Historical Analysis and Future Projections of Meteorological Drought in Northeast Thailand Using Statistically Downscaled Climate Models

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Abstract

Drought is a reoccurring meteorological hazard that seriously affects agricultural production, water resources and the livelihoods of rural people. The current study investigates the past, observed drought conditions as well as future climate change scenario in Northeast Thailand by combining historical meteorological observations, satellite-derived precipitation datasets, and statistically downscaled Global Climate Model (GCM) outputs. The SPI based on fitting the Gamma-distribution and through probability-of-normal transformation was employed in 12-month periods to describe drought severity and duration from 1994 to 2023. Future scenarios were projected using CanESM2 (CMIP5) and CanESM5 (CMIP6) under RCP4.5 and RCP8.5 emission pathways for mid-century (2041–2070) and late-century (2071–2100) periods. The accuracy of the climate projections was improved through bias correction via Quantile Mapping (QM) and empirical downscaling with Multiple Linear Regression (MLR), with calibration and validation of the models undertaken through a split sampling approach (70% calibration and 30% validation) over the baseline period (1994-2023). Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) rainfall datasets were incorporated primarily to fill gaps and extend the temporal continuity of station records. However, CHIRPS-based spatial maps were not produced, as the study focused on temporal drought patterns. The performance evaluation showed notable improvements, with R^2 values over 0.70 for precipitation and over 0.85 for temperature, along with RMSE reductions of 25 to 40% across representative stations. Historical analysis revealed an increase in the occurrence and intensity of events droughts at representative stations like Nongkai, Khon Kaen, and Ubon Ratchathani. In addition, RCP8.5 projections have depicted a growth in the number of extreme events where SPI values have fallen below -1.5 and their frequency is foreseen to double by 2100. The results demonstrate that satellite-derived precipitation datasets combined with statistically downscaled climate models can support regional drought assessment based on representative stations. Moreover, the results reflect a pressing need for water management, early warning systems, and climate-resilient crops. This work supports the National Adaptation Plan of Thailand and regional drought mitigation strategies with respect to evolving climatic conditions.

Keywords: Drought Assessment; Global Climate Models (GCMs), Northeast Thailand; Remote Sensing, Statistical Downscaling

1. Introduction

Drought is one of the deadliest natural disasters occurs as a result of low rainfall, unusually high temperatures, and high evaporation rates for a particular region. It has many adverse impacts on water supply, agricultural production, energy generation, ecosystem and many more. Recent findings have shown that drought disasters are increasingly occurring more frequently, with increased duration and intensity across the globe [1]. Economically developing regions rely heavily on rain-fed crop and have low adaptive capacity have a higher vulnerability to this disaster. Northeastern Thailand (Isan) is considered one area that meets all the climatic, geographical, and socio-economic criteria to be frequently affected by severe droughts [2].

The Northeast part is the largest and has almost one third of the population of the country. Almost 94% of its population lives in rural areas and depends mainly on agriculture with rice as the dominant subsistence crop [3]. The region, a tropical savanna, distinctly follows a wet and dry season pattern [4][5] and [6]. Despite the predominance of the rainy season in annual rainfall, it is highly variable in both temporal and spatial perspectives. Because of this, Isan is therefore facing hydrological extremes, namely meteorological and agricultural droughts [7]. Historical analyses revealed that the trend for increased drought occurrences was mainly attributed to El Niño-Southern Oscillation (ENSO) phenomena, land cover change, and regional climatic change [8]. Drought events in this region have caused substantial economic and social impacts, particularly affecting smallholder farmers, agricultural productivity, and rural household income [7] and [9].

It is important to understand the current and future drought conditions for planning water resources and agricultural sustainability within the area. For different scenarios, Global Climate Models (GCMs) are the greatest valuable tools for predicting future climate conditions. GCMs are capable of modeling the most important factors in the climate system, such as temperature, precipitation, and evapotranspiration, and their complex interactions in the climate system [10]. However, the use of GCMs is not feasible because of their coarse resolution [11]. Therefore, downscaling methods are necessary to address the issue between the low spatial resolution of GCMs and the high-resolution data needed for regional planning.

Recent studies have found that the recovery mechanism after drought conditions can be supported by the application of early warning systems, climate-resilient agricultural management, and effective water governance. Drought monitoring and preparedness planning have been most effective in improving early response operations [11] and [12]. Climate-resilient agricultural practices and water conservation, together with ecosystems that support adaptation, help build resilience and enable faster recovery in drought-affected areas [13] and [14]. In Southeast Asia, drought-resilient infrastructure, water storage, and farming advice have been effective in reducing economic effects and supporting recovery during protracted drought periods [7] and [9]. These results indicate that the combination of drought monitoring with drought adaptation policy approaches can effectively minimize the socio-economic effects of droughts in Northeastern Thailand.

