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Mapping the Spatio-Temporal Dynamics of Drought in Northeast Thailand

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Abstract

Drought, a globally significant natural disaster, imposes considerable economic and environmental impacts, severely impacting agriculture and socio-economic annually. This study aims to investigate the spatiotemporal dynamics of drought in Northeast Thailand by integrating remote sensing (RS) and ground observations with machine learning models. Machine learning (ML) algorithms were employed to combine these data. The study utilized five RS parameters: Vegetation Condition Index (VCI), Enhanced Vegetation Index (EVI), Temperature Condition Index (TCI), topography, and precipitation, along with ground-based data such as the Standardized Precipitation Evapotranspiration Index (SPEI). Various ML techniques, including XGBoost, Random Forest, and Extra Trees, were applied to assess the relationships among the variables. The results indicate that the Extra Trees model outperforms others in predicting drought indices. For short-term predictions, the model achieved an R^2 ranging from 65.26% to 94.28%, an RMSE between 1.58% and 33.28%, and an MAE ranging from 0.09% to 18.55%. For long-term predictions, the R^2 ranged from 78.73% to 94.8%, the RMSE from 4.55% to 31.93%, and the MAE from 0.45% to 18.14%. Key variables contributing to the model's accuracy include precipitation (27%–67%), topography (19%–37%), and land surface temperature (6%–21%). The study examined both short-term and long-term drought conditions using the Standardized Precipitation Evapotranspiration Index (SPEI). The short-term analysis revealed significant drought events in June 2015 and April 2016, as well as recurrent droughts from late 2018 through 2019, and the early months of 2020 and 2021. In the long-term analysis, sustained negative SPEI values from mid-2015 to 2016 signaled the onset of drought, while a prolonged negative trend from mid-2018 to 2020 marked an extended drought period lasting several months, emphasizing the severity and duration of the event. In conclusion, the study provides a framework for strategic planning in drought management by integrating RS and ground observation data.

Keywords: Drought, GIS, Remote Sensing, Machine Learning

1. Introduction

Drought, being a significant global natural calamity, incurs substantial costs and inflicts extensive damage on agriculture the environment and the socio-economic fabric annually (Bahta & Myeki, 2022). The monitoring and forecast of drought can assist policymakers in their response to drought situations (Fu et al., 2022). The occurrence of drought has become more frequent on a global scale due to the combined impacts of climate change and human activity. Typically, droughts occur both in a sequential and concurrent manner. The main factors contributing to drought include uneven and insufficient precipitation, along with insufficient rainfall distribution in specific areas (Carrillo et al., 2023). the primary impact of drought in Thailand is predominantly on the agricultural sector (Marks, 2011).

Thailand, located in Asia, is very susceptible to fluctuations and shifts in climatic patterns (Sedtha et al., 2023), as well as extreme weather events such as droughts and floods. The region of Northeast Thailand is situated within the tropical zone, characterized by predominantly sandy soil that has a limited capacity to retain water (Suzuki et al., 2007). The frequency and severity of droughts have increased, causing significant damage to the agricultural and economic sectors, resulting in reduced crop yields and hardships for farmers (Arpakorn & Chen, 2021). The northeast of Thailand has 5 provinces, which cover an area of about 63,554 square kilometers, or one-third of the whole country. On the Korat plateau, droughts usually occur when there is a lack of rain for a long period of time, especially in the northeastern region, when there will be a decrease in the amount of rain. As a result, the amount of water stored in reservoirs and dams is much less than before. This causes agricultural areas to lack water.

This research uses machine learning XGBoost (XGB), Random Forest (RF), and Extra Trees Regressor (ETR) to integrate remote sensing and ground observation data from the Thai Meteorological Department to calculate drought indices. The study focuses on leveraging Landsat 8 satellite data from 2014 to 2023 to analyze drought conditions using the Google Earth Engine and scikit-learn and analyzing the spectral indices The Vegetation Condition Index (VCI), Enhanced Vegetation Index, Temperature Condition Index (TCI), a Digital Elevation Model (DEM), Climate Hazards Group InfraRed Precipitation (CHIPRS) and the Standardized Precipitation Evapotranspiration Index (SPEI) were used, along with accuracy, R^2, RMSE, and MAE for the assessment performance of machine learning models (XGB, RF, and ETR) for drought mapping in the northeast region of Thailand.

1.1 Study Area

The purpose of this research is to investigate the effects of drought in the northeast of Thailand. It's between the latitudes of 14° and 16° N and the longitudes of 101° and 106°. The terrain is on the Korat plateau because most of it is a plateau shown in Figure 1. Slopes from west to east. The edge of the area is a high mountain. Most of the area is covered with rocks. The plain area is a large basin of land. The Korat Basin covers three-quarters of the entire northeastern region. It is considered the widest plain in Thailand, with an average height of 120–170 meters above mean sea level. The area in the middle of the basin is a low plain. The Mun River is the main river that drains water from the plain edge of the basin. It is the most important tributary of the Mekong River. Its origin is in Nakhon Ratchasima Province.

