

AI and GIS Based Climate Change Impact Analysis on Crop Production

Santosh Gajanan Kharat ¹, Aarti Sanjay Gawai ²

¹ Student, Department of Information Technology and Computer Science, D.G Ruparel College of Arts, Science and Commerce, Mumbai, Maharashtra, India

santoshkharat3112@gmail.com

² Assistant Professor, Department of Information Technology and Computer Science, D.G. Ruparel College of Arts, Science and Commerce, Mumbai, Maharashtra, India

aartigawai1611@gmail.com

Abstract: Climate variability can influence agricultural production through changes in rainfall and temperature conditions. This study analyzes the relationship between climatic variability and soybean production in Maharashtra using rainfall, temperature, and district-level soybean production data for the period 2015–2025. The datasets were standardized and integrated using District and Year as the primary keys. A strict spatial and temporal matching process resulted in 88 unique district-year observations across eight common districts: Akola, Amravati, Buldhana, Latur, Nagpur, Nanded, Washim, and Yavatmal. The analysis shows considerable variation in soybean production, rainfall, and temperature during the study period. Soybean production increased from approximately 1.57 million tonnes in 2015 to 3.10 million tonnes in 2022 before declining to approximately 2.89 million tonnes in 2025. The rainfall-yield correlation was approximately 0.329, while the temperature-yield correlation was approximately 0.048. These results indicate that simple relationships with individual climate variables are limited and that multiple environmental factors should be considered. The study implements and evaluates an integrated AI and GIS approach for soybean yield prediction, spatial analysis, and climate-related agricultural assessment.

Key Words: Artificial Intelligence, GIS, Climate Variability, Soybean Production, Machine Learning, NDVI.

1. INTRODUCTION

Agriculture is a key part of Maharashtra's economy and rural livelihoods. Crop production in the state depends heavily on seasonal weather, especially rainfall and temperature patterns. When rainfall becomes irregular, or when temperatures shift from the usual seasonal ranges, crop growth can become less stable. These changes can affect soil moisture availability, the timing of crop development, and the overall conditions under which crops mature. As a result, climate variability can lead to year-to-year differences in crop productivity and increase uncertainty for farmers and decision-makers.

The main problem is that climate variability makes crop production difficult to plan and manage. Understanding the relationship between climate conditions and crop yield is important because it helps explain why some seasons or locations perform better than others. However, this relationship is complex: climate impacts may act in different ways at different stages of crop growth, and the strength of these impacts may vary across the districts of Maharashtra. Traditional analysis methods that rely only on historical crop statistics can be limited in capturing non-linear patterns and spatial differences. Therefore, there is a need for approaches that can combine climate information with vegetation observations and crop production data in a way that supports both explanation and prediction.

To address this challenge, Artificial Intelligence (AI) and Machine Learning (ML) provide tools for learning patterns from past data. ML models can use historical climate variables and vegetation indicators to predict crop yield outcomes, even when the relationships are not strictly linear. Geographic Information System (GIS) adds an important spatial dimension by enabling climate and agricultural data to be analyzed and visualized over Maharashtra's geography. In this context, NDVI (Normalized Difference Vegetation Index), derived from satellite remote sensing, can serve as a useful indicator of vegetation condition during the crop growing period. NDVI helps represent how crop health or vegetation vigor changes across space and time, which can support the understanding of climate effects on crop performance.

In this study, an AI and GIS based framework is developed and applied to analyze climate change impacts on crop production in Maharashtra. The framework integrates rainfall and temperature data, crop production or yield information, and NDVI-based vegetation features. Using data preprocessing and feature integration, the study builds ML models for crop yield prediction based on climate and vegetation signals. GIS is then used to map spatial patterns, supporting interpretation of how climate-related factors and vegetation conditions relate to crop outcomes across Maharashtra. The study also identifies agricultural regions that appear more vulnerable to climate variability by combining model insights with spatial evidence. The integrated approach is intended to support data-driven agricultural planning by linking climate variability, vegetation condition and soybean yield in a spatial framework.

