Pol. J. Environ. Stud. Vol. XX, No. X (XXXX), 1-17
DOI: *10.15244/pjoes/204000* ONLINE PUBLICATION DATE: 2025-06-06

Original Research

Geospatial Assessment of Drought Hazard in Aceh Besar Regency - Indonesia for Mitigation Planning

Ahmad Farhan[1, 2], Muhammad Syukri[1, 3]°*, Saumi Syahreza[1, 3], Taufan Hidayat[1, 4]

[1]Graduate School of Mathematics and Applied Science, Universitas Syiah Kuala, Banda Aceh, 23111, Indonesia
[2]Department of Physics Education, Faculty of Teacher Training and Education, Universitas Syiah Kuala, Darussalam, Banda Aceh-23111, Indonesia
[3]Department of Physics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, 23111, Indonesia
[4]Department of Agrotechnology Faculty of Agriculture, Universitas Syiah Kuala, Darussalam, Banda Aceh 23111, Indonesia

Received: 25 February 2025
Accepted: 13 April 2025

Abstract

Drought in Aceh Besar Regency is a recurring phenomenon, yet current management remains focused on short-term solutions. The objective of this study is to develop a drought hazard mapping model using Geographic Information Systems (GIS) to analyze the spatial distribution of drought hazard levels. The model incorporates key variables, including average annual rainfall, slope gradient, soil type, geology, distance from water sources, and land cover. The results indicate varying drought hazard across districts, with Kota Jantho having the largest affected area in both moderate (198.67 km²) and high-hazard (376.18 km²) categories, while Krueng Barona Jaya and Peukan Bada have the smallest. These disparities highlight the need for targeted mitigation strategies. The findings underscore that drought poses a significant threat to several districts, necessitating proactive adaptation measures. The developed model provides a reliable tool for assessing drought distribution and serves as a scientific basis for effective drought mitigation planning. Implementing hazard-based strategies can optimize water resource management, minimize drought impacts, and enhance regional resilience.

Keywords: drought, geographic information system, hazard mapping, mitigation, planning

Introduction

One of the major natural disasters that remains a significant challenge in Indonesia is drought. According to a report by the National Disaster Management Coordinating Board [1], historical data analysis indicates that drought occurrences in Indonesia are significantly linked to the El Niño-Southern Oscillation (ENSO) phenomenon. Since 1844, there have been 43 recorded drought events in Indonesia, with only six of them unrelated to El Niño. The strong impact of El Niño contributes to an extended dry season compared to the rainy season, ultimately increasing the likelihood of prolonged drought disasters [2].

Aceh Besar Regency is one of the regions in Indonesia that frequently experiences drought. Research

*e-mail: m.syukri@usk.ac.id
°ORCID iD: 0000-0002-2053-5411

indicates that drought in this area is influenced by the El Niño phenomenon, leading to extended dry periods and reduced availability of clean water. Additionally, drought in Aceh Besar occurs annually, particularly during the transition from the rainy season to the dry season (inter-monsoon period), and affects almost all areas within the regency. To address this issue, the local government manually collects data to identify drought-affected areas. Mitigation efforts are then carried out by distributing clean water to areas experiencing drought and water shortages.

Several researchers have highlighted that drought is one of the most complex and recurrent natural hazards, affecting ecological, economic, social, agricultural, cultural, and political aspects in different ways [3, 4]. In the digital economy era, cross-border e-commerce plays a crucial role in enhancing regional competitiveness and driving the transformation of international trade. Various policies, such as cross-border e-commerce pilot zones and urban civilization initiatives, have been implemented in China to optimize economic growth and urban sustainability through industrial innovation, institutional reform, and the strengthening of digital infrastructure. This study explores the impact of these strategies, highlighting how sustainable development in cross-border e-commerce and urban policies can contribute to stable and sustainable economic growth [5-7]. Furthermore, drought is a recurring and long-lasting phenomenon, ranking among the most economically damaging natural disasters globally [8]. The frequency and intensity of drought events are projected to increase due to rising water demand driven by population growth, constrained and unpredictable water supplies, and climate variability. Drought is typically classified into three categories: meteorological, agricultural, and hydrological [9, 10]. However, prior studies have primarily categorized drought based on characteristics of water deficits [11] or its impacts [12] into four types: meteorological drought, hydrological drought, agricultural drought, and socio-economic drought.

The study on earthquake disaster risk in Bener Meriah, Aceh, Indonesia, using a GIS approach. They analyzed the 2013 earthquake event (6.2 on the Richter scale) by overlaying hazard, vulnerability, and capacity factors based on the National Agency for Disaster Countermeasure (known as BNPB) Regulation 2/2012 standard [13]. They investigated geothermal potential at Mount Seulawah, Aceh, by estimating land surface temperature (LST) through remote sensing, utilizing the split-window algorithm (SWA) and lineament density analysis to evaluate geothermal manifestations [14]. They monitored agricultural drought in rice fields in Aceh Besar Regency using Sentinel-2A satellite data, applying the Vegetation Condition Index (VCI) and Normalized Difference Vegetation Index (NDVI) to assess drought severity over five planting seasons [15]. They analyzed the distribution of Green Open Space (GOS) in Banda Aceh using high-resolution Planetscope-3A satellite imagery, employing supervised classification and NDVI transformation to categorize land cover into eight categories, achieving an accuracy rate of 76.036% and a kappa value of 0.726 [16].

Fundamentally, every disaster impacts different regions in unique ways. Therefore, disaster risk assessment is essential to determine potential losses, impacts, and mitigation efforts, including drought risk in Aceh Besar Regency. The risks associated with drought in this region include reduced water supply for daily needs, crop failures, environmental degradation, and even social conflicts. The BNPB has mapped the drought risk index for Aceh Province at a scale of 1:1,300,000, categorizing Aceh Besar Regency as a low-risk area [17]. However, this mapping covers a broad scale and is not detailed enough for effective disaster management at the local level. Additionally, given that drought is a recurring event with uncertain onset and duration, continuous monitoring and identification of drought risk factors are necessary to develop a drought risk model. Furthermore, drought hazard, vulnerability, and risk maps are needed to support drought disaster mitigation planning [2].

To date, disaster risk models have evolved alongside research advancements in disaster risk assessment. Some models integrate hazard with vulnerability [18, 19], while others incorporate probability with potential losses [20]. Additionally, some researchers argue that disaster risk is influenced by susceptibility, exposure, and vulnerability factors [21]. Another approach calculates disaster risk as susceptibility multiplied by vulnerability and divided by capacity [14, 17].

This study has broad implications for scientific development, researchers, government agencies, and the general public. From a scientific perspective, the research contributes to enhancing knowledge related to detection methods and approaches for drought disaster management. Additionally, this study is useful in assessing the hazard of regions to drought based on social, economic, and environmental factors, allowing for a comprehensive drought hazard analysis in the study area. For researchers, this study expands knowledge on technological applications and approaches in drought disaster mitigation. For government agencies, it provides valuable information on drought hazard levels in Aceh Besar Regency, which can serve as a guideline for formulating more effective drought mitigation policies. Meanwhile, for the general public, this research enhances awareness of drought-prone areas and serves as an early warning system, particularly for residents in high-hazard drought zones.

Based on this background, the objective of this study is to develop a drought hazard mapping model using GIS to identify the spatial distribution of drought hazard levels in Aceh Besar Regency, considering both drought and regional hazard. By the end of this research, recommendations and guidelines will be formulated as a reference for planning and implementing drought disaster mitigation strategies in Aceh Besar Regency. This study differs from previous research not only in terms of the study location but also in its objectives, variables used, analytical methods, and the comprehensiveness of the discussion. This study incorporates a comprehensive set of variables, including average annual rainfall, slope gradient, soil type, geology, distance from water sources, and land cover, to develop a drought hazard mapping model. This approach enhances spatial accuracy compared to traditional single-parameter or meteorological-based drought assessments. The study provides a validated mapping model that can serve as a scientific basis for policymakers and stakeholders in Aceh Besar Regency to implement more effective drought response and resilience strategies, bridging the gap between hazard assessment and practical application.

Materials and Methods

The data required for this study consists of two types: spatial data and non-spatial data. Spatial data includes raster data in the form of a Digital Elevation Model (DEM) and vector data, which consists of maps related to variables associated with drought susceptibility. Meanwhile, non-spatial data includes tabular data, such as demographic data and supporting information providing a general overview of the study area (Fig. 1). For more details, refer to Table 1.

A spatial approach using a quantitative method that employs statistical indicators to measure and compare various variables has been utilized in this study. The spatial approach aims to analyze drought disasters from a spatial perspective. Data collection was conducted through institutional surveys and literature reviews, utilizing secondary data. The data analysis techniques applied include scoring analysis, weighting, and map overlay.

Scoring is the process of converting responses into numerical values, representing quantitative measures [22]. The scoring process is based on theories related to drought hazard factors, references from previous research, and empirical field experiences regarding the extent to which each class influences drought. A higher influence on drought results in a higher score. The scoring for these parameters is conducted linearly within the classes of a particular drought parameter, with scores ranging from 1 to 5. A score of 1 is assigned to classes with minimal influence on drought, while a score of 5 is given to classes with a significant impact on drought.