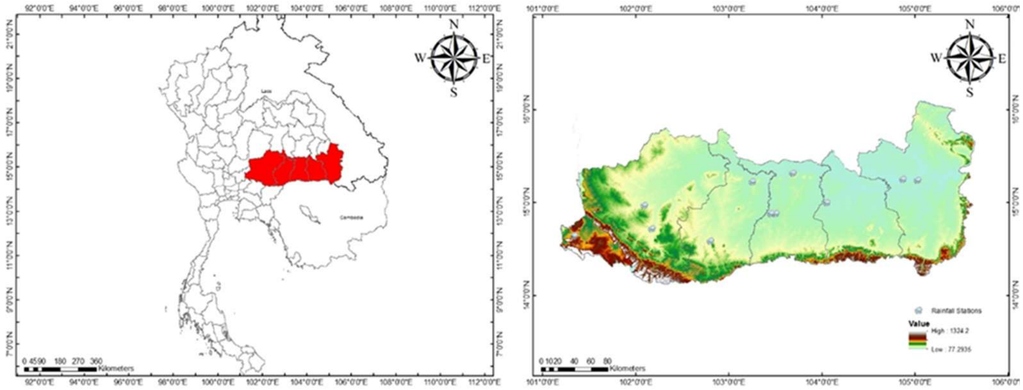

Figure 1 Study area

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1.2 Research Problem

Drought poses a significant challenge to Thailand, particularly in the northeastern region, where sandy soil and erratic rainfall exacerbate its impacts on agriculture and water resources. Despite the critical need for effective drought monitoring, traditional methods often fall short in providing accurate spatiotemporal data. This research addresses these gaps by integrating remote sensing data from Landsat 8 with machine learning models XGBoost (XGB), Random Forest (RF), and Extra Trees Regressor (ETR) to analyze and map drought conditions from 2014 to 2023. The study aims to enhance drought prediction accuracy and provide valuable insights for better agricultural and water resource management in the region.

1.3 Objectives

- To analyze and investigate the spatio-temporal patterns of drought occurrences in the Northeast region of Thailand from 2014 to 2023 using Landsat 8 satellite data.
- To assess and compare the performance of machine learning models between specifically XGBoost (XGB), Random Forest (RF), and Extra Trees (ETR) for accurate drought monitoring in Northeast Thailand.
- To map the spatial distribution of drought events in the Northeast of Thailand from 2014 to 2023.

2. Research method

2.1 Workflow of research

This workflow explains, from beginning to completion, the methods for conducting this investigation. It displays all data variables and sources, including data preprocessing and remote sensing data such as vegetation, temperature, topography, and precipitation. While ground observations were calculated using the SPEI, the data were processed and converted from vector to raster formats for model prediction. Three machine learning algorithms were used to estimate drought in the study area and to identify the most effective model with the most important feature variables. Finally, the spatial distribution of drought area was computed using zonal statistic from the best model output as shown in Figure 2.

2.2 Remote sensing data

The remote sensing data used in this study were sourced from Landsat 8, which offers a 30-meter spatial resolution. The dataset includes atmospherically corrected surface reflectance and land surface temperature, derived from the Landsat 8 OLI/TIRS ("LANDSAT/LC08/C02/T1_L2") sensors (Perez & Vitale, 2023), using Band 2 (blue), Band 4 (red), Band 5 (near infrared), and Band 10 (surface temperature). This data covered a period of 10 years, from 2014 to 2023. This data was used to analyze the drought indices VCI, EVI, and TCI, and topography. This study used a DEM from Copernicus ("COPERNICUS/DEM/GLO30") (Guth et al., 2021) the DEM is a Digital Surface Model (DSM) that represents the surface of the Earth including buildings, infrastructure and vegetation, as summarized in Table 1. This DEM is derived from an edited DSM named WorldDEM™. Precipitation data were obtained from Climate Hazards Group InfraRed Precipitation ("UCSB-CHG/CHIRPS/DAILY") with Station Data (CHIRPS), which is a quasi-global rainfall dataset (Gwatida et al., 2023). CHIRPS incorporates 0.05°-resolution satellite imagery with in-situ station data to create a gridded rainfall time series for trend analysis and seasonal drought monitoring in Google Earth Engine.

