Sensitivity and its Potential Impact on Economic Crops in Nakhon Ratchasima, Thailand

Suwit Ongsomwang*, Siripon Kamontum

School of Mathematics and Geoinformatics, Institute of Science, Suranaree University of Technology, Nakhon Ratchasima 30000, Thailand

*Corresponding Email: suwit@sut.ac.th

Abstract

Agricultural drought sensitivity (ADS) is highly diverse across regions, primarily due to differences in climate, soil types, and farming practices. Agricultural drought impacts depend on drought intensity, severity, duration and timing relative to crop growth stages. Therefore, spatial and temporal pattern assessments of ADS and its potential impact on economic crops in three scenarios via multicriteria decision-making methods were conducted. As a result, the spatial distributions of the ADS index and its classification at 3 m7, 3 m10 and 6 m10, covering the planting and growing periods, displayed different patterns. The percentages of moderate, high and very high severity levels at 3 m7, 3 m10 and 6 m10 covered 56.06%, 59.14%, and 56.02%, respectively, of the study area. These results suggest that the study area is moderately sensitive to agricultural drought. A high and very high severity level of ADS at the district and subdistrict levels persistently occurred in three periods, with 8 districts and 72 subdistricts; these persistent areas should be intensively monitored for agricultural drought by the Department of Agricultural Extension (DOAE) and the Department of Disaster Prevention and Mitigation (DDPM). In addition, the potential impact areas of ADS with moderate, high, and very high severity levels indicated that ADS has a high potential impact on rice and corn. Nevertheless, it has a moderate effect on cassava and sugarcane. Hence, if drought occurs, rice and sugarcane areas should be prioritized with a field survey on the impact of drought by DOAE and DDPM. This research methodology can be used as a guideline for managing crops via the DOAE and monitoring agricultural drought via the DDPM. The government should establish early warning systems for droughts jointly by government agencies and universities to prevent and mitigate the impact of drought in the future.

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Introduction

Agricultural drought links meteorological drought characteristics to agricultural impacts, associating precipitation shortages most immediately with relatively high evapotranspiration levels and soil moisture deficits [1]. Agricultural drought usually occurs at a critical time during the growing season, directly reduces soil moisture, and leads to crop failure [2]. Agricultural drought sensitivity (ADS) highly varies across regions, primarily due to differences in climate, soil types, and farming practices. The impacts of drought on agriculture depend on its intensity, severity, duration and timing relative to crop growth stages. In addition, drought events with similar intensities and durations could have different impacts on agriculture depending on crop eco-physiology and the system's local adaptive capacity [3].

The Intergovernmental Panel on Climate Change (IPCC) defined sensitivity as "the degree to which a

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system is affected, either adversely or beneficially, by climate-related stimuli" [4]. According to the IPCC report on extreme events in 2012, the issue of quantifying loss and damage from extreme climate events such as droughts has become essential for policy implementation [5].

Thailand frequently suffers from droughts resulting from a shortage of rainfall, reduced flow in surface and subsurface rivers, and poor land management practices. The entire country was affected by severe droughts in 1979, 1994, and 1999; the northeastern region, which has the highest poverty rates, is particularly vulnerable to drought [6]. Nakhon Ratchasima Province, which is an important agricultural production area in the region, is one of the most vulnerable areas where water resources are limited because of little rain [7], with a limited agricultural irrigation system [8].

Recently, monitoring and assessing drought conditions have become a local priority and have led to early warning systems or monitoring of agricultural drought to improve strategies to mitigate drought-related impacts. The use of advanced machine learning methods as data-driven methods tends to become a central alternative to conventional methods on the basis of statistical analysis and/or domain expertise [9]. Sutanto et al. [10] developed drought impact functions via machine learning approaches (logistic regression and random forest) to predict drought impacts with lead times of up to 7 months ahead on the basis of observed and forecasted hydrometeorological drought hazards such as the standardized precipitation index (SPI), standardized precipitation evaporation index (SPEI), and standardized runoff index (SRI) from the EU-funded Enhancing Emergency Management and Response to Extreme Weather and Climate Events. Mokhtari and Akhoondzade [11] used a data fusion technique, the wavelet transform, for combining multiple satellite datasets, including MODIS vegetation index products, MODIS snow cover (MOD10CM), MODIS land surface temperature, MODIS evapotranspiration products, TRMM monthly precipitation estimation, SMOS monthly soil moisture L3 products and applied machine learning algorithms, including an artificial neural network (ANN), support vector regression (SVR), decision tree (DT), and random forest (RF), for drought forecasting in Iran.

Drought research in Thailand and Southeast Asia has extensively examined the increasing frequency and severity of droughts, their impacts on agriculture and water resources, and the development of monitoring and mitigation strategies. For example, Tanguy et al. [12] analyzed drought indicator-to-impact relationships in Thailand via a combination of correlation analysis and machine learning algorithms (RFs). In the correlation analysis, they examined the relationships between meteorological drought indicators (SPI and SPEI) and vegetation indices (vegetation condition index (VCI) and vegetation health index (VHI)) as proxies for crop yield and forest growth impacts. The relationships between meteorological drought indicators and vegetation indices vary depending on land use, season, and region.

A review of drought studies from Earth observation (EO) products in Southeast Asia between 2000 and 2021 by Ha et al. [13] revealed that drought research in the region is increasing, with a majority (70%) of the studies being undertaken in Vietnam, Thailand, Malaysia and Indonesia. These countries also accounted for nearly 97% of the economic losses due to drought extremes. Vegetation indices from multispectral optical remote sensors remain a primary source of data for drought monitoring in the region. Many studies did not provide an accuracy assessment of drought mapping products, whereas precipitation was the primary data source for validation. Approximately 81% of the research focused on the local and national scales. They claimed that the remaining challenges were large-area and long-term-series drought measurements, the combined drought approach, machine learning-based drought prediction, and the integration of multisensor remote sensing products.

To assess ADS, many researchers have focused on factors and variables and applied selected factors to predict ADS via geospatial modeling. The key factors generally include climate [14–16], soil properties [17–19], topography [20–22], land use and land cover [23], hydrological factors [24–30], socioeconomic factors [31–32], and drought indices [33–34].

This study focused on the spatial and temporal patterns of ADS and their impacts on economic crops in Nakhon Ratchasima Province. Multiple factors and variables associated with ADS, including in situ long-term rainfall data, geographic information system (GIS) and remote sensing data, detailed socioeconomic data and crop statistics at the subdistrict level, are first extracted and transformed into standard geospatial data in raster format with a 30 m resolution in a geographic information system (GIS) environment and are integrated for assessing ADS and its impact on crops via well-known and frequently used multicriteria decision-making (MCDM) methods [35-36], the analytic hierarchy process (AHP) and weighted linear combination (WLC). This study will generate three different scenarios of ADS according to climate factors with dynamic variables in three periods (3m7: May–July, 3m10: August–October, and 6m10: May–October), which cover the planting and growing periods of crops. This approach can provide detailed spatial and temporal patterns of ADS and potential impacts on economic crops at the district and subdistrict levels, which makes it different from other studies. The results of this study can be applied for managing crops and monitoring and mitigating drought by relevant government agencies, such as the Department of Agricultural Extension (DOAE), Department of Disaster Prevention and

Mitigation (DDPM), Royal Irrigation Department (RID), Department of Water Resources (DWR), and Department of Groundwater Resources (DGR).

The specific objectives of the study were (1) to assess the spatial and temporal patterns of agricultural drought sensitivity at the district and subdistrict levels and (2) to evaluate the potential impact of agricultural drought sensitivity on economic crops.

Materials and methods

1) Study area

The study area is Nakhon Ratchasima Province, with 32 districts and 288 subdistricts, and covers an area of approximately 20,729 km^2 (Figure 1).

2) Data

The input data for assessing ADS include (1) daily rainfall records (2002–2022) from 37 stations from the Thai Meteorological Department (TMD), (2) the MOD31A-NDVI product between 2002 and 2022 from the USGS website (https://earthexplorer.usgs.gov), (3) the MOD11B-LST product between 2002 and 2022 from the USGS website (https://earthexplorer.usgs.gov), (4) land use data from 2008, 2011, 2015, 2017, and 2019, and 2023 from the Land Development Department (LDD), (5) the agricultural irrigation area from the RID, (6) the soil series of the LDD for soil drainage extraction, (7) the SRTM DEM from the USGS website (https://earthexplorer.usgs.gov) for landform and elevation extraction, (8) the waterbody in 2023 for Euclidean distance extraction, (9) the river network and subbasin boundaries from the DWR for drainage density extraction, and (10) inventory crop data concerning yield, production and harvested areas of in-season rice, cassava, sugarcane.

3) Methods

The workflow of the research methodology for assessing the spatial and temporal patterns of ADS and its potential impact on economic crops is displayed in Figure 2. Brief information on each significant step is described separately in the following sections.

