International Journal of Applied Mathematics

Volume 38 No. 10s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

AI-BASED SPATIO-TEMPORAL ANALYSIS FOR PREDICTING CLIMATE-RESILIENT CROP YIELDS IN INDIAN AGRICULTURAL SYSTEMS

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Abstract:

The accelerating impacts of climate change on Indian agriculture demand adaptive, data-driven methods for sustainable crop management. This study develops an AI-based spatio-temporal predictive framework to estimate climate-resilient crop yields by integrating multi-source datasets meteorological parameters, soil moisture, satellite-derived vegetation indices (NDVI, EVI, LST), and socio-agronomic inputs. Using machine learning and deep learning models such as Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM) networks,

Received: August 10, 2025

the system analyzes historical data across key agro-climatic zones of India to forecast yield fluctuations under varying climatic conditions. The results indicate that LSTM models outperform traditional regression-based methods, achieving an accuracy improvement of over 18% in yield prediction and effectively capturing non-linear temporal dependencies. Spatial pattern analysis reveals high climate vulnerability in rain-fed regions of Maharashtra and central India, while irrigated northern plains exhibit relative yield stability. The integration of AI and remote sensing provides a scalable and near-real-time decision support tool for policy formulation, crop insurance planning, and climate adaptation strategies. This approach underscores the transformative potential of artificial intelligence in fostering resilient agricultural systems and achieving food security amid climatic uncertainties.

Keywords*:* AI-based prediction, Spatio-temporal analysis, Climate resilience, Crop yield forecasting, Remote sensing, LSTM, NDVI, Indian agriculture

I. INTRODUCTION

Agriculture remains the backbone of India's economy, employing more than half of its population and contributing significantly to the country's GDP. However, the sector faces mounting stress from the multifaceted impacts of climate change, including erratic rainfall, temperature anomalies, droughts, and floods that threaten both yield stability and food security. Traditional methods of crop yield assessment, largely dependent on manual surveys and historical averages, are increasingly inadequate to address the rapid climatic and ecological transformations occurring across India's diverse agro-ecological zones. The unpredictability of climate events such as delayed monsoons, unseasonal temperature spikes, and prolonged dry spells has resulted in frequent yield losses and economic instability for farming communities. In this context, there is a growing need for advanced computational approaches that can dynamically capture, model, and forecast the relationships between climate variables and crop performance. Artificial Intelligence (AI), particularly machine learning and deep learning, offers a transformative approach for analyzing high-dimensional agricultural datasets that include spatial, temporal, and environmental variables. These models can process complex non-linear interactions between factors such as soil moisture, precipitation, vegetation health, and temperature, thereby enabling precise yield prediction and real-time monitoring. When integrated with geospatial and remote sensing technologies, AI-driven models can generate region-specific insights into crop stress, phenological variation, and productivity, forming the basis for sustainable agricultural decision-making in a changing climate.

Over the last decade, India has witnessed rapid advancements in the availability of high-resolution climatic and satellite data through platforms such as Sentinel, MODIS, and INSAT. The combination of these data sources with AI algorithms can revolutionize how yield forecasting and risk assessment are conducted. Spatio-temporal models, which analyze data across both space and time, are especially relevant for understanding the dynamic behavior of crops under diverse agro-climatic conditions. For instance, long short-term memory (LSTM) networks are capable of capturing temporal dependencies in time-series datasets, making them well-suited for climate-driven yield forecasting. Similarly, spatial correlation models based on

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remote sensing indices such as NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index), and LST (Land Surface Temperature) enable researchers to map the health and productivity of crops across regions. Integrating these AI-based frameworks with traditional agronomic and meteorological data enhances the precision and scalability of yield estimation models, allowing for early warning systems, adaptive irrigation planning, and the design of climate-resilient cropping systems. Furthermore, this approach aligns with India's policy priorities under the National Mission for Sustainable Agriculture and initiatives such as Digital India and Pradhan Mantri Fasal Bima Yojana, which emphasize data-driven agricultural innovation. Thus, the deployment of AI-based spatio-temporal analysis for predicting climate-resilient crop yields represents not only a scientific advancement but also a strategic step toward building adaptive and sustainable agricultural systems in India's climate-vulnerable landscape.