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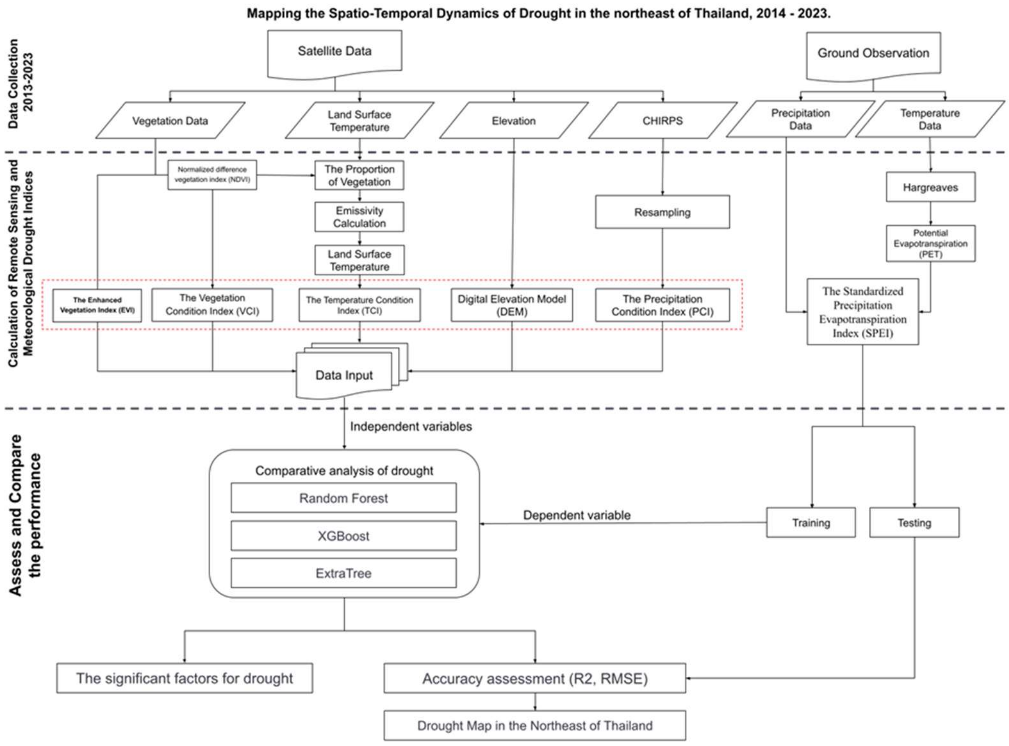

Figure 2 Methodology framework of this study

Table 1 Summary formula remote sensing

Indices	Formula
NDVI	$NDVI = \frac{(NIR - red)}{(NIR + red)}$
EVI	$EVI = \frac{(NIR - red)}{(NIR + 6 \times Red - 7.5 \times Blue + 1)}$
VCI	$VCI = \frac{(NDVI - NDVI_{min})}{(NDVI_{max} - NDVI_{min})} \times 100$
TCI	$TCI = \frac{(LST - LST_{min})}{(LST_{max} - LST_{min})} \times 100$

2.3 Ground Observation Data

The ground observations cover a period of 11 years from 2013 to 2023 because SPEI 12 requires data from the previous year to calculate the period to ensure accurate and comprehensive assessments of drought severity over a full year. The meteorological data, including precipitation and temperature data, are collected monthly from 11 weather stations across the northeast of Thailand. The data were obtained from the Thai Meteorological Department.

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Table 2 Summary of data collections

Type Sources	Dataset	Index	Spatial resolution	Period	Source
Remote sensing data	Landsat 8	VCI	30 m	2014- 2023	USGS
		EVI			
		TCI			
	GLO-30	DEM			Copernicus
	CHIPRS	PCI			USGS/ CHC
Ground station data	Precipitation Temperature	SPEI	11 stations	2013 - 2023	TMD

2.4 Data Preprocessing

The variables, including precipitation (CHIRPS), temperature-based indices, vegetation indices, and topography, represent key components influencing soil moisture dynamics and evapotranspiration. Therefore, these variables were retained in the modeling framework based on their physical relevance to drought processes rather than removed through automated feature selection procedures.

Missing data in CHIRPS precipitation and station-based SPEI records were limited and occurred intermittently. These gaps were addressed through temporal aggregation and quality-controlled interpolation prior to model training to ensure dataset continuity. Only pixels and stations with complete records over the analyzed periods were included in the final model fitting to minimize uncertainty.

2.5 Cross-validation

A five-fold cross-validation (k = 5) was applied to evaluate model performance and generalization ability. The dataset was partitioned into five mutually exclusive subsets, with each subset sequentially used as the validation set while the remaining four subsets were used for model training. Performance metrics were averaged across all folds to obtain a robust and unbiased estimate of predictive performance and to mitigate the risk of overfitting. For each model, the number of trees (n_estimators) was set to 200 based on grid search hyperparameter tuning, while all other learning parameters were retained at their default settings.

2.6 Accuracy Assessment

The estimation of drought using XGB, RF, and ETR models was constructed by machine learning methods. The models were trained using 70% of the data and validated with the remaining 30%. In this study, the assessment comparison between the regression models was evaluated in terms of the difference between the actual values and the predicted values. R-squared (R^2) and Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) were commonly used metrics. R^2 helps to understand the proportion of variance explained by the model, while RMSE indicates the average magnitude of the residuals or errors made by the model. When comparing models, higher R-squared values and lower RMSE values generally indicate better model performance using Equations (1)–(3). These are defined as follows.

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$$MAE = \frac{1}{n}\sum_{i=1}^{n} |P_i - O_i| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (P_i - O_i)^2} \tag{2}$$

$$R^2 = \frac{\sum_{i=1}^{n} (P_i - \bar{O}_i)^2}{\sum_{i=1}^{n} (P_i - \bar{O}_i)^2} \tag{3}$$

2.7 Mapping the Spatial Distribution Drought

After training the drought models and identifying suitable models and significant factors, model accuracy was evaluated using R^2, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) for the study area. The selected model was then used to calculate drought values for each pixel for each year. To further analyze the spatial distribution of drought, zonal statistics using the mean drought index values were computed within the QGIS geographic information system (GIS) platform (Kalu et al., 2025).

