Climate Resilient Agriculture Vulnerability Mapping of Indian Districts – Directions for Future Policy Planning

Anandajit Goswami[1*], Swati Hans[2¶], Tanu Dua[3¶], Indu Kashyap[4¶]

[1]School of Behavioural and Social Sciences, Manav Rachna International Institute of Research and Studies, India

[2]Department of Computer Science and Engineering, Manav Rachna International Institute of Research and Studies, India

[3]Department of Computer Science and Engineering, Manav Rachna International Institute of Research and Studies, India

[4]Department of Computer Science and Engineering, Manav Rachna International Institute of Research and Studies, India

* anandajit.fbss@mriu.edu.in

¶ These authors contributed equally to this work.

Abstract

Climate change poses significant risks to agriculture, especially in agro-dependent, climate-vulnerable regions and states of India. This study applies a machine learning-based Long Short-Term Memory (LSTM) model to assess agricultural risks, climate vulnerability in various Indian states with diverse climatic variables to address India's 2070 net-zero goal. It addresses the existing research gaps between the predictive analytical models for climate vulnerability mapping and their application for policy implementation in India.

Our predictive modelling analysis based on the AI ML applications presents a district-wise climate vulnerability mapping across India's four major climatic zones. Based on district-specific vulnerability mapping across the four zones of India, this paper proposes a comprehensive framework for policy implementation and an action plan to address climate-induced agricultural vulnerability in the country. The model leverages climate variables such as temperature and rainfall, along with agronomic factors, to forecast systemic and non-systemic risks across states. Through our LSTM Model, the effect of climate factors has been analyzed in various districts of India for the Kharif and Rabi seasons. Our LSTM Model assists in finding the key districts requiring immediate attention in terms of policy execution and implementation at a sub-national level to address the district-specific climate and agricultural vulnerability.

Key findings indicate substantial variability in risk profiles of the chosen districts of India, underscoring the need for tailored policies to enhance crop resilience and mitigate future climate-led agricultural vulnerabilities. By integrating predictive analytics, the research provides actionable insights for policymakers to design adaptive measures, ensuring sustainable agricultural practices, improved farmer incomes, and food security. As an outcome, this novel approach bridges the gap between predictive modelling and policy applications for mitigating future agricultural and climate vulnerability of chosen Indian states and districts, paving the way for climate-resilient agricultural systems driven by subnational, decentralized, climate-resilience-based governance systems for the future.

Keywords: Climate Risk, Crop Prediction, Machine Learning, Policy Framework, Agricultural Sustainability

Introduction

Climate factors such as temperature, precipitation, and extreme weather events can have a significant impact on crop yields and overall production. To perform a comprehensive risk analysis, likely region-specific climate variables to influence crop production required to be systematically identified and assessed. For example, in areas where drought is a common occurrence, a risk analysis would focus on the potential impact of drought on crop yields. To conduct a risk analysis, one would start by identifying the specific climate factors that are likely to have an impact on crop production in a given region. For example, in areas where drought is a common occurrence, a risk analysis would focus on the potential impact of drought on crop yields. Once the climate factors have been identified, a risk assessment can be done to determine the likelihood of these factors occurring and the potential impact they would have on crop production. This assessment would take into account factors such as the vulnerability of the crops to specific climate factors, the potential for adaptation or mitigation measures, and the economic impact of reduced crop yields. Based on the results of the risk analysis, farmers and policymakers can develop strategies to mitigate the risks associated with climate factors and ensure that crop production remains stable and sustainable. This may include the development of drought-resistant crop varieties, the implementation of irrigation systems or the establishment of early warning systems to alert farmers to potential weather events.

Overall, a risk analysis tool based on the AI/ML approach will prove to support the understanding of the potential impacts of climate factors on crop production and develop strategies to mitigate these risks. By taking a proactive approach to understand, mitigate climate risks, farmers and policymakers can help to ensure that crop production remains resilient and sustainable for farmers in the face of a changing climate.

Research Gap

A systematic literature review of studies on agricultural vulnerability from climate risks in India shows that there is a wide range of literature on Climate Change and Resilience, Adaptation, and Sustainability of Agriculture in India (CCRASAI). A bibliometric review of 572 articles [1] between 1994 and 2022 on climate resilience, adaptation, and agricultural sustainability in India by addressing climate vulnerability shows that there was an evident upward trend in CCRASAI publications during this period, with steady growth appearing after 2007. Studies have been largely conducted for Delhi, Tamil Nadu, West Bengal, Andhra Pradesh, and Karnataka, and mostly concentrated in the southern plateau, the trans-Gangetic and middle Gangetic plains, and the Himalayan regions. The research on CCRASAI with a focus on climate and agricultural vulnerability emphasizes the focus on analyzing the effects of CC, creating adaptation strategies, and promoting sustainable agricultural practices. In this regard, a research gap exists in terms of the measurement of district-specific climate vulnerability and the potential risks of that on district-specific agricultural vulnerability for districts and states of India. This paper aims to bridge that gap by addressing climate vulnerability through a predictive model based mitigation-focused perspective, thereby contributing to India's broader objective of achieving Net Zero emissions by 2070.

India has already announced an international commitment to reaching a net-zero carbon-neutral economy by 2070 to reduce the human-induced impacts of climate change. To achieve this target, India has to follow a decarbonized growth path across the agriculture, industry, and services sectors. However, a decarbonized path can be taken if sectors are protected against climate risks. To protect the various sectors against climate risks, the various sectors across the States of India have to be protected against climate risks. Policies can be drafted against climate risks only when climate vulnerabilities are predicted for the future across various scenarios for various districts, considering the wide range of risk scenarios. It is with this context that a machine learning model is created that will predict the future agricultural vulnerability and climate risks across districts of the Indian Economy to attain the path of a carbon-neutral economy in India. Currently, a significant research gap exists in understanding district-specific climate risks arising from agricultural vulnerability across various regions of India. This research provides the first evidence-based direction towards understanding district-specific agricultural and climate vulnerability in India. Such an evidence-based approach and direction will therefore help in policy planning and execution, and could help the sub-national governments to execute and prioritize districts for policy planning and decisions to address climate risks generated by agricultural vulnerability in India. This, in a way, will therefore also contribute to National and state-level policy-making in India to prepare the country to address the carbon-neutral growth path and attain a zero-carbon economy by 2070. The next section therefore creates a background for that by undertaking the literature review.

Background

Literature Review

Khosla, Dharavath, and Priya (2020) [2] have applied modular artificial neural networks (MANNs) to predict the amount of rainfall that can occur during the monsoon season in Visakhapatnam in the upcoming years. After predicting rain, they made a feature selection to select only essential climate and weather variables in predicting various kharif crops in Visakhapatnam. Finally, using only those variables, they predicted the yield of bajra, maize, rice, and ragi. It can be seen from the results that in recent years less area is given to crops if we compare the area given to crops in the year 1997; this is because owing to the increasing population in the city, the area which was given to crops earlier has now been used as a residential area. In this study, they predicted the yield of various kharif crops in Visakhapatnam. To accommodate the prediction strategies for Kharif, they have presented a methodology named MANNs-SVR in this study. By using MANNs-SVR, firstly, they predicted the occurrence of rainfall in the region of Visakhapatnam. Then, by using attributes that give the most information about the production of Kharif crops in Visakhapatnam, they predicted the amount of common crops like rice, ragi, maize and bajra that can be yielded in the upcoming years. Most past studies mainly focused on image processing and prediction using statistical models. However, machine learning approaches can work faster in computation and are more efficient than the statistical methods proposed in the past. Such approaches can predict the yield of various crops in various cities through various attributes/factors like fertilizers used, irrigation and many more. If those parameters are considered, the accuracy of our predictions can be increased. While only rainfall and area have been utilized to predict crop yield, actual yield outcomes are influenced by a broader set of factors, including fertilizer application, irrigation practices, and other agronomic inputs. If those parameters are considered, the accuracy of predictions will increase. Hence, there is still substantial space for improving the projections. Smart farming approaches increasingly incorporate region-specific crop production, data collection across global contexts facilitated by database management systems, representing a novel and emerging criterion in advancing modern agricultural technologies (Joshi & Kaushik, 2021)[9]. To feed India's increasing population, the latest technical methodologies must be incorporated into the agricultural sector. In addition, farmers require timely advice to predict crop productivity so that they can make proper strategies to increase the yield of their crops. Precision agriculture is an approach that uses technology to ensure that soil and crops get what they need for optimum productivity and health. In precision agriculture, real-time farm and weather data are collected using sensors to make predictions to help farmers make correct farm-related decisions. Small sensors are deployed on the farm, collecting and sending the data to the relevant data storage node. The data collected is huge in volume and can be processed by using big data analytics. Big data provides facilities like data storage, data processing, and data analysis with accuracy. So, its use in agriculture can benefit farmers and the nation's economic growth. With the help of big data analytics and related machine learning algorithms, crop productivity can be increased by many folds.