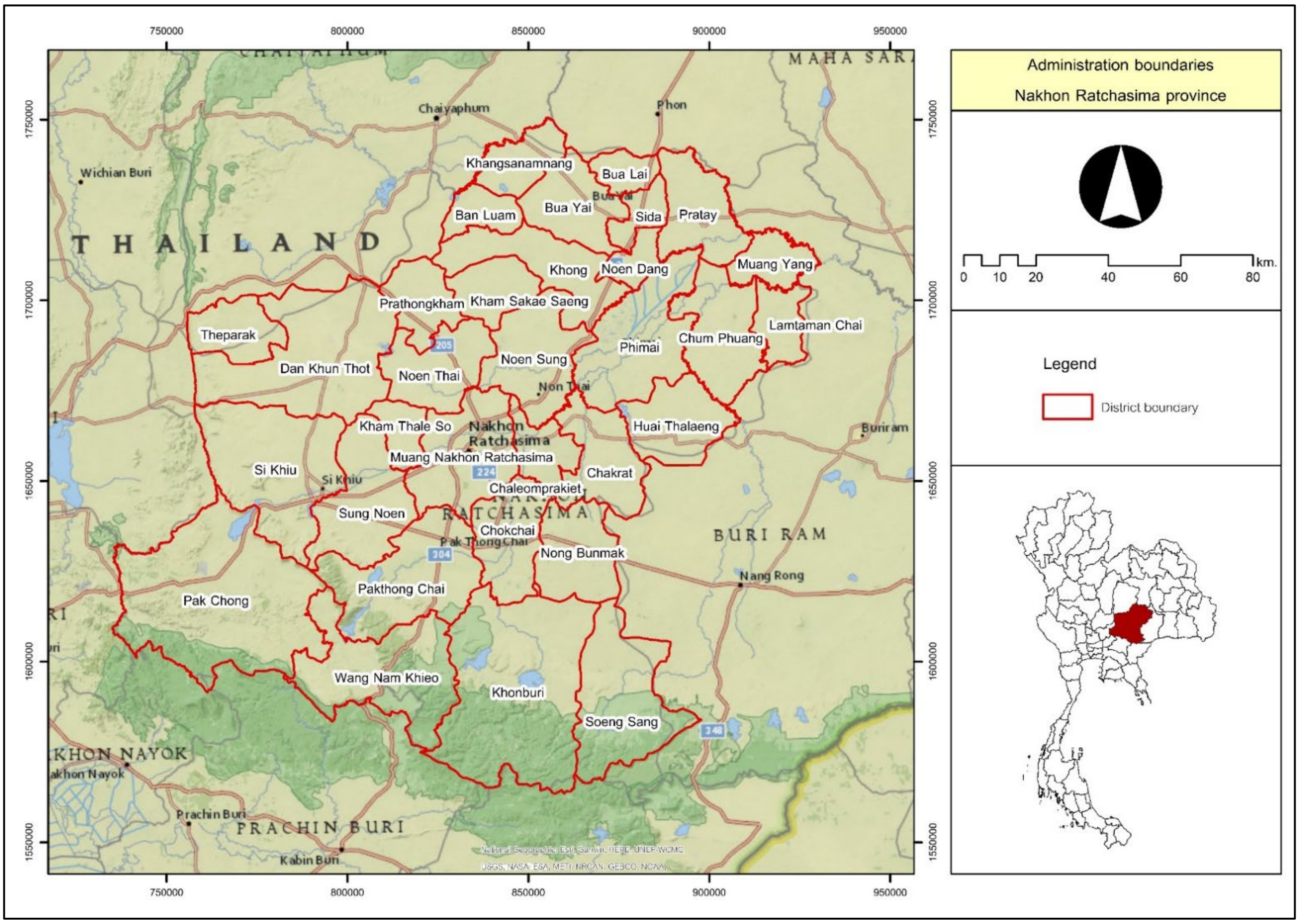


Figure 1 Location and administrative boundaries of the study area.

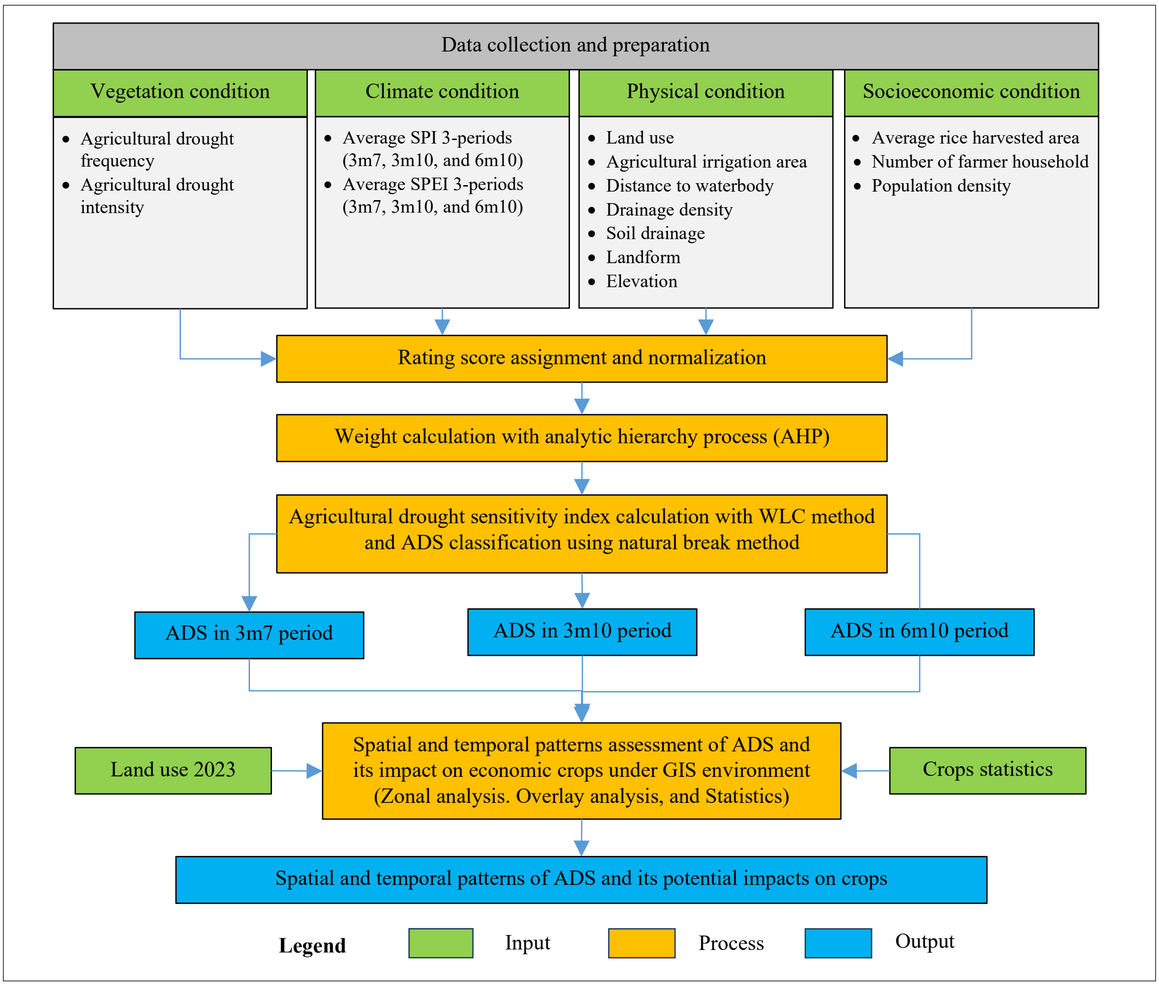


Figure 2 Workflow of the research methodology.

Step 1: Data collection and preparation

The selected factors for ADS assessment under four conditions, i.e., vegetation, climate, physical and socioeconomic conditions, are collected and prepared in a GIS environment. The selected factors in vector format, including land use data, agricultural irrigation area, distance to water bodies, drainage density, soil drainage, average rice harvested area, number of farmer households, and population density, were converted into raster format with a 30 m resolution. Moreover, the other factors selected in raster format, which were initially collected at different resolutions, e.g., the MOD31A-NDVI product with a 120 m resolution, were resampled to a 30 m resolution. The conversion and resampling operations introduce errors [37], which could affect the results of assessing the ADS and evaluating the spatial and temporal patterns of the ADS and its potential impact on crops. Brief information on the preparation of each factor is described separately in the following sections.

(1) Vegetation conditions Two indicators representing vegetation conditions for the ADS are agricultural drought frequency and intensity. This study identified agricultural drought frequency on the basis of VCI computed via the normalized difference vegetation index (NDVI) from MOD31A-NDVI products over the phenological period (May–October) of in-season rice via Equation (1) with the spatial modeler module in ERDAS Imagine software. A VCI value of 100% indicates healthy vegetation conditions. In contrast, if VCI values are nearly 0%, poor vegetation conditions are identified [38].

$$VCI=100*\frac{(NDVI_i\text{-}NDVI_{min})}{(NDVI_{max}\text{-}NDVI_{min})} \qquad \text{(Eq. 1)}$$

where $NDVI_i$ is the filtered NDVI image in the phenological period, $NDVI_{max}$ is the multiyear maximum NDVI in the phenological period, and $NDVI_{min}$ is the multiyear minimum NDVI in the phenological period.

As a representative of vegetation conditions, a VCI equal to or less than 35% in the cropping season was identified as agricultural drought. All VCI images were reclassified with a threshold value of ≤ 0.35 as 1, whereas the other values were reclassified as 0. After that, all reclassified images (1 and 0) were added together and divided by the number of images (210 images from 21 years) with the Raster Calculator function under ESRI ArcMap software and reclassified into five rating scores by the natural break (NB) method with the reclassify function under ESRI ArcMap software.

Agricultural drought intensity was calculated on the basis of average historical VCI values (0–100%) during the phenological period. All VCI images were reclassified with a threshold value of ≤ 0.35, while the other values were reclassified as 0. After that, all reclassified images were added and divided by the number of years (21 years) with the Raster Calculator function in ESRI ArcMap software. The extracted value was reclassified into five rating scores via the NB method with the reclassify function in ESRI ArcMap software.

(2) Climate condition Two factors that characterize climate conditions for ADS are the average SPI and SPEI, as suggested by previous reports [33–34, 39]. The SPI, which represents meteorological drought exposure, was calculated from rainfall data (2002–2022) from 37 stations in three SPI periods via SPI generator software. The calculated SPI value in each period was averaged, and each average value was interpolated via the inverse distance weighted (IDW) method via ESRI ArcMap software. They were later reclassified into five rating scores via the NB method with the reclassify function in ESRI ArcMap software.

Moreover, the SPEI, which is a specific characteristic of the climate of the region [40], was calculated on the basis of monthly rainfall and temperature data (2002–2022). Herein, monthly rainfall data, which were retrieved from 37 stations, and monthly temperature data, which were retrieved from MODIS LST data (MOD11C3 product), were applied to calculate the SPEI of three periods via SPEI software. After that, they were averaged and interpolated via the IDW method via ESRI ArcMap software and reclassified into five rating scores via the NB method with the reclassify function via ESRI ArcMap software.

(3) Physical condition The seven factors that characterize the physical conditions of the ADS are land use, agricultural irrigation area, soil drainage, slope, elevation, distance to a waterbody and drainage density.

(3.1) Land use The land use data from 2008, 2011, 2015, 2017, 2019, and 2023 from LDD were first reclassified into five rating scores according to land use type and then averaged for five rating scores with the raster calculation function in ESRI ArcMap software. The very high level of land use sensitivity to drought is paddy fields because they require more water than other crops do. In contrast, water bodies and miscellaneous land are less affected by drought.

(3.2) Agricultural irrigation area In accordance with the ADS, the agricultural irrigation area was manually assigned rating scores for irrigated and rain-fed agricultural areas [41], with values of 5 and 1, respectively, via the reclassify function in ESRI ArcMap software.

(3.3) Distance to the waterbody Areas closer to water bodies are less vulnerable to water shortages than are areas far from water bodies [41]. Euclidean distance was applied to calculate the distance to water bodies via Euclidean distance via ESRI ArcMap software and was manually reclassified into five rating scores via the NB method via the reclassify function in ESRI ArcMap software.

(3.4) Drainage density The drainage density values, which were calculated via the total length of stream channels in a drainage basin divided by the surface area of the basin [42], were reclassified into five rating scores via the NB method via the reclassify function in ESRI ArcMap software.

(3.5) Soil drainage The soil drainage properties of the soil series from the LDD [43] were manually reclassified into five rating scores by the reclassify function in ESRI ArcMap software.

(3.6) Landform Landform classification was classified on the basis of the percentage of slope [44] and manually reclassified into five rating scores via the reclassify function in ESRI ArcMap software.

