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Normalized Difference Vegetation Index based Drought Prediction Model using Enhanced-Long Short-Term Memory Algorithm

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Abstract

One serious natural calamity that affects ecosystems, water supplies, and agriculture worldwide is drought. To lessen the consequences of drought, early detection of its circumstances is essential. By combining Normalized Difference Vegetation Index (NDVI) with Enhanced-Long Short-Term Memory (E-LSTM) algorithm for drought prediction model, this study offers an innovative approach for drought prediction. NDVI, a widely used satellite-derived vegetation index, is used to monitor vegetation health, which correlates with drought severity. The drought prediction model in this study uses E-LSTM's capacity to capture long-range dependencies to forecast drought conditions by examining temporal patterns of NDVI data over time with other related climate variables like temperature, rainfall and surface soil moisture, then results indicate its effectiveness in providing accurate early drought warnings. This research aims to fill the gap of issuing early warning for a slow onset type hazard like drought. The Root Mean Squared Error (RMSE) of 0.0571 is used to evaluate the model's performance.

Keywords: *Drought Prediction, Enhanced Long Short-Term Memory (E-LSTM), Normalized Difference Vegetation Index (NDVI), Remote Sensing, Machine Learning.*

1 Introduction

A frequent natural calamity, drought has a major impact on environmental health, water availability, and agricultural output [1]. Due to its complexity, slow appearance, lack of a clear commencement, and dependence on multiple factors, drought is challenging to forecast and measure. As a result, the severity and frequency of droughts differ over time and space [2]. In order to parameterize drought, different meteorological and land surface characteristics are considered in drought research [3]. To lessen the effects of drought, especially in areas where agriculture is the main economic driver, early warning is crucial [4]. When evaluating drought conditions, vegetation health measures like the Normalized Difference Vegetation Index (NDVI) have shown themselves to be reliable agents. The NDVI is a satellite-derived indicator that measures the health and density of vegetative cover, both of which are directly impacted by the availability of moisture [5]. This study

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employs NDVI data in time-series to model and predict drought conditions through Enhanced-Long Short-Term Memory (E-LSTM) networks, a variant of Recurrent Neural Networks (RNN). A complex method of predicting drought conditions is an NDVI-based Drought Prediction Model trained with E-LSTM that incorporates weather-related variables like temperature, rainfall, and surface soil moisture. Using the temporal learning capabilities of E-LSTM networks, this methodology takes advantage of the strengths of the main meteorological and hydrological drivers of drought as well as vegetation response (as measured by NDVI). Effective drought prediction is thus critical for mitigating the negative repercussions of droughts and fostering long-term resilience in drought-prone areas. As NDVI prediction can be contributed to forecast drought for early warning, informed decision-making tools, and real-time monitoring, the result of this research plays a significant role in enhancing various essential elements of drought management and resilience.

This paper is organized as following. A literature review of the related work will be described in Section 2 to study the existing research works on applying satellite-based indicator for detecting drought condition and prediction to issue early warning for drought condition in applying E-LSTM. Materials and methods applied of the research work will be appeared as Section 3. The results from the research will present as Section 4. Lastly, the results will be interpreted and the research's practical implications will be discussed in section 5. The paper will conclude with the outlooks for future work to extend the accuracy of the prediction model and improvement to be applicable in the real-world.

2 Related Work

With the normalized difference vegetation index, or NDVI, changes in the region's vegetation cover and the trend of crop-related drought occurrence can be investigated [6]. NDVI is mainly used to define the area of drought and desertification as a way to monitor drought and NDVI can be extracted from satellite images [7]. In order to ensure sustainable food production, NDVI is crucial because it enables farmers to monitor crop wellness and locate areas where concern. Furthermore, NDVI is a crucial component of studies for climate change and supports researchers in comprehending how growth of plant and yield are impacted by environmental changes because vegetation is extremely prone to changes in the seasons and climate [8]. NDVI can be used to monitor drought, but it is insufficient to provide early warning since impact-based forecasting and early warning are required to obtain more current as well as historical information. Time and scale affect the connection between NDVI and climate parameters. Globally, temperature has a notable effect on the NDVI [9]. In regional scale, it was occurred that the precipitation was the main factor for influencing to NDVI [10]. A key factor in agricultural performance is the amount of moisture in the soil, which also controls how solar energy is divided into sensible and latent energy and how precipitation is divided into runoff and infiltration [11]. A correlation exists between soil moisture and NDVI because soil moisture is important for plant growth. Low soil moisture can cause stress and unhealthy in plants, which can lower NDVI levels. Consequently, NDVI can be applied to track content in soil moisture and identified regions that are under drought stress [12]. Remote sensing satellites that record NDVI with a spatial resolution of 0.03 km to 8 km include the Landsat series, the Advanced Very High-Resolution Radiometer (AVHRR), and the Moderate Resolution Imaging Spectroradiometer (MODIS) [13][14][15]. Among these satellites, satellite images acquired by the series of Landsat satellite are widely used. Since 1972, the Landsat satellites have been gathering information about the Earth's surface. Landsat is a useful tool for determining NDVI and researching vegetation dynamics due to its suitable moderate spatial resolution, spectral bands, long-term data record, and free availability. Even though other satellites offer advantages, Landsat is still essential for a lot of applications regarding vegetation.

