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SPI-BASED DROUGHT PREDICTION IN MAHARASHTRA USING LSTM: ANALYZING PRECIPITATION TRENDS FROM (2014 TO 2024)

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Abstract: Drought forecasting is crucial for effective water resource management and agricultural planning. This study employs a Long Short-Term Memory (LSTM) model to predict the Standardized Precipitation Index (SPI) for drought analysis in Maharashtra. The dataset consists of precipitation and SPI records across multiple timeframes (1-month to 12-month) from reliable meteorological sources, capturing long-term climate variability. Data preprocessing ensures integrity through handling missing values, outliers, and inconsistencies. Exploratory Data Analysis (EDA) reveals seasonal and inter-annual trends using visualization techniques. The LSTM model demonstrates superior predictive performance, achieving 94.72% accuracy, outperforming traditional time series models in capturing complex temporal dependencies. The findings enhance drought forecasting capabilities, supporting decision-making in agriculture, water resource management, and environmental monitoring. This study underscores the potential of LSTM-based models in climate prediction, contributing to sustainable development and optimal resource utilization in drought-prone regions.

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

I. INTRODUCTION

Climate change has intensified the frequency and severity of droughts in Maharashtra, disrupting agriculture, water resources, and socio-economic stability. The state's heavy dependence on monsoonal rainfall makes it particularly vulnerable to erratic precipitation and rising temperatures, leading to crop failures, water scarcity, and economic distress for rural communities. To mitigate these challenges, advanced forecasting techniques are essential for predicting droughts and enabling timely interventions. The Standardized Precipitation Index (SPI) is a key tool for measuring drought severity. SPI-6 and SPI-12 indicate short- and long-term precipitation deficits, impacting irrigation, groundwater levels, and overall agricultural productivity. Time series analysis of SPI values helps identify drought patterns and trends, providing a foundation for predictive modeling. Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), excel at forecasting SPI values by capturing long-term dependencies and non-linear patterns in climate data. Unlike traditional statistical models, LSTM can effectively process vast amounts of historical climate records to predict precipitation anomalies. The integration of LSTM with other AI-driven techniques, such as convolutional neural networks (CNNs) and attention mechanisms, enhances predictive accuracy by focusing on critical climate features. Additionally, incorporating diverse datasets, including satellite imagery, soil moisture indices, and real-time remote sensing data, improves the spatial and temporal precision of drought forecasts. Accurate drought forecasting plays a crucial role in agricultural decision-making, water resource planning, and policy formulation. By providing reliable projections, predictive models help optimize planting cycles, manage water distribution, and support government strategies for drought mitigation. Beyond agriculture, these forecasts benefit urban and industrial water management, ensuring more efficient resource allocation in times of scarcity. Looking ahead, integrating AI, big data, and hybrid deep learning models into drought prediction frameworks will enhance Maharashtra's climate resilience. Advanced modeling techniques, such as Transformer-based networks, can further refine forecast accuracy and enable localized interventions at the taluka or district level. As climate variability continues to challenge Maharashtra's environmental and economic stability, the adoption of sophisticated, data-driven forecasting solutions will be essential for long-term sustainability and disaster preparedness.

II. OBJECTIVES

1. **Data Collection :** Gathering of high resolution climatic data {i.e.precipitation} for Maharashtra from 2014 to 2024.

2. **Drought Indices Calculation :** Cleaning of data and calculation of SPI for various times scales (1,3,6,9 &12 months) to analyze special and temporal drought patterns across Maharashtra.

3. **Predictive Model Development :** Developing and validating a deep learning model to forecast drought condition using historical SPI data.