Statistical downscaling technique bridges this gap by building empirical relationships between large-scale atmospheric conditions (predictors) and local climate patterns (predictands) using historical data as a foundation [15]. Common techniques used include bias correction, quantile mapping, and weather typing. Each technique offers specific strengths and limitations, particularly in capturing climate extremes. In drought studies, these methods correct biases in precipitation and temperature projections as well as improve the accuracy of indices (i.e., SPI).

Long-term drought events were detected using SPI-12 within the study area. It is a widely used index for detecting meteorological and hydrological droughts, particularly suitable in data scarce areas [16]. It is a probability-based index calculated from fitted precipitation distributions followed by standardization using cumulative probability transformation. When combined with downscaled GCM outputs, it provides a robust basis for analyzing past and future drought conditions, making it useful for assessing long-term hydrological droughts [17] and [18].

Many studies used statistical downscaling technique to evaluate temperature and rainfall trends; however, only limited studies focused on drought characteristics particularly using multi-model ensembles of GCMs and standardized indices such as SPI [17][18][19] and [20]. The novelty of this research lies in integrating CMIP5 and CMIP6 projections with statistically downscaled SPI-12 analysis for Northeast Thailand, providing long-term drought projections up to 2100 with improved regional accuracy. Building upon an earlier work that mapped drought vulnerability zones across Northeast Thailand [21], the present study investigates temporal drought patterns and projects future drought event conditions under different climate

change situations. The specific objectives of this study are to:

i. quantify historical drought characteristics using the SPI-12 by integrating observed and satellite-based precipitation datasets, thereby establishing a baseline for temporal variability and severity.
ii. assess trends in drought frequency, duration, and intensity across the baseline period; and
iii. project future drought conditions under RCP4.5 and RCP8.5 scenarios for the mid-century (2041–2070) and late-century (2071–2100) using statistically downscaled GCM outputs.

The research provides a regional assessment made possible by the integration of multi-model ensemble techniques, bias correction techniques, and drought indices. The results can be used in climate adaptation, agricultural water management, and policy formulation related to water resources in Northeast Thailand. The research has the potential to be useful for various stakeholders such as the provincial water departments, agricultural extension officers, farmers, disaster management departments, and policy makers at the National Adaptation Plan in Thailand.

2. Methodology

2.1 Study Area

Northeast Thailand (Isan) is a geographically extensive area and has been recognized as the most drought-vulnerable region in the country. It is situated between latitudes 16°–18°N and longitudes 102°–106°E shown in Figure 1, described by a tropical savanna climate with two well-differentiated wet (May–October) and dry (November–April) seasons [21]. The average annual temperature in this area is 27.1 °C and the average humidity is 72.3% [21] and [22]. The region relies heavily on seasonal monsoon rains and has a long dry season. This causes ongoing water shortages from November to April. Its distribution is very inconsistent, affected by the landscape and the El Niño-Southern Oscillation (ENSO). Although precipitation records were available from 96 stations across Northeast Thailand, three representative stations, Nongkai (upper region), Khon Kaen (central region), and Ubon Ratchathani (lower region), were selected for detailed SPI analysis because they possess relatively complete long-term meteorological records and collectively represent the major climatic zones of the region. This study uses a combined method to assess historical drought patterns and predict future drought conditions in Northeast Thailand. This analysis relies on climate records, remote sensing data, and outputs from Global Climate Models (GCMs). The methodological framework of the study is shown in Figure 2. Figure 2 illustrates the overall implemented workflow of this work. The framework begins with the collection of observed meteorological data and satellite-derived precipitation datasets, followed by preprocessing and gap filling.