One of the most important instruments on NASA's Terra & Aqua satellites is the MODIS (Moderate-Resolution-Imaging-Spectroradiometer). MODIS uses various spectral bands, including some in the thermal infrared spectrum, to estimate Earth's radiance. LST, or the Earth's surface temperature, is calculated using these observations. MODIS offers high temporal frequency (a maximum of four times every day) as well as a variety of spatial resolutions (between 1 and 6 km) for LST data [16]. MODIS LST is widely applied for the area of the agriculture monitoring and drought monitoring because of its high temporal resolution, wide coverage, and multiple thermal bands [17].

A popular rainfall dataset in scientific research, especially in areas like hydrology, agriculture, and climate studies, is CHIRPS (Climate-Hazards-Group-InfraRed-Precipitation with Stations) because of its high resolution, long time span, and global coverage. Particularly in areas with few ground-based observations, CHIRPS data is essential for detecting and tracking drought conditions [18]. CHIRPS data is exceptionally good at monitoring monthly precipitation and is appropriate for determining drought [19]. Monthly CHIRPS data can demonstrate to track the rainy and dry seasons by forecasting for onset and withdraw of rainy season because it can provide for the understanding of rainfall patterns [20].

The Soil Moisture Active Passive (SMAP) project was initiated by NASA in 2015, since then, it has produced useful surface soil moisture (SSM) data that has been utilized extensively in a wide range of scientific fields. SMAP is a crucial tool for comprehending Earth's hydrological processes and how they interact with other systems because of its high resolution and nearly worldwide coverage, which enable the monitoring of SSM with unprecedented accuracy. The primary causes of drought are a lack of precipitation, a lessening in soil moisture, and an increase in temperature. Additionally, several studies demonstrated the effectiveness of the SMAP soil moisture in tracking agricultural drought and weather conditions. In order to detect drought, SSM demonstrated a dependable and anticipated response by gathering data on seasonal variations in evapotranspiration, land surface temperature, and precipitation [21]. Analyzing the normalized differential vegetation index's (NDVI) lagged correlation agreement with soil moisture, which can be helpful in providing vital evidence on drought in agriculture in worldwide and support this more focused, comprehensive method to global monitoring and forecasting in agriculture, is how the system's accuracy is determined [22]. Because soil moisture shortages can result in agricultural and hydrological droughts, SMAP data helps in the identification and monitoring of drought conditions. It performed reasonably well and had an adequate level of accuracy when it came to tracking drought in a particular area [24].

Recurrent neural networks (RNNs) of LSTM (Long Short-Term Memory) network type introduced by Hochreiter and Schmidhuber in 1997, are especially well-suited for time series forecasting tasks, such as weather forecasting. LSTMs can overcome vanishing gradient problem occurred in the traditional RNNs through a specialized architecture with "gates" that regulate the flow of information. These gates enable the network to identify long-term trends in the data by selectively remembering or forgetting historical information. LSTM networks have been demonstrated effective in a variety of weather forecasting applications. LSTM models can reliably anticipate temperature changes on a variety of time frames, ranging from long-term seasonal forecasts to short-term hourly forecasts [25]. Moreover, the ability of LSTM networks to forecast precipitation types and amounts, such as rainfall, hail and snowfall, is essential for managing resources of water and forecasting floods [26]. LSTM networks can be used to predict the frequency and intensity of extreme weather events like heatwaves, droughts, and storms, which can assist in disaster preparedness and mitigation [27].