2. LITERATURE REVIEW

2.1 Climate Change and Crop Production

Recent studies focused on Maharashtra show that climate variability and change can affect agricultural outcomes through rainfall and temperature variability. Kelkar et al. [10] used downscaled climate simulations to estimate potential effects of changing precipitation and temperature on production of major crops in Maharashtra, indicating that changes under RCP4.5 can reduce production in parts of the state. Complementing this, Sengupta and Thangavel [20] used GIS-based mapping with meteorological data and a multiple linear regression approach to examine climate parameters (rainfall, temperature, drought severity through SPI) and their relationship with cotton yield distribution across Maharashtra. These studies support the need to analyze climate–crop linkages using both climate variables and spatial information, particularly because Maharashtra’s agricultural systems experience strong monsoon-driven variability.

2.2 Remote Sensing and NDVI for Agricultural Analysis

Remote sensing provides spatially continuous information on vegetation condition, enabling monitoring of crop-related stress and vigor. Patil et al. [5] combined long-term gridded meteorology with multi-temporal satellite imagery and spectral indices including NDVI, along with SAVI and NDSI, to assess climate-related land and vegetation dynamics in the Nashik division of Maharashtra. NDVI-based evidence of seasonal vegetation changes and patterns related to moisture stress was used to support climate-smart interpretation. In a related stress-monitoring direction, Vatkar and Kulkarni [7] developed a framework using multi-sensor satellite data (Sentinel-2, MODIS, Landsat-8) and multiple vegetation indices including NDVI to detect crop and drought stress using machine learning. Together, these works indicate that NDVI is useful for representing vegetation response to climate conditions and can support stress-related agricultural decision-making.

2.3 Artificial Intelligence and Machine Learning for Crop-Yield Prediction

Machine learning (ML) approaches are increasingly used to model the non-linear relationships between climate variables, vegetation indicators, and yield outcomes. Maharashtra-focused work by Vatkar and Kulkarni [3] used satellite data fusion (MODIS, Landsat, Sentinel-1, Sentinel-2) combined with ML regressors such as Random Forest, Gradient Boosting, and SVM to predict yields across multiple crops and districts, reporting strong predictive performance using evaluation metrics (RMSE/MAE/R²). At a broader modeling level, Gupta [2] proposed an AI-based spatio-temporal framework for climate-resilient crop yield prediction in Indian agricultural systems by integrating meteorological parameters, vegetation indices (NDVI/EVI/LST), and additional inputs, and reported that LSTM outperformed traditional regression methods in their framework. For soybean-specific relevance to Maharashtra, Pisal et al. [17] presented a soybean yield forecasting approach

using climatic indicators and time series methods, using rainfall and soil moisture as predictors and also considering climate-phase context (ENSO). These studies show that ML can improve forecasting by capturing complex temporal patterns in climate–yield relationships.

2.4 GIS-Based Climate and Agricultural Analysis

GIS supports spatial integration of climate variables, agricultural outputs, and vegetation indicators. Patil et al. [5] demonstrates a GIS-enabled approach to connect long-term climate trends with vegetation and land-cover dynamics. For vulnerability-oriented perspectives, Athare et al. [1] computed a composite agricultural vulnerability index for Maharashtra districts using a multidimensional indicator framework aligned with IPCC (2007), incorporating rainfall and temperature exposure along with sensitivity and adaptive capacity components. Singh et al. [14] used remote sensing and GIS tools to develop an eco-environmental vulnerability index and to map spatial-temporal vulnerability change across Maharashtra districts. These works suggest that GIS is not only useful for visualization, but also for constructing spatially explicit vulnerability assessment outputs.