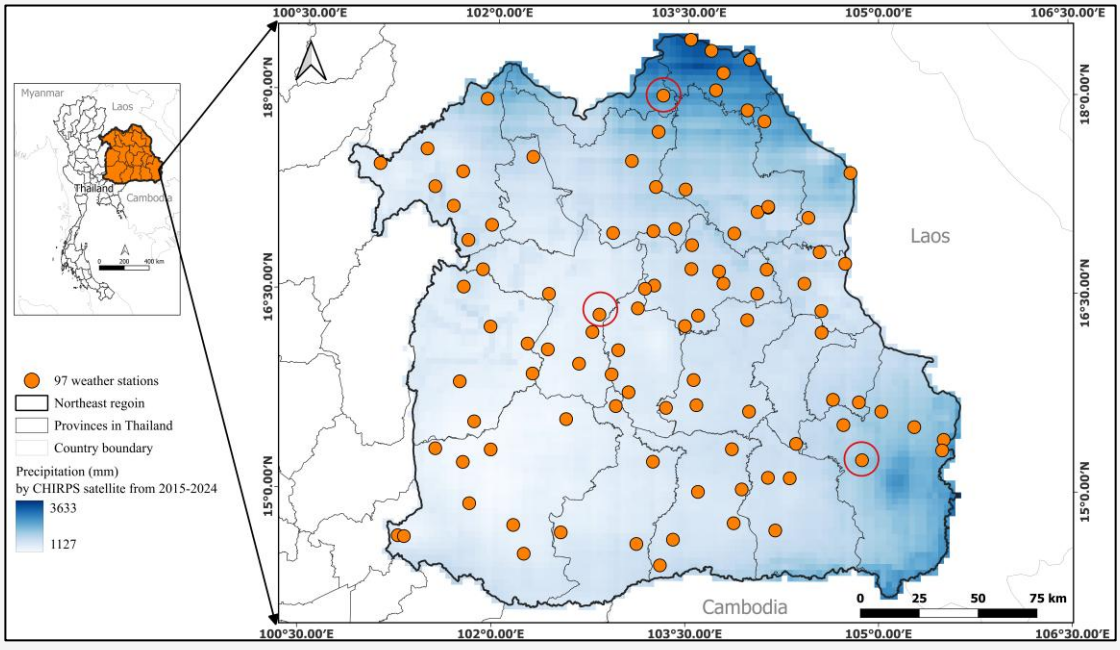


Figure 1: Study area map-showing weather stations and representative stations in Northeast Thailand

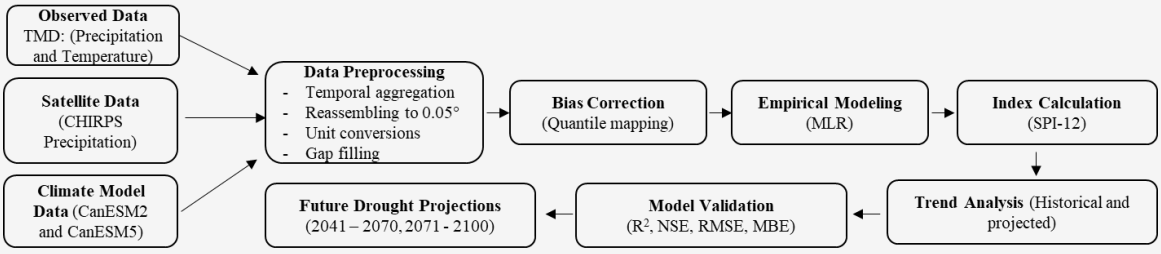


Figure 2: Drought monitoring using downscaled climate model study workflow

Climate projections from GCMs were then bias corrected using Quantile Mapping (QM) and statistically downscaled using Multiple Linear Regression (MLR). The corrected precipitation data were subsequently used to calculate SPI-12 for historical and projected periods, allowing analysis of drought trends and future drought scenarios in Northeast Thailand.

2.2 Data Collection and Preprocessing

2.2.1 Observed meteorological data

Monthly rainfall data for 96 stations from 1994 to 2023 were collected by the Thai Meteorological Department (TMD) and selected provincial agricultural offices. Three representative stations were then selected for detailed SPI-based temporal drought analysis. Due to missing or incomplete temperature records across some stations, only rainfall data were used for drought index (SPI) calculation, while temperature data were only used separately for climate projection analysis. Temperature data were therefore not used in the SPI computation. Temperature records were available for only some of the meteorological stations in the study region. However, the study focused specifically on three stations namely Nongkai, Khon Kaen, and Ubon Ratchathani, selected as representative stations in the region for drought analysis and climate projection. Temperature data from these stations were used to evaluate the performance of global climate models (GCMs), as well as to carry out bias correction and downscaling. Rainfall data, on the other hand, were used solely to calculate the SPI.

2.2.2 Satellite and gridded datasets

The CHIRPS dataset was used to supplement observed precipitation over the representative stations. CHIRPS provides quasi-global precipitation estimates at 0.05° (~5 km) spatial resolution and daily, pentadal, and monthly temporal resolutions from 1981 to near-present [23]. For this study, monthly CHIRPS data were extracted corresponding to each station and merged with observed records to fill gaps as well as to extend the temporal coverage [24][25] and [26]. Observed station precipitation data remained the primary source for SPI calculation, while CHIRPS values were used only to fill missing monthly observations by extracting the grid cell corresponding to each station. This ensured a consistent and continuous precipitation time series for drought index calculation; however, no CHIRPS-based spatial maps were produced, as the study was designed to focus on temporal drought patterns [27].

2.3 Climate Model Data

Projections of future climate were derived from the Canadian Earth System Model (CanESM2/CanESM5) obtained through the Coupled Model Intercomparison Project Phase 5 and 6 (CMIP5 and CMIP6). CanESM2 (CMIP5) and CanESM5 (CMIP6) were selected as they represent two subsequent generations of climate models and have been widely employed in regional climate projection studies for Southeast Asia. The use of these two models allows comparison between CMIP5 and CMIP6 projections while maintaining consistency with the statistical downscaling framework applied in this study. Two climate change scenarios were selected including RCP4.5 and RCP8.5 [28] and [29]. Representative Concentration Pathways (RCPs) are greenhouse gas concentration scenarios used to project future climate conditions. RCP4.5 an intermediate stabilization scenario in which greenhouse gas emissions peak around mid-century and then decline, whereas RCP8.5 represents a high-emission, business-as-usual pathway associated with continued increases in greenhouse gas concentrations, leading to stronger warming and more severe climate impacts. These scenarios are widely used in climate impact studies to assess potential future climate variability under different emission trajectories.

