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Spatial-Based Analysis of Rice Field Drought Levels in West Sumatra Province

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ABSTRACT

Drought is a natural disaster that significantly impacts the agricultural sector, water availability, and public welfare. This study aims to identify drought in rice fields in West Sumatra using the Standardised Precipitation Index (SPI) and Normalised Difference Drought Index (NDDI) methods. The SPI is used to determine drought based on rainfall deviations from normal conditions over a given period. The NDDI is used to measure drought conditions based on soil moisture and vegetation conditions. The novelty of this study lies in the spatial-temporal integration of SPI and NDDI for West Sumatra, an approach rarely applied in Indonesia, as well as in linking rainfall variability with paddy vegetation responses for early detection of agricultural drought. The SPI analysis identified 370 drought events, affecting a total of 2,377.40 ha, or 1.01% of the total rice fields, in July 2023, while the NDDI analysis revealed a much wider drought coverage, reaching 198,772.11 ha (84.76%) categorised as severe to extremely dry. The difference in results between the two indices indicates that statistically adequate rainfall does not necessarily reflect sufficient groundwater availability to support vegetation growth. These findings emphasise the importance of integrating meteorological indicators with land and crop conditions for more accurate agricultural drought monitoring. These findings support adaptive planting patterns and efficient irrigation management, enhancing agricultural resilience to drought and contributing to SDG 2 (Zero Hunger) and SDG 6 (Clean Water and Sanitation).

Keywords: Climate variability, drought, GIS, NDDI, rice field, SPI

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INTRODUCTION

According to the Intergovernmental Panel on Climate Change (IPCC) report (2023), there is an increase in the intensity, frequency, and duration of various extreme weather events, including droughts, which are caused by climate change and impact the agricultural sector (IPCC, 2023). Global climate change is causing changes in rainfall patterns in many countries, including Indonesia (Irsyad & Oue, 2020). Shifts in rainfall patterns also cause shifts in the rainy and dry seasons in a region (Avia, 2019). These seasonal shifts impact the availability of air, which indicates the onset of drought (Lesik et al., 2020).

Drought occurs almost every year in Indonesia and increases sharply during El Niño conditions, leading to decreased agricultural production (Novianti, 2019). West Sumatra Province also faces the challenge of drought, despite being known for its high rainfall. However, the uneven distribution of rainfall in the region and the impact of climate change make certain areas in this province vulnerable to drought (Hermawan & Komalaningsih, 2008). In 2022, 87 hectares of rice fields in West Sumatra Province experienced drought, according to data from the Regional Technical Implementation Unit of the Food Crop and Horticulture Protection Centre of West Sumatra Province. The dry season occurred in eight regencies and cities: Pesisir Selatan Regency, Agam Regency, Solok Regency, Sijunjung Regency, 50 Cities, Tanah Datar Regency, West Pasaman Regency, and Solok City (Agusri, 2022). Based on this description, a study of the extent and distribution of drought is needed to mitigate the drought disaster in West Sumatra Province.

The SPI is a very useful tool for monitoring meteorological drought that uses rainfall data in its analysis (Dutta et al., 2015). The simple calculation, minimal data usage (only rainfall) and flexibility of the SPI make this method recommended by the World Meteorological Organisation (WMO) as the preferred indicator for monitoring meteorological drought (Hayes et al., 2011; Purnamasari et al., 2017). The SPI method is widely used because it is relatively easy, can provide good comparative values, and is able to identify levels of wetness and dryness simultaneously (Mckee et al., 1993; Sunusi & Auliana, 2025). This method measures rainfall deficits at different time scales. The average time selected to determine drought using this method is a monthly period scale, which is 1, 3, 6, 12, 24, or 48 months. Previous research has shown that the SPI method can well identify drought conditions in an area, such as research by Shah in 2015. The results of this study show that the drought obtained by the SPI method is almost the same as the actual drought situation (Shah et al., 2015). Furthermore, research by Yusman in 2025 showed that the SPI method can identify the level and distribution of drought that occurred in Agam Regency (Yusman et al., 2025).

The SPI requires long-term rainfall data with high temporal resolution to achieve superb results. Areas with limited or low-quality data will face difficulties in calculating the SPI accurately (Wicaksanti et al., 2019). The weakness of the SPI method is that the input data is only rainfall. When a lot of data is missing, it will give wrong results, because the program will provide output for every input given (WMO & GWP, 2016). However, SPI alone cannot adequately represent the spatial response of drought on rice vegetation because it is based solely on precipitation anomalies. This limitation creates a research gap in drought assessment, particularly for agricultural areas where drought impacts are expressed not only through rainfall deficits but also through changes in vegetation condition and surface water availability. Therefore, integrating SPI with a remote sensing-based drought index such as NDDI is necessary to provide complementary information on meteorological drought and its spatial manifestation in rice fields. Therefore, to obtain more accurate drought information, a drought analysis was conducted using the Normalised Difference Drought Index (NDDI) method. The NDDI method is a drought index that, in its analysis, is based on vegetation density and water availability simultaneously, thus providing more comprehensive results for drought-prone areas (Rahman et al., 2017). The NDDI method was developed by Yingxin Gu in 2007 and combines two parameters: the wetness index (NDWI) and the vegetation index (NDVI) (Gu et al., 2007). The NDDI drought index is more effective in describing the level of drought in a region due to its greater accuracy, particularly in reflecting vegetation response to drought stress (Luqman et al., 2022).

Drought analysis using the SPI and NDDI is crucial for rice paddies, given that rice plants are highly sensitive to changes in water availability. The SPI can detect meteorological drought, which affects rainfall as the primary source of irrigation, while the NDDI captures the impact of drought on rice vegetation spatially. Unlike prior studies limited to district-level or single-index drought analysis, this study integrates SPI and NDDI indices at the provincial scale to capture meteorological and vegetation-based drought interactions. The combination of these two indices can provide a more comprehensive picture of drought dynamics in rice paddies, supporting more precise data-driven mitigation and agricultural planning efforts. Identifying rice fields affected by drought is crucial for providing early warning, reducing farmer losses, and ensuring national food security. This information enables the government and farmers to take preventive and mitigating measures such as adjusting cropping patterns, providing drought-resistant varieties, and allocating emergency aid to mitigate the impacts of more severe droughts. This study is also aligned with the Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger) and SDG 6 (Clean Water and Sanitation), by supporting climate-resilient agriculture, food security, and more effective irrigation and water-resource management.

The drought analysis methods frequently used in Indonesia are the SPI and SPEI, which display two sets of data: a map of areas likely to experience drought and a drought index graph for each province in Indonesia, displaying the upper and lower limits of the model (Adiningsih et al., 2016; Sutanto, 2017) states that several models have been developed and applied in Indonesia using low- and medium-resolution remote sensing data, either singly or in combination. The accuracy of models developed to date using GMS, MTSAT, TRMM, QMorph, MODIS, AVHRR, Landsat-7, SPOT-4, and ALOS data is generally adequate at the national to district levels, with an average coefficient of variation ranging from 60% to 80%. Many drought studies have been conducted using a single index. In this study, the SPI and NDDI indices were combined. This study aims to identify drought in rice fields in West Sumatra Province using the Standardised Precipitation Index (SPI) and Normalised Difference Drought Index (NDDI) methods.