Shank, Hoogenboom and McClendon (2008) [10] used ANN (Artificial Neural Network) to determine the dew point of temperature. They used weather data from twenty locations in Georgia, United States, to construct an ANN for estimating Georgia's dew point temperature. These models accurately predicted various freezing conditions and heat wave occurrences, which can affect crop production. Therefore, it can be stated that ANN models have the potential to predict additional information about the crop system and management. It is useful for the prognostication of different meteorological variables for the prediction of better agricultural yield in the future. In this research, Artificial Intelligence/ Machine Learning / Artificial Neural Network algorithms have been investigated/explored to design an efficient system for accurate crop yield prediction/forecasting.

LSTMs can effectively model the temporal dependencies inherent in climatic data, leading to more accurate and reliable rainfall forecasts. This improved predictive capability is essential for agricultural planning and water resource management, as it enables stakeholders to make informed decisions based on anticipated weather patterns. The study by Varalakshmi, Nazeer, Srimanth, Krishna, & Sahool (2023) [11] quoted that rainfall prediction is a significant factor in agricultural countries such as India because it is a major factor in food production. They discovered that the usage of a deep-learning model for rainfall prediction in agriculture can surely improve the accuracy of model predictions. As a result, they proposed an LSTM-based rainfall prediction to improve the accuracy of rainfall forecasting. LSTM networks are well-suited for classification, processing, and prediction of time series data because there may be delays of unknown duration between important events in a time series. They demonstrated that LSTM-based models outperform traditional methods in capturing the complex, non-linear relationships present in climate data, thereby offering a robust tool for enhancing agricultural productivity and sustainability. Their results show that these deep learning models can predict weather features accurately enough to compete with traditional models.

Bhardwaj et al. (2023) [12] proposed an innovative deep learning based approach to achieve increased accuracy in price prediction of crops. The proposed approach uses graph neural networks (GNNs) in conjunction with a standard convolutional neural network (CNN) model to exploit geospatial dependencies in the prices of crops. This method performs at least 20% better results as seen in the literature while working effectively with noisy legacy data.

Anuradha et al. (2023) et al. [13] found that by analyzing factors such as season, area, temperature, humidity, moisture, soil type, crop type and nutrient levels, the study aims to predict future crop yields accurately. Additionally, the model uses data on crop production in different districts and years to train and test various machine learning (ML) Techniques like Decision tree, Linear regression, K-Nearest Neighbors along with a deep learning architecture. They found that to predict crop yields, the KNN model can be preferred over linear regression and decision trees. Among the three models, the KNN model has the lowest RMSE and MAE values, indicating that it is the most accurate and reliable model for predicting crop yields. The LSTM architecture model also increased the accuracy and had a lower error rate, which indicated it to be the best compared with the three machine learning models.

Ramya et al. (2023) [14] discovered that the soil ingredients (like Nitrogen, Phosphorus, Potassium), crop rotation, soil humidity, atmospheric and surface temperature, precipitation etc. play an efficient role in cultivation. The model is created by using a deep learning (RNN) technique. They also implemented some other algorithms to compare the accuracy of the prediction. The model predicts the best crops that should be grown on land with less expenses among several crops available after analyzing the prediction parameters.

Patel & Rane, (2023) [17] developed and applied a smart system that can suggest suitable crops for farmers across India. This system help the farmers choose the best crop based on factors like Nitrogen, Phosphorus, Potassium, PH Value, Humidity, Temperature, and Rainfall. They have evaluated machine learning algorithms like Decision Tree, Support Vector Machine (SVM), Logistic Regression (LR), Gaussian NB and discovered that Decision Tree, Gaussian NB had the best accuracy among them.

The existing literature clearly indicates that climate variables significantly influence future agricultural yields, thereby impacting farmers' livelihoods and long-term livelihood security. Also, deep learning model helps in better prediction of the best crops that should be grown on land on the basis of different parameters. Therefore, the importance of LSTM approaches in understanding the vulnerability of farmers for future climate scenarios is scientifically proven across the developed country context. Hence, for a country like India with a wide variety of climatic zones across the states and a large-scale dependence of population (around 74%) on agricultural yields for the future, the relevance of the LSTM approach in predicting the agricultural risk for farmers across climate scenarios increases manifold. Moreover, a machine learning based LSTM model can facilitate efficient, effective agricultural policy making for the future by understanding the nature, degree of agricultural risk across the states of India, which is currently missing. The present research, therefore, addresses the above-mentioned research and policy gap by testing the following hypothesis.

Hypothesis

Hypothesis 1: There is an existence of varying agricultural risk across the districts of India in various regions which will vary in the future under different climate scenarios.

Hypothesis 2: Agricultural risks need to be hedged through effective policymaking with a district-specific prioritized approach.

The above two hypothesis will be explored and proven affirmative or non-affirmative through an evidence-based AI/ML based modelling approach in this paper. The two hypotheses will be explored by addressing the following objectives.

Objectives

- To assess and create policy prescriptions for hedging climate vulnerability-led agricultural yield risks of districts of various regions of India through an Artificial Intelligence (AI) - Machine Learning Methodology and Tool
- To enable a prioritized policy framework for hedging such climate vulnerability-led agricultural yield risks of districts of various regions of India

Research questions

The above objectives are explored through the following research questions which are –

a) What is the district-specific agricultural vulnerabilities of the states of India with respect to rice production arising from climate vulnerabilities of the future time horizon of 2070?

b) What is the state-specific climate policy frameworks and prioritized implications owing to the district-specific agricultural climate vulnerabilities of the states of India to address the net zero goal of 2070 in India?

c) What are the short and long-term climate policy and adaptation measures and outcomes for addressing district-specific agricultural climate vulnerabilities of the states of India to attain the net zero 2070 goal of India?

Research Methodology

Methodology Structure and Process:

The proposed research of this paper employs an innovative approach that integrates machine learning techniques with climate analytics to predict agricultural risks in terms of futuristic yield variation of rice associated with climate variability in India. A Long Short-Term Memory (LSTM) based neural network model is utilized to identify district-specific risks and varying trends in rice production under varying climatic scenarios of varying temperature and rainfall. The study fills critical research gaps in understanding systemic and non-systemic agricultural risks while informing policy measures to mitigate these risks. The projections are aligned with India's long-term sustainability goals, extending to the year 2070, to support future-ready climate-resilient agricultural planning, policies, and practice. The methodological process of the LSTM model is as follows (Fig 1.) –

Fig 1. Machine Learning architecture using LSTM model for Prediction of Rice Production

Long Short-Term Memory (LSTM) networks are an advanced variant of recurrent neural networks (RNNs) optimized for processing sequential data, making them particularly effective for applications in climate and agricultural forecasting. Unlike traditional machine learning models such as Random Forests and K-Means Clustering, which lack intrinsic mechanisms to capture temporal dependencies, LSTMs are specifically designed to retain long-term patterns through their gated memory structure. This characteristic is especially beneficial in rainfall prediction, where accurately modelling sequential dependencies significantly improves forecasting precision. By incorporating forget, input, and output gates, LSTMs address challenges such as the vanishing gradient problem, thereby facilitating efficient learning from extended temporal sequences in time-series datasets.