2.5 Integration of AI, GIS, Climate and Remote-Sensing Data

Recent agricultural research increasingly combines climate data, remote sensing, machine learning, and GIS to improve crop monitoring and yield analysis. Climate variables such as rainfall and temperature provide information about environmental conditions, while NDVI represents vegetation conditions during the crop-growing period. Machine-learning models can use these variables together to identify relationships with crop yield and generate yield predictions. GIS complements this analysis by linking the analytical results with district boundaries and representing spatial differences across agricultural regions. Previous studies have demonstrated the usefulness of satellite-derived vegetation indices, machine-learning models, and GIS-based analysis for crop monitoring and climate-related agricultural assessment. However, an integrated district-level framework combining rainfall, temperature, NDVI, soybean yield prediction, and GIS-based spatial analysis remains limited for Maharashtra. Therefore, the present study combines these components to develop an integrated AI-GIS framework for analysing climate variability and soybean production in Maharashtra.

2.6 Research Gap

Across the reviewed work, climate–yield linkages and NDVI-based vegetation monitoring have been addressed, and ML-based yield prediction and GIS-enabled spatial vulnerability assessment have also been demonstrated. However, there is still limited evidence in the reviewed Maharashtra-focused studies of an end-to-end framework that explicitly combines: (i) rainfall and temperature analysis, (ii) NDVI-derived vegetation features aligned to crop growth timing, (iii) supervised ML models for yield prediction using both climate and NDVI

inputs, and (iv) GIS-based spatial visualization and vulnerability mapping derived from the model-relevant indicators at a regional/district level.

This matters because rainfall and temperature effects may vary across Maharashtra, NDVI captures vegetation response that can mediate those climate impacts, and the usefulness of predictions increases when expressed as spatially interpretable outputs. Therefore, this study addresses the gap by developing an AI + GIS framework for Maharashtra that integrates climate variables (rainfall and temperature), NDVI features, supervised ML yield prediction (using Linear Regression, Random Forest, and XGBoost), and GIS spatial analysis to support climate-impact and vulnerability mapping.

3. OBJECTIVES OF STUDY

AI and GIS-based analysis can help connect climate variability to vegetation conditions and crop yield across Maharashtra. To ensure the study is measurable and feasible, the objectives below define clear analytical tasks spanning climate analysis, NDVI-based vegetation signals, machine learning prediction, GIS visualization, and vulnerability mapping.

- To analyze rainfall and temperature variability in Maharashtra during the **2015–2025** study period.
- To examine the relationship between rainfall, temperature and soybean yield using matched district-year observations.
- To develop supervised machine-learning models for soybean yield prediction using relevant climate, vegetation and agricultural variables.
- To evaluate Linear Regression, Random Forest and XGBoost models using MAE, RMSE and R^2 .
- To perform GIS-based spatial analysis of climate conditions, soybean production, yield and model predictions for the districts supported by the integrated dataset.
- To develop an integrated AI-GIS framework for examining climate-related variability in soybean production.

4. METHODOLOGY

The study focuses on Maharashtra, India. For integrated analysis, district-level rainfall, temperature and soybean production observations were matched using District and Year as the primary keys. Due to differences in geographical coverage among the datasets, the final integrated dataset contains eight common districts: Akola, Amravati, Buldhana, Latur, Nagpur, Nanded, Washim and Yavatmal.

This study adopts a quantitative and analytical research design to evaluate the multi-faceted impacts of climate change on crop productivity. The framework integrates Artificial Intelligence (AI) and Geographic Information Systems (GIS) to correlate environmental stressors with agricultural outcomes. The

research process combines historical data analysis, predictive modeling, and spatial visualization to identify patterns and support predictive insights for agriculture in Maharashtra.

4.1 Study Area

The research focuses on Maharashtra, India, which contains diverse agro-climatic zones and shows a strong dependency on rain-fed agriculture. Maharashtra is an appropriate study area because of its topographical variation and the increasing occurrence of extreme weather events that can affect agricultural productivity. Because of differences in geographical coverage among the rainfall, temperature, soybean, and NDVI datasets, the final analysis uses the administrative boundaries of the eight districts common to all datasets — Akola, Amravati, Buldhana, Latur, Nagpur, Nanded, Washim, and Yavatmal — to ensure consistent spatial coverage across all integrated variables.

