Responses of Adaptive Capacity to Agricultural Drought Vulnerability and Its Impact, Nakhon Ratchasima, Thailand

Ongsomwang, S.
School of Mathematics and Geoinformatics, Institute of Science, Suranaree University of Technology, Nakhon Ratchasima 3000, Thailand, E-mail: suwit@sut.ac.th

DOI: https://doi.org/10.52939/ijg.v21i8.4363

Abstract
Thailand frequently suffers from droughts due to a shortage of rainfall, and the northeast region is particularly vulnerable to drought. The effect of climate change on water resources directly relates to agricultural drought vulnerability. The study aims to assess the response of adaptive capacity to agricultural drought vulnerability and its impact. This study integrated agricultural drought exposure and sensitivity without and with adaptive capacity in the framework of climate change adaptation for assessing the response of adaptive capacity (groundwater use in agriculture) on agricultural drought vulnerability and drought impact in 3m7 (May to July), 3m10 (August to October, and 6m10 (May to October). As a result, based on severity level change detection between agricultural drought vulnerability classification without and with groundwater use, areas of decreasing severity by combining moderate, high, and very high severity levels after applying groundwater use in agriculture in 3m7, 3m10, and 6m10 cover an area of 4,408.50 sq.km, 4,776.09 sq.km, and 7,149.33 sq.km, respectively. In addition, based on the changed area of agricultural drought vulnerability impact on economic crops without and with groundwater use in agriculture, the affected areas, by combination of moderate, high, and very high severity levels for rice, sugarcane and corn, decreased in 3 periods. Still, the areas affected by a combination of moderate, high, and very high severity levels for cassava increased in three periods. These findings suggest a significant role for groundwater use in agriculture in mitigating the impact of drought. Therefore, a feasibility study on the use of groundwater in agriculture is recommended.

Keywords: Adaptive Capacity, Agricultural Drought Exposure, Agricultural Drought Sensitivity, Agricultural Drought Vulnerability, Groundwater Suitability Classification for Agriculture Uses

1. Introduction

Drought is a complex phenomenon due to its unpredictable onset and termination, variable duration, uncertain frequency and intensity, and nonspecific spatial extent. Drought has multiple negative impacts, even within a single domain [1]. Drought impacts on agriculture rely on its intensity, severity, duration and timing relative to crop growth stages. Additionally, drought events with comparable intensity and duration can have varying impacts on agriculture, depending on the crops and local adaptive capacity [2]. According to the Intergovernmental Panel on Climate Change (IPCC) report on extreme events in 2012, quantifying loss and damage from extreme climate events, such as droughts, has become essential for effective policy implementation [3].

Thailand regularly suffers from droughts due to a shortage of rainfall, reduced flow in surface and sub-surface rivers, and poor land management practices. The whole country was affected by severe droughts in 1979, 1994, and 1999. In particular, the northeastern region, which has the highest poverty rates, is vulnerable to drought [4]. The severe drought in Thailand in 1999 resulted in agricultural production losses estimated at approximately 26 billion Thai Baht (US$840 million), primarily due to reduced off-season rice production in MY2019/20 [5] Conceptually, vulnerability is a relative measure that indicates the degree to which a system is susceptible to damage (harm) due to the occurrence of an event [6]. The vulnerability of the system should encompass exposure, sensitivity and adaptive capacity components [7]. Based on the definition, exposure is a measure of the degree to which the systems under consideration are in areas susceptible to hazard [8]

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online)

Sensitivity is defined as “the degree to which a system is affected, either adversely or beneficially, by climate-related stimuli” [9]. Adaptive capacity is defined as ‘‘the ability to adjust, take advantage of opportunities, or cope with consequences” [10]. Recently, there has been an increasing number of drought vulnerability assessments in the framework of two approaches: (1) climate change adaptation (CCA) and (2) disaster reduction risk (DRR) [11]. Many researchers applied the CCA approach to assess vulnerability and its impact related to the effect of climate change [12][13][14][15][16][17][18] and [19].

In this study, the framework of Fontaine and Steinemann [12], which includes exposure, sensitivity, and adaptive capacity, was applied to assess the response of adaptive capacity to agricultural drought vulnerability and its associated impact. The specific objectives are (1) to classify the suitability of groundwater uses in agriculture as a proxy of adaptive capacity and (2) to assess the responses of adaptive capacity to agricultural drought vulnerability and its impact.

2. Methods

2.1 Study Area

Nakhon Ratchasima province is Thailand’s largest province, situated in the central part of the country, far from the coastal zone. Nakhon Ratchasima province covers an area of about 20,729 sq.km and has 288 sub-districts in 32 districts (Figure 1).

2.2 Sources of Data

The collected and prepared data are summarized below:

- Rainfall data from 1975 to 2022 from 37 stations from the Thai Meteorological Department (TMD) for Standardized Precipitation Index (SPI) calculation.
- MOD31A-NDVI product from 2002 to 2022 from the U.S. Geological Survey (USGS) website (https://earthexplorer.usgs.gov) for Vegetation Condition Index (VCI) extraction.
- MOD11B-LST product from 2002 to 2022 from the USGS website for Land Surface Temperature (LST) extraction.
- Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) from the USGS website for landform and elevation extraction.
- Land use data in 2008, 2011,2015, 2017, 2019, and 2023 from the Land Development Department (LDD) for land use extraction.
- Soil series from the LDD for soil drainage extraction.
- Agricultural irrigation area from the Royal Irrigation Department (RID) for irrigated areas and rain-fed agricultural areas extraction.

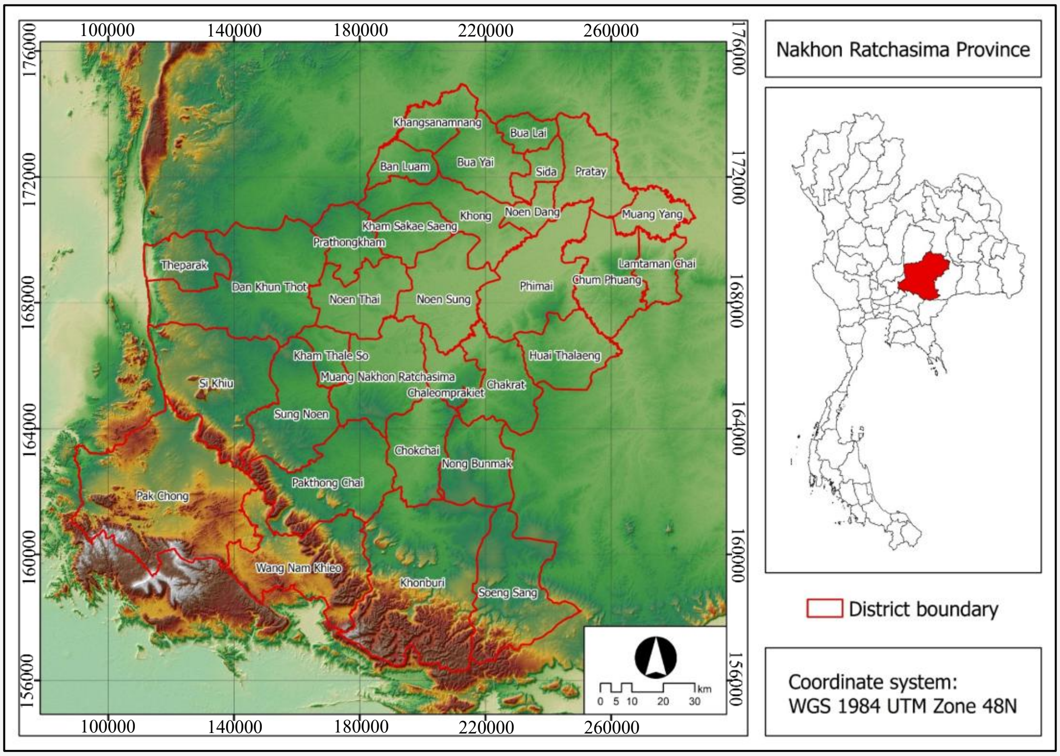


Figure 1: Nakhon Ratchasima province

- Waterbody in 2023 from the LDD for Euclidean distance calculation.
- River network and sub-basin boundary from the Department of Water Resources (DWR)for drainage density calculation.
- Average rice harvested area from 2011 to 2023 from the Nakhon Ratchasima Provincial Agriculture and Cooperatives Office (NKM-PACO).
- Number of rice farmer households in 2023 from the NKM-PACO.
- Population data in 2023 from the Department of Provincial Administrative (DOPA).
- Potential groundwater yield from the Department of Groundwater Resources (DGR).

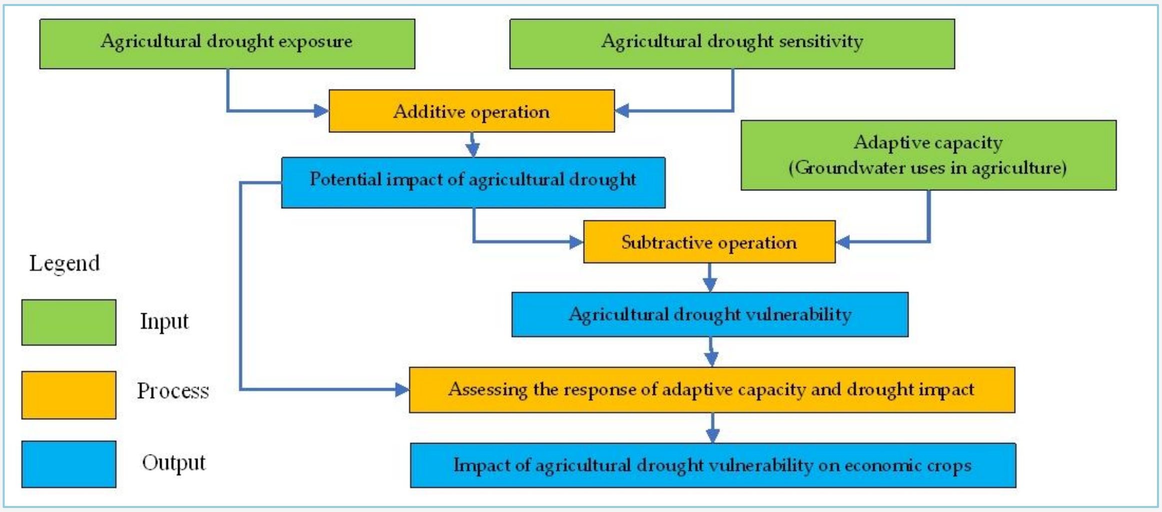
2.3 Methodology

In overview, three components related to climate change adaptation were initially examined: agricultural drought exposure, agricultural drought sensitivity, and adaptive capacity (groundwater use in agriculture). Later, the potential impact of agricultural drought vulnerability, both without and with groundwater use in agriculture, was assessed to describe the response of adaptive capacity to agricultural drought vulnerability and drought impact (Figure 2). A brief description of the research methodology is summarized below.