(3.7) Elevation The elevation classification was extracted from the SRTM DEM according to the standard of LDD [44], and the data were manually reclassified into five rating scores via the reclassify function in ESRI ArcMap software.

(4) Socioeconomic conditions Socioeconomic factors included average rice harvested area (2011–2023), farmer households in 2023 and population density in 2023 at the subdistrict level.

(4.1) Average rice harvested area The average rice harvested areas between 2011 and 2023 at the subdistrict level, as suggested by Shahid and Behrawan [45], were calculated and reclassified into five ADS levels via the NB method via the reclassify function in ESRI ArcMap software.

(4.2) Number of farmer households The number of farmer households is sensitive to agricultural drought [46]. The areas will be more vulnerable when the proportion of farmer households increases. The number of farmer households in 2023 at the subdistrict level was extracted and reclassified into five rating scores via the NB method via the reclassify function in ESRI ArcMap software.

(4.3) Population density Shahid and Behrawan [45] applied population density to assign ADS. The population density in 2023 at the subdistrict level was extracted and reclassified into five rating scores via the NB method via the reclassify function in ESRI ArcMap software.

Step 2: Rating score assignment and normalization

Since all the factors of the ADS have different units, the rating scores of each factor, which were manually assigned, were normalized into the same standard with a standardized rank method [47] via Eq. 2 and reclassified into five rating scores via the NB method via the reclassify function under ESRI ArcMap.

$$v=a+(b-a)*\left[\frac{V-A}{B-A}\right] \quad \text{(Eq. 2)}$$

where v is the new rating value that is between the a and b values, V is the original rating value that is between the A and B values, A is the minimum of the original rating values, B is the maximum of the original rating values, a is the new minimum standardized rating value of 1, and b is the new maximum standardized rating value of 3.

Step 3: Weight calculation with the analytic hierarchy process

The weight of each factor on the ADS was determined via the AHP, a decision-making method used by individuals and organizations to rank alternatives they are considering on the basis of pairwise comparisons [48]. This method helps obtain a single assessment value on the basis of different indicators or criteria [49].

To calculate the weights of individual factors under the AHP, a multicriteria evaluation with a linear combination weighting system (LCWS) was conducted via IDRISI Selva software. In practice, the WEIGHT module was first used to generate a pairwise comparison matrix with a standard numeric scale from 1–9, which lies between "equal importance" and "extreme importance", to define the pairwise importance of each of the two indicators via a research group discussion based on the characteristics of the factors. After that, the MCE module was used to calculate the principal eigenvector of the pairwise comparison matrix to produce the best-fit set of weights [50–51].

Step 4: Agricultural drought sensitivity index calculation and classification.

The normalized rating score and weight of each factor were first applied to calculate the ADS index for three periods (3 m7, 3 m10 and 6 m10) with the WLC method [52] via Eq. 3 with the raster calculator in ESRI ArcMap software.

$$A_i=\sum_{j=1}^{n} w_j \cdot a_{ij} \quad \text{(Eq. 3)}$$

where A_i is the total importance of the alternative when all the criteria are considered simultaneously, w_j denotes the relative weight of importance of criterion C_j, and a_{ij} is the performance value of alternative A_i when it is evaluated in terms of criterion C_j.

After that, the ADS indices of the three periods were reclassified into five levels—very low, low, moderate, high and very high—for ADS classification via the NB method with the reclassify function in ESRI ArcMap software.

Step 5: Assessment of the spatial and temporal patterns of ADS

Spatial and temporal patterns of ADS classification at the district and subdistrict levels in the three periods were assessed via zonal analysis, with the majority operation performed via the Zonal Statistics function in ESRI ArcMap software.

Step 6: Potential impact assessment of the ADS on economic crops

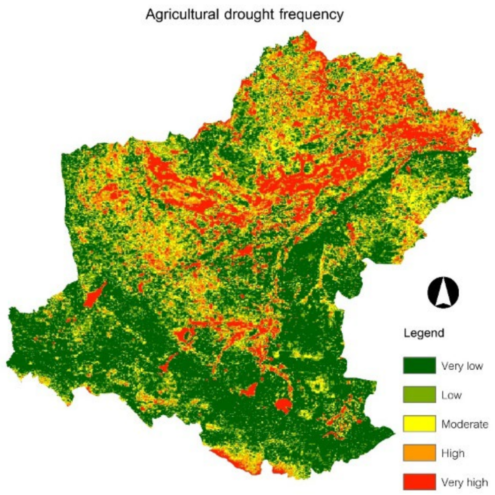
The potential impact of ADS in three periods on economic crops (rice, cassava, sugarcane and corn) was assessed via overlay analysis on the basis of ADS classification and LDD land use data from 2023 via the GIS analysis module of ERDAS Imagine software.

In addition, Pearson bivariate correlation analysis was applied to characterize the linear relationship between the ADS index in the three periods and crop statistics (yield, production, and harvested areas) at the subdistrict level. In practice, the 288 centroid points of subdistrict boundaries were first generated via the feature-to-point function in ESRI ArcMap software, and they were subsequently used to extract the ADS index value of each period via the Extract Multi Values to Points function in ESRI ArcMap software. After that, the average yield, production, and harvested areas of each crop between 2011 and 2023 were appended to the 288 centroid points via Join Field under ESRI ArcMap software. Finally, the attribute data of 288 centroid points with the ADS index of three periods and crop statistical values were exported in MS Excel format for Pearson bivariate correlation analysis via SPSS statistical software.

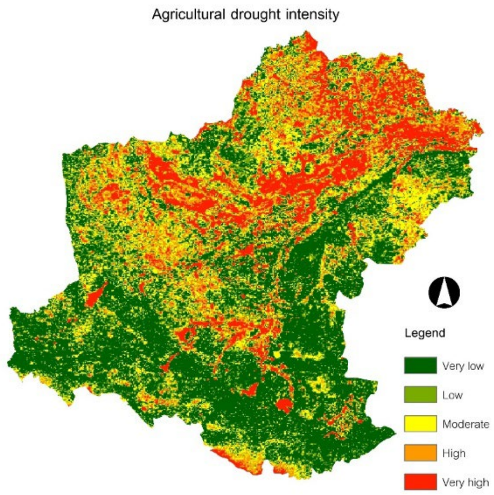
Results and discussion

1) Factor maps for agricultural drought sensitivity assessment

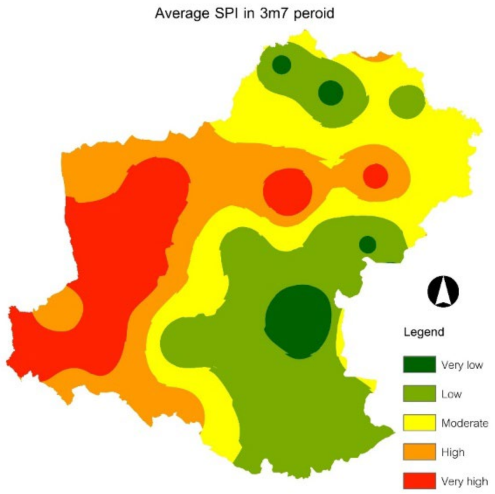
The spatial distributions of the selected factors for ADS assessment, which are based on a literature review, are displayed in Figure 3. These maps indicate the potential ADS of each factor, which varies from very low to very high. The dynamic factors, which include the average SPI and SPEI in three periods (3m7, 3m10, and 6m10), play significant roles in generating three scenarios of ADS in three periods, covering the planting and growing of economic crops. A summary of the normalized rating score of each factor for ADS index calculation and classification is reported in Table 1. Details of the potential ADS according to rating scores are reported in Supplementary material (SM) 1–18. The normalized rating scores of each factor are further applied to calculate the ADS index via the WLC method. High normalized rating scores increase the ADS index value.