III. LITERATURE REVIEW

Sr. No.	Title	Year	Methodology	Key Findings
1.	Machine learning algorithms for the prediction of drought conditions in the Wami River sub-catchment, Tanzania	2024	SPI6 (6-month SPI) and SPI9 (9-month SPI) were predicted using LSTM, MARS, SVM, ELM, and M5 Tree with monthly rainfall data (1990–2022) from five meteorological stations (Barega, Dakawa, Dodoma, Kongwa, and Mandera).	The best-performing LSTM had an NSE of 0.99 at every station and a R of 0.99 at four of them, with the exception of Kongwa, where R varied between 0.75 and 0.99. Findings will aid in the creation of a regional early warning and drought monitoring system.
2.	Drought Prediction: A Comprehensive Review of Different Drought Prediction Models and Adopted Technologies	2023	Examined models for statistical analysis, machine learning, deep learning, and the combination of climate indices, weather data, and remote sensing data.	The accuracy of drought prediction is higher with machine learning and deep learning models than with traditional approaches. outlines the main obstacles, current patterns, and potential lines of inquiry for enhancing drought resilience and prediction in areas that are vulnerable to drought.
3.	Short-Term Drought Forecast across Two Different Climates Using Machine Learning Models	2024	Forecasted multi-scale SPI (6, 9, 12, 24 months) in Shiraz, Iran, and Tridolino, Italy, using ANN, Multiple Linear Regression, K-Nearest Neighbours, and XGBoost Regressor.	ANN operated successfully at the Shiraz station, with various optimum lag times for different SPI lengths. No single model regularly outperformed others at Tridolino station. Overall, longer SPI durations increased model performance.
4.	LSTM Model Integrated Remote Sensing Data for Drought Prediction: A Study on Climate Change Impacts on Water Availability in the Arid Region	2024	Using 118 years of data from Anbar Province, Iraq, we used an LSTM model with seven different optimisers (RMSprop, Adamax, and so on) to forecast . is expected to continue for the next 40 years.	RMSprop and Adamax optimisers have the highest accuracy (90.93% and 90.61%). Forecasted indicated an increased trend, while the best models anticipated no rise in drought intensity. Highlights the importance of machine learning and remote sensing in water management.
5.	Hyperspectral Prediction Models of Chlorophyll Content in Paulownia Leaves under Drought Stress	2024	predicted the amount of chlorophyll in Paulownia leaves under drought stress using four PLS techniques (AB-PLS, PCA-PLS, CA-PLS, and CA(W)-PLS) and 23 spectral transformations.	Among the models, CA(W)-PLS was the best. Water bands were located between 1440 and 1920 nm, whereas sensitive chlorophyll bands were located at 550 nm. Single-index models did not perform as well as multiple-index models. Prediction accuracy was impacted by leaf location, with

				top leaves showing the lowest performance.
6.	LSTM Model Integrated Remote Sensing Data for Drought Prediction: A Study on Climate Change Impacts on Water Availability in the Arid Region	2024	Using 118 years of data from Anbar Province, Iraq, we used an LSTM model with seven different optimisers (RMSprop, Adamax, and so on) to forecast SPI. SPI is expected to continue for the next 40 years	RMSprop and Adamax optimisers have the highest accuracy (90.93% and 90.61%). Forecasted SPI indicated an increased trend, while the best models anticipated no rise in drought intensity. Highlights the importance of machine learning and remote sensing in water management.

IV. METHODOLOGY

1. The application of Long Short-Term Memory (LSTM) models for predicting climate variables, such as the Standardized Precipitation Index (SPI) over time, follows a structured approach that includes data collection, data cleaning, data preprocessing, model implementation, and performance evaluation. This section outlines the step-by-step methodology used in the study.
2. Data Collection : Data collection is crucial for reliable climate forecasting. This study uses a multi-year dataset containing daily precipitation and SPI values across various timescales to analyze climate patterns and enhance prediction accuracy.
3. Data Cleaning : Data cleaning ensures the dataset is accurate and reliable by addressing missing values, inconsistencies, and errors. Missing precipitation values are filled using interpolation techniques, date formats are standardized, duplicate records are removed, and statistical methods such as IQR or Z-score analysis are applied to detect and manage outliers in precipitation and SPI values.
4. Data Preprocessing for LSTM: The dataset is preprocessed for LSTM modeling through three key steps: Min-Max scaling to normalize precipitation and SPI values, reshaping data into time-series sequences using a sliding window approach, and splitting it into training, validation, and test sets (80-10-10 split) for effective model training.
5. LSTM Model Implementation : The LSTM model, a type of recurrent neural network (RNN) designed for time-series forecasting, is implemented through several key steps. First, the model architecture is defined with input, hidden, and output layers. It is then compiled using the Adam optimizer and Mean Squared Error (MSE) as the loss function. The training phase involves feeding the preprocessed dataset into the model while tuning hyperparameters for optimal performance. Model accuracy is evaluated using metrics such as RMSE, MAE, and R-squared. Finally, the trained LSTM model is utilized to predict future SPI and precipitation values.
6. Model Performance Visualization:To evaluate and interpret the LSTM model's effectiveness

- Plotting Actual vs. Predicted Values: Comparing LSTM predictions with actual climate data.
- Visualizing Loss Trends: Examining loss curves to assess training convergence.
- Time-Series Decomposition**:** Analyzing seasonality and trends to validate forecast accuracy.