2.3.1 Agricultural drought exposure

The agricultural drought exposure (ADE) was assessed by combining the meteorological drought frequency (MDF) and meteorological drought intensity (MDI) indices, which were separately calculated based on SPI values in 3m7 period (May to July), 3m10 period (August to October), and 6m10 period (May to October), covering planting, growing and harvesting periods of economic crops (rice, cassava, sugarcane and corn) in Nakhon Ratchasima province, using multiplication operation (Figure 3).

For the MDF index, monthly rainfall data (1975 – 2022) from 37 stations were used to calculate the SPI [20] for 3 periods with four drought severity categories: near normal drought (NND), moderate drought (MD), severe drought (SD) and extreme drought (ED) with weight [20] as show in Table 1. The probability of drought occurrence for four categories (NND, MD, SD, and ED) of each period at each station was calculated, and a continuous surface of data was separately interpolated using the Inverse Distance Weighted (IDW) method [21].



Modified from Fontaine and Steinemann [12]

Figure 2: Overview of research methodology

Table 1: Drought severity classification with weight based on SPI values [20]

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

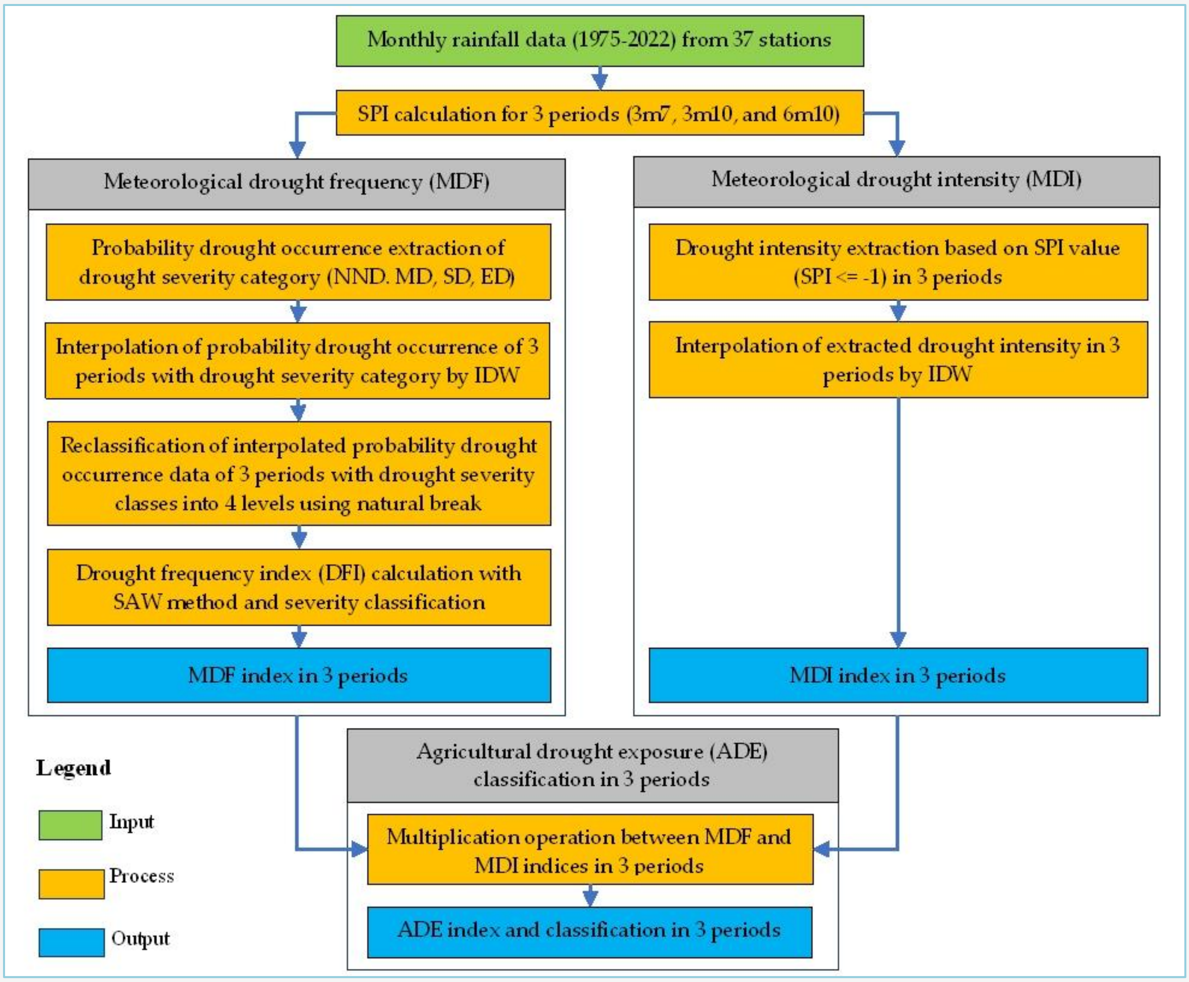


Figure 3: Workflow of agricultural drought exposure assessment

Later, the interpolated probability of drought occurrence of each category in 3 periods was reclassified into four levels: low, moderate, high, and very high, using the Natural Break (NB) method and assigned a rating of each level with a value of 1, 2, 3, and 4, respectively. The MDF index of each period with drought severity category was integrated using Simple Additive Weighting (SAW) [22] and [23].

Meanwhile, the MDI index is reflected in the precipitation deficiency and the drought severity measures by SPI when it is less than -1 and equals -1 for the specific period. The MDI index of each period at each station was extracted based on SPI values less than or equal to -1 [24], and the extracted MDI value of each period at 37 stations was separately interpolated to create the MDI index using the IDW method. Finally, the MDF and MDI indices were combined by multiplication to form the ADE index, and then reclassified into five ADE severity levels (very low, low, moderate, high, and very high) using the NB method.

2.3.2 Agricultural drought sensitivity

The agricultural drought sensitivity (ADS) was assessed using the Analytical Hierarchical Process (AHP) and the Weighted Linear Combination (WLC) method based on selected factors under four conditions (vegetation, climate, physical and socio-economic) (Figure 4).

(1) Vegetation Condition: Two factors representing vegetation conditions for ADS are agricultural drought frequency (ADF) and agricultural drought intensity (ADI). This study identified ADF based on the Vegetation Condition Index (VCI), computed using the Normalized Difference Vegetation Index (NDVI) from MOD31A-NDVI products, over a phenological period (May-October) from 2002 to 2022, as described in Equation 1.

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

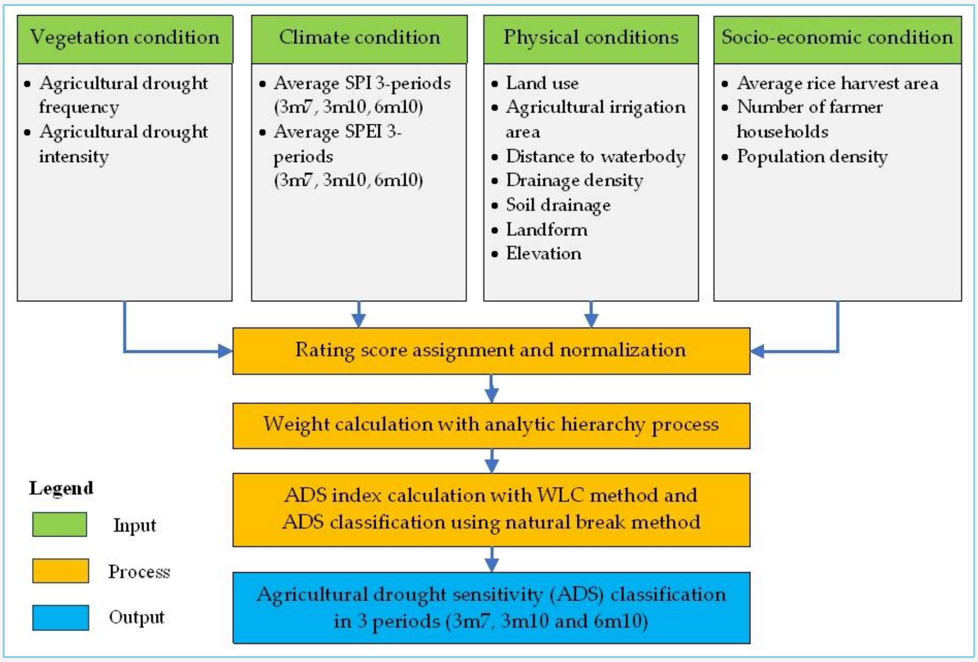


Figure 4: Workflow of agricultural drought sensitivity assessment

If VCI values are 100%, it indicates healthy vegetation conditions. In contrast, if VCI values are nearly 0%, it is identified as poor vegetation condition [25]. VCI is defined in Equation 1:

$$VCI = \frac{NDVI_i - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \times 100$$

Equation 1

Where:

$NDVI_i$ is the filtered NDVI image in the phenology period,

$NDVI_{max}$ is the multi-year maximum NDVI in the phenology period,

$NDVI_{min}$ is the multi-year minimum NDVI in the phenology period.

As a representative of vegetation conditions, VCI values equal to or less than 35% during the phenology period were identified as indicative of agricultural drought. All VCI images were reclassified with a threshold value of ≤ 0.35 as 1, while 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) for ADF. The extracted value was reclassified into five rating scores by the NB method. Meanwhile, ADI was calculated using VCI values (0-100%) in the phenology period. Herein, all VCI images were reclassified with a threshold value of ≤ 0.35 as their values, while other values were reclassified as 0. After that, all reclassified images were added and averaged by the number of years for ADI. The extracted value was reclassified into five rating scores by the NB method.

(2) Climate Condition: Two factors that characterize climate conditions for ADS [26] and [27] were average SPI and average Standardized Precipitation Evapotranspiration Index (SPEI). The average SPI was extracted from rainfall data (2002–2022) of 37 stations in 3 periods (3m7, 3m10 and 6m10). Then, they were interpolated using the IDW method and reclassified into five rating scores by the NB method. Meanwhile, SPEI, specifically characteristics of the region's climate [28], was calculated based on monthly rainfall and temperature (2002–2022). Here, monthly rainfall data were extracted from 37 stations, while the monthly average temperature was extracted from MODIS LST data. Monthly rainfall and temperature data were used to calculate the average SPEI for 3 periods (3m7, 3m10 and 6m10) using the SPEI calculator. They were interpolated using the IDW method and reclassified into five rating scores by the NB method.

(3) Physical Condition: Seven factors that characterize physical conditions for ADS are land use, agricultural irrigation area, distance to the water body, drainage density, landform, and elevation.

(3.1) Land Use: Land use data in 2008, 2011, 2015, 2017, 2019, and 2023, as reported by the LDD, were reclassified into five rating scores based on land use

type and then averaged across these five rating scores. Paddy fields are susceptible to drought since they require more water than other crops. On the contrary, waterbodies and miscellaneous land are less affected by drought.