This study employs the ranking method for weighting, which is among the simplest techniques for assigning weight values [24]. Each parameter is ranked based on importance. The ranking determination is subjective; for instance, the most important parameter is assigned a value of 1, an important parameter is given

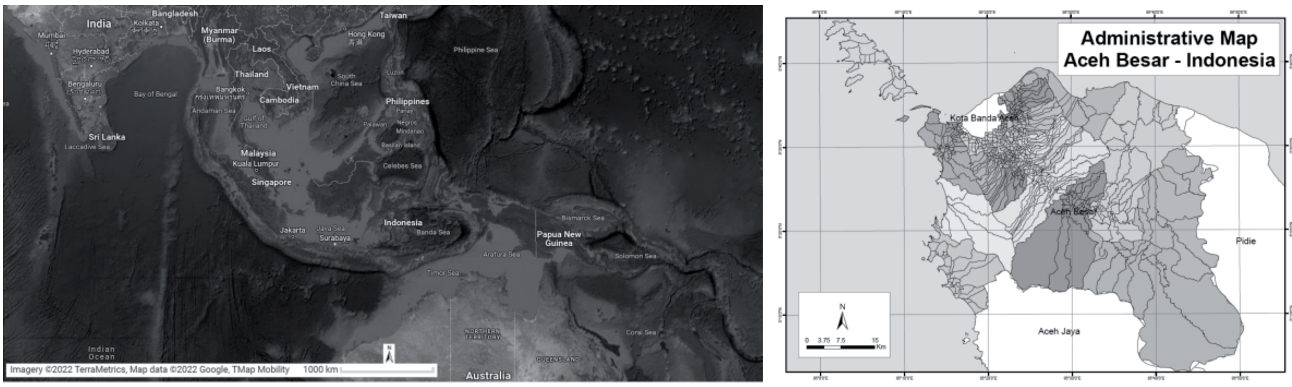

Fig. 1. Study Area [14].

Table 1. The data supports the drought analysis.

Data	Data Format	Source
Administrative boundary map	Vektor	Regional Development Planning Agency/ Badan Perencanaan Pembangunan Daerah (Bappeda)
Rainfall data and maps	Vektor	Meteorology, Climatology, and Geophysics Agency/ Badan Meteorologi, Klimatologi, dan Geofisika (BMKG)
Digital Elevation Model (DEM-SRTM)	Raster	CGIAR [23]
Soil type map	Vektor	Geological Agency/ Badan Geologi
Geological map	Vektor	Geological Agency/ Badan Geologi
River network map	Vektor	Geospatial Information Agency/ Badan Informasi Geospasial (BIG)

a value of 2, and a less important parameter is assigned a value of 3. Alternatively, a reverse approach can be applied, where a less important parameter is given a value of 1, an important one a value of 2, and the most important one a value of 3. The weighting is calculated using Eq. (1) [2].

$$Wj = \frac{(n-r_j+1)}{\sum(n-r_p+1)} \tag{1}$$

where *Wj* is the normalized weight for the *j* (*j = 1, 2, 3,... n*), *n* is the total number of parameters, r_j is the ranking position or importance level of a given parameter, and *p* represents the parameters (*p = 1, 2, 3,... n*).

Results and Discussion

The variables used to develop the drought hazard mapping model include annual average rainfall, slope gradient, soil type, geology/rock composition, distance from water sources, and land cover. These variables were analyzed using a scoring approach and then assigned weights accordingly.

Annual rainfall data is obtained from the latest datasets provided by relevant government agencies, such as BMKG. If such data is unavailable, it can be retrieved from CHIRPS (Climate Hazards Group InfraRed Precipitation), as shown in Fig. 2a). The classification and scoring for annual rainfall data are presented in Table 2.

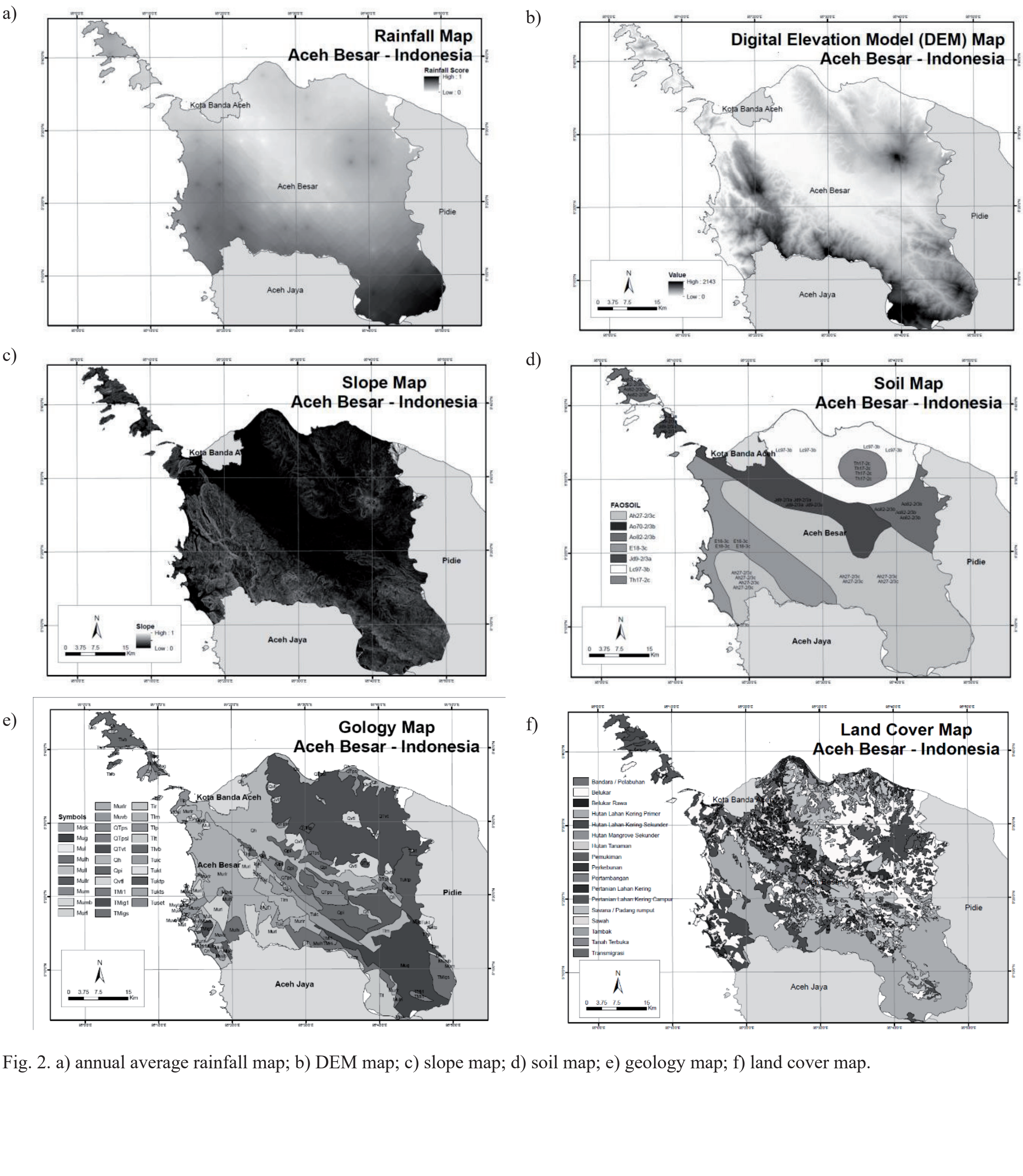

Fig. 2. a) annual average rainfall map; b) DEM map; c) slope map; d) soil map; e) geology map; f) land cover map.

Table 2. Rainfall, soil, and land cover classification.

Parameter	Score		
	Low = 0.333	Medium = 0.666	High = 1
Rainfall	> 3,000 mm	1,500 - 3,300 mm	< 1,500
Soil Type	Organic/Peat	-	Non-Organic/Mineral
Land cover	Forest	Plantation/Garden	Dryland Farming, Shrubland, Grassland

In Fig. 2b), the DEM map represents the terrain elevation of the study area, providing a raster-based representation of surface topography. It is used to analyze variations in elevation, which play a crucial role in assessing drought susceptibility, as elevation influences factors such as water flow, soil moisture retention, and vegetation distribution. In Fig. 2c), the Slope map is derived from the DEM and illustrates the degree of inclination across the terrain. Slope influences water runoff, infiltration rates, and soil erosion potential, making it a critical parameter in drought hazard assessment. Steeper slopes tend to experience higher runoff and lower water retention, whereas flatter areas retain more moisture, affecting the overall drought hazard classification. The next step is to create a soil type classification map and geology map (Fig. 2d) and 2e)). Peat soil is categorized as a low-hazard class, while all other soil types fall into the high-hazard class (Table 2). The land cover data layer was analyzed to generate a land cover classification map (Fig. 2f)). The classification of land cover related to drought hazard was divided into three land types, each assigned specific scores and weights, as shown in Table 2.