MATERIALS AND METHODS

Research Area

West Sumatra Province, located on the island of Sumatra, Indonesia (0°54’-3°30’S, 98°36’-101°53’E), covers 4,212,043.87 hectares across 19 regencies/cities, as shown in Figure 1. It borders North Sumatra Province to the north, Riau and Jambi Provinces to the east, Bengkulu Province to the south, and the Indian Ocean to the west. Based on 2022 data from the Geospatial Information Agency (BIG), processed in ArcGIS, West Sumatra Province covers 234,504.93 hectares of rice paddy land. The SPI requires long-term rainfall data with high temporal resolution

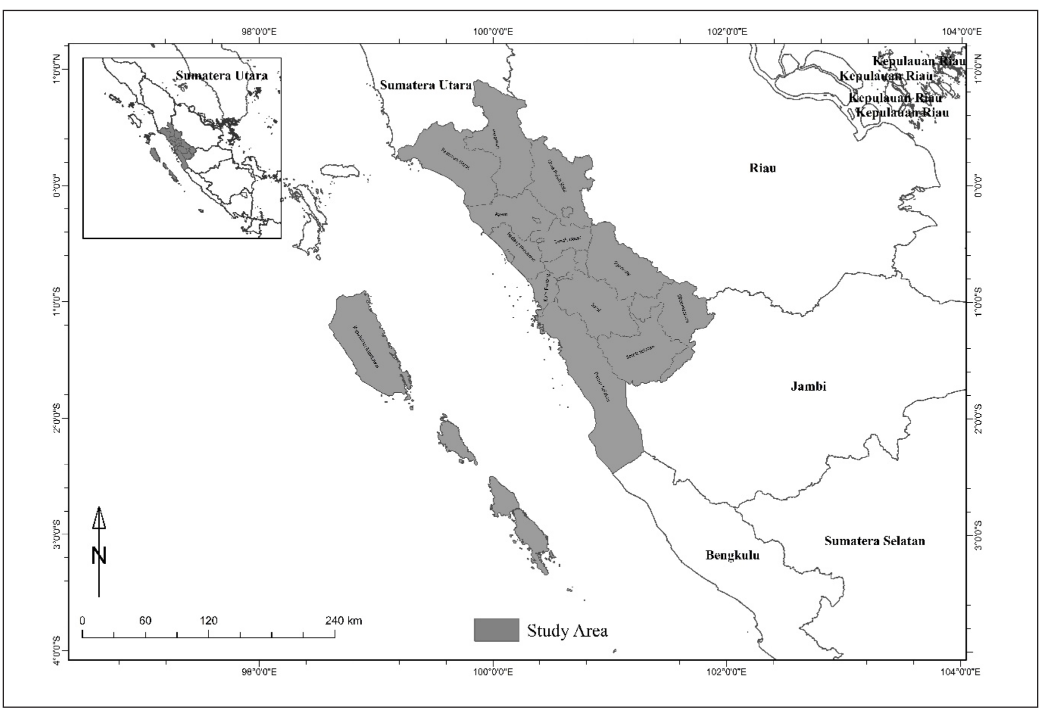

Figure 1. Map of research locations in West Sumatra province

Data Source

This study uses secondary data, namely rainfall data for the last 30 years (1994-2023). This data was obtained from the West Sumatra Provincial Water Resources and Construction Agency and the West Sumatra Meteorology, Climatology, and Geophysics Agency (https://dataonline.bmkg.go.id/). Landsat 8 satellite imagery was obtained from the USGS website (http://earthexplorer.usgs.gov/). Administrative boundary data and rice field land use data for West Sumatra Province were obtained from the Geospatial Information Agency (BIG) website (http://tanahair.indonesia.go.id).

Rainfall Data Completeness Analysis

In this study, two methods were used to complete missing rainfall data: the Reciprocal Method and rainfall data from NASA POWER (Prediction of Worldwide Energy Resources). The reciprocal method was used to complete missing data at each rainfall station with up to two months of missing data. Rainfall data from the observation stations were used as the primary data source. When rainfall observations were unavailable for more than two consecutive months, the missing observations were supplemented using rainfall data from NASA POWER to maintain the continuity of the rainfall time series for SPI calculation. The NASA POWER rainfall data used were obtained from the website https://power.larc.nasa.gov/data-access-viewer/. The variables used in the reciprocal method were rainfall data and the distance between the nearest station and the station where the missing rainfall data was sought, using the Equation 1.

$$\frac{\frac{Pa}{Dxa^2}+\frac{Pb}{Dxb^2}+\ldots+\frac{Pn}{Dxn^2}}{\frac{1}{Dxa^2}+\frac{1}{Dxb^2}+\ldots+\frac{1}{Dxn^2}} \quad [1]$$

Rainfall Data Consistency Analysis

Rainfall data consistency analysis aims to verify the accuracy of field data. Rainfall data consistency is tested using the Double Mass Curve method, which compares the monthly cumulative rainfall from station A (on the y-axis) with the cumulative rainfall from a reference station (on the x-axis). The reference station used is the average of several stations closest to the station whose consistency is being tested (Maulina et al., 2022). These cumulative values are then plotted on a Cartesian x-y coordinate system, and the resulting curve is examined to observe changes in slope (trend). These changes in slope can indicate discrepancies in the data that need to be analysed to ensure the consistency of rainfall data. The consistency value ranges from 0 to 1; the closer the value is to 1, the more consistent the data quality is.

Drought Analysis Using the Standardised Precipitation Index (SPI) Method

The SPI index value can be calculated based on the gamma distribution, which is defined as the following frequency or probability function in Equations 2 to 5:

$$G(x)=\int_0^x g(x)=\frac{1}{\beta^{\alpha}T(\alpha)}\int_0^x x^{a-1}\, e^{-x/\beta}dx \quad [2]$$

where is:

$$\alpha=\frac{1}{4A}\left(1+\sqrt{1+\frac{4A}{3}}\right) \quad [3]$$

$$A=ln(\bar{x})-\frac{\sum ln(x)}{n} \quad [4]$$

$$\beta=\frac{\bar{x}}{a} \quad [5]$$

Where T (a) is the gamma function, while n is the number of observed rainfall data, $\bar{x}$ is the average monthly rainfall (mm/month), and x is the monthly rainfall data (mm/month). The following is a classification of drought levels based on the SPI index (Table 1).

Image Selection for Drought Analysis Using the Normalised Difference Drought Index (NDDI) Method

The imagery used in this study is Landsat 8, which has two sensors: the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). Launched in 2013, the Landsat 8 satellite has continued and enriched the uninterrupted multispectral record of the Earth's surface since the inception of the Landsat program in 1972 (Ihlen, 2019). The imagery used in the

Table 1
Classification of SPI drought index values

SPI Index Value	Drought Classification
≤ -2	Extremely dry
-1.99 s/d -1.50	Severely dry
-1.49 s/d -1.0	Moderately dry
-0.99 s/d 0.99	Near normal
1.00 s/d 1.49	Moderately wet
1.50 s/d 1.99	Severely Wet
2	Extremely Wet

Source: Sunusi & Auliana, 2025

NDDI drought analysis was selected based on the months with the lowest rainfall and the highest incidence of SPI drought events. This was done to observe drought conditions in West Sumatra Province during the period of lowest rainfall, a critical time for assessing drought severity. By selecting imagery from drier months, the analysis can focus more on the impact of water shortages on vegetation and soil surface conditions.

In addition to rainfall, cloud cover is also an important factor in image selection. Clouds can impair image quality by reducing contrast and obscuring ground surface details, thus affecting the accuracy of data interpretation (Zhu & Woodcock, 2012). To minimise this impact, images with minimal cloud cover are prioritised for use in analysis. Landsat 8 is equipped with Quality Assessment (QA) bands that enable cloud identification and masking so that only cloud-free areas are used in the analysis (Foga et al., 2017).

Image Pre-Processing

Prior to calculating NDVI, NDWI, and NDDI, the selected Landsat 8 OLI/TIRS imagery underwent several pre-processing steps to ensure the quality and consistency of the satellite data. First, the Landsat 8 Level 2 Surface Reflectance product was selected to minimise atmospheric effects and provide surface reflectance data suitable for spectral index calculations. Second, cloud and cloud-shadow masking was performed using the Quality Assessment (QA_PIXEL) band to remove pixels affected by clouds, cloud shadows, and other unwanted atmospheric conditions. Third, the relevant spectral bands were extracted, namely Band 4 (Red), Band 5 (NIR), and Band 6 (SWIR-1), which were required for the calculation of NDVI and NDWI (Table 2). Fourth, the imagery was clipped to the boundary of West Sumatra Province to limit the analysis to the research area and reduce unnecessary data processing. Finally, the pre-processed bands were used to calculate NDVI and NDWI, which were subsequently combined to derive the NDDI values. All image pre-processing and spectral index calculations were performed using ArcGIS software.