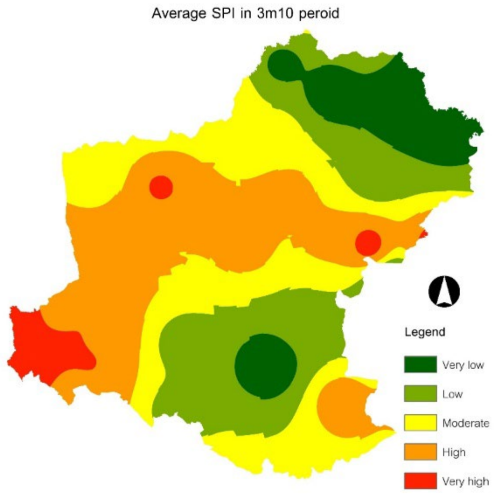
Agricultural drought frequency



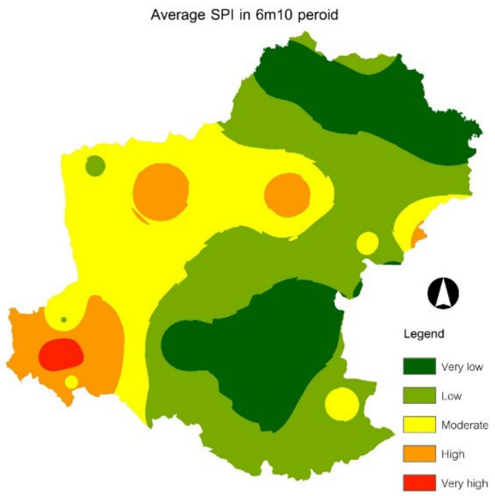
Agricultural drought intensity



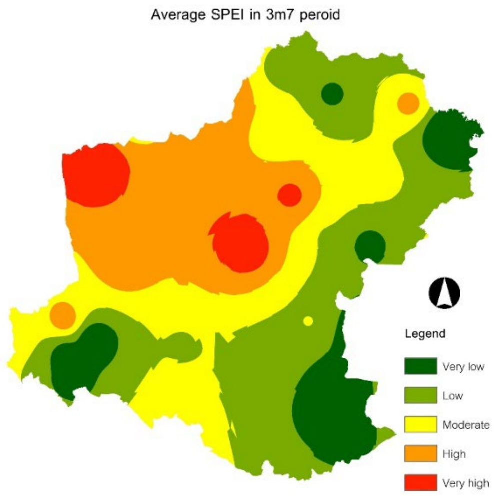
Average SPI in 3m7



Average SPI in 3m10

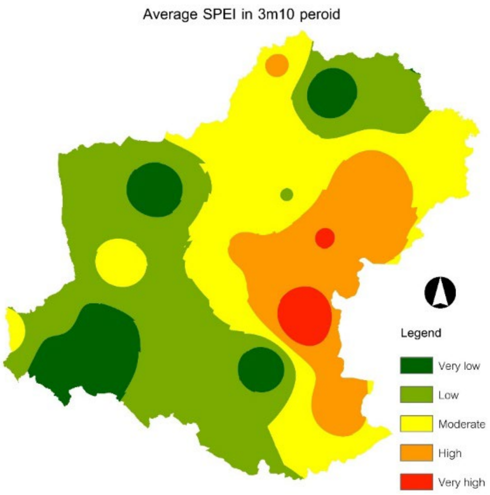


Average SPI in 6m10

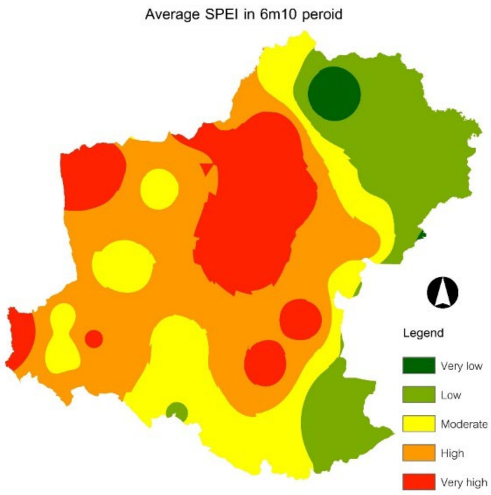


Average SPEI in 3m7

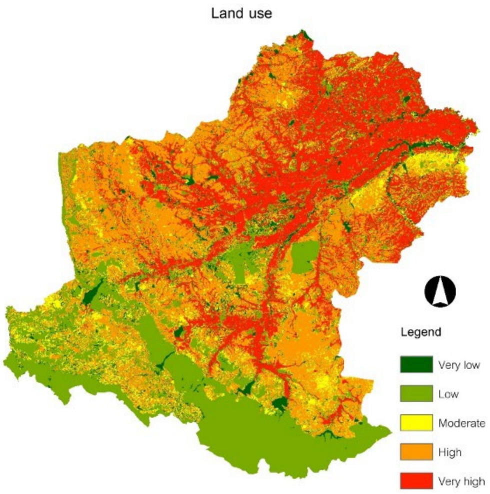
Figure 3 Spatial distribution of the factors for the ADS assessment.



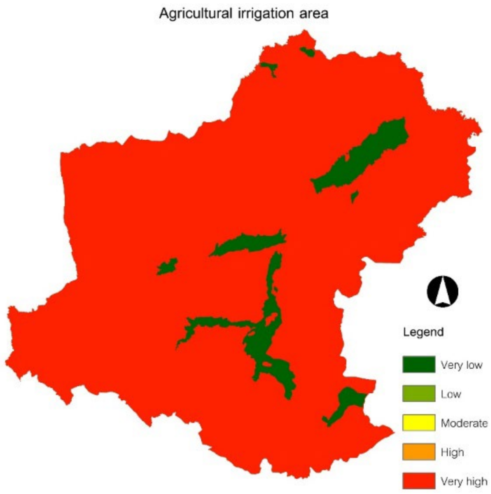
Average SPEI in 3m10



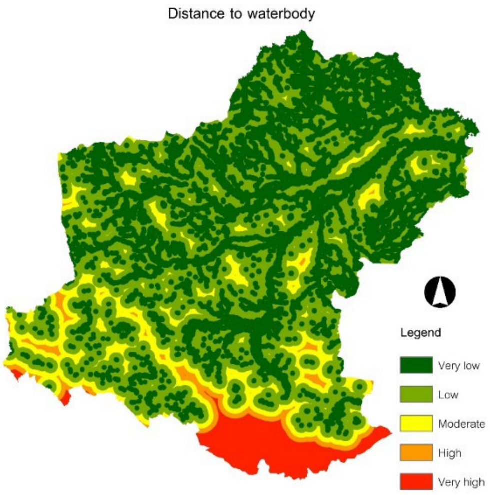
Average SPEI in 6m10



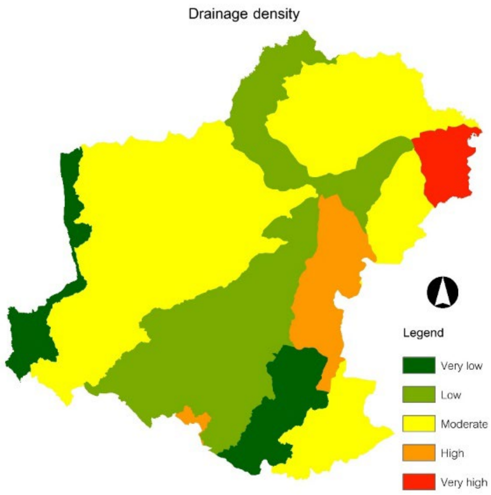
Land use



Agricultural irrigation area



Distance to waterbody



Drainage density

Figure 3 Spatial distribution of the factors for the ADS assessment (*continued*).

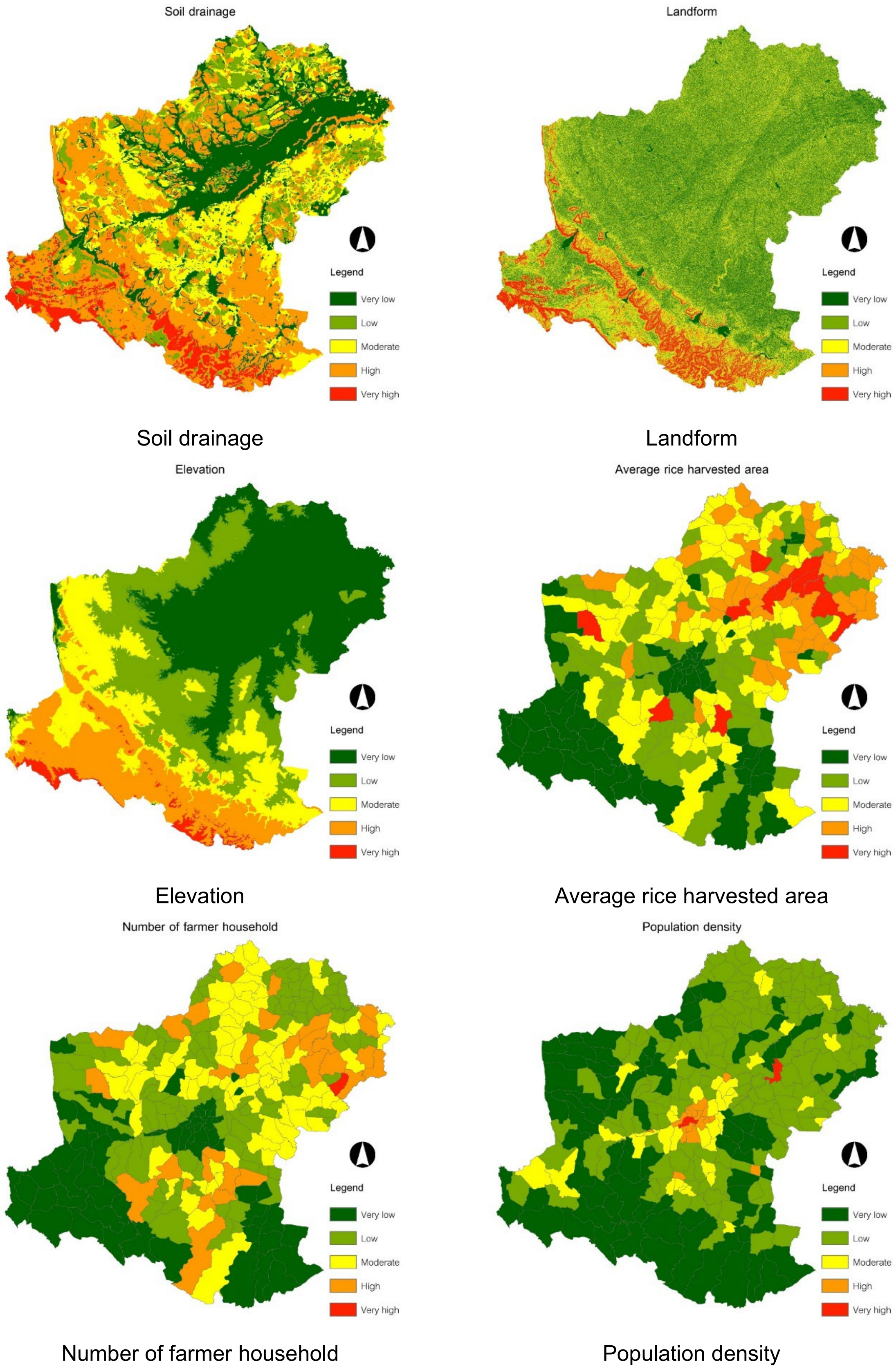


Figure 3 Spatial distribution of the factors for the ADS assessment (*continued*).

Table 1 Normalized rating score of the factor for ADS index calculation and classification

No.	Factor	Normalized rating score				
		Very low	Low	Moderate	High	Very high
1	Agricultural drought frequency (F01)	1	1.5	2	2.5	3
2	Agricultural drought intensity (F02)	1	1.5	2	2.5	3
3	Average SPEI: 3m7, 3m10, 6m10 (F03)	1	1.5	2	2.5	3
4	Average SPI: 3m7, 3m10, 6m10 (F04)	1	1.5	2	2.5	3
5	Land use (F05)	1	1.5	2	2.5	3
6	Agricultural irrigation area (F06)	1	Not apply	Not apply	Not apply	3
7	Distance to waterbody (F07)	1	1.5	2	2.5	3
8	Drainage density (F08)	1	1.5	2	2.5	3
9	Soil drainage (F09)	1	1.5	2	2.5	3
10	Landform (F10)	1	1.5	2	2.5	3
11	Elevation (F11)	1	1.5	2	2.5	3
12	Average rice yield (F12)	1	1.5	2	2.5	3
13	Farmer household (F13)	1	1.5	2	2.5	3
14	Population density(F14)	1	1.5	2	2.5	3

2) Analytic hierarchy process and weighting

A pairwise comparison matrix among the influential factors on the ADS is reported in Table 2. The pairwise comparison among the selected factors is assigned here on the basis of the characteristics of each factor via a research group discussion. In this study, agricultural drought frequency and intensity, which were extracted from the VCI for representing vegetation conditions, were assigned as the most important factors compared with other factors. Likewise, the average SPEI in three periods (3m7, 3m10, and 6m10), which were extracted from the SPEI on the basis of rainfall and temperature for representing climate conditions, was also assigned as the most important factor compared with the other factors. In contrast, population density, which was extracted from population density in 2023 at the subdistrict level to represent socioeconomic conditions, was assigned as the least important factor compared with other factors since the population density in the study area experienced marginal changes. The relatively important pairwise comparison matrix among factors on the ADS dictates their weights under the AHP [48].

The results of the weight of each factor under the AHP are reported in Table 3, with a consistency ratio of 0.08. The result of the AHP is acceptable since the consistency ratio is less than 0.1, as suggested by [48]. As a result of the AHP, the most important factors are agricultural drought frequency and agricultural drought intensity, with a weight value of 0.1749. In contrast, the least important factor is population density, with a weight value of 0.0089. In addition, the weights of the average SPEI and SPI in the three periods are equal, with values of 0.1555 and 0.1510, respectively. The normalized rating and weight scores were further applied to calculate the ADS index for three periods via the WLC method.