Forget Gate: $f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$ (1)

Input Gate: $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$ (2)

Candidate Cell State: $C^{\sim}{}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$ (3)

Cell State Update: $C_t = f_t \odot C_{t-1} + i_t \odot C^{\sim}{}_t$ (4)

Output Gate: $o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$ (5)

Hidden State: $h_t = o_t \odot tanh(C_t)$ (6)

In these equations, x_t represents the input vector at time step t, encompassing variables such as temperature, humidity, and previous rainfall measurements. The hidden state h_t captures the temporal dynamics of the data, while the cell state C_t maintains long-term information. The weight matrices W and bias terms b are parameters learned during the training process, and σ denotes the sigmoid activation function. The element-wise multiplication operator is represented by $\odot$.

Data Collection

The data for this study is derived from reliable sources such as the **Indian Agriculture Statistics Records [15] [16],** supplemented by other national and regional datasets. The data includes:

a) Agricultural Indicators:

This comprehensive dataset ensures the study captures the diverse climatic and agricultural conditions across India by means of data on crop yield, cultivation area, and production trends for major crops across various districts and states obtained from open government platform of India [15].

b) Climatic Variables:

Historical records of temperature, rainfall, and extreme weather events were obtained from GeoQuery by AidData[16] which provides granular, spatially-referenced climate data for precise analysis.

Data Preprocessing

The raw data underwent rigorous preprocessing to ensure accuracy and consistency for model training:

a) Handling Missing Values:

Missing values in crop production data were incorporated according to trend lines from prior years for different districts, maintaining data integrity and continuity.

b) Normalization:

The data was normalized using a MinMax Scaler, transforming all features to a consistent scale between 0 and 1. This step eliminated potential biases caused by large variations in data ranges.

c) Formatting for Time-Series Analysis:

Historical data sequences were structured such that records from four consecutive years served as inputs to predict outcomes for the subsequent year. This format aligns with the temporal design of LSTM networks.

Training and prediction of future risk using LSTM

The core of this research lies in the application of a Long Short-Term Memory (LSTM) neural network to forecast future risks. This structured training approach ensured the model captured complex relationships between climate factors and agricultural outcomes, making it a valuable tool for future agricultural planning and policy-making. Key aspects of the model include:

a) Architecture:

The LSTM model features an input layer to process historical data, hidden layers for capturing long-term dependencies, and an output layer to generate predictions. This architecture is optimized for handling sequential and time-dependent datasets.

b) Training Strategy:

Historical data from four consecutive years were used as an input to predict outcomes for the fifth year. This time-series arrangement is aligned with the temporal dependencies of climate and crop data.

c) Training Parameters:

The model was trained over **12 epochs** with a **batch size of 5,** balancing training efficiency and prediction accuracy.

d) Integration of Training and Test Data:

Training datasets were combined with test datasets to enhance prediction robustness and reduce model variance.

e) Outputs:

The trained model provided district-specific predictions of crop production risks, considering changes in temperature and rainfall. These outputs were further validated against actual production records to confirm accuracy. In this study, visualization techniques were integrated as a critical component of the research methodology to analyze, interpret and communicate the model's predictions effectively. The visual representation of results facilitated a deeper understanding of the relationship between climate variables and agricultural risks, offering actionable insights for stakeholders.

Model Validation and Error Analysis

Ensuring the accuracy of predictions is a critical aspect of the methodology which include the following:

a) Error Analysis and Correction:

Discrepancies in predictions are addressed through iterative model refinement, ensuring the reliability of risk assessments across all districts.In this process, the model predictions were further validated and corrected for rice crop across districts over a time frame of 2025-2070. This was done in response to the changes in climatic variables like temperature and rainfall. The validation score (RMSE) below measures the differences between predicted values and actual values of the LSTM model. It represents the standard deviation of the residuals (prediction errors) and describes the accuracy of the model on the given dataset

b) Validation Score:

Model performance is assessed using standard statistical measures, including Root Mean Square Error (RMSE). These metrics quantified the deviations between predicted and actual values. The validation score provides a quantitative measure of the LSTM model's accuracy in predicting agricultural risks and crop production under varying climate scenarios. It helps assess how well the model generalizes to unseen data and ensures its reliability for practical applications. **In this research, validation scores are derived using statistical metrics, Root Mean Square Error (RMSE)**, which evaluate the deviation between actual and predicted values.Within the model, the lower the RMSE score, the better the accuracy and predictability of the model. Some of the district wise model validation score is shown below in the Table 1 for Kharif season and in Table 2 for Rabi Season.

Table 1. District-wise Model Validation Score (Kharif Season)

Training Dataset(Output variable)	District	**Rice Train Score**
Crop Production (Kharif Season)	East Godavari	**0.0165 RMSE**
	Tawang	**0.0587 RMSE**
	Thane	**0.1552 RMSE**
	Surat	**0.0694 RMSE**
	Karnal	**0.0538 RMSE**
	Bhopal	**0.0601 RMSE**
	Gwalior	**0.3427 RMSE**
	Hoshangabad	**0.5675 RMSE**
	Indore	**0.0657 RMSE**
	Jabalpur	**0.0430 RMSE**
	Panna	**0.0492 RMSE**
	Ratnagiri	**0.1230 RMSE**
	Vellore	**0.0880 RMSE**

Table 2. District-wise Model Validation Score (Rabi Season)

Training Dataset(Output variable)	District	**Rice Train Score**
Crop Production (Rabi Season)	East Godavari	**0.0227 RMSE**
	Thane	**0.1102 RMSE**
	Surat	**0.0529 RMSE**
	Ratnagiri	**0.0792 RMSE**

Key patterns emerging from the Kharif and Rabi Season Crop Production Data:

Key Patterns in production of various districts in the Kharif Season

a) **East Godavari, Jabalpur, Panna, Karnal: These districts have the lowest RMSE values**, meaning the model predictions are highly accurate. These districts indicate that the model is performing well with minimal prediction errors.

b) **Tawang, Bhopal, Indore, Surat, Vellore, Ratnagiri** show **moderate RMSE values**, meaning the model is relatively reliable but has some prediction errors. These districts need slight improvements in model tuning, but predictions are still within an acceptable range.

c) **Gwalior, Hoshangabad, and Thane have very high RMSE values** requiring significant improvements, such as feature engineering, hyperparameter tuning, or additional training data, as the model has **difficulty predicting rice production in these districts**

Key Patterns of crop production of various districts in the Rabi Season

a) **East Godavari**, **Surat** have the **lowest RMSE values**, meaning the model provides highly accurate predictions. The LSTM model is **performing well in these districts** with minimal prediction errors.

b) **Ratnagiri**, **Thane** has a **moderate RMSE**, indicating the model has some prediction errors but is still reliable. The model's accuracy in these districts is moderate and predictions can be improved with further optimization.

By combining machine learning and climate risk analytics, this methodology offers a robust framework for addressing the challenges of agricultural sustainability and climate adaptation. The findings and results indicated in the next section will empower stakeholders to implement data-driven, future-ready policies that could safeguard India's agricultural productivity against the uncertainties of a changing climate for the future time horizon of 2070.

Results

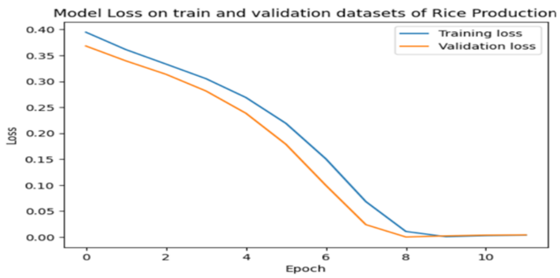
The visual representation of results facilitated a deeper understanding of the relationship between climate variables and agricultural risks, offering actionable insights for stakeholders. Predicted risk values are plotted for the corresponding year to visualize risk trends.