Drought Analysis Using the Normalised Difference Drought Index (NDDI) Method

The analysis of drought severity levels is carried out by utilising remote sensing technology because changes in the reflectance of crops reflect physiological and morphological

Table 2
Landsat 8 OLI and TIRS spectral bands resolution

Name	Spectral Bands	Wavelength (µm)	Spatial Resolution (m)
Band 4	Red	0.636-0.673	30
Band 5	Nir	0.851-0.879	30
Band 6	Swir-1	1.566-1.651	30

Source: Ihlen, 2019

responses to water stress experienced by the plants (Patil et al., 2024). The Normalised Difference Vegetation Index (NDVI) is the result of a normalised reflectance comparison between the near-infrared (NIR) band and the red band, which is widely used to monitor vegetation conditions on the Earth's surface. NDVI serves as a simple yet effective quantitative indicator to describe the density and health condition of vegetation through remote sensing methods, as in Equations 6 and 7.

$$NDVI = \frac{\rho NIR\text{-}\rho RED}{\rho NIR+\rho RED} \quad [6]$$

In the case of Landsat 8, NDVI is calculated using Equation 7.

$$NDVI = \frac{Band\ 5\text{-}Band\ 4}{Band\ 5+Band\ 4} \quad [7]$$

NDVI values are influenced by spatial factors such as climate, soil characteristics, and topography; thus, ecosystems with higher productivity exhibit distinct radiometric responses compared to less productive ones. Temporal variations in NDVI-based drought indices were derived from satellite imagery and analysed using GIS tools to evaluate drought severity across the study area.

The Normalised Difference Water Index (NDWI) is an important spectral index used to monitor water content and surface moisture conditions. It is particularly effective in distinguishing water bodies from vegetation and soil by exploiting the reflectance differences between the green and near-infrared (NIR) spectral bands. In this study, NDWI was calculated using satellite imagery to assess spatiotemporal variations in surface water availability and moisture conditions within the study area, as in Equation 8.

$$NDWI = \frac{\rho NIR\text{-}\rho SWIR}{\rho NIR+\rho SWIR} \quad [8]$$

NDWI for Landsat 8 was calculated using Equation 9.

$$NDVI = \frac{Band\ 5\text{-}Band\ 6}{Band\ 5+Band\ 6} \quad [9]$$

The NDDI is an index used to identify drought levels. The NDDI drought index value is obtained by combining two parameters: the Normalised Difference Water Index (NDWI) and the Normalised Difference Vegetation Index (NDVI). The NDDI index value can be calculated using Equation 10.

$$NDDI = \frac{NDVI\text{-}NDWI}{NDVI{+}NDWI} \qquad [10]$$

NDDI is a more sensitive indicator for drought compared to the two indicators above, namely NDVI and NDWI. Elevated NDDI values signify dry conditions, coinciding with reduced NDVI and NDWI values. In contrast, lower NDDI values represent areas with adequate water availability, where both NDVI and NDWI increase, indicating well-hydrated and vigorous vegetation (Patil et al., 2024). Classification of NDDI Drought Index Values is presented in Table 3 and the data processing flowchart in Figure 2.

Table 3
Classification of NDDI Drought Index Values

Class	NDDI	Category
1	-1 to 0	No drought
2	0 to 0.1	Starting to dry
3	0.1 to 0.2	Moderate
4	0.2 to 0.3	Severe
5	0.3 to 0.4	Extreme
6	0.4 to 1	Very extreme

Source: Artikanur et al., 2022

Analysis of Potentially Drought-Prone Rice Fields Using the SPI and NDDI Methods

After obtaining the Standardised Precipitation Index (SPI) and Normalised Difference Drought Index (NDDI) drought index values, the data were used to create a drought

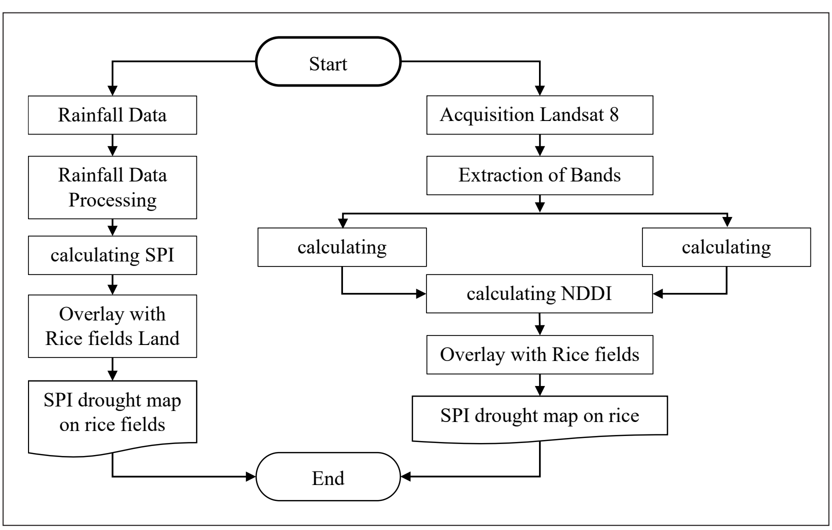

Figure 2. Data processing flowchart

distribution map, showing affected areas with varying degrees of drought. The SPI drought distribution map was created spatially using ArcGIS software.

The drought-analysis month was selected based on the minimum monthly rainfall observed during the 1994-2023 period. Monthly rainfall records were first analysed to identify the month with the lowest long-term rainfall condition. The selected month was subsequently used to represent the period with the greatest potential for meteorological drought and to generate the spatial distribution of SPI in West Sumatra Province.

The inverse distance weighted (IDW) interpolation method was used to interpret the SPI drought index values to obtain a map of the drought distribution in West Sumatra Province. The IDW interpolation method was applied to estimate SPI values at unsampled locations based on the weighted contribution of surrounding rainfall stations. The weighting decreases with increasing distance from the prediction location, such that closer stations have a greater influence on the estimated value. The interpolation was performed in ArcGIS using the specified power parameter and neighbourhood setting. The resulting continuous SPI surface was subsequently classified according to the adopted SPI drought categories.

The interpolated SPI drought map was subsequently overlaid with the rice-field spatial dataset using a GIS overlay operation. The rice-field dataset was first projected to the same coordinate reference system as the SPI raster. The SPI raster was then clipped and intersected with the rice-field polygons to identify the spatial extent and proportion of rice fields within each drought severity class.

The NDDI drought map was created using two important indicators: vegetation condition (NDVI) and water availability (NDWI). Through processing satellite imagery data using ArcGIS, a map was produced showing drought-affected areas in West Sumatra. This map is then combined with rice field data so that an overview of the distribution of drought in rice fields in each region is obtained.

Next, a comparative analysis of the SPI and NDDI results is carried out to see more comprehensive drought results. The inverse distance weighted (IDW) interpolation method was used to interpolate the SPI drought index values to obtain a map of the drought distribution in West Sumatra Province. The Inverse Distance Weighted (IDW) interpolation method was selected because the SPI values were obtained from discrete rainfall stations, and the spatial interpolation assumes that rainfall conditions at locations closer to an observation station are more similar than those at more distant locations. IDW assigns greater weights to nearby stations and progressively lower weights to more distant stations. This method was considered appropriate for the present study because the objective was to generate a spatial distribution map of SPI values based on the available rainfall station network. Compared with geostatistical methods such as Kriging, IDW does not require the estimation and fitting of a variogram or prior modelling of spatial autocorrelation. Therefore, considering the objective of the study and the characteristics of the available rainfall station data, IDW was selected as a practical method for spatial interpolation of

SPI values. Then the map is overlaid with data on rice fields. So, a map of the distribution of SPI drought in rice fields is obtained.