3. Results and Discussion

3.1 Analysis of Spatio-Temporal of Drought

Precipitation data collected from 11 stations of the Thai Meteorological Department, which had data for 10 years, from 2014 to 2023. The average annual precipitation range from 1,100-1,800 mm per year, with the highest average recoreded in 2022 at 1,848 mm and the lowest mean value in 2018 at 1,175 mm as shown in Figure 3.

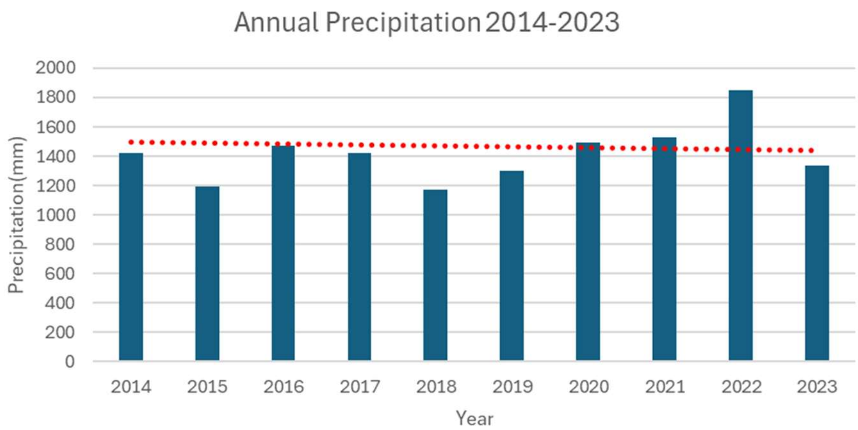

Figure 3 Average annual precipitation

This study analyzes both short-term and long-term precipitation patterns, utilizing the Standardized Precipitation Evapotranspiration Index (SPEI) as a metric to gauge drought conditions. Short-term observations revealed instances of drought, particularly notable in June 2015 and April 2016, with recurring drought conditions evident towards the end of 2018 and 2019, as well as at the onset of 2020 and 2021. These findings underscore the cyclical nature of reduced precipitation and the consequential threat of water scarcity within shorter time frames.

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Although the annual precipitation in some years during 2018–2020 was close to the long-term mean, persistent drought conditions were still observed, as reflected by sustained negative SPEI values. This phenomenon can be explained by the structure of the SPEI index, which incorporates both precipitation and potential evapotranspiration (PET). During this period, increased air temperature and enhanced evapotranspiration demand, likely associated with El Niño events and monsoon break conditions, intensified soil moisture deficits despite near-normal rainfall totals. Similar findings have been reported in previous drought studies in Thailand, where temperature-driven evapotranspiration played a critical role in prolonging drought severity (Arpakorn & Chen, 2021).

Furthermore, this study investigation into long-term precipitation trends, evaluated over the SPEI, revealed sustained negative SPEI values from mid-year 2015 to 2016, indicative of emerging drought conditions. Notably, from mid-year 2018 to 2020, the persistent negativity of SPEI values highlighted a protracted period of drought across multiple months, emphazing the severity and duration of the drought, as shown in Figure 4.

