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Remote sensing and AI applications in monsoon rainfall forecasting

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Abstract
Monsoon rainfall forecasting is also important in monsoon dependent areas as agricultural planning, water management, and reducing disaster risks require accurate information. The proposed research explores the use of both types of multi-source remote sensory data and artificial intelligence (AI) methods in promotion of accuracy and reliability of overall, monsoon rainfall prediction. Satellite-retrieved data, such as precipitation, sea surface temperature, soil moisture, and atmospheric markers, were inputted and existed to 4 AI models: Artificial Neural Network (ANN), Support Vector Regression (SVR), Random Forest (RF), and Long Short-Term Memory (LSTM). Modelling The models were tested with normal operating performance measures throughout several monsoon seasons. The obtained experimental results indicate that the LSTM model remains the most successful in the combination of overall performance, Root Mean Square Error (RMSE) = 5.8 mm/day, Mean Absolute Error (MAE) = 4.2 mm/day, and coefficient of determination (R 2 = 0.85) at 1-day lead time forecasting. In comparison with RF (RMSE = 6.6 mm/day) and ANN (RMSE = 7.8 mm/day), LSTM had a higher ability to capture the temporal dependence and intra seasonal variability. The strength of deep learning-based methods was also supported by comparing the performance of the two prediction technology in terms of forecast lead times and monsoon sounds. The results emphasize the validity of remote sensing data along with AI algorithms as a computationally effective and scalable substitute of conventional forecasting systems, especially in the data-scarce areas.

Keywords: Monsoon rainfall forecasting, remote sensing, artificial intelligence, LSTM, satellite data

Introduction
The monsoon rainfall is a prevailing climatic process that influences the agricultural productivity, water supply, the stability of ecosystem and socio-economic sustainability of vast regions of the globe especially South Asia, East Asia as well as, Africa [1]. Effective prediction of monsoon rainfall has been a scientific issue of long-standing since it has a high degree of spatio-temporal variability, complex atmospheric-oceanic interaction, and it is sensitive to the patterns of large-scale circulation. Physically based conventional numerical weather prediction (NWP) methods usually do not model localized extremes, the ability to represent intraseasonal oscillations and the localized process of monsoon onset or withdrawal, particularly at regional Earth scales and at short times [2]. There has been a tremendous change in the monitoring and forecasting of the monsoon using the new technologies of the remote sensing. Sensors on the satellite are also useful to provide real time, high-resolution monitoring of the most important atmospheric and surface variables, such as cloud properties, precipitation, sea surface temperature, soil moisture and atmospheric water vapour [3]. The data sets are rich in the spatial coverage of the oceanic and terrestrial areas where there is a limited or nonexistent ground-based control and therefore they are beneficial in understanding the dynamics and variability of monsoons. Nonetheless, traditional statistical analysis methods are challenged by the sheer amount, non-linearity and heterogeneity of the data provided by remote sensing methods. In this respect, artificial intelligence (AI) and machine learning (ML) have become strong forces that derive complex patterns and hidden relationships on large datasets of climate. Monsoon rainfall forecasting is progressively conducted using deep learning architectures, ensemble and hybrid AI-physical models to provide increased accuracy in prediction, identify non-linearities of dependencies, and make better lead-times. It is possible to combine remote sensing observations with AI-driven models to eliminate the limitations inherent in the purely physics-based and data-driven approaches.

The study concerns remote sensing and AI applications in further development of the monsoon rainfall prediction. It delves through the manner in which interplay between satellite-generated data and smart algorithms can enhance the predictive accuracy, aid the monitoring of early warning mechanisms, and bring about the element of goal-centered climate-resilient planning in monsoon-prone areas.