Validation of Drought Maps

The reliability of the drought maps derived from the SPI and NDDI methods was assessed using an independent reference dataset representing actual drought conditions. The validation dataset was not used in the calculation of the SPI or NDDI indices to maintain the independence of the assessment. Spatial matching was conducted by assigning the reference observations to the corresponding rice-field polygons or validation units, while temporal matching was performed by selecting drought maps corresponding to the same observation period as the reference data. Only observations with consistent spatial and temporal coverage were included in the validation analysis.

The drought classification derived from the SPI and NDDI maps was compared with the corresponding reference drought conditions. These metrics were used to quantify the agreement between the mapped drought classes and the independent reference data.

The validation results were subsequently used to evaluate the reliability of the SPI and NDDI approaches in identifying drought-prone rice fields in West Sumatra Province. Differences between the mapped drought conditions and the reference observations were also examined to identify areas where the indices may overestimate or underestimate actual drought conditions.

RESULTS

Rainfall

The rainfall data used in this study come from 47 rainfall stations distributed throughout the regencies/cities in West Sumatra Province, with an observation period of 30 years (1994-2023). An analysis of the monthly average rainfall shows a consistent seasonal pattern, with rainfall peaks occurring in November at 384 mm and the lowest values in July at 192 mm. This condition indicates that West Sumatra has a monsoon climate characterised by a rainy season at the end of the year and a dry season in the middle of the year, as shown in Table 4.

Rainfall Data Consistency

It is a crucial step in ensuring the accuracy and reliability of data analysis before use in drought analysis based on the Standardised Precipitation Index (SPI). Data consistency is crucial because inconsistencies can arise from recording errors, equipment failure, differences in measurement methods, or changes in environmental conditions, which can potentially introduce bias and lead to incorrect interpretations. The results of the consistency test are shown in Table 5.

Table 4
Monthly precipitation from 1994-2023

No	Station Name	Month											
		Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
1	Batang Kapas	265	212	243	229	175	220	200	226	244	310	355	311
2	Batu Busuk	256	190	307	313	252	268	244	283	291	339	445	371
3	Bendung Batang Hari	275	254	275	337	268	186	157	206	218	253	377	329
4	Bendung Koto Tuo	260	233	261	269	251	282	236	292	321	357	456	371
5	Canduang	215	171	257	291	181	137	137	158	168	221	279	262
6	Danau Diatas	254	182	223	284	240	187	124	171	166	220	300	310
7	Durian Simpai Silago	237	223	276	302	197	181	164	177	205	273	371	309
8	Ganggo Mudiak	282	230	347	402	284	271	210	329	326	377	447	411
9	BMKG Padang Panjang	322	298	350	408	248	212	199	262	298	359	445	459
10	Gumarang	276	238	304	313	239	196	191	252	290	332	422	369
11	Gunung Nago	311	221	326	301	297	308	272	333	388	431	520	396
12	Jalan Balantai	220	188	245	231	175	182	154	179	182	232	285	274
13	Kampung IV	231	201	290	304	229	330	221	304	286	351	391	313
14	Kandang IV	394	346	489	573	394	317	324	367	406	472	568	542
15	Kasang	324	285	334	329	265	306	255	332	375	387	451	395
16	BMKG Sumatera Barat	389	304	371	442	297	275	249	354	402	385	521	455
17	Komplek PU Sedasi	298	329	319	346	244	170	173	199	203	252	351	331
18	Koto Baru Piruko	225	195	249	285	204	151	155	170	200	232	365	300
19	Ladang Padi	310	253	359	375	349	328	311	305	337	435	527	423
20	Limau Manih	245	162	264	257	220	248	195	265	272	300	395	351
21	Lintau Buo	212	183	201	208	149	121	90	138	135	204	234	240
22	Lubuak Napar	357	289	438	472	296	294	239	349	348	388	516	484
23	Lunang	209	213	231	208	216	170	151	202	202	250	301	253
24	Manggopoh	224	167	219	240	191	163	165	254	264	279	343	309
25	BMKG Teluk Bayur	324	251	316	305	286	340	319	336	395	392	527	472
26	BMKG Minang Kabau	305	300	361	316	253	305	282	327	359	403	481	420
27	Muaro Labuh	125	116	130	146	113	86	89	104	111	121	161	142
28	Muaro Tantang	258	195	273	318	234	210	191	253	236	295	349	328
29	Nanggalo Tarusan	279	209	289	272	222	250	222	277	277	350	416	364
30	Padang Aro	259	246	304	276	208	206	165	183	200	217	309	265
31	Padang Sidodang	198	184	252	272	193	170	144	159	190	234	316	261
32	Paraman Talang	357	299	410	451	331	245	233	341	356	367	456	422
33	Rao	247	183	235	240	189	145	143	184	206	262	323	296
34	Saniang Baka	254	220	248	256	192	143	135	194	209	215	289	288
35	Santok	265	212	256	223	181	202	231	280	287	366	426	323
36	Sijunjung	230	202	216	279	190	146	136	165	169	196	292	250
37	Silapiang	368	287	376	401	263	200	226	325	324	363	449	390

Table 4 (*continued*)

No	Station Name	Month											
		Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
38	Sontang	177	166	170	230	141	132	110	154	192	209	303	293
39	Suko Mananti	247	192	306	350	278	261	242	315	302	358	432	353
40	Suliki	244	210	245	304	161	153	136	174	243	286	298	314
41	Sumani	181	140	174	185	131	106	95	156	142	193	237	250
42	Sungai Ipuh	234	204	233	231	159	115	105	129	189	201	298	202
43	Surantiah	265	198	213	186	155	168	189	214	223	266	334	308
44	Tanjung Pati	219	171	210	261	145	120	125	149	186	201	302	254
45	Tapan Bakir	357	317	354	298	302	292	233	285	330	425	461	386
46	Tarusan	315	213	278	257	204	219	194	256	280	321	371	363
47	Ujung Gading	336	320	395	395	241	245	278	425	419	488	564	478
	Average	269	226	286	302	226	212	192	245	263	306	384	340

Table 5
Rainfall data consistency test values

No	Station Name	R^2 Value	No	Station Name	R^2 Value
1	Batang Kapas	0.9977	25	BMKG Teluk Bayur	0.9976
2	Batu Busuk	0.9973	26	BMKG Minang Kabau	0.9927
3	Bendung Batang Hari	0.9986	27	Muaro Labuh	0.9816
4	Bendung Koto Tuo	0.9948	28	Muaro Tantang	0.9979
5	Canduang	0.9958	29	Nanggalo Tarusan	0.9996
6	Danau Diatas	0.9956	30	Padang Aro	0.9921
7	Durian Simpai Silago	0.9954	31	Padang Sidodang	0.9952
8	Ganggo Mudiak	0.9964	32	Paraman Talang	0.9989
9	BMKG Padang Panjang	0.9846	33	Rao	0.9796
10	Gumarang	0.9959	34	Saniang Baka	0.9673
11	Gunung Nago	0.9951	35	Santok	0.9844
12	Jalan Balantai	0.9959	36	Sijunjung	0.9747
13	Kampung IV	0.9985	37	Silapiang	0.9935
14	Kandang IV	0.9999	38	Sontang	0.9982
15	Kasang	0.9981	39	Suko Mananti	0.9961
16	BMKG Sumatera Barat	0.9998	40	Suliki	0.9761
17	Komplek PU Sedasi	0.9930	41	Sumani	0.9993
18	Koto Baru Piruko	0.9947	42	Sungai Ipuh	0.9914
19	Ladang Padi	0.9977	43	Surantiah	0.9835
20	Limau Manih	0.9937	44	Tanjung Pati	0.9910
21	Lintau Buo	0.9798	45	Tapan Bakir	0.9955
22	Lubuak Napar	0.9996	46	Tarusan	0.9981
23	Lunang	0.9460	47	Ujung Gading	0.9950
24	Manggopoh	0.9617			

Standardised Precipitation Index (SPI) Drought Index

The SPI drought analysis is conducted monthly, based on 30 years of rainfall data (1994-2023). SPI calculations are performed monthly to identify rainfall variability and more accurately detect drought periods. An SPI value <-1 indicates drought conditions, with severity varying from moderately dry to extremely dry depending on the magnitude. The following shows the number of SPI drought events from 1994 to 2023 (Table 6).