The capacity of LSTM to learn time-dependent hydrological processes allowed it to surpass Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Networks (ANNs). Temporal relationships in time-series data are essential for comprehending drought development, but they are not naturally captured by the majority of conventional machine learning models, such as RF SVM, and ANNs [28]. Traditional machine learning models need manual creation of lagged variables (such as past temperature or rainfall), which is time-consuming and frequently suboptimal, in contrast to LSTM, which automatically learns temporal patterns [29]. When correlations between variables and drought indices vary over time, SVMs and decision trees frequently perform poorly in terms of generalization, even if some models (such as ANN) can manage nonlinearity. It is found that RF and SVM were less flexible when it came to capturing dynamic drought evolution [30].

3 Problem Formulations or Methodology

3.1 Data Collection

The collecting of data is a fundamental stage in creating an accurate and dependable drought prediction model, particularly when utilizing remote sensing technology. This research aims to predict the NDVI value for drought early warning using LSTM of machine learning algorithm. To create a reliable LSTM-based drought prediction model, we used the Google Earth Engine (GEE) platform to collect multi-source satellite time-series data. Four major datasets were used in this study: Landsat 8 NDVI (LC08/C02/T1_TOA), CHIRPS rainfall estimations, MODIS Land Surface Temperature (LST), and SMAP Surface Soil Moisture.

3.1.1 NDVI from Landsat 8

In order to detect drought conditions, NDVI from Landsat 8 was utilized which can indicate vegetation stress caused by drought. Landsat-8 imagery's Normalized Difference Vegetation Index (NDVI), which has a great spatial resolution and spectral capabilities, makes it an effective tool for identifying and tracking drought situations. The red and near-infrared (NIR) bands are utilized to determine the NDVI, which is a trustworthy measure of the health and vigor of vegetation. The 30-meter-resolution data provided by Landsat-8's Operational Land Imager (OLI) makes it particularly useful for in-depth local and regional drought evaluations. With its 30-meter spatial resolution, Landsat 8 provides a good balance between coverage and detail. Because of its high spatial resolution, long-term data consistency, and demonstrated sensitivity to vegetative stress, Landsat-8 NDVI is an essential tool for identifying and evaluating the effects of drought. It helps with agricultural, water resource management, and environmental preservation by enabling prompt responses to drought situations through integration with decision-support systems. The NDVI is calculated by the following equation (1) and is depends on variations in electromagnetic spectrum's red and near-infrared regions:

$$NDVI = (NIR - Red) / (NIR + Red) \tag{1}$$

where the words Red and NIR, respectively, represent the observations of spectral reflectance in the visible red and near-infrared bands. The NDVI scale has values between -1 and 1. Clouds and water are usually represented by negative values, whereas bare earth is represented by positive values near zero. Larger amounts of vegetation are indicated by higher positive NDVI values, ranging from thin vegetation (0.1~0.5) to dense green vegetation (0.6 and above) [22]. The calculated observed NDVI values for the area of interest are described at Table 1.

Table 1: Observed NDVI values from Landsat-8

NDVI	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Jan	0.30	0.37	0.43	0.39	0.40	0.29	0.34	0.39	0.42	0.48
Feb	0.29	0.25	0.34	0.33	0.33	0.30	0.29	0.36	0.32	0.42
Mar	0.23	0.22	0.26	0.25	0.22	0.25	0.18	0.28	0.21	0.32
Apr	0.19	0.24	0.27	0.27	0.24	0.23	0.24	0.34	0.27	0.27
May	0.25	0.26	0.32	0.26	0.28	0.17	0.25	0.25	0.38	0.24
Jun	0.30	0.20	0.24	0.24	0.24	0.26	0.23	0.26	0.28	0.30
Jul	0.13	0.25	0.26	0.25	0.24	0.33	0.23	0.27	0.36	0.28
Aug	0.26	0.13	0.28	0.24	0.19	0.26	0.25	0.42	0.23	0.26
Sep	0.26	0.29	0.31	0.46	0.35	0.32	0.34	0.41	0.33	0.32
Oct	0.42	0.36	0.33	0.23	0.48	0.40	0.35	0.37	0.47	0.43
Nov	0.50	0.47	0.55	0.52	0.52	0.60	0.49	0.52	0.52	0.65
Dec	0.41	0.52	0.47	0.44	0.52	0.43	0.50	0.44	0.44	0.55

The NDVI scale has values between -1 and 1. Clouds and water are usually represented by negative values, whereas bare earth is represented by positive values near zero. Larger amounts of vegetation are indicated by higher positive NDVI values, ranging from thin vegetation (0.1~0.5) to dense green vegetation (0.6 and above) [27]. The classification for the NDVI is presented as in Table 2.