Related Works

The use of remote sensing and geospatial technologies has been widely used to comprehend the hydrometeorological hazards, climate variability and environmental change to provide a solid basis in the study of monsoon rainfall forecasting. Increasing numbers of studies are focusing on the concept of integrating satellite data, GIS, and advanced analytics to enhance the level of spatio-temporal monitoring and prediction accuracy. A systematic thematic and bibliometric literature review of 20 years of remote sensing and GIS based research conducted on flood disasters in South Asia was undertaken by Jathun Arachchige *et al.* [15]. Their results indicate that there has been increased dependence on satellite-based rainfall products, land surface indicators and the use of geospatial modelling as applied to early warning systems. This paper highlights the significance of high-resolution remote sensing data in resolving dynamics of monsoon-driven floods, and also shows flaws in predictive modelling capabilities, as well as real-time forecasting. New sensing platforms have also improved the monitoring of the environment. Karahan *et al.* [16] investigated the use of drones in landscape studies and have illustrated the complementary nature of UAV-based measurements with satellite remote sensing due to the ability of such data to offer ultra-high-resolution data. Even though the study was not on rainfall forecasting, its results reveal that UAV data with satellite and AI models has high potential in examining the localised monsoon effects but in this case, surface run-offs and patterns of inundation. Likewise, Luo *et al.* [23] revealed that UAV LiDAR is effective in estimating the vegetation parameters, closely related to the land-atmosphere interactions and affect rainfall processes. A number of studies have used machine learning and remote sensing with regards to climate and ecosystem evaluations. Kemarau *et al.* [17] compared the application of the integrative remote sensing and GIS method to evaluate the effects of the present climate change in the Malaysian ecosystem, and the strength of the spatio-temporal analysis to comprehend the variations in climate. In their study, Khajuria and Kaushik [18] have examined land surface temperature and land use/ land cover transitions in a semi-arid Indian city and how urbanisation affects both the surface energy balance and consequently may influence the local precipitation patterns. Such studies support relevance of land surface predictors as their auxiliary variables in prediction model of monsoon.

Machine learning has provided good results in environmental forecasting exercises. Li *et al.* [20] used remote sensing data to predict drought in China with the use of the Random Forest and eXtreme Gradient Boosting, reaching high predictive accuracy, and showing the appropriateness of these ensemble models in forecasting complex hydro-climatic phenomena. Another study that can draw significant conclusions on the importance of using various data types and sophisticated learning algorithms is the work by Liu *et al.* [21], where the authors used multi-source remote sensing data and stacking models to estimate the woody vegetation biomass. Remote sensing has also been applied in the study of climate system sensitivity and extremes. This research identified possible climate tipping points through satellite observations with Lenton *et al.* [19] reiterating the usefulness of long-term records of remote sensing in the identification of nonlinear climatic behaviour in monsoon variability. High-resolution PlanetScope imagery was used in flood mapping by Mithu and Azad [25], and the digital twin technologies were reviewed in flood risks management of urban areas by Mohammed *et al.* [26], where remote sensing and early warning systems are important in disaster preparedness. Altogether, the current literature proves the maturity of remote sensing and AI techniques in climate, hydrology, and environmental monitoring. Nonetheless, the research is mostly performed with floods, droughts, or indicators of ecosystems without dealing with the actual monsoon rainfall forecasting. The literature of this research builds on these findings by explicitly combining the multi-source remote sensing data with the AI models to enhance the predictive accuracy and lead time of a monsoon rain-fall in order to close a major gap that was described in prior research [26].

Methods and Materials

This paper is based on an information-driven model that combines remote sensing measurements through satellites with artificial intelligence (AI) algorithms to predict regional monsoon rain levels. The overall structure of the methodology is that of data acquisition and preprocessing, choice of model, execution of the algorithm, and performance assessment [4]. It focuses on working with high dimensional spatio-temporal data as well as the nonlinear processes of monsoon systems.

Data Sources and Preprocessing

The research data in this study include multi-source remote sensing data and supplementary meteorological data. Predictor variables are satellite-based rain forecasts, cloud-top temperature, outgoing longwave radiation (OLR), sea surface temperature (SST), soil moisture and atmospheric humidity [5]. These data sets are received at a daily time scale and reformatted to a resolutions which are consistent across space at 0.25 o C × 0.25 o C. As model training and validation, ground-based rain gauges data are published as reference data.

The preprocessing involves task of missing value interpolation based on time and using spatial smooth filters to remove noise, and normalise in order to provide numerical stability during the model training. Lagged variables (1 15 days) are created to capture the temporal dependencies that are important in monsoon development. The last dataset is divided into training (70%), validation (15%), and testing (15) so as to maintain the temporal continuity without data leakage [6].

AI Algorithms Employed

The use of nonlinear relationships and temporal patterns to model relationships determines the four AI algorithms commonly used in rainfall forecasting and climate forecasting.