Spatial Drought Distribution Based on the SPI Method in Rice Fields

The drought distribution map was created to identify affected areas during the observation period. This map displays the spatial distribution and intensity of drought, allowing identification of areas with the highest severity (Yusman et al., 2025). This information is obtained from the SPI drought index calculation, which is then visualised in spatial maps to provide a more comprehensive picture of drought distribution. By integrating paddy field land use data in West Sumatra, covering an area of 234,504.93 ha, with the SPI drought distribution map for July 2023 using an overlay technique, information was obtained regarding the spatial variation in drought impacts (Figure 3).

The map in Figure 3 illustrates the distribution of drought in West Sumatra Province based on the SPI Index values for July in 2014, 2017, 2020, and 2023. July was chosen as the focus of the analysis due to the high frequency of drought events during the 1994-2023 period, which coincides with the dry season or the transition phase leading to the peak of the dry season in most parts of Indonesia, including West Sumatra. During this period, rainfall generally decreases significantly compared to previous months, increasing the potential for drought. The results of this analysis allow for the identification of impacted areas in paddy fields in each district/city, which is presented in detail in Table 7.

Table 6
Number of drought events based on SPI method analysis 1994-2023

Month	Drought Level			Amount
	Extremely Dry	Severely Dry	Moderately Dry	
January	22	32	93	147
February	59	70	152	281
March	18	26	86	130
April	15	17	66	98
May	31	56	164	251
June	51	80	181	312
July	80	90	200	370
August	70	69	125	264
September	73	73	97	243
October	91	60	79	230
November	6	12	48	66
December	22	23	54	99

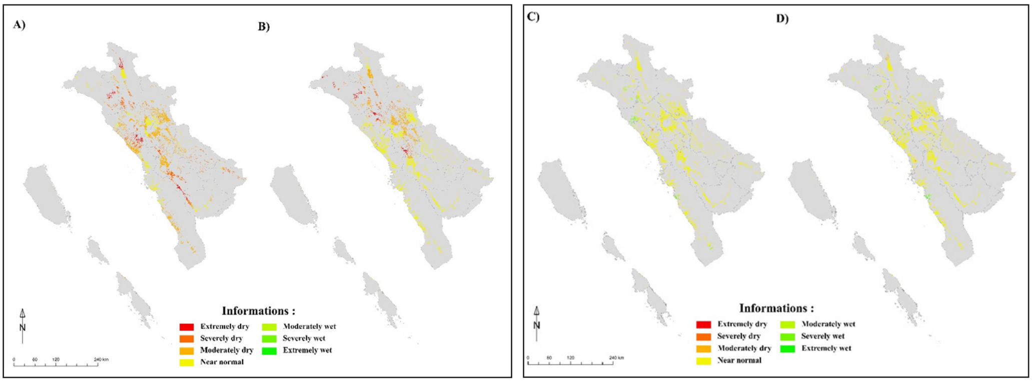

Figure 3. Spatial drought distribution of SPI in West Sumatra (A) 2014; (B) 2017; (C) 2020 and (D) 2023

Table 7
SPI Drought Area in Rice Fields in July 2023

No	Regency/City	Drought Level					
		Severely Dry (ha)	**Moderately Dry (ha)**	**Near Normal (ha)**	**Moderately Wet (ha)**	**Severely Wet (ha)**	**Extremely Wet (ha)**
1	Agam	0	0	27,885.49	65.18	0	0
2	Dharmasraya	0	0	4,405.08	518.46	0	0
3	Kepulauan Mentawai	0	0	294.57	0	0	0
4	Bukittinggi City	0	0	537.82	0	0	0
5	Padang City	6.45	340.56	6,596.90	10.57	0	0
6	Padang Panjang City	0	0	668.00	0	0	0
7	Pariaman City	0	0	2,088.51	0	0	0
8	Payakumbuh City	0	0	3,215.59	0	0	0
9	Sawahlunto City	0	0	1,528.70	0	0	0
10	Solok City	0	0	1,053.27	0	0	0
11	Lima Puluh Kota	0	0	25,462.00	0	0	0
12	Padang Pariaman	0	0	23,850.44	1,097.55	0	0
13	Pasaman	0	2,030.39	19,348.34	0	0	0
14	Pasaman Barat	0	0	7,537.60	1,118.11	688.15	0
15	Pesisir Selatan	0	0	21,591.83	1,167.22	1,812.27	287.87
16	Sijunjung	0	0	12,442.86	0	0	0
17	Solok	0	0	31,834.66	0	0	0
18	Solok Selatan	0	0	10,026.75	5.55	0	0
19	Tanah Datar	0	0	24,988.19	0	0	0
	Total	6.45	2,370.95	225,356.60	3,982.64	2,500.42	287.87

Spatial Drought Distribution Based on the NDDI Method in Rice Fields

The NDDI-based drought distribution map was created to identify the areas most affected by drought during the observation period. The NDDI considers the relationship between the vegetation index (NDVI) and the wetness index (NDWI), thus providing a more accurate spatial depiction of drought levels (Luqman et al., 2022). The distribution map is visualised as a colour gradient representing drought categories, ranging from normal to very extreme. Thus, the NDDI map shows not only the spatial distribution but also the intensity of drought in each region. Therefore, it can be used as a reference in formulating drought mitigation strategies in West Sumatra Province. The drought distribution map of West Sumatra Province, analysed using the NDDI method, is presented in Figure 4.

Based on Figure 4, the spatial distribution of drought in West Sumatra Province, analysed using the Normalised Difference Drought Index (NDDI), shows significant variations in drought severity. Areas dominated by green represent normal conditions with adequate moisture availability, while those coloured yellow to orange depict severe to extreme droughts that have the potential to hamper agricultural productivity. Meanwhile, areas coloured red indicate very extreme conditions with potentially serious impacts.

The analysis results show that the drought, based on the NDDI index, in July 2023 had a significant impact on rice fields in various regencies/cities in West Sumatra Province. Integrating the NDDI distribution map with the rice field map yields more comprehensive information, showing variations in drought severity across regions. This spatial-temporal information is crucial because it provides an overview of the drought dynamics experienced by rice fields during the observation period, as shown in the following Table 8.