Table 2: Classification of NDVI

Ranges of NDVI Values	**Severity Level**	**Vegetation Status**
Between -1 and 0	Severe	Dead Plant, Object or Water Body
Between 0 and 0.33	Moderate	Unhealthy plants
Between 0.33 and 0.66	Mild	Moderately healthy plants
Between 0.66 and 1	No Drought	Very healthy plants

3.1.2 Rainfall from CHIRPS

Rainfall data of Climate-Hazards-Group-InfraRed-Precipitation-with-Stations (CHIRPS) is ideal for drought prediction because of a number of features that correspond to the particular requirements of drought forecasting and monitoring. It can be used in a variety of areas, even those with poor rain gauge networks, because of its quasi-global coverage (50°S to 50°N latitude). It can record very fine spatial variations in rainfall patterns with a 0.05° spatial resolution, or around 5 km. Due to its wide coverage, CHIRPS enable reliable monitoring in areas that are frequently affected by droughts. The CHIRPS monthly rainfall data is appropriate for analyzing drought conditions. The monthly rainfall data were also extracted for 10 years of the same temporal resolution with Landsat-8 NDVI.

3.1.3 MODIS Temperature

Data from MODIS (Moderate-Resolution-Imaging-Spectroradiometer), LST (Land Surface Temperature) is useful for forecasting drought. Near-global coverage from MODIS makes it possible to monitor drought across large areas. Its high temporal frequency (observations made several times a day) makes it possible to detect the quick changes in LST, which is essential for tracking the beginning and development of drought. This is particularly useful in places where there aren't enough ground-based weather stations. Monthly temperature data was collected for ten years at the same temporal resolution.

3.1.4 Surface soil moisture from SMAP

Soil moisture data, particularly from missions like SMAP (Soil Moisture Active Passive), is exceptionally valuable for drought prediction due to its direct and immediate relationship with drought conditions. SMAP provides global coverage with a relatively high temporal resolution (2-3 days), allowing for frequent monitoring of soil moisture changes. The data is available at various spatial resolutions, suitable for regional and local-scale drought monitoring. Ten years of monthly soil moisture data were gathered with the same temporal resolution.

The parameters using in this research were collected by using the Google Earth Engine (GEE). GEE is a robust cloud-based tool for visualizing and analyzing geographic data. It offers a vast collection of satellite imagery and other geospatial datasets, as well as tools for large-scale processing and analysis. The study area was chosen the Central Dry Zone in Myanmar based on its vulnerability to drought, and the time frame examined was 2015–2024.

3.2 Data pre-processing and Data splitting

In order to ensure that satellite data is reliable, consistent, and appropriate for additional analysis, data preparation is an essential step after data acquisition. Preprocessing data is essential for E-LSTM algorithm for drought prediction to produce reliable and accurate time series prediction results. Missing data points were handled through interpolation methods, ensuring continuous time-series data for E-LSTM modeling. Different temporal resolutions are present in the datasets used in this research. To ensure consistent and uniform temporal resolutions for all datasets, all datasets were transformed into monthly datasets by taking the mean values respectively.

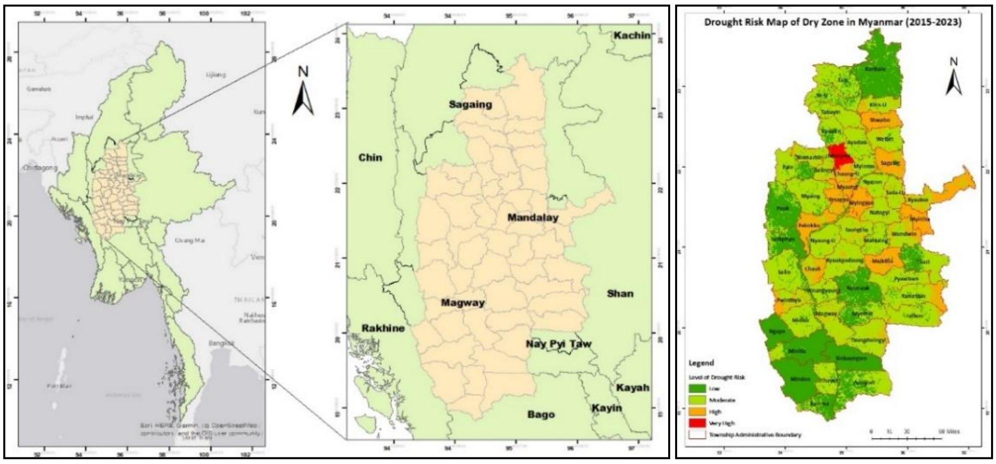
Training and test sets have been created from this collected data, respectively. The training set covered the period from January 2015 to December 2021, and the testing set covered the term of January 2022 to December 2024.