Two variables (i.e., precipitation (pr) and monthly near surface temperature (tas)) were considered for data downloading from the Earth System Grid Federation (ESGF) in NetCDF format for historical and future model outputs. The climate model datasets were provided from the Earth System Grid Federation (ESGF) data portal (https://esgf-node.llnl.gov/). The historical period (1994–2023)

was used as baseline for assessment, whereas future projections were extracted for mid-century (2041–2070) and the late-century (2071–2100). Using subsetting function of ESGF during download, data were clipped to the geographical extent of Northeast Thailand to reduce processing time and file size. From the GCM outputs, the monthly time steps were then aligned with the baseline period (1994–2023). It was performed to ensure the consistency of comparing historical model simulations with observed datasets. NetCDF files were then imported into RStudio using the "ncdf4" and "raster" packages. Units were converted where necessary and data were regridded to match the resolution of satellite datasets (0.05°) using bilinear interpolation. The coordinate reference system was set to WGS84 for consistency with other datasets. Bias correction of the processed GCM data was done using QM and adjusted using MLR before using for SPI calculations.

2.4 Statistical Downscaling of GCM Data

Since GCM outputs of CanESM2 and CanESM5 are coarse in resolution; therefore, statistical downscaling techniques were applied to make projections more relevant at the regional scale. It was done in RStudio using a two-step approach given below.

2.4.1 Bias correction

Quantile Mapping (QM) was used to correct biases in GCM-simulated precipitation distributions by aligning model percentiles with observed distributions [30] and [31]. The bias correction was then applied to monthly data using observed records as the reference, ensuring better representation of extremes. Also, separate transfer functions were developed for representative stations to save local climate characteristics. In this study, QM was applied by adjusting the cumulative distribution of modeled precipitation to match the observed precipitation distribution, allowing systematic biases in the climate model outputs to be corrected prior to the statistical downscaling process.

2.4.2 Empirical regression modeling

Prior to regression modelling, QM was applied to correct systematic biases in the GCM outputs, and the bias-corrected variables were subsequently used as inputs to the MLR models. MLR models were developed to relate large-scale atmospheric predictors, including geopotential height (Z), sea-level pressure (SLP), and relative humidity (RH), to local precipitation variability at the representative stations. These variables were selected because they represent key atmospheric circulation and moisture conditions influencing precipitation variability in Northeast Thailand. The MLR framework is defined in Equation 1:

$$P = \beta_0 + \beta_1 Z + \beta_2 SLP + \beta_3 RH + \varepsilon \quad \text{Equation 1}$$

Where P represents local precipitation, Z is geopotential height, SLP is sea-level pressure, RH is relative humidity, β_0 is the intercept, β_1, β_2 and β_3 are model coefficients associated with the atmospheric predictors, and ε is the residual error term.

The predictors were derived from the large-scale atmospheric variables available in the GCM datasets and were applied consistently across the representative stations to establish statistical relationships with local precipitation. Potential redundancy among atmospheric predictors was considered during predictor selection by avoiding the simultaneous inclusion of variables representing similar atmospheric information. The final predictors were retained based on their physical relevance to precipitation variability and their contribution to model performance during calibration and validation. Model performance was assessed from a split-sample calibration validation approach (70% calibration and 30% validation). The downscaled outputs were resampled to 0.05° to match CHIRPS datasets. These were further reprojected to WGS84 and synchronized with baseline and projection periods. Since MLR is a linear statistical downscaling approach, no hyperparameter tuning was required. Model development was based on predictor screening and evaluation using RMSE, NSE, MBE, and R^2 statistics.

2.5 Drought Index Calculation

The Standardized Precipitation Index (SPI) was used to quantify drought severity based on monthly precipitation data. It was calculated at a 12-month timescale (SPI-12) to characterize long-term moisture variability relevant to hydrological drought. SPI was calculated using the standard probability-based formulation [32]. Monthly precipitation totals were fitted to a Gamma probability distribution and transformed into cumulative probability using Equation 2.

$$G(x) = \int_0^x \frac{x^{a-1} e^{-x/\beta}}{\beta^{\alpha} \Gamma(a)} dx \quad \text{Equation 2}$$

Since the Gamma distribution is defined only for positive precipitation values, zero precipitation events were incorporated using Equation 3:

$$H(x) = q + (1-q)G(x)$$

Equation 3

Where q represents the probability of zero precipitation. The adjusted cumulative probability was then transformed into a standard normal variate to obtain *SPI*:

The cumulative probability is converted to a standard normal variate to obtain SPI using Equation 4:

$$SPI = \emptyset^{-1}[H(x)]$$

Equation 4

Where x is the monthly precipitation, α and β are the Gamma shape and scale parameters, Γ is the Gamma function, and $\emptyset^{-1}$ denotes the inverse cumulative standard normal distribution. Zero precipitation values were incorporated into the cumulative probability calculation following the standard SPI formulation by adjusting the cumulative distribution to account for the probability of zero rainfall. The adequacy of the fitted Gamma distribution was evaluated using the Kolmogorov–Smirnov (KS) goodness-of-fit test at a 5% significance level.
It was calculated in R using the SPEI package, which implements Gamma distribution fitting and probability-to-normal transformation using validated algorithms following the procedure used in another research [33]. Previous studies have demonstrated that *SPI* is a robust and reliable index for characterizing drought severity and duration across different climatic regions and time scales, particularly for long-term drought assessment [34] and [35]. And drought categories are defined in Table 1 [32].