3) Agricultural drought sensitivity index calculation and classification

The spatial distributions of the ADS index and classification of the three periods are displayed in Figure 4. The areas of the ADS classification in the three periods are summarized in Table 4.

Table 2 Pairwise comparison matrix for AHP among factors of the ADS in three periods (3m7, 3m10 and 6m10)

No.	Factors	The important value between pairwise factors													
		F01	F02	F03	F04	F05	F06	F07	F08	F09	F10	F11	F12	F13	F14
1	Agricultural drought frequency (F01)	1	1	1	1/3	1/3	1/5	1/5	1/5	1/5	1/7	1/7	1/9	1/9	1/9
2	Agricultural drought intensity (F01)	1	1	1	1/3	1/3	1/5	1/5	1/5	1/5	1/7	1/7	1/9	1/9	1/9
3	Average SPEI: 3m7, 3m10, 6m10 (F03)	1	1	1	1	1/3	1/5	1/5	1/5	1/5	1/7	1/7	1/9	1/9	1/9
4	Average SPI: 3m7, 3m10, 6m10 (F04)	1/3	1/3	1	1	1/5	1/5	1/5	1/5	1/5	1/7	1/7	1/9	1/9	1/9
5	Land use (F05)	1/3	1/3	1/3	1/5	1	1/3	1/3	1/3	1/3	1/5	1/5	1/7	1/7	1/7
6	Agricultural irrigation area (F06)	1/5	1/5	1/5	1/5	1/3	1	1	1/3	1/3	1/3	1/5	1/7	1/7	1/7
7	Distance to waterbody (F07)	1/5	1/5	1/5	1/5	1/3	1	1	1/3	1/3	1/3	1/3	1/5	1/7	1/7
8	Drainage density (F08)	1/5	1/5	1/5	1/5	1/3	1/3	1/3	1	1	1/3	1/3	1/5	1/7	1/7
9	Soil drainage (F09)	1/5	1/5	1/5	1/5	1/3	1/3	1/3	1	1	1/3	1/3	1/5	1/7	1/7
10	Landform (F11)	1/7	1/7	1/7	1/7	1/5	1/3	1/3	1/3	1/3	1	1	1/5	1/5	1/5
11	Elevation (F12)	1/7	1/7	1/7	1/7	1/5	1/5	1/3	1/3	1/3	1	1	1/3	1/3	1/3
12	Average rice harvested area (F12)	1/9	1/9	1/9	1/9	1/7	1/7	1/5	1/5	1/5	1/5	1/3	1	1	1/3
13	Number of farmer households (F13)	1/9	1/9	1/9	1/9	1/7	1/7	1/7	1/7	1/7	1/5	1/3	1	1	1/3
14	Population density (F14)	1/9	1/9	1/9	1/9	1/7	1/7	1/7	1/7	1/7	1/5	1/3	1/3	1/3	1

Remark: A number of 1 is equally important, 1/3 is moderately less important, 1/5 is strongly less important, 1/7 is very strongly less important, and 1/9 is extremely less important.

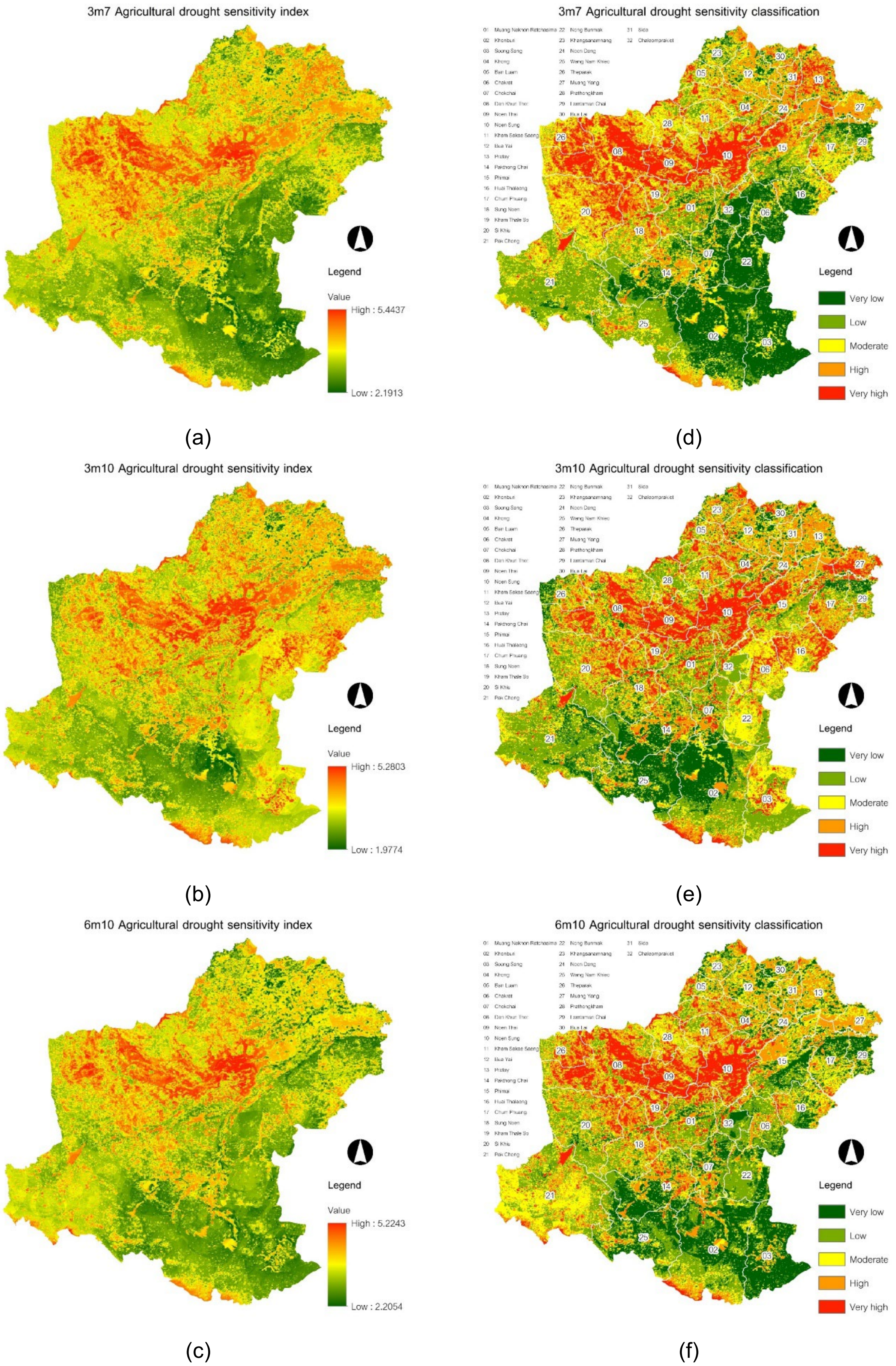


Figure 4 Spatial distributions of the ADS index and classification: (a) 3m7, (b) 3m10, (c) 6m10, (d) 3m7, (e) 3m10, and (f) 6m10.

Table 3 Weights of each factor on the ADS in three periods (3 m7, 3 m10 and 6 m10)

No.	Factors	Weight
1	Agricultural drought frequency (F01)	0.1749
2	Agricultural drought intensity (F02)	0.1749
3	Average SPEI: 3m7, 3m10, and 6m10 (F03)	0.1555
4	Average SPI: 3m7, 3m10, and 6m10 (F04)	0.1510
5	Land use (F05)	0.0820
6	Agricultural irrigation area (F06)	0.0570
7	Distance to waterbody (F07)	0.0530
8	Drainage density (F08)	0.0385
9	Soil drainage (F09)	0.0385
10	Landform (F10)	0.0239
11	Elevation (F11)	0.0194
12	Average rice yield (F12)	0.0115
13	Farmer household (F13)	0.0110
14	Population density (F14)	0.0089

Remark: Consistency ratio = 0.08

Table 4 Area of ADS classification in three periods (3 m7, 3 m10 and 6 m10)

Severity level	Area of ADS (%)		
	3m7: May-July (Planting period)	3m10: August-October (Growing period)	6m10: May-October (Planting and growing period)
Very low	20.11	13.20	18.60
Low	23.83	27.66	25.38
Moderate	23.07	23.83	23.85
High	20.82	21.30	21.10
Very high	12.17	14.01	11.07
Total	100.00	100.00	100.00

Table 5 Correlation matrix of the ADS indices and their correlation coefficient values for the three periods

	Correlation coefficient value		
	ADS index in 3m7	ADS index in 3m10	ADS index in 6m10
ADS index in 3m7 (Planting period)	1	0.8249	0.9277
ADS index in 3m10 (Growing period)		1	0.8783
ADS index in 6m10 (Planting and growing period)			1

Table 6 Correlation matrix of ADS classification and their correlation coefficient values for the three periods

	Correlation coefficient value		
	ADS classification in 3m7	ADS classification in 3m0	ADS classification in 6m10
ADS classification in 3m7 (Planting period)	1	0.7784	0.8787
ADS classification in 3m10 (Growing period)		1	0.8311
ADS classification in 6m10 (Planting and growing period)			1

As a result, the spatial distribution of the ADS index in three different periods displays different patterns according to the normalized rating and weighting scores of each factor for calculating the ADS index via the WLC method [50]. However, the results of the spatial correlation analysis among the ADS indices in the three periods (Figures 4 (a to c) via the spatial modeler module in ERDAS Imagine software reveal a strong positive linear relationship [53], as reported in Table 5. The correlation coefficient (R) values vary from 0.8249 to 0.9277. A high correlation coefficient value suggests substantial redundancy in the information content among the ADS indices in the three periods [54].

Moreover, the spatial distribution of the ADS classification, with high and very high levels at 3m7 in the planting period of crops, was in the northwest and northeast. The spatial distribution of high and very high ADS levels within 3m10 during the growing period of crops is located in northern. The spatial distri-bution of high and very high ADS in the 6m10 area covering the planting and growing periods of crops occurred in the northwest and northeast regions. The spatial patterns of ADS classification in the three periods (Figures 4 (d to f) display different patterns according to the ADS index. The R values among the ADS classifications in the three periods via the spatial modeler module in the ERDAS Imagine software show a strong positive linear relationship [53], as reported in Table 6. The R values vary from 0.7784 to 0.8787. These findings indicate substantial redundancy in the information content among ADS classifications in the three periods [54].

Furthermore, the percentage of severity levels of the ADS, including moderate, high and very high, at 3m7, 3m10 and 6m10, as shown in Table 4, covers

56.06%, 59.14%, and 56.02% of the study area, respectively. These results revealed moderate sensitivity to agricultural drought during the three periods in the study area.

