SPI-Based Drought Forecasting in Maharashtra Using LSTM: A Decadal Analysis (2014-2024)

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Abstract— **The study, *Maharashtra Drought Analysis Data*, utilizes the LSTM (Long Short-Term Memory) model to predict climate variables such as the Standardized Precipitation Index (SPI) to enhance drought forecasting in Maharashtra. The methodology begins with meticulous data collection from reliable meteorological sources, focusing on the dataset, which contains records of precipitation, and SPI across various timeframes (1-month to 12-month). This database spans several years, capturing temporal climate variability for long-term trend analysis. Data are preprocessed to handle missing values, outliers, and inconsistencies to ensure integrity and reliability of time series analysis. Exploratory Data Analysis (EDA) uses visualization techniques to identify trends, seasonal, and long-term climate variability to comprehend SPI behavior. Joint temperature charts and line plots highlight inter-annual and seasonal climate trends. LSTM shows a better prediction performance of 94.72% in comparison to other time series models, representing complex temporal relationships with precision. The study enhances decision-making and forecasting drought, with application in agriculture, water resources management, and environmental monitoring in Maharashtra. The study demonstrates the strength of LSTM to climate forecasting, providing valuable information for overcoming the effect of drought, minimizing the optimal resource utilization, and achieving sustainable development.**

Keywords — Drought prediction, Drought analysis, Remote sensing, Standardized Precipitation Index (SPI), Precipitation trends.

I. INTRODUCTION

Climate change has emerged as one of the largest 21st-century challenges with long-term consequences for environmental stability, biodiversity, food security, and human livelihoods worldwide. Climate variability is most debilitating in already environmentally challenged regions, such as Maharashtra, a geographically and climatically diverse state in western India. Maharashtra is plagued by recurring extreme weather events, such as droughts, which are further aggravated by irregular monsoon patterns, uncertain precipitation levels, and relentlessly rising temperatures. Climatic changes threaten the socio-economic stability of the region, particularly because agriculture—the primary livelihood of millions—is extremely dependent on monsoonal rains. Uncertain rains and water scarcity have led to repeated crop failures, economic uncertainty, and increased vulnerability of rural communities, and therefore these problems must be addressed using advanced analytical tools and forecasting capabilities. Employing scientific forecasting techniques for predicting droughts, quantifying their severity, and implementing measures for effective mitigation is needed for enhancing Maharashtra's resilience to climate change and for protecting its socio-economic fabric[2].

Droughts, or extended periods of subnormal precipitation, have deep and lasting implications beyond transient shortage of water. They interrupt farm cycles, diminish yields of crops, and subject tremendous strain to water resources, which is brought over into economic loss and social tension. Maharashtra's reliance upon the monsoon cycle for water and agriculture use further intensifies the effects of rainfall fluctuation[1]. Maharashtra has experienced a gradual rise in the frequency and severity of drought incidents over the last three decades due to declining amounts of precipitation, irregular distribution of rainfall, and increased temperature. All these further increase the vulnerabilities of rain-fed agriculture, which constitutes a vast percentage of Maharashtra's cultivation habits. Farmers, who depend greatly on frequent and timely monsoon rains, often suffer from disastrous losses owing to extended dry spells or unseasonal weather conditions. The vulnerable situation calls for efficient forecasting systems that are able to effectively predict droughts so that appropriate action can be initiated to offset their impact. Successful drought forecasting systems have the capability to minimize agricultural losses, make water resources planning more logical, and support decision-making processes that help the region become climate-resilient[5][7].

Standardized Precipitation Index (SPI) is now an essential index of drought duration and severity. It quantifies precipitation anomalies on multi-timescales, providing insightful information about short-term, medium-term, and long-term components of drought. For Maharashtra, SPI-6 (six-month) and SPI-12 (twelve-month) are important since they indicate medium- and long-term deficits in precipitation with immediate policy ramifications for agricultural cycles and water management policy. Negative SPI-6 values reflect short-term water deficit, impacting irrigation requirements and short-term agriculture yields, whereas negative SPI-12 values reflect long-term drought impacts resulting in groundwater depletion, extended crop failure, and wider socio-economic consequences[4]. Time series analysis of SPI values provides data on trends and patterns of precipitation anomalies, providing a foundation for predictive modeling and facilitating effective resource management. With SPI values, the stakeholders can better predict drought risk and institute remedial interventions to mitigate their negative impacts on agriculture, water resources, and rural livelihoods[7].