Table 1: SPI ranks with seven different severities

SPI values	Severity level
≥ 2.00	Extremely wet
1.50 to 1.99	Very wet
1.00 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.00 to -1.49	Moderate drought
-1.50 to -1.99	Severe drought
≤ -2.00	Extreme drought

Both historical and projected climate datasets were processed to calculate SPI, allowing comparison at 12 months' timescale, as it gives stable results at 12 months' timescale for better understanding of the situation.

2.6 Model Performance and Accuracy Assessment
Model performance was assessed using multiple statistical indicators including Root Mean Square Error (RMSE), Nash–Sutcliffe Efficiency (*NSE*), Mean Bias Error (*MBE*), and Coefficient of Determination (R^2). Whereas, *RMSE* quantifies the average deviation between modeled and observed precipitation values given in Equation 5 [36]. NSE measures the predictive skill of the model in replicating observed variability given in Equation 6 [37]. *MBE* identifies overestimation or underestimation tendencies given in Equation 7 [37], while R^2 evaluates the extent to which downscaled model captures the variance in observed data given in Equation 8 [38].

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

Equation 5

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}$$

Equation 6

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)$$

Equation 7

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left[(O_i - \bar{O})(P_i - \bar{P})\right]}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2 \sum_{i=1}^{n}(P_i - \bar{P})^2}} \right)^2$$

Equation 8

Where, n, O, and P represent total number of data points, observed and predicted SPI's respectively and $\bar{O}_i$ is the mean of the observed values.

The SPI obtained from bias-corrected GCM outputs was validated against observed drought events over the baseline period (1994–2023). The QM approach most generally provided improved model fits at the representative stations, as they matched observed patterns of rainfall. The NSE averages vary from 0.60 to 0.78, while R^2 values are above 0.70 and 0.85 for rainfall and temperature, respectively, across validation sites. After correction, RMSE values decreased by approximately 25 to 40%. Therefore, these validation results provide supplementary support for the suitability of this downscaling framework to study historical climate variability and the reliability of future drought projections.

2.7 Descriptive Trend Analysis (1994-2023)

Descriptive metrics were used on SPI-12 and precipitation records from key stations to analyze temporal trends. The number of moderate, severe, and extreme drought events were counted for each decade: 1994-2003, 2004-2013, and 2014-2023. Moreover, changes in mean SPI-12 values at each station over these decades were presented to highlight variation in overall drought trends. Persistence was further assessed by counting multi-month periods featuring extended dryness characterized by SPI-12 < -1.0. A drought event was defined as a continuous period during which SPI-12 remained ≤ -1.0, and events were considered independent when separated by at least one time step with SPI > −1.0.

3. Results

The findings from the historical drought analysis and future projections based on statistically downscaled GCM outputs are given below.

3.1 Historical Drought Variability (1994–2023)

In this study, SPI was used to represent prolonged drought conditions in Northeast Thailand. Monthly rainfall data from 1994 through 2023 were used. SPI detects hydrological droughts as an accumulation of rainfall deficiencies or excesses during a period of 12 months allowing the determination of more extended drought events. SPI-12 values were calculated for three representative stations: Nongkai, Khon Kaen, and Ubon Ratchathani. This temporally oriented analysis complements earlier drought-vulnerability mapping with historical trends, necessary for future assessments [21]. The SPI-12 analysis showed temporal drought variability across the three representative stations during the baseline period. The most critical events happened in the late 1990s, mid-2000s, and mid-2010s. Nongkai faced extreme droughts in 1998, 1999, 2005, 2007, and 2015. Khon Kaen had similar extremes in the late 1990s, 2005, and from 2013 to 2015. Notable droughts that hit Ubon Ratchathani occurred during the years 1998, 1999, 2004, 2005, and during 2015-2016. Severe to moderate droughts have struck the region quite frequently, indicating the continuous deficit in rainfall. However, wet years with above-average rainfall also mark the recovery periods. These historical patterns form a strong basis for examining future changes in drought occurrence and intensity according to projected climate scenarios. These observations are consistent with the decadal descriptive analysis presented in Section 2.7, which suggests greater drought variability and more frequent drought occurrences during the later decades of the study period. However, no formal statistical trend significance test was performed. These station-specific drought events may not appear individually in Figure 3, which presents the overall regional SPI-12 pattern rather than separate station-level series.