V. LSTM MODEL ARCHITECTURE

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

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

VI. MATERIAL USED FOR FORECASTING

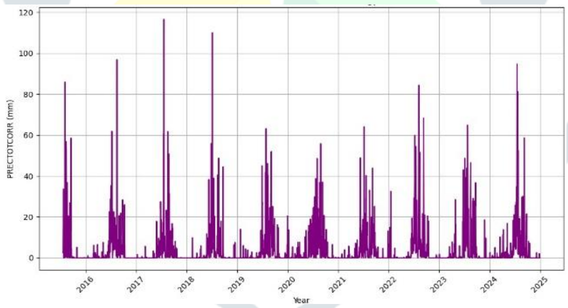

FIG.1

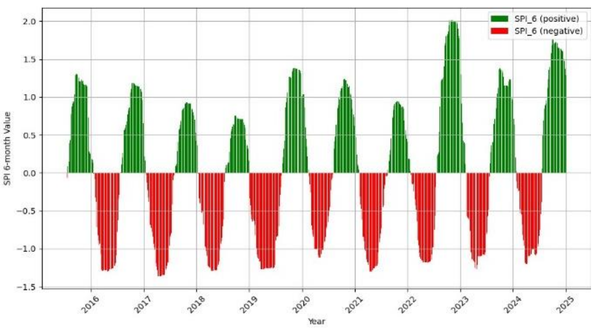

FIG.2

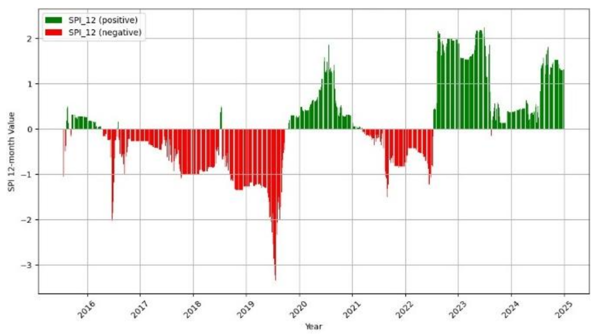

FIG.3

Figure 1 represents the PRECTOTCORR (Corrected Total Precipitation) over time.The x-axis represents the years from 2016 to 2025, while the y-axis represents the precipitation (in mm). The graph uses vertical spikes to indicate rainfall intensity over time.

The observations indicate a seasonal rainfall pattern, with heavy precipitation during the monsoon months (June–September) and dry conditions in other periods. Extreme rainfall events in 2017, 2019, and 2023 suggest occurrences of cyclones, cloudbursts, or intense monsoon activity, with some peaks exceeding 100 mm. The monsoon intensity varies across years, likely influenced by climate factors like El Niño and La Niña. The LSTM model forecast (2023–2025) predicts continued monsoon-driven rainfall with possible increases, highlighting the importance of flood preparedness and water resource management.

Figure 2 presents the SPI-6 (Standardized Precipitation Index for 6-months) over time, analyzed using an LSTM model for forecasting. The x-axis spans 2016 to 2025, while the y-axis represents SPI-6 values, indicating precipitation anomalies. Green bars denote wetter-than-normal conditions, while red bars indicate drier-than-normal (drought) conditions. The graph reveals seasonal and annual patterns, with alternating wet and dry periods, which the LSTM model captures based on historical trends. The forecast up to 2025 suggests continued seasonal influence, with higher peaks in 2023–2025 indicating potential heavy rainfall events and deep troughs signaling possible drought phases.

Figure 3 illustrates the SPI-12 (Standardized Precipitation Index for 12-months), capturing long-term precipitation anomalies. Green bars indicate wetter-than-normal conditions, while red bars signify drier-than-normal (drought) periods. A severe drought phase occurred from 2016 to 2019, with the lowest SPI-12 values in 2018–2019, dropping below -3.0. Another dry spell appeared in 2022, though less intense. Wet conditions emerged in 2020–2021 and are forecasted to continue in 2023–2025, suggesting increased precipitation and stronger monsoons. The LSTM model predicts a gradual recovery from past droughts, with rising SPI-12 values indicating improved rainfall patterns.