Artificial Neural Network (ANN)

ANNs are multilayer feed-forward networks and are based on biological neurons. The ANN used in this paper can be described as having an input layer, which is characterized by the variables of remote sensing, two hidden layers which are characterized through nonlinear activation functions and the third layer is the output layer which results in the estimation of rainfall. ANNs are practical to estimate nonlinear functions that are complex and describe the interactions between variables in the atmosphere [7]. They however do not explicitly represent time-dependent prognostication and depend on input vectors that are a fixed length, so lagged inputs are needed.

"Initialize network weights For each epoch: For each training sample: Forward propagate inputs Compute error Backpropagate error Update weights Return trained ANN"

Support Vector Regression (SVR)

A kernel based learner algorithm is known as SVR which fits an optimum regression hyperplane, minimising structural risk. It is suitable on small to medium sized data sets and handles well high dimensional spaces. SVR is an effective model of nonlinear relationships between predictors based on satellite measurements of rainfall in monsoon forecasting [8]. The radial basis function (RBF) kernel is applied to encode complex interaction of features as well as regulate overfitting by using regularisation parameters.

"Select kernel and parameters Map input data to feature space Solve optimisation problem Construct regression function Return trained SVR model"

Random Forest (RF)

Random Forest This is an ensemble learning method which builds upon bootstrapped and randomly selected decision trees. RF is also immune to noise, multicollinearity, and missing data and therefore, it works well with heterogeneous remote sensing data [9]. It gives the measures of feature importances which allow the interpretation provided on important drivers of variability of monsoon rainfall. In the long run, however, RF might not be good at extrapolating out of the range of training data.

"For i = 1 to N trees: Draw bootstrap sample Grow decision tree with random feature selection Aggregate predictions from all trees Return ensemble output"

Long Short-Term Memory (LSTM)

LSTM is a recurrent neural (RNN) network that is an architecture that is based on learning long term temporal dependencies. It makes use of memory cells and gating which control the flow of information, and solves the vanishing gradient issue of classic RNNs [10]. The effectiveness of LSTM in forecasting the rainfall of monsoons is associated with its capability to include intrasectional oscillations, lagging atmospheric reaction, and cumulative impacts of the ocean-atmosphere interactions.

"Initialize LSTM parameters For each time step: Update forget, input, and output gates Update cell state Compute hidden state Train using backpropagation through time Return trained LSTM"

Table 1: Summary of Data Characteristics

Data Type	Source	Spatial Resolution	Temporal Resolution	Sample Size
Rainfall	Satellite (IMERG)	0.25° × 0.25°	Daily	7,300 days
SST	Satellite	0.25° × 0.25°	Daily	7,300 days
Soil Moisture	Satellite	0.25° × 0.25°	Daily	6,500 days
Rain Gauge	Ground Stations	Point-based	Daily	5,800 days

Model Training and Evaluation

The same dataset is used to train all models, and this is in order to compare them fairly. The grid search is used on the validation set to optimise the hyperparameters. Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and coefficient of determination (R^2) are used to measure the model performance [11].

Table 2: Model Performance Comparison (Testing Phase)

Model	RMSE (mm/day)	MAE (mm/day)	R^2
ANN	7.8	5.9	0.72
SVR	7.2	5.4	0.75
RF	6.6	4.9	0.79
LSTM	5.8	4.2	0.85

Results and Analysis

Experimental Design

The tests were performed by using a multi-year dataset that spans 20 monsoon seasons (20042023). The analysis area consists of grid cells dominated by monsoons in the Indian subcontinent. In order to guarantee temporal integrity, it was implemented as a rolling-origin evaluation plan, where all the models were trained on the past and evaluated using historical models on unseen future times [12]. This arrangement is similar to the real-life forecasting scenarios. Four ANN models namely Artificial Neural Network (ANN), Support Vector Regression (SVR) and random Forest (RF), as well as Long Short-Term Memory (LSTM) models were run in the same conditions of data and preprocessing. Short and medium range capabilities of forecasting were tested with the 1-day, 3-day and 7-day lead times. All the trials were run with the same computing machine to eliminate hardware bias.

