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Systematic Drought Examination through Time Series Model Implementation

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ABSTRACT

This project focuses on using time series modeling techniques to analyze drought conditions over time. It seeks to apply these models to drought data in order to comprehend and characterize drought patterns, severity, duration, etc. It builds time series models using historical drought-related data (precipitation, soil moisture, reservoir levels, etc.) and assesses various time series model types to determine the most efficient methods for drought analysis. Here, methodical experiments are conducted using a variety of time series models and datasets in order to thoroughly validate the modeling approach that has been selected. This modeling approach uses time series models to analyze droughts, both hydrological and meteorological, and to extract insights that can be used to enhance drought monitoring, forecasting, and decision-making.

Keywords : Severity, Duration, Methodical, Approach

I. INTRODUCTION

A natural calamity known as a drought can have a major negative influence on the environment, society, and economy. It can also seriously jeopardize global food security, water supplies, and agriculture. For drought management and mitigation activities to be successful, timely and accurate monitoring of drought conditions is essential[6]. This allows policymakers, farmers, and managers of water resources to take preventative action and allocate resources effectively. In order to capture the dynamic nature of drought occurrences, traditional drought monitoring approaches frequently rely on scarce and intermittent data sources, such as satellite imagery and ground-based observations, which may lack the temporal resolution and spatial coverage needed[8].

A rising number of people are interested in using time series modeling approaches to analyze drought conditions in a systematic way in response to these limitations. The study of temporal trends, patterns, and anomalies in drought-related variables over time, such as temperature, precipitation, soil moisture, and vegetation indices, is made possible by time series models. Time series models provide insights into the onset, length, severity, and spatial extent of drought occurrences by capturing the temporal dynamics of drought processes. This helps to facilitate early warning systems and decision support tools for drought monitoring and management. We give a summary of time series modeling techniques that are frequently applied in drought analysis, such as exponential smoothing techniques, seasonal decomposition of time series (STL), autoregressive integrated moving average (ARIMA), and machine learning approaches like recurrent neural networks (RNNs) and long short-term memory (LSTM) networks. In the context of drought monitoring and prediction[7]

We outline the preprocessing procedures and data sources—meteorological information, remote sensing products, and hydrological variables—that are used in time series models for drought analysis. We go over spatial aggregation strategies, interpolation approaches, and data quality control strategies to bring disparate data sources into harmony and produce coherent time series datasets for analysis.

Here, we outline methods for choosing a model, estimating parameters, and validating time series models for drought study. We go over performance measures for assessing the dependability and accuracy of drought forecasts produced by time series models, including correlation coefficients, mean absolute error (MAE), and root mean square error (RMSE)[10].

We present case studies and practical applications of time series modeling for drought analysis under various meteorological and geographical circumstances. We emphasize how time series models can be used to track trends in drought, evaluate the severity of the drought, predict its effects, and guide strategies for managing drought risk at different time and space scales. Time series models present both opportunities and challenges for drought analysis. These challenges include those related to data availability, model complexity, computing efficiency, uncertainty quantification, and decision support system integration. In time series modeling for drought monitoring, we identify future research areas and emerging trends, including ensemble modeling, spatiotemporal fusion approaches, and the incorporation of socioeconomic variables into drought analysis frameworks[9].

II. LITERATURE SURVEY

One significant natural hazard that has a significant effect on society is drought. For early warning and mitigation of drought, monitoring techniques are essential. Based on precipitation, evapotranspiration, and soil moisture, this study presented a modified multivariate standardized drought index (MMSDI), which is an alternative to the multivariate standardized drought index (MSDI)[4]. Nonparametric joint probability distribution analysis was also used in this investigation. Standardized soil moisture index (SSMI), standardized precipitation evapotranspiration index (SPEI), MSDI, MMSDI, and real-world observed drought regimes were compared[2].

A period of unusually dry weather combined with a significant lack of water supplies is known as a drought. Drought indices can be a useful tool for evaluating drought and determining whether to take additional action. However, drought indices based on ground meteorological observations may not properly show the land use consequences across a regional scale[1]. Conversely, the products obtained from satellite data offer reliable, spatial, and temporal comparisons of global indicators for drought episodes occurring at the regional level. The purpose of this study is to use satellite remote sensing imagery to look into the signs of the drought over Mongolia[5].