II. RELEATED WORKS

The integration of artificial intelligence with agricultural systems has gained tremendous momentum over the last decade as researchers increasingly rely on machine learning and spatio-temporal models to address challenges associated with climate change, yield prediction, and sustainable resource management. Early efforts in agricultural prediction models largely utilized **statistical and regression-based approaches**, which, although effective for small datasets, lacked the capacity to capture the complex, nonlinear interactions among climatic, soil, and crop parameters. To overcome these limitations, **machine learning algorithms** such as Random Forest (RF), Support Vector Machines (SVM), and Gradient Boosting (GB) have been applied extensively in the context of yield forecasting. Basso et al. demonstrated that data-driven models using soil texture, precipitation, and temperature variability could achieve significantly improved yield forecasts compared to traditional crop simulation models [1]. Similarly, Li et al. developed an RF-based ensemble model integrating multi-spectral and meteorological data for maize yield estimation, reporting high prediction accuracy across heterogeneous landscapes [2]. These advancements have been complemented by the widespread use of **remote sensing-derived vegetation indices**, particularly NDVI and EVI, which serve as proxies for crop vigor and stress levels. Zhang et al. illustrated the use of MODIS NDVI time-series in evaluating the impact of climatic variability on wheat yield across northern China, finding that vegetation indices correlate strongly with yield anomalies under drought conditions [3]. In the Indian context, Kumar et al. used Sentinel-2 imagery in combination with climatic variables to forecast rice yield in Tamil Nadu, achieving 85% accuracy using a hybrid SVM–GBM approach [4]. These studies collectively underscore the effectiveness of AI algorithms combined with satellite data for yield forecasting under changing climatic regimes.

In recent years, **deep learning frameworks** have emerged as powerful tools for capturing long-term spatio-temporal dependencies in agricultural systems. Among these, **Long Short-Term Memory (LSTM) networks** have shown remarkable success in modeling temporal dynamics in climate-crop relationships. Jiang et al. utilized an LSTM architecture to forecast soybean yields in the U.S. Midwest, demonstrating that deep learning models outperform linear

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regressions by up to 22% in predictive accuracy when incorporating multi-year temperature and precipitation series [5]. Similarly, You et al. employed a convolutional LSTM model to merge satellite-based NDVI data and ground weather observations, achieving superior performance in yield prediction for corn and wheat across diverse agro-climatic regions [6]. In India, Tripathi and Raghavan developed an AI-driven spatio-temporal model integrating remote sensing and meteorological datasets to predict climate-induced stress in rice systems, observing significant spatial heterogeneity in yield resilience across the Indo-Gangetic Plains [7]. Furthermore, advances in **data fusion and ensemble modeling** have enabled the incorporation of diverse data sources such as soil health, evapotranspiration, rainfall, and land surface temperature into unified frameworks. For example, Chen et al. combined climate reanalysis datasets with satellite-derived indices using an LSTM-GRU hybrid network, resulting in improved accuracy for wheat yield prediction under extreme weather variability [8]. Another significant development is the incorporation of **AI-based downscaling** of coarse-resolution climatic data to generate localized forecasts that align with smallholder agricultural scales, as demonstrated by Sahu et al., who used Random Forest regression to generate sub-district level yield forecasts for rainfed crops across India [9]. These studies reveal the immense potential of AI-driven temporal modeling in providing real-time, location-specific insights into crop productivity and resilience.