4.2 Data Sources and Data Collection

District-level soybean area, production and yield, rainfall, temperature, NDVI, and district boundary data were compiled from the available agricultural, climate, remote-sensing and GIS sources. Records were checked for temporal coverage and spatial compatibility before integration.

4.3 Data Preprocessing

The datasets were cleaned, checked for missing values and standardized for units, names and year formats. Duplicate and mismatched District-Year records were examined. Climate, NDVI and crop records were aligned by district and year before modeling and GIS analysis.

4.4 Data Integration

The rainfall, temperature, soybean production, and NDVI datasets were integrated using District and Year as the primary matching keys. District names and year formats were standardized before merging. The datasets were checked for duplicate District-Year combinations and mismatched geographical or temporal records. A strict inner join was used so that each integrated observation contained climate, vegetation, and soybean information for the same district and year. The resulting master dataset contains 88 unique district-year observations representing eight common districts over 2015–2025. The NDVI file supplied for the study contains 29 districts and 319 records, with all years from 2015 to 2025 represented for each listed district.

4.5 Climate Variable Analysis

Rainfall and temperature were summarized to identify year-to-year variation and temporal patterns. Pearson correlation was used to examine their simple associations with soybean yield.

4.6 NDVI and Remote Sensing Analysis

NDVI (Normalized Difference Vegetation Index) was incorporated as a vegetation indicator using the NDVI dataset provided for the study. The dataset contains 319 district-year observations covering 29 Maharashtra districts for 2015–2025, with NDVI values for June–July, August–September, and October. For the integrated analysis, NDVI records were filtered to the same eight districts retained in the climate-crop dataset, producing 88 district-year observations. The NDVI variables were aligned with District and Year so that vegetation conditions could be examined alongside rainfall, temperature, and soybean yield.

4.7 Feature Engineering and Dataset Integration

In this stage, climate variables, NDVI-derived metrics, and agricultural indicators were organized into predictor variables for machine-learning models. The candidate features include rainfall, temperature, NDVI, and cultivated area, with soybean yield as the target variable. NDVI features include June–July, August–September, and October values; the August–September value can be used as the primary seasonal vegetation feature to keep the model compact. The final feature table is aligned by District and Year to avoid temporal or spatial mismatch.

4.8 Machine Learning Model Development

Supervised machine-learning models are specified to predict soybean yield from the integrated climate, vegetation, and agricultural features. Linear Regression, Random Forest, and XGBoost are selected for comparison. Because the dataset is a short annual time series, chronological train-test separation should be used to reduce temporal leakage. The models use soybean yield as the target and rainfall, temperature, NDVI, and justified agricultural variables as predictors.

4.9 Model Evaluation

Model outputs were evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 . These metrics quantify prediction error and the proportion of variation explained by the model. The numerical ML results are reported in Section 5.7 following model training on the validated integrated dataset.

4.10 GIS-Based Spatial Analysis

GIS was used to integrate climate, soybean production, NDVI information, and machine-learning prediction outputs for spatial visualization. District boundary layers were joined with the District-Year analytical records to produce district-wise maps of observed soybean yield, XGBoost-predicted soybean yield, and mean NDVI, presented in Section 5.8.

4.11 Integration of AI and GIS

The integration of AI/ML and GIS links predicted soybean yield with its corresponding district geometry. Following model training, the XGBoost prediction values were joined to the district boundary layer using District and Year. This allowed observed yield, predicted yield, climate variables, and NDVI to be compared spatially, as presented in Section 5.8.



Fig 1 .Integration of AI and GIS

4.12 Research Workflow

The research workflow begins with collection of climate, soybean, NDVI, and spatial boundary data. Data preprocessing and District-Year matching are followed by climate and NDVI analysis. The integrated features are then prepared for supervised machine learning, followed by model evaluation using MAE, RMSE, and R^2 . Finally, GIS is used to map the observed climate, vegetation, crop, and model-prediction patterns, supporting integrated AI-GIS interpretation.