The LSTM is one of the best methods for time series prediction of drought indicators such as SPI. Recurrent neural network (RNN) models of the LSTM type are capable of identifying long-term patterns in sequential data. LSTM is particularly helpful in forecasting precipitation anomalies and drought trends because, in contrast to other statistical models, it can learn intricate, non-linear patterns in climate data. By controlling the input flow, the memory cells that make up LSTM allow the model to capture crucial temporal correlations and eliminate extraneous noise. This feature enables LSTM to model intricate patterns in SPI-6 and SPI-12 values with very high accuracy, and it is hence a valuable tool in the projection of drought. Employing historical climate records, LSTM has the ability to predict short and long-term precipitation anomalies, and this can be used in planning for droughts and resource planning. It is a great alternative to conventional forecasting methods because of its capacity to analyze vast amounts of climatic data and reveal hidden patterns.

Besides its standalone applications, the power of LSTM can also be utilized extensively through its application along with other data-driven approaches for creating solutions to the increasing complexity of climate variability. For instance, hybrid models incorporating LSTM and attention techniques or convolutional neural networks (CNNs) can further enhance prediction accuracy through the focus of the most important features in the climate data sets. Additionally, through the utilization of multiple sources of varied data types, such as satellite imagery, soil moisture indices, and contemporaneous remote-sensing data, inputs to the model can be enhanced and it can provide forecasts at a higher level of accuracy. Such improved methodologies provide forecasts at the taluka or district level, enabling regional governments, farmers, and water resource departments to implement effective and targeted interventions. The development of such high-end frameworks is not only a necessity to manage the urgency of the drought problem but also to enhance long-term capacities against the largescale forces of climate change[8].

The value of accurate drought forecast extends beyond the planning of short-term resources, for it also plays a crucial role in long-term sustainability in Maharashtra's agri-socio-economic systems. Agriculture in the state, extremely susceptible to climatic fluctuation, depends upon reliable projections for optimal planting calendars, the efficient management of water resources, and minimizing the impact of crop damage. Additionally, effective drought forecasting informs policy decisions and resource management, enabling the government and the stakeholders to allocate the greatest exposures to target communities and areas. In addition to agriculture, drought forecasts can further inform water management for urban and industrial applications that are faced with increasing competition over limited water resources. By providing a scientific basis for decision-making, advanced projection models like LSTM enable the generation of adaptive capacity and the cultivation of resilience towards climate change[9].

Along with the short-term advantages of drought forecasting, the integration of data-driven approaches with sophisticated deep learning models like LSTM provides the possibility of future scalability and innovation. Sophisticated technologies like artificial intelligence (AI), big data, and hybrid deep learning models can be applied in conjunction with traditional forecasting techniques to identify sophisticated, non-linear patterns in climate time series. For example, by utilizing spatial and temporal interdependencies, LSTM can be integrated with CNNs or Transformer-based models to improve the accuracy and dependability of drought forecasts. These hybrid models can also be employed to combine other streams of data, like satellite images, soil moisture, and real-time remote sensing data, to enhance the spatio-temporal resolution of forecasts. By providing high-resolution forecasts at the taluka or district level, these new approaches can allow decision-makers to implement localized and targeted interventions, thereby maximizing the allocation of resources and minimizing the socio-economic impacts of droughts. With Maharashtra continuing to struggle with the effects of climatic variability, the use of an integrated and technology-driven framework towards drought prediction and management will be essential to ensure the state's environmental robustness and well-being of the people.

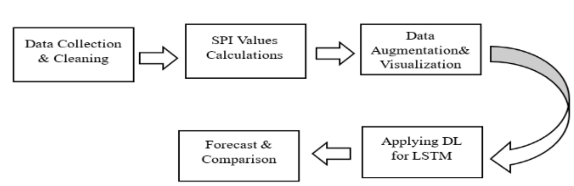
II. RELATED WORK

Drought forecasting has been comprehensively explored based on a large variety of statistical, machine learning, and deep learning models. Traditional statistical techniques such as Autoregressive Integrated Moving Average (ARIMA) and Multiple Linear Regression (MLR) have been extensively utilized for precipitation and SPI-based drought forecasting (Mishra & Desai, 2019). Although such models are efficient in identifying linear trends, they collapse when confronted with nonlinear climate variability, limiting their forecasting capability with long-term drought forecasting.