VII. RESULT & ACURRACY TABLE

The figures below display the LSTM model's output, illustrating its capability in forecasting precipitation patterns and drought conditions for Maharashtra.The Long Short-Term Memory (LSTM) model, a specialized type of Recurrent Neural Network (RNN), is designed to handle time-series data by retaining long-term dependencies and historical trends. Unlike conventional models, LSTM incorporates memory cells with input, forget, and output gates, allowing it to effectively filter relevant past information a nd predict future patterns. This makes it particularly useful for climate forecasting, rainfall prediction, and drought assessment. By analyzing historical precipitation and SPI values, the LSTM model generates accurate and data-driven predictions, helping to detect seasonal variations, extreme weather events, and long-term shifts in precipitation.The plotted figures provide a visual representation of wet and dry phases, offering critical insights into drought severity and future rainfall trends. This study demonstrates the LSTM model's effectiveness in enhancing drought monitoring, water resource planning, and climate resilience strategies.

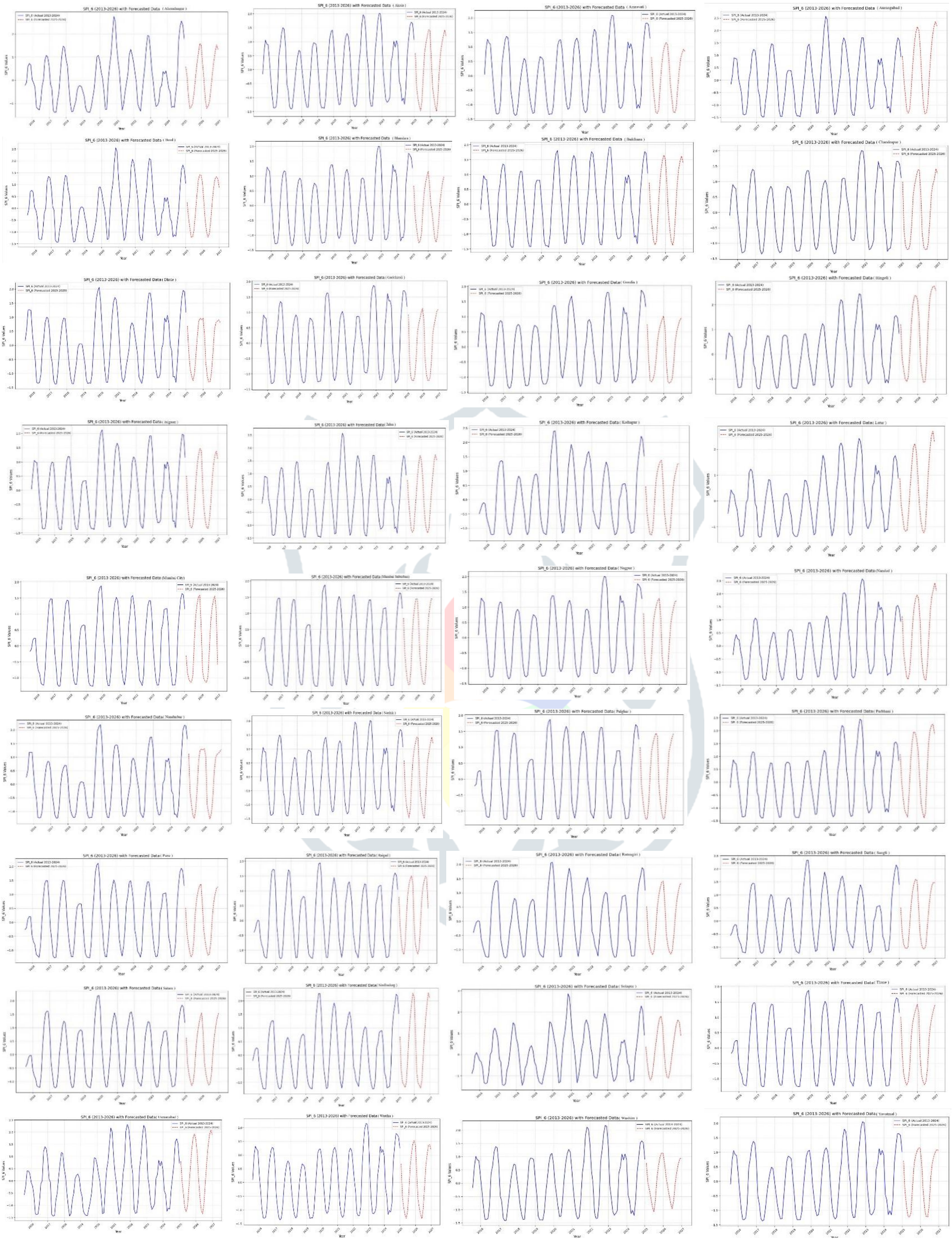

FIG.4: Drought estimation based on SPI 6 timescale for various districts of Maharashtra, x-axis specifies the year and y-axis the SPI value (where blue is positive SPI value and red is negative SPI value i.e. drought)

