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

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## 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 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.

## Introduction

Climate factors such as temperature and precipitation can have a significant impact on crop production. To perform a comprehensive risk analysis, likely region-specific climate variables to influence crop production are required to be systematically identified and assessed [1]. For example, in areas where drought is a common occurrence, a risk analysis would focus on the potential impact of drought on crop yields [7]. To conduct a risk analysis, identification of climate factors that are likely to have an impact on crop production in a given region plays important role. For example, in areas where drought is a common occurrence, a risk analysis would focus on the potential impact of precipitation on crop production [3, 7]. 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 production. 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 [6, 7]. Overall, a risk analysis tool based on the AI/ML approach is used in this article that will prove to support the understanding of the potential impacts of climate factors on crop production and develop strategies to mitigate these risks [2, 5]. This study considers rice, which is the most commonly used crop. This research determines climate and seasonal vulnerability of rice production by analyzing the effects of climate change on different climatic zones of India during Kharif and Rabi season overcoming lack of broader spatio-temporal analysis [2, 11, 13, 14]. By taking a proactive approach to understand and mitigate climate risks, farmers and policymakers can help to ensure that rice production remains resilient and sustainable for farmers in the face of a changing climate [19].

# 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 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 and 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 [9] . 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, Machine Learning algorithms have been investigated to design an efficient system for accurate crop yield prediction. 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 and 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. [5, 9] 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 percent 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 and 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 percent) 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.

## 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. Many models are created and verified with data from specific areas (such Visakhapatnam [2] or portions of Tamil Nadu [13] ), but their generalizability throughout India's various agro-ecological zones is not tested. This calls into question the applicability and transferability of the model to other areas with distinct crop types, soil types, and weather patterns [2,14,17]. Furthermore, although models like LSTM [11] and RNN [14] have demonstrated efficacy in identifying temporal patterns in meteorological data, their geographical generalizability is still restricted, especially when consideri4ng India's heterogeneous agro-climatic zones. One major obstacle to the widespread use of prediction tools for region-specific decision-making is the lack of spatiotemporal deep learning models that can take into consideration both seasonal patterns and regional heterogeneity. Study shows models are designed for specific crop varieties or are limited to the Kharif season (e.g., Khosla et al. [2], Anuradha et al. [13]

, Ramya et al. [14] ). The lack of unified models for forecasting season-wise and crop-wise yield variability limit their usefulness in assisting with comprehensive agricultural planning in India, where multi-cropping throughout Rabi and Kharif is typical. This research emphasizes on climate and seasonal vulnerability by analyzing the effects of climate change on rice production in different districts of India during Kharif and Rabi season. A critical research gap persists in the assessment of climate vulnerability at the district level. This study addresses that gap by applying a spatiotemporal machine learning model to 16 climatically diverse districts across India, thereby providing a robust framework to support data-driven, region-specific policy formulation. Also, this study aims to bridge existing gaps of seasonal variability by addressing through predictive modeling of rice production for both the Kharif and Rabi seasons. This research provides 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. 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. 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. Thereby, offering data-driven insights to support climate-resilient agricultural planning and contributing to India's broader objective of achieving Net Zero emissions by 2070. 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

1. To assess and create policy prescriptions for hedging climate vulnerability-led agricultural rice production risks of districts of India through an Artificial Intelligence (AI) - Machine Learning Methodology and Tool

2. To enable a prioritized policy framework for hedging such climate vulnerability-led agricultural risks of rice production in various districts of India

# Research questions

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

- 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?
- 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?
- 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 shown in Fig 1 –

**Fig 1. Machine Learning architecture using LSTM model for Prediction of Rice Production**
This architecture describes the process followed in predicting the rice production in future considering climate and other agriculture factors

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 as shown in equations Eq (1 to 6) . This characteristic is especially beneficial in 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.

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

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

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

$$\text{Cell State Update:} \quad C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{4}$$

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

$$\text{Hidden State:} \quad h_t = o_t \odot \tanh(C_t) \tag{6}$$

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 $\sigma$ denotes the sigmoid activation function. The element-wise multiplication operator is represented by $\odot$. Below mentioned steps are involved in methodology to predict production of rice in coming future.Google Colab to used to implement LSTM model and predict rice production.

### Step 1: Data Collection

The data for this study is derived from reliable sources such as the Indian Agriculture Statistics Records from open government platform of India [15] and Climate data of previous years of various districts from GeoQuery by AidData [16]. The data includes:

1. **Agricultural Indicators:** This comprehensive dataset ensures the study captures the diverse agricultural conditions across India by means of data containing year, state, district, season, temperature, rainfall, cultivation area and production of rice across 16 districts obtained from open government platform of India for year 1997-2012 [15] .From 2013-2024 ,data has been interpolated using data from 1997-2012.
2. **Climatic Variables:** Historical records of temperature and rainfall of 16 districts of India for both Kharif and rabi season from year 1997-2024 were obtained from GeoQuery by AidData [16] which provides granular, spatially-referenced climate data for precise analysis . Both the agriculture and climate variables are considered together in a single dataset to form complete 2184 records including training records(1232) and test records(952) ready for next phase of rice production forecasting. Test records are generated for future years by interpolation.

### Step 2: Data Preprocessing

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

- 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.
- 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.
- 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.

### Step3: 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:

1. 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.

2. 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.

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

4. Integration of Training and Test Data: Training datasets were combined with test datasets to enhance prediction robustness and reduce model variance.

5. Outputs: The trained model provided district-specific predictions of rice production for future year 2025 to 2070, considering changes in temperature and rainfall. . Outputs of the model are shown in detail in Results section that facilitate a deeper understanding of the relationship between climate variables and agricultural risks, offering actionable insights for stakeholders for future. These outputs were further validated by finding RMSE(Root Mean Square Error) i.e validation score described in next step.

### Step4: Model Validation using RMSE

Model performance is assessed using standard statistical measures, Root Mean Square Error (RMSE). This metric 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. Within the model, the lower the RMSE score, the better the accuracy and predictability of the model. RMSE generated using below formula in Eq 7

$$RMSE = \sqrt{\sum (\text{Predicted}_i - \text{Actual}_i)^2 / n}, \tag{7}$$

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.

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.

**Table 1. District-wise Model Validation Score(RMSE) for Crop production in Kharif Season**

| Output Variable | District | RMSE Score |
|---|---|---|
| Rice Production | 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 |

This table presents the validation score of different districts which shows accuracy of predictions of various districts.

**Table 2. District-wise Model Validation Score(RMSE) for Crop production in Rabi Season**

| Output Variable | District | RMSE Score |
|---|---|---|
| Rice Production | East Godavari | 0.0227 RMSE |
| | Thane | 0.1102 RMSE |
| | Surat | 0.0529 RMSE |
| | Ratnagiri | 0.0792 RMSE |

The validation score for each district is displayed in this table, demonstrating the precision of the predictions made for each district throughout the Rabi season.

# Results

## Prediction results of Rice production for various districts during Kharif Season

The following Fig 2, 3, 4, 5 and 6 shows the Actual v/s Predicted Rice Production for various districts of India in the Kharif season. Below shown results showcase two graphs for each district, one demonstrate validation loss with each epoch and other shows change in actual and predicted values from year 1997-2070.

**Fig 2. Model Validation Loss and Prediction of East Godavari and Tawang for Kharif Season** Figure shows the rice predictions and model accuracy for East Godavari and Tawang

**Fig 3. Model Validation Loss and Prediction of Thane, Surat and Karnal for Kharif Season**Figure shows the rice predictions and model accuracy for Thane, Surat and Karnal.

**Fig 4. Model Validation Loss and Prediction of Bhopal, Gwalior and Hoshangabad for Kharif Season** Figure shows the rice predictions and model accuracy for Bhopal, Gwalior and Hoshangabad.