Since the advent of artificial intelligence, machine learning models like Support Vector Machines (SVMs), Decision Trees (DT), and Random Forest (RF) have been used to classify drought and predict its severity (Gupta et al., 2020). The models are more predictive in nature compared to traditional methods but lack the ability to detect sequential patterns of climate over a time horizon. To overcome this drawback, deep learning techniques like Recurrent Neural Networks (RNNs) and LSTM networks, have been utilized for time-series forecasting in climatology (Zhang et al., 2021).Previous studies have emphasized the potential of LSTM to capture long-range dependencies in climatological data and make it a potential candidate for drought forecasting. Xie et al. (2022) and Kumar & Singh (2023) confirmed that LSTM models outperform conventional statistical and machine learning models in forecasting the SPI values more accurately. Additionally, hybrid models incorporating LSTM and Convolutional Neural Networks (CNN-LSTM) or Attention Mechanisms have also proved to work effectively in boosting prediction efficiency (Wang et al., 2023).

For Maharashtra, earlier studies have examined drought trends using SPI and conventional statistical models (Deshpande et al., 2020). There is less work that has been performed on the application of deep learning for drought forecasting using SPI for the state of Maharashtra. This study fills this gap by using LSTM to forecast SPI values for the period 2014-2024 to improve early warning systems of drought and supply valuable information in water resources and agricultural planning in Maharashtra.

III. BLOCK DIAGRAM



The block diagram shows step by step approach to learn drought. It starts with Data Collection & Cleaning. This process gathers weather data like rainfall and temperature from weather stations, satellites, and historical records. To make sure the data is quality, we use methods like filling missing data, eliminating unusual numbers, and getting everything to line up.

Then there is SPI (Standardized Precipitation Index) Calculation. This applies mathematics to determine how abnormal the rainfall is across various time scales. SPI values assist us in classifying droughts according to severity, which allows us to identify droughts early. Data Augmentation & Visualization follows. Here, we decompose time information and generate new data points to improve our dataset. We also use images such as graphs and color maps to illustrate weather patterns and the evolution of droughts. Deep Learning Implementation with LSTM phase entails the learning of a LSTM network to identify long-term dependencies and also non-linear relationships from the climate data. Random Forest and XGBoost may also be combined with it to provide more accurate predictions.

At the Forecast & Comparison step, the model that has been trained provides forecasts for drought, and these forecasts are compared with performance metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The variance between forecast values and actual values is utilized to optimize the model for greater reliability.

IV. METHODOLOGY

Applications of the LSTM model's technique to predict climate variables, such as Standardized Precipitation Index (SPI) over time, is a methodical process that encompasses data collection, data cleaning, data visualization, and model application. All these processes are essential to make sure that the data is well prepared, cleaned, and analyzed to produce accurate predictions. This involves data collection, managing inconsistency, trend plotting, and future time series forecast of climate metrics with the application of LSTM. Below is a step-by-step description of the steps.

1. Data Collection

Data collection is the foundation of any predictive modeling exercise, particularly in climatology. The availability and integrity of the data directly affect the forecasting model's strength and dependability. In forecasting precipitation and SPI, a robust dataset guarantees models can detect temporal and spatial variation of climate variables, which are required to make effective forecasts. For this study, the dataset "nagpur_spi.csv" was employed, which contains daily weather data, some of the major variables being temperature (max and min), rainfall, and SPI values for different timescales (1-month, 3-month, 6-month, 9-month, and 12-month). The dataset contains data for several years, hence it is a broad historical foundation on which climate patterns could be assessed and future weather forecasts could be established.