The weighting concept for drought hazard component variables is based on the extent to which each variable contributes to drought occurrence, as explained: the drought process begins with a decrease in rainfall intensity, serving as the initial indicator of drought occurrence. Rainwater flows from higher to lower areas, making the slope gradient of a region a significant factor. Furthermore, the availability and retention of water in the soil are influenced by the soil type and the geological composition of the area, assessed based on their permeability. These four conditions are indirectly related to the availability of surface water sources. In terms of drought hazard, the distance from a water source also plays a crucial role. Additionally, land cover depends on soil type, geological structure, and rock composition. Based on this analysis, the parameter variables are ranked according to their influence on drought hazard (Fig. 3). The most influential variable is assigned the highest weight, followed by the others in decreasing order. The weights are then normalized using the ranking method, following Eq. (1). After assigning scores and weights, all drought hazard variables are overlaid. The drought hazard map is generated by combining or summing the total scores from the thematic maps representing the contributing factors. The final map is then reclassified into five hazard classes using the Natural Breaks method, ensuring that the classification retains the essential characteristics of each category.

Based on the analysis conducted, three drought hazard classes have been identified in Aceh Besar Regency: Not Vulnerable, Medium, and Highly Vulnerable. The detailed classification is presented in the following table. Based on Table 3 and Fig. 4, the drought hazard level in the study area can be analyzed based on two main categories: medium and high. The variation in land area within these two categories reflects different levels of drought hazard across sub-districts.

The largest area in the medium hazard category is Kota Jantho (198.67 km²), followed by Lhoong (100.39 km²) and Kuta Cot Glie (85.03 km²). Other sub-districts with significant areas in this category include Lembah Seulawah (82.36 km²) and Seulimeum

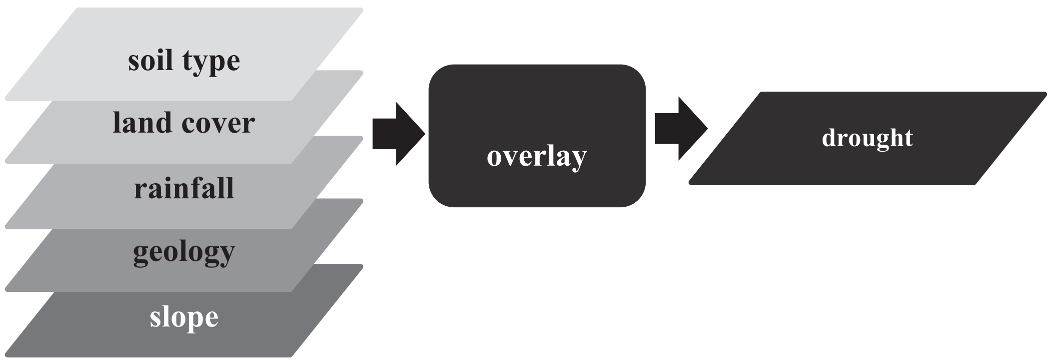

Fig. 3. Drought hazard mapping model.

Table 3. Drought-prone area coverage in Aceh Besar Regency.

Sub-district	Medium (Km^2)	High (Km^2)
Sukamakmur	3.34	40.29
Seulimeum	71.12	317.98
Ingin Jaya	2.56	20.59
Simpang Tiga	0.89	25.71
Baitussalam	1.78	16.47
Kuta Baro	8.68	51.75
Lhoong	100.39	48.53
Darussalam	7.01	31.16
Montasik	5.12	57.10
Kuta Cot Glie	85.03	232.83
Darul Kamal	1.00	23.71
Blang Bintang	2.78	39.62
Darul Imarah	3.90	19.59
Kota Jantho	198.67	376.18
Indrapuri	34.95	167.72
Pulo Aceh	19.48	42.63
Mesjid Raya	35.62	90.26
Peukan Bada	18.92	13.13
Kuta Malaka	1.22	22.59
Krueng Barona Jaya	0.11	6.12
Lhoknga	49.97	33.39
Lembah Seulawah	82.36	224.49
Leupung	125.77	38.84

(71.12 km²). These areas have considerable drought potential in the medium category, which could impact water availability for agriculture, consumption, and local ecosystems. On the other hand, the smallest areas in the medium category are Krueng Barona Jaya (0.11 km²), Simpang Tiga (0.89 km²), and Darul Kamal (1.00 km²). The limited extent of these areas suggests a relatively lower hazard of medium-level drought compared to other sub-districts. In the high hazard category, the largest area is Kota Jantho (376.18 km²), significantly higher than other sub-districts. Seulimeum (317.98 km²) and Kuta Cot Glie (232.83 km²) also have substantial land areas classified under high hazard. This indicates that these three sub-districts are highly susceptible to severe drought, which can threaten water resources and environmental sustainability. Conversely, the smallest areas in the high hazard category are Peukan Bada (13.13 km²), Krueng Barona Jaya (6.12 km²), and Darul Imarah (19.59 km²). Although these areas have a relatively smaller extent in the high hazard category, the impacts of drought must still be considered, particularly in terms of water resilience and community well-being.

Sub-districts with large high-hazard areas, such as Kota Jantho, Seulimeum, and Kuta Cot Glie, require special attention in water resource management. Mitigation efforts such as reservoir construction, groundwater management, and water-efficient irrigation technologies could help reduce drought impacts. Additionally, sub-districts with large medium-hazardareas, such as Lhoong, Lembah Seulawah, and Seulimeum, need strong adaptation strategies to prevent worsening drought conditions. Reforestation programs and soil conservation efforts can help maintain water availability in these regions.

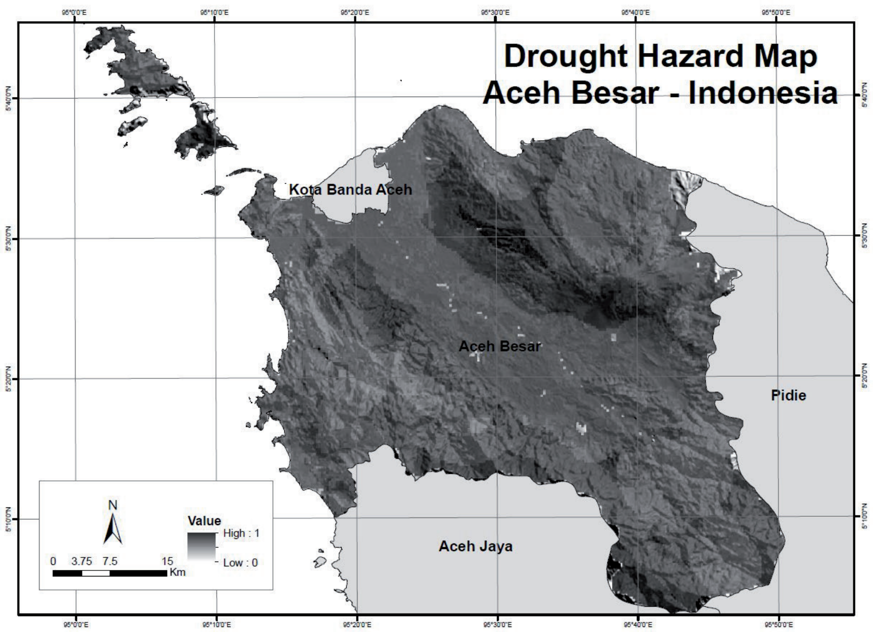

Fig. 4. Drought hazard map of Aceh Besar Regency.

Tabel 4. A comprehensive review of agricultural drought monitoring, water scarcity analysis, and drought hazard assessment across global regions.