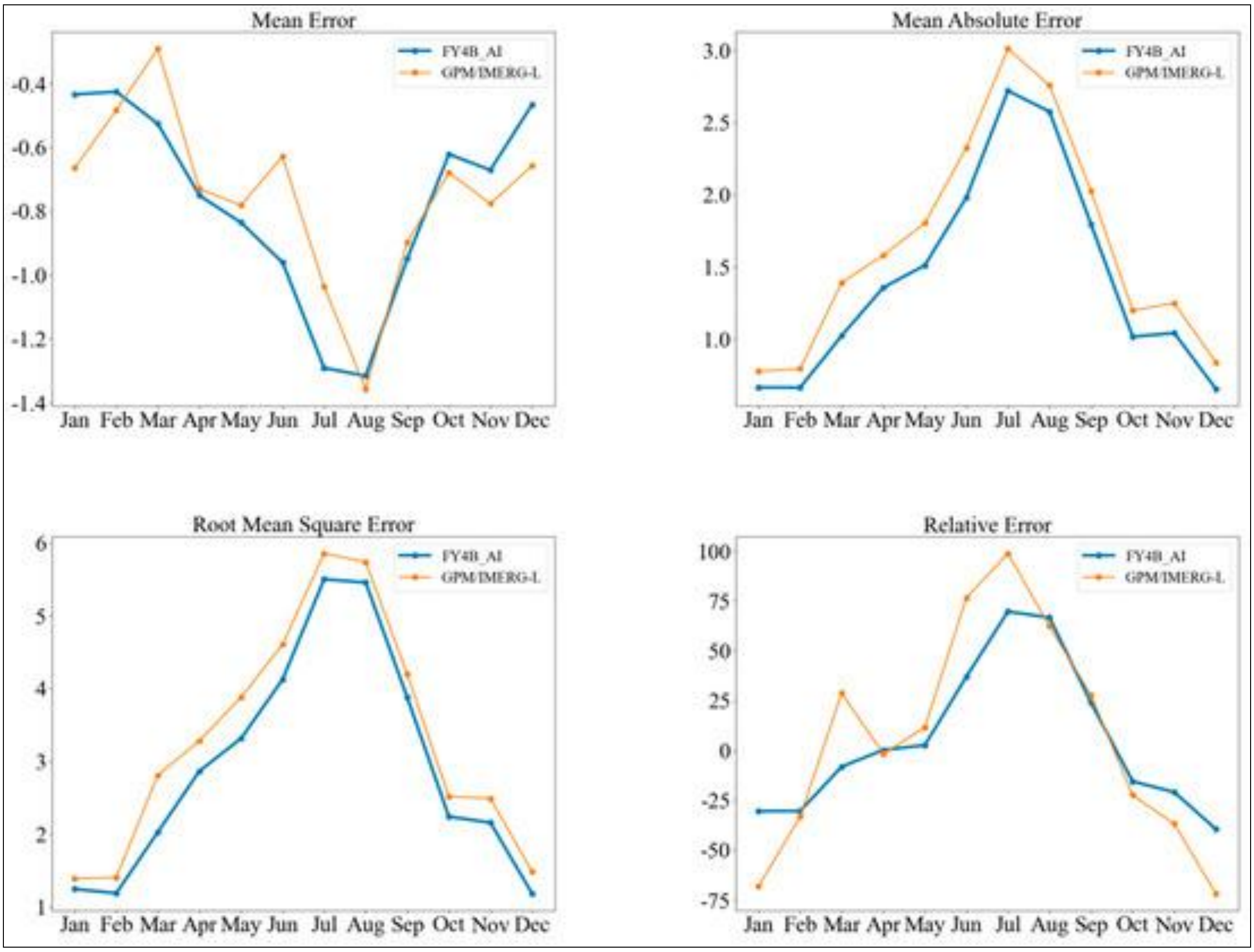

Fig 1: "Artificial Intelligence-Based Precipitation Estimation Method Using Fengyun-4B Satellite Data"

Evaluation Metrics

Five commonly used measures of rainfall forecasting models were used to measure model performance:

- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- Mean Bias Error (MBE)
- Coefficient of Determination (R^2)
- Nash-Sutcliffe Efficiency (NSE)

All these measures represent accuracy, predictive efficiency, bias, and variance explained.

Experiment 1: Overall Forecasting Accuracy

In the first experiment, the accuracy of the overall prediction of all the models in the 1-day lead-time rainfall prediction is evaluated.