2. Data Cleaning

Cleaning data is an essential preprocessing task in any machine learning or deep learning or data analysis pipeline. It removes inconsistencies, errors, and inaccuracy from the data, rendering it eligible for trustful analysis and model creation. For data sets that include Standardized Precipitation Index (SPI) and precipitation data, the cleaning process is particularly important since such data usually contain time-dependent values, missing records, or outliers due to collection errors or environmental extremes. The cleaning process involves:

Dealing with Missing Values: Applying interpolation methods like linear or spline interpolation to replace missing precipitation values.

Standardizing the Date Format: Ensuring all dates follow a consistent format (YYYY-MM-DD) and checking for gaps in time-series data.

Eliminating Duplicates: Eliminating duplicate records to preserve data integrity.

Outlier Handling and Detection: Application of statistical tools such as Interquartile Range (IQR) or Z-score testing to identify and handle outliers in precipitation and SPI values.

3. Data Preprocessing for LSTM

The data must be transformed into a suitable format for the LSTM model:

Feature Scaling: Scaled precipitation and SPI values by using Min-Max scaling to the range [0,1].

Time Series Reshaping: Transformation of the dataset into sequences for training the LSTM model. Sliding window method is employed in order to extract input-output pairs.

Dataset Splitting: Partitioning the dataset into training, validation, and test sets (e.g., 80-10-10 split).

4. LSTM Model Implementation

LSTM is a recurrent neural network (RNN) model that is highly effective in time-series prediction. The steps involved in implementation are:

Specifying the LSTM Architecture: Developing an LSTM model with stacked layers, i.e., input, hidden, and output layers.

Compiling the Model: Implementing an optimizer such as Adam and a loss function such as (MSE) Mean

Squared Error for training.

Model Training: Passing preprocessed data to the LSTM model and hyper parameter optimization to achieve maximum accuracy.

Model Accuracy Measurement: Measuring accuracy with statistics like RMSE , MAE and R-squared for testing accuracy.

Future Value Prediction: Using the learned model to forecast future SPI and precipitation values.

5. Model Performance Visualization

In order to test and examine the effectiveness of LSTM model:

Plotting Actual vs. Predicted Values: A comparison of LSTM predictions and actual climate values.

Graphing Loss Trends: Graphing loss curves to track training convergence.

Time-Series Decomposition: Breaking down seasonality and trend to help improve forecast precision.

By this method, the LSTM model effectively leverages past climate data to make accurate SPI and precipitation predictions, facilitating more informed climate decision-making.

V.LSTM MODEL ARCHITECTURE

LSTM network is a deep architecture of learning for time series prediction that is trustworthy. LSTM excels in learning long-term patterns and sequential data patterns and thus is best used for the prediction of future values from previous trends. LSTM networks surpass the constraints of conventional time-series models by incorporating memory cells as well as using the use of application of gating mechanisms (input, forget, and output gates) for controlling the input of information. What new information is to be remembered is defined by the input gate, what to forget by the forget gate, and how the final output is to be controlled in terms of cell state updated by the output gate. These enable LSTM to store helpful past information without facing problems such as vanishing gradients. In contrast to traditional statistical models, LSTM does not need manual stationarity transformations like differencing and can learn automatically non-linear patterns of time series. The model is made up of multiple layers of hidden components, each dealing with sequential relationships and learning abstract features of the data. By utilizing its ability to recall, LSTM is particularly capable of identifying trends, seasonality, and randomness within time series data and is thus an appropriate method for forecasting applications such as drought monitoring, financial prediction, and climate prediction.

1. LSTM Output Equation

The final output of the LSTM layer is computed as:

$$h_t = o_t \odot \tanh(C_t)$$

Where:

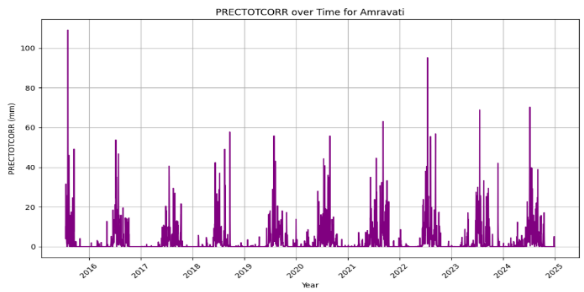
- h_t : Hidden state (LSTM output)
- o_t : Output gate activation
- $\tanh(C_t)$: Transformed cell state