**Fig 5. Model Validation Loss and Prediction of Indore, Jabalpur and Panna for Kharif Season** Figure shows the rice predictions and model accuracy for Indore, Jabalpur and Panna.

**Fig 6. Model Validation Loss and Prediction of Ratnagiri and Vellore for Kharif Season** Figure shows the rice predictions and model accuracy for Ratnagiri and Vellore.

## Prediction results of Rice production for various districts during Rabi Season

Fig 7 and Fig 8 presents the prediction results and validation loss of various districts in Rabi season from year 1997-2070.

**Fig 7. Model Validation Loss and Prediction of East Godavri, Thane and Surat for Rabi Season** Figure shows the rice predictions and model accuracy for East Godavri, Thane and Surat.

**Fig 8. Model Validation Loss and Prediction of Ratnagiri for Rabi Season** Figure shows the rice predictions and model accuracy for Ratnagiri.

## Key findings from validation score in the Kharif Season

1. Highly accurate Predictions: East Godavari, Jabalpur, Panna, Karnal 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.

2. Moderately Accurate Predictions: 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.

3. Least accurate Predictions : 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 findings from validation score in the Rabi Season

1. Highly accurate Predictions: 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.

2. Moderately Accurate Predictions: 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.

## Key Findings from Predictions of Rice Production

Based on the model results or predictions for the next 45 years, risk zones are identified by the model analysis after mapping the future variation in their agricultural vulnerability and climate variability.

## Risk Zones and Priority Districts

The table 3 and 4 below highlights how the rice production is changing in the Kharif and Rabi Season within the time frame of 2025-2070 across various districts. It also categorizes each district into three risk zones –Low, Moderate and High on the basis of change in production. Based on production trends, the risk zones categorize the susceptibility of agriculture. Low Risk Zones indicate improvement or resistance with a positive or moderate decline (up to -0.1). Between -0.1 and -0.5, moderate risk zones consistently diminish, indicating manageable risks that require adaptive interventions. Severe declines in High Risk Zones (more than -0.5) indicate an urgent need for intervention to avoid significant productivity loss.

## Risk Zones and Priority Districts during Kharif Season

The table 3 below highlights change in production of districts from 2025-2070 during Kharif season and risk zones which require attention. East Godavari and Panna emerge as low-risk zones, with Panna showing consistent positive growth and East Godavari maintaining slight positive gains, though gradually decreasing. Bhopal, Karnal, and Surat also fall into this category due to their minimal or slowly improving declines, suggesting relatively stable agricultural performance. Moderate risk zones include Hoshangabad, Indore, and Tawang, where rice production is consistently declining but at a moderate rate, with some signs of gradual recovery. In contrast, high-risk zones consist of Thane, Gwalior, Jabalpur, Ratnagiri, and Vellore—districts that exhibit sharp and worsening declines in production, particularly in the latter periods. This classification highlights the varying degrees of climate impact on rice production and can inform region-specific adaptation strategies.

**Table 3. Percentage change in Rice Production(2025-2070) and Risk Zones for Kharif Season**

| District | 2025-2040 | 2041-2055 | 2056-2070 | Risk Zone |
|---|---|---|---|---|
| East Godavari | 0.0515 | 0.0224 | 0.0087 | Low |
| Tawang | -0.353 | -0.2406 | -0.184 | Moderate |
| Thane | -0.9451 | -1.6179 | -2.538 | High |
| Surat | -0.1197 | -0.0808 | -0.0617 | Low |
| Karnal | -0.1716 | -0.1166 | -0.08946 | Low |
| Bhopal | -0.0541 | -0.0365 | -0.0278 | Low |
| Gwalior | -0.3523 | -0.6252 | -0.9685 | High |
| Hoshangabad | -0.2074 | -0.1404 | -0.1075 | Moderate |
| Indore | -0.2063 | -0.1399 | -0.10719 | Moderate |
| Jabalpur | -0.8583 | -0.6212 | -0.5024 | High |
| Panna | 0.1657 | 0.1103 | 0.0835 | Low |
| Ratnagiri | -1.087 | -1.4943 | -2.0709 | High |
| Vellore | -0.7871 | -1.3694 | -2.0297 | High |

The above table shows the risk associated with each district as well as the percentage change in rice output during the Kharif season for the following three time periods: 2025–2040, 2041–2055, and 2056–2070.

## Risk Zones and Priority Districts during Rabi Season

The table 4 shows change in production during Rabi season from 2025-2070. It also identifies the risk zones which require immediate action. Based on the trends, East Godavari and Thane show a consistent decline in production over all three periods; however, the rate of decline gradually lessens over time. This pattern suggests a moderate level of risk, where the districts are vulnerable but may be responding positively to adaptation efforts or evolving climate conditions. Surat, on the other hand, experiences a sharp and sustained decline in rice production throughout the forecasted periods, with only a marginal improvement in the rate of decrease. This places Surat in the high-risk zone, indicating significant vulnerability that requires urgent policy and agronomic interventions. In contrast, Ratnagiri demonstrates a remarkable shift from a slight decline in the first period to strong positive growth in the later years, suggesting effective resilience strategies or favorable environmental conditions. Therefore, Ratnagiri falls into the low-risk zone. This analysis highlights regional disparities in climate impact on rice production and underscores the need for localized strategies to manage agricultural risk.

**Table 4. Percentage change in Rice Production(2025-2070) and Risk Zones for Rabi Season**

| District | 2025-2040 | 2041-2055 | 2056-2070 | Risk Zone |
|---|---|---|---|---|
| East Godavari (Andhra Pradesh) | -0.17404 | -0.1179 | -0.0903 | Moderate |
| Thane (Maharashtra) | -0.2209 | -0.1504 | -0.1156 | Moderate |
| Surat (Gujarat) | -0.7774 | -0.5423 | -0.4216 | High |
| Ratnagiri (Maharashtra) | -0.0468 | 0.3736 | 0.6872 | Low |

Above table presents percentage change in rice production in Rabi season for different districts over three time periods: 2025-2040, 2041-2055, and 2056-2070 and risk associated with that district.

# Discussion

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 shows how three risk zones for districts are identified i.e low, moderate, and high risk zones for the Kharif and Rabi seasons. Each risk zone has been prioritized based on the agricultural 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 internalized 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.

Based on the analysis, the model suggests the following policy matrix in Table 5 for the Kharif season and in Table 6 for the Rabi season. In Table 5, Climate-related agricultural trends and policies for four Indian districts during the Kharif season (2025–2070) are described in the policy matrix. Slow but steady expansion is evident in East Godavari, necessitating the integration of national sustainability plans with climate policies such as APSAPCC. Because of high-risk zones, Thane and Ratnagiri experience steady reductions, highlighting the need for significant assistance from MSAAPCC and alignment with PMFBY, PMKSY, and RKVY. Under GSAPCC, Surat is seeing a minor decline and requires moderate policy interventions that are coordinated across key schemes. Convergence with national initiatives and climate-resilient planning are generally stressed as ways to reduce hazards. In Table 6, Climate-related agricultural patterns in four districts throughout the Rabi season (2025–2070) are examined in this policy matrix. A slow deterioration is evident in East Godavari, necessitating further APSAPCC interventions and adaptive farming. Thane is seeing a slight drop, which suggests that water-saving measures and improved Rabi insurance are necessary. Due to a sharp decline in productivity, Surat urgently needs precision farming, drought resistance, and systemic policy adjustments. Despite a negative variance, Ratnagiri's increasing productivity suggests that agroforestry, varied farming, and sustainable soil practices should be promoted to maintain gains. Strategies must be specific to each district, taking into account trends in variation and risk levels.