(3.2) Agricultural Irrigation Area: According to ADS, agricultural irrigation area was manually assigned rating scores for irrigated areas and rain-fed agricultural areas [29].

(3.3) Distance to the Water Body: Areas nearer to waterbodies are less susceptible to water shortages due to their higher recharge potential [29]. Euclidean distance was applied to calculate the distance to water bodies, and the results were reclassified into five rating scores using the NB method.

(3.4) Drainage Density: Drainage density values, calculated as the total length of rivers in a drainage basin divided by the basin's surface area [30], were reclassified into five rating scores using the NB method.

(3.5) Soil Drainage: The soil drainage properties of the soil series from the LDD were reclassified into five rating scores [31].

(3.6) Landform: Landform classification was classified based on the percentage of slope [32] and reclassified into five rating scores.

(3.7) Elevation: The elevation classification was extracted from SRTM DEM according to the standard of LDD [32] and reclassified into five rating scores.

(4) Socio-economic Condition: Socio-economic factors include the average harvested rice area (2011-2023), the number of farmer households in 2023, and population density in 2023 at the sub-district level.

(4.1) Average Rice Harvested Area: Average rice harvested areas (2011-2023) at the sub-district level were calculated and reclassified into five rating scores by the NB method.

(4.2) Number of Farmer Households: The number of farmer households is sensitive to agricultural drought [33]. The areas will be more vulnerable when the proportion of farmer households increases. The number of farmer households in 2023 was extracted and reclassified into five rating scores by the NB method.

(4.3) Population Density: Population density was applied by [34] to assign agricultural drought sensitivity. Population densities in 2023 were extracted and reclassified into five rating scores by the NB method.

Since all factors of ADS have different units, so rating score of each factor was normalized into a shared standard using a standardized rank value [35]. After that, the weight of each factor on ADS was calculated using the AHP method, based on pairwise comparisons with a standard scale of 1 to 9 [36]. Value 9 indicates that the factor is extremely important than others, while value 1 indicates equal importance. The AHP was executed by generating a pairwise comparison matrix and calculating its principal eigenvector to obtain the best-fit set of weights using the Weight and MCE modules [37] within IDRISI software. Finally, the normalized rating score and weight of each factor (Table 2) were applied to calculate the ADS index for 3 periods using Equation 2 [38]:

$$A_i = \sum_{j=1}^{n} w_j a_{ij}$$

Equation 2

Where, A_i is total importance of the alternative when all the criteria are considered simultaneously, w_j denotes the relative weight of importance of the criterion C_j, and a_{ij} is the performance value of the alternative A_i when it is evaluated in terms of the criterion C_j. Finally, the ADS index was reclassified into five severity levels (very low, low, moderate, high, and very high) for ADS classification using the NB method. The spatial distribution of all factors for ADS classification is displayed in Figure 5.

2.3.3 Adaptive capacity (Groundwater uses in agriculture)

Groundwater suitability classification for agricultural uses, which represents adaptive capacity, was analyzed using the WLC method [38] based on suitability factors for groundwater use in agriculture, including potential groundwater yield, land use (as of 2023) from LDD, and landform (Table 3 and Figure 6). Finally, the groundwater suitability index was reclassified into five suitable levels (Not suitable, Low suitability, Moderate suitability, Highly suitable, and Very highly suitable) using the NB method.

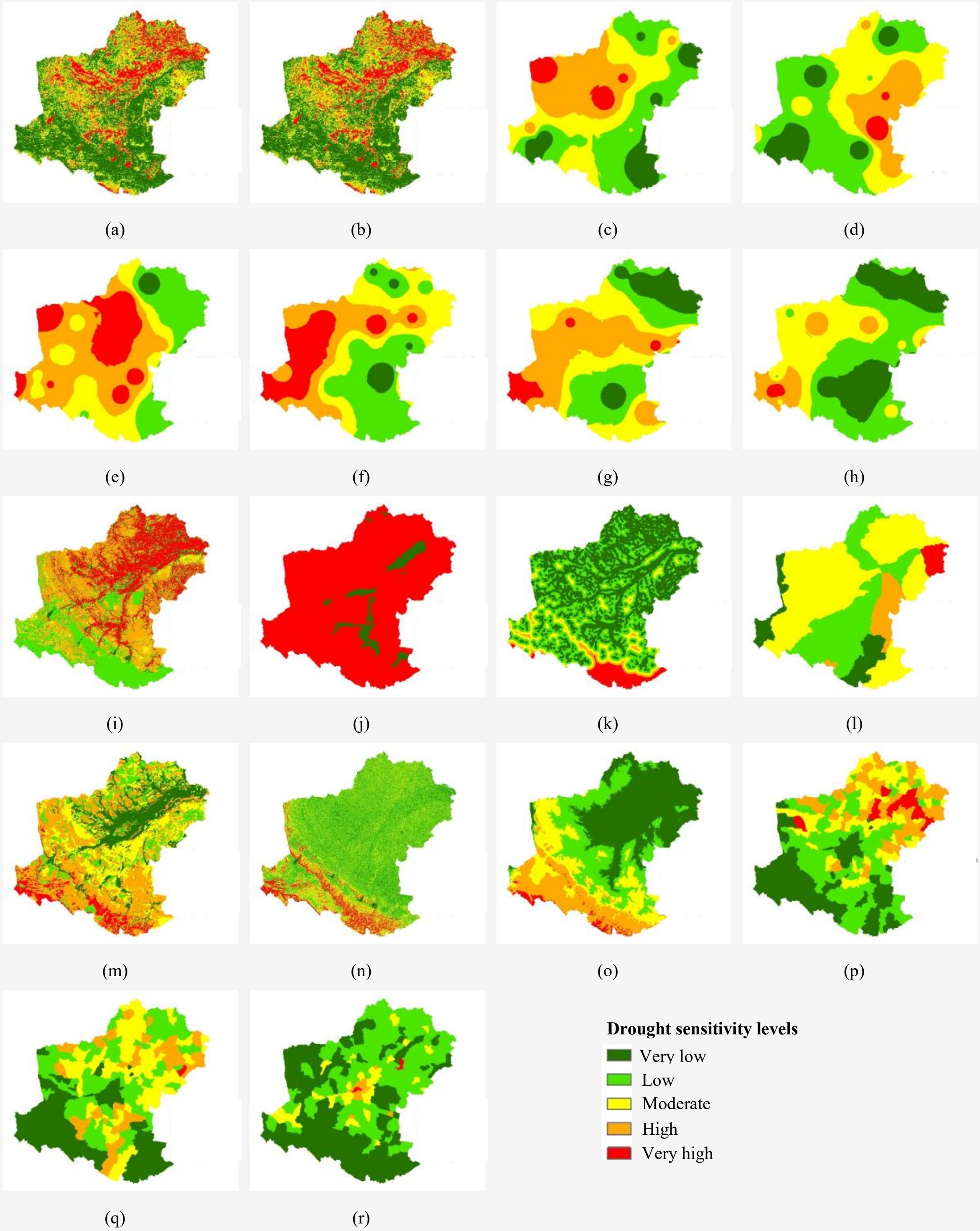


Figure 5: Spatial distribution of the factors for agricultural drought sensitivity assessment: (a) agricultural drought frequency, (b) agricultural drought intensity, (c) average SPEI in 3m7, (d) average SPEI in 3m10, (e) average SPEI in 6m10, (f) average SPI in 3m7, (g) average SPI in 3m10, (h) average SPI in 6m10, (i) land use, (j) agricultural irrigation area, (k) distance to waterbody, (l) drainage density, (m) soil drainage, (n) landform, (o) elevation, (p) average rice harvested area, (q) number of farmer household, (r) population density

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) |

Table 2: Normalized rating and weight for agricultural drought sensitivity assessment

Factor	Normalized rating score					Weight
	Very low	Low	Moderate	High	Very high	
Agricultural frequency drought	1.0	1.5	2.0	2.5	3.0	0.175
Agricultural intensity drought	1.0	1.5	2.0	2.5	3.0	0.175
Average SPEI in 3m7, 3m10 and 6m10	1.0	1.5	2.0	2.5	3.0	0.156
Average SPI in 3m7, 3m10 and 6m10	1.0	1.5	2.0	2.5	3.0	0.151
Land use	1.0	1.5	2.0	2.5	3.0	0.082
Agricultural irrigation area	1.0	Not apply	Not apply	Not apply	3.0	0.057
Distance to waterbody	1.0	1.5	2.0	2.5	3.0	0.053
Drainage density	1.0	1.5	2.0	2.5	3.0	0.039
Soil drainage	1.0	1.5	2.0	2.5	3.0	0.039
Landform	1.0	1.5	2.0	2.5	3.0	0.024
Elevation	1.0	1.5	2.0	2.5	3.0	0.019
Average rice harvested area	1.0	1.5	2.0	2.5	3.0	0.012
Number of farmer households	1.0	1.5	2.0	2.5	3.0	0.011
Population density	1.0	1.5	2.0	2.5	3.0	0.009

Table 3: Rating and weight of suitability factors for groundwater use in agriculture

Suitability	Groundwater yield	Land use types	Landform	Rate
Not suitable	Waterbody	Other land uses	Waterbody	0
Low suitability	Yield < 2 cubic m/hr.	Cassava	Denudational hills and a dissected erosion surface	1
Moderate suitability	Yield 2-10 cubic m/hr.	Sugarcane	High Terrace	2
Highly suitable	Yield 10-20 cubic m/hr.	Corn	Low and middle terraces	3
Very highly suitable	Yield > 20 cubic m/hr.	Paddy field	Flood Plain	4
Weight	**3**	**2**	**1**	

Note: The waterbody category includes groundwater yield and landform, as surface waters are not considered suitable for groundwater use in agriculture

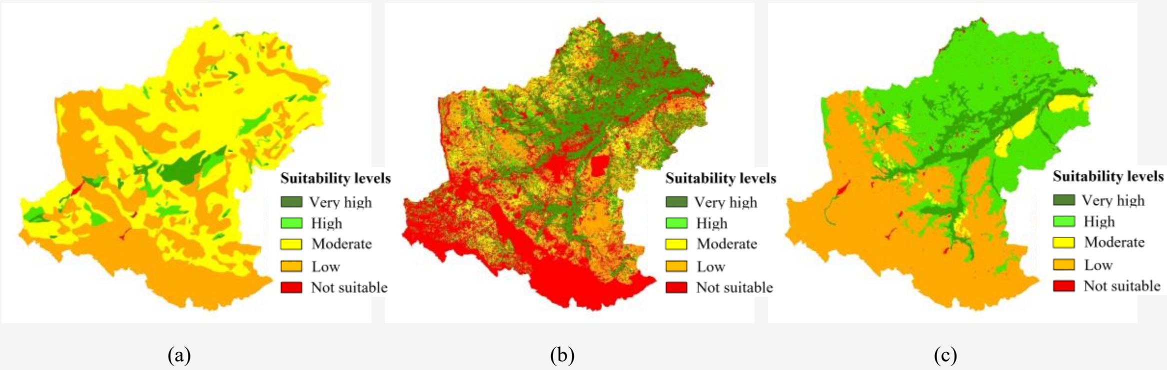


Figure 6: Spatial distribution of the factors for groundwater suitability classification: (a) potential groundwater yield, (b) land use types, (c) landform

2.3.4 Assessing the potential impact of agricultural drought vulnerability on economic crops without and with groundwater use in agriculture

The ADE and ADS were first combined to assess the potential impacts of agricultural drought using an additive operation without adaptive capacity (groundwater use in agriculture) and then reclassified into five severity levels (very low, low, moderate, high, and very high) using the NB method. Then, the derived data were used to examine spatial and temporal patterns at the district and subdistrict levels through zonal analysis with a majority operation, and to assess the impacts on economic crops based on LDD land use data in 2023 using overlay analysis. In addition, the derived potential impact of agricultural drought data was combined with adaptive capacity (groundwater use in agriculture) using a subtraction operation to calculate the agricultural drought vulnerability (ADV) index. The ADV index was then reclassified into five severity levels using the NB method for ADV classification. Later, the spatial and temporal patterns of ADV at district and sub-district levels were assessed using zonal analysis with majority operation. Their impacts on economic crops were assessed using overlay analysis based on the 2023 LDD land use data.