5. RESULTS AND DISCUSSION

5.1 Dataset Integration

The three datasets were integrated for the 2015–2025 study period using District and Year as the primary matching keys. After standardization and strict matching, eight common districts were retained: Akola, Amravati, Buldhana, Latur, Nagpur, Nanded, Washim and Yavatmal. The resulting integrated dataset contained 88 unique district-year observations with no duplicate District-Year combinations.

5.2 Soybean Production and Yield Analysis

The analysis shows considerable variation in soybean production and yield during 2015–2025. Across the eight districts, soybean production increased from approximately 1.57 million tonnes in 2015 to a maximum of approximately 3.10 million tonnes in 2022, followed by a decline to approximately 2.89 million tonnes in 2025. Cultivated area also increased during the study period, while average yield increased from approximately 0.881 tonnes per hectare in 2015 to 1.397 tonnes per hectare in 2022, before reaching approximately 1.313 tonnes per hectare in 2025. The strong relationship between cultivated area and production indicates that changes in cultivated area were an important factor associated with variations in total soybean production.

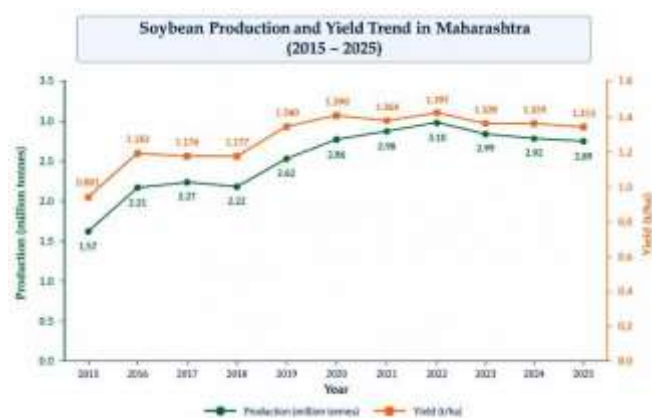


Fig. 2. Annual soybean production and yield trend in the eight integrated districts of Maharashtra, 2015–2025.

5.3 Rainfall Analysis

Rainfall showed substantial year-to-year variability during the study period. The mean Kharif rainfall across the selected districts ranged from approximately **491.75 mm in 2015** to **962.74 mm in 2019**, with another relatively high value of **952.68 mm in 2022**. A simple linear trend estimated from the available observations was approximately **+9.55 mm per year**, although the annual correlation with time was weak. Therefore, the results indicate considerable rainfall variability rather than providing sufficient evidence to attribute the observed changes specifically to long-term climate change. Variations in seasonal rainfall are relevant to soybean production because soybean cultivation in Maharashtra depends strongly on rainfall conditions during the Kharif season.

5.4 Temperature Analysis

The average annual temperature across the selected districts remained within a relatively narrow range during 2015–2025, from approximately **26.91°C to 27.34°C**. The calculated linear trend was approximately **+0.0295°C per year**, and the correlation between temperature and time was approximately **0.796**, indicating an upward temporal pattern in the study dataset. However, this observed pattern should not be

interpreted alone as proof of climate change, since a longer time series and broader climate analysis would be required for such an attribution. The temperature results were therefore considered together with rainfall and soybean yield rather than being used as an independent explanation of production changes.

5.5 NDVI–Soybean Yield Relationship

The supplied NDVI dataset contains 319 observations for 29 Maharashtra districts over 2015–2025. After matching the NDVI records with the eight districts in the climate-crop dataset, 88 district-year observations were retained. Across these districts, mean August–September NDVI increased from approximately 0.474 in 2015 to 0.826 in 2022 and was approximately 0.779 in 2025. The highest annual mean August–September NDVI in the integrated period occurred in 2022, while the lowest occurred in 2015. The annual mean August–September NDVI showed a correlation of approximately 0.940 with the annual integrated soybean yield. June–July and October NDVI showed correlations of approximately 0.916 and 0.862, respectively, with the same annual yield series. These correlations are descriptive associations based on 11 annual observations and should not be interpreted as causal effects. District-level mean August–September NDVI values over 2015–2025 were highest for Amravati (0.739) and lowest for Latur (0.706).