**Table 5. Policy Matrix for Kharif Season**

| District | Pattern of Variation | Policy Implications | Way Forward | Risk Zone |
|---|---|---|---|---|
| East Godavari (Andhra Pradesh) | Gradual gain but slowing growth (avg variation: .0275) | Implementation of APSAPCC for climate-resilient agriculture | Integration with PMFBY, PMKSY, and NMSA for insurance, irrigation, and sustainability | Low |
| Thane (Maharashtra) | Consistent decline (-1.7003 avg variation) | Adoption of MSAAPCC to support farmers | Alignment with PMFBY, PMKSY, and RKVY for comprehensive agricultural support | High |
| Surat (Gujarat) | Slight decline (-0.0874 avg variation) | Execution of GSAPCC to strengthen agricultural resilience | Coordination with PMFBY, PMKSY, and NMSA for crop insurance, irrigation, and sustainability | Low |
| Ratnagiri (Maharashtra) | Consistent decline | Adoption of MSAAPCC to support farmers | Alignment with PMFBY, PMKSY, and RKVY for comprehensive agricultural support | High |

Above table presents Policy matrix for four districts as per the risk associated with them during Kharif season.

**Table 6. Policy Matrix for Rabi Season**

| District | Pattern of Variation | Policy Implications | Way Forward | Risk Zone |
|---|---|---|---|---|
| East Godavari (Andhra Pradesh) | Gradual decline (avg variation -0.1274) | Need for adaptive farming practices and improved irrigation | Strengthening APSAPCC with targeted interventions for Rabi crops | Low |
| Thane (Maharashtra) | Moderate decline (avg variation -0.1623) | Expansion of climate-smart agricultural policies | Enhancement of Rabi crop insurance and water conservation strategies | Moderate |
| Surat (Gujarat) | 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 |
| Ratnagiri (Maharashtra) | substantial and accelerating growth in production. (avg variation -0.338) | Encouraging mixed cropping and diversified farming | Promoting agroforestry and sustainable soil management | Low |

The policy matrix for four districts is shown in the above table according to the risk that each district faces during the Rabi season.

# Conclusion

This paper based on LSTM structure with spatial and temporal data, maps out the district-specific climate and agricultural vulnerability. Additionally, it highlights the impact of climate on future agricultural crop production in an empirical way through artificial intelligence based machine learning applications. The LSTM model is utilized to predict future rice production at the district level. The 16 districts reviewed span various climatic zones of India. Output of the model shows how rice production can vary in all these districts in next 46 years from 2025-2070 considering both the agricultural and climatic factors. On these predictions, District-Riskzone mapping is build in which 16 districts are mapped to three risk zones - low, moderate, and high risk zones. Several high-risk zones identified for urgent intervention to enhance rice production. These include Thane, Vellore, Gwalior, Ratnagiri, and Jabalpur during the Kharif season, and Surat during the Rabi season. Such predictions through an evidence-based approach, empirically provides a strong foundation for subnational climate policy planning and execution for addressing a climate resilient net-zero pathway of India by 2070. Policy matrix provides key highlights for improving production in high-risk zones.

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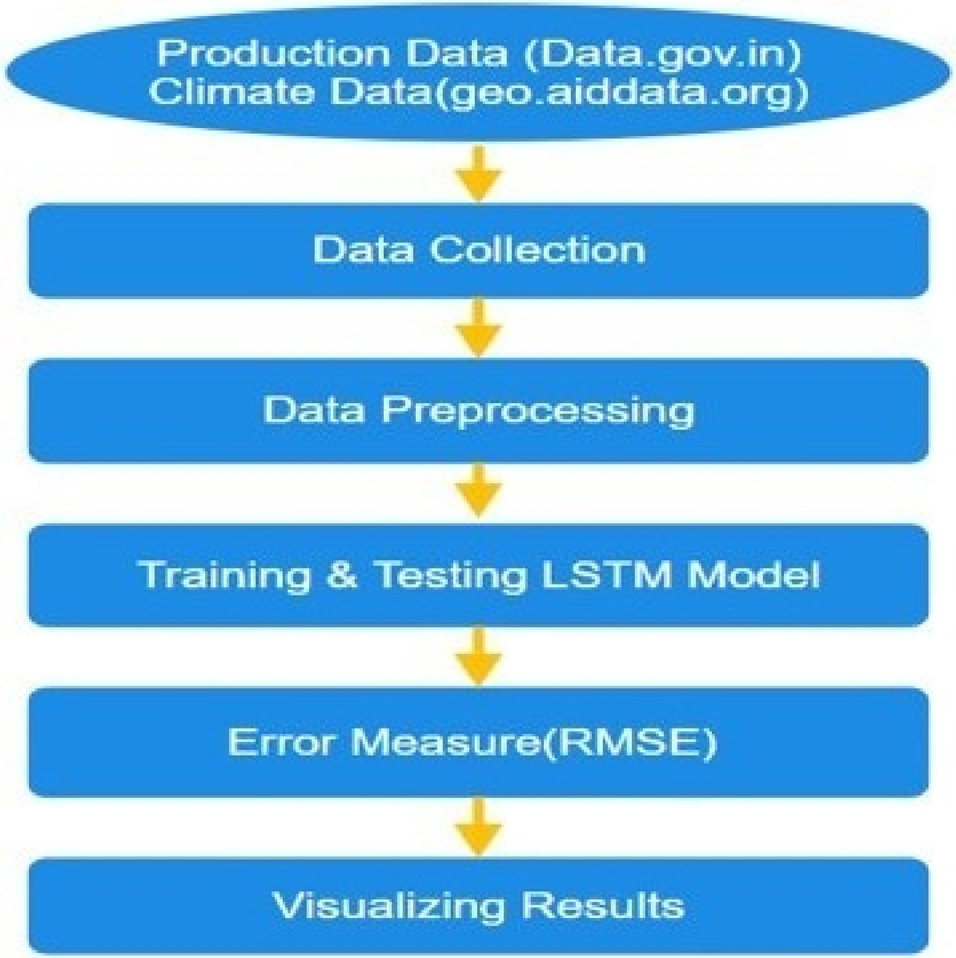
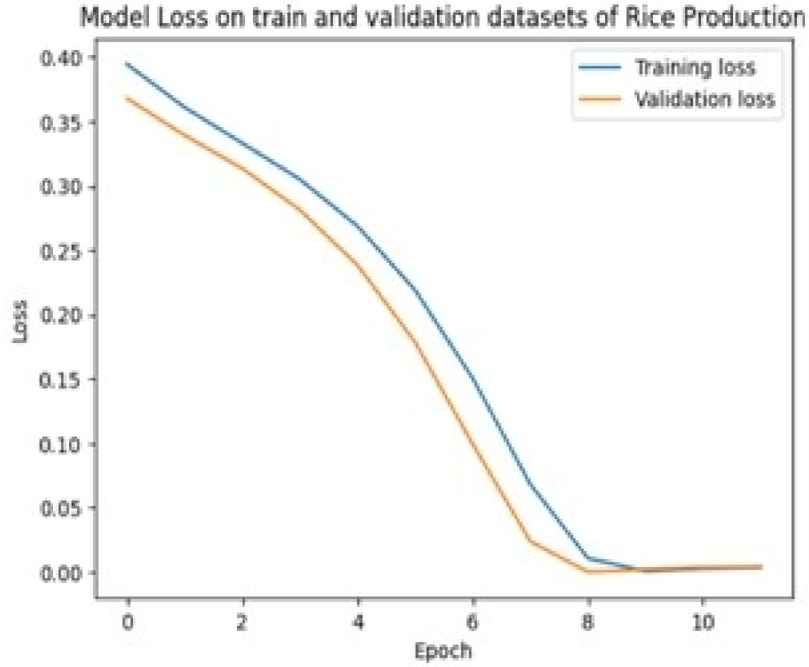
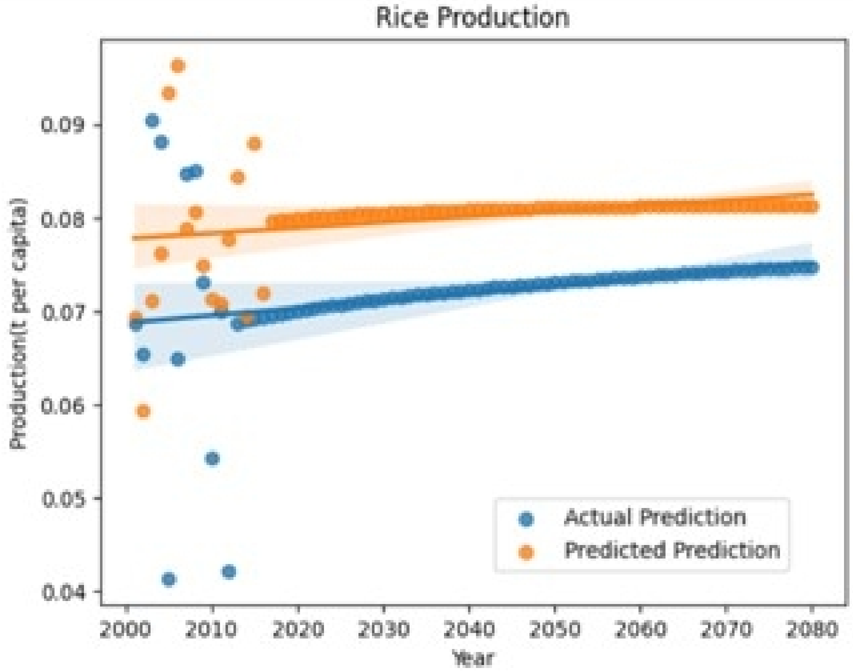