Figure 3 shows the overall SPI-12 drought pattern derived from the statistically downscaled outputs of CanESM2 and CanESM5 for the representative stations. The single series shows the overall regional SPI-12 drought pattern and does not correspond to either CanESM2 or CanESM5 individually. It provides an integrated representation of drought variability over the study region based on the representative stations. A progressive shift from near-normal conditions during the historical period toward more persistent negative SPI values under future climate scenarios, particularly under RCP8.5, is indicated. This pattern suggests an increasing likelihood of prolonged drought conditions in the region. The stronger drought response under RCP8.5 is consistent with the projected changes in precipitation patterns and the overall shift toward drier conditions under the higher-emission scenario. The results projected under the RCP4.5 pathway in 2041-2070 raise the frequency of severe drought events. On the other hand, projections under the RCP8.5 scenario for 2071-2100 show that severe and extreme droughts will strike almost twice as frequently as during the historical period. These projected changes are expected to result in more intense and frequent events of prolonged drought conditions, which indicate high drought risk for agricultural systems, water resources, and livelihoods in the Northeast Thailand.

3.2 Performance of Statistical Downscaling and Bias Correction

The effectiveness of bias correction and downscaling techniques was evaluated by comparing the corrected GCM outputs with observed climate data for the baseline period (1994–2023). QM effectively reduced biases in both precipitation and temperature simulations. For precipitation, monthly RMSE values reduced by 25–40% on average across models. MLR models exhibited moderate to good predictive performance, with average R^2 values of 0.70 for precipitation and 0.85 for temperature across validation stations, and the Nash-Sutcliffe Efficiency (NSE) values for downscaled precipitation ranged from 0.60 to 0.78**,** indicating good agreement with observed patterns. However, seasonal patterns and extreme values were better captured in the downscaled datasets as compared to raw GCM outputs.

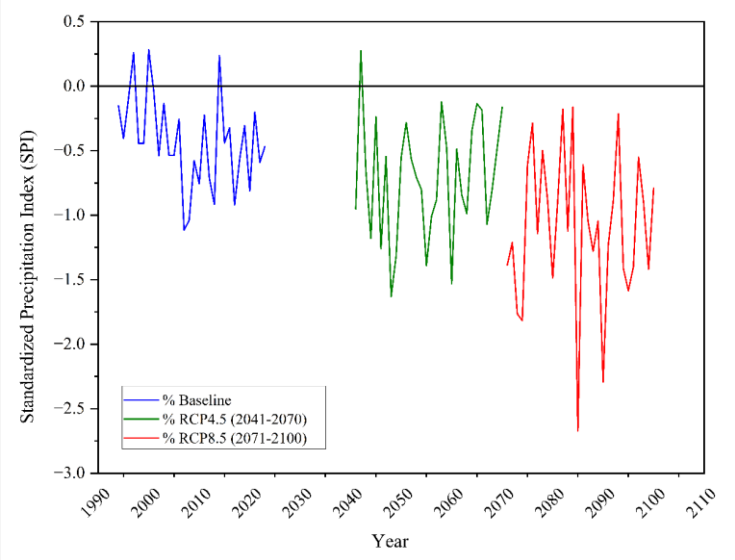


Figure 3: Regional SPI-12 drought pattern derived from statistically downscaled CanESM2 and CanESM5 outputs using the representative stations for the historical period and selected future scenarios in Northeast Thailand

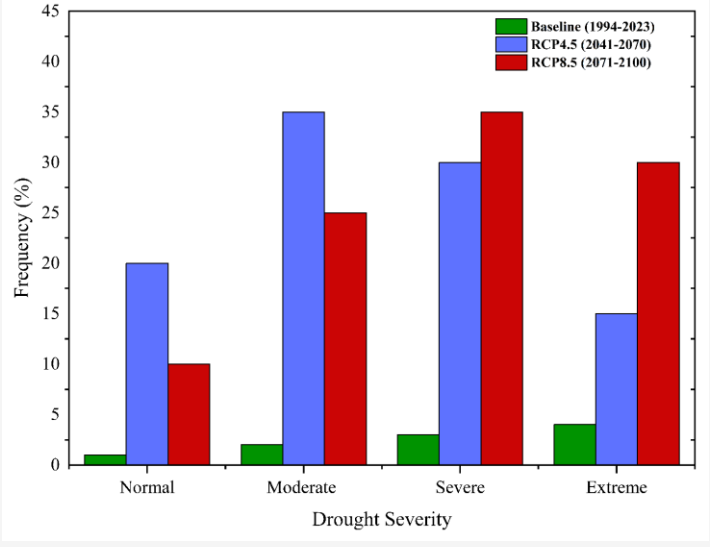


Figure 4: Comparison of drought severity classes in Northeast Thailand during the baseline period (1994–2023) and under future climate scenarios RCP4.5 (2041–2070) and RCP8.5 (2071–2100), highlighting temporal drought variability