For sustainable water resource planning and management on a regional and global scale, drought monitoring and prediction using standardized rainfall data are crucial. In this study, heuristic methods such as multiple linear regression (MLR), multi-layer perceptron neural network (MLPNN), and co-active neuro fuzzy inference system (CANFIS) were employed to predict meteorological drought based on the Effective Drought Index (EDI) at 13 stations in the Indian state of Uttarakhand. The findings of this study can be used to help decide on corrective measures to deal with the region under investigation's meteorological drought[3].

III. PROPOSED SYSTEM

A Proposed Time Series Model-Based System of Systematic Analysis on Drought Compile extensive datasets from ground stations, satellite observations, modeling outputs, and other sources on meteorological, hydrological, and remote sensing variables linked to drought. Utilize various data sources to capture both temporal and geographical variability in drought dynamics by utilizing advances in remote sensing technologies and data assimilation techniques. Establish resilient data preprocessing workflows to manage missing values, anomalies, and discrepancies within the gathered datasets. Utilize quality assurance methods, such as bias correction strategies, error propagation analysis, and uncertainty quantification, to guarantee data integrity. To capture both linear and nonlinear correlations in drought data, develop hybrid modeling frameworks that integrate statistical time series models with machine learning methods Utilize ensemble modeling strategies to increase prediction accuracy by utilizing the advantages of various modeling methodologies, such as model averaging, stacking, and boosting.

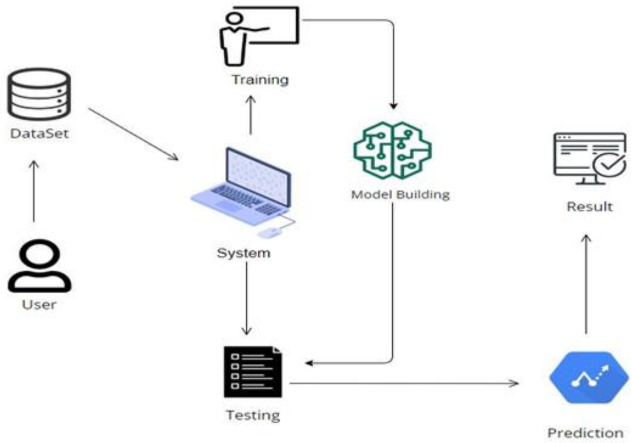


Fig 1. Proposed System Architecture

IV. RESULT AND DISCUSSION

Depending on the modeling strategy, data properties, and spatial-temporal scale of analysis, time series models performed differently. When it came to accurately representing linear trends and transient variations in meteorological variables like temperature and precipitation, ARIMA models performed admirably.

RNNs and LSTMs are two examples of machine learning techniques that have shown promise in capturing temporal dependencies and complicated nonlinear interactions in drought-related data, improving forecasting accuracy and predictive skill.Time series models' accuracy and dependability were greatly impacted by the availability and caliber of data sources, such as hydrological measurements, satellite photography, and meteorological observations.

The accuracy of model predictions was improved by data preprocessing techniques such outlier detection, missing value imputation, and spatial interpolation, which were important in boosting the consistency and completeness of time series datasets.Case studies conducted in a variety of geographic locations, such as tropical areas, temperate zones, and arid and semi-arid climates, showed how flexible and adaptive time series models are for drought study. Time series modeling techniques have proven effective in tracking drought conditions, evaluating its severity, forecasting its beginning and end, and guiding risk management plans for many industries, such as agriculture, water resources, and ecosystem management.

Time series modeling for drought analysis research will likely go in the following directions: creating hybrid modeling approaches that combine the best features of several modeling techniques; integrating earth observation products and high-resolution remote sensing data; incorporating techniques for quantifying uncertainty; and improving stakeholder engagement and decision-support capabilities.