Furthermore, the changes in severity levels of agricultural drought vulnerability, both without and with groundwater use, across three periods were assessed using post-classification comparison change detection [39]. Meanwhile, the impacts of agricultural drought vulnerability on economic crops, both without and with groundwater use in agriculture, were compared to describe the response of adaptive capacity to agricultural drought vulnerability and drought impact.

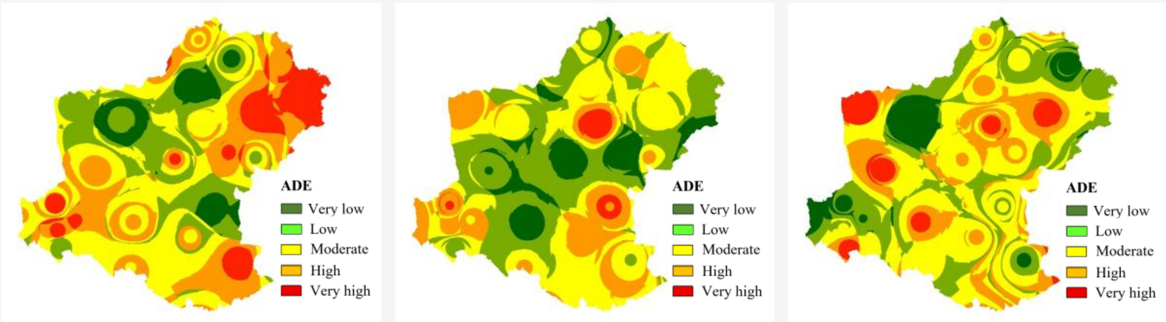
3. Results and Discussion

3.1 Classification of Agricultural Drought Exposure

The results of the agricultural drought exposure (ADE) over three periods are displayed in Figure 7 and Table 4. As a result, the spatial patterns of ADE classification in the three periods (Figure 7) display a completely different pattern in the study area due to variations in the rainfall data from 1975 to 2022, collected from 37 stations for SPI calculation. These findings are consistent with the previous studies of many researchers [15][24][28][40][41][42][43][44] [45][46][47][48][49] and [50]. The correlation coefficient (R) values among ADE severity across the 3 periods show weak negative and positive linear relationships, with values ranging from -0.140 to 0.031 [51]. See Table A1 in Appendix A. These results indicate the dissimilarity of ADE patterns among the 3 periods. Additionally, suppose the severity at moderate, high and very high levels of the ADE in each period is combined. In that case, the ADE in 6m10 (May to October), which covers the planting, growing, and harvesting periods of crops, exhibits the highest severity and spans an area of 14,257.41 sq km, or 68.78%. See details in Table 4. This finding suggests that drought exposure affects crops at all stages of growth.

3.2 Classification of Agricultural Drought Sensitivity

The results of the agricultural drought sensitivity (ADS) in three 3 periods are displayed in Figure 8 and Table 5. As a result, the spatial patterns of ADS classification in 3 periods (Figure 8) show a slightly different pattern according to the normalized rating and weighting scores of each factor for calculating the ADS index using the WLC method [36][37][38] [52][53] and [54]. The R values for ADS severity across the 3 periods display a strongly positive linear relationship, with values ranging from 0.779 to 0.879 [51]. See Table A2 in Appendix A. These results imply a similarity in ADS patterns among the three periods. Additionally, suppose the severity at moderate, high, and very high levels of the ADS in each period is combined; the ADS in 3m7, 3m10, and 6m10 covers an area of 11,620.68 sq km, 12,259.13 sq km, and 11,612.39 sq km, or 56.06%, 59.14%, and 56.02%, respectively. See details in Table 5. These findings suggest that drought is sensitive to crops in all growing stages.

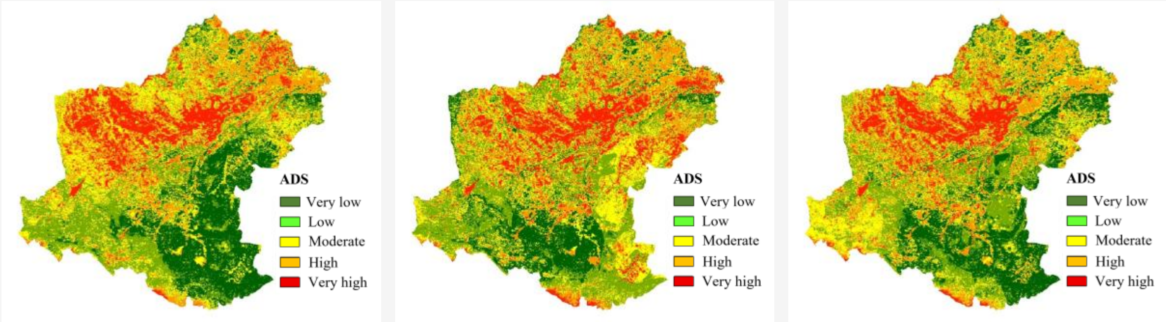


(a) (b) (c)

Figure 7: Spatial distribution of agricultural drought exposure in 3 periods: (a) 3m7, (b) 3m10, (c) 6m10

Table 4: Area and percentage of agricultural drought exposure classification in 3 periods

Severity level	Classification of agricultural drought exposure					
	3m7 (May-June)		3m10 (July-October)		6m10 (May-October)	
	Sq.km	Percent	Sq.km	Percent	Sq.km	Percent
Very low	1,971.33	9.51	1,616.86	7.80	1,276.91	6.16
Low	5,605.12	27.04	7,798.25	37.62	5,194.69	25.06
Moderate	5,155.30	24.87	6,882.03	33.2	5,926.42	28.59
High	5,115.92	24.68	3,809.99	18.38	5,860.09	28.27
Very high	2,881.33	13.90	621.87	3.00	2,470.90	11.92
Total	**20,729.00**	**100**	**20,729.00**	**100**	**20,729.00**	**100**

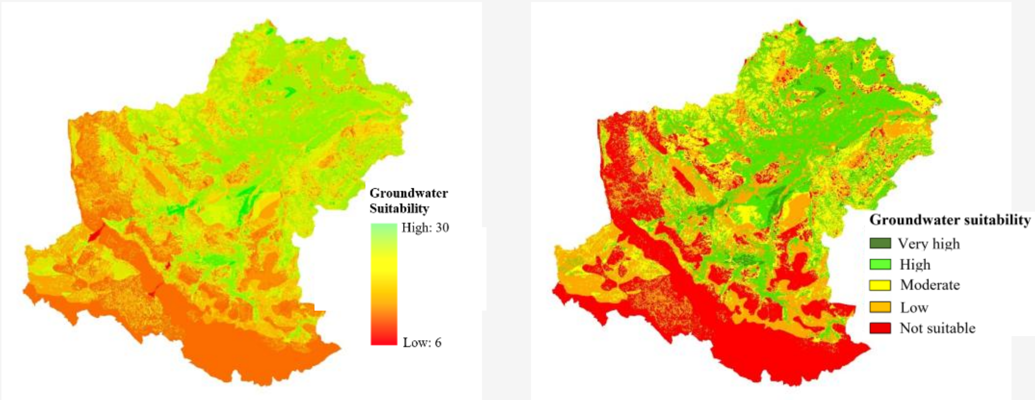


(a) (b) (c)

Figure 8: Spatial distribution of agricultural drought sensitivity in 3 periods: (a) 3m7, (b) 3m10, (c) 6m10

Table 5: Area and percentage of agricultural drought sensitivity classification in 3 periods

Severity level	Classification of agricultural drought sensitivity					
	3m7 (May-June)		3m10 (July-October)		6m10 (May-October)	
	Sq.km	Percent	Sq.km	Percent	Sq.km	Percent
Very low	4,168.60	20.11	2,736.23	13.2	3,855.59	18.6
Low	4,939.72	23.83	5,733.64	27.66	5,261.02	25.38
Moderate	4,782.18	23.07	4,939.72	23.83	4,943.87	23.85
High	4,315.78	20.82	4,415.28	21.3	4,373.82	21.1
Very high	2,522.72	12.17	2,904.13	14.01	2,294.70	11.07
Total	**20,729.00**	**100.00**	**20,729.00**	**100**	**20,729.00**	**100**



(a) (b)

Figure 9: Spatial distribution of groundwater suitability
(a) suitability index (b) classified groundwater index

3.3 Classification of Groundwater Suitability for Agriculture Uses

The groundwater suitability for agriculture uses, which represents an adaptive capacity for mitigating agricultural drought, is displayed in Figure 9 and Table 6. As a result, the most dominant suitable class is not suitable according to the rating and weighting scores of each factor for calculating the groundwater suitable index using the WLC method [38] and [54]. Additionally, if the moderate, highly suitable, and very highly suitable classes for groundwater use in agriculture are considered, these suitable classes are situated in floodplain and terrace landforms over paddy areas, accounting for 9,304.49 sq km, or 44.88%. Based on the groundwater well data from 2023, provided by the Department of Groundwater Resources, the number of groundwater wells distributed in the moderate, highly, and very highly suitable classes at district and sub-district boundaries is 1,324 wells (51.32%) and 1,261 wells (48.87%), respectively. See details in Table 7. Thus, the classification of groundwater for agricultural use is acceptable.