Topic	Methodological Approaches	Findings and Key Insights	Ref.
Reviews recent scientific advancements in drought research, emphasizing its increasing frequency and anthropogenic influences.	The synthesis of current and emerging developments in drought concepts, classifications, indices, and their sector-specific applications through a comprehensive literature review.	Anthropogenic activities such as urbanization and deforestation, along with climate change, have intensified drought frequency and severity, necessitating improved drought monitoring, management, and mitigation strategies to support ecosystem recovery and public health resilience.	[25]
Improving drought monitoring and assessment by integrating satellite-derived soil moisture (SM) data and evaluating its applicability for agricultural drought characterization.	The study combines ESA CCI and GLDAS SM products to generate a continuous dataset, extends the soil water deficit index (SWDI) for long-term drought analysis, and employs probability detection, correlation analysis, and grey incidence analysis (GIA) to investigate drought propagation dynamics.	The SWDI demonstrated strong agreement with in situ drought records, with most stations achieving high probability detection (POD > 0.9); meteorological droughts transitioned to agricultural droughts within 1–2.5 months, while vegetation drought responses varied by land cover type, with significant time lags observed in forested regions.	[26]
This study evaluates the accuracy and applicability of integrating remote sensing data with ground-based measurements in Poland's Agricultural Drought Monitoring System (ADMS) to improve Climatic Water Balance (CWB) assessments.	The study compares CWB indices derived from ground meteorological stations and MODIS-based potential evapotranspiration data using statistical analyses, including Pearson's correlation coefficient (r), Mann–Kendall trend test (Z-index), mean absolute error (MAE), and root mean square error (RMSE) over a ten-year period.	The moderate correlation ($r = 0.06$ to 0.68) between the two data sources, with CWB values consistently higher when estimated from ground measurements; trend consistency was observed in 34 out of 43 stations, though discrepancies increased during warmer months, particularly at the end of May.	[27]
The study addresses the complexity of agricultural drought and its impact on crops. It highlights the limitations of existing univariate, bivariate, and multivariate drought analyses in integrating drought evolution with crop growth.	■ Introduces the Evolution Process-based Multi-sensor Collaboration (EPMC) framework, which integrates drought development with crop phenology. ■ Introduces the Process-based Accumulated Drought Index (PADI) to quantify cumulative drought impacts on crops.	■ The effectiveness of the PADI Index provides weekly evaluations of cumulative drought severity rather than single-time assessments. Shows good correlation with short-term SPI at the onset of drought and long-term SPI at later stages. ■ Performance Comparison with Other Drought Indices shows that PADI outperforms the Palmer Drought Severity Index (PDSI) and multi-time scale Standardized Precipitation Index (SPI) in tracking drought impacts. ■ Correlation with Crop Yield Loss is PADI correlates well with wheat yield loss (Spearman rank correlation coefficient $\rho = 0.66$ to 0.77, $p<0.05$). ■ The significance of the EPMC Framework is that it provides an innovative and integrated approach to agricultural drought assessment; enhances drought impact monitoring by incorporating multi-sensor data and crop growth factors; and offers practical applications for drought impact assessment and early warning systems.	[28]
The study analyzes agricultural drought characteristics in China and evaluates different drought indices for monitoring.	■ Used remote sensing (1982–2018) datasets: precipitation, soil moisture, LST, and NDVI. ■ Compared SPI, SSI, MSDI, and VHI anomalies at 1-, 3-, and 6-month timescales across four regions.	■ MSDI had the strongest correlation with VHI, outperforming SPI and SSI. ■ Drought index correlation with VHI was weaker at 1 month but stronger at 3- and 6-month timescales. ■ VHI increased across most of China, except North China. ■ MSDI was the most effective index for agricultural drought monitoring.	[29]

→

Increasing drought awareness in Central Europe, particularly in the Czech Republic, due to severe droughts in 2000, 2003, 2012, and 2015, causing significant economic damage.	■ Developed the Czech Drought Monitor (2012–2014) as an online platform for real-time drought monitoring and forecasting. Uses four key components: weekly soil moisture estimates (from satellite scatterometer data), Daily SoilClim model (based on 55 years of meteorological data), satellite-based vegetation indices for early drought impact warnings, and expert reports on soil moisture and drought effects.	■ Drought events in 2000, 2003, and 2015 were among the most severe in terms of spatial extent, magnitude, and duration since 1961. ■ Large-scale and localized droughts pose significant risks, highlighting the need for high-resolution monitoring and forecasting tools.	[30]
Evaluation of the Soil Moisture Agricultural Drought Index (SMADI) as a global estimator for agricultural drought using remote sensing data.	■ SMADI combines MODIS LST, NDVI, and surface soil moisture (SSM) from SMOS. ■ Applied globally at 0.05° resolution every 15 days from 2010 to 2015. ■ Compared SMADI with existing agricultural drought indices and documented drought occurrences at local, regional, and global scales.	■ Local & Regional: Showed good consistency with agricultural drought indices in the Iberian Peninsula, identifying 2012 and 2014 as the driest years. ■ USA: Matched well with US Drought Monitor (USDM) maps, detecting major drought events. ■ Global: Recognized over 80% of documented drought events for more than 50% of their duration. ■ Advantages: SMADI is simple, fast, and relies on readily available data, making it a valuable tool for early warning systems.	[31]
Drought Severity Index (DSI) application for agricultural drought monitoring in China (2000–2014) using NDVI and ET/PET datasets.	■ DSI computation to track spatial and temporal drought patterns. ■ Modified Mann-Kendall trend test for drought trend analysis. ■ Pearson correlation to assess the relationship between crop yield and drought-affected areas.	■ DSI effectively monitors agricultural droughts, but cannot determine drought termination due to vegetation recovery lag (1–2 months). ■ Severe drought periods identified: 2000–2001 and 2007–2009, mainly affecting northeastern, northern, and southwestern China. ■ Maize and wheat are highly vulnerable, with significant yield losses expected during droughts. ■ Agricultural irrigation introduces monitoring uncertainty, as northern China experiences frequent droughts but fewer crop losses. ■ DSI has potential for broader agricultural drought monitoring applications beyond China.	[32]
Evaluates the effectiveness of three remote sensing-based drought indices, VHI, TVDI, and DSI, for monitoring agricultural drought in the rain-fed and irrigated agricultural regions of Shaanxi and Henan provinces, China.	The correlation between these drought indices and the standardized precipitation index (SPI), soil moisture, winter wheat yield, and National Meteorological Drought Monitoring (NMDM) maps was examined to determine their suitability for large-scale drought monitoring.	DSI demonstrated the strongest correlation with SPI and soil moisture, making it the most reliable index; drought indices performed better in rain-fed areas (Shaanxi) than irrigated regions (Henan), with winter wheat being particularly sensitive to water stress during the jointing and grain-filling stages.	[33]

Utilization of microwave remote sensing for large-scale agricultural drought monitoring through SM and vegetation observations.	■ Overview of microwave remote sensing fundamentals and recent research advancements in drought indicators. ■ Discussion of challenges and research gaps in integrating microwave-based SM and vegetation data with hydro-meteorological datasets. ■ Case study in Senegal demonstrating the effectiveness of satellite- and model-based data (rainfall, SM, and vegetation) for drought monitoring.	■ SM and vegetation indicators provide direct insights into plant water availability and productivity, integrating multiple hydro-meteorological factors. ■ Microwave remote sensing enables large-scale, high-frequency drought monitoring, making it a valuable tool for operational applications. ■ Challenges remain in effectively combining microwave-derived SM and vegetation data with other meteorological datasets, requiring further research. ■ The Senegal case study confirms the added value of microwave remote sensing in enhancing drought monitoring capabilities. ■ Future advancements in data integration and methodology could further improve agricultural drought assessment.	[34]
Development and validation of a Comprehensive Drought Monitoring Index (CDMI) by integrating precipitation, soil water, and heat balance, and crop growth for agricultural drought assessment.	■ Principal Component Analysis (PCA) was used to construct CDMI by incorporating atmospheric, soil, and crop factors from the early stages of drought. ■ The index was validated using drought coverage, affected areas, relative soil moisture, and crop yield. ■ CDMI was applied for long-term drought monitoring (June–September) in Henan Province, focusing on summer maize.	■ CDMI showed strong negative correlations with drought-affected areas (-0.68) and drought coverage (-0.73), confirming its reliability. ■ Positive correlations were observed between CDMI, relative soil moisture (0.91), and maize yield (0.52), indicating its effectiveness in assessing drought impact. ■ Severe drought years in Henan Province were identified (2000, 2001, 2004, 2006, 2008, and 2014), with July–August 2014 experiencing the most intense drought. ■ Henan Province has a high frequency of severe droughts, highlighting the need for effective monitoring and mitigation strategies. ■ CDMI, derived from multisource remote sensing data, is a reliable tool for agricultural drought monitoring and assessment.	[35]
Develops and validates a new remote sensing-based integrated drought index, the Geographically Independent Integrated Drought Index (GIIDI), for improved drought monitoring across diverse climate regions.	Employs a local Ordered Weighted Averaging (OWA) model to integrate multiple remote sensing-based indices (TCI, VCI, SMCI, and PCI) and validates GIIDI's performance against established drought indices (PDSI, SPI, SPEI) across climate divisions in the continental United States.	GIIDI demonstrated superior correlation with in-situ drought indicators and outperformed existing indices in both short- and long-term drought monitoring, highlighting its potential for enhancing global drought assessment across different biomes and climates.	[36]
Develops a Combined Drought Indicator for Ethiopia (CDI-E) to improve agricultural drought monitoring in a highly drought-prone region.	CDI-E integrates four satellite-based agro-meteorological variables (SPI, LST anomaly, std NDVI, and SM anomaly) using PCA and is validated against 3-month SPI and crop yield data across 36 crop-growing zones in Ethiopia from 2001 to 2015.	CDI-E effectively detected historical drought events, showed strong correlations with SPI ($r > 0.65$) and crop yields ($r > 0.5$) in several regions, and demonstrated potential for use in agricultural drought monitoring and early warning systems to support decision-making in food-insecure areas.	[37]
The Integrated Agricultural Drought Index (IDI) for improved agricultural drought monitoring using multiple meteorological and hydrological variables.	IDI is developed using remote sensing data and a back-propagation (BP) neural network, incorporating precipitation, LST, NDVI, soil water capacity, and elevation, while capturing the lagging effect of NDVI with respect to precipitation and temperature changes.	IDI effectively monitors drought onset, duration, extent, and intensity in the North China Plain, correlates well with SPI-3, SPEI-3, and 10 cm depth soil moisture data, and offers a machine learning-based framework adaptable for global agricultural drought assessment.	[38]