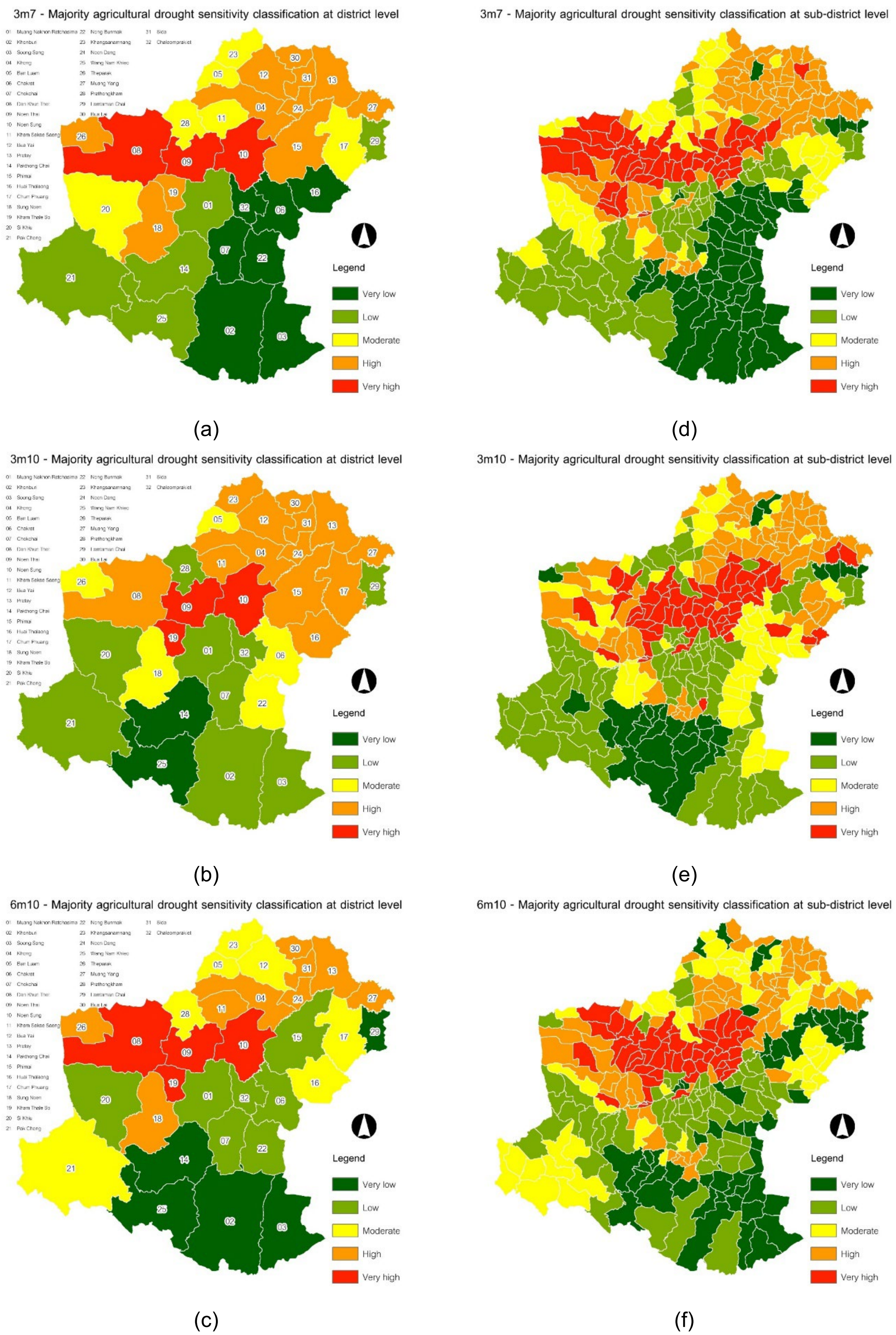


Figure 5 Spatial and temporal patterns of majority ADS severity at the district and subdistricts in (a) 3m7, (b) 3m10, (c) 6m10, and (d) 3m7, (e) 3m10, and (f) 6m10, respectively.

4) The severity of agricultural drought sensitivity in districts and subdistricts

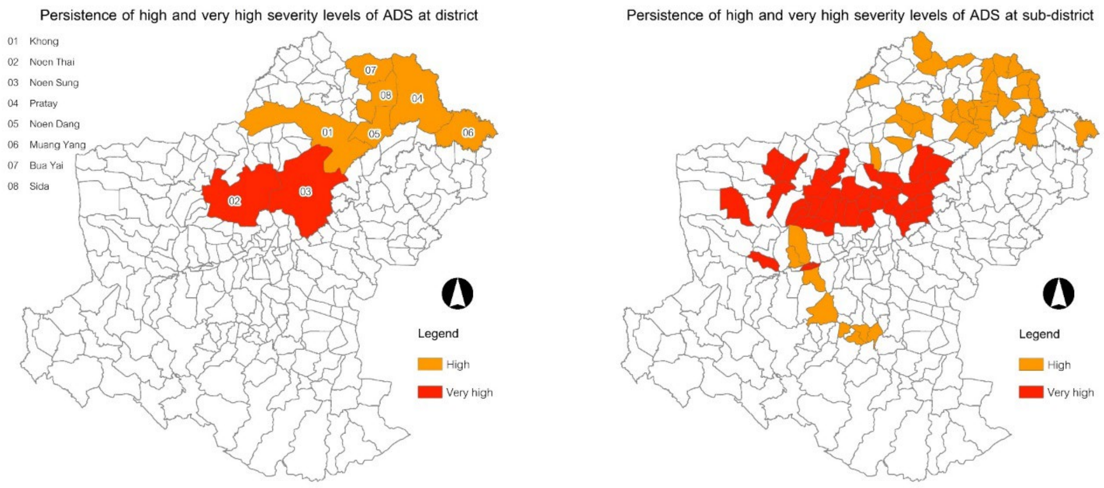
The severity levels of the ADS at the district and subdistrict levels in the three periods are displayed in Figure 5. The numbers of districts and subdistricts with severity levels of ADSs in the three periods are reported in Table 7.

By comparing the combined number of districts and subdistricts at high and very high severity levels of ADS, an ADS of 3m10, covering a growing period of crops, shows the most sensitive drought period, with 16 districts and 132 districts. ADS at a high severity level at the district level that occurred in three periods persisted in 6 districts: Khong, Pratay, Noen Dang, Muang Yang, Bua Lai and Sida. Similarly, the ADS at a very high severity level repeatedly occurred in three periods in 2 districts, i.e., Noen Thai and Noen Sung. Moreover, at the subdistrict level, ADS at high and very high severity levels constantly occurs in three periods in 38 and 34 subdistricts, respectively. Thus, the persistence of high and very high severity levels of ADS in these districts and subdistricts, as shown in Figure 6, should be focused on monitoring and preventing agricultural drought in the future by relevant government agencies, including the DOAE and the DDPM.

In addition, the primary land use types in 2023 over the persistence of high and very high severity levels of ADS in the three periods were explored via overlay analysis with GIS Analysis module in ERDAS Imagine software, as reported in Tables 8 to 9. As a result, the dominant land use type associated with the persistence of high and very high severity levels of ADS in the three periods is rice fields, with a high percentage compared with other land use types. These findings suggest that if agricultural drought occurs in the study area, rice fields should be intensively managed to minimize drought impacts by farmers with support from government agencies, including the DOAE, RID, DWR, and DGR.

Table 7 Number of districts and subdistricts with different severity levels of ADS in the three periods.

ADS severity	Number of districts and subdistricts					
	3m7 (May-July)		3m10 (August-October)		6m10 (May-October)	
	District	Subdistrict	District	Subdistrict	District	Subdistrict
Very low	7	58	2	28	5	53
Low	5	57	9	79	7	66
Moderate	6	48	5	49	7	52
High	11	75	13	75	9	69
Very high	3	50	3	57	4	48
Total	32	288	32	288	32	288



(a) (b)

Figure 6 Spatial distributions of the persistence of high- and very high-severity ADS in three periods at the (a) district and (b) subdistrict levels.

Table 8 Overlay analysis between the persistent severity level of ADS in three periods in districts and land use types in 2023 from LDD

Land use type	Percent of land use types in each persistent severity level in a specific district				
	Very low	Low	Moderate	High	Very high
Urban and built-up areas	0%	36.07%	4.20%	6.92%	9.41%
Rice	0%	24.60%	34.39%	70.56%	66.53%
Cassava	0%	16.82%	23.25%	4.84%	6.74%
Sugarcane	0%	2.27%	26.33%	3.93%	2.88%
Corn	0%	1.43%	0.05%	0.01%	3.51%
Other agricultural uses	0%	7.30%	4.37%	3.91%	2.36%
Forestland	0%	0.37%	1.10%	2.15%	0.45%
Waterbody	0%	2.55%	3.85%	3.84%	3.27%
Miscellaneous land	0%	8.60%	2.45%	3.84%	4.85%
Total		100.00%	100.00%	100.00%	100.00%

Table 9 Overlay analysis of the persistent severity level of ADS in three periods in subdistricts and land use types in 2023 from LDD

Land use type	Percent of land use types in each persistent severity level in specific subdistrict				
	Very low	Low	Moderate	High	Very high
Urban and built-up areas	8.25%	17.98%	4.63%	6.88%	8.33%
Rice	21.73%	15.36%	31.73%	63.99%	59.11%
Cassava	29.63%	19.73%	24.29%	8.77%	12.47%
Sugarcane	7.02%	11.53%	25.26%	4.72%	3.82%
Corn	0.21%	6.57%	1.77%	1.80%	4.83%
Other agricultural uses	9.76%	9.56%	5.85%	3.98%	2.14%
Forestland	18.31%	9.33%	1.83%	1.97%	0.91%
Waterbody	2.02%	2.94%	2.94%	3.87%	3.24%
Miscellaneous land	3.08%	6.98%	1.69%	4.02%	5.15%
Total	100.00%	100.00%	100.00%	100.00%	100.00%

Furthermore, significant factors in ADS classification were explored to describe the relationships between ADS classification in three periods and their factors via spatial correlation analysis with the spatial modeler module under ERDAS Imagine software, as summarized in SM 19–21.

For the ADS classification at 3m7 (the planting period), the agricultural drought frequency, agricultural drought intensity and average SPEI had strong positive linear relationships with the ADS. In contrast, the average SPI and land use had a moderate positive linear relationship with the ADS.

Moreover, for the ADS classification at 3m10 (growing period), the agricultural drought frequency and agricultural drought intensity exhibited strong positive linear relationships with the ADS. In contrast, land use and average rice harvested areas had a moderate positive linear relationship with the ADS, but elevation had a moderate negative linear relationship with the ADS.

Moreover, for the ADS classification at 6m10 (the planting and growing period), the agricultural drought frequency and agricultural drought intensity had strong positive linear relationships with the ADS. In contrast, the average SPEI, average SPI and land use had moderate positive linear relationships with the ADS.