Table 6: Area and percentage of groundwater suitability for agriculture uses

Suitability class	Classification of groundwater suitability for agriculture uses	
	Sq.km	Percent
Not suitable	5,858.84	28.26
Low suitability	5,565.67	26.85
Moderate suitability	3,962.31	19.11
Highly suitable	5,047.32	24.35
Very highly suitable	294.86	1.42
Total	**20,729.00**	**100**

Table 7: Number of existing groundwater wells in 2023 at groundwater suitable classes for agriculture use at the district and sub-district levels

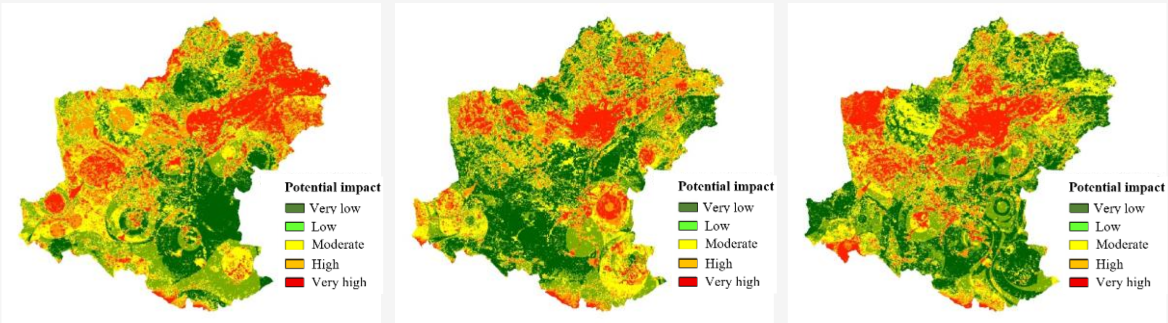
Suitability class	District boundary		Sub-district boundary	
	Number of wells	Percent	Number of wells	Percent
Not suitable	764	29.61	604	23.41
Low suitability	492	19.07	715	27.71
Moderate suitability	493	19.11	546	21.16
Highly suitable	831	32.21	691	26.78
Very highly suitable	0	0.00	24	0.93
Total	**2,580**	**100.00**	**2,580**	**100.00**

Table 8: Area and percentage of potential impacts of agricultural drought classification in 3 periods

Severity level	Classification of potential impacts of agricultural drought					
	3m7 (May-June)		3m10 (July-October)		6m10 (May-October)	
	Sq.km	Percent	Sq.km	Percent	Sq.km	Percent
Very low	3,592.34	17.33	5,186.40	25.02	4,952.16	23.89
Low	4,572.82	22.06	4,614.28	22.26	5,178.10	24.98
Moderate	5,020.56	24.22	4,831.93	23.31	4,651.59	22.44
High	4,203.84	20.28	3,768.53	18.18	2,918.64	14.08
Very high	3,339.44	16.11	2,327.87	11.23	3,028.51	14.61
Total	**20,729.00**	**100.00**	**20,729.00**	**100.00**	**20,729.00**	**100.00**

Table 9: Number of districts and sub-districts at different severity levels of potential impacts of agricultural drought classification in 3 periods

Severity level	Classification of potential impacts of agricultural drought					
	3m7 (May-June)		3m10 (July-October)		6m10 (May-October)	
	District	Sub-district	District	Sub-district	District	Sub-district
Very low	6	65	10	90	8	68
Low	6	44	1	32	6	74
Moderate	8	63	7	63	12	64
High	5	56	11	58	1	21
Very high	7	60	3	45	5	61
Total	**32**	**288**	**32**	**288**	**32**	**288**



(a) (b) (c)

Figure 10: Spatial distribution of the potential impact of agricultural drought vulnerability classification in three periods: (a) 3m7, (b) 3m10, (c) 6m10

3.4 Classification of Potential Impacts of Agricultural Drought Vulnerability

The spatial and temporal patterns of the potential impacts of agricultural drought vulnerability in 3 periods are displayed in Figure 10 and reported in Table 8 and Table 9. As a result, the spatial patterns of potential impacts of agricultural drought vulnerability (excluding groundwater use in agriculture) differ across regions in three periods.

These results indicate the influence of ADE and ADS in each period. The R values among the potential impacts of agricultural drought vulnerability severity across the three periods show a moderately positive linear relationship, with values ranging from 0.431 to 0.519 [51]. See Table A3 in Appendix A.

In addition, if the moderate, high and very high severity levels of the potential impacts of agricultural drought vulnerability classification in each period are considered, the highest potential impacts of agricultural drought vulnerability occurred in 3m7 (May to July), accounting for 12,563.84 sq km or 60.61%. In contrast, the lowest potential impacts of agricultural drought vulnerability classification occurred from May to October (6m10), accounting for 10,598.74 sq km, or 51.13%. See details in Table 8. This finding suggests that the planting and growing periods of crops are sensitive to drought.

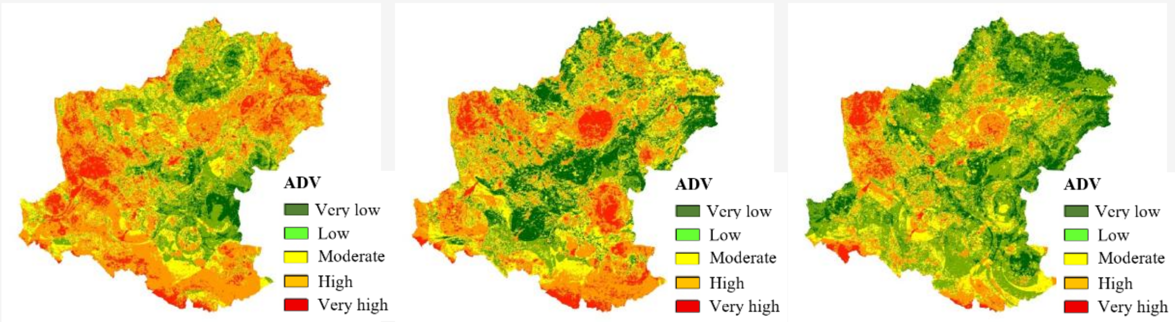
Moreover, if the majority of severity classes, including moderate, high, and very high, of the potential impact of agricultural drought vulnerability at district and sub-district levels are considered, the potential impact of agricultural drought vulnerability at the district level occurred at its highest in 3m10 (August to October), accounting for 21 districts. The potential impact of agricultural drought vulnerability at the sub-district level was highest from May to July (3m7), affecting 179 sub-districts. See details in Table 9. These districts and sub-districts should focus on monitoring and preventing agricultural drought in the future through the efforts of relevant government agencies.

3.5 Potential Impacts of Agricultural Drought Vulnerability on Economic Crops

The potential impact of ADV affecting economic crops in different periods is summarized in Table 10. As a result, when considering the moderate, high, and very high severity levels of the potential impact of ADV in each period, the highest potential impact of ADV occurred from May to July (3m7). It affected rice, cassava, sugarcane, and corn in 2023, covering a total area of 4,763.79 sq.km, 2,087.00 sq.km, 1,170.44 sq.km, and 578.61 sq.km, respectively. See details in Table 10. This finding confirms that planting and growing periods are sensitive to drought, as previously mentioned.

3.6 Classification of Agricultural Drought Vulnerability

The spatial patterns of the agricultural drought vulnerability (ADV) in 3 periods are displayed in Figure 11 and reported in Table 11 and Table 12. As a result, the spatial patterns of agricultural drought vulnerability differ among regions in three periods. These results indicate the influence of suitability classification for groundwater use in agriculture in each period. The R values among ADV severity levels across the three periods display a strongly positive linear relationship, with values ranging from 0.457 to 0.559 [51]. See Table A4 in Appendix A.



(a) (b) (c)

Figure 11: Spatial distribution of agricultural drought vulnerability classification in 3 periods: (a) 3m7, (b) 3m10, (c) 6m10

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

Table 10: Potential impact of agricultural drought vulnerability on economic crops in 3 periods

Crops	Severity level	Potential impact of agricultural drought vulnerability in					
		3m7		3m10		6m10	
		Sq.km	Percent	Sq.km	Percent	Sq.km	Percent
Rice	Very low	583.54	9.58	569.08	9.34	691.21	11.34
	Low	745.40	12.23	932.52	15.31	1,152.57	18.92
	Moderate	1,194.78	19.61	1,420.72	23.32	1,619.02	26.57
	High	1,579.36	25.92	1,779.59	29.20	1,108.81	18.20
	Very high	1,989.65	32.66	1,390.81	22.83	1,521.11	24.97
	Total	**6,092.73**	**100.00**	**6,092.73**	**100.00**	**6,092.73**	**100.00**
Cassava	Very low	974.80	25.30	874.81	22.70	925.77	24.02
	Low	791.85	20.55	966.85	25.09	1,092.24	28.34
	Moderate	977.72	25.36	1,016.18	26.37	820.64	21.30
	High	767.87	19.93	654.24	16.98	524.97	13.62
	Very high	341.41	8.86	341.57	8.86	490.03	12.72
	Total	**3,853.65**	**100.00**	**3,853.65**	**100.00**	**3,853.65**	**100.00**
Sugarcane	Very low	417.95	20.40	649.17	31.68	485.98	23.72
	Low	460.36	22.47	566.27	27.64	576.43	28.13
	Moderate	591.89	28.89	478.79	23.37	504.33	24.62
	High	402.96	19.67	252.34	12.32	285.52	13.94
	Very high	175.59	8.57	102.19	4.99	196.49	9.59
	Total	**2,048.75**	**100.00**	**2,048.75**	**100.00**	**2,048.75**	**100.00**
Corn	Very low	48.41	6.18	144.85	18.50	170.14	21.72
	Low	156.08	19.93	175.01	22.35	167.56	21.40
	Moderate	241.13	30.79	220.16	28.11	167.79	21.43
	High	228.26	29.15	156.26	19.95	125.68	16.05
	Very high	109.22	13.95	86.82	11.09	151.94	19.40
	Total	**783.10**	**100.00**	**783.10**	**100.00**	**783.10**	**100.00**

Table 11: Area and percentage of agricultural drought vulnerability classification in 3 periods

Severity level	Classification of agricultural drought vulnerability					
	3m7 (May-June)		3m10 (July-October)		6m10 (May-October)	
	Sq.km	Percent	Sq.km	Percent	Sq.km	Percent
Very low	1,032.82	4.98	3,259.99	15.73	3,090.49	14.91
Low	4,375.10	21.11	3,802.52	18.34	8,752.20	42.22
Moderate	4,203.54	20.28	4,890.66	23.59	4,201.52	20.27
High	8,841.86	42.65	6,939.48	33.48	3,842.46	18.54
Very high	2,275.68	10.98	1,836.35	8.86	842.32	4.06
Total	**20,729.00**	**100.00**	**20,729.00**	**100.00**	**20,729.00**	**100.00**

Table 12: Number of districts and sub-districts at different severity levels of agricultural drought vulnerability in 3 periods

Severity level	Classification of agricultural drought vulnerability					
	3m7 (May-June)		3m10 (July-Oct)		6m10 (May-Oct)	
	District	Sub-district	District	Sub-district	District	Sub-district
Very low	1	11	8	72	2	27
Low	11	96	1	32	26	191
Moderate	0	34	7	57	0	17
High	20	140	15	116	3	50
Very high	0	7	1	11	1	3
Total	**32**	**288**	**32**	**288**	**32**	**288**

In addition, if the moderate, high and very high severity levels of ADV in each period are considered, the highest impacts of ADV occurred in 3m7 (May to July), accounting for 15,321.08 sq km or 73.91%. In contrast, the lowest impacts of ADV occurred from May to October (6m10), accounting for 8,886.30 sq km, or 42.87%. See details in Table 11.