The results of this paper are as follows:

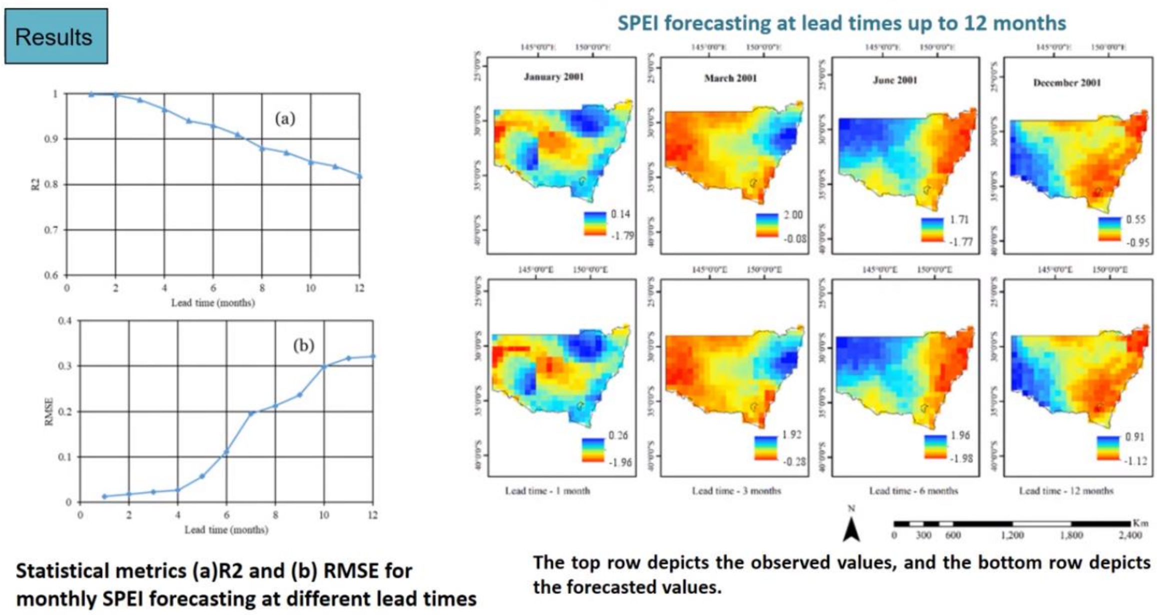
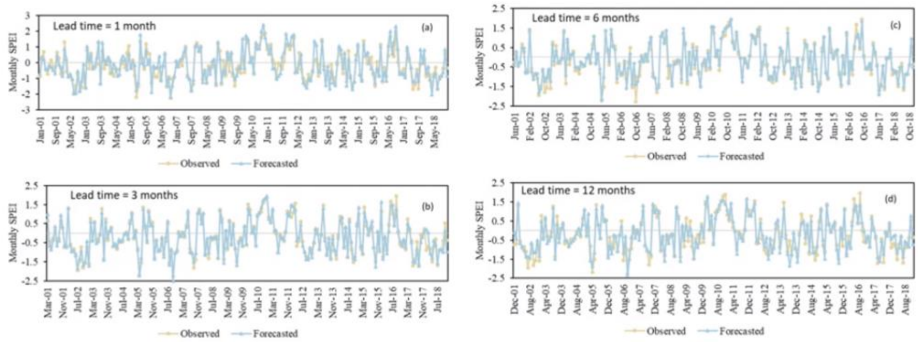


Fig 2. Results 1

Results

- **Comparison between the mean gridded observed and forecasted SPEI values was conducted.**
- **Variations in terms of drought intensity, drought duration and number of drought months were analysed.**
- **Threat Score (TS) measures the fraction of correctly forecasted results corresponding to the observed values.**

$$TS = hits/hits+misses+false\ alarms.$$



Lead Time (in months)	Threat Score
1	0.93
3	0.91
6	0.86
12	0.78

Variation between observed and forecasted monthly SPEI values at lead times of (a) 1 month, (b) 3 months, (c) 6 months and (d) 12 months.