Production Data (Data.gov.in)
Climate Data(geo.aiddata.org)
Data Collection
Data Preprocessing
Training & Testing LSTM Model
Error Measure(RMSE)
Visualizing Results

Figure

**1. EAST GODAVARI**

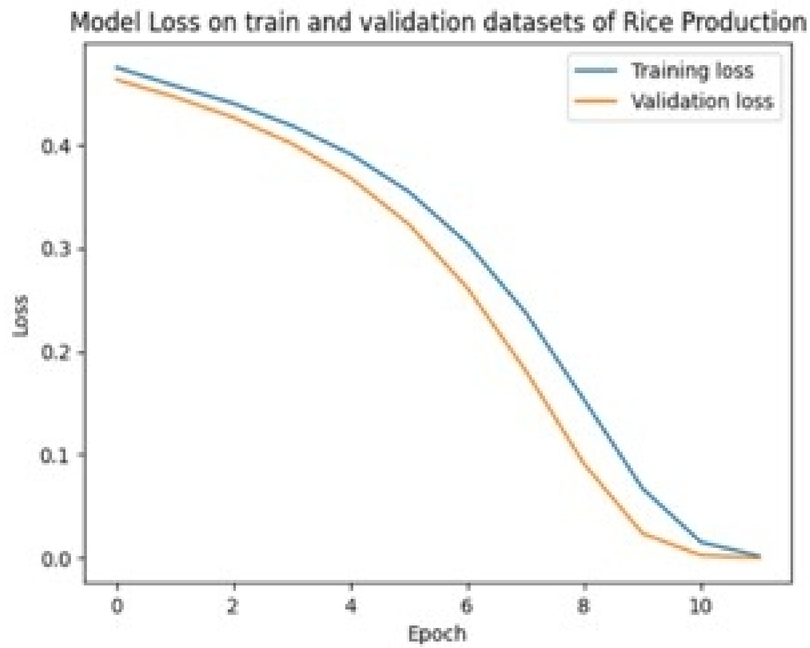
**Train Score: 0.0165 RMSE**

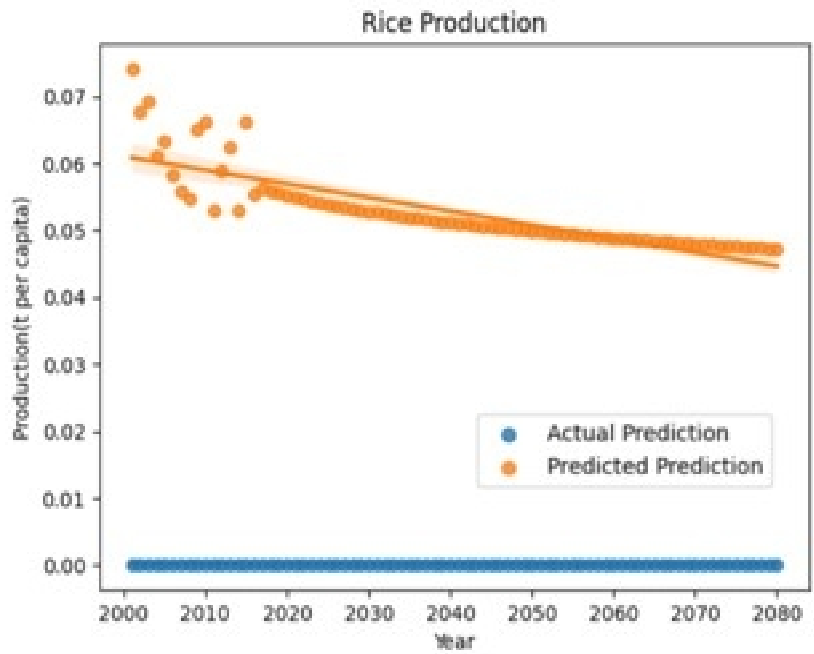



**2. TAWANG**

**Train Score: 0.0587 RMSE**



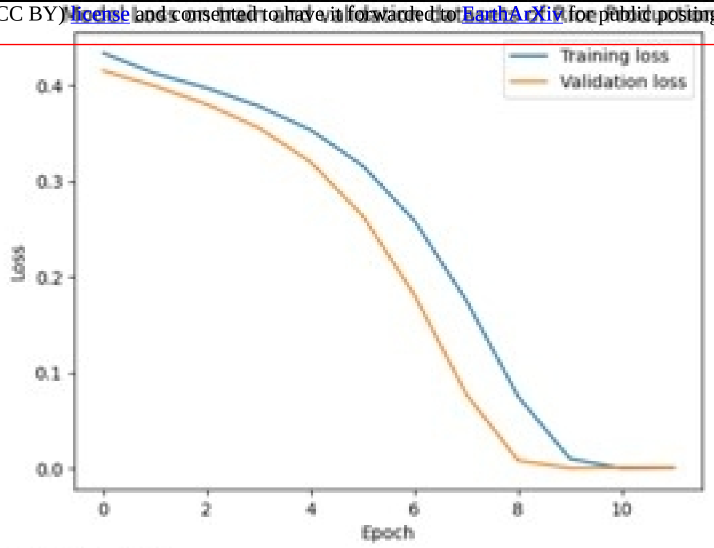