2. LSTM Cell State Update Equation

LSTM employs a series of gates to manage information flow. The cell state update formula is:

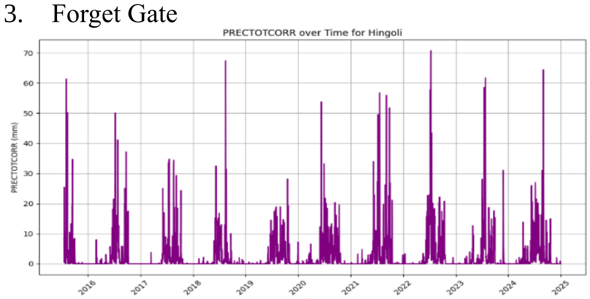
$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

Where:



- C_t : Present condition of the
- f_t : Ignore the activation of the gate.
- C_{t-1} : Prior cell condition
- i_t : Input gate activation
- $\tilde{C}_t$: Candidate cell state
- $\odot$: Element-wise multiplication

3. Forget Gate



Determines what portion of the previous cell state should be retained or forgotten.

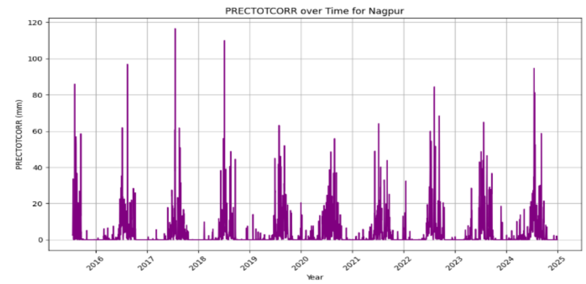
$$f_t = \sigma(W_f . [h_{t-1}, x_t] + b_f)$$

Where:

- f_t : orget activation of the gate (values 0–1)
- σ : The function of sigmoid activation
- W_f : The forget gate's weight matrix
- h_{t-1} : The prior time step's hidden state
- x_t : Input current
- b_f : A word that is biased

4. Input Gate

Selects the new data that should be kept in the



cell state.

$$i_t = \sigma(W_i . [h_{t-1}, x_t] + b_i)$$
$$\tilde{C}_t = \tanh(W_c . [h_{t-1}, x_t] + b_C)$$
$$C_t = f_t . C_{t-1} + i_t . \tilde{C}_t$$

Where:

- i_t : Input gate activation
- $\tilde{C}_t$: Candidate cell state (new information to be added)
- W_i , W_c : Weight matrices
- b_i , b_C : Bias terms
- C_t : Updated cell state

RESULT

Fig.1

Fig.2

Fig.3

Figures 1, 2, and 3 provide examples of the Corrected Total Precipitation (PRECTOTCORR) over time for Nagpur, Amravati, and Hingoli from 2016 to 2025. The x-axis represents years, while the y-axis shows precipitation in millimeters.

The analysis reveals seasonal rainfall trends, with significant precipitation occurring during the monsoon season (June–September) and dry months showing minimal rainfall. Extreme rainfall events were observed in 2017, 2019, and 2023, with peaks exceeding 100 mm, likely due to cyclones or intense monsoon activity.Monsoon variability across years is influenced by climate fluctuations and changing rainfall patterns.

The LSTM model forecast (2023-2025) predicts continued seasonal trends with recurring monsoon spikes. A slight increase in precipitation is expected, highlighting flood risk assessment and water resource management needs. These results highlight the significance of catastrophe preparedness and climate monitoring in the area.

VI.CONCLUSION

The Maharashtra Drought Analysis Data study showcases the effectiveness of the LSTM model in forecasting SPI values, significantly improving drought prediction accuracy. Through rigorous data preprocessing and visualization, the study ensures reliable climate trend analysis, supporting critical sectors such as water resource management and agriculture. SPI-based insights facilitate early drought detection, enabling proactive mitigation strategies. Furthermore, the study highlights LSTM's broader applicability in climate forecasting and its role in strengthening data-driven decision-making. By providing accessible and actionable insights, this research contributes to Maharashtra's climate resilience, promoting sustainable resource management and improved drought preparedness.