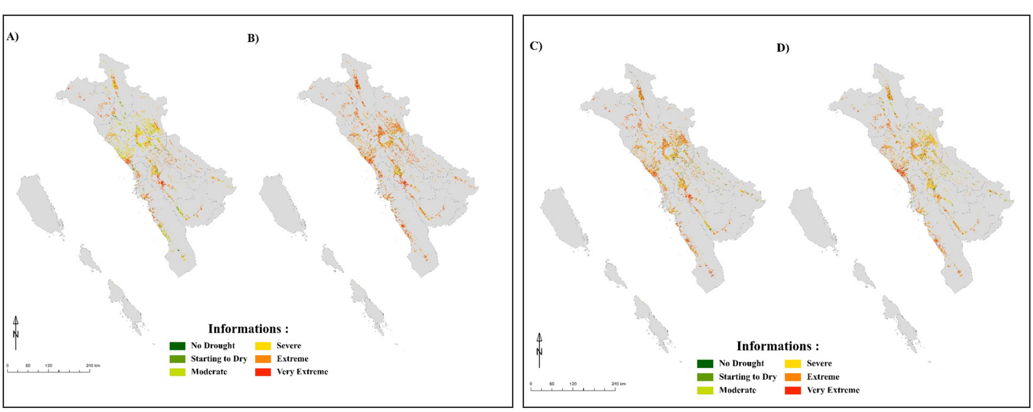

Figure 4. Spatial drought distribution of NDDI in West Sumatra (A) 2014; (B) 2017; (C) 2020; and (D) 2023

Table 8
NDDI drought extent in rice fields in July 2023

No	Regency/City	Area based on Drought Level (ha)					
		Very Extreme	Extreme	Severe	Moderate	Starting to Dry	No Dry
1	Agam	4,381.77	12,903.88	7,801.89	1,579.56	619.80	663.77
2	Dharmasraya	548.65	1,823.54	1,219.57	403.31	251.45	677.03
3	Kepulauan Mentawai	5.39	55.86	155.18	21.88	7.52	48.74
4	Bukittinggi City	193.79	188.92	91.36	27.95	15.73	20.08
5	Padang City	2,282.17	2,075.88	1,481.41	487.85	278.07	349.09
6	Padang Panjang City	117.37	326.52	191.04	25.16	5.58	2.33
7	Pariaman City	731.39	642.28	418.19	108.35	63.61	124.70
8	Payakumbuh City	258.45	1,224.04	1,248.48	274.66	117.98	91.98
9	Sawahlunto City	35.26	381.69	792.66	175.37	67.17	76.57
10	Solok City	156.58	243.61	393.29	119.90	63.56	76.34
11	Lima Puluh Kota	1,378.85	8,223.94	12,345.66	2,165.47	738.74	609.34
12	Padang Pariaman	8,799.41	8,603.63	5,127.69	1,118.64	573.39	725.23
13	Pasaman	5,282.67	6,974.47	5,309.21	1,991.66	926.02	894.69
14	Pasaman Barat	3,377.29	3,850.77	1,419.32	358.27	158.58	179.64
15	Pesisir Selatan	7,678.25	8,446.08	5,999.23	1,430.21	681.40	623.99
16	Sijunjung	668.04	3,022.05	5,038.83	1,954.07	962.61	797.26
17	Solok	3,660.62	9,905.65	12,207.14	3,124.39	1,177.19	1,759.67
18	Solok Selatan	1,501.39	4,402.76	2,918.43	616.40	319.60	273.70
19	Tanah Datar	2,351.10	8,275.75	9,633.75	2,280.30	1,000.75	1,446.54
	Total	43,408.45	81,571.33	73,792.33	18,263.40	8,028.74	9,440.68

Comparison of Drought Using the SPI and NDDI Methods

Based on the drought analysis using the Standardised Precipitation Index (SPI) in July 2023, rice fields in West Sumatra Province were generally classified as being in the normal category. However, a total of 2,377.40 ha of rice fields experienced drought, consisting of 6.45 ha classified as severely dry and 2,370.95 ha as moderately dry. However, this contrasts with the results of the NDDI drought analysis, which indicated drought conditions categorised as "moderate to very extreme." This discrepancy between the SPI and NDDI analysis results relates to land and water resource management in agricultural areas.

Uneven rainfall distribution requires the support of technical irrigation channels capable of distributing water regularly and measurably. Limited irrigation networks and infrastructure result in insufficient water supply, especially during periods of prolonged rainfall deficit. Without adequate irrigation infrastructure, rainwater that should be optimally utilised for agricultural needs is lost as surface runoff without being fully utilised by plants.

The discrepancy between SPI and NDDI should not necessarily be interpreted as an inconsistency between the two methods, but rather as an indication that they represent different dimensions of drought. SPI primarily reflects meteorological drought based on rainfall anomalies, whereas NDDI captures the response of vegetation and surface moisture conditions. Consequently, rice fields may remain in a normal meteorological condition according to SPI while experiencing water stress detected by NDDI because of differences in irrigation access, soil moisture conditions, topography, land management, and crop growth stage. This finding highlights the importance of integrating meteorological and remote-sensing indicators to obtain a more comprehensive understanding of agricultural drought conditions.

Recommendations for Drought Disaster Mitigation in Rice Fields

The integration of SPI and NDDI provides useful information for supporting drought management in rice-growing areas. SPI can be used to identify meteorological drought and provide an early indication of rainfall deficits, while NDDI can provide spatial information on the response of vegetation and surface moisture conditions at the agricultural field scale. The combined information can therefore support the prioritisation of drought interventions by identifying areas where rainfall deficits coincide with vegetation and surface moisture stress. Areas consistently identified as drought-prone can be prioritised for irrigation scheduling, water allocation, rehabilitation of irrigation infrastructure, and water conservation measures. In addition, NDDI-based spatial information can support local authorities in identifying rice fields that require closer monitoring during dry periods and can complement conventional rainfall-based drought monitoring.

In areas classified as mild to moderate drought, mitigation measures can be implemented through adjusting cropping patterns based on climate-based planting calendars, utilising organic mulch to reduce evaporation rates, and constructing water conservation microstructures such as rorak, infiltration ditches, and small dams. This approach is not only able to maintain optimal soil moisture but also extends water availability during the dry season, thus supporting the continuity of the plant growth phase (Wu et al., 2024).

Meanwhile, in areas classified as experiencing severe to extremely dry (extreme) drought, more intensive interventions are needed, such as the construction of reservoirs, water reservoirs, or retention dams to capture and store rainwater runoff during the rainy season. This infrastructure serves as a water reserve that can be gradually utilised during prolonged dry periods and is expected to increase the resilience of rice production in rain-fed areas (Dangnga et al., 2019). Furthermore, for drought-affected rice fields that still have irrigation systems but are damaged, rehabilitation and revitalisation of irrigation networks are necessary to ensure efficient and equitable water distribution. Integrating water conservation technology, infrastructure improvements, and the implementation of adaptive cultivation practices is key to building a drought-resilient agricultural system, particularly in the face of the challenges of climate change and extreme weather variability.

DISCUSSION

Based on Table 4, the climate classification of (Anam et al., 2023; Oldeman & Frère, 1982), months with rainfall ≥ 200 mm are categorised as wet, 100-200 mm as humid, and < 100 mm as dry. The analysis shows that the average monthly rainfall in West Sumatra during the 1994-2023 period generally falls within the wet category, except for July, which is on the threshold of transitioning to the humid category. Quite high spatial variability was identified in July, with several stations recording wet conditions, while three other stations—Lintau Buo (90 mm/month), Muaro Labuah (89 mm/month), and Sumani (95 mm/month)—showed dry conditions. These findings indicate that, although July is generally wet to humid, certain areas experience significant rainfall deficits. This rainfall distribution pattern shows significant spatial and temporal variability. The analysis reveals a gradual decline in accumulated rainfall since May, reaching its lowest point in July, indicating the onset of the dry season, marked by a consistent decrease in rainfall intensity. This situation directly impacts water availability for irrigation, potentially reducing agricultural productivity, particularly for commodities sensitive to water deficits.

The results of the consistency test (Table 5) show that rainfall data from all stations have a very good level of reliability, indicated by the coefficient of determination (R^2) value, which is generally close to 1. According to (Maulina et al., 2022), the closer the R^2 value is to 1, the higher the data consistency, while a value close to 0 indicates data inconsistency. Based on the analysis results from 47 rain gauge stations, the average R^2 value from all stations was 0.9912. This value reflects high consistency, so it can be concluded that there were no significant changes in the quality of rainfall data at each station during the observation period.