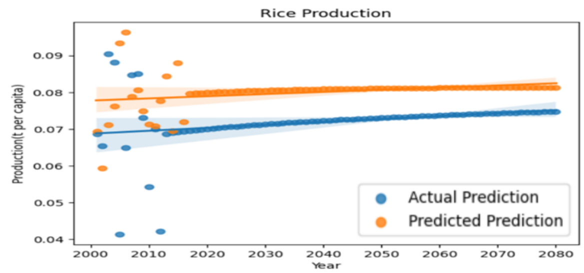
The following Table 3 represents the Actual v/s Predicted Rice Production for various districts of India in the Kharif season

Table 3. Prediction Results and Error Measure for districts in Kharif Season

1. EAST GODAVARI

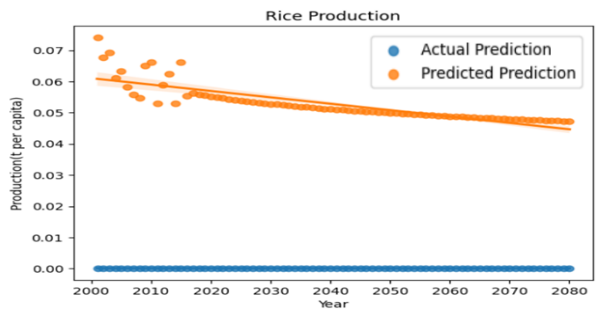
Train Score: 0.0165 RMSE





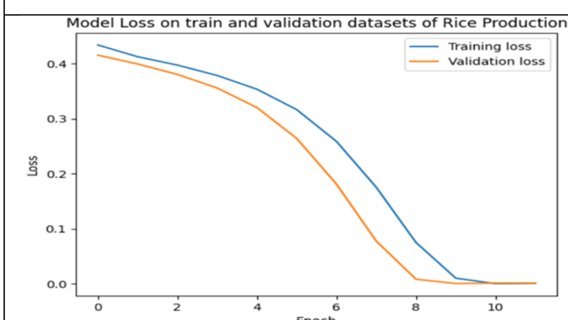
2. TAWANG

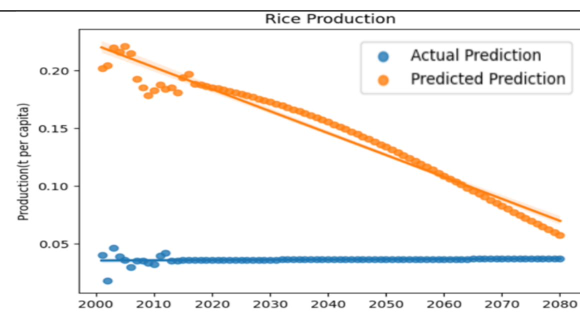
Train Score: 0.0587 RMSE



3. THANE

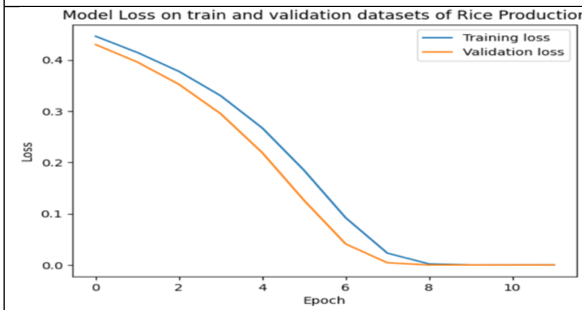
Train Score: 0.1552 RMSE

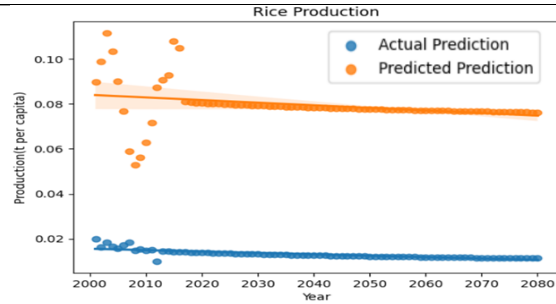




4. SURAT

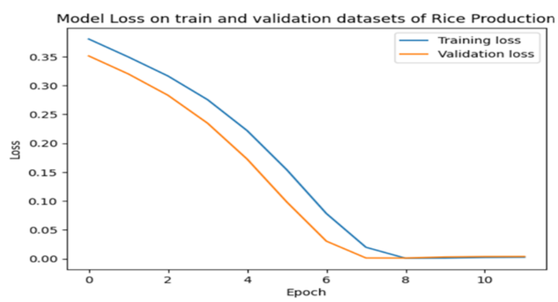
Train Score: 0.0694 RMSE

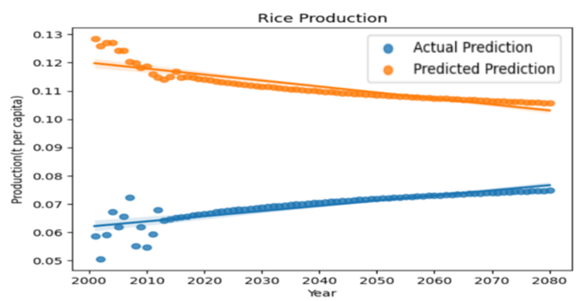




5. KARNAL

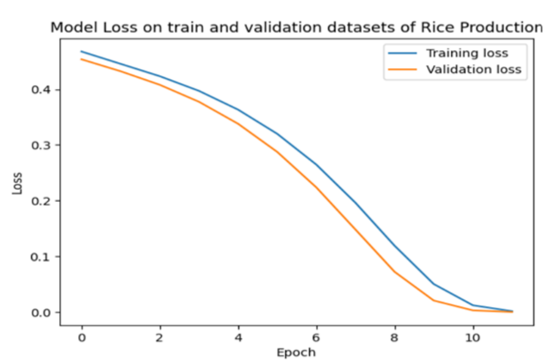
Train Score: 0.0538 RMSE

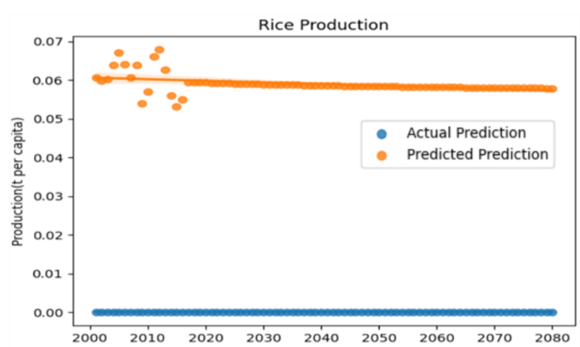




6. BHOPAL

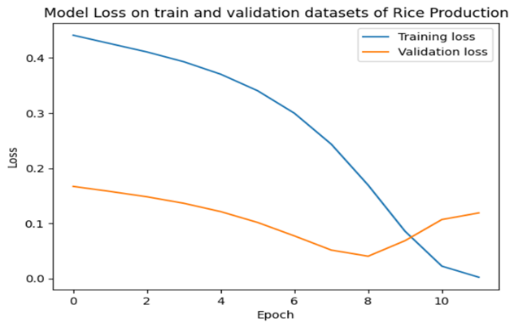
Train Score: 0.0601 RMSE

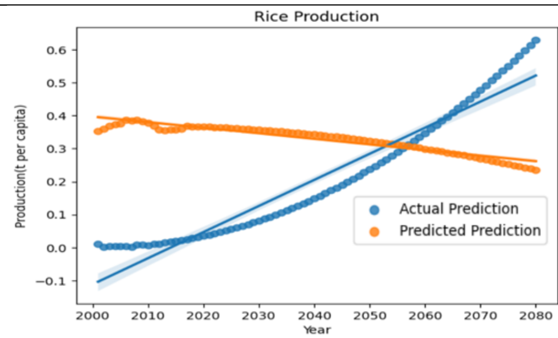




7. GWALIOR

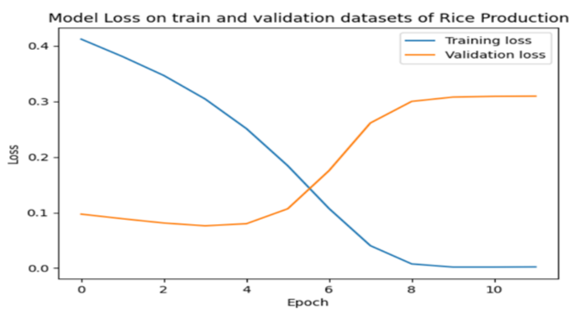
Train Score: 0.3427 RMSE

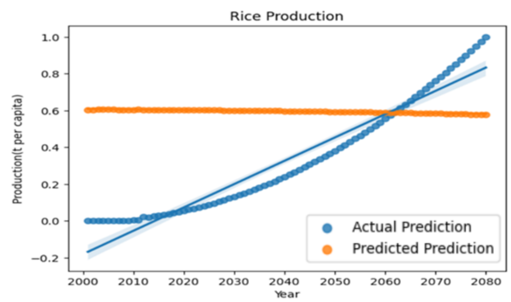




8. HOSHANGABAD

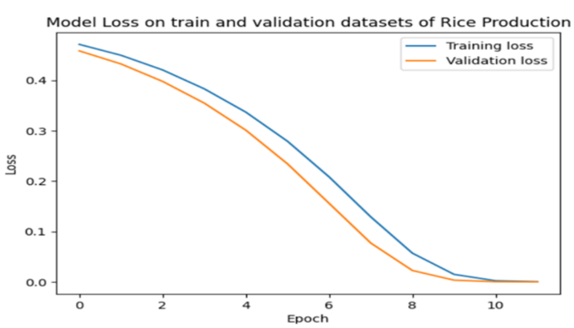
Train Score: 0.5675 RMSE

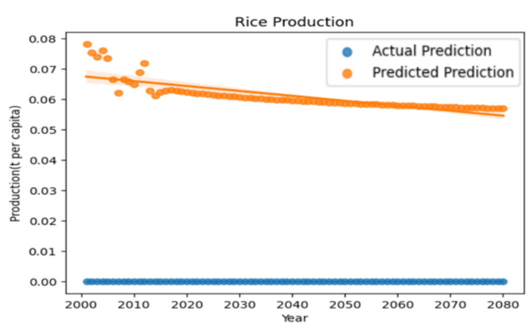




9. INDORE

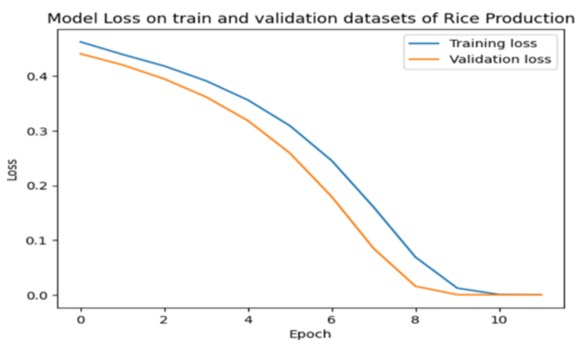
Train Score: 0.0657 RMSE

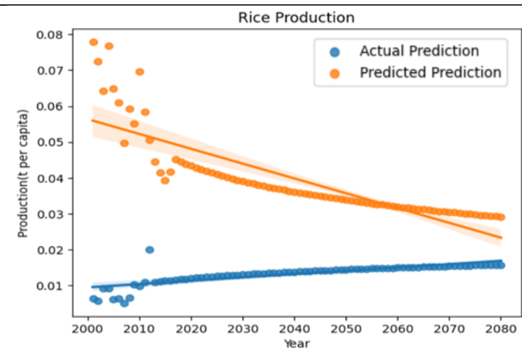




10. JABALPUR