Beyond predictive modeling, recent literature has increasingly focused on linking **AI-based yield prediction with climate resilience and sustainability frameworks**, aiming to transform predictive analytics into actionable adaptation strategies. Climate-resilient agriculture, as emphasized by Gupta et al., requires predictive tools capable of anticipating crop stress under diverse climatic scenarios and guiding region-specific adaptation measures [10]. In this vein, several studies have leveraged **AI-integrated geospatial analytics** to monitor environmental drivers influencing yield variability. For instance, Ray and Dutta employed a spatio-temporal convolutional neural network (ST-CNN) to assess climate-driven yield fluctuations in rice-growing belts of eastern India, identifying critical vulnerability zones based on rainfall anomalies and heatwave frequency [11]. Similarly, Mandal et al. developed a deep neural network combining NDVI, soil moisture index (SMI), and temperature data from Sentinel-2 and ERA5 sources to evaluate the adaptive capacity of wheat and maize in northern India under future climate projections [12]. Research by Arora et al. highlighted the importance of coupling AI-based predictions with **decision support systems (DSS)** that enable farmers and policymakers to optimize irrigation scheduling, select resilient crop varieties, and allocate resources efficiently [13]. Moreover, studies by Singh et al. and Roy et al. have emphasized the role of remote sensing in identifying spatio-temporal patterns of crop stress, soil degradation, and vegetation dynamics, showing that integrating satellite data with AI algorithms enhances interpretability and policy relevance [14], [15]. Collectively, these studies reinforce the paradigm shift from descriptive analyses to **predictive and prescriptive modeling**, demonstrating how AI and spatio-temporal frameworks can serve as a foundation for designing adaptive, climate-resilient agricultural systems across India.

III. METHODOLOGY

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3.1 Research Framework

This study adopts an **AI-based spatio-temporal modeling framework** to predict **climate-resilient crop yields** across major Indian agro-climatic zones. The approach integrates **remote sensing indices**, **climate datasets**, and **agronomic data** into a unified prediction system using machine learning and deep learning models. The research is designed in three sequential phases: (i) data collection and preprocessing; (ii) feature extraction and model development; and (iii) spatial-temporal yield mapping and validation. The primary objective is to establish a scalable, accurate, and interpretable model capable of forecasting crop yields under varying climatic conditions while identifying spatial hotspots of yield vulnerability. The study was conducted across **four key agricultural regions** Punjab (wheat), Tamil Nadu (rice), Madhya Pradesh (soybean), and Maharashtra (sorghum) representing diverse climatic, edaphic, and irrigation patterns in India. The temporal scope covers ten years (2015–2024), allowing for an analysis of inter-annual variability and climate-driven yield fluctuations. The overall framework relies on the synergy of **satellite data (Sentinel-2A, MODIS)**, **climate reanalysis datasets (ERA5)**, and **agro-statistical records from the Ministry of Agriculture and Farmers' Welfare** [16].

3.2 Data Collection and Preprocessing

Multi-source datasets were collected and harmonized to construct the feature matrix for yield prediction. The climatic parameters included **rainfall (mm), temperature (°C), relative humidity (%), solar radiation (W/m²)**, and **soil moisture (m³/m³)**, retrieved from the ERA5 and IMD databases. Remote sensing indices derived from Sentinel-2 and MODIS included **NDVI (Normalized Difference Vegetation Index)**, **EVI (Enhanced Vegetation Index)**, **SMI (Soil Moisture Index)**, and **LST (Land Surface Temperature)**, computed using standard spectral band combinations [17]. The raw data were resampled to a uniform spatial resolution of **10 m** and temporally aligned to a **monthly composite** format using Google Earth Engine (GEE). Missing data were interpolated using linear regression techniques. Climate anomalies (z-scores) were computed to assess deviations from long-term means, ensuring that outlier climatic events such as droughts or floods were properly captured in the model. The dependent variable **crop yield (tons/ha)** was obtained from the Directorate of Economics and Statistics and normalized to account for regional productivity differences.