These findings confirm the influence of various factors on ADS, as suggested by researchers, particularly climate [14–16], topography [20–22], land use and land cover [23], socioeconomic factors [31–32] and drought indices [33–34].

5) Potential impact area of agricultural drought sensitivity on economic crops

The potential impact areas of the ADS in the three periods on the existing area of each economic crop (rice, cassava, sugarcane and corn) in 2023 from the LDD are reported in Table 10.

As a result, the potential impact areas of ADS with combined moderate, high and very high severity levels on rice in 2023 in the 3m7 (planting period), 3m10 (growing period) and 6m10 (planting and growing periods) periods cover areas of 82.72%, 85.76% and 80.38% of the total area (6,092.73 km^2). The high percentage of potential impact areas on rice implies that ADS has a high impact on rice since rice requires high amounts of water during the planting and growing periods. In practice, paddy rice is usually grown in level basins that are flooded with water throughout most of the growing season [55].

Table 10 Potential impact area of ADS on economic crops in 2023

Economic crop	Severity level of ADS	Area in each period (%)		
		3m7: May-July Planting period	3m10: August-October Growing period	6m10: May-October Planting and growing
Rice	Very low	5.82	3.15	5.84
	Low	11.47	11.08	13.78
	Moderate	23.60	20.52	24.59
	High	34.90	34.96	34.69
	Very high	24.22	30.28	21.10
	Total	100.00	100.00	100.00
Cassava	Very low	28.28	9.79	19.59
	Low	19.98	28.46	30.48
	Moderate	22.20	33.01	22.03
	High	18.50	19.82	18.50
	Very high	11.04	8.90	9.40
	Total	100.00	100.00	100.00
Sugarcane	Very low	22.08	8.09	16.73
	Low	28.23	33.50	33.33
	Moderate	28.85	33.25	27.53
	High	15.34	18.68	17.32
	Very high	5.50	6.47	5.09
	Total	100.00	100.00	100.00
Corn	Very low	2.85	6.74	4.72
	Low	24.19	32.15	20.97
	Moderate	29.07	26.29	30.86
	High	25.35	21.69	26.47
	Very high	18.54	13.13	16.99
	Total	100.00	100.00	100.00

In contrast, the potential impact areas of ADS with combined moderate, high and very high severity levels on cassava in 2023 at 3m7, 3m10 and 6m10 covered areas of 51.74%, 61.73% and 49.93%, respectively, of the total area (3,853.65 km^2). The moderate percentage of the potential impact area on cassava suggested that ADS has a moderate impact on cassava since cassava requires less water than does rice during the planting and growing periods. Owing to its hot and dry conditions, a favorable climate is suitable for cassava production [56].

Like cassava, the potential impact areas of ADS with combined moderate, high and very high severity levels on sugarcane in 2023 at 3m7, 3m10 and 6m10 covered 49.69%, 58.40% and 49.94% of its total area (2,048.75 km^2). The moderate percentage of the potential impact area on sugarcane suggested that ADS has a moderate impact on sugarcane. Sugarcane requires less water than does rice during the planting and growing periods. In practice, after the sugarcane from the original plant is harvested, a portion of the stalk of the sugarcane is left underground, resulting in the successful growth of the sugarcane for approximately 2–3 years [57].

Like rice, the potential impact areas of ADS with combined moderate, high and very high severity levels on corn in 2023 at 3m7, 3m10 and 6m10 covered areas of 72.96%, 61.11% and 74.32%, respectively, of its total area (783.10 km^2). The high percentage of potential impact areas on corn indicates that ADS has a high impact on corn since corn requires high amounts of water during the planting and growing periods [58].

These findings suggest that if drought occurs in the study area, rice and sugarcane areas should be the priority areas with a field survey by DOAE and DDPM to mitigate the impact of ADS.

6) Relationship between agricultural drought sensitivity and economic crop statistics

Table 11 reports a Pearson bivariate correlation analysis between the ADS index in 3 periods and the normalized average yield (kg per 1,600 m^2), average production (kg) and average harvested areas (1,600 m^2) between 2011 and 2023 for in-season rice, cassava, sugarcane and corn at the subdistrict level, with 288 samples.

For the crop yield data, the ADS indices at 3m7 and 3m10 exhibited significant negative linear relationships with the average cassava yield, with R values of -0.136 and -0.119, respectively. Similarly, the ADS indices at 3m7, 3m10 and 6m10 were significantly negatively correlated with the average sugarcane yield, with R values of -0.159, -0.119 and -0.140, respectively. In contrast, the ADS index at 6 m10 shows a significant positive linear relationship with the average corn yield, with an R value of 0.140, which is an unexpected result. Nevertheless, the ADS indices at 3m7 and 3m10 show an insignificant linear relationship with the average corn yield, which is an unexpected result. Additionally, the ADS index in the three periods shows an insignificant negative linear relationship with the average in-season rice yield, as expected.

Table 11 Bivariate correlation analysis between the ADS and economic crop statistics in the 3 periods

Economic crop statistics	Correlation coefficient in each period		
	3m7 (Planting period)	3m10 (Growing period)	6m10 (Planting and growing period)
Average yield of in-season rice	-0.073	-0.019	-0.032
Average yield of cassava	-0.136*	-0.119*	-0.043
Average yield of sugarcane	-0.159**	-0.119*	-0.140*
Average yield of corn	0.100	-0.042	0.140*
Average production of in-season rice	0.220**	0.239**	0.148*
Average production of cassava	-0.113	-0.109	-0.086
Average production of sugarcane	-0.106	-0.066	-0.084
Average production of corn	0.138*	-0.062	0.106
Average harvested area of in-season rice	0.271**	0.284**	0.180**
Average harvested area of cassava	-0.264**	-0.230**	-0.227**
Average harvested area of sugarcane	-0.1043	-0.0848	-0.1028
Average harvested area of corn	0.140*	-0.0742	0.1044

Remark: ** The correlation is significant at the 0.01 level (2-tailed), and *. The correlation is significant at the 0.05 level (2-tailed).

For the crop production data, the ADS indices at 3m7, 3m10, and 6m10 were significantly positively linearly related to the average in-season rice production, with R values of 0.220, 0.239, and 0.148, respectively, which was an unexpected result. Similarly, the ADS index at 3m7 showed a significant positive linear relationship with average corn production, with an R value of 0.138, which was an unexpected result. In addition, the ADS index in the three periods shows an insignificant negative linear relationship with average cassava and sugarcane production, as expected.

For the crop harvested area data, the ADS index in the three periods had a significant negative linear relationship with the average cassava harvested area, with R values of -0.264, -0.230, and -0.227, as expected. In contrast, the ADS index in the three periods had a significant positive linear relationship with the average in-season rice harvested area, with R values of 0.271, 0.284, and 0.180, which was an unexpected result. Similarly, the ADS index at 3m7 showed a significant positive linear relationship with the average corn harvested area, with an R value of 0.140, which was an unexpected result. In addition, the ADS in the three periods shows an insignificant negative linear relationship with the average harvested area of sugarcane, as expected.

As a result, the ADS index in different periods can be adequately applied to describe the relationship with the survey data of average yield, production, and harvested areas of cassava and sugarcane as the expected results, even though the ADS in three periods covering the planting and growing periods of cassava and sugarcane vary from place to place and from time to time.

In contrast, the ADS index in different periods cannot be adequately applied to describe the relationship with the average yield, production, and harvested areas of corn as expected. Likewise, the ADS index in different periods cannot be applied appropriately to describe the relationship between average production and harvested areas of in-season rice.

These findings are comparable to those of a previous study by Tanguy et al. [12], who reported that crops suffer some negative impacts from meteorological drought (positive correlations), even during the wet season. The relationships between drought indicators and crop yield depend on land use, season, and region.

Conclusion

An assessment of the spatial and temporal patterns of ADS and its impact on economic crops was successfully conducted on the basis of the integration of multiple factors on ADS with the AHP and WLC methods. As a result, the spatial distributions of the ADSs at 3m7, m10 and 6 m10 displayed different patterns. Areas with severe levels of ADS, including moderate, high and very high levels, at 3m7, m10 and 6 m10 covered 56.06%, 59.14%, and 56.02% of the study area, respectively. These results suggested that the three periods in the study area were moderately sensitive to agricultural drought. The persistent high and very high severity levels of the ADS classification in the three periods at the district and subdistrict levels included 8 districts and 72 subdistricts. Therefore, these districts and subdistricts should focus on monitoring and preventing agricultural drought via the DOAE and DDPM. Additionally, the persistence of high and very high severity levels of ADS in those districts and subdistricts primarily occurred in rice fields. Thus, if agricultural drought occurs in the study area, rice fields should be intensively managed to minimize drought impacts by farmers with support from the DOAE, RID, DWR, and DGR. Furthermore, the potential impact areas of ADS in the three periods based on land use in 2023 revealed high impacts of ADS on rice and corn, with values of more than 80% and 60%, respectively, but moderate impacts of ADS on cassava and sugarcane, with values of less than 50% and 50%, respectively.

Accordingly, if drought occurs in the study area, rice and sugarcane areas should be the priority areas with a field survey by DOAE and DDPM to mitigate drought impact.

In conclusion, the research workflow can be used as a guideline for managing crops via the DOAE and monitoring agricultural drought via the DDPM. The government should establish early warning systems for droughts jointly by government agencies and universities to prevent and mitigate the impact of drought. Furthermore, advanced machine learning algorithms such as ANNs and RFs should be examined to predict agricultural drought impacts.

References

[1] AMS (American Meteorological Society). Drought — An information statement of the American Meteorological Society. American Meteorological Society, 2013. [Online] Available from: https://www.ametsoc.org/index.cfm/ams/about-ams/ams-statements/archive-statements-of-the-ams/drought/ [Accessed 15 November 2024].

[2] Heim, R.R. A review of twentieth-century drought indices used in the United States. Bulletin of the American Meteorological Society, 2002, 83(8), 1149–1165.

[3] Kramer, P.J., Boyer, J.S. Water relations of plants and soils. Academic Press, San Diego, CA, USA, 1995, 495p.

[4] IPCC (Intergovernmental Panel on Climate Change). Overview of impacts, adaptation, and vulnerability to climate change. *In:* McCarthy, J.J., Canziani, O.F., Leary, N.A., Dokken, D.J., White, K.S. Climate change 2001: Impacts, adaptation, and vulnerability. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2001, 1535p.

[5] IPCC. Determinants of risk: Exposure and vulnerability. *In:* Field, C.B., Barros, V., Stocker, T.F., Dahe, Q., Dokken, D.J., Ebi, K.L., …, Midgley, P.M. Managing the risks of extreme events and disasters to advance climate change Adaptation. Cambridge and New York, Cambridge University Press, 2012, 582p.