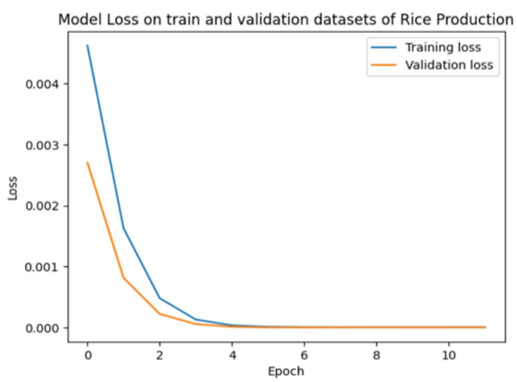
Train Score: 0.0430 RMSE

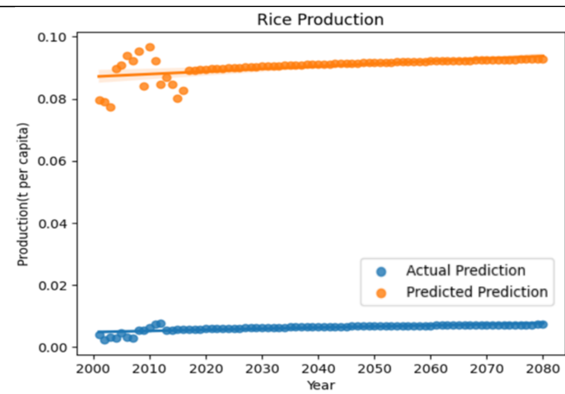




11. PANNA

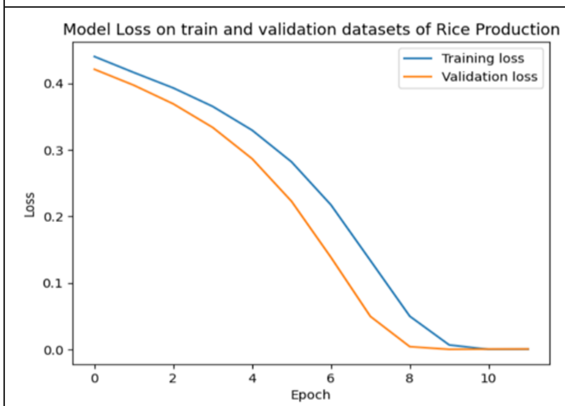
Train Score: 0.0492 RMSE

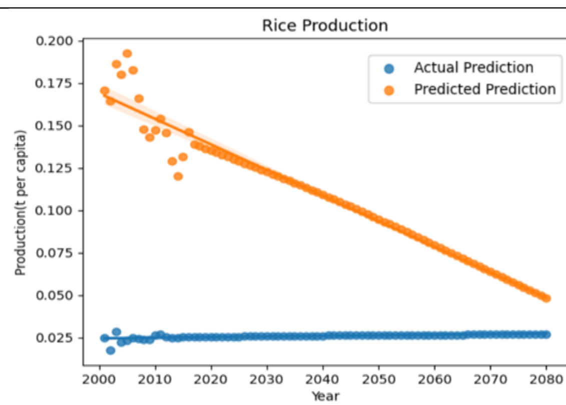




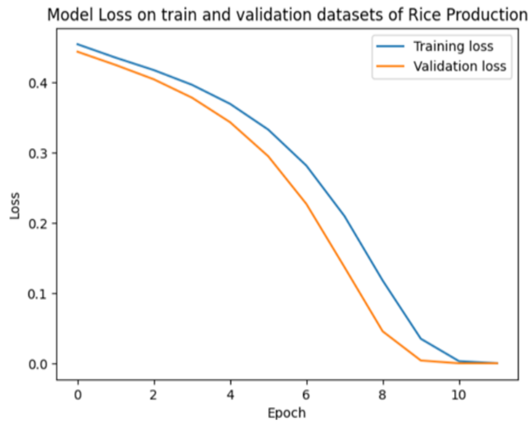
12. RATNAGIRI

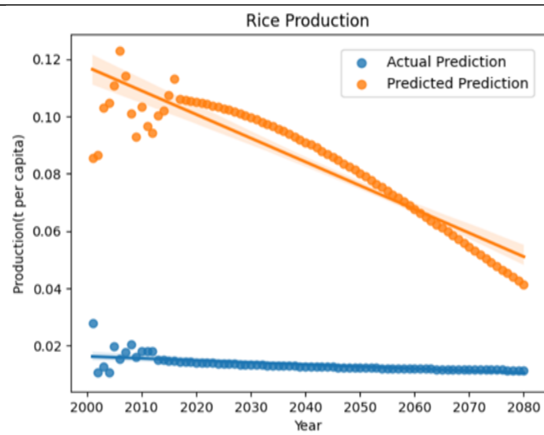
Train Score: 0.1230 RMSE





13. VELLORE
Train Score: 0.0880 RMSE

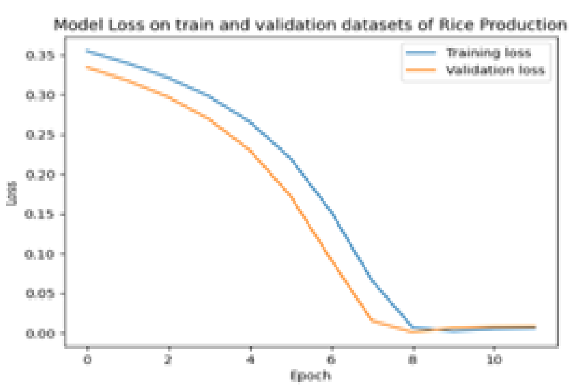


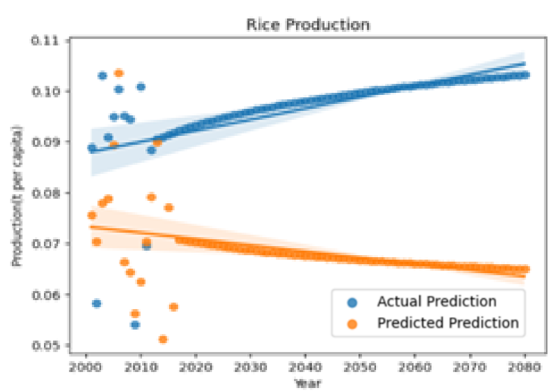


Predictions: The following Table 4 represents the actual v/s Predicted Rice Production for various districts of India in the Rabi season

Table 4. Prediction Results and Error Measure for districts in Rabi Season

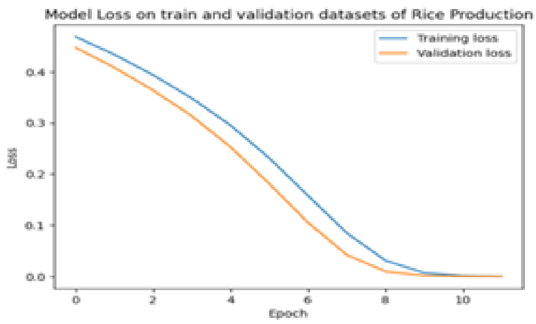
a) EAST GODAVARI
Train Score: 0.0227 RMSE

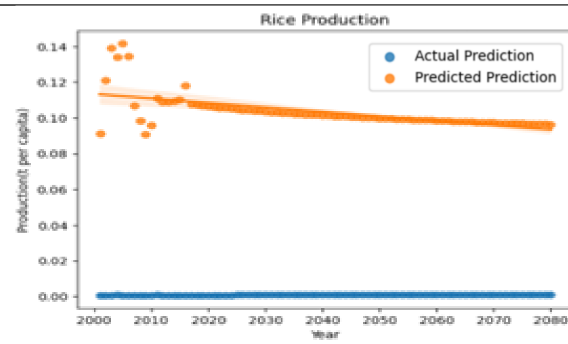




b) **THANE**

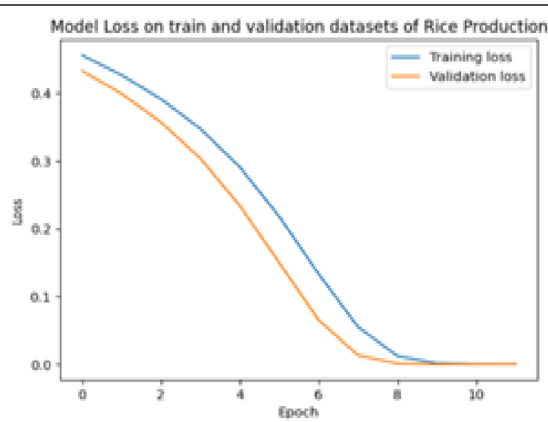
Train Score: 0.1102 RMSE

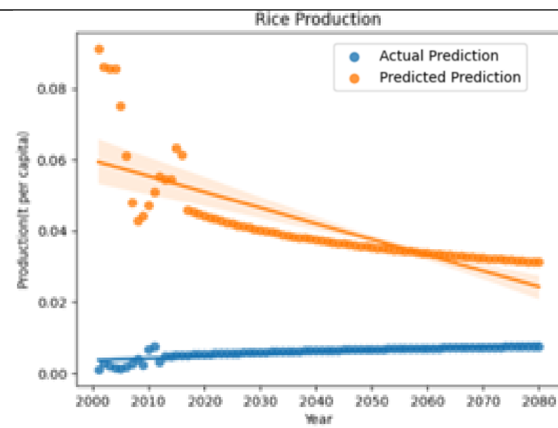




c) **SURAT**

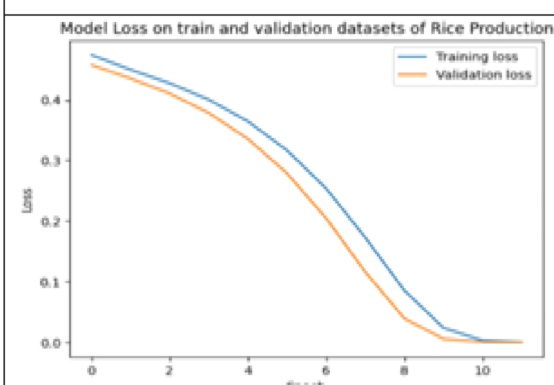
Train Score: 0.0529 RMSE

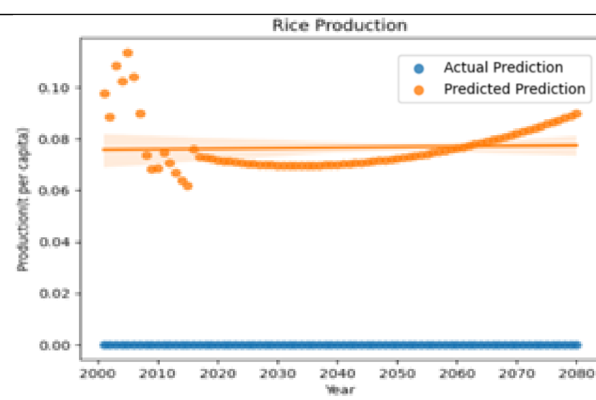




d) **RATNAGIRI**

Train Score: 0.0792 RMSE





District-Specific Predicted Rice Production Variability in Response to Climate Change

District -Specific Trend Variation changes in rice production with response to climate change in Kharif Season is measured as a percentage change in rice production w.r.t actual change in temperature and rainfall. The next section indicates the various risk zones and priority districts for implementing climate resilient agricultural policies for addressing the net zero goal of India by 2070.

Risk Zones and Priority Districts

Based on the model results and future predictions for the next 70 years, districts and cities are divided into different risk zones by the model analysis after mapping the future variation in their agricultural vulnerability and climate variability. The risk zones are :

- **High-Risk Zones:** These regions experience significant declines in agricultural output and are highly susceptible to climate change. Urgent actions are necessary, such as diversifying crops, utilizing drought-resistant seed varieties and improving irrigation systems.
- **Moderate-Risk Zones:** These areas face occasional disruptions but they can mitigate risks by adopting climate-smart agricultural practices, enhancing soil conservation and improving irrigation techniques.
- **Low-Risk Zones:** While these locations are not greatly impacted short term, proactive measures like early warning systems and sustainable farming practices are important to ensure their resilience against potential future climate variability.