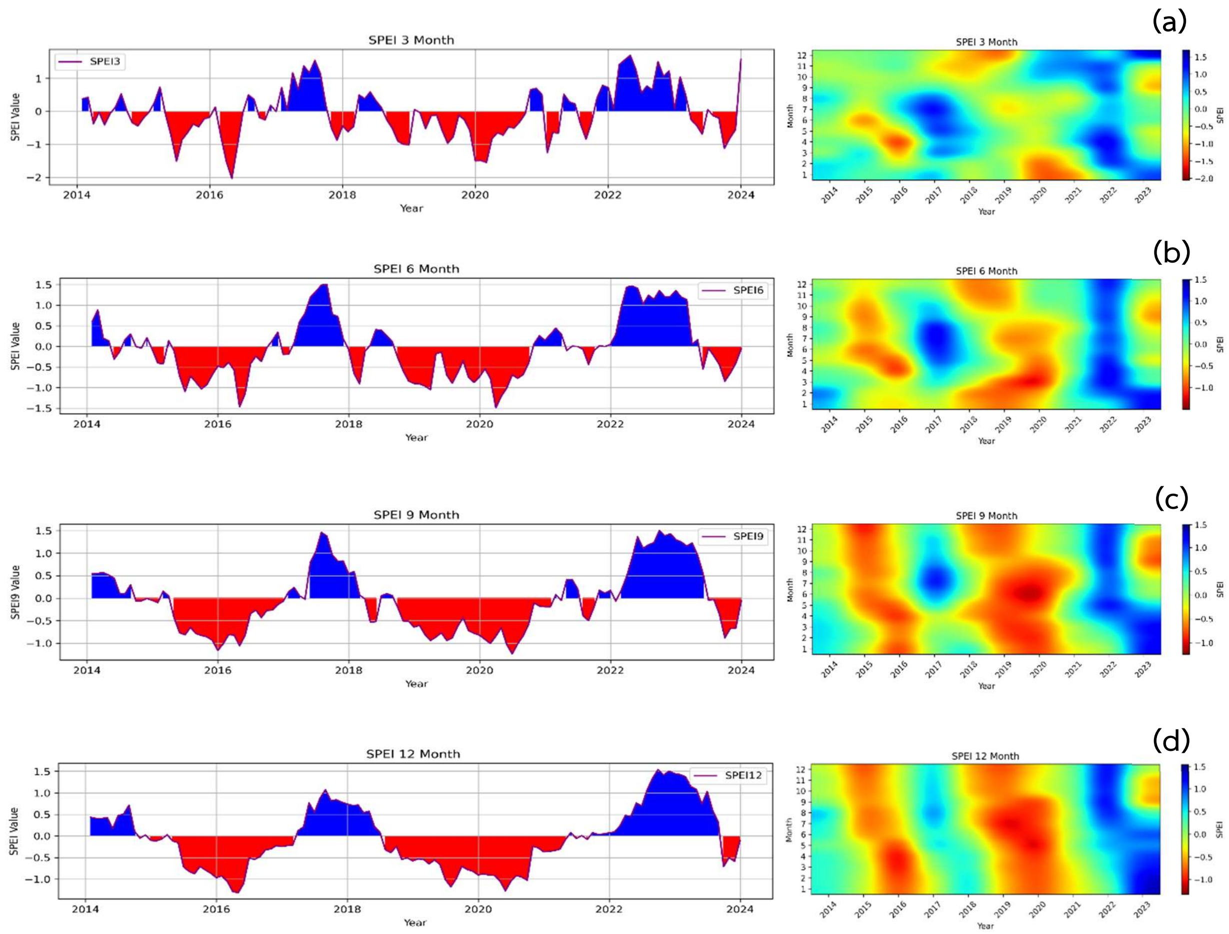

Figure 4 The evolution of SPEI indicating the development of drought at (a) 3-month, (b) 6-month, (c) 9-month, and (d) 12-month time scale in Northeast Thailand from 2014–2023

3.2 Performances of Machine Learning Models

The Extra Trees model outperforms for drought index prediction in the Northeast region of Thailand, demonstrating competitive performance across various metrics and datasets. The analysis, aimed at assessing the congruence between predicted and observed values, were consistently performed across various metrics. For both SPEI3 and SPEI6, the correlation coefficients (R values) ranged from 65.26% to 94.28% and 78.73% to 94.8%, respectively, indicating the model's ability to capture the nuances of drought dynamics. This proficiency not only elucidates the model's discernment of the relative significance of pertinent drought variables but also indicates its reliability in forecasting. The Root Mean Squared Error (RMSE), serving as an indicator of predictive capability, exhibited low values spanning from 1.58% to 33.28% and 4.55% to 31.93% for SPEI3 and SPEI6, respectively. Such minimal RMSE values signify a close relationship between predicted and observed values, meaning that prediction errors were comparatively low. Likewise, Mean Absolute Error (MAE) ranges of 0.09% to 18.55% and 0.45% to 18.14% for SPEI3 and SPEI6, respectively, further indicate the model's accuracy, with lower MAE values indicating better agreement between predicted and observed values. Moreover, this study uses cross-validation for a model assessment approach that effectively mitigates the risk of overfitting the training data.

Although the Extra Trees Regressor (ETR) exhibited high overall predictive accuracy, the presence of potential spatial bias should be acknowledged. Model sensitivity may vary between lowland floodplain areas and higher-elevation regions. In Northeast Thailand, irrigated lowland areas often display delayed drought responses due to surface water storage and regulated water supply, whereas upland areas respond more rapidly to precipitation deficits because of shallow soils and limited water-holding capacity. Consequently, ETR predictions may slightly overestimate drought severity in upland regions while underestimating short-term drought impacts in lowland areas. Acknowledging this spatial bias is essential for the appropriate interpretation of model outputs and drought risk assessment, as summarized in Table 3.

Analysis of the error distribution suggests that model bias at the provincial level is generally limited but may be influenced by local hydrological conditions and water management practices rather than climatic drivers alone. Overall, the error patterns support the robustness of the proposed approach while indicating opportunities for further improvement through the integration of higher-resolution or socio-hydrological datasets.

The ETR model used to generate drought distribution maps in the Northeast region of Thailand. Its performance and accuracy make it a compelling choice for further research and practical applications in drought assessment and monitoring, as shown in Figure 5.

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Table 3 Accuracy assessment of Machine Learning