REFERENCES

[1] Andrew Watford, Chris T. Bauch, Madhur Anand, Dynamical systems-inspired machine learning methods for drought prediction, Ecological Informatics, Volume 84, 2024, 102889, ISSN 1574-9541.

[2] Fang Liu, Hongbo Zhang, Yihang Li, Zhiyuan Ning, Shuai Hao, Synchronicity analysis of meteorological variables on agricultural drought in the Loess Plateau, China, Journal of Hydrology: Regional Studies, Volume 57, 2025, 102176, ISSN 2214-5818 .

[3] Chengfan Li, Chengzhi Wu, Lan Liu, Lili Yan, Jung Yoon Kim, Xuefeng Liu, Jingxin Han, Junjuan Zhao, MIFFNet: Feature fusion-oriented classification of volcanic lithology from remote sensing image, Alexandria Engineering Journal, 2024, ISSN 1110-0168.

[4] Johannes Laimighofer, Gregor Laaha, How standard are standardized drought indices? Uncertainty components for the SPI & SPEI case, Journal of Hydrology, Volume 613, Part A, 2022, 128385, ISSN 0022-1694.

[5] Hang Yu, Long Wang, Jianlong Zhang, Yuanfang Chen, A global drought-aridity index: The spatiotemporal standardized precipitation evapotranspiration index, Ecological Indicators, Volume 153, 2023, 110484, ISSN 1470-160X.

[6] Admore Mureva, Chipo Magombedze, Justice Muvengwi, Luke Jimu, Monicah Mbiba, Assessing structure, spatial patterning, and size class distribution of miombo woodland species along a precipitation gradient, South African Journal of Botany, Volume 171, 2024, Pages 173-184, ISSN 0254-6299.

[7] Siyu Wang, Kexin Lv, Jun Ma, Qun'ou Jiang, YuFei Ren, Feng Gao, Nizami Syed Moazzam, A multi-source data fusion method to retrieve soil moisture dynamics and its influencing factors analysis in the ecological zone of the eastern margin of the Tibetan Plateau, Ecological Indicators, Volume 169, 2024, 112877, ISSN 1470-160X.

[8] Minghui Yan, Jingwen Kou, Weijing Ma, Yuqin Jian, Haijiang Yang, Bing Xue, Xiaohua Gou, Scale effect of population and area exposed to water scarcity based on different recurrence periods: A case study of Gansu Province, China, Ecological Indicators, Volume 157, 2023, 111254, ISSN 1470-160X.

[9] Fang Wan, Fei Zhang, Yu Wang, Shaoming Peng, Xiaokang Zheng, Study on the propagation law of meteorological drought to hydrological drought under variable time Scale: An example from the Yellow River Water Supply Area in Henan, Ecological Indicators, Volume 154, 2023, 110873, ISSN 1470-160X.

[10] Md. Ashhab Sadiq, Showmitra Kumar Sarkar, Saima Sekander Raisa, Meteorological drought assessment in northern Bangladesh: A machine learning-based approach considering remote sensing indices, Ecological Indicators, Volume 157, 2023, 111233, ISSN 1470-160X.

[11] Chenli Xue, Aurora Ghirardelli, Jianping Chen, Paolo Tarolli, Investigating agricultural drought in Northern Italy through explainable Machine Learning: Insights from the 2022 drought, Computers and Electronics in Agriculture, Volume 227, Part 1, 2024, 109572, ISSN 0168-1699.

[12] Peter Babyenda, Jane Kabubo-Mariara, Sule Odhiambo, Adaptation to climate variability and household welfare outcomes in Uganda, Climate Services, Volume 36, 2024, 100523, ISSN 2405-8807.

[13] Donghoon Lee, Frank Davenport, Shraddhanand Shukla, Greg Husak, Chris Funk, James Verdin,

Contrasting performance of panel and time-series data models for subnational crop forecasting in Sub-Saharan Africa, Agricultural and Forest Meteorology, Volume 359, 2024, 110213, ISSN 0168-1923.