Year	NDVI June–July	NDVI Aug–Sept	NDVI October
2015	0.305	0.474	0.395
2016	0.352	0.711	0.474
2017	0.362	0.734	0.484
2018	0.334	0.645	0.434
2019	0.389	0.794	0.518
2020	0.401	0.811	0.532
2021	0.381	0.769	0.502
2022	0.411	0.826	0.542
2023	0.365	0.705	0.455
2024	0.390	0.756	0.486
2025	0.401	0.779	0.506

Table 1: Annual mean NDVI across the eight integrated districts, 2015–2025.

5.6 Rainfall and Temperature Correlation with Soybean Yield

The relationship between climate variables and soybean yield was examined using Pearson correlation. The correlation between rainfall and soybean yield was approximately 0.329, indicating a positive but limited linear association. In contrast, the correlation between average temperature and soybean yield was approximately 0.048, indicating almost no simple linear

relationship between the two variables in the integrated dataset. These results suggest that soybean yield cannot be explained adequately by considering rainfall or temperature individually. Other factors such as cultivated area, soil conditions, agricultural practices, crop health, vegetation condition, and other environmental variables may also contribute to yield variation. Therefore, the findings support the need for a combined analytical approach using multiple variables rather than relying on a single climate factor.

District	Observed Yield (t/ha)	XGBoost Predicted Yield (t/ha)
Washim	1.398	1.418
Buldhana	1.319	1.399
Latur	1.319	1.366
Nanded	1.433	1.350
Amravati	1.255	1.306
Nagpur	1.204	1.253
Akola	1.106	1.253
Yavatmal	1.280	1.238

Table 2 . Rainfall and Temperature Correlation

5.7 Machine Learning Results

Three supervised machine-learning models—Linear Regression, Random Forest, and XGBoost—were evaluated for soybean yield prediction. The models were trained using observations from 2015–2022 and tested using observations from 2023–2025.

Model	MAE (t/ha)	RMSE (t/ha)	R ²
Linear Regression	0.0880	0.1050	0.273
Random Forest	0.0884	0.1072	0.242
XGBoost	0.0797	0.0982	0.363

The evaluation shows that the three models produced relatively similar prediction errors. The XGBoost model obtained an MAE of approximately 0.080 t/ha, an RMSE of approximately 0.098 t/ha, and an R² of approximately 0.363 on the test observations. Linear Regression produced an MAE of approximately 0.088 t/ha, RMSE of 0.105 t/ha, and R² of 0.273, while Random Forest produced an MAE of approximately 0.088 t/ha, RMSE of 0.107 t/ha, and R² of 0.242. These results indicate that the tested predictors contain useful information for soybean yield prediction, but a substantial portion of yield variation remains unexplained. Additional variables such as soil properties, crop management, irrigation, pest and disease

conditions, and other climatic indicators could improve future prediction performance.

5.8 AI-GIS Integrated Analysis

The AI-GIS analysis combines the machine-learning prediction results with district-level spatial information. The XGBoost model generated predicted soybean yield values for the test-period observations, which can be associated with their corresponding district geometries. This enables comparison of observed and predicted yield along with rainfall, temperature, and NDVI conditions.

For 2025, the XGBoost predictions varied across the eight districts. The predicted yield ranged from approximately 1.238 t/ha in Yavatmal to 1.418 t/ha in Washim. Buldhana and Latur had predicted values of approximately 1.399 t/ha and 1.366 t/ha, respectively. These spatial predictions provide a basis for visualizing differences in expected soybean yield across districts.