3.3 Projected Drought Conditions under RCP4.5 and RCP8.5

Future drought scenarios were generated using statistically downscaled GCM data under RCP4.5 and RCP8.5 for the mid-century (2041–2070) and late-century (2071–2100) periods shown in Figure 4. Mean annual temperatures are projected to increase by 1.5–2.2°C under RCP4.5 and 2.8–4.0°C under RCP8.5 by the late 21st century. The inter-model range between CanESM2 and CanESM5 outputs is considered to reflect projection variability. Whereas precipitation shows mixed trends, slight increases during peak monsoon months but overall reduced rainfall in pre- and post-monsoon seasons. Furthermore, increased evapotranspiration driven by warming offsets minor gains in precipitation, exacerbating drought risk. SPI projections under both RCPs indicate an increase in drought occurrence, duration, and severity**.** Under RCP8.5**,** extreme droughts (SPI $\leq$ -2.0) are projected to occur approximately twice as often as in the baseline period. The mid-century period (2041–2070) already exhibits notable shifts toward drier conditions, with further intensification in the late-century period.

Table 2: Overall summary of the results

Parameters	Baseline (1994–2023)	RCP4.5 (2041–2070)	RCP8.5 (2071–2100)
Avg. Annual Temperature (°C)	27.1	28.8–29.2	30.1–31.2
Total Annual Precipitation (mm)	1,168.4	±5% change	-2 to -8%
Avg. SPI-12 Value	-0.35	-0.65	-1.10
Drought Frequency (per decade)	3–4 events	6–7 events	8–9 events

3.4 Drought Severity Trends under Baseline and Projected Scenarios

Drought characteristics were analyzed using SPI-12, RCP4.5, and RCP8.5 showing increasing events in terms of frequency and severity across the study area. Figure 4 clearly shows the results for different drought categorizes (i.e., moderate, severe, and extreme). The most common drought events were 'moderate' under historical baseline period; while under RCP4.5, there is an evident increase in severe droughts whereas under RCP8.5, both severe and extreme drought events were clearly observed. This upward trend shows that there is an increasing risk of drought occurrence in Northeast Thailand in the future in frequency as well as severity. These results are also supported by the previous works showing increased evapotranspiration as a result of rising temperatures [22] and [38]. Therefore, proactive drought strategies are required in the region.

The summary comparing key climatic and drought-related parameters for the baseline period (1994–2023) with mid- and late-century projections under RCP4.5 and RCP8.5 scenarios is given in Table 2. The results clearly indicate a warming trend under both scenarios, with higher temperature increases under RCP8.5. Precipitation projections show variability, with minor changes under RCP4.5 and a declining tendency under RCP8.5. A progressive intensification in long-term moisture deficits was noted based on average SPI-12 values. It is important to note that SPI values are standardized based on the historical reference period; however, when summarized across selected stations and aggregated time periods, small deviations from zero may occur. These deviations may be more pronounced when applied to projected climate data, reflecting shifts in precipitation patterns. Furthermore, drought frequency also increases notably, from 3–4 events per decade in the baseline to 6–7 events under RCP4.5 and 8–9 events under RCP8.5, indicating a tendency toward more frequent and prolonged droughts in the future. The ±5% change represents the relative percentage deviation of projected values compared to the baseline (1994–2023) mean, indicating the magnitude of change under future scenarios.

4. Discussions

This research enhances the probabilistic approach of the SPI by employing a Gamma distribution on precipitation and then normalizing the outcomes. This method allows for the creation of drought categories and reduces any potential for prejudice inherent in the direct approach to normalization. The work examines drought conditions and forecasts future events in Northeast Thailand using meteorological data, along with statistical analysis to interpret the results of General Circulation Models (GCMs). The level of drought is measured by the SPI. The discussion interprets the main results by placing them into the existing literature and underlining their implications for drought monitoring, climate response, and local policy formulation. Analysis of the SPI for the period 1994-2023 shows an increased occurrence and severity of droughts, particularly in the central and southeastern regions of Northeast Thailand. Recent studies also show a high level of drought event in the entire region of Northeast Thailand [21]. It showed that over 70% of the region at risk of moderate to severe drought. These results confirm regional assessments that drought risk is due to a combination of climatic and human factors in the region [2] and [6]. The observed drought patterns may also be influenced by large-scale climate processes that affect the hydroclimatic variability in the regions. For instance, changes in the monsoon patterns and the large-scale circulation processes such as the El Niño-Southern Oscillation (ENSO) may play an important role in modulating the rainfall patterns and intensities in Southeast Asia.

The spatial resolution and accuracy for climate projections were enhanced in GCM output via statistical downscaling with QM and MLR. The observed and downscaled datasets showed a close fit with R^2 of precipitation and temperature above 0.70, 0.85 respectively. These findings are consistent with recent study which applied hybrid machine leaning models (i.e., Random Forests (RF) and Support Vector (SVM) Regression) for hydrological drought prediction in the region [39]. The RF models are known for their strong classification performance.