[14] Masilin Gudoshava, Maureen Wanzala, Elisabeth Thompson, Jasper Mwesigwa, Hussen Seid Endris, Zewdu Segele, Linda Hirons, Oliver Kipkogei, Charity Mumbua, Wawira Njoka, Marta Baraibar, Felipe de Andrade, Steve Woolnough, Zachary Atheru, Guleid Artan, Application of real time S2S forecasts over Eastern Africa in the co-production of climate services, Climate Services, Volume 27, 2022, 100319, ISSN 2405-8807.

[15] Mohammed Achite, Enes Gul, Nehal Elshaboury, Muhammad Jehanzaib, Babak Mohammadi, Ali Danandeh Mehr, An improved adaptive neuro-fuzzy inference system for hydrological drought prediction in Algeria, Physics and Chemistry of the Earth, Parts A/B/C, Volume 131, 2023, 103451, ISSN 1474-7065.

[16] 16 Khalid En-Nagre, Mourad Aqnouy, Ayoub Ouarka, Syed Ali Asad Naqvi, Ismail Bouizrou, Jamal Eddine Stitou El Messari, Aqil Tariq, Walid Soufan, Wenzhao Li, Hesham El-Askary,Assessment and prediction of meteorological drought using machine learning algorithms and climate data,Climate Risk Management,Volume 45,2024,100630,ISSN 2212-0963.

[17] Christossy Lalika, Aziz Ul Haq Mujahid, Mturi James, Makarius C.S. Lalika,Machine learning algorithms for the prediction of drought conditions in the Wami River sub-catchment, Tanzania,Journal of Hydrology: Regional Studies,Volume 53,2024,101794,ISSN 2214-5818,https://doi.org/10.1016/j.ejrh.2024.101794.

[18] Nandgude, N.; Singh, T.P.; Nandgude, S.; Tiwari, M. Drought Prediction: A Comprehensive Review of Different Drought Prediction Models and Adopted Technologies. *Sustainability* 2023, *15*, 11684.

[19] Nandgude, Neeta & Singh, T. & Nandgude, Sachin & Tiwari, Mukesh. (2023). Drought Prediction: A Comprehensive Review of Different Drought Prediction Models and Adopted Technologies. Sustainability. 15. 11684. 10.3390/su151511684.

[20] Piraei, R.; Niazkar, M.; Gangi, F.; Eryılmaz Türkkan, G.; Afzali, S.H. Short-Term Drought Forecast across Two Different Climates Using Machine Learning Models. *Hydrology* 2024, *11*, 163.

[21] Afan, H.A.; Almawla, A.S.; Al-Hadeethi, B.; Khaleel, F.; AbdUlameer, A.H.; Khan, M.M.H.; Ma'arof, M.I.N.; Kamel, A.H. LSTM Model Integrated Remote Sensing Data for Drought Prediction: A Study on Climate Change Impacts on Water Availability in the Arid Region. *Water* 2024, *16*, 2799.

[22] Zhang, Y.; Ru, G.; Zhao, Z.; Wang, D. Hyperspectral Prediction Models of Chlorophyll Content in Paulownia Leaves under Drought Stress. *Sensors* 2024, *24*, 6309.

[23] Oruc, S.; Tugrul, T.; Hinis, M.A. Beyond Traditional Metrics: Exploring the Potential of Hybrid Algorithms for Drought Characterization and Prediction in the Tromso Region, Norway. *Appl. Sci.* 2024, *14*, 7813.

[24] Lupa-Condo, N.E.; Lope-Ccasa, F.C.; Salazar-Joyo, A.A.; Gutiérrez-Rosales, R.O.; Jellen, E.N.; Hansen, N.C.; Anculle-Arenas, A.; Zeballos, O.; Llasaca-Calizaya, N.W.; Mayta-Anco, M.E. Phenotyping for Effects of Drought Levels in Quinoa Using Remote Sensing Tools. *Agronomy* 2024, *14*, 1938.

[25] Zou, M.; Xie, D.; Xu, L.; Dai, K.; Liang, S.; Guo, M.; Qin, X.; Zhao, W. Trade-Off and Synergy Mechanism of Agricultural Water Resource Spatial Allocation in Monsoon Climate Areas Based on Machine Learning: A Case Study of Reservoir Layout Optimization in Shandong Province, China. *Agronomy* 2024, *14*, 1902.