Table 6 above presents the number of drought events based on the SPI Index, grouped into three levels of severity: Extremely dry, Severely dry, and Moderately dry, during the January-December period of 1994-2023. The data demonstrate variations in drought intensity and frequency throughout the year, clearly illustrating the dry season pattern in the study area. The analysis shows that the highest number of drought events occurred in July, with a total of 370 events, consisting of 80 Extremely dry events, 90 Severely dry events, and 200 moderately dry events. Besides July, the months with a relatively high frequency of drought were June (312 events), August (264 events), and September (243 events). This pattern indicates that the mid-year period is a critical phase with a higher risk of drought compared to other months. This phenomenon aligns with the characteristics of Indonesia's tropical climate, where the peak dry season generally occurs in the middle of the year and is characterised by a significant decrease in rainfall, including in West Sumatra.

Based on the SPI analysis, drought conditions in West Sumatra show interannual variation. In July 2014 and 2017, several regions, particularly Pasaman and West Pasaman Regencies, experienced high-intensity drought, as indicated by the predominance of red on the SPI map (Figure 3). This condition indicates a significant rainfall deficit compared to normal conditions. Conversely, other regions during the same period remained within the normal category with relatively stable rainfall. Meanwhile, hydrological conditions in July 2020 and 2023 tended to be better, with most areas of West Sumatra Province falling within the normal category based on the SPI index. This finding indicates interannual climate dynamics influencing rainfall patterns and drought vulnerability in the region.

The results of the temporal NDDI drought analysis method for July 2014, 2017, 2020, and 2023 indicate spatially fluctuating drought dynamics (Figure 4). 2017 was recorded as the period with the most severe drought, indicated by a significant increase in areas categorised as extreme to very extreme in various districts/cities. These conditions were likely influenced by regional climate anomalies and may partly reflect differences in irrigation access and local water management. Conversely, conditions in 2023 were relatively better, marked by a decrease in the extent of extreme and very extreme droughts, although severe droughts still predominated in some regions. This fact shows an indication of improving hydrometeorological conditions but also confirms that the risk of drought remains an ongoing issue for the agricultural sector in West Sumatra. Spatially, drought vulnerability appears consistent across the West Pasaman, South Pesisir, and South Solok Regencies. These three regions have extensive rice paddy fields, but most still rely on rain-fed irrigation systems, making them highly vulnerable to seasonal rainfall declines. In contrast, Solok City shows a significant reduction in the area affected by extreme drought, which can be attributed to the relatively better availability of irrigation infrastructure, smaller area coverage, and more efficient water resource management. These findings indicate that differences in drought vulnerability across regions are determined not only by climate variability but also by local adaptive capacity, the availability of irrigation infrastructure, and the effectiveness of water resource management.

The spatial discrepancy between SPI and NDDI can also be explained by differences in topography, irrigation systems, land management, and rice crop phenology. Topographic conditions influence surface runoff, drainage, water accumulation, and soil moisture retention. Areas with relatively flat terrain may retain water for longer periods, whereas areas with higher slopes tend to experience greater runoff and faster drainage, potentially increasing agricultural water stress even when rainfall conditions are relatively normal. In addition, differences in irrigation infrastructure and water distribution capacity may cause unequal water availability among rice fields. Irrigated areas with adequate and well-maintained irrigation networks are generally more capable of maintaining crop water availability during short-term rainfall deficits, whereas rain-fed or poorly served areas are more vulnerable to water stress.

Land management practices may further modify the response of rice fields to rainfall variability. Practices such as water management, soil moisture conservation, field drainage, organic matter management, and cropping patterns can affect the amount of water retained and available to crops. Consequently, two areas receiving similar rainfall may exhibit different vegetation and surface moisture conditions as detected by NDDI. Crop phenology is also an important consideration because rice water requirements and vegetation responses vary among growth stages. During the vegetative and reproductive stages, increasing canopy development and crop water requirements may result in stronger responses to water deficits. Therefore, differences in planting dates and crop growth stages among rice fields can contribute to spatial variations in NDDI values. These factors demonstrate that agricultural drought is a multidimensional phenomenon in which rainfall deficits interact with local physical conditions, irrigation availability, land management, and crop development. Thus, the integration of meteorological and satellite-based indicators provides a more comprehensive assessment of drought conditions in rice fields than relying on rainfall-based indicators alone.

CONCLUSION

West Sumatra Province experienced periods of drought, which tended to occur in July between 1994 and 2023. Analysis using the Standardised Precipitation Index (SPI) recorded 370 drought events during this period. In July 2023, the area of rice fields affected by drought, based on the SPI, was categorised as dry and somewhat dry, with a total area of 2,377.40 ha, or 1.01% of the total rice field area in West Sumatra Province. The most severely affected area, classified as somewhat dry, was Pasaman Regency, with an area of 2,030.39 ha. Results of the drought analysis using the Normalised Difference Drought Index (NDDI) showed that the extent of the drought was categorised as severe, extreme, and very extreme, with a total area of 198,772.11 ha, or 84.76% of the total rice field area in West Sumatra Province. The most severely affected area, classified as very extreme, was Padang Pariaman Regency, with an impact area of 8,799.41 ha.

The integration of SPI and NDDI provides complementary information for drought assessment in rice fields in West Sumatra. SPI characterises rainfall anomalies at the meteorological scale, whereas NDDI captures spatial variations in vegetation and surface moisture stress. The resulting drought information can support drought management by helping identify priority areas for irrigation allocation, water conservation, irrigation-network rehabilitation, and adaptive crop management. However, because independent field-scale drought observations were limited, the NDDI results should be considered a spatial assessment rather than a fully validated agricultural drought product. Further research should incorporate soil-moisture observations, agricultural drought records, and crop productivity data to strengthen quantitative validation.

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REFERENCES

Adiningsih, E. S., Sofan, P., & Prasasti, I. (2016). Pemanfaatan teknologi penginderaan jauh untuk monitoring kejadian iklim ekstrem di Indonesia [Utilization of remote sensing technology for monitoring extreme weather events in Indonesia]. *Jurnal Sumberdaya Lahan*, *10*(2), 67-78. https://www.neliti.com/publications/133809/pemanfaatan-teknologi-penginderaan-jauh-untuk-monitoring-kejadian-iklim-ekstrem

Agusri. (2022). *87 Hektar lahan pertanian di Sumbar mengalami kekeringan* [87 hectares of agricultural land in West Sumatra experience drought]. TVRI Sumbar. https://www.tvrisumbar.co.id/berita/detil/4455/87-hektar-lahan-pertanian-di-sumbar-mengalami-kekeringan.html

Anam, A. R., Cakra, A. P., Wardoyo, W. A. A., Asary, S. M., & Virgianto, R. H. (2023). Pemetaan tipe iklim Oldeman tahun 2022-2100 berdasarkan skenario SSP5-8.5 menggunakan model ACCESS-CM2 [Oldeman climate type mapping for 2022-2100 based on SSP5-8.5 scenario using the ACCESS-CM2 model]. *JIPFRI (Jurnal Inovasi Pendidikan Fisika dan Riset Ilmiah), 7*(1), 20-27. https://doi.org/10.30599/jipfri.v7i1.2046

Artikanur, S. D., Widiatmaka, Setiawan, Y., & Marimin. (2022). Normalized Difference Drought Index (NDDI) computation for mapping drought severity in Bojonegoro Regency, East Java, Indonesia. *IOP Conference Series: Earth and Environmental Science, 1109*, Article 012027. https://doi.org/10.1088/1755-1315/1109/1/012027

Avia, L. Q. (2019). Change in rainfall per-decades over Java Island, Indonesia. *IOP Conference Series: Earth and Environmental Science, 374*, Article 012037. https://doi.org/10.1088/1755-1315/374/1/012037

Dangnga, M. S., Halimah, A. S., & Asniar, A. (2019). Reservoir building impact for rice farming rain fed. *Journal Galung Tropika, 8*(3), 224-234. https://doi.org/10.31850/jgt.v8i3.499

Dutta, D., Kundu, A., Patel, N. R., Saha, S. K., & Siddiqui, A. R. (2015). Assessment of agricultural drought in Rajasthan (India) using remote sensing derived Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI). *The Egyptian Journal of Remote Sensing and Space Science, 18*(1), 53-63. https://doi.org/10.1016/j.ejrs.2015.03.006