→

Development of the ADM-SPEI approach, a Standardized Precipitation Evapotranspiration Index (SPEI)-based method for agricultural drought monitoring (ADM), tailored to local agro-climatic conditions.	■ Three-phase approach adaptable to any region. The Analytical Hierarchy Process (AHP): Experts select the most suitable evapotranspiration calculation method for the region; Modification of SPEI (AD-SPEIcrop) is adjusted to the Vojvodina region by replacing reference evapotranspiration (ET_0) with crop evapotranspiration (ETc). ■ Validation phase: a comparison with crop yields and well-known drought indices (SPI, SPEI, SC-PDSI); expert evaluation and statistical correlation analysis.	■ AD-SPEIcrop strongly correlates with crop yields, particularly during critical crop developmental stages. ■ Better performance than standard SPEI, providing a more accurate reflection of drought impact on crops. ■ Effectively detects dry and wet periods, outperforming SPI, SPEI, and SC-PDSI in agricultural drought monitoring. ■ ADM-SPEI approach is adaptable for different agro-climatic conditions, proving its practical applicability.	[39]
Development of a Combined Drought Indicator for Marathwada (CDI-M) to enhance agricultural drought monitoring in semi-arid regions of India. Addresses limitations of traditional drought assessment methods that rely on single-parameter in-situ measurements.	■ Multi-source satellite and model-based input parameters analyzed monthly (2001–2018) are SPI-3 (Standardized Precipitation Index), LST, SM, and NDVI. ■ Two CDI-M calculation methods tested are method-I: expert judgment-based parameter weighting; method-II: PCA-based weighting approach. ■ Validation is CDI-M results compared with secondary crop yield data across Kharif and Rabi harvesting seasons.	■ CDI-M effectively identified moderate to extreme drought years (e.g., 2002, 2009, 2015–2016). ■ Increasing drought severity and frequency ($p \leq 0.05$) were observed, especially in Latur, Jalna, and Parbhani districts. ■ PCA-based CDI-M (Method-II) had a stronger correlation ($r \geq 0.60$) with crop yields than the expert-judgment method ($r \geq 0.4$). ■ Higher correlation ($r > 0.65$) between CDI-M and crop yields during drier years, highlighting its predictive capability. ■ CDI-M proves to be an effective tool for drought monitoring and provides valuable insights for agricultural drought management in India.	[40]
Trend analysis of Potential Evapotranspiration (PET) and CWB to assess wetness and dryness episodes in Peninsular Malaysia.	■ PET estimation using Thornthwaite parameterization based on monthly temperature data. ■ Trend and slope analysis for PET and CWB using the Mann-Kendall test; Spearman's rho test; and Thiel-Sen estimator. ■ SPEI applied at 1-, 3-, 6-, and 12-month scales to identify drought episodes and recurrence intervals.	■ Increasing PET trends detected in most regions on both annual and monthly scales. ■ Annual CWB shows an increasing trend in most regions, except in Pahang, where a declining trend suggests water deficit. ■ Excess water availability is most prominent in January, especially on the west coast, the east coast, and the southwest regions, benefiting crop water requirements. ■ Drought recurrence intervals are consistent for lower severity events, while higher drought probability is noted in some regions. ■ Findings aid policymakers in water resource management and drought mitigation planning. ■ Future research should consider topographic influences and expand the analysis to East Malaysia with more meteorological data.	[41]

Evaluation of water availability indicators to assess agricultural drought impacts on rainfed maize silage yields in Central Europe (Czech Republic).	■ 16 water availability indicators analyzed for their ability to explain maize yield variability. ■ Field experiment data (2011–2015) from 4 locations across the Czech Republic. ■ Statistical analysis is simple precipitation totals for July vs. maize silage yield variability (64% explained variance); the sum of actual evapotranspiration (ETa) from May to August showed the highest correlation ($R^2 = 0.77$) with yield variability; drought impact assessment for the extreme drought year (2015).	■ July precipitation alone explained 64% of yield variability, making it a simple yet effective drought indicator. ■ ETa (May–August) was the best predictor ($R^2 = 0.77$) for silage maize yield response. ■ 2015 drought had the lowest ETa values, leading to severe yield losses across the entire Czech Republic. ■ Hybrid selection based on FAO numbers alone is not a sufficient adaptation strategy, although higher FAO hybrids may offer slight yield advantages in drought years. ■ Farmers should diversify maize hybrids with different FAO values to reduce risk and adapt to drought variability.	[42]
The role, benefits, and limitations of the WEI+ (Water Exploitation Index Plus) as a tool for managing water resources in highly regulated river basins with conjunctive use of surface and groundwater.	Integrates hydrological and water allocation models to address data gaps in water accounting and compares WEI+ with other water scarcity indices, applying the analysis to the Tagus River transboundary basin, which experiences significant flow regulation and seasonal water variability.	WEI+ proves more effective than other water scarcity indices in identifying severe water stress conditions, particularly in summer and agricultural areas, while also highlighting Portugal's strong dependence on upstream water flows from Spain.	[43]
The study examines drought vulnerability and water stress in Finland, despite the country having ample water resources.	■ Water use-to-availability analysis conducted using a reference drought scenario. ■ Water Depletion Index (WDI) is used to assess water stress levels. ■ Historical drought data (1939–1942) were used to model discharges and runoffs for a severe but realistic scenario. ■ Global models tested as a screening tool for drought assessment in data-scarce regions.	■ South and Southwest Finland are most vulnerable to water shortages during severe droughts. ■ Drought mitigation strategies are necessary for high-risk areas. ■ Findings can inform EU River Basin Management Plans to enhance drought preparedness.	[44]
The study examines the impact of catchment restoration initiatives on water resources and drought resilience in Ethiopia.	■ Metadata analysis of 106 peer-reviewed journal articles covering 361 paired-catchment case studies. ■ Focus on soil and water conservation (SWC) techniques, including exclosures, fanya juu, and soil/stone bunds in highly degraded regions. ■ Hydrological comparisons between treated and control catchments using runoff depth, runoff coefficients, and well water levels.	■ Treated catchments showed significantly lower runoff depth (97 mm/yr vs. 168 mm/yr, $p < 0.0001$). ■ Runoff coefficients were also lower in treated areas (13% vs. 25%, $p < 0.0001$), improving water infiltration into the soil and aquifers. ■ Shallow well water levels improved significantly, rising from 18 m to 2 m post-restoration. ■ Restoration efforts strengthened upstream-downstream hydrological connectivity, reducing drought impacts on agriculture and livelihoods. ■ Catchment restoration has dual benefits: increasing water availability and enhancing drought resilience. ■ Recommends expanding restoration efforts to other degraded landscapes for improved water security and climate adaptation.	[45]
Groundwater management challenges in Balochistan, Pakistan, emphasizing policy shortcomings, governance issues, and the need for sustainable groundwater policies.	Historical groundwater policies, assesses farmers' perceptions, analyzes drivers of tubewell adoption, and employs an empirical tubewell adoption model to evaluate the impact of electricity subsidies on groundwater use.	Uncontrolled tubewell expansion, electricity subsidies, and weak governance have led to severe groundwater depletion, necessitating short-term reforms in subsidy policies and long-term sustainable groundwater management strategies with institutional support and stakeholder involvement.	[46]

→

The study examines how drought affects nutrient acquisition in plants, specifically the relationship between reduced nitrogen (N) and phosphorus (P) concentrations and the levels of nutrient-uptake proteins in roots.	The measured biomass, plant %N and P, root nutrient uptake rates, and the concentrations of key nutrient-uptake proteins (NRT1 for nitrate, AMT1 for ammonium, and PHT1 for phosphorus) in drought-sensitive (Hordeum vulgare, Zea mays) and drought-tolerant (Andropogon gerardii) grasses under mid and late drought conditions.	Drought reduced nutrient acquisition more than growth, with P uptake declines correlating strongly with decreases in P-uptake protein levels, whereas N uptake was less correlated with N-uptake proteins; overall, drought-induced decreases in total protein per gram root contributed to lower nutrient-uptake protein concentrations and reduced nutrient absorption in both drought-sensitive and drought-tolerant species.	[47]
Investigates drought characteristics and water resource availability in the Jhelum River Basin under global warming and anthropogenic influences.	■ Trend analysis (1979–2017) of PET and CWB using Thornthwaite parameterization. ■ SPEI applied at 3-, 6-, and 12-month scales to characterize drought events. ■ Spatial patterns of drought severity analyzed using Average Recurrence Interval (ARI). ■ Cross wavelet analysis used to assess the influence of ENSO and ENSO-M events on drought conditions.	■ Annual PET is increasing, while annual CWB is decreasing across all selected stations. ■ Monthly PET trends upward, while monthly CWB trends downward across most months. ■ Drought frequency: 65 long-term, 69 intermediate-term, and 74 short-term drought events detected. ■ Western Jhelum basin experiences more severe droughts with long return periods. ■ Drought conditions significantly influenced by ENSO and ENSO-M events, affecting the entire basin.	[48]
Evaluates PET variability, water availability, and long-term drought occurrences in the Awash River Basin (ARB) under climate change scenarios.	■ PET and water availability analysis for 1995–2009 and future projections for the 2050s and 2070s. ■ Uses Representative Concentration Pathways (RCP4.5 and RCP8.5) climate change scenarios. ■ Assesses drought frequency across three locations: Holetta, Koka Dam, and Metehara.	■ Increase in PET projected from March to August in the 2050s and throughout the year in the 2070s. ■ Water shortages observed in most months, with mild to extreme droughts occurring in 40–50% of the analyzed years. ■ Rising PET and declining water availability, combined with population growth, will exacerbate droughts and food insecurity. ■ Recommends integrated watershed management, forest rehabilitation, and water body conservation to mitigate climate change impacts.	[49]
Advocates for impact-based drought monitoring that integrates drought hazards with their societal and environmental consequences, such as crop yield losses, food security, and water availability.	There is a need for integrating satellite observations, remote sensing, AI-driven data analysis, and standardized impact assessment models to link drought events with cascading hazards like heatwaves, wildfires, and floods.	While impact-based drought monitoring offers significant benefits for risk management and decision-making, its implementation is hindered by the lack of consistent drought impact data, disconnection between monitoring tools and impact models, and limited understanding of local water availability dynamics.	[50]
Investigates agricultural drought risk assessment from the perspective of grain yield.	■ Uses PCA to derive hazard factors from precipitation, temperature, humidity, and soil moisture. ■ Applies a regression method to separate sensitive yield from total grain yield, representing drought sensitivity. ■ Defines adaptive capacity based on the trend component of grain yield and exposure using crop planting area. ■ Proposes unit and regional drought risk concepts for assessment. ■ Analyzes spatial and temporal variations in agricultural drought risk using data from four cities in Heilongjiang Province, China.	■ The proposed drought risk assessment method is statistically reasonable and effective. ■ The methodology is particularly suitable for arid and semi-arid regions where grain yield is highly sensitive to drought. ■ The approach provides valuable insights for disaster prevention and mitigation strategies.	[51]