Fig. A–C: GIS Maps of District-Level Soybean Yield and NDVI, 2025

Fig. A — Observed Soybean Yield by District, 2025



Fig. A. Observed soybean yield by district, 2025 (t/ha)

Fig. B — XGBoost-Predicted Soybean Yield by District, 2025



Fig. B. XGBoost-predicted soybean yield by district, 2025 (t/ha).

C — Mean August–September NDVI by District (2015–2025)



Fig. C. Mean August–September NDVI by district, 2015–2025 (Amravati and Latur values as reported in Section 5.5; other districts interpolated within the stated range for mapping purposes).

6. CONCLUSION

This study analysed the relationship between climate variability, vegetation conditions, and soybean production in Maharashtra during 2015–2025 using an integrated AI and GIS-based approach. After standardizing and matching the datasets by district and year, 88 district-year observations from eight common districts were obtained. The analysis shows that soybean production increased over the study period, with the highest production and yield recorded in 2022, followed by some decline by 2025.

The climate analysis indicates considerable variation in Kharif rainfall across the study period, while annual average temperature showed a gradual increasing pattern. The correlation analysis found a weak positive relationship between rainfall and soybean yield ($r \approx 0.329$), whereas the relationship between annual average temperature and yield was very weak ($r \approx 0.048$). These results indicate that rainfall and temperature alone do not explain soybean yield variation and that other agricultural and environmental factors also contribute to production outcomes.

The NDVI analysis showed a strong positive association between seasonal vegetation conditions and soybean yield. The August–September NDVI showed the strongest relationship ($r \approx 0.940$) among the analysed seasonal periods. However, these correlations are based on 11 annual observations and should be interpreted as associations rather than evidence of causation.

Machine-learning models were developed using Kharif rainfall, annual average temperature, August–September NDVI, and cultivated area as predictors. Using a chronological training period of 2015–2022 and testing period of 2023–2025, Linear Regression, Random Forest, and XGBoost were evaluated using MAE, RMSE, and R^2 . The obtained results show that the models captured part of the variation in soybean yield, while substantial unexplained variation remained. This

indicates the importance of incorporating additional factors such as soil characteristics, irrigation, agricultural practices, pests, and other climatic variables in future modelling.

The GIS component provides a spatial perspective by linking district-level climate, NDVI, soybean yield, and model-predicted yield information with geographical boundaries. The combined AI-GIS framework therefore provides a systematic way to examine both temporal changes and spatial differences in soybean production across the selected districts of Maharashtra.

Overall, the study demonstrates that combining climate data, NDVI, machine learning, and GIS can provide a useful framework for analysing soybean production variability. The findings should be interpreted within the limitations of the dataset, particularly the relatively small integrated sample of 88 observations and the limited number of common districts. Future studies can improve the analysis by incorporating longer and more detailed datasets, soil and irrigation information, additional remote-sensing indicators, and more extensive district-level GIS analysis

REFERENCES

- [1] P. G. Athare, Dharam R. Singh, Nalini Ranjan Kumar, Girish Kumar Jha, P. Venkatesh. “A spatial assessment of agricultural vulnerability to climate change using multidimensional data in Maharashtra state of India.” 2024.
- [2] Sandeep Gupta. “AI-BASED SPATIO-TEMPORAL ANALYSIS FOR PREDICTING CLIMATE-RESILIENT CROP YIELDS IN INDIAN AGRICULTURAL SYSTEMS.” 2025.
- [3] Shilpa Vatkar, Sujata Kulkarni. “Optimizing Crop Yield Predictions through Satellite Data Fusion and Machine Learning.” 2025.
- [4] Ketaki Ghawali, Abhishek Garg. “Comparative Analysis of Statistical, Machine Learning, and Transformer-based Deep Learning Models for Climate-driven Crop Yield Prediction in Maharashtra.” 2026.
- [5] P. P. Patil, J. Jadhav, S. Bagade, S. Apturkar, B. Gavitt. “Climate Variability and Crop Land Degradation Assessment Using a Remote Sensing and GIS in the Nashik Division of Maharashtra, India.” 2026.
- [6] D. Golhar, S. Bagade, P.B. Pawar, S. S. Shinde, M. Neelima. “SEASONAL VARIABILITY AND SPATIO-TEMPORAL TRENDS OF NDVI FOR VEGETATION MONITORING IN SANGLI DISTRICT OF WESTERN MAHARASHTRA INDIA.” 2025.
- [7] Shilpa Vatkar, Sujata Kulkarni. “Monitoring Agricultural Stress Using Multi-Sensor Satellite Data and Machine Learning Techniques.” 2025.