The table 5 below highlights how in various districts the rice production is changing in the Kharif Seasons within the time frame of 2025-2070.

Table 5. Percentage change in Rice Production in Kharif Season for three periods in the range 2025-2070

District	2025-2040	2040-2055	2055-2070
East Godavari	0.0515	0.0224	0.0087
Tawang	-0.353	-0.2406	-0.184
Thane	-0.9451	-1.6179	-2.538
Surat	-0.1197	-0.0808	-0.0617
Karnal	-0.1716	-0.1166	-0.08946
Bhopal	-0.0541	-0.0365	-0.0278
Gwalior	-0.3523	-0.6252	-0.9685
Hoshangabad	-0.2074	-0.1404	-0.1075
Indore	-0.2063	-0.1399	-0.10719
Jabalpur	-0.8583	-0.6212	-0.5024
Panna	0.1657	0.1103	0.0835
Ratnagiri	-1.087	-1.4943	-2.0709
Vellore	-0.7871	-1.3694	-2.0297
Panna	0.1657	0.1103	0.0835

Table 6 presents percentage change in rice production in Rabi season for different districts over three time periods: 2025-2040, 2041-2055, and 2056-2070.

Table 6. Percentage change in Rice Production in Rabi Season for three periods in the range 2025-2070

District	2025-2040	2040-2055	2055-2070
East Godavari (Andhra Pradesh)	-0.17404	-0.1179	-0.0903
Thane (Maharashtra)	-0.2209	-0.1504	-0.1156
Surat (Gujarat)	-0.7774	-0.5423	-0.4216
Ratnagiri (Maharashtra)	-0.0468	0.3736	0.6872

District wise analysis of change in Rice Production in Kharif Season

Based on the risk zoning and analysis, the model suggests the following policy matrix for Kharif season in Table 7 for future consideration. It also presents district wise analysis of percentage change in rice production of Kharif season for different districts over 2025-2070.

Table 7. District-Wise Analysis with future consideration for Kharif Season

District	Timeline	Pattern of Variation	Policy Implications	Way Forward	Risk Zone	Season
East Godavari (Andhra Pradesh)	2025-2070	Gradual gain but slowing	Implementation of APSAPCC for climate-	Integration with PMFBY, PMKSY, and	Low	Kharif

		growth (avg variation: .0275)	resilient agriculture	NMSA for insurance, irrigation, and sustainability		
Thane (Maharashtra)	2025-2070	Consistent decline (-1.7003 avg variation)	Adoption of MSAAPCC to support farmers	Alignment with PMFBY, PMKSY, and RKVY for comprehensive agricultural support	High	Kharif
Surat (Gujarat)	2025-2070	Moderate decline (-0.0874 avg variation)	Execution of GSAPCC to strengthen agricultural resilience	Coordination with PMFBY, PMKSY, and NMSA for crop insurance, irrigation, and sustainability	Moderate	Kharif

Ratnagiri (Maharashtra)	2025-2070	Consistent decline (-1.5507 avg variation)	Adoption of MSAAPCC to support farmers	Alignment with PMFBY, PMKSY, and RKVY for comprehensive agricultural support	High	Kharif

Key Observations

Some of the key observations from our analysis of Kharif season production are as follows -

a) Positive Growth Districts

- East Godavari: Shows a declining but stagnant, steady positive trend. Growth reduces from 0.0515% (2025-2040) to 0.0087% (2056-2070).
- Panna: Continues to have a positive trend, though declining (0.1657% → 0.0835%).

b) Declining Production Districts

These districts show a negative trend, indicating a continuous decrease in rice production:

- Tawang: Declining reduction in production loss (-0.353% → -0.184%), meaning the rate of decline is slowing.
- Surat, Karnal, Bhopal: Moderate declines means show minor losses but relatively stable trends but at a slower rate.
- Gwalior, Hoshangabad, Indore, Jabalpur : All showing continuous decline, though the reduction rate decreases over time.

- Thane, Ratnagiri and Vellore: Severe declines in production indicating critical production challenges.

District wise analysis of change in Rice Production in Rabi Season

Table 8 given below, showcases district wise analysis of percentage change in rice production in Rabi season for different districts over 2025-2070. It also describes risk zones and their future considerations in below policy matrix.

Table 8. District-Wise Analysis with future consideration for Rabi Season

District	Timeline	Pattern of Variation	Policy Implications	Way Forward	Risk Zone	Season
East Godavari (Andhra Pradesh)	2025-2070	Gradual decline (avg variation -0.1274)	Need for adaptive farming practices and improved irrigation	Strengthening APSAPCC with targeted interventions for Rabi crops	Low	Rabi
Thane (Maharashtra)	2025-2070	Moderate decline (avg	Expansion of climate-smart	Enhancement of Rabi crop insurance and	Moderate	Rabi

		variation - 0.1623)	agricultural policies	water conservation strategies		
Surat (Gujarat)	2025-2070	Severe decline (avg variation-0.5804)	Focus on improving drought resilience in winter crops	Implementation of precision farming and better irrigation practices. Policy intervention and structural changes are likely needed to reverse this trend	High	Rabi
Ratnagiri (Maharashtra)	2025-2070	substantial and accelerating growth in production. (avg variation -0.338)	Encouraging mixed cropping and diversified farming	Promoting agroforestry and sustainable soil management	Low	Rabi

Key Observations

Some of the key observations from our analysis of Rabi season production are as follows –

a) **Positive Growth Districts**

- Ratnagiri (Only Positive Growth District):Only districts showing positive growth in production. Indicates strong agricultural recovery or scope of implementing improved adaptive farming techniques.

b) **Declining Production Districts**

- East Godavari: Consistent decline in production across all periods. The rate of decline slows down over time, suggesting stabilization. Key Concern is Continuous decline, though at a reducing rate.
- Thane: Negative production trend, but like East Godavari, the decline rate slows. Key Concern is Consistent loss in production, though the impact lessens over time.
- Surat: Highest production loss among all districts and needs intervention. The decline is steep but gradually decreasing, meaning production loss is still severe but slightly improving.

Policy Relevance

The research results and findings of this study create a prioritized policy plan for each district based on the Kharif and Rabi seasons. The results presented in Table 5 and 6 clearly shows how for the Kharif and Rabi seasons, three risk zones for districts are identified for each district i.e low, moderate, and high risk zones. Each risk zone has been prioritized based on the agricultural yield variability of rice production of these districts in response to the climate vulnerabilities of the future arising from temperature and rainfall change. Further, based on the risk profile of each of the districts, the relevant measures and action plan need to be drawn and internalized in the relevant subnational policy action plan by keeping the time horizon of 2070 in mind to make India climate resilient and carbon neutral at the same time. For instance, for the Rabi Season, Surat shows a severe decline in rice production, whereas for the Kharif season, Surat, Karnal, and Bhopal show minor losses but relatively stable trends and Thane, Ratnagiri, Vellore show severe decline in production.

This also indicates the fact that the policy prioritization of the districts and the corresponding state-level subnational climate action plan for a climate resilient policy of addressing district-specific climate-led agricultural vulnerability has to internalize the crop seasonality. The policy action plan has to be rooted in the local seasonal reality. In this regard, for the Rabi Season, East Godavari, Thane shows a level of medium risk, which hints towards moderate in situ adaptation efforts for the Rabi Season. However, it might change with the crop seasonality. For the Rabi Season, Ratnagiri is the only district that is at low risk and is expected to perform better than the overall average performance of the other districts, indicating the chance of future successful adaptation measures and favorable agro-climatic conditions. These results are important for policy formulation as they have to be internalised and integrated into the Pradhan Mantri Fasal Bima Yojana (PMFBY), Pradhan Mantri Krishi Sinchayee Yojana (PMKSY), and National Mission for Sustainable Agriculture (NMSA) to enhance crop insurance coverage, irrigation efficiency, and sustainable farming practices for the future with a district specific action plan to pave a climate resilient agricultural growth of India which also attains carbon neutrality by 2070.