Foga, S., Scaramuzza, P. L., Guo, S., Zhu, Z., Dilley, R. D., Beckmann, T., Schmidt, G. L., Dwyer, J. L., Hughes, M. J., & Laue, B. (2017). Cloud detection algorithm comparison and validation for operational Landsat data products. *Remote Sensing of Environment, 194*, 379-390. https://doi.org/10.1016/j.rse.2017.03.026

Gu, Y., Brown, J. F., Verdin, J. P., & Wardlow, B. (2007). A five-year analysis of MODIS NDVI and NDWI for grassland drought assessment over the central Great Plains of the United States. *Geophysical Research Letters, 34*(6), Article L06407. https://doi.org/10.1029/2006GL029127

Hayes, M., Svoboda, M., Wall, N., & Widhalm, M. (2011). The Lincoln Declaration on drought indices: Universal meteorological drought index recommended. *Bulletin of the American Meteorological Society, 92*(4), 485-488. https://doi.org/10.1175/2010BAMS3103.1

Hermawan, E., & Komalaningsih, K. (2008). Characteristics of the Indian Ocean Dipole Mode in the Indian Ocean and its relationship with rainfall behavior in West Sumatra based on mother wavelet analysis. *Jurnal Sains Dirgantara, 5*(2), 109-129

Ihlen, V. (2019). *Landsat 8 data users handbook* (Version 5.0). U.S. Geological Survey. https://www.usgs.gov/media/files/landsat-8-data-users-handbook

Irsyad, F., & Oue, H. (2020). Predicting future dry season periods for irrigation management in West Sumatra, Indonesia. *Paddy and Water Environment, 19*(4), 683-697. https://doi.org/10.1007/s10333-021-00867-2

Intergovernmental Panel on Climate Change (IPCC). (2023). Sections. In Core Writing Team, H. Lee, & J. Romero (Eds.), *Climate change 2023: Synthesis report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 35-115), IPCC. https://doi.org/10.59327/IPCC/AR6-9789291691647

Lesik, E. M., Sianturi, H. L., Geru, A. S., & Bernandus, B. (2020). Analisis pola hujan dan distribusi hujan berdasarkan ketinggian tempat di Pulau Flores [Analysis of rainfall patterns and rainfall distribution based on altitude on Flores Island]. *Jurnal Fisika: Fisika Sains dan Aplikasinya, 5*(2), 118-128. https://doi.org/10.35508/fisa.v5i2.2451

Luqman, A. D., Wiyono, R. U. A., & Hidayah, E. (2022). Akurasi pemetaan kekeringan lahan pertanian menggunakan metode Normalized Difference Drought Index (NDDI) di kecamatan Wuluhan dan Rambipuji Jember [Accuracy of agricultural land drought mapping using the Normalized Difference Drought Index (NDDI) method in Wuluhan and Rambipuji Districts, Jember]. *Pertemuan Ilmiah Tahunan HATHI Ke-38*, 111-120.

Maulina, S. M., Christiana, R., & Widodo, M. L. (2022). Rainfall analysis for estimation of flood discharge and mainstay discharge with FJ Mock method (Case study: Kapuas River, Tayan Hilir District, Sanggau Regency). *Akselerasi: Jurnal Ilmiah Teknik Sipil, 3*(2), 17-22. https://doi.org/10.37058/aks.v3i2.4580

Mckee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. In *Proceedings of the Eighth Conference on Applied Climatology* (pp. 179-184). American Meteorological Society.

Novianti, R. (2019). Analisa indeks kekeringan dengan metode Standardized Precipitation Index 3 (SPI3) dan kejadian puso di Provinsi Jawa Barat [Analysis of drought index using the Standardized Precipitation Index 3 (SPI3) method and crop failure incidence in West Java Province]. *Institut Pertanian Bogor, 3,* 1-50. http://repository.ipb.ac.id/handle/123456789/98024

Oldeman, L. R., & Frère, M. (1982). *Technical report on a study of the agroclimatology of the humid tropics of Southeast Asia*. Food and Agriculture Organization of the United Nations.

Patil, P. P., Jagtap, M. P., Khatri, N., Madan, H., Vadduri, A. A., & Patodia, T. (2024). Exploration and advancement of NDDI leveraging NDVI and NDWI in Indian semi-arid regions: A remote sensing-based study. *Case Studies in Chemical and Environmental Engineering, 9*, Article 100573. https://doi.org/10.1016/j.cscee.2023.100573

Purnamasari, I., Pawitan, H., & Renggono, F. (2017). Analisis penjalaran kekeringan meteorologi menuju kekeringan hidrologi pada Das Larona [Analysis of the progression from meteorological drought to hydrological drought in the Larona Watershed]. *Jurnal Pengelolaan Sumberdaya Alam dan Lingkungan*

(Journal of Natural Resources and Environmental Management), 7(2), 163-171. https://doi.org/10.29244/jpsl.7.2.163-171

Rahman, F., Sukmono, A., & Yuwono, B. D. (2017). Analysis of agricultural land drought using the NDDI method and BNPB Regulation Number 02 of 2012 (case study: Kendal Regency in 2015). *Jurnal Geodesi Undip, 6*(4), 274-284. https://doi.org/10.14710/jgundip.2017.18152.

Shah, R., Bharadiya, N., & Manekar, V. (2015). Drought index computation using Standardized Precipitation Index (SPI) method for Surat District, Gujarat. *Aquatic Procedia, 4*, 1243-1249. https://doi.org/10.1016/j.aqpro.2015.02.162

Sunusi, N., & Auliana, N. H. (2025). Assessing SPI and SPEI for drought forecasting through the power law process: A case study in South Sulawesi, Indonesia. *MethodsX, 14*, Article 103235. https://doi.org/10.1016/j.mex.2025.103235

Sutanto, S. J. (2017). Wawasan mengenai sistem peringatan dini kekeringan di Indonesia [Insight towards drought early warning system in Indonesia]. *Jurnal Sumber Daya Air, 13*(1), 53-68. https://doi.org/10.32679/jsda.v13i1.158

Wicaksanti, W. R., Hadiani, R. R. R., & Setiono, S. (2019). Analisis kekeringan hidrologi berdasarkan Standardized Precipitation Index (SPI) di daerah aliran Sungai Tirtomoyo Kabupaten Wonogiri [Hydrological drought analysis based on the Standardized Precipitation Index (SPI) in the Tirtomoyo River Basin, Wonogiri Regency]. *Matriks Teknik Sipil, 7*(3), 272-281. https://doi.org/10.20961/mateksi.v7i3.36498

World Meteorological Organization (WMO) & Global Water Partnership (GWP). (2016). *Handbook of drought indicators and indices* (M. Svoboda & B. A. Fuchs, Eds.). Integrated Drought Management Programme. https://library.wmo.int/records/item/55169-handbook-of-drought-indicators-and-indices

Wu, X., Xu, H., He, H., Wu, Z., Lu, G., & Liao, T. (2024). Agricultural drought monitoring using an enhanced soil water deficit index derived from remote sensing and model data merging. *Remote Sensing, 16*(12), Article 2156. https://doi.org/10.3390/rs16122156

Yusman, R. D., Irsyad, F., Arlius, F., Saputra, R. A., & Yanti, D. (2025). Analysis rice field drought potential using the Standardized Precipitation Index (SPI) method. *Jurnal Teknik Pertanian Lampung (Journal of Agricultural Engineering), 14*(2), 494-505. https://doi.org/10.23960/jtep-l.v14i2.494-505

Zhu, Z., & Woodcock, C. E. (2012). Object-based cloud and cloud shadow detection in Landsat imagery. *Remote Sensing of Environment, 118*, 83-94. https://doi.org/10.1016/j.rse.2011.10.028