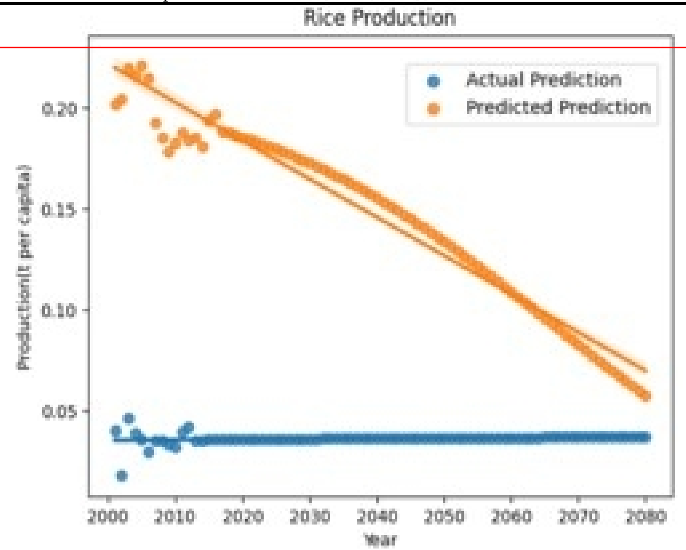

Figure

## 3. THANE

## Train Score: 0.1552 RMSE

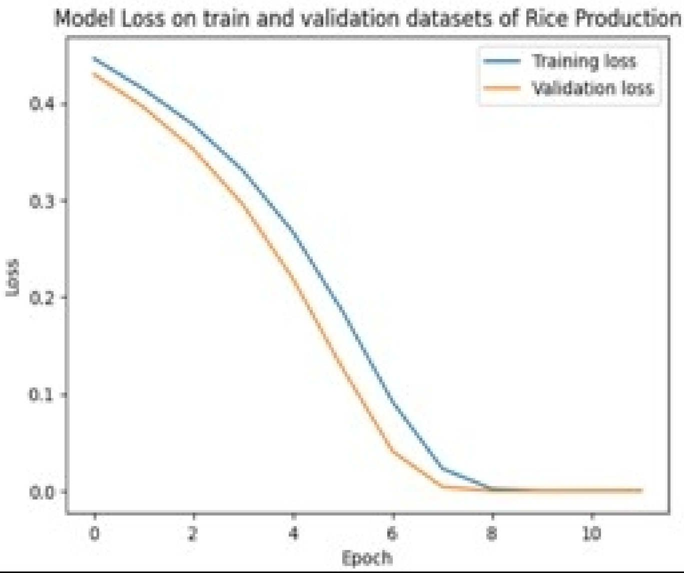


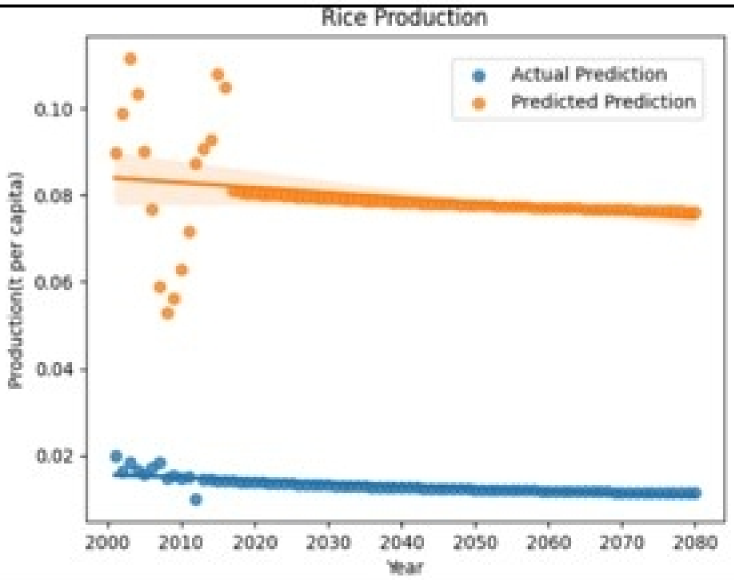



## 4. SURAT

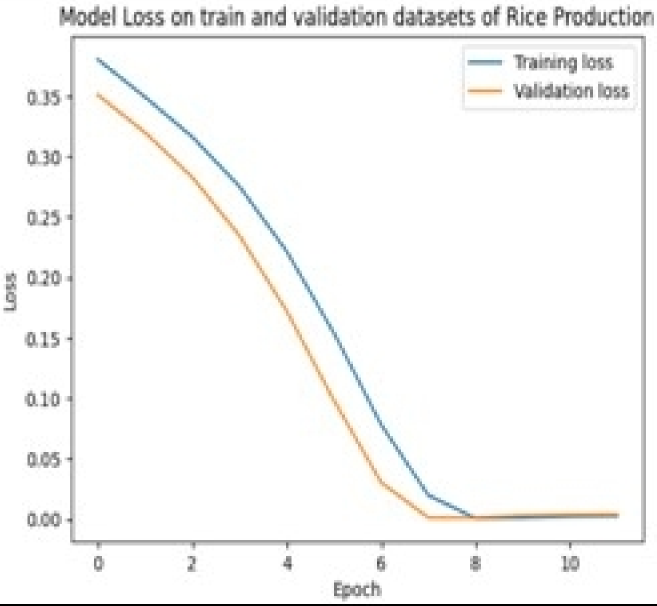
## Train Score: 0.0694 RMSE

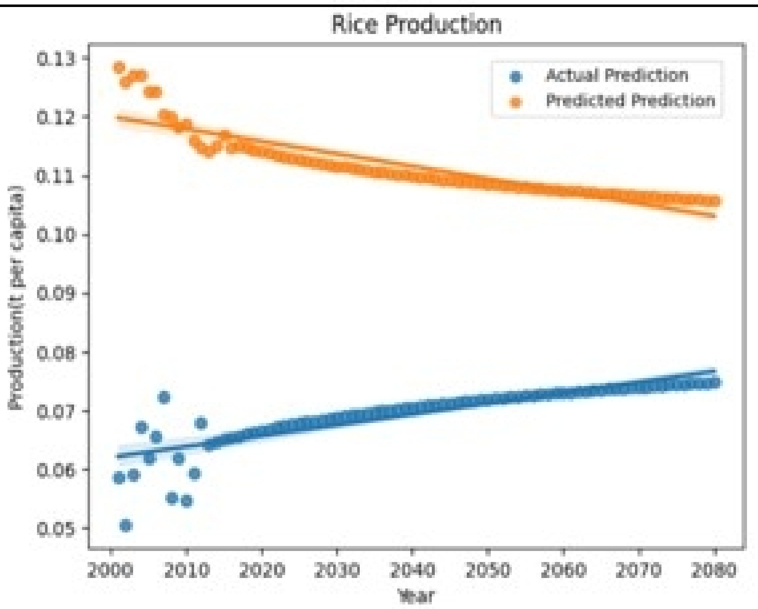



## 5. KARNAL

## Train Score: 0.0538 RMSE



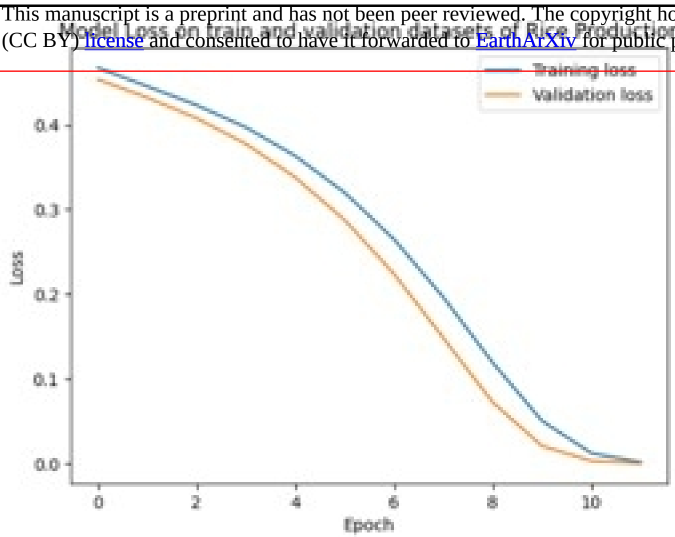