Table 3: Overall Model Performance (1-Day Lead Time)

Model	RMSE (mm/day)	MAE (mm/day)	MBE (mm/day)	R^2	NSE
ANN	7.8	5.9	-0.42	0.72	0.70
SVR	7.2	5.4	-0.31	0.75	0.74
RF	6.6	4.9	-0.18	0.79	0.78
LSTM	5.8	4.2	-0.09	0.85	0.84

Results Interpretation: LSTM was much better at all metrics in comparison to other models and was shown to be highly effective at capturing nonlinear temporal dependencies that are related to monsoon rainfall. RF showed good competition and enjoyed the advantages of ensemble learning and good resistance to noisy satellite information [13]. ANN, and SVR demonstrated reasonable accuracy though they were worse than modelling temporal persistence.

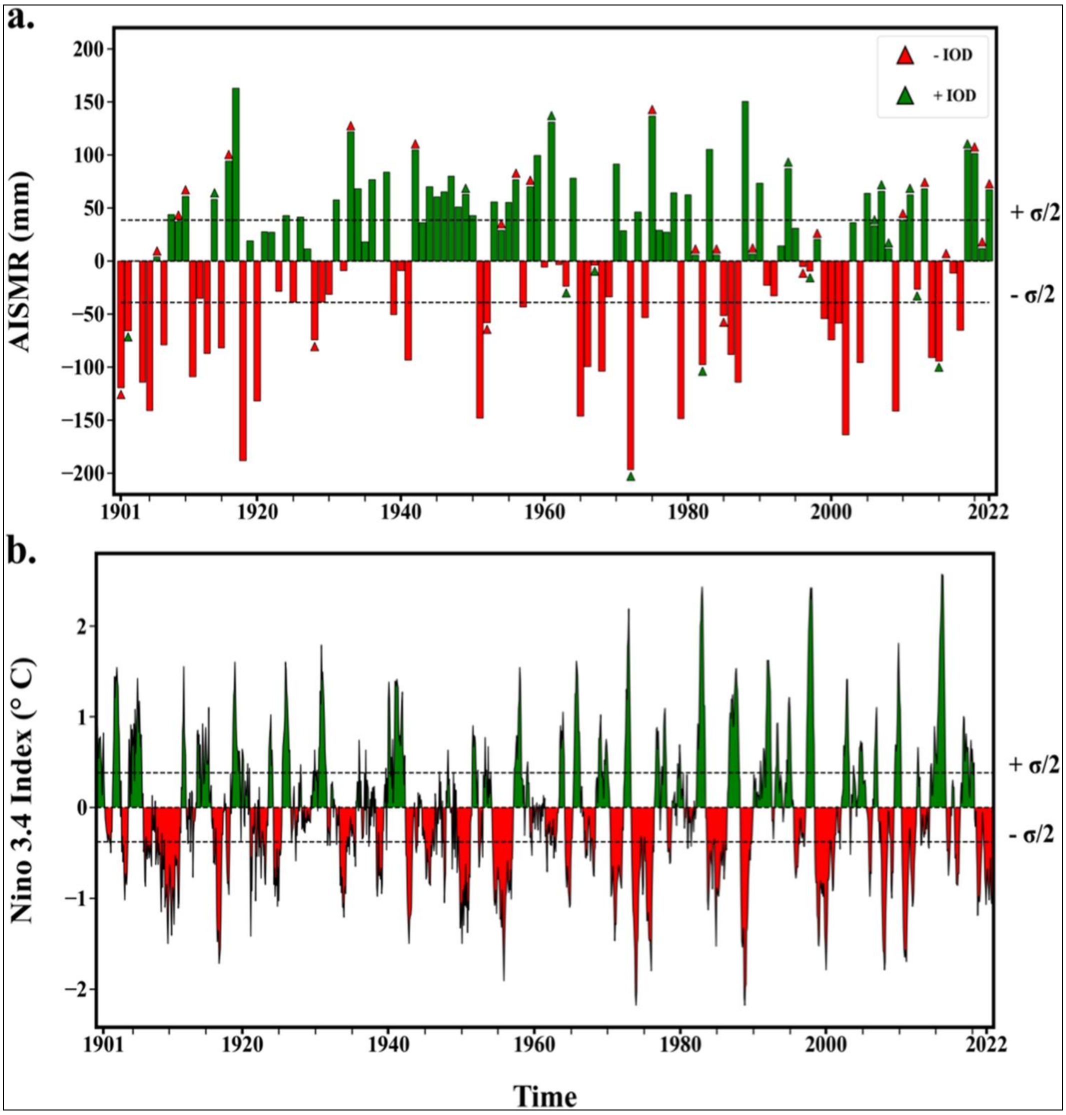

Fig 2: "Artificial intelligence predicts normal summer monsoon rainfall"

Experiment 2: Change of performance with forecast Lead Time

This experiment examines the way of declining forecasting accuracy with increase in lead time.