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

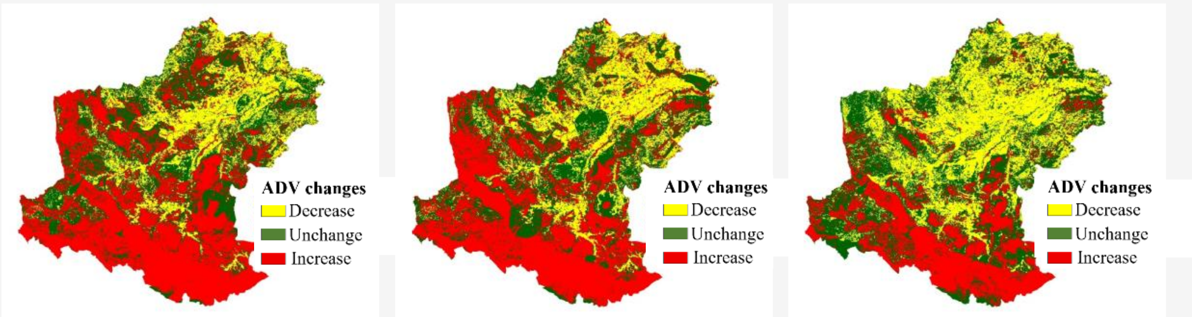
This finding suggests that the planting and growing periods of crops are sensitive to drought. Furthermore, if the majority of severity classes, including moderate, high, and very high, of ADV at district and sub-district levels are considered, the severity of ADV at these levels occurred at its highest in 3m10 (August to October), accounting for 23 districts and 184 sub-districts, respectively. See details in Table 12. Thus, from August to October, these districts and sub-districts should focus on monitoring and preventing agricultural drought in the future through relevant government agencies.

3.7 Impact of Agricultural Drought Vulnerability on Economic Crops

The results of the impact of agricultural drought vulnerability (ADV) affecting economic crops in different periods are summarized in Table 13. As a result, if the moderate, high and very high severity levels of ADV in each period are considered, the ADV in 3m7 (May to July) affected rice, cassava, sugarcane and corn with a total area of 2,400.04 sq.km, 2,423.62 sq.km, 798.81 sq.km, and 325.25 sq.km, respectively. See details in Table 13. This finding confirms that the planting and growing periods of crops are sensitive to drought, as mentioned in Section 3.5.

Table 13: Impact of agricultural drought vulnerability on economic crops in 3 periods

Crops	Severity level	Agricultural drought vulnerability in					
		3m7 (May to July)		3m10 (August to October)		3m10 (May to October)	
		Sq.km	Percent	Sq.km	Percent	Sq.km	Percent
Rice	Very low	1,151.38	18.9	1,302.82	21.38	1,569.47	25.76
	Low	2,541.23	41.71	2,979.14	48.9	2,785.12	45.71
	Moderate	1,407.83	23.11	1,158.83	19.02	973.64	15.98
	High	979.04	16.07	415.18	6.81	756.22	12.41
	Very high	13.17	0.22	236.67	3.88	8.19	0.13
	Total	**6,092.73**	**100**	**6,092.73**	**100**	**6,092.73**	**100**
Cassava	Very low	396.45	10.29	243.44	6.32	171.23	4.44
	Low	1,033.47	26.82	1,243.67	32.27	1,411.77	36.64
	Moderate	859.63	22.31	853.04	22.14	902.73	23.43
	High	1,374.34	35.66	781.4	20.28	979.63	25.42
	Very high	189.65	4.92	731.98	19	388.17	10.07
	Total	**3,853.65**	**100**	**3,853.65**	**100**	**3,853.65**	**100**
Sugarcane	Very low	360.43	17.59	484.8	23.66	394.54	19.26
	Low	889.51	43.42	1,033.82	50.46	985.28	48.09
	Moderate	454.14	22.17	319.92	15.62	348.7	17.02
	High	334.29	16.32	145.77	7.12	270.61	13.21
	Very high	10.38	0.51	64.44	3.15	49.61	2.42
	Total	**2,048.75**	**100**	**2,048.75**	**100**	**2,048.75**	**100**
Corn	Very low	57.05	7.28	154.52	19.73	182.29	23.28
	Low	400.8	51.18	396.74	50.66	326.98	41.75
	Moderate	218.92	27.96	146.76	18.74	122.89	15.69
	High	103.88	13.27	66.87	8.54	130.2	16.63
	Very high	2.45	0.31	18.22	2.33	20.74	2.65
	Total	**783.1**	**100**	**783.1**	**100**	**783.1**	**100**



(a) (b) (c)

Figure 12: Spatial distribution of severity changes of agricultural drought vulnerability without and with groundwater use in three periods: (a) 3m7, (b) 3m10, (c) 6m10

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

3.8 Severity Change of Agricultural Drought Vulnerability by Adaptive Capacity

Spatial severity changes of agricultural drought vulnerability (ADV) without and with groundwater use in 3 periods for describing "from-to-change" information [39] are displayed in Figure 12 and reported in Tables 14-16. As a result, in Figure 12, the spatial pattern of severity changes in 3 periods, which include (1) decreasing severity levels as gain, (2) unchanged severity level, and (3) increasing severity levels as loss, which slightly differ from one region to another region. These results indicate the influence of groundwater use in agriculture. The R values for the severity changes of ADV, both with and without groundwater use, across three periods show a strongly positive linear relationship, with values ranging from 0.742 to 0.789 [51]. See Table A5 in Appendix A. In addition, based on severity level change detection between ADV classification without and with groundwater use in Tables 14-16, areas of decreasing severity levels after applying groundwater use in agriculture in 3m7, 3m10, and 6m10 cover an area of 4,408.50 sq.km, 4,776.09 sq.km, and 7,149.33 sq.km, or 21.28%, 23.05%, and 34.51%, respectively. Conversely, areas of increasing severity levels after applying groundwater use in agriculture in 3m7, 3m10, and 6m10 cover an area of 9,651.24 sq.km, 9,139.34 sq.km, and 5,790.55 sq.km, or 46.58%, 44.11%, and 27.95%, respectively. In the meantime, areas of unchanged severity levels after applying groundwater use in agriculture in 3m7, 3m10, and 6m10 covered an area of 6,659.27 sq.km, 6,803.56 sq.km, and 7,779.12 sq.km, or 32.14%, 32.84%, and 37.55%, respectively. These results indicate the responses of adaptive capacity to agricultural drought vulnerability in three periods, characterized by trade-offs among different severity levels.

3.9 Change of Agricultural Drought Vulnerability Impact on Crops by Adaptive Capacity

The change in agricultural drought vulnerability impact on economic crops, both without and with groundwater use in agriculture, which represents adaptive capacity, is compared in Table 17.

Table 14: Detection of severity level change between agricultural drought vulnerability Without and with groundwater use in 3m7

ADV without groundwater use	Agricultural drought vulnerability (ADV) with groundwater use (Sq.km)					
	Very low	Low	Moderate	High	Very high	Total
Very low	977.24	1,848.36	765.82	0.00	0.00	3,591.42
Low	55.08	1,372.48	1,234.18	1,906.55	0.00	4,568.29
Moderate	0.00	1,079.19	973.04	2,966.24	0.00	5,018.47
High	0.00	72.96	1,207.42	1,992.01	930.08	4,202.47
Very high	0.00	0.00	21.05	1,972.79	1,344.51	3,338.35
Total	**1,032.32**	**4,372.99**	**4,201.51**	**8,837.59**	**2,274.59**	**20,719.00**

Table 15: Detection of severity level change between agricultural drought vulnerability without and with groundwater use in 3m10

ADV without groundwater use	Agricultural drought vulnerability (ADV) with groundwater use (Sq.km)					
	Very low	Low	Moderate	High	Very high	Total
Very low	2,319.92	1,679.14	1,185.52	0.00	0.00	5,184.58
Low	858.91	918.70	1,356.04	1,475.92	0.00	4,609.58
Moderate	79.58	1,124.92	965.06	2,660.19	0.00	4,829.75
High	0.00	77.93	1,360.09	1,546.95	782.53	3,767.50
Very high	0.00	0.00	21.60	1,253.07	1,052.93	2,327.60
Total	**3,258.41**	**3,800.69**	**4,888.31**	**6,936.13**	**1,835.46**	**20,719.00**

Table 16: Detection of severity level change between agricultural drought vulnerability Without and with groundwater use in 6m10

ADV without groundwater use	Agricultural drought vulnerability with groundwater use (Sq.km)					
	Very low	Low	Moderate	High	Very high	Total
Very low	1,963.25	2,987.53	0.00	0.00	0.00	4,950.78
Low	1,050.40	2,448.51	1,677.30	0.00	0.00	5,176.21
Moderate	75.35	2,287.04	1,159.05	1,125.72	0.00	4,647.16
High	0.00	986.46	564.81	1,366.40	0.00	2,917.67
Very high	0.00	38.45	798.34	1,348.49	841.91	3,027.19
Total	**3,089.00**	**8,747.98**	**4,199.50**	**3,840.61**	**841.91**	**20,719.00**

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

Table 17: Changed area of agricultural drought vulnerability impact on economic crops without and with groundwater use in agriculture

Crops	Severity level	Changed area of agricultural drought vulnerability impact on crops without and with groundwater use in agriculture (Sq.km)					
		3m7		3m10		6m10	
		Without	With	Without	With	Without	With
Rice	Very low	583.54	1,151.38	569.08	1,302.82	691.21	1,569.47
	Low	745.4	2,541.23	932.52	2,979.14	1,152.57	2,785.12
	Moderate	1,194.78	1,407.83	1,420.72	1,158.83	1,619.02	973.64
	High	1,579.36	979.04	1,779.59	415.18	1,108.81	756.22
	Very high	1,989.65	13.17	1,390.81	236.67	1,521.11	8.19
	Total	**6,092.73**	**6,092.73**	**6,092.73**	**6,092.73**	**6,092.73**	**6,092.73**
Cassava	Very low	974.8	396.45	874.81	243.44	925.77	171.23
	Low	791.85	1,033.47	966.85	1,243.67	1,092.24	1,411.77
	Moderate	977.72	859.63	1,016.18	853.04	820.64	902.73
	High	767.87	1,374.34	654.24	781.4	524.97	979.63
	Very high	341.41	189.65	341.57	731.98	490.03	388.17
	Total	**3,853.65**	**3,853.65**	**3,853.65**	**3,853.65**	**3,853.65**	**3,853.65**
Sugarcane	Very low	417.95	360.43	649.17	484.8	485.98	394.54
	Low	460.36	889.51	566.27	1,033.82	576.43	985.28
	Moderate	591.89	454.14	478.79	319.92	504.33	348.7
	High	402.96	334.29	252.34	145.77	285.52	270.61
	Very high	175.59	10.38	102.19	64.44	196.49	49.61
	Total	**2,048.75**	**2,048.75**	**2,048.75**	**2,048.75**	**2,048.75**	**2,048.75**
Corn	Very low	48.41	57.05	144.85	154.52	170.14	182.29
	Low	156.08	400.8	175.01	396.74	167.56	326.98
	Moderate	241.13	218.92	220.16	146.76	167.79	122.89
	High	228.26	103.88	156.26	66.87	125.68	130.2
	Very high	109.22	2.45	86.82	18.22	151.94	20.74
	Total	**783.1**	**783.1**	**783.1**	**783.1**	**783.1**	**783.1**