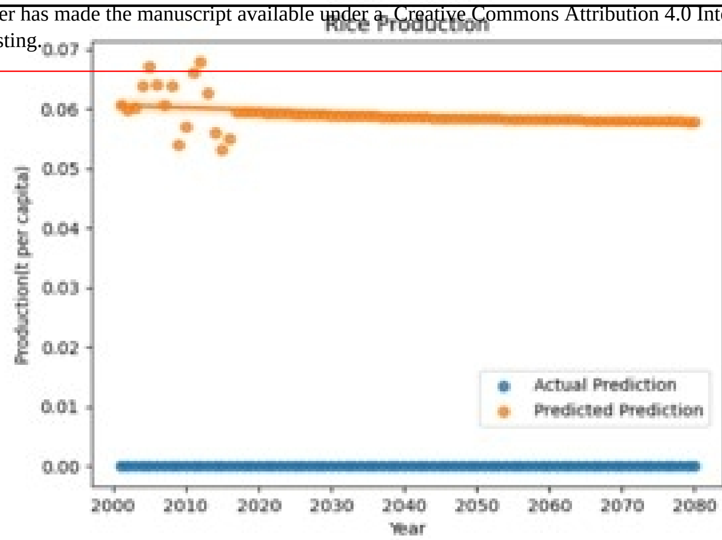

Figure

## 6. BHOPAL

### Train Score: 0.0601 RMSE

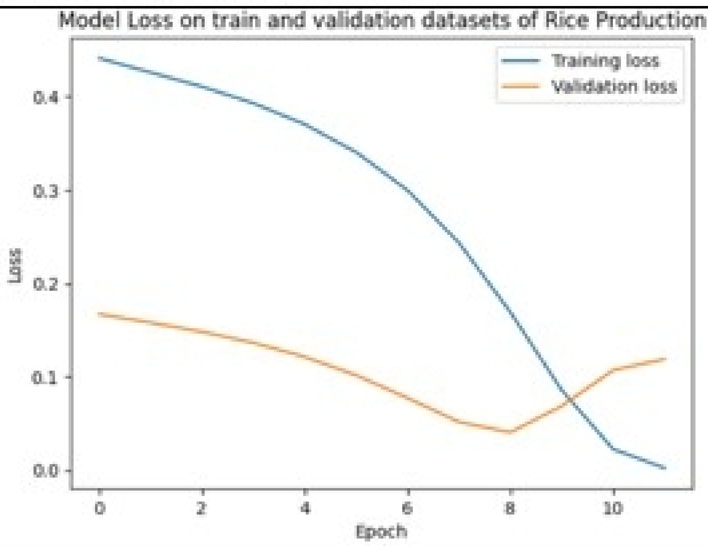


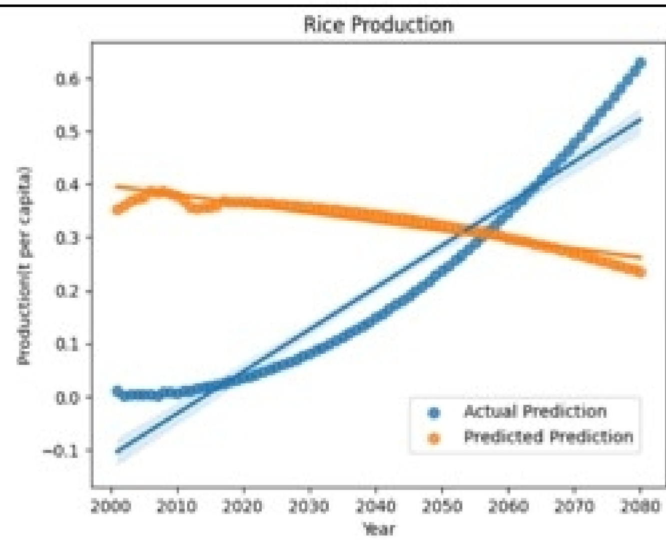



## 7. GWALIOR

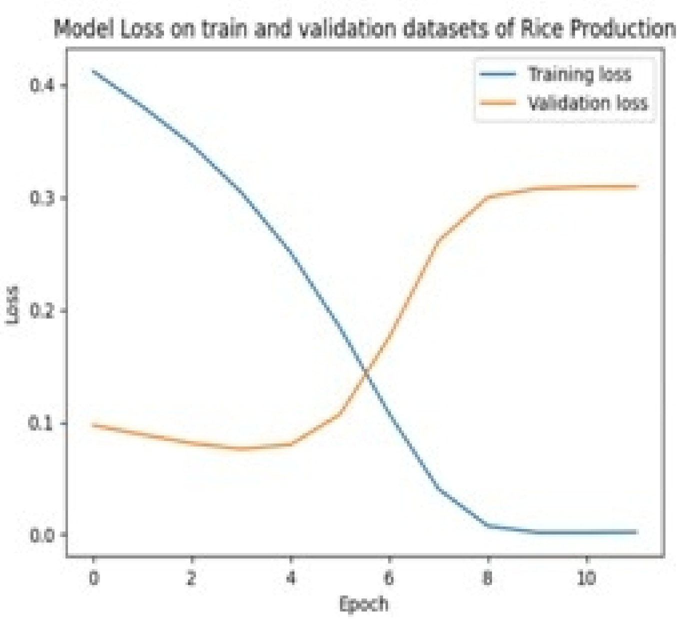
### Train Score: 0.3427 RMSE

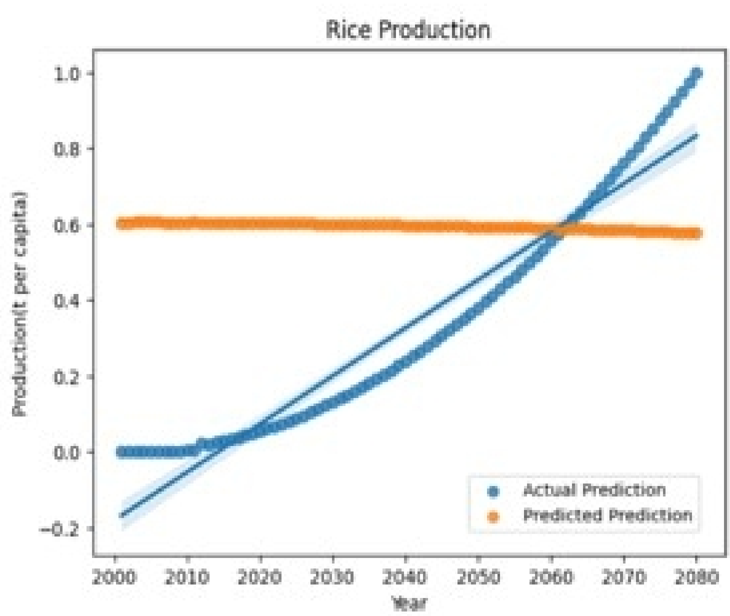