3.3 Methodology

After collecting and cleaning for the preparation of the necessary dataset for drought prediction model, an E-LSTM neural network-based drought prediction model designed especially for Myanmar's Central Dry Zone. This area is especially susceptible to the effects of drought and is distinguished by its distinct dry and rainy seasons. In order to forecast future drought conditions, the model will make use of historical remote sensing data (Landsat 8 NDVI, CHIRPS Rainfall, MODIS Land Surface Temperature, SMAP Surface Soil Moisture).

3.3.1 Study Area

The Dry Zone Greening Department claims that the central dry zone of Myanmar is more than 54,000 km in size and includes 15 districts (Kanblu, Kyaukse, Magway, Meiktila, Minbu, Monywa, Myingyan, Nyaung-U, Oke Ta Ra, Pakokku, Sagaing, Shwebo, Thayet, Yamethin, Yinmarbin) with 54 townships distributed throughout the four regions of Magway, Mandalay, Sagaing (Lower) and Nay Pyi Taw. It is home to about 25% of the country's population. Compared to other regions of the country, the research area received less rainfall due to the Rakhine mountain ranges located along the west of the study area, which can cause a weakening of the southwest monsoon onset. The temperature is extremely high; in March, April, and May, it used to rise above 40 degrees Celsius. Communities in those areas are more vulnerable to drought, which may harm food security, resulting of variations in land use and land cover, which also contribute to aridness by combining high temperatures and low rainfall. The research's study area and drought risk level map are depicted in Fig 1(a) and (b), respectively.



(a) (b)

Fig 1. Study Area

The necessary parameters, namely monthly Rainfall, temperature, surface soil moisture, and NDVI, for predicting NDVI for the upcoming month in this research were acquired from the respective satellites within the same timeframe. Apart from the rainfall, temperature and surface soil moisture, NDVI values are calculated by using the formula described in above equation (1).

After collection the necessary data, data cleaning, handling the missing values, performing the normalization process as the data pre-processing. Then creating the drought database to get the historical drought record for the study area by using the acquired NDVI data from the past in order to detect the drought conditions of the study area. Finding correlation between among these four parameters for every months of the study period was also performed for the understanding how individual input features correlate with the target variable can help in feature selection for E-LSTM drought prediction model.

3.3.2 Model Development

The Enhanced-LSTM (E-LSTM) model architecture drought prediction consists of multiple layers of LSTM cells, which are intended to identify patterns that persist in the NDVI data in time-series. In this research, multiple time-series data of four input data were fed to the E-LSTM as the multivariate time-series to forecast the NDVI value for the upcoming month to predict drought.

The inputs to the E-LSTM model are sequences of past monthly data for Rainfall, Temperature, Surface Soil Moisture and NDVI values for 10 years, and the output is a prediction of future drought severity. Depending on the forecasted NDVI values as referenced in Table 2, drought severity was categorized into different levels such as “no drought”, “mild drought”, “moderate drought” and “severe drought”. The workflow for the drought prediction model is as described in Fig 2.