SPEI	ML	Accuracy	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
SPEI3	XGBoost	MAE	6.12	2.24	0.8	8.75	14.5	14.7	19.9	16.3	0.9	0.07
		RMSE	14.1	8.3	5.05	17.6	25.9	24.4	34.1	28.2	5.67	1.35
		R^2	88.6	72.1	63.2	87.5	81.4	92.4	83.0	82.4	75.1	66.1
	RF	MAE	5.07	1.63	0.55	5.95	11.0	10.6	16.7	13.4	1.03	0.12
		RMSE	13.8	7.83	4.56	16.1	24.3	21.9	32.9	26.2	6.27	2.23
		R^2	89.1	75.2	69.7	89.4	83.5	93.9	84.2	84.8	71.1	69.3
	ET	MAE	5.04	2.19	0.75	6.55	11.5	11.6	18.5	15.6	1.2	0.09
		RMSE	12.2	8.27	4.97	14.8	22.5	21.3	33.2	28.0	6.08	1.58
		R^2	91.4	72.1	65.2	91.1	85.9	94.2	83.9	82.6	73.1	69.7
SPEI6	XGBoost	MAE	2.07	20.2	11.6	10.1	19.2	8.93	9.61	0.29	0.5	2.4
		RMSE	12.1	35.4	27.1	25.0	35.9	20.7	20.4	4.29	3.52	10.7
		R^2	79.2	83.7	91.5	89.7	85.8	91.0	90.2	80.9	90.5	87.9
	RF	MAE	2.36	15.7	9.09	7.52	14.8	5.04	6.38	0.33	0.52	2.16
		RMSE	13.5	32.6	25.8	24.0	32.9	17.2	18.6	4.91	3.97	12.1
		R^2	74.1	86.1	92.3	90.6	88.1	93.8	91.8	77.9	88.1	84.8
	ET	MAE	2.36	18.1	9.45	8.31	15.4	5.46	7.55	0.45	0.76	2.82
		RMSE	11.7	31.9	22.9	22.1	31.4	15.8	18.5	4.92	4.55	12.0
		R^2	80.3	86.7	94.0	92.0	89.2	94.8	91.9	78.7	84.8	85.0

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Figure 5 Overall accuracy: (a) R^2, (b) RMSE, (c) MAE from SPEI 3 and (d) R^2, (e) RMSE, (f) MAE from SPEI 6

3.3 The Importance of Variables

This study investigated the importance of remote sensing and topographic variables in estimating the Standardized Precipitation Evapotranspiration Index (SPEI) at both 3- and 6-month time scales during 2014–2023. Permutation importance analysis was applied to ensure comparability among predictors and to assess their relative contributions. Results indicate that CHIRPS precipitation, elevation (DEM), and the Temperature Condition Index (TCI) were the most influential variables for both SPEI-3 and SPEI-6, while vegetation-based indices such as EVI and VCI played secondary roles.

The influence of CHIRPS and DEM reflects the strong control of rainfall variability and topography on drought processes in Northeast Thailand. Precipitation directly governs soil moisture availability, whereas elevation influences soil depth, runoff, and water storage capacity, thereby modulating evapotranspiration and vegetation stress. These findings highlight the physical relevance of the selected predictors and support their application for drought monitoring and water resource management. The relative importance of variables is shown in Figure 6.

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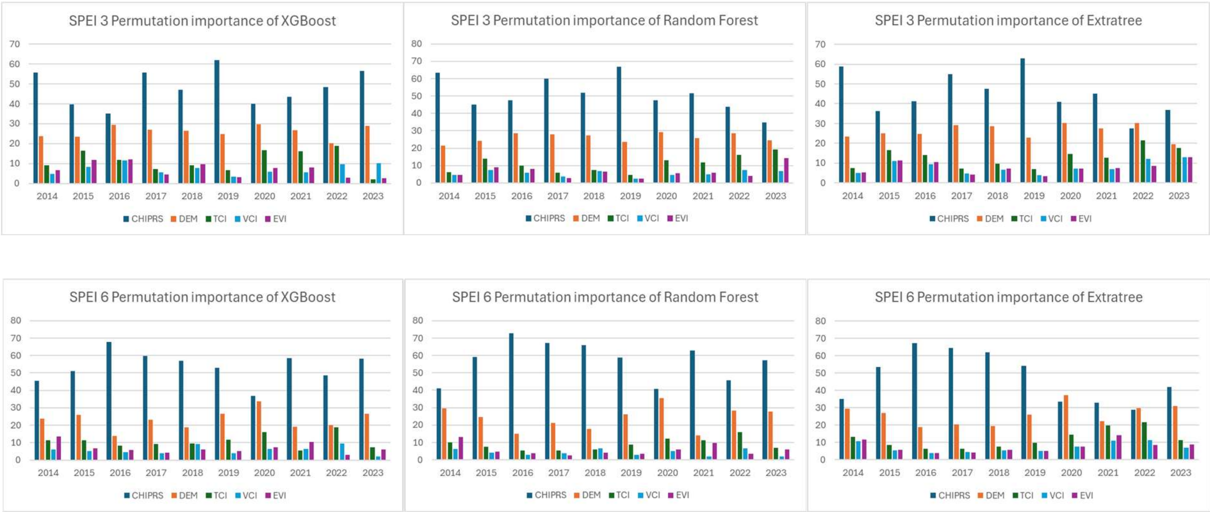

Figure 6 The relative importance (%) of the drought factors

3.4 Mapping the Spatial Distribution Drought

The spatial mapping of drought distribution in Northeast Thailand from 2014 to 2023 was conducted using the Extra Trees model. Long-term drought indicators, particularly SPEI 6, consistently demonstrate a higher frequency of drought area categories compared to short-term indicators like SPEI 3. Analysis of short-term drought events reveals temporal patterns, including predominant short-term light droughts in 2014, with a resurgence in 2017 and expanded influence in 2018. Moderate drought conditions persisted in Buriram (BRM) through 2019, while significant instances of drought, ranging from light to extreme severity, were observed across different areas, notably impacting Sisaket (SSK) in 2019 and sporadic moderate droughts in Buriram (BRM). Substantial instances of moderate to extreme drought were reported in Ubon Ratchathani (UBN) and Nakhon Ratchasima (NMA) based on data from the Office of Natural Resources and Environmental Policy and Planning, as shown in Figure 7.