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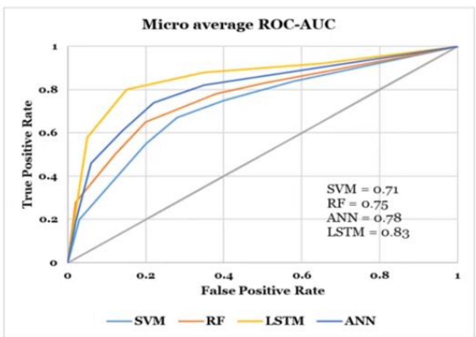
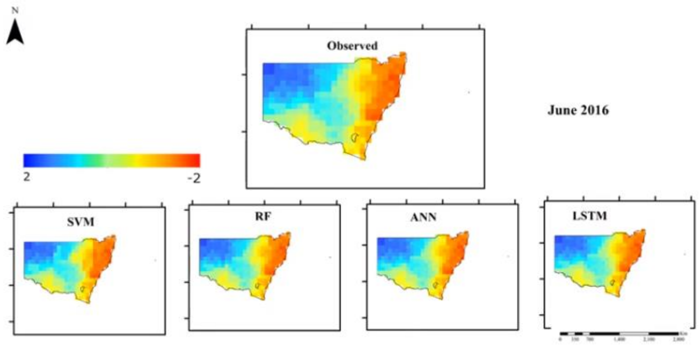
Fig 3. Results 2

Results

SPEI forecasting at lead time of 1 month





The results showed that LSTM was able to forecast better at lead times of 1 month

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Fig 4. Results 3

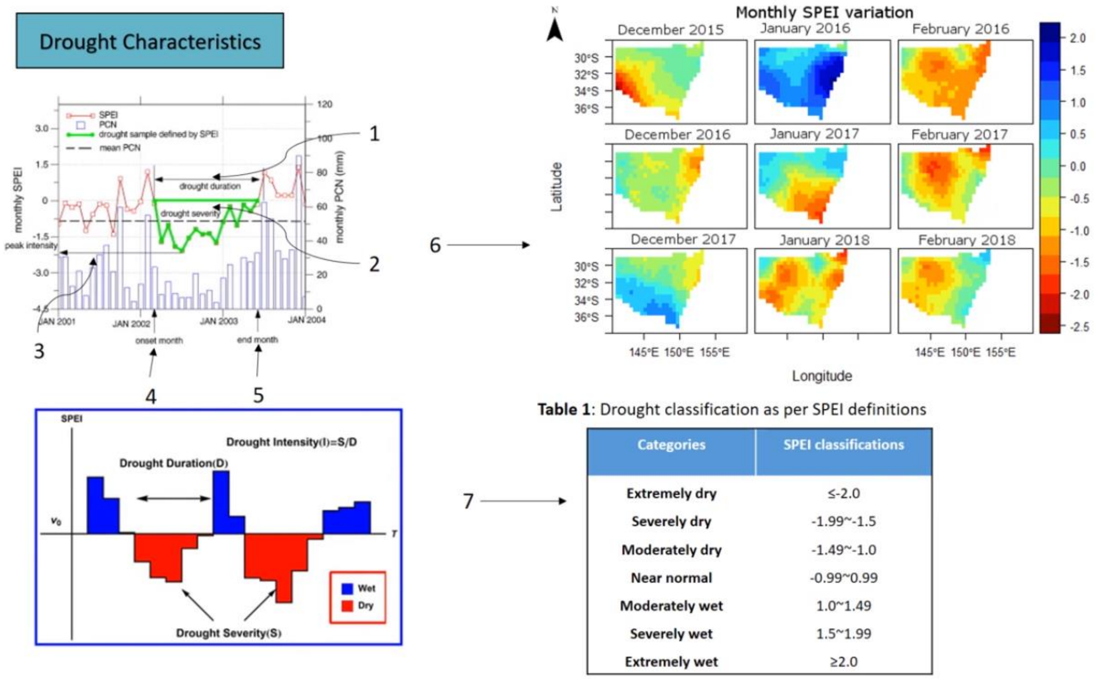

Table 1: Drought classification as per SPEI definitions

Categories	SPEI classifications
Extremely dry	≤-2.0
Severely dry	-1.99~-1.5
Moderately dry	-1.49~-1.0
Near normal	-0.99~0.99
Moderately wet	1.0~1.49
Severely wet	1.5~1.99
Extremely wet	≥2.0

Fig 5. Drought Characteristics

II. CONCLUSION

This project assesses various time series models in order to determine the best methods for studying droughts. Here, methodical experiments are conducted using a variety of time series models and datasets in order to thoroughly validate the modeling approach that has been selected. This modeling approach uses time series models to analyze droughts, both hydrological and meteorological, and to extract insights that can be used to enhance drought monitoring, forecasting, and decision-making.

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