As a result, in Table 17, the affected areas, combining moderate, high, and very high severity levels for rice, sugarcane, and corn, decreased in three periods. In the 3m7, covering the planting and growing periods of rice, sugarcane, and corn, the affected areas decreased to 2,363.75 sq.km, 371.63 sq.km, and 253.36 sq.km, respectively. In the 3m10 period, covering the growing and harvesting periods of rice, sugarcane, and corn, the affected areas decreased to 2,780.44 sq.km, 303.19 sq.km, and 231.39 sq.km, respectively. In 6m10, covering the planting, growing, and harvesting periods of rice, sugarcane, and corn, the affected areas decreased to 2,510.89 sq.km, 317.42 sq.km, and 231.39 sq.km, respectively. These findings indicate the adaptive capacity responses to the impact of drought on rice, sugarcane, and corn, as an expected result. In contrast, the affected areas, combining moderate, high, and very high severity levels for cassava, increased in three periods. The affected areas in 3m7, 3m10, and 6m10 are 336.62 sq.km, 354.43 sq.km, and 434.89 sq.km, respectively. These findings indicate that the responses of adaptive capacity to drought impacts on cassava are an unexpected result. In practice, cassava requires less water than other crops during the planting and growing periods. The favorable climate, characterized by hot and dry conditions, is well-suited for cassava production [55].

4. Conclusions

The response of adaptive capacity to agricultural drought vulnerability and its impact was examined within the framework of climate change adaptation, which comprises agricultural drought exposure, sensitivity, and adaptive capacity. Groundwater suitability classification for agriculture use was used to represent the adaptive capacity for mitigating the impact of agricultural drought. The groundwater suitability classification indicated that the most dominant suitable class is not suitable according to the rating and weighting scores of each factor used to calculate the suitable groundwater index via the weighted linear combination method. However, the number of groundwater wells distributed in the moderate, highly, and very highly suitable classes at district and sub-district boundaries is 1,324 wells (51.32%) and 1,261 wells (48.87%), respectively. In addition, the spatial and temporal severity changes, combining moderate, high, and very high levels of agricultural drought vulnerability, without and with groundwater use, indicated that the decreasing severity areas in 3m7, 3m10, and 6m10 covered an area of approximately 21.28%, 23.05%, and 34.51%, respectively.

Conversely, the increasing severity areas in 3m7, 3m10, and 6m10 covered an area of about 46.58%, 44.11%, and 27.95%, respectively. In the meantime, areas of unchanged severity levels in 3m7, 3m10, and 6m10 covered an area of 32.14%, 32.84%, and 37.55%, respectively. In addition, the change in agricultural drought vulnerability impact on economic crops after applying groundwater use in agriculture over three periods resulted in a decrease in the affected areas for rice, sugarcane, and corn, which combined moderate, high, and very high severity levels in the three periods. Conversely, the affected areas, combining moderate, high, and very high severity levels for cassava, increased in three periods. Nevertheless, these results indicate the responses of adaptive capacity on agricultural drought vulnerability and its impact on crops. Therefore, the Thai government should conduct a further feasibility study on groundwater use in agriculture to mitigate the impact of drought on economic crops.

Acknowledgments
The author acknowledges the support of the Fundamental Fund (FF) grant number FF1-103-67-12-06(F) from Thailand Science Research and Innovation, Ministry of Higher Education, Science, Research and Innovation. The author also acknowledges the School of Mathematics and Geoinformatics, Institute of Science, at Suranaree University of Technology, for supporting the facilities to undertake this research.

References

[1] United Nations Convention to Combat Desertification (UNCCD). (2023). *Global Drought Snapshot 2023. The Need for Proactive Action.* New York, United Nations Convention to Combat Desertification.

[2] Kramer, P. J. and Boyer, J. S., (1995). *Water Relations of Plants and Soils*. California. Academic Press.

[3] Cardona, O. D., van Aalst. M. K., Birkmann. J., Fordham. M., McGregor. G., Perez. R., Pulwarty, R. S., Schipper, E. L. F. and Sinh, B. T., (2012). Determinants of Risk: Exposure and Vulnerability. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*. Field, C. B., Barros. V., Stocker, T. F., Qin, D., Dokken, D. J., Ebi, K. L., Mastrandrea, M. D., Mach, K. J., Plattner, G-K., Allen, S. K., Tignor, M., and Midgley, P. M., (eds.). A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge, UK, and New York, USA, 65-108.

[4] World Bank Group. (2023). *Thailand Economic Monitor: Coping with Droughts and Floods; Building a Sustainable Future.* World Bank, Bangkok.

[5] Prasertsri, P., (2020). *The Impact of Drought on Agriculture in 2020*. USDA, Bangkok.

[6] Smit, B., Burton, I., Klein, R. J. and Street, R., (1999). The Science of Adaptation: A Framework for Assessment. *Mitigation and Adaptive Strategies for Global Change,* Vol. 4, 199–213. https://doi.org/10.1023/A:1009652531101.

[7] IPCC (Intergovernmental Panel on Climate Change). (2007). *Assessing Key Vulnerabilities and the Risk from Climate Change*. Fourth Assessment Report, Geneva.

[8] Carrão, H., Naumann, G. and Barbosa, P., (2018). Global Projections of Drought Hazard in a Warming Climate: A Prime for Disaster Risk Management. *Climate Dynamics*, Vol. 50, 2137–2155. https://doi.org/10.1007/s00382-017-3740-8.

[9] IPCC. (2001). Emergent Findings. *Climate Change 2001: Impacts, Adaptation, and Vulnerability*. McCarthy, J. J., Canziani, O. F., Leary, N. A., Dokken, D. J., White, K. S. Cambridge University Press, Cambridge, United Kingdom and New York, USA, 3-8.

[10] IPCC. (2014). *Foundations for Decision Making. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects.* Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Field, C. B., Barros, V. R., Dokken, D. J., Mach, K. J., Mastrandrea. M. D., Bilir, T. E., Chatterjee, M., Ebi, K. L., Estrada, Y. O., Genova, R. C., Girma, B., Kissel, E. S., Levy, A. N., MacCracken, S., Mastrandrea, P. R. and White, L. L., (eds). Cambridge University Press, Cambridge, United Kingdom and New York, USA, 198-228.

[11] Thavorntam, W., and Shahnawaz. (2022). Evaluation of Drought in the North of Thailand using Meteorological and Satellite-Based Drought Indices. *International Journal of Geoinformatics*, Vol. 18(5), 13–26. https://doi.org/10.52939/ijg.v18i5.2367.

[12] Fontaine, M. M. and Steinemann, A. C., (2009). Assessing Vulnerability to Natural Hazards: Impact-Based Method and Application to Drought in Washington State. *Natural Hazards Review*, Vol. 10(1), 11–18. https://doi.org/10.1061/(ASCE)1527-6988(2009)10:1(11).

[13] Antwi-Agyei, P., Fraser, E. D., Dougill, A. J., Stringer, L. C., and Simelton, E., (2012). Mapping the Vulnerability of Crop Production to Drought in Ghana using Rainfall, Yield and Socio-Economic Data. *Applied. Geography*, Vol. 32(2), 324–334. https://doi.org/10.1016/j.apgeog.2011.06.010.

[14] Preedapirom, P., Robert, O., Onchang, R., and Jeefoo, P. (2024). Drought Monitoring Using MODIS Satellite-Based Data in Kamphaeng Phet Province, Thailand. *International Journal of Geoinformatics*, Vol. 20(1), 1–11. https://doi.org/10.52939/ijg.v20i1.3019.

[15] Dung, T., Nguyen, L., and Thy, P. (2025). Using Landsat Satellite Data to Explore Drought Index during the Dry Season Period 1990–2024 in Thu Duc City of Ho Chi Minh City, Vietnam. *International Journal of Geoinformatics*, Vol. 21(3), 139–150. https://doi.org/10.52939/ijg.v21i3.4003.

[16] Suwanlee, S., Keawsomsee, S., Sangjan, W., Som-ard, J., Siripattanachotikul, K., Ninsawat , S., and Nudthawud, H. (2024). Spatio-Temporal Drought Monitoring in the Chi River Basin from 2001–2020 Using MODIS Time Series Data and Google Earth Engine. *International Journal of Geoinformatics*, Vol. 21(1), 43–55. https://doi.org/10.52939/ijg.v21i1.3789.

[17] Mulyanti, H., Istadi, I. and Gernowo, R., (2023). Assessing Vulnerability of Agriculture to Drought in East Java, Indonesia: Application of GIS and AHP. *Geoplanning: Journal of Geomatics and Planning*, Vol. 10(1), 55-72. https://doi.org/10.14710/geoplanning.10.1.55-72.

[18] Babel, M. S., Chawrua, L., Khadka, D., Tingsanchali, T. and Shanmungam, M. S., (2024). Agricultural Drought Risk and Local Adaptation Measures in the Upper Mun River Basin, Thailand. *Agricultural Water Management*, Vol. 292. https://doi.org/10.1016/j.agwat.2023.108655.

[19] Bashit, N., Ristianti, N., and Ulfiana, D. (2022). Drought Assessment Using Remote Sensing and Geographic Information Systems (GIS) Techniques (Case Study: Klaten District). *International Journal of Geoinformatics*, Vol. 18(5), 115–127. https://doi.org/10.52939/ijg.v18i5.2393.

[20] McKee, T. B., Doesken, N. J. and Kleist, J., (1993). The Relationship of Drought Frequency and Duration to Time Scales. *Proceedings of the 8th Conference on Applied Climatology,* 17–22 January 1993. American Meteorological Society Boston, MA, 179-184.

[21] Tadesse, T., Wardlow, B., Svoboda, M. and Brown, J., (2010). The Vegetation Outlook (Vegout): A New Method for Predicting Vegetation Seasonal Greenness. *GIScience & Remote Sensing*, Vol. 47(1), 25-52. https://doi.org/10.2747/1548-1603.47.1.25.

[22] Malczewski, J., (2006). GIS-Based Multicriteria Decision Analysis: A Survey of the Literature. *International Journal of Geographical Information Science*, Vol. 20(7), 703-726. https://doi.org/10.1080/13658810600661508.