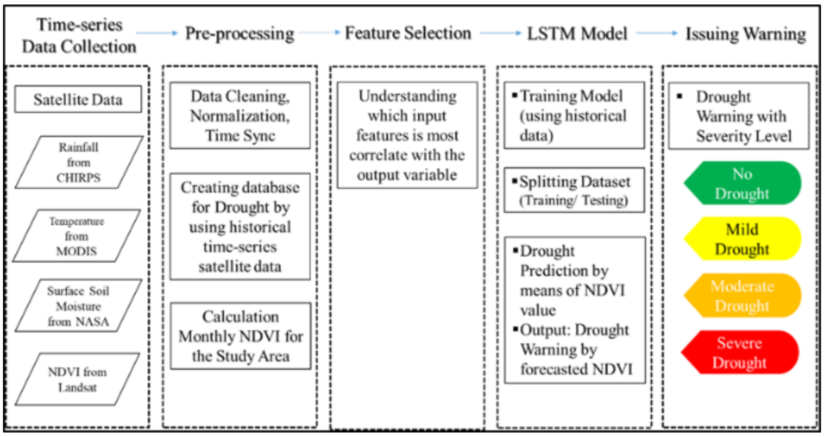


Fig 2. Drought Prediction Model

In this study, the model was employed two stacked E-LSTM layers with 64 hidden units, each to capture complicated temporal relationships between these input values. In order to maximize computing efficiency and gradient stability, training of the model was conducted using a batch size of 16. The model was also trained for 100 epochs to allow the network to fine-tune its weights and reduce prediction errors, ensuring enough learning and convergence. In order to provide precise forecasts of the desired outcome, this configuration attempts to find a stability between complexity of model and computational efficiency. The Drought Prediction Model equipped with the E-LSTM by using timeseries of rainfall, temperature, soil moisture and NDVI was deployed and trained. The mathematical expression for E-LSTM for drought prediction model can be expressed as in Equation (2):

$$N_i = [\sigma\,(v_i^t\, R_t \pm b_i), \sigma\,(v_i^t\, T_t \pm b_i), \sigma\,(v_i^t\, S_t \pm b_i), \sigma\,(v_i^t\, N_t \pm b_i)]^R \qquad (2)$$

where N_i - NDVI prediction for Drought,

R_t - Rainfall of ‘t’th month

T_t - Temperture of ‘t’th month

S_t - Surface Soil Moisture of ‘t’th month

N_t - NDVI value of ‘t’th month

v_i^t - validation for overfitting of previous time

b_i - base of ‘i’th -1 trained value

All the monthly input variables to the E-LSTM were applied trainable weight by softmax as the relative significance of input features (rainfall, temperature, soil moisture, and NDVI) for drought prediction is dynamically quantified by trainable weights in LSTM models. This enables the model to suppress noisy or irrelevant features (e.g., ignore temperature in winter-dominated droughts), reveal physical relationships through weight magnitudes (interpretability), and adjust to regional climate patterns (e.g., prioritise NDVI in arid regions vs. rainfall in humid zones). In doing so, the standard LSTM was enhanced all the time being depending on the seasonal changes with weight magnitudes to the input features and the prediction accuracy of the model is getting higher.

A variety of time spans were used to train the model:12-months, 24-months, 36-months, 48-months, 60-months, 72-months, 84-months, 96-months, 108-months and 120-months, respectively. A validation set consisting of 30% of the trained data was utilised to track the model's performance accuracy. After training the Drought Prediction Model with different time spans, a drought database for the study area was created as shown in Table 3. The predicted NDVI for drought can be seen as the last row in the database, and can also be known whether it was predicted or observed by the control Boolean variable named “isPrediction.” If this Boolean variable value “FALSE” means that this data is not predicted, otherwise it is predicted.

Table 3: A Drought Database for the Study Area

date	temperature	rainfall	soil_moisture	drought_score	createdAt	isPrediction	__v
2015-01	36.54	0.12	30.33	0.3	2025-05-15T11:34:29.978Z	FALSE	0
2015-02	41.25	4.39	20.34	0.29	2025-05-15T11:34:29.980Z	FALSE	0
2015-03	48.45	3.59	26.11	0.23	2025-05-15T11:34:29.982Z	FALSE	0
2015-04	53.58	17.19	28.37	0.19	2025-05-15T11:34:29.983Z	FALSE	0
2015-05	46.67	90.66	66.25	0.25	2025-05-15T11:34:29.985Z	FALSE	0
2015-06	42.35	123.8	100.3	0.3	2025-05-15T11:34:29.986Z	FALSE	0
2015-07	36.21	360.49	213.24	0.13	2025-05-15T11:34:29.988Z	FALSE	0
2015-08	27.41	160.23	225.66	0.26	2025-05-15T11:34:29.989Z	FALSE	0
2015-09	39.51	181.4	217.8	0.26	2025-05-15T11:34:29.991Z	FALSE	0
2015-10	37.03	157.85	211.49	0.42	2025-05-15T11:34:29.992Z	FALSE	0
2015-11	37.09	45.92	141.29	0.5	2025-05-15T11:34:29.995Z	FALSE	0
2015-12	35.47	2.56	70.28	0.41	2025-05-15T11:34:29.997Z	FALSE	0
2016-01	35.29	0.21	33.75	0.37	2025-05-15T11:34:29.998Z	FALSE	0
2016-02	27.55	4.5	26.21	0.25	2025-05-15T11:34:30.000Z	FALSE	0
2016-03	47.37	5.07	22.27	0.24336845	2025-05-15T11:34:30.002Z	TRUE	