→

The development of a comprehensive spatial drought vulnerability mapping approach to support effective drought mitigation strategies.	A multi-criteria decision-making approach integrating geospatial techniques and the AHP was used to assess 17 criteria across meteorological, agricultural, hydrological, and socio-economic drought categories, with weighted overlays to generate vulnerability maps.	The results indicate that approximately 77% of northwestern Bangladesh is moderately to extremely vulnerable to drought, demonstrating the effectiveness of the proposed approach, which was successfully validated using receiver operating characteristics (ROC) and area under the curve (AUC) techniques.	[52]
The study focuses on assessing drought vulnerability in Namakkal district, Tamilnadu, India, using GIS and multi-criteria decision-making techniques.	A combination of GIS and theAHP was employed to analyze eight parameters, including rainfall, land use/land cover, slope, soil type, NDVI, NDWI, and population, to generate a Drought Vulnerability Assessment (DVA) map.	62% of the Namakkal district falls under mild drought conditions, highlighting the effectiveness of GIS and AHP in mapping drought-prone areas, with a suggestion that nanotechnology could mitigate drought stress and improve crop yield.	[53]
Focuses on drought severity estimation, system vulnerability assessment, drought risk evaluation, and preparedness planning.	■ Advocates for technocratic support, systematic organizational and institutional structures, and active public participation. ■ Emphasizes scientifically sound but practical methods for drought characterization and risk assessment.	■ A proactive, structured approach is essential for effective drought risk management. ■ Simple yet scientifically valid methods can improve drought preparedness and reduce vulnerability.	[54]
Assesses drought risk in China by addressing previous subjectivity in risk evaluation methods.	■ Uses historical drought loss data to predict future high-risk areas. ■ Maps regional differentiation of drought risk across China. ■ Quantifies the contribution of exposure and vulnerability factors to drought risk.	■ High and extreme high-risk areas cover 4.3% of China's land area. ■ Identifies five major high-risk regions, including Northeast China, North China, and parts of Northwest and Southwest China. ■ Heilongjiang Province (32%) and Ningxia Hui Autonomous Region (26%) have the highest proportions of high-risk areas. ■ High exposure and high vulnerability are key contributors to drought risk. ■ Recommends protecting cultivated land and reducing dependence on primary industries to mitigate drought impacts.	[55]
Examines the impact of prolonged drought in Iran, particularly its effects on rural economies and agricultural production.	■ Uses a quantitative risk assessment approach. ■ Assesses drought risk based on hazard (SPI and SDI indices) and vulnerability (exposure, sensitivity, adaptive capacity). ■ Focuses on wheat farmers in Kermanshah Township, selecting 293 farmers through multistage cluster sampling. ■ Develops a drought risk map for Kermanshah Township.	■ The majority of villages in Kermanshah are at high environmental risk due to drought. ■ Risk management and early warning systems are crucial for mitigating drought impacts. ■ Findings can help policymakers design early warning systems to empower farmers and promote resilient farming.	[56]
Agricultural drought risk assessment in Australia, focusing on Northern New South Wales.	■ Developed a comprehensive agricultural drought risk assessment approach incorporating hazard, vulnerability, exposure, and mitigation capacity. ■ Used geospatial techniques and fuzzy logic to create indices for each risk component. ■ Applied the approach to map the spatial distribution of drought risk in the study area. ■ Validated results using a drought inventory map.	■ 19.2% of the area is at very high agricultural drought risk, while 41.7% is at moderate to high risk. ■ The spatial drought risk information can help authorities develop proactive drought mitigation strategies.	[57]

Overall, this data provides crucial insights into drought hazard levels across different sub-districts. Proper mitigation and adaptation measures are essential to minimize drought impacts and ensure water security in high-hazard areas.

Table 4 provides a brief review of studies related to agricultural drought monitoring, drought and water availability analysis, and drought hazard assessment, highlighting various methodologies and applications. It presents research efforts that utilize remote sensing, drought indices, and geospatial techniques to assess drought severity, water scarcity, and their impacts on agriculture and ecosystems. The reviewed studies also emphasize the development of new drought indicators and hazard assessment models to enhance drought preparedness and mitigation strategies across different geographical regions.

Based on the analysis of drought hazard levels in Aceh Besar Regency, the active involvement of various stakeholders is essential to develop effective mitigation strategies [58, 59]. The local government should design GIS-based policies to prioritize areas with the most severe impacts, such as Kota Jantho, Seulimeum, and Kuta Cot Glie, in water infrastructure planning and environmental conservation efforts [60, 61].

Relevant agencies, such as the Public Works Department and Agriculture Department, should focus on strengthening irrigation systems and improving water use efficiency in the agricultural sector to mitigate the effects of drought. Additionally, academics and researchers can contribute by developing data-driven drought prediction models to provide more accurate recommendations for mitigation planning [62, 63].

Similarly, water-related challenges extend beyond shipyards [64]. In Hudaira Drain, arsenic contamination poses severe health risks. GIS analysis reveals high arsenic concentrations in industrial zones, with strong correlations between drain water, groundwater, and soil. Alarmingly, 75% of children and 50% of adults are at risk of arsenic exposure through groundwater consumption. The potential for excess lifetime cancer risk is significant, necessitating urgent mitigation efforts [65]. Elsewhere, environmental hazards continue to impact communities. The Kostanay region faces heightened wildfire risks due to dry conditions and a shifting climate. Remote sensing data identifies key factors: fuel availability, geomorphology, and meteorology, driving fire outbreaks. High-risk zones dominate the landscape, emphasizing the need for improved fire prevention strategies [66]. Geological disasters further compound environmental threats. In Heitai, landslides endanger infrastructure and human lives. A novel risk assessment method maps disaster-bearing zones, quantifying economic and life risks. GIS-based modeling highlights areas of extreme hazard, reinforcing the need for proactive mitigation measures [67].

The community should also be actively involved through educational programs and awareness campaigns on water resource management and the implementation of soil and forest conservation practices to reduce future drought risks. Through synergistic collaboration between the government, academia, private sector, and local communities, a sustainable mitigation system can be established to address the annual drought threats in this region.

Despite the valuable insights provided by this study, several limitations should be acknowledged. First, the drought hazard mapping model relies on the availability and accuracy of spatial data, including annual average rainfall, slope gradient, soil type, geology, distance from water sources, and land cover. Any inconsistencies or gaps in these datasets may affect the precision of the analysis. Second, this study focuses solely on hazard mapping without integrating socio-economic factors, such as population density, water demand, and agricultural dependency, which are critical in assessing the overall drought risk. Incorporating these factors in future research could provide a more comprehensive risk assessment framework. Third, the study employs a static GIS-based approach to drought hazard mapping, which does not account for temporal variations in drought conditions. Seasonal changes and climate variability may significantly influence drought intensity and distribution. A dynamic modeling approach, incorporating real-time climate data and predictive models, would enhance the accuracy and applicability of the findings. Finally, while the study highlights the spatial distribution of drought hazard levels, it does not evaluate the effectiveness of existing mitigation strategies. Future research should include an assessment of current drought management policies and their impact on reducing drought vulnerability in Aceh Besar Regency. Addressing these limitations in future studies will contribute to a more robust understanding of drought hazards and improve the development of targeted and sustainable mitigation strategies.