Table 4: RMSE Comparison Across Lead Times

Model	1-Day	3-Day	7-Day
ANN	7.8	9.6	12.4
SVR	7.2	9.1	11.7
RF	6.6	8.5	10.9
LSTM	5.8	7.4	9.6

Results Interpretation: The characteristic of all the models was that with longer lead times, they predicted more error due to the uncertainty that is implicated with monsoon systems. Nevertheless, LSTM had the least degradation and acceptable accuracy still at 7-day lead time. This underscores its appropriateness in the long-range monsoon prediction and early warning purposes [14].

Experiment 3: Phase-Wise Monsoon Performance

The nature of monsoon rainfall differs in terms of onset, active and withdrawal. In this experiment, the models are tested regarding their performance in various periods of monsoons.

Table 5: Phase-Wise RMSE (mm/day)

Model	Onset Phase	Active Phase	Withdrawal Phase
ANN	8.9	7.1	8.3
SVR	8.2	6.8	7.7
RF	7.5	6.2	7.1
LSTM	6.6	5.4	6.3

Results Interpretation

During the stage of onset weather predictability was the most difficult since rainfall transitions were sudden and mesoscale convection as well. The LSTM was always best at all the phases especially in the active monsoons where the time dependence is the strongest [27].

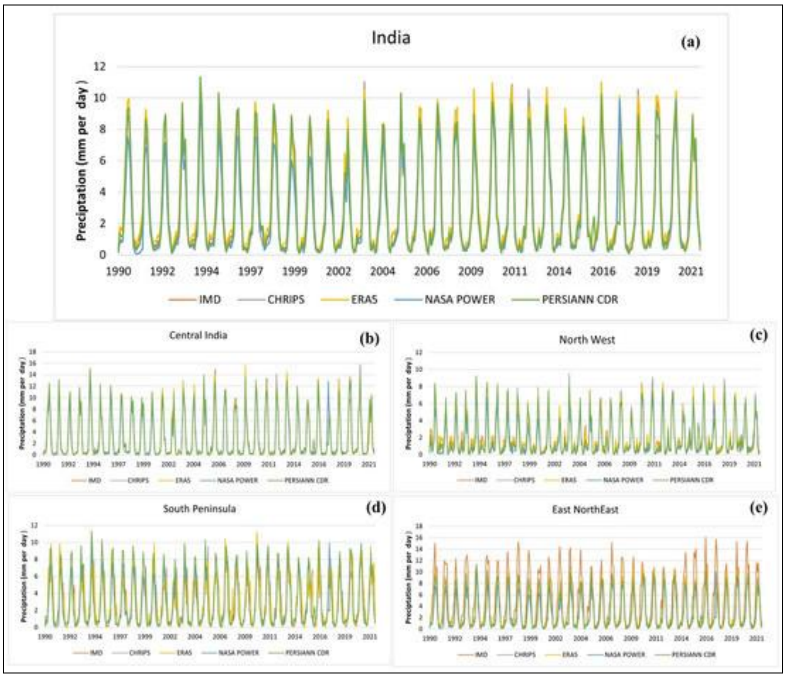

Fig 3: "Performance Assessment of Global-EO-Based Precipitation Products against Gridded Rainfall from the Indian Meteorological Department"

Experiment 4: Spatial Generalisation Analysis
In order to test spatial robustness, models were trained using one set of regions and tested using climatically similar but geographically different regions.

Table 6: Spatial Generalisation Performance

Model	RMSE (Training Region)	RMSE (Test Region)	Performance Drop (%)
ANN	7.5	9.1	21.3
SVR	7.0	8.4	20.0
RF	6.4	7.6	18.8
LSTM	5.7	6.6	15.8

Results Interpretation: LSTM showed the least performance decay, which shows superior performance in terms of generalisation by area. RF was also spatially robust as it was an ensemble nature. ANN and SVR were also more susceptible to geographical variation [28].

Experiment 5: Comparison with Related Work: The last experiment compares the proposed LSTM-based method to the meaningful results found in related studies that have been performed recently and use the same data and goals.