Conclusion and Outcome

The paper, for the first time, through an application of an LSTM structure and detailed spatial and temporal data, maps out the district-specific climate and agricultural vulnerability. Additionally, it highlights the impact of crop seasonality on future agricultural and climate vulnerability in an empirical way through artificial intelligence based machine learning applications. In the context of understanding district-specific climate and agricultural vulnerability of India and its associated mapping into low, moderate, and high risk zones, this research covers a wide range of districts across various climatic zones of India and does not restrict itself to a particular geographical region. Hence, it takes into account substantial economic, agro climatic variability to come up with district-specific predictions of the future. Such predictions through an evidence-based approach, empirically therefore provides a strong foundation for data and evidence-based subnational climate policy planning and execution for addressing a climate resilient net-zero pathway of India by 2070.

References:

1. Baraj, B., Mishra, M., Sudarsan, D., da Silva, R. M., & Santos, C. A. G. (2024). Climate change and resilience, adaptation, and sustainability of agriculture in India: A bibliometric review. *Heliyon, 10*(8), e29586. https://doi.org/10.1016/j.heliyon.2024.e29586
2. Khosla, E., Dharavath, R., & Priya, R. (2020). Crop yield prediction using aggregated rainfall-based modular artificial neural networks and support vector regression. *Environment, Development and Sustainability, 22*(6), 5687–5708. https://doi.org/10.1007/s10668-019-00445-x

3. Kang, Y., Khan, S., & Ma, X. (2009). Climate change impacts on crop yield, crop water productivity, and food security—A review. *Progress in Natural Science, 19*(12), 1665–1674. https://doi.org/10.1016/j.pnsc.2009.08.001
4. Kannan, E., & Sundaram, S. (2011). Analysis of trends in India's agricultural growth. *Working Paper No. 276*. Institute for Social and Economic Change, Bangalore.
5. Kumar, A., & Bhattacharya, S. (2015). Crop yield prediction using Agro Algorithm in Hadoop. *International Journal of Computer Science and Information Technology & Security, 5*(2), 271–274.
6. Mo, X., Liu, S., Lin, Z., Xu, Y., Xiang, Y., & McVicar, T. R. (2005). Prediction of crop yield, water consumption, and water use efficiency with a SVAT-crop growth model using remotely sensed data on the North China Plain. *Ecological Modelling, 183*(2), 301–322. https://doi.org/10.1016/j.ecolmodel.2004.07.032
7. Moriondo, M., Giannakopoulos, C., & Bindi, M. (2011). Climate change impact assessment: The role of climate extremes in crop yield simulation. *Climatic Change, 104*(3–4), 679–701. https://doi.org/10.1007/s10584-010-9871-0
8. Panda, S. S., Ames, D. P., & Panigrahi, S. (2010). Application of vegetation indices for agricultural crop yield prediction using neural network techniques. *Remote Sensing, 2*(3), 673–696. https://doi.org/10.3390/rs2030673
9. Joshi, A., & Kaushik, V. (2021). Big data and its analytics in agriculture. In *Bioinformatics for Agriculture: High-throughput Approaches* (pp. 71–83). Springer. https://doi.org/10.1007/978-981-33-4791-5_4

10. Shank, D. B., Hoogenboom, G., & McClendon, R. W. (2008). Dewpoint temperature prediction using artificial neural networks. *Journal of Applied Meteorology and Climatology, 47*(6), 1757–1769. https://doi.org/10.1175/2007JAMC1693.1
11. Varalakshmi, T., Nazeer, S. K., Srimanth, V., Naga Sai Krishna, S., & Sahool, S. K. (2023). Downpour forecasting using deep learning. *Journal of Engineering Sciences, 14*(3).
12. Bhardwaj, M. R., et al. (2023). An innovative deep learning-based approach for accurate agricultural crop price prediction. *arXiv preprint arXiv:2304.09761*. https://doi.org/10.1109/CASE56687.2023.10260494
13. Anuradha, T., et al. (2023). Estimating crop yields using machine learning techniques. *Journal of Survey in Fisheries Sciences, 10*(2S), 2778–2782.
14. Ramya, P., et al. (2023). Crop yield prediction using a recurrent neural network. *International Research Journal of Modernization in Engineering Technology and Science, 5*(3), 476–480. https://doi.org/10.56726/IRJMETS35358
15. Open Government Data Platform India. (n.d.). District-wise season-wise crop production statistics. *Government of India*. https://www.data.gov.in/catalog/district-wise-season-wise-crop-production-statistics-0
16. AidData. (n.d.). GeoQuery: A tool for spatial data. *AidData GeoQuery Platform*. https://geo.aiddata.org/query/#!/status/629e24d1809e383f4a3c3722
17. Patel, M., & Rane, A. (2023). *Crop recommendation system*. Devang Patel Institute of Advanced Technology and Research, CHARUSAT. Retrieved from https://www.researchgate.net/publication/370056714_Crop_Recommendation_System

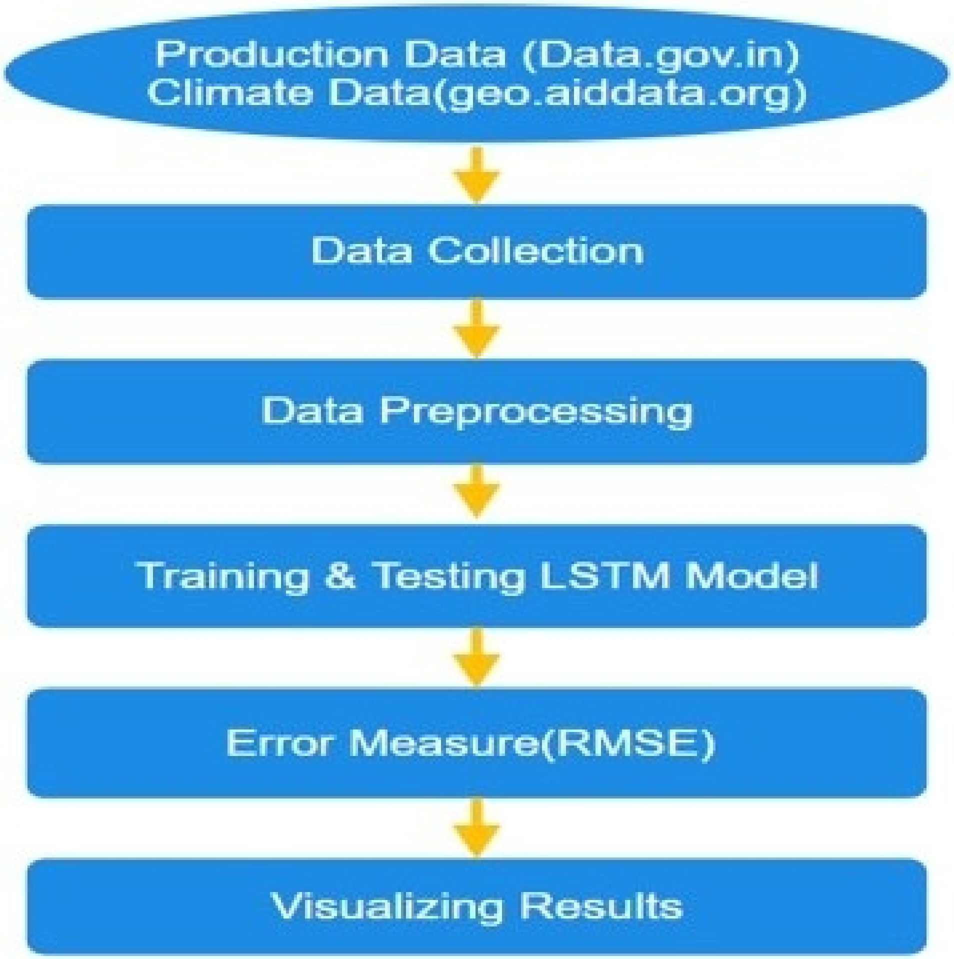


Fig 1. Machine Learning architecture using LSTM model for Prediction of Rice Production

Figure 1