Conclusions

Drought in Aceh Besar Regency is a recurring phenomenon that occurs annually, and until now, its management has remained short-term in nature. Therefore, continuous monitoring and analysis of drought hazard factors are necessary to develop a more comprehensive drought hazard mapping model. This model can serve as a basis for more effective and sustainable drought mitigation planning.

Based on the analysis of land area within the medium and high hazard categories, several sub-districts exhibit higher drought hazard levels than others. The Kota Jantho sub-district has the largest affected area in the medium category (198.67 km^2), while Krueng Barona Jaya has the smallest affected area (0.11 km^2). In the high hazard category, Kota Jantho also recorded the largest affected area (376.18 km^2), whereas Peukan Bada had the smallest affected area (13.13 km^2).

These variations in affected areas indicate differences in drought hazard levels across regions, which should be carefully considered in mitigation strategies.

The drought hazard mapping model using GIS to identify the spatial distribution of drought hazard levels in Aceh Besar Regency based on key variables such as: annual average rainfall; slope gradient; soil type; geology/rock type; distance from water sources; land cover, with this mapping model, mitigation strategies can be focused on high-hazard areas, allowing for more precise and effective prevention and response measures. The drought poses a significant threat in several sub-districts of Aceh Besar Regency. Therefore, hazard-based mitigation and adaptation efforts are needed to support optimal water resource management, reduce drought impacts, and enhance regional resilience against future drought disasters.

Acknowledgements

The authors would like to thank Prof. Akhyar and Fikri Kurniawan for their technical support throughout this research.

Conflict of Interest

The authors declare no conflict of interest.

References

1. BAKORNAS P.B. Pengenalan Karakteristik Bencana dan Upaya Mitigasinya di Indonesia, Cetakan Edisi II. **2007** [In Indonesian].
2. FAIZAH N., BUCHORI I. Model Pemetaan Risiko Kekeringan di Kabupaten Bima, Nusa Tenggara Barat. Jurnal Pembangunan Wilayah dan Kota. **15** (2), 138, **2019** [In Indonesian].
3. KAMARA J.K., SAHLE B.W., AGHO K.E., RENZAHO A.M.N. Governments' policy response to drought in Eswatini and Lesotho: a systematic review of the characteristics, comprehensiveness, and quality of existing policies to improve community resilience to drought hazards. Discrete dynamics in Nature and Society. **2020** (1), 1, **2020**.
4. DHAWALE R., SCHUSTER-WALLACE C.J., PIETRONIRO A. Assessing the multidimensional nature of flood and drought vulnerability index: A systematic review of literature. International Journal of Disaster Risk Reduction. **112**, 1, **2024**.
5. YANG L., LIU J., YANG W. Impacts of the sustainable development of cross-border e-commerce pilot zones on regional economic growth. Sustainability. **15** (18), 13876, **2023**.
6. YANG L., DONG J., YANG W. Analysis of regional competitiveness of China's cross-border e-commerce. Sustainability. **16** (3), 1007, **2024**.
7. YANG W., YANG Y., CHEN Z., GU Y. Systemic Impacts of National Civilized Cities on Sustainable Development: A Quasi-Experimental Analysis of Economic and Environmental Outcomes in China. Systems. **13** (1), 23, **2025**.
8. BUSZTA J., WÓJCIK K., SANTOS C.A.G., KOZIOŁ K., MACIUK K. Historical Analysis and Prediction of the Magnitude and Scale of Natural Disasters Globally. Resources. **12** (9), 106, **2023**.
9. BHARAMBE K.P., SHIMIZU Y., KANTOUSH S.A., SUMI T., SABER M. Impacts of climate change on drought and its consequences on the agricultural crop under worst-case scenario over the Godavari River Basin, India. Climate Services. **32**, 1, **2023**.
10. DING Y., GONG X., XING Z., CAI H., ZHOU Z., ZHANG D., SUN P., SHI H. Attribution of meteorological, hydrological and agricultural drought propagation in different climatic regions of China. Agricultural Water Management. **255** (C), **2021**.
11. AGHAKOUCHAK A., MIRCHI A., MADANI K., BALDASSARRE G.D., NAZEMI A., ALBORZI A., ANJILELI H., AZARDERAKHSH M., CHIANG F., HASSANZADEH E., HUNING L.S. Anthropogenic drought: Definition, challenges, and opportunities. Reviews of Geophysics. **59** (2), **2021**.
12. HISDAL H., TALLAKSEN L.M., GAUSTER T., BLOOMFIELD J.P., PARRY S., PRUDHOMME C., WANDERS N. Hydrological drought characteristics. In Hydrological Drought. **2024**.
13. FARHAN A., NASUTION A.I., AKHYAR. Earthquake disaster map using GIS analysis: a case study of Bener Meriah-Aceh, Indonesia. Arabian Journal of Geosciences. **17** (1), **2024**.
14. AKHYAR, SARY C.A. Identification of geothermal potential zone associated with land surface temperature derived from Landsat 8 data using split-window algorithm. Journal of Applied Research and Technology. **22** (1), **2024**.
15. SUGIANTO, RUSDI M., BUDI M., FARHAN A. Agricultural Droughts Monitoring of Aceh Besar Regency Rice Production Center, Aceh, Indonesia–Application Vegetation Conditions Index using Sentinel-2 Image Data. Journal of Ecological Engineering. **24** (1), 159, **2023**.
16. BUDI M., AKHYAR H. Green open space detection and mapping using planetscope-3A image with vegetation index approach and supervised classification in Banda Aceh, Indonesia. In Forum Geografic. **20** (2), **2021**.
17. BNPB. Peraturan Kepala Badan Nasional Penanggulangan Bencana Nomor 02 Tahun 2012 Tentang Pedoman Umum Pengkajian Risiko Bencana (Perka BNPB 2/2012: Regulation of the Head of the National Disaster Management Agency Number 02 of 2012 About General Guidelines for Disaster Risk Assessment). **2012** [In Indonesian].
18. YU M., YANG C., LI Y. Big Data in Natural Disaster Management: A Review. Geosciences. **8** (5), 165, **2018**.
19. ZHOU L., WU X., XU Z., FUJITA H. Emergency decision making for natural disasters: An overview. International Journal of Disaster Risk Reduction. **27**, **2018**.
20. BIANCHI S., CIURLANTI J., OVEREND M., PAMPANIN S. A probabilistic-based framework for the integrated assessment of seismic and energy economic losses of buildings. Engineering Structures. **269** (4), 114852, **2022**.
21. KAREEM H.H., ATTAEE M.H., OMRAN Z.A. Extraction of the Spatial and Temporal Surface Water Bodies Using High Resolution Remote Sensing Technology. Journal of Ecological Engineering. **24** (11), 135, **2023**.
22. DJAALI, MULJONO P. Pengukuran Dalam Bidang Pendidikan. Jakarta: Grasindo. **2007** [In Indonesian].