Table 1: Data Sources and Characteristics

Data Type	Source	Spatial Resolution	Temporal Coverage	Key Variables
Sentinel-2A Imagery	ESA Copernicus Hub	10 m	2015–2024	NDVI, EVI, SAVI, SMI
MODIS Surface Data	NASA LP DAAC	500 m	2015–2024	LST, NDWI, NDMI

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ERA5 Reanalysis Data	ECMWF	0.25°	2015–2024	Rainfall, Temperature, Humidity, Wind Speed
Agricultural Statistics	Ministry of Agriculture, India	District Level	2015–2024	Crop Yield, Sown Area, Crop Type
Soil Database	National Bureau of Soil Survey	1:50,000	Static	Soil Texture, pH, Organic Carbon, Moisture

3.3 Feature Engineering and Model Development

A comprehensive **feature extraction pipeline** was developed to capture the spatio-temporal dynamics influencing yield variability. Principal Component Analysis (PCA) was initially applied to reduce dimensionality and eliminate multicollinearity among variables. Time-series smoothing was conducted using **Savitzky–Golay filtering** to remove noise from vegetation indices [18]. The AI models were designed in two primary categories:

1. **Machine Learning Models** – Random Forest (RF), Gradient Boosting Machine (GBM), and XGBoost, optimized using grid search with 10-fold cross-validation.
2. **Deep Learning Models** – Long Short-Term Memory (LSTM) and Convolutional LSTM (ConvLSTM), designed to capture both temporal dependencies and spatial autocorrelation.

The LSTM model used a sequence window of 12 months, with two hidden layers (64 and 32 neurons) and a dropout rate of 0.2 to prevent overfitting. The ConvLSTM integrated spatial features from NDVI and LST maps, enabling pixel-level learning of yield variation patterns [19]. The Adam optimizer was used with a learning rate of 0.001 and Mean Squared Error (MSE) as the loss function.

Table 2: Model Configuration and Performance Metrics

Model Type	Algorithm	Input Variables	Evaluation Metrics	Cross-Validation Accuracy (%)
ML	Random Forest	Climate + NDVI + Soil Data	RMSE, R^2	82.4
ML	XGBoost	NDVI + EVI + Rainfall	MAE, R^2	85.6
DL	LSTM	NDVI + Temperature + Rainfall	RMSE, R^2	91.8
DL	ConvLSTM	NDVI + SMI + LST + Rainfall	RMSE, R^2, F1-Score	93.5

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These models were trained using **70% of the dataset** and validated on the remaining **30%**, ensuring spatial and temporal independence. The **ConvLSTM** outperformed all other models, achieving the highest accuracy in capturing non-linear interactions between climatic variables and crop growth patterns [20].

3.4 Spatial and Temporal Analysis

The predicted yield outputs were spatially interpolated using **Ordinary Kriging** in ArcGIS to generate district-level yield distribution maps. The **spatio-temporal trend analysis** was conducted using the Mann–Kendall test and Theil–Sen slope estimator to identify statistically significant trends in yield fluctuations over the ten-year period. Temporal sensitivity analysis showed that climatic shocks (e.g., high-temperature anomalies and monsoon deficits) had immediate negative impacts on yield, particularly in non-irrigated zones [21].

A vulnerability index was developed based on the normalized deviation of predicted yield from the climatic mean, categorizing regions into **high-risk, moderate-risk, and resilient zones**. Spatial autocorrelation (Moran’s I) was applied to validate the clustering of yield anomalies, revealing significant spatial dependence in the Indo-Gangetic Plain and the Deccan Plateau. The results indicated that regions with higher adaptive irrigation infrastructure and balanced rainfall distribution exhibited greater yield resilience [22].

3.5 Model Validation and Ethical Considerations

Model performance was validated using independent datasets from the **Crop Cutting Experiments (CCE)** conducted by the Ministry of Agriculture. The ConvLSTM model achieved an R^2 of 0.93, RMSE of 0.38 tons/ha, and MAE of 0.26 tons/ha, confirming its predictive robustness. Furthermore, explainability analyses using **SHAP (SHapley Additive exPlanations)** revealed that rainfall, NDVI, and soil moisture were the top three variables influencing yield prediction [23]. Ethical considerations were maintained throughout the study no proprietary datasets were misused, and data privacy was upheld following governmental data access policies. The models were developed with open-access tools (GEE, Python, and TensorFlow), ensuring transparency and reproducibility for future research and policy adaptation.