Long-term drought indicators (SPEI 6) consistently exhibited higher frequencies, particularly notable in 2015 and 2018, affecting various parts of Northeast Thailand. Additionally, in 2020, drought conditions were observed in Nakhon Ratchasima (NMA). Significant insights were garnered through the analysis of area percentages extracted from the drought maps, indicating a notable increase in the affected areas across different drought classes over extended time periods, specifically for SPEI 3 and SPEI 6-month scales. This observation implies that prolonged periods of deficient precipitation contribute to the heightened frequency of drought occurrences. Such a thorough examination underscores the spatial variability of drought events across various districts of Northeast Thailand throughout the period spanning 2014 to 2023, as showed in Figure 8.

Short-term SPEI is particularly useful for early warning systems, supporting timely responses in agricultural planning during the cropping season. In contrast, long-term SPEI represents cumulative water deficits and is more relevant for strategic water resource management, reservoir operation, and drought mitigation policies at provincial and national levels.

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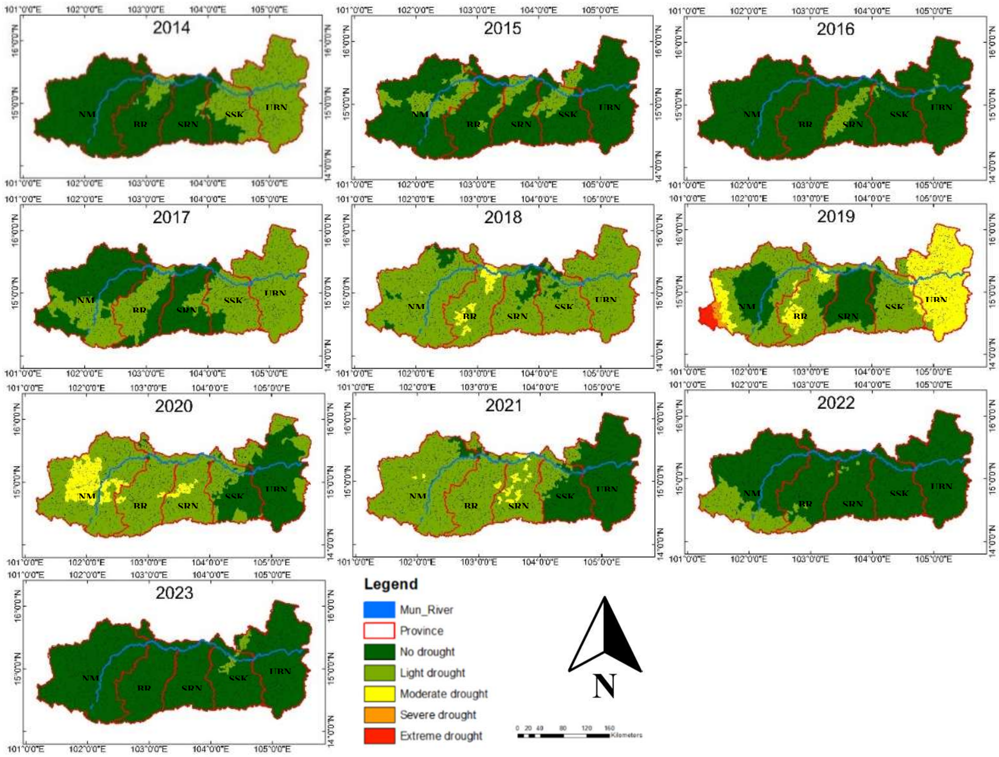

Figure 7 Short-term drought distribution map in Northeast Thailand from 2014 – 2023