4 Model Evaluation

The NDVI prediction results for every January of the study period from 2015 to 2024 by the E-LSTM drought prediction model. The evaluation for the model was performed on the results for every January, as the weather condition is not too wet or dry, and it is a favorable condition to assess the vegetation condition, especially for the study area in this research. It is significant that for most years, the predicted NDVI values closely follow observed trends. In contrast, 2020 shows a notable discrepancy, with an actual value of 0.29 compared to a forecasted value of 0.4247. It was an outlier for 2020 and possibly due to environmental or anthropogenic anomalies (e.g., drought, land-use change, global pandemic effects. To assess the predictive accuracy of the E-LSTM model, common performance metric of Root Mean Squared Error (RMSE) was applied that is the standard deviation of the prediction error. It is calculated by taking the square root of the total of the square differences between the actual value (X) and the anticipated value (Y). The mathematical presentation for RMSE is in Equation (3).

$$RMSE = \frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2 \qquad (3)$$

It is evident that, with the exception of January 2020, the results for each January during the ten-year study period of 2015-2024 are quite comparable with the observed NDVI values as shown in Figure 3.

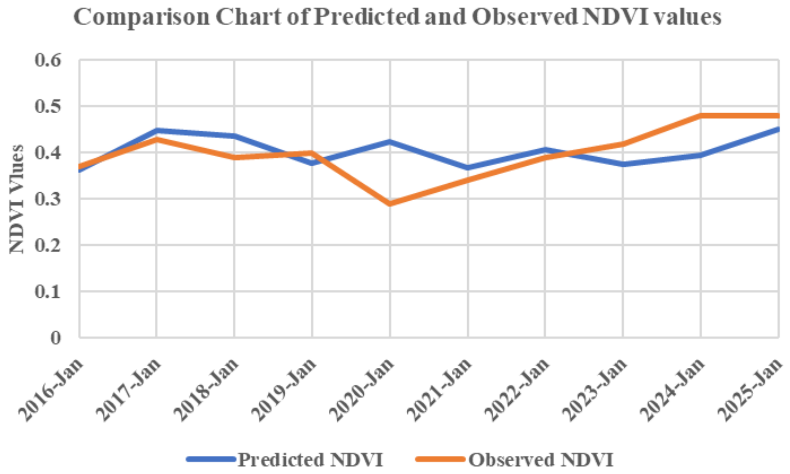


Fig 3. Comparison Chart for Predicted and Observed NDVI values

It was because the year 2020 had unprecedented meteorological conditions, such as record temperatures, wildfires, and ocean heat, according to the World Meteorological Organization. The model captures the majority of the wider drought patterns and offers a reliable foundation for NDVI estimates across time. The predicted NDVI values by E-LSTM was also compared with the values by the standard LSTM with same input parameters for same time span as in Table 4 and it is found that the RMSE for the standard LSTM was 0.104.

Table 4: Comparison of predicted NDVI values by Standard and Enhanced LSTMs

	Predicted NDVI (LSTM)	**Predicted NDVI (E-LSTM)**	**Observed NDVI**
2016-Jan	0.406	0.363	0.37
2017-Jan	0.516	0.449	0.43
2018-Jan	0.466	0.437	0.39
2019-Jan	0.438	0.377	0.4
2020-Jan	0.516	0.425	0.29
2021-Jan	0.429	0.369	0.34
2022-Jan	0.500	0.408	0.39
2023-Jan	0.440	0.374	0.42
2024-Jan	0.440	0.395	0.48
2025-Jan	0.550	0.450	0.48