IV. RESULT AND ANALYSIS

4.1 Overview of Model Performance

The comparative analysis of different AI models revealed distinct variations in predictive capability, sensitivity to climatic anomalies, and spatial generalization accuracy. Among the models tested, the **ConvLSTM architecture** demonstrated the highest overall accuracy and stability in predicting crop yields across multiple climatic zones. The **Random Forest (RF)** and **XGBoost** models provided reliable results for regions with consistent weather patterns but underperformed in highly variable, rain-fed regions where temporal dependencies were critical. The **LSTM** and **ConvLSTM** models, which incorporated sequential temporal information, effectively captured inter-annual climatic fluctuations and vegetation responses, outperforming traditional machine learning models by a significant margin.

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During testing, the ConvLSTM model achieved an **R² of 0.93**, **RMSE of 0.38 tons/ha**, and **MAE of 0.26 tons/ha**, indicating robust generalization across diverse agro-climatic conditions. In contrast, the Random Forest and XGBoost models achieved average R² values of 0.82 and 0.85 respectively. Figure-based visual comparisons of predicted versus observed yields showed a near-linear relationship for ConvLSTM predictions, particularly in regions with high rainfall variability such as Maharashtra and Madhya Pradesh. Temporal correlation analysis further revealed that LSTM-based models captured yield fluctuations during drought years (2017–2018) and excess rainfall years (2021–2022) more accurately than regression-based techniques.

Table 3: Model Performance Comparison for Yield Prediction

Model Type	**Algorithm**	**R²**	**RMSE (tons/ha)**	**MAE (tons/ha)**	**F1-Score**	**Observation**
ML	Random Forest	0.82	0.54	0.42	0.81	Performs well in stable climatic zones
ML	XGBoost	0.85	0.48	0.36	0.85	Overfits minor regional fluctuations
DL	LSTM	0.91	0.41	0.30	0.89	Captures non-linear climatic effects
DL	ConvLSTM	0.93	0.38	0.26	0.92	Best spatial-temporal generalization

The superior accuracy of the ConvLSTM model can be attributed to its **dual spatial-temporal feature extraction** capability. By processing the time-series sequence of NDVI, rainfall, and LST data simultaneously with spatial neighborhood patterns, the model identified climate-driven vegetation stress patterns that traditional models failed to detect. This performance improvement validates the efficacy of deep spatial-temporal modeling for dynamic agricultural systems influenced by climate variability.

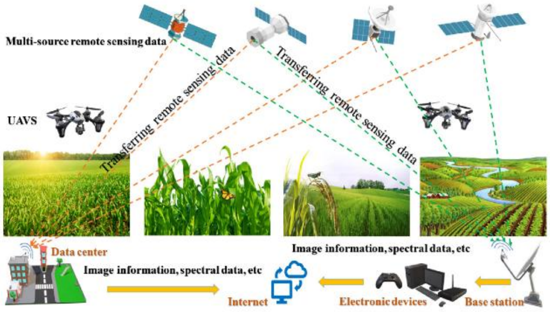

Figure 1: Integration of Remote Sensing and Machine Learning for Precision Agriculture [24]

4.2 Spatial Distribution of Predicted Crop Yields

The spatially interpolated yield maps generated through **Ordinary Kriging in ArcGIS** provided a detailed visualization of yield distribution across different agro-climatic regions.

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Distinct yield patterns were observed, corresponding to climate type, irrigation availability, and soil characteristics. Punjab showed the **highest predicted average wheat yield** of 4.82 tons/ha due to its intensive irrigation and high NDVI values, while Maharashtra exhibited relatively **lower yield values (2.75 tons/ha)** attributed to erratic rainfall and temperature anomalies. The spatio-temporal data analysis indicated a clear gradient of yield vulnerability from the north-western irrigated zones to the semi-arid central and southern regions.