However, using statistical techniques also led to solid results. These techniques have the added benefits of being easier to understand and more efficient in terms of computation. Climate projection in RCP4.5 and RCP8.5 showed a consistent increase in the mean temperature and a shift in rainfall distribution. Late-century projections were from 2071 to 2100. Also, a noticeable rise in drought frequency and severity could be observed under RCP8.5. Events for SPI value below -1.5, representing severe and extreme droughts, were expected to happen twice as often than during the baseline period. These results are largely in accordance with other CMIP-based studies conducted in Southeast Asia, which also observed an increase in frequency and variability of droughts under future climate change scenarios. Comparable drought conditions have been reported in previous studies conducted in Thailand and Southeast Asia [7][9][20] and [22]. These studies also indicate increasing drought risk under future climate change scenarios, particularly under higher-emission pathways. The findings of this study align with previous reports showing that proactive drought monitoring, climate-resilient agricultural practices, and adaptive water management strategies can significantly reduce recovery time and long-term socio-economic losses [40]. The central and southeastern parts of the country, including areas of Nongkai, Khon Kaen, and Ubon Ratchathani, have been identified as the most vulnerable areas due to their low water storage capacity because of the sandy soil and rain-fed agriculture. This study also confirmed that the most important factors in classifying droughts are those caused by climate, such as precipitation, and related climatic factors.

The mapping showed that the regions with high drought risk are closely related to areas where intensive agricultural activities are practiced with inadequate irrigation infrastructure [31]. Future projections show that drought occurrences will be more frequent, in line with other studies that have shown droughts to be recurrent in the region [2] and [9]. Sustainable certification systems and adaptive governance play a crucial role in strengthening agricultural resilience to climate risks [41]. It is important to note that the use of two GCMs in this analysis is limited in the sense that it does not take into account the entire spectrum of uncertainty in projections. This is because different models may have structural differences that affect projections in specific regions. However, the overall projections in this analysis regarding increased temperatures and variability in precipitation are consistent with the overall projections in regional climates. From a policy perspective, the findings from our work may be used as a basis for developing early warning systems based on SPI values such as SPI $\leq$ -1.0 for drought onset detection. In addition, the increased number of drought occurrences justifies the need to step up water resource management, such as storage and irrigation techniques. Moreover, resilient agricultural planning may be implemented to mitigate the effects of drought in Northeast Thailand by adjusting crop types and planting schedules. All these implications apply to both mid-century and late-century, indicating the continuous increase in drought risk under various climate scenarios.

5. Conclusion and Recommendations

SPI, using observed climate data and statistically downscaled outputs of GCMs, was applied to assess drought trends and future projections in Northeast Thailand. The combination of high-resolution historical data with projections from CanESM2 and CanESM5 under RCP4.5 and RCP8.5 scenarios was an effective way to show how drought frequency and severity have increased across the region. It identified short and long-term drought events. It has also brought into focus the drier conditions of the past 30 years, concurrent with rising temperatures and changed rainfall. Projected SPI values over the course of the mid- and late 21st century show that drought risk continues to increase in severity but pronounced under the RCP8.5 scenario. The projected rise in severity is primarily associated with changes in precipitation patterns. This may exacerbate the existing challenges in agriculture, water supply, and rural livelihoods. By this integrative approach, coarse-resolution GCM data can be turned into information useful at the regional scale. The process thus provides locally relevant information on risk due to drought, usable in regional climate change adaptation and resource management efforts. These findings highlight the increasing variability in precipitation patterns as a key driver of future drought risk in the region. This study contributes to the field through the use of statistical downscaling (QM-MLR) along with SPI to provide insights into drought variability in Northeast Thailand at a regional level.

This research indicates that current and future climate conditions are increasing drought as a threat to the study area. It highlights the importance of drought monitoring systems, adoptive farming techniques with changing climates, and flexible water management strategies. These results can be useful for improving drought preparedness and climate adaptation in Northeast Thailand. The projected increase in drought frequency and severity highlights the need to strengthen drought early-warning systems, promote climate-resilient crop selection, and improve water-storage and irrigation

efficiency at both regional and community levels. In practical terms, SPI thresholds (e.g., SPI ≤ −1.0) can be used by stakeholders for early warning, enabling timely decisions on water allocation, irrigation planning, and drought response measures. Future studies may emphasize hydrological modeling, assessments of socio-economic vulnerability, and the application of regional climate models to improve local drought projections and hence enable more-informed decision-making. These recommendations are based on the limitations identified in the current study, particularly regarding the GCM ensemble and the precipitation-based approach of SPI.

- Future studies may incorporate land use, crop type, and socio-economic factors to produce more holistic drought risk assessments for policy and planning.
- Combining SPI with indices like SPEI or PDSI, and linking with hydrological models (e.g., SWAT, HEC-HMS), can enhance understanding of drought impacts on water availability and ecosystem services.
- Using high-resolution RCMs from CORDEX-SEA and expanding GCM ensembles may improve the accuracy and resolution of future drought projections.
- Future studies may apply the Mann–Kendall non-parametric trend test and Sen's slope estimator to statistically evaluate the significance and magnitude of long-term drought trends.

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