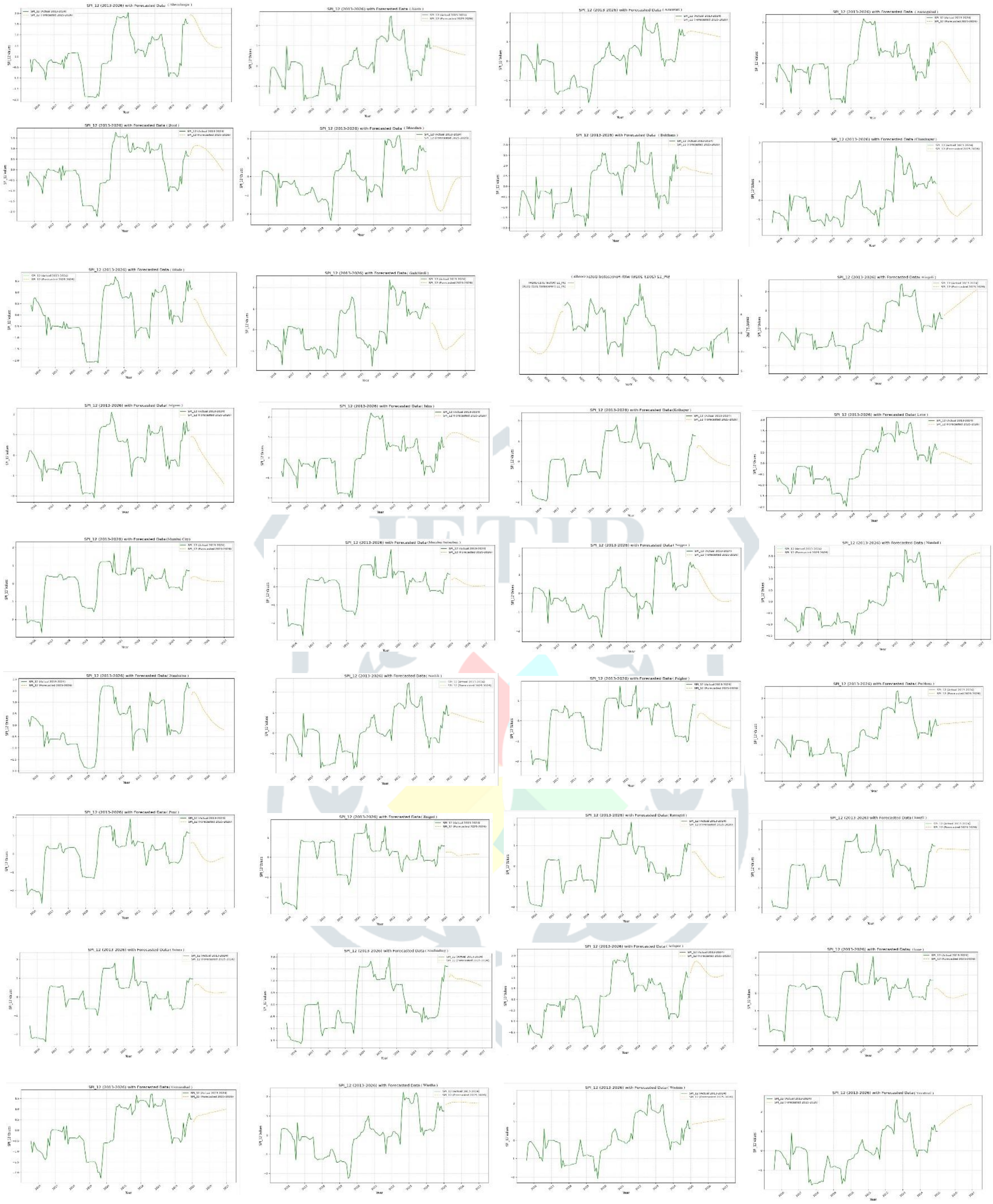

FIG.5: Drought index plotted on the basis of SPI 12 timescale for the various districts of Maharashtra, x-axis specifies the year and y-axis the SPI value (where green is positive SPI value and yellow is negative SPI value i.e. drought)