[6] World Bank Group. Thailand economic monitor: Coping with droughts and floods; Building a sustainable future. Bangkok, The World Bank, 2023. [Online] Available from: https://documents1.worldbank.org/curated/en/099062723120576672/pdf/P1797380ebb6c50f70b38f024336050ebcc.pdf [Accessed 1 December 2024].

[7] Homdee, T., Pongput, K., Kanae, S. A comparative performance analysis of three standardized climatic drought indices in the Chi River basin, Thailand. Agricultural and Natural Resource, 2016, 50, 211–219.

[8] Punprasit, J. Geographic information system for drought risk area assessment by regression analysis in Lop Buri province. M.Sc. Thesis, Faculty of Graduate Studies, Mahidol University. 2006.

[9] Houmma, I.H., El Mansouri, L., Gadal, S., Gadal, S., Garba, M., Hadria, R. Modelling agricultural drought: a review of latest advances in big data technologies. Geomatics, Natural Hazards and Risk, 2022, 13(1), 2737–2776.

[10] Sutanto, S.J., van der Weert, M., Blauhut, V., Van Lanen, H.A. Skill of large-scale seasonal drought impact forecasts. Natural Hazards Earth System Sciences, 2020, 20(6), 1595–1608.

[11] Mokhtari, R., Akhoondzade, M. Data fusion and machine learning algorithms for drought forecasting using satellite data. Journal of the Earth and Space Physics, 2021, 46(4), 231–246.

[12] Tanguy, M., Eastman, M., Magee, E., Barker, L.J., Chitson, T., Ekkawatpanit, C., …, Visessri, S. Indicator-to-impact links to help improve agricultural drought preparedness in Thailand. Natural Hazards Earth System Sciences, 2023, 23, 2419–2441.

[13] Ha, T.V., Huth, J., Bachofer, F., Kuenzer, C. A Review of earth observation-based drought studies in Southeast Asia. Remote Sensing, 2022, 14, 3763.

[14] Lin, B.B. Resilience in agriculture through crop diversification: Adaptive management for environmental change. BioScience, 2011, 61(3), 183–193.

[15] Mishra, A.K., Singh, V.P. A review of drought concepts. Journal of Hydrology, 2010, 391(1–2), 202–216.

[16] Lobell, D.B., Schlenker, W., Costa-Roberts, J. Climate trends and global crop production since 1980. Science, 2011, 333(6042), 616–620.

[17] Hudson, B.D. Soil organic matter and available water capacity. Journal of Soil and Water Conservation, 1994, 49(2), 189–194.

[18] Lal, R. Enhancing crop yields in the developing countries through restoration of the soil organic carbon pool in agricultural lands. Land Degradation & Development, 2006, 17(2), 197–209.

[19] Brady, N.C., Weil, R.R. The nature and properties of Soils. 14th Edition. Pearson Prentice Hall, 2008, 750p.

[20] Daly, C., Neilson, R.P., Phillips, D.L. A statistical-topographic model for mapping climatological precipitation over mountainous terrain. Journal of Applied Meteorology and Climatology, 1994, 33(2), 140–158.

[21] Wilson, J.P., Gallant, J.C. Terrain analysis: Principles and applications. John Wiley & Sons, 2000, 516p.

[22] Morgan, J.A., LeCain, D.R., Pendall, E., Blumenthal, D.M., Kimball, B.A., Carrillo, Y., …, West, M. C4 grasses prosper as carbon dioxide eliminates desiccation in warmed semi-arid grassland. Nature, 2011, 476, 202–206.

[23] Jackson, R.B, Randerson, J.T, Canadell, J.G., Anderson, R.G., Avissar, R., Baldocchi, D.D., …, Pataki, D.E. Protecting climate with forests. Environmental Research Letters, 2008, 3(4), 044006.

[24] Siebert, S., Burke, J., Faures, J.M., Frenken, K., Hoogeveen, J., Döll, P., Portmann, F.T. Groundwater use for irrigation – A global inventory. Hydrology and Earth System Sciences, 2010, 14(10), 1863–1880.

[25] Hao, Z., AghaKouchak, A. A Nonstationary analysis of droughts in the United States. Geophysical Research Letters, 2014. 41(11), 4014–4021.

[26] Zhang, L., Nan, Z., Xu, Y., Li, S. Hydrological impacts of land use change and climate variability in the headwater region of the Heihe River Basin, Northwest China. PLoS ONE, 2016, 11(6), e0158394.

[27] You, Q., Fang, N., Liu, L., Yang, W., Zhang. L., Wang, Y. Effects of land use, topography, climate and socio-economic factors on geographical variation pattern of inland surface water quality in China. PLoS ONE, 2019, 14(6), e0217840.

[28] Smith, J.A., Jones, M.B. Impact of land cover changes on hydrological responses and agricultural drought sensitivity. Journal of Hydrology, 2021, 595, 123–134.

[29] Williams, L.R., Taylor, K.D. Interplay between land use and hydrological systems: Effects on drought conditions. Environmental Research Letters, 2022, 17(4), 045001.

[30] Ayalew, A.D., Wagner, P.D., Tigabu, T.B., Sahlu, D., Fohrer, N. Hydrological responses to land use and land cover change and climate dynamics in the Rift Valley Lakes Basin, Ethiopia. Journal of Water and Climate Change, 2023, 14(8), 2788.

[31] Brown, T.A., Green, S.E. Socio-economic determinants of agricultural drought sensitivity: A Review. Environmental Economics and Policy Studies, 2020, 22(3), 321–335.

[32] Li, H., Zhang, Q., Wu, X. Linking socio-economic factors to water quality and drought risks: Evidence from China. Water Resources Research, 2021, 57(6), e2020WR028522.

[33] Palmer, W.C. Meteorological drought. Washington, D.C., 1965, 58p.

[34] McKee, T.B., Doesken, N.J., Kleist, J. The relationship of drought frequency and duration to time Scales. In Proceedings of the 8th Conference on Applied Climatology, Anaheim, CA. Boston, 17–22 January 1993.

[35] Shao, M., Han, Z., Sun, J., Xiao, C., Zhang, S., Zhao, Y. A review of multi-criteria decision making applications for renewable energy site selection. Renewable Energy, 2020, 157, 377–403.

[36] Taherdoost, H., Madanchian, M. Multi-criteria decision making (MCDM) methods and concepts. Encyclopedia, 2023, 3, 77–87.

[37] Lunetta, R.S., Congalton, R.G., Fenstermaker, L.K., Jensen, J.R., McGwire, K.C., Tinney, L.R. Remote sensing and geographic information system data Integration: Error sources and research issues. Photogrammetric Engineering & Remote Sensing, 1991, 57(6), 677–687.

[38] Kogan, F.N. Droughts of the late 1980s in the United States as derived from NOAA polar-orbiting satellite data. Bulletin of the American Meteorological Society, 1995, 76(5), 655–668.

[39] WMO (World Meteorological Organization). Standardized precipitation index user guide (WMO-No. 1090), Geneva, 2012.

[40] Vicente-Serrano, S.M., Begueria, S., Lopez-Moreno, J.I. A multi-scalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. Journal of Climate, 2010, 23, 1696-1718.

[41] Jain, V.K., Pandey, R.P., Jain, M.K. Spatial-temporal assessment of vulnerability to drought. Natural Hazards, 2015, 76, 443–469.

[42] Pandey, R.P., Pandey, A., Galkate, R.V., Byun, H.R., Mal, B.C. Integrating hydro-meteorological and physiographic factors for assessment of vulnerability to drought. Water Resources Management, 2010, 24, 4199–4217.

[43] Prathumchai, K., Honda, K., Nualchawee, K. Drought risk evaluation using remote sensing and GIS: A case study in Lop Buri Province. In Proceedings of the 22nd Asian Conference on Remote Sensing, National University of Singapore, Singapore, 5-9 November 2001.

[44] LDD (Land Development Department). Land use plans, Lamtakhong watershed. Land Office of Soil Survey and Land Use Planning, Land Development Department, 2009, 206 pp.

[45] Shahid, S., Behrawan, H. Drought risk assessment in the western part of Bangladesh. Natural Hazards, 2008, 46, 391–413.

[46] Pei, W., Fu, Q., Liu, D., Li, T.-X., Cheng, K. Assessing agricultural drought vulnerability in the Sanjiang Plain based on an improved projection pursuit model. Natural Hazards, 2016, 82, 683–701.

[47] Tsangaratos, P., Pizpikis, T., Vasileiou, E., Pliakas, F., Schuth, C., Kallioras, A. Development of multi-criteria decision support system (DSS) coupled with GIS for identifying optimal locations for soil aquifer treatment (sat) facilities. In Proceedings

of the 13th International Congress, Chania, September 2013.

[48] Saaty, R.W. The analytic hierarchy process-what it is and how it is used. Math Modeling, 1987, 9(3–5), 161–176.

[49] Benmouss, K., Laaziri, M., Khoulji, S., Kerkeb, M.L., El Yamami, A. AHP-based approach for evaluating ergonomic criteria. Procedia Manufacturing, 2019, 32, 856–863.

[50] Eastman, J.R., Kyem, P.A.K., Toledano, J. A procedure for multi-objective decision making in GIS under conditions of competing objectives. Proceedings, EGIS'93, 1993, 438–447.

[51] Eastman, J.R., Jin, W., Kyem, P.A.K., Toledano, J. Raster procedures for multi-criteria/multi-objective decisions. Photogrammetric Engineering and Remote Sensing, 1995, 61(5), 539–547.

[52] Malczewski, J. On the use of weighted linear combination method in GIS: Common and best practices approaches. Transactions in GIS, 2000, 4(1), 5–22.

[53] Cohen, J. Statistical power analysis for the behavioral sciences. 2nd edition. Hillsdale, NJ: Lawrence Erlbaum, 1988, 567p.

[54] Jensen, J.R. Introductory digital image processing: A remote sensing perspective. 4th Edition. Columbia, University of South Carolina, 2015, 623p.

[55] Brouwer, C., Prins, K., Heibloem, M. Determination of the irrigation schedule for paddy rice. Irrigation Water Management: Irrigation Scheduling, 1989. [Online] Available from: https://www.fao.org/4/t7202e/t7202e07.htm#4.1%20introduction [Accessed 20 January 2025].

[56] Walderich, A. Cassava industry in Thailand-Statistics & Facts. Statista, 2024. [Online] Available from: https://statista.com/topics/11099/cassava-industry-in-thailand [Accessed 20 January 2025].

[57] Yamane, T. Sugarcane. Britannica, 2025. [Online] Available from: https://www.britannica.com/plant/sugarcane [Accessed 20 January 2025].

[58] Bayer Crop Science United States. Corn irrigation timing and water use efficiency. Bayer Crop Science, 2021. [Online] Available from: https://www.cropscience.bayer.us/articles/bayer/corn-irrigation-timing [Accessed 20 January 2025].