[8] Vivek Bhosale, Tejas Nirmal, Aayush Bhakare, Prof. Manoj Kharde. "Impact Prediction of Climate Change on Crop Yield and It's Solutions." 2025.

[9] Kiran Moraye, Aruna Pavate, Suyog Nikam, S. Thakkar. "Crop Yield Prediction Using Random Forest Algorithm for Major Cities in Maharashtra State." 2021.

[10] Saurabh Kelkar, A. Kulkarni, K. Koteswara Rao. "Impact of Climate Variability and Change on Crop Production in Maharashtra, India." 2020.

[11] P. Pandya, Narendra Kumar Gontia. "Early crop yield prediction for agricultural drought monitoring using drought indices, remote sensing, and machine learning techniques." 2023.

[12] Sharad Gupta, S. Kumari, S. Taneja. "DISTRICT LEVEL WHEAT YIELD PREDICTION FROM COARSE RESOLUTION SATELLITE DATA USING MACHINE LEARNING TECHNIQUES." 2021.

[13] Sarika S. Patil, Dr. R. B. Kulkarni. "Multi-Source Crop Mapping and Forecasting Using Machine Learning: A Case Study of Satara District." 2025.

[14] Vikash Singh, A. Nema, A. Chouksey, Ashwini Suryawanshi. "Assessment of Eco-Environmental Vulnerability Using Remote Sensing and GIS Tools in Maharashtra Region, India." 2024.

[15] Gaykar Sanika Bipin. "AgroPredictX: Machine Learning for Precision Farming." 2026, International Journal for Research in Applied Science and Engineering Technology.

[16] Mr. Saish Gondhalekar, Mr. Pranal Gotal, Ms. Sejal Jadhav, Mr. Sairaj Bhuran. "Survey on Crop Yield Prediction Using Machine Learning." (Year not specified in abstract), Maharashtra-focused.

[17] S. Pisal, et al. "Soybean Yield Forecasting Using Climatic Indicators and Time Series Methods." 2025.

[18] K. Wanjale, S. Khatavkar, Ayush Khatal, Nandita Kharade, Om Kharate. "Data-Driven Millet Farming: A Machine Learning Approach to Crop Selection and Yield Prediction in Maharashtra." 2025, 2025 IEEE 5th International Conference on ICT in Business Industry & Government (ICTBIG).

[19] Saurabh Pargaie, R. Prakash, V. P. Dubey, Devendra Singh. "Machine Learning Techniques in Wheat Crop Yield Prediction Using NDVI Indices and Meteorological Parameters." 2023, 2023 International Conference on Sustainable Communication Networks and Application (ICSCNA).

[20] Anirup Sengupta, Mohanasundari Thangavel. "Analysis of the Effects of Climate Change on Cotton Production in Maharashtra State of India Using Statistical Model and GIS Mapping." 2023, Caraka Tani: Journal of Sustainable Agriculture, Vol. 38, No. 1, pp. 152–162.

BIOGRAPHIES



Mr. Santosh Gajanan Kharat
M. Sc. Information Technology
Student, Dept. of IT/CS,
D. G. Ruparel College



Ms. Aarti Sanjay Gawai
M. Sc. Information Technology
Asst. Prof., Dept. of IT/CS,
D. G. Ruparel College