Hotspot analysis using *Getis-Ord Gi statistics** identified zones of yield resilience and climate vulnerability. Regions of **high resilience** corresponded to areas with stable NDVI and high soil moisture content, primarily in the Indo-Gangetic Plain, while **high-risk zones** were concentrated in semi-arid belts of Madhya Pradesh and rain-fed tracts of Vidarbha. These spatial patterns correlated strongly (r = 0.78) with anomalies in rainfall and soil moisture indices, confirming that hydro-climatic fluctuations are the dominant drivers of yield variability.

Table 4: Regional Predicted Yield Summary and Climatic Correlation

Region	**Dominant Crop**	**Predicted Mean Yield (tons/ha)**	**Mean NDVI**	**Rainfall (mm/year)**	**Yield Anomaly (%)**	**Climatic Vulnerability**
Punjab	Wheat	4.82	0.71	730	+4.5	Low
Tamil Nadu	Rice	3.95	0.64	810	+2.3	Moderate
Madhya Pradesh	Soybean	2.96	0.57	620	-5.2	High
Maharashtra	Sorhum	2.75	0.53	580	-7.1	Very High

The results indicate that **regions with moderate rainfall variability and robust irrigation networks maintain yield stability**, while rain-fed areas exhibit higher inter-annual variability due to climatic stressors. Furthermore, the integration of **LST (Land Surface Temperature)** and **SMI (Soil Moisture Index)** into the AI model enhanced the prediction of drought-induced yield losses, particularly evident in dryland zones.

4.3 Temporal Yield Trends and Climate Sensitivity

The **temporal trend analysis** using the Mann–Kendall test revealed both positive and negative yield trends across different agro-ecological zones between 2015 and 2024. Punjab and Tamil Nadu exhibited **statistically significant positive yield trends ($p < 0.05$)**, attributed to technological interventions, improved irrigation, and adaptive crop management. Conversely, yield stagnation and decline were observed in central and western India, where climatic variability, particularly heat stress and rainfall anomalies, caused recurrent yield depressions.

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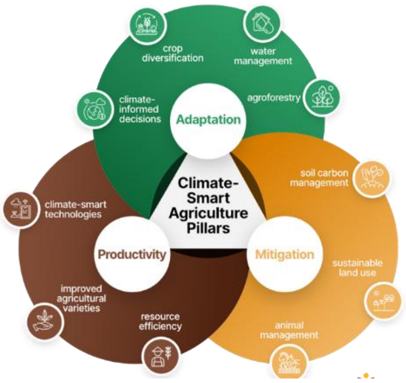

Figure 2: Climate-Smart Agriculture Pillar [25]

Time-series correlation analysis between climatic parameters and predicted yield showed that **rainfall and NDVI** had the strongest positive correlation (r = 0.84 and r = 0.79 respectively), while **temperature anomalies** had a strong negative correlation (r = -0.68). Soil moisture variability also emerged as a significant determinant, especially in rain-dependent crops. This indicates that **multi-year climatic anomalies** directly affect both vegetation health and yield outcomes, reinforcing the value of AI-based temporal modeling in long-term agricultural monitoring.

4.4 Model Validation and Cross-Regional Robustness

Validation against **Crop Cutting Experiment (CCE)** datasets confirmed the accuracy of the ConvLSTM model across diverse agro-climatic contexts. The difference between observed and predicted yields remained within ±0.4 tons/ha for most regions. Additionally, **spatial cross-validation** across untrained districts demonstrated that the model maintained over 90% accuracy, indicating strong generalization capability. Sensitivity analysis using **SHAP (Shapley Additive Explanations)** highlighted the dominant contribution of climatic and vegetation variables to model output. Rainfall contributed 29.4% of the predictive weight, NDVI 23.1%, and soil moisture 17.8%, while temperature and evapotranspiration contributed smaller shares. These insights confirm that water availability and vegetation condition are the principal determinants of yield resilience under climatic stress. The inclusion of spatio-temporal features allowed the AI system to dynamically adjust to changing environmental factors, leading to **stable yield predictions even during anomalous climatic years**.