## 8. HOSHANGABAD

### Train Score: 0.5675 RMSE



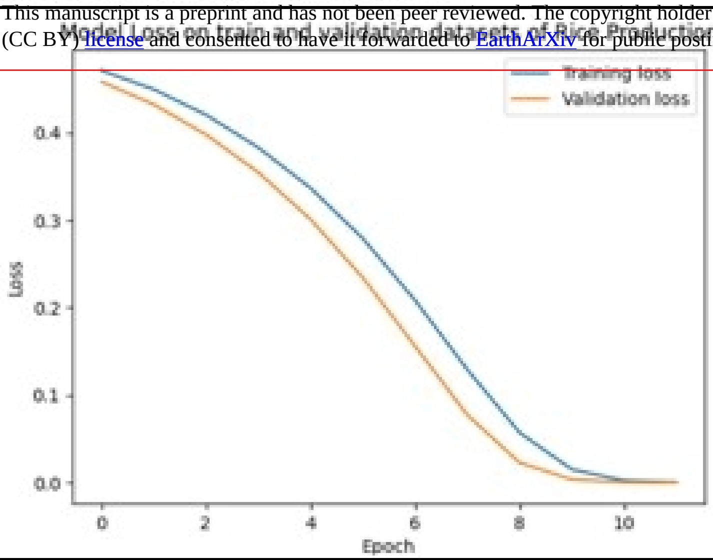



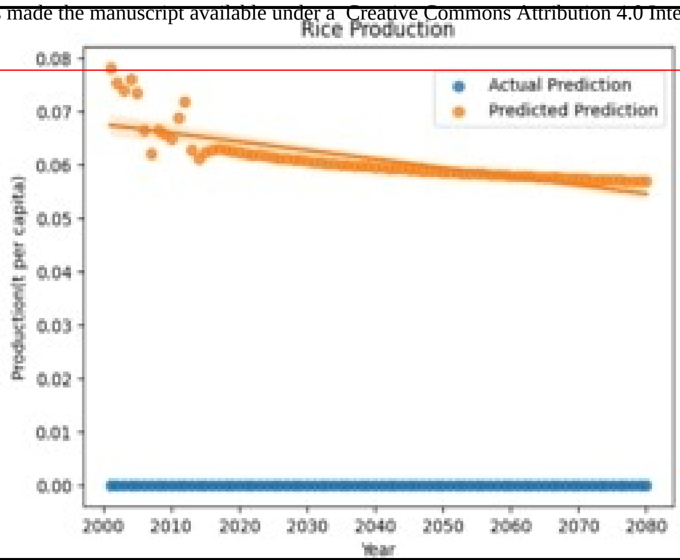

Figure

# 9. INDORE

## Train Score: 0.0657 RMSE

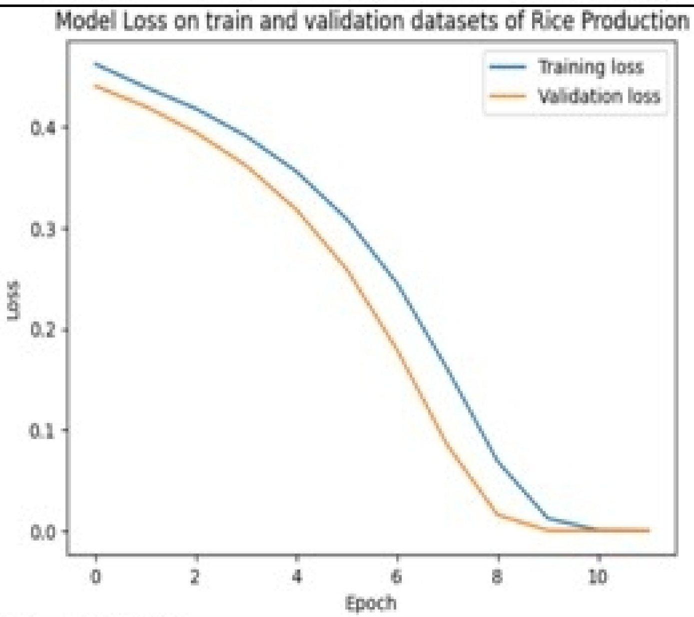


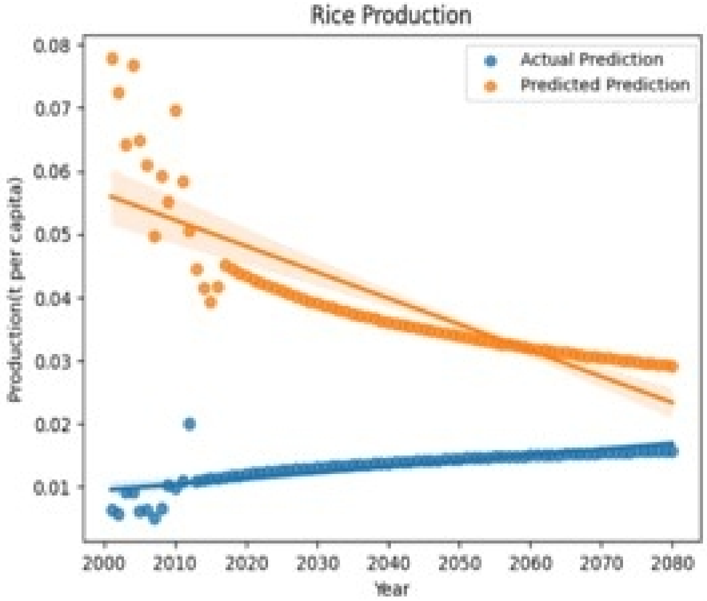



# 10. JABALPUR

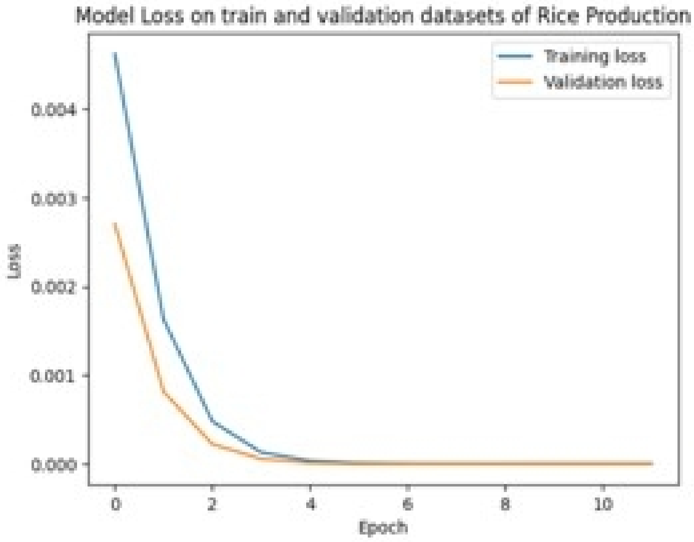
## Train Score: 0.0430 RMSE

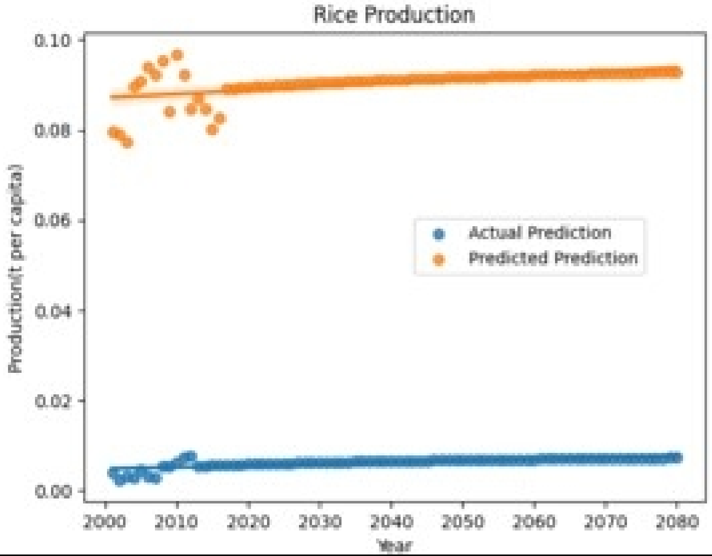