5. Results and Discussion

A wide range of drought-related variables obtained from the remote sensing datasets can be fed into deep learning or machine learning models like the E-LSTM to increase the predictive accuracy of the models and teach them complicated, non-linear correlations. The model was trained with different time spans, and the predicted NDVI values were close to the observed NDVI values over time. The model can capture multiple facets of drought development thanks to the synergy between diverse indicators, producing predictions that are more accurate and dependable. It can be said that the predicted NDVI values for most of years closely match the trends that have been noticed. Over the course of the decade, the anticipated NDVI exhibits comparatively consistent behavior. Moreover, the Drought Risk Mapping Tool can be provided to decision-makers in the disaster management and agricultural sectors to ensure the prevention and mitigation of drought risk measures based on the results from research work as shown in Fig 4. This mapping tool can provide not only a prediction of the NDVI value for the drought severity of the coming month but also access to the historical records of the drought severity from its drought database to perform the necessary analysis by the decision makers.

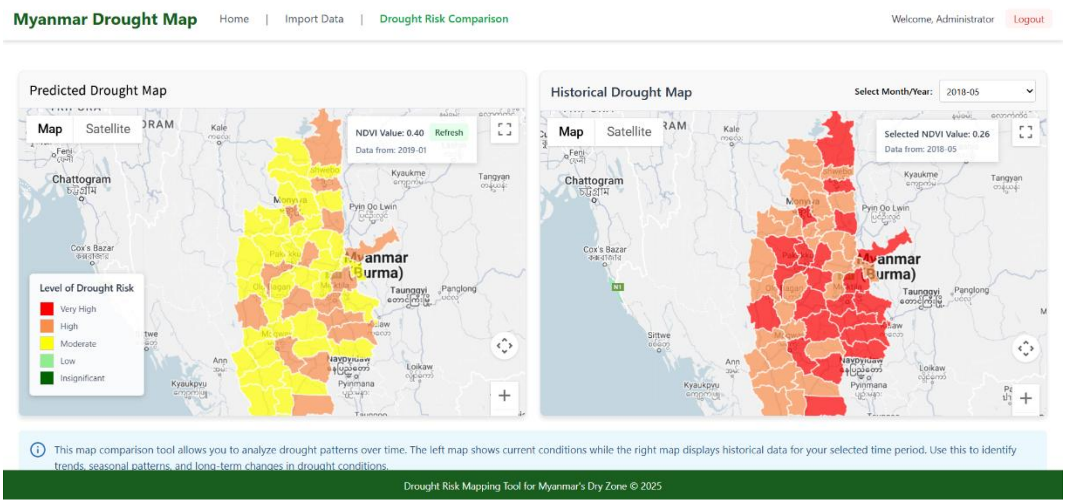


Fig 4. Drought Risk Mapping Tool for Study Area

The E-LSTM model demonstrated superior performance in predicting NDVI values, with an RMSE of 0.059. Long-term patterns and variations in NDVI data, which correlate to different phases of drought development, were taken by the model. The E-LSTM model showed a substantially lower error rate than conventional techniques, especially for medium and severe drought situations. Predicted and observed drought conditions for different time periods were visually compared, and the accuracy was great, particularly in areas that had protracted dry spells, mainly in the central parts of the research region.
We also carried out a sensitivity analysis to determine how different hyperparameters affected the model's performance. It was discovered that two crucial elements in improving the model's prediction power were the ideal number of E-LSTM units and the learning rate.

6. Conclusion

The integration of Landsat-8 for detailed vegetation monitoring, MODIS for frequent vegetation and temperature updates, CHIRPS for accurate rainfall estimates in a potentially data-sparse region, and SMAP for vital soil moisture information can get better accuracy and efficacy of the models for drought prediction in the study area for this research, the

Central Dry Zone of Myanmar, which is susceptible to agricultural drought and experiences distinct dry seasons. This will support improved agricultural planning and water resource management.

This study shows how E-LSTM networks and NDVI data together with climate variables can be combined to accurately predict drought. In predicting drought conditions, the model in this research performs better than conventional statistical and machine learning techniques, offering a reliable instrument for early warning systems. To further improve the model's accuracy and resilience, future research will concentrate on incorporating other environmental factors like land-use land cover and evapotranspiration. Furthermore, real-time drought monitoring and prediction are made possible by the operational integration of real-time satellite data into the system. In conclusion, the use of more than one parameter in E-LSTM models for drought prediction improves the precision, resilience, and generalizability of the forecasts; it also better captures complex relationships and temporal dynamics; and it yields more reliable early warnings and observations. A comprehensive awareness of drought conditions is made possible by this multi-parameter approach, which enhances readiness and decision-making.

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