23. SRTM 90m Digital Elevation Database. Available online: https://bigdata.cgiar.org/srtm-90m-digital-elevation-database/ Indonesian, (accessed on 18 February 2025).
24. EZELL B., LYNCH C.J., HESTER P.T. Methods for Weighting Decisions to Assist Modelers and Decision Analysts: A Review of Ratio Assignment and Approximate Techniques. Applied Sciences. **11** (21), 10397, **2021**.
25. HAILE G.G., TANG Q., LI W., LIU X., ZHANG X. Drought: Progress in broadening its understanding. WIREs Water. **7** (2), **2020**.
26. ZHOU K., LI J., ZHANG T., KANG A. The use of combined soil moisture data to characterize agricultural drought conditions and the relationship among different drought types in China. Agricultural Water Management. **243**, **2021**.
27. SZEWCZAK K., ŁOŚ H., PUDEŁKO R., DOROSZEWSKI A., GLUBA L., ŁUKOWSKI M., RAFALSKA-PRZYSUCHA A., SŁOMIŃSKI J., USOWICZ B. Agricultural Drought Monitoring by MODIS Potential Evapotranspiration Remote Sensing Data Application. Remote Sensing. **12** (20), **2020**.
28. ZHANG X., CHEN N., LI J., CHEN Z., NIYOGI D. Multi-sensor integrated framework and index for agricultural drought monitoring. Remote Sensing of Environment. **188**, 141, **2017**.
29. JAVED T., LI Y., RASHID S., LI F., HU Q., FENG H., CHEN X., AHMAD S., LIU F., PULATOV B. Performance and relationship of four different agricultural drought indices for drought monitoring in China's mainland using remote sensing data. Science of the Total Environment. **759**, **2021**.
30. TRNKA M., HLAVINKA P., MOŽNÝ M., SEMERÁDOVÁ D., ŠTĚPÁNEK P., BALEK J., BARTOŠOVÁ L., ZAHRADNÍČEK P., BLÁHOVÁ M., SKALÁK P., FARDA A., CZECH. Drought Monitor System for monitoring and forecasting agricultural drought and drought impacts. International Journal of Climatology. **40** (14), **2020**.
31. SÁNCHEZ N., GONZÁLEZ-ZAMORA Á., MARTÍNEZ-FERNÁNDEZ J., PILES M., PABLOS M. Integrated remote sensing approach to global agricultural drought monitoring. Agricultural and Forest Meteorology, **259** (3), **2018**.
32. ZHANG Q., YU H., SUN P., SINGH V.P., SHI P. Multisource data based agricultural drought monitoring and agricultural loss in China. Global and Planetary Change. **172**, **2019**.
33. HUANG J., ZHUO W., LI Y., HUANG R., SEDANO F., SU W., DONG J., TIAN L., HUANG Y., ZHU D., ZHANG X. Comparison of three remotely sensed drought indices for assessing the impact of drought on winter wheat yield. International Journal of Digital Earth. **13** (4), **2020**.
34. VREUGDENHIL M., GREIMEISTER-PFEIL I., PREIMESBERGER W., CAMICI S., DORIGO W., ENENKEL M., SCHALIE R.V.D., STEELE-DUNNE S., WAGNER W. Microwave remote sensing for agricultural drought monitoring: Recent developments and challenges. Frontiers Water. **4**, **2022**.
35. ZHANG Z., XU W., SHI Z., QIN Q. Establishment of a comprehensive drought monitoring index based on multisource remote sensing data and agricultural drought monitoring. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. **14**, 2113, **2021**.
36. RHEE J., IM J., CARBONE G.J. Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data. Remote Sensing of Environment. **114** (12), 2875, **2010**.
37. BAYISSA Y.A., TADESSE T., SVOBODA M., WARDLOW B., POULSEN C., SWIGART J., ANDEL S.J.V. Developing a satellite-based combined drought indicator to monitor agricultural drought: A case study for Ethiopia. GIScience and Remote Sensing. **56** (5), **2019**.
38. LIU X., ZHU X., ZHANG Q., YANG T., PAN Y., SUN P. A remote sensing and artificial neural network-based integrated agricultural drought index: Index development and applications. Catena. **186** (2), **2020**.
39. BEZDAN J., BEZDAN A., BLAGOJEVIĆ B., MESAROŠ M., PEJIĆ B., VRANEŠEVIĆ M., PAVIĆ D., NIKOLIĆ-ĐORIĆ E. SPEI-based approach to agricultural drought monitoring in Vojvodina region. Water. **11** (7), **2019**.
40. KULKARNI S.S., WARDLOW B.D., BAYISSA Y.A., TADESSE T., SVOBODA M.D., GEDAM S.S. Developing a remote sensing-based combined drought indicator approach for agricultural drought monitoring over Marathwada, India. Remote Sensing. **12** (13), 2091, **2020**.
41. HUI-MEAN F., YUSOP Z., YUSOF F. Drought analysis and water resource availability using standardised precipitation evapotranspiration index. Atmospheric Research. **201**, 102, **2018**.
42. ŽALUD Z., HLAVINKA P., PROKEŠ K., SEMERÁDOVÁ D., JAN B., TRNKA M. Impacts of water availability and drought on maize yield-A comparison of 16 indicators. Agricultural Water Management. **188**, 126, **2017**.
43. SONDERMANN M.N., OLIVEIRA R.P.D. Using the WEI+ index to evaluate water scarcity at highly regulated river basins with conjunctive uses of surface and groundwater resources. Science of the Total Environment. **836**, 155754, **2022**.
44. AHOPELTO L., VEIJALAINEN N., GUILLAUME J.H., KESKINEN M., MARTTUNEN M., VARIS O. Can there be water scarcity with abundance of water? Analyzing water stress during a severe drought in Finland. Sustainability. **11** (6), **2019**.
45. MEAZA H., ABERA W., NYSSEN J. Impacts of catchment restoration on water availability and drought resilience in Ethiopia: A meta-analysis. Land Degradation & Development. **33** (4), 547, **2022**.
46. KHAIR S.M., MUSHTAQ S., REARDON-SMITH K. Groundwater governance in a water-starved country: public policy, farmers' perceptions, and drivers of tubewell adoption in Balochistan, Pakistan. Groundwater. **53** (4), 626, **2015**.
47. BISTA DEEPESH R., HECKATHORN S.A., JAYAWARDENA D.M., MISHRA S., BOLDT J.K. Effects of Drought on Nutrient Uptake and the Levels of Nutrient-Uptake Proteins in Roots of Drought-Sensitive and Tolerant Grasses. Plants. **7** (2), 28, **2018**.
48. HIMAYOUN D., ROSHNI T. Spatio-temporal variation of drought characteristics, water resource availability and the relation of drought with large scale climate indices: a case study of Jhelum basin, India. Quaternary International. **525**, **2019**.
49. TADESE M., KUMAR L., KOECH R. Long-term variability in potential evapotranspiration, water availability and drought under climate change scenarios in the Awash River Basin, Ethiopia. Atmosphere. **11** (9), 883, **2020**.
50. AGHAKOUCHAK A., HUNING L.S., SADEGH M., QIN Y., MARKONIS Y., VAHEDIFARD F., LOVE C.A., MISHRA A., MEHRAN A., OBRINGER R., HJELMSTAD A. Toward impact-based monitoring of

drought and its cascading hazards. Nature Reviews Earth & Environment. **4** (8), 582, **2023**.
51. PEI W., FU Q., LIU D., LI T., CHENG K., CUI S. A novel method for agricultural drought risk assessment. Water Resources Management. **33** (6), 2033, **2019**.
52. HOQUE M.A.A., PRADHAN B., AHMED N. Assessing drought vulnerability using geospatial techniques in northwestern part of Bangladesh. Science of the Total Environment. **705**, **2020**.
53. SIVAKUMAR V.L., KRISHNAPPA R.R., NALLANATHEL M. Drought vulnerability assessment and mapping using Multi-Criteria decision making (MCDM) and application of Analytic Hierarchy process (AHP) for Namakkal District, Tamilnadu, India. Materials Today: Proceedings. **43** (2), 1592, **2021**.
54. TSAKIRIS G. Drought risk assessment and management. Water Resources Management. **31** (10), 1, **2017**.
55. ZHAO J., ZHANG Q., ZHU X., SHEN Z., YU H. Drought risk assessment in China: evaluation framework and influencing factors. Geography and Sustainability. **1** (3), **2020**.
56. SHARAFI L., ZARAFSHANI K., KESHAVARZ M., AZADI H., PASSEL S.V. Drought risk assessment: Towards drought early warning system and sustainable environment in western Iran. Ecological Indicators. **114** (3), 106276, **2020**.
57. HOQUE M.A.A., PRADHAN B., AHMED N., SOHEL M.S.I. Agricultural drought risk assessment of Northern New South Wales, Australia using geospatial techniques. Science of the Total Environment. **756**, **2021**.
58. ROZAKI Z., WIJAYA O., RAHMAWATI N., RAHAYU L. Farmers' disaster mitigation strategies in Indonesia. Reviews in Agricultural Science. **9**, 178, **2021**.
59. SUPANGAT BUDI A., BASUKI T.M., INDRAJAYA Y., SETIAWAN O., WAHYUNINGRUM N., PURWANTO PUTRA P.B., SAVITRI E., INDRAWATI D.R., AULIYANI D. Sustainable Management for Healthy and Productive Watersheds in Indonesia. Land. **12** (11), 1963, **2023**.
60. BROWN G., KYTTÄ M. Key issues and research priorities for public participation GIS (PPGIS): A synthesis based on empirical research. Applied Geography. **46** (1), 122, **2014**.
61. CECCATO V.A., SNICKARS F. Adapting GIS Technology to the Needs of Local Planning. Environment and Planning B: Planning and Design. **27** (6), 923, **2000**.
62. ULLAH H., SANTIAGO-ARENAS R., FERDOUS Z., ATTIA A., DATTA A. Improving water use efficiency, nitrogen use efficiency, and radiation use efficiency in field crops under drought stress: A review. Advances in Agronomy. **156**, **2019**.
63. PRODHAN F.A., ZHANG J., HASAN S.S., SHARMA T.P.P., MOHANA H.P. A review of machine learning methods for drought hazard monitoring and forecasting: Current research trends, challenges, and future research directions. Environmental Modelling and Software. **149** (1), 105327, **2022**.
64. RIZWAN T., HUSAINI H., HUSIN H., AKHYAR A., JALIL Z. Identification Shipyard Model Suitable for Kutaraja Fishing Port in Aceh, Indonesia. Polish Journal of Environmental Studies. **32** (2), 1755, **2023**.
65. JAVAID A., AHMAD S.R., QADIR A. Health Risk Surveillance of Arsenic in Wastewater, Groundwater, and Agricultural Land along Hudaira Drain, Pakistan Using GIS Techniques. Polish Journal of Environmental Studies. **28** (2), 681, **2019**.
66. ZHANAR O., MERUERT U., ZHANDOS M., ALTYN Z., ZHARAS B., KARSHYGA T. Evaluation of Natural Fire Hazard Factors of the Forest Area in the Kostanay Region. Polish Journal of Environmental Studies, **34** (3), 2939, **2025**.
67. SONG X., YANG P. Landslide Hazard Risk Assessment Based on Disaster Bearing Body: a Case Study of Heitai Landslide Group in Yongjing County, Gansu Province. Polish Journal of Environmental Studies. **33** (1), 847, **2024**.