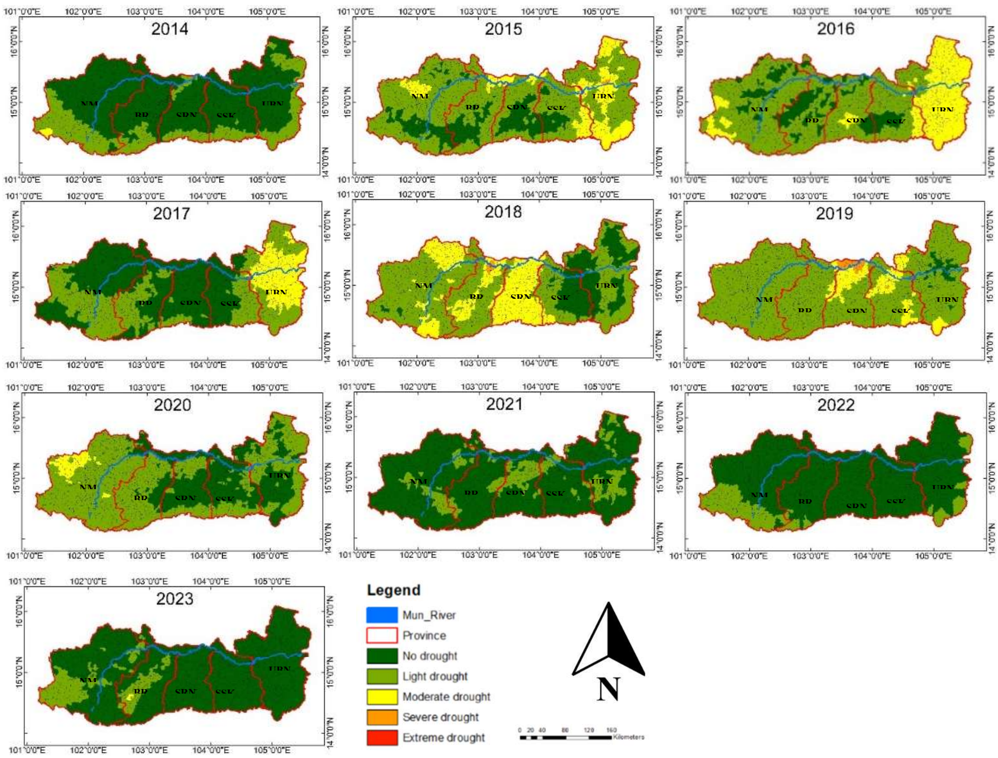

Figure 8 Long-term drought trends distribution map in Northeast of Thailand from 2014–2023

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4. Conclusions

This study found patterns of drought occurrences, attributing them predominantly to insufficient rainfall. Noteworthy drought events were observed in 2018, 2019, and 2020 for short-term droughts, and in 2015, 2016, 2018, 2019, and 2020 for long-term droughts. These findings align with the recurring El Niño phenomenon, which typically induces diminished rainfall across the study area. Data from the Hydro-Informatics Institute of the Ministry of Higher Education substantiate these observations, accentuating the sustained presence of El Niño-induced drought conditions from late 2014 through 2016 and a resurgence in 2019. The consistent association between El Niño occurrences and reduced rainfall highlights its pivotal role in precipitating drought phenomena within the region.

The results indicate that the Extra Trees model outperforms others in predicting drought indices with high accuracy. For short-term predictions, the model achieved an R^2 ranging from 65.26% to 94.28%, an RMSE between 1.58% and 33.28%, and an MAE ranging from 0.09% to 18.55%. For long-term predictions, the R^2 ranged from 78.73% to 94.8%, the RMSE from 4.55% to 31.93%, and the MAE from 0.45% to 18.14%. Key variables contributing to the model's accuracy include precipitation (27%–67%), topography (19%–37%), and land surface temperature (6%–21%). The feature importance of these variables significantly enhanced model performance.

Short-term drought occurrences were analyzed in this study in Northeast Thailand. The occurrence of short-term light droughts was observed in 2014, predominantly impacting Ubon Ratchathani (UBN), which reappeared in 2017, followed by a more extensive influence across the study area in 2018. Additionally, moderate drought conditions were discerned in Buriram (BRM) during this timeframe, persisting through 2019. Extreme drought affected 0.47% of the total area, severe drought impacted 0.56%, moderate drought affected 24%, and light drought was observed in 45% of the entire area. Noteworthy was the identification of light drought conditions in Sisaket (SSK) in 2019, alongside sporadic occurrences of moderate drought in Buriram (BRM). Meanwhile, Ubon Ratchathani (UBN) experienced notable instances of moderate drought, with Nakhon Ratchasima (NMA) notably afflicted by extreme drought conditions, consistent with data indicating that the drought situation in Nakhon Ratchasima (NMA) Province is still ongoing. The water volume in four large water storage reservoirs in the province continues to decrease (Office of Natural Resources and Environmental Policy and Planning). This trend persisted into 2020 with a moderate drought in Nakhon Ratchasima (NMA) and a light drought in Buriram (BRM) and Surin (SRN). Furthermore, similar conditions were observed in 2021 in these areas.

Long-term drought trends were also evident, with long-term drought indicators (SPEI 6) consistently exhibited a higher frequency in the area drought category. There was a slight occurrence of a long-term drought in 2014, whereas 2015 witnessed a severe drought in Ubon Ratchathani (UBN). This trend of moderate drought persisted through 2016 and 2017, In 2018, severe drought affected 0.47% of the total area, while moderate drought encompassed 27% and light drought covered 51% of the entire region. A severe drought exhibited a pronounced occurrence in the north of Buriram (BRM) during 2018, coinciding with instances of moderate drought in Nakhon Ratchasima (NMA) and various areas within Surin (SRN). In 2019, the study area experienced a prevalence of light drought affecting 83% of the total area, accompanied by a moderate drought affecting 12%. Notably, a distinct area comprising 1.4% encountered severe drought conditions, predominantly observed in Surin (SRN).

Despite the strong performance of the proposed approach, several limitations should be noted. The 30-m spatial resolution of Landsat data may not fully capture fine-scale agricultural variability, and drought classification relied solely on SPEI without incorporating other indices such as SPI or NDMI. These limitations provide directions for future improvement.

Future research should extend the geographic scope, encompassing diverse regions beyond Northeast Thailand, to gain a more comprehensive understanding of drought dynamics and management strategies. Exploring alternative modeling approaches and incorporating additional environmental variables could further enhance insights into the complexities of drought occurrence and mitigation efforts. Therefore, future research should be conducted to extract information with deep learning methods or neural network and monitor the drought using remote sensing data, as well as to evaluating the impact of these data changes on the regional environment.

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