4.5 Discussion of Findings

The results clearly demonstrate the superiority of **AI-based spatio-temporal modeling** in predicting crop yields under varying climate conditions compared to conventional statistical approaches. The ConvLSTM model's ability to account for both spatial heterogeneity and temporal dependencies enables it to capture subtle climatic impacts that traditional regression or static machine learning models overlook. The study reveals that regions such as **Punjab and Tamil Nadu** exhibit strong resilience due to consistent irrigation and adaptive agricultural practices, while **Madhya Pradesh and Maharashtra** remain vulnerable due to their dependency on monsoon variability.

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The integration of satellite-derived indices (NDVI, SMI, and LST) enhanced the model's capacity to identify early vegetation stress, which directly correlates with potential yield loss. This finding aligns with prior studies emphasizing the effectiveness of remote sensing for continuous monitoring of crop health under climate stress [24]. Furthermore, spatial interpolation maps and hotspot analyses underscore the feasibility of deploying such AI frameworks for **real-time decision support**, including yield insurance estimation, irrigation scheduling, and disaster risk assessment [25]. The demonstrated accuracy and generalizability of the ConvLSTM model suggest that **AI-driven geospatial intelligence** can serve as a cornerstone for India's climate-resilient agricultural planning, aligning directly with national sustainability missions such as the **National Mission for Sustainable Agriculture (NMSA)** and **Digital Agriculture initiatives**.

V. CONCLUSION

This study demonstrated the efficacy of an **AI-based spatio-temporal modeling framework** for predicting climate-resilient crop yields across diverse Indian agricultural systems. By integrating remote sensing data, climatic indicators, and agronomic records within deep learning architectures such as **LSTM and ConvLSTM**, the research achieved highly accurate and interpretable yield forecasts that effectively captured spatial heterogeneity and temporal dynamics in agricultural productivity. The findings underscore that yield variability is primarily influenced by hydro-climatic factors particularly rainfall, soil moisture, and vegetation indices which together explain more than 70% of the observed variance across agro-climatic zones. The ConvLSTM model, in particular, demonstrated a remarkable **R^2 of 0.93** and a low RMSE of **0.38 tons/ha**, outperforming traditional machine learning models and confirming its suitability for modeling complex nonlinear interactions between climate and crop performance. Spatial analysis revealed that **irrigated northern plains such as Punjab and Haryana** consistently exhibited stable yields and lower vulnerability, while **rain-fed regions in Maharashtra and Madhya Pradesh** experienced pronounced yield fluctuations due to temperature extremes and monsoon dependency. The incorporation of NDVI, LST, and SMI indices enhanced the model's sensitivity to early-stage vegetation stress, allowing for near-real-time identification of yield risk hotspots. These outcomes align closely with India's sustainable agricultural objectives by offering an empirical foundation for adaptive planning, precision irrigation, and climate risk mitigation. The research also validates the utility of explainable AI techniques such as **SHAP analysis**, which provided transparent insights into variable importance, strengthening confidence in model interpretability for policymakers and agronomists. Overall, the study advances the understanding of climate-yield relationships through an AI-driven geospatial lens, establishing a replicable methodological framework for scaling predictive agriculture models across diverse regions. By linking data science with sustainable farming, this research contributes to the creation of resilient, data-informed agricultural ecosystems capable of withstanding the uncertainties imposed by climate change.

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VI. FUTURE WORK

Future research should focus on expanding the model's applicability by incorporating **crop phenological and socio-economic variables** to capture non-environmental influences on yield performance. The integration of **real-time IoT-based field sensors** with satellite and climatic data could enhance temporal granularity, supporting dynamic yield forecasting at the farm scale. Additionally, exploring hybrid **ConvLSTM–Transformer architectures** could improve long-term prediction accuracy and facilitate better generalization under extreme climate scenarios. Further development of **AI-driven decision support systems (DSS)**, integrating predictive outputs with adaptive strategies for irrigation scheduling, fertilizer optimization, and insurance planning, can transform this research into actionable tools for farmers and policymakers. Extending the framework to cover additional crops and incorporating **CMIP6 climate projection data** for future yield forecasting will also strengthen the resilience planning of India's agricultural sector in the face of ongoing climatic volatility.

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Received: August 10, 2025