[23] Kaliszewski, I. and Podkopaev, D., (2016). Simple Additive Weighting - A Metamodel for Multiple Criteria Decision Analysis Methods. *Expert Systems with Applications*, Vol. 54, 155–161. https://doi.org/10.1016/j.eswa.2016.01.042.

[24] Sehgal, V. K. and Dhakar, R., (2016). Geospatial Approach for Assessment of Bioeconomic Vulnerability to Agricultural Drought and Its Intraseasonal Variations. *Environmental Monitoring and Assessment*, Vol. 188(3), 197-214. https://doi.org/10.1007/s10661-016-5187-5.

[25] Kogan, F. N., (1995). Droughts of the Late 1980s in the United States as Derived from NOAA Polar-Orbiting Satellite Data. *Bulletin of the American Meteorological Society*, Vol. 76(5), 655–668.

[26] Hayes, M., Svoboda, M., Wall, N. and Widhalm, M., (2011). The Lincoln Declaration on Drought Indices: Universal Meteorological Drought Index Recommended. *Bulletin of the American Meteorological Society*, Vol. 92(4), 485–488.

[27] WMO (World Meteorological Organization). (2012). *Standardized Precipitation Index User Guide*. WMO-No. 1090, Geneva.

[28] Vicente-Serrano, S. M., Begueria, S. and Lopez-Moreno, J. I., (2010). A Multi-Scalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. *Journal of Climate*, Vol. 23, 1696–1718. https://doi.org/10.1175/2009JCLI290 9.1

[29] Jain, V. K., Pandey, R. P. and Jain, M. K., (2015). Spatial-Temporal Assessment of Vulnerability to Drought. *Natural Hazards*, Vol. 76, 443-469. https://doi.org/10.1007/s11069-014-1502-z.

[30] Pandey, S., Pandey, A. C., Galkate, R. V., Byun, H. R. and Mal, B. C., (2010). Integrating Hydro-Meteorological and Physiographic Factors for Assessment of Vulnerability to Drought. *Water Resources Management*, Vol.

24(15), 4199-4217. https://doi.org/10.1007/s11269.010.9653.5.

[31] Prathumchai, K., Honda, K. and Nualchawee, K., (2001). Drought Risk Evaluation using Remote Sensing and GIS: A Case Study in Lop Buri Province. *Proceedings of the 22nd Asian Conference on Remote Sensing*, 5-9 November 2001, Singapore. National University of Singapore, Singapore Institute of Surveyors and Valuers: Asian Association on Remote Sensing.

[32] LDD (Land Development Department). (2009). *Land Use Plans, Lamtakhong Watershed.* Land Office of Soil Survey and Land Use Planning, Land Development Department, Bangkok, Thailand (in Thai).

[33] Pei, W., Fu, Q., Liu, D., Li, T. and Cheng, K., (2016). Assessing Agricultural Drought Vulnerability in the Sanjiang Plain Based on an Improved Projection Pursuit Model. *Natural Hazards*, Vol. 82, 683-701. https://doi.org/10.1007/s11069-016-2213-4.

[34] Shahid, S. and Behrawan, H., (2008). Drought Risk Assessment in the Western Part of Bangladesh. *Natural Hazards*, Vol. (46), 391-413. https://doi.org/10.1007/s11069-007-9191-5.

[35] Tsangaratos, P., Pizpikis, T., Vasileiou, E., Pliakas, F., Schuth, C. and Kallioras, A., (2013). Development of Multi-Criteria Decision Support System (DSS) Coupled with GIS for Identifying optimal Locations for Soil Aquifer Treatment (Sat) Facilities. *Proceedings of the 13th International Congress, Chania 2013.* The Geological Society of Greece, Vol. XLVII.

[36] Saaty, R. W., (1987). The Analytic Hierarchy Process-What It Is and How It Is Used. *Mathematical Modeling*, Vol. 9(3-5), 161-176.

[37] Eastman, J. R., Jin, W., Kyem, P. A. K. and Toledano, J., (1995). Raster Procedures for Multi-Criteria/Multi-Objective Decisions. *Photogrammetric Engineering & Remote Sensing*, Vol. 61(5), 539-547.

[38] Malczewski, J., (2000). On the Use of Weighted Linear Combination Method in GIS: Common and Best Practice Approaches. *Transactions in GIS*, Vol. 4(1), 5-22. https://doi.org/10.1111/1467-9671.00035.

[39] Jensen, J. R., (2015). *Introductory Digital Image Processing: A Remote Sensing Perspective*. Illinois. Pearson Education, Inc.

[40] Sönmez, F. K., Komuscu, A.U., Erkan, A. and Turgu, E., (2005). An Analysis of Spatial and Temporal Dimension of Drought Vulnerability in Turkey using the Standardized Precipitation Index. *Natural Hazards*, Vol. 35, 243-264. https://doi.org/10.1007/s11069-004-5704-7.

[41] Patel, N. R., Chopra, P. and Dadhwal, V. K., (2007). Analysis Spatial Patterns of Meteorological Drought using Standardized Precipitation Index. *Meteorological Applications*, Vol. 14(4), 329-336. https://doi.org/10.1002/met.33.

[42] Nosrati, K. and Zareiee, A. R., (2011). Assessment of Meteorological Drought using SPI in West Azerbaijan Province, Iran. *Journal of Applied Sciences and Environmental Management.* Vol. 15(4), 563-569.

[43] Dhakar, J., Sehgal, V. K. and Pradhan, S., (2013). Study on Inter-Seasonal and Intra-Seasonal Relationships of Meteorological and Agricultural Drought Indices in the Rajasthan State of India. *Journal of Arid. Environments*, Vol. 97, 108-119. https://doi.org/10.1016/j.jaridenv.2013.06.001.

[44] Wambua, R. M., Mutua, B. M. and Raude, J. M., (2018). Detection of Spatial, Temporal and Trend of Meteorological Drought using Standardized Precipitation Index (SPI) and Effective Drought Index (EDI) in the Upper Tana River Basin, Kenya. *Open Journal of Modern Hydrology*, Vol. 8(3), 83-100. https://doi.org/10.4236/ojmh.2018.83007.

[45] Caloiero, T. and Veltri, S., (2019). Drought Assessment in the Sardinia Region (Italy) during 1922–2011 using the Standardized Precipitation Index. *Pure and Applied Geophysics*, Vol. 176, 925-935. https://doi.org/10.1007/s00024-018-2008-5.

[46] Pandhumas, T., Kuntiyawichai, K., Jothityangkoon, C. and Suryadi, F. X., (2020). Assessment of Climate Change Impacts on Drought Severity using SPI and SDI over the Lower Nam Phong River Basin, Thailand. *Engineering and Applied Science Research*. Vol. 47(3), 326-338.

[47] Mehr, A. D., Sorman, A. U., Kahya, E. and Afshar, M. H., (2020). Climate Change Impacts on Meteorological Drought using SPI and SPEI: A Case Study of Ankara, Turkey. *Hydrological Sciences Journal*, Vol. 65(2), 254-268. https://doi.org/10.1080/02626667.2019.1691218.

[48] Mohammed, S., Alsafadi, K., Enaruvbe, G. O., Bashir, B., Elbeltagi, A., Széles, A., Alsalman, A. and Harsanyi, E., (2022). Assessing the Impacts of Agricultural Drought (SPI/SPEI) on Maize and Wheat Yields Across Hungary. *Scientific Reports*, Vol. 12. https://doi.org/10.1038/s41598-022-12799-w.

[49] He, Q., Wang, M., Liu, K., Li, B. and Jiang, Z., (2023). Spatiotemporal Analysis of Meteorological Drought Across China Based on the High-Spatial-Resolution Multiscale SPI

Generated by Machine Learning. *Weather Climate Extremes*, Vol. 40. https://doi.org/10.1016/j.wace.2023.100567.

[50] Omar, A. A., Chiang, J. L. and Daud, B. H., (2023). Spatiotemporal Analysis of Meteorological Drought using Standardized Precipitation Index (SPI) in Gabiley Region, Somaliland. *Journal of Geoscience and Environment Protection*. Vol. 11, 47-59. https://doi.org/10.4236/gep.2023.115003.

[51] Cohen, J., (1988). *Statistical Power Analysis for the Behavioral Sciences.* New Jersey. Lawrence Erlbaum Associates, Publishers.

[52] Eastman, J. R., Kyem, P. A. K. and Toledano, J. A., (1993). Procedure for Multi-Objective Decision Making in GIS under Conditions of Competing Objectives. Proceedings, EGIS'93. 438-447.

[53] Benmouss, K., Laaziri, M., Khoulji, S., Kerkeb, M. L. and El Yamami, A., (2019) AHP-Based Approach for Evaluating Ergonomic Criteria. *Procedia Manufacturing*. Vol. 32, 856-863

[54] Thammaboribal, P., Triapthti, N., and Lipiloet, S. (2025). Using of Analytical Hierarchy Process (AHP) in Disaster Management: A Review of Flooding and Landslide Susceptibility Mapping. *International Journal of Geoinformatics*, Vol. 21(4), 177–196. https://doi.org/10.52939/ijg.v21i4.4091.

[55] Walderich, A., (2025). *Cassava Industry in Thailand-Statistics & Facts.* Statista. [Online] Available: https://statista.com/topics/11099/cassava-industry-in-thailand. (Accessed May 20, 2025).

Appendix A

Table A1: Correlation matrix of agricultural drought exposure (ADE) severity levels in 3 periods

ADE	ADE-3m7	ADE-3m10	ADE-6m10
ADE-3m7	1.000		
ADE-3m10	-0.140	1.000	
ADE-6m10	0.031	-0.001	1.000

Table A2: Correlation matrix of agricultural drought sensitivity (ADS) severity levels in 3 periods

ADS	ADS-3m7	ADS-3m10	ADS-6m10
ADS-3m7	1.000		
ADS-3m10	0.779	1.000	
ADS-6m10	0.879	0.831	1.000

Table A3: Correlation matrix of potential impacts of agricultural drought vulnerability (PI-ADS) severity levels in 3 periods

PI-ADS	PI-ADS-3m7	PI-ADS-3m10	PI-ADS-6m10
PI-ADS-3m7	1.000		
PI-ADS-3m10	0.431	1.000	
PI-ADS-6m10	0.478	0.519	1.000

Table A4: Correlation matrix of agricultural drought vulnerability (ADV) severity levels in 3 periods

ADV	ADV-3m7	ADV-3m10	ADV-6m10
ADV-3m7	1.000		
ADV-3m10	0.457	1.000	
ADV-6m10	0.503	0.559	1.000

Table A5: Correlation matrix of severity changes of agricultural drought vulnerability without and with groundwater use in 3 periods

ADV	ADV with groundwater use in 3m7	ADV with groundwater use in 3m10	ADV with groundwater use in 6m10
ADV without groundwater use in 3m7	1.000		
ADV without groundwater use in 3m10	0.789	1.000	
ADV without groundwater use in 6m10	0.743	0.742	1.000