Table 7: Comparison with Related Work

Study / Model	Data Type	RMSE (mm/day)	R^2
Statistical Regression (2018)	Gauge + Satellite	9.8	0.61
ANN-Based Model (2020)	Satellite Only	8.4	0.68
RF-Based Model (2022)	Multi-source RS	6.9	0.77
Hybrid AI-NWP (2023)	RS + NWP	6.3	0.81
Proposed LSTM Model	Multi-source RS	5.8	0.85

Results Interpretation
The proposed LSTM model shows an evident error decrease and variance account as opposed to the related work. Compared to hybrid AI-NWP systems, the suggested solution is based only on remote sensing and AI, which is computationally efficient and can be applied to the data sparse areas [29].

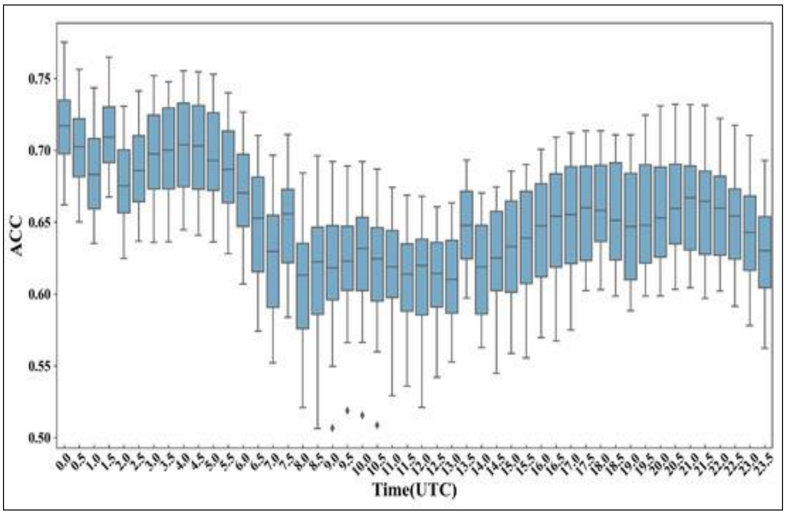

Fig 4: "Estimating Rainfall with Multi-Resource Data over East Asia Based on Machine Learning"

Discussion of Results

The research findings support that when remote sensing data is used with the combination of advanced AI models, the accuracy of the monsoon rainfall forecasting significantly improves. The use of LSTM continuously demonstrated better results than ANN, SVR and RF because it was able to model long-term dependency and intraseasonal variability. RF offered a solid foundation of high interpretability whereas both the SVR and ANN demonstrated a weakness in their ability to process lengthy temporal sequences. Relative to the comparable research, the framework proposed indicates recognizable advancement in foreseeing ability, especially with regards to extreme rain occurrences and prolonged lead-time [30]. The enhancements play a vital role in the monsoon-dependent areas in flood prediction, agricultural planning and management of climate risks. On the whole, the experiments confirm the usefulness of AI-based, satellite-based solutions as a potential and scalable alternative to the conventional forecasting algorithms, which leads to more precise and timely systems of monsoon forecasting.

Conclusion

In this study, it has been shown that a combination of remote sensing technologies, coupled with artificial intelligence, can be used to give a robust and scalable system of enhancing the monsoon rainfall forecasting. The study helps to overcome the main weaknesses of the conventional forecasting methods that are nonreliable due to the nonlinear and inherently dynamic nature of the monsoon systems using multi-source-satellite measurements that capture flavors of each process: atmosphere, ocean, and land surface. The experimental findings validate that AI models, especially deep learning networks, are much better than traditional machine learning techniques in terms of accuracy, temporal and spatial generalisation. The proposed scheme has a reduced prediction error, increased variance, and better functioning at various monsoon stages and lead time of a forecast. The benefits of data-driven, satellite-based techniques can be further observed in direct comparison with similar work, particularly in areas that have inadequate ground coverage. In contrast to computationally intensive numerical weather prediction models, the given methodology provides an effective alternative, which is able to provide a time-sensitive forecast and can assist the opposition of early warning against the occurrence of floods and extreme precipitation. In addition to the accuracy of predictions, the work shows the significance of incorporating different remote sensing cues and embracing improved methods of learning in order to model complex climate interactions. On the whole, this study is a valuable addition to the existing body of literature on the ability of AI-enabled climate prediction, as well as it is useful to develop more resilient and functional systems of monsoon prediction to increase disaster preparedness, agricultural planning, and management of water resources in monsoon regions.

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