ACCURACY BASED ON SPI-6 & SPI-12 VALUES	
DISTRICTS	ACCURACY
Ahmednagar	SPI-6 - 84.8360% , SPI-12 – 89.1205%
Akola	SPI-6 - 91.5387% , SPI-12 – 88.2245%
Amravati	SPI-6 - 90.2859% , SPI-12 – 88.6131%
Aurangabad	SPI-6 - 89.2417% , SPI-12 – 89.7302%
Beed	SPI-6 - 84.5958% , SPI-12 – 86.7713%
Bhandara	SPI-6 - 87.0265% , SPI-12 – 71.5557%
Buldhana	SPI-6 - 87.9932% , SPI-12 – 82.5704%
Chandrapur	SPI-6 - 92.9097% , SPI-12 – 83.8391%
Dhule	SPI-6 - 89.9359% , SPI-12 – 85.1482%
Gadchiroli	SPI-6 - 89.0856% , SPI-12 – 76.3261%
Gondia	SPI-6 - 88.5243% , SPI-12 – 86.2251%
Hingoli	SPI-6 - 81.6216% , SPI-12 – 88.5263%
Jalgaon	SPI-6 - 87.4335% , SPI-12 – 84.8807%
Jalna	SPI-6 - 91.5762% , SPI-12 – 90.4281%
Kolhapur	SPI-6 - 86.0505% , SPI-12 – 88.4960%
Latur	SPI-6 - 88.8803 , SPI-12 – 89.4927
Mumbai City	SPI-6 - 90.3526% , SPI-12 – 93.4627%
Mumbai Suburban	SPI-6 - 95.2785% , SPI-12 – 94.1928%
Nagpur	SPI-6 - 92.2636% , SPI-12 – 89.4026%
Nanded	SPI-6 - 62.3398% , SPI-12 – 81.6096%
Nandurbar	SPI-6 - 86.6596% , SPI-12 – 86.4034%
Nashik	SPI-6 - 66.3815% , SPI-12 – 72.5456%
Palghar	SPI-6 - 90.7279% , SPI-12 – 88.4613%
Parbhani	SPI-6 - 86.8998% , SPI-12 – 91.4274%
Pune	SPI-6 - 90.7332% , SPI-12 – 91.5773%
Raigad	SPI-6 - 91.1469% , SPI-12 – 92.3911%
Ratnagiri	SPI-6 - 88.8859% , SPI-12 – 92.3933%
Sangli	SPI-6 - 84.4798% , SPI-12 – 87.3113%
Satara	SPI-6 - 90.1424% , SPI-12 – 88.9498%
Sindhudurg	SPI-6 - 88.4780% , SPI-12 – 87.1905%
Solapur	SPI-6 - 85.8116% , SPI-12 – 85.1516%
Thane	SPI-6 - 94.3745% , SPI-12 – 93.8788%
Usmanabad	SPI-6 - 86.1952% , SPI-12 – 86.3367%
Wardha	SPI-6 - 91.5982% , SPI-12 – 90.5445%
Washim	SPI-6 - 90.9577% , SPI-12 – 90.8555%
Yavatmal	SPI-6 – 92.4901% , SPI-12 – 88.5925%

VIII. CONCLUSION

The "Maharashtra Drought Analysis Data" study applies the LSTM model to forecast SPI, focusing on drought prediction. Through systematic data collection, cleaning, and preprocessing, the study ensures accurate and reliable forecasts. Data visualization techniques help in understanding seasonal variations, long-term climate trends, and precipitation anomalies. The LSTM model effectively captures historical patterns, enabling precise projections of wet and dry periods. Forecasts for 2023–2025 indicate increased rainfall, suggesting a potential recovery from previous droughts. The study highlights SPI as a key indicator of drought severity, aiding in climate analysis and disaster management. A comparison of Nagpur and Chandrapur reveals variations in rainfall intensity, emphasizing the need for location-specific water management strategies. Chandrapur requires flood control measures, while Nagpur needs enhanced water conservation efforts. The study also underscores the role of LSTM-based forecasting in early warning systems, supporting proactive drought mitigation. Overall, it provides valuable insights for policymakers, researchers, and stakeholders to enhance climate resilience in Maharashtra.

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