# 11. PANNA

## Train Score: 0.0492 RMSE

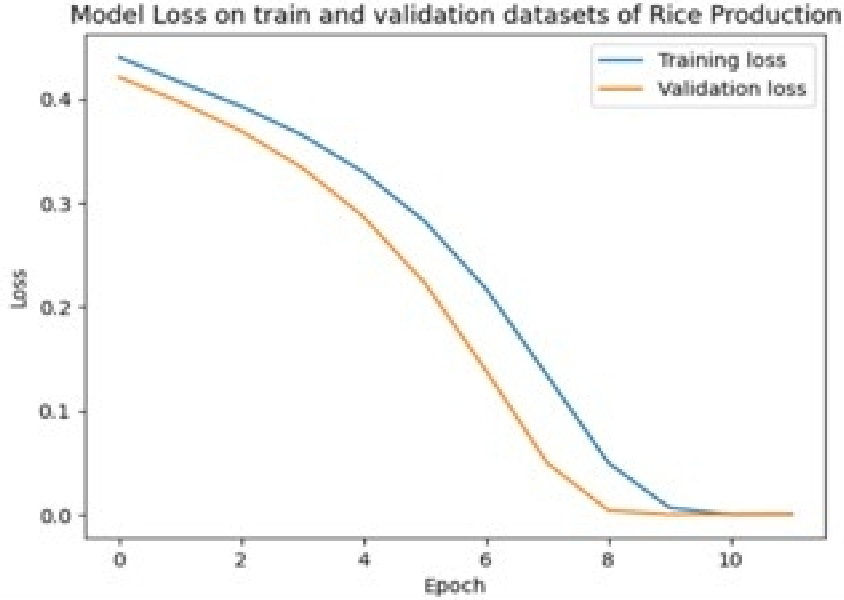


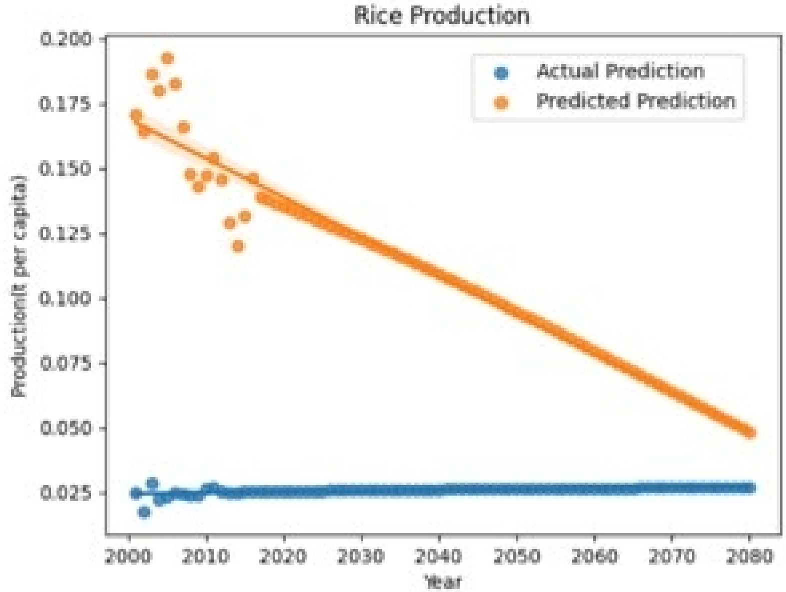




Figure

**12. RATNAGIRI**

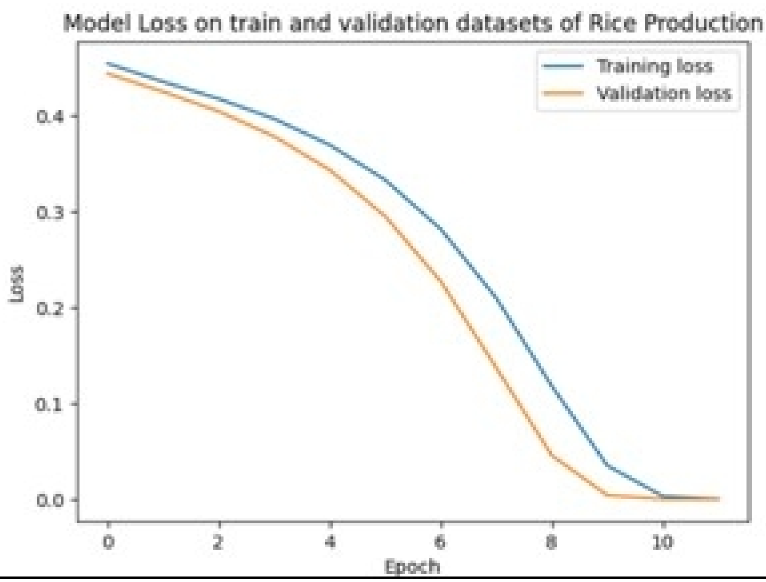
**Train Score: 0.1230 RMSE**

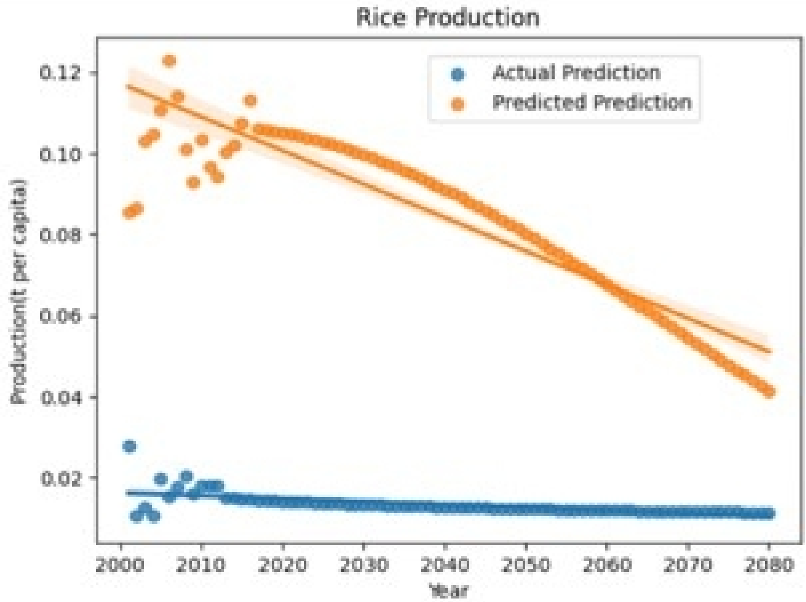



**13. VELLORE**

**Train Score: 0.0880 RMSE**



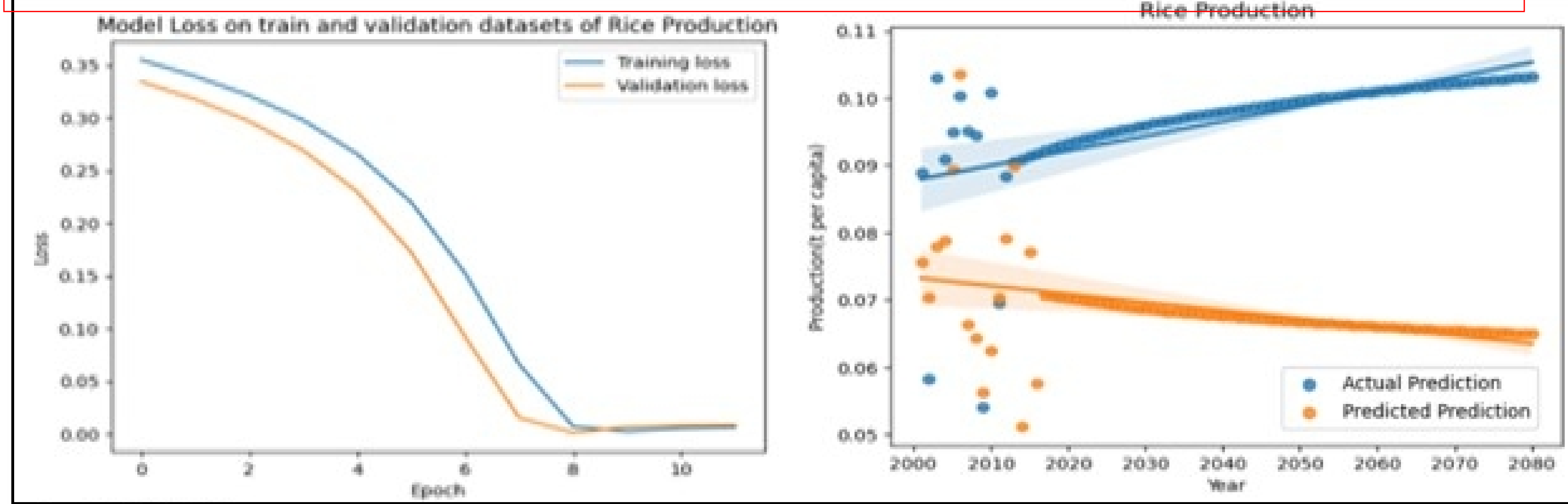




Figure

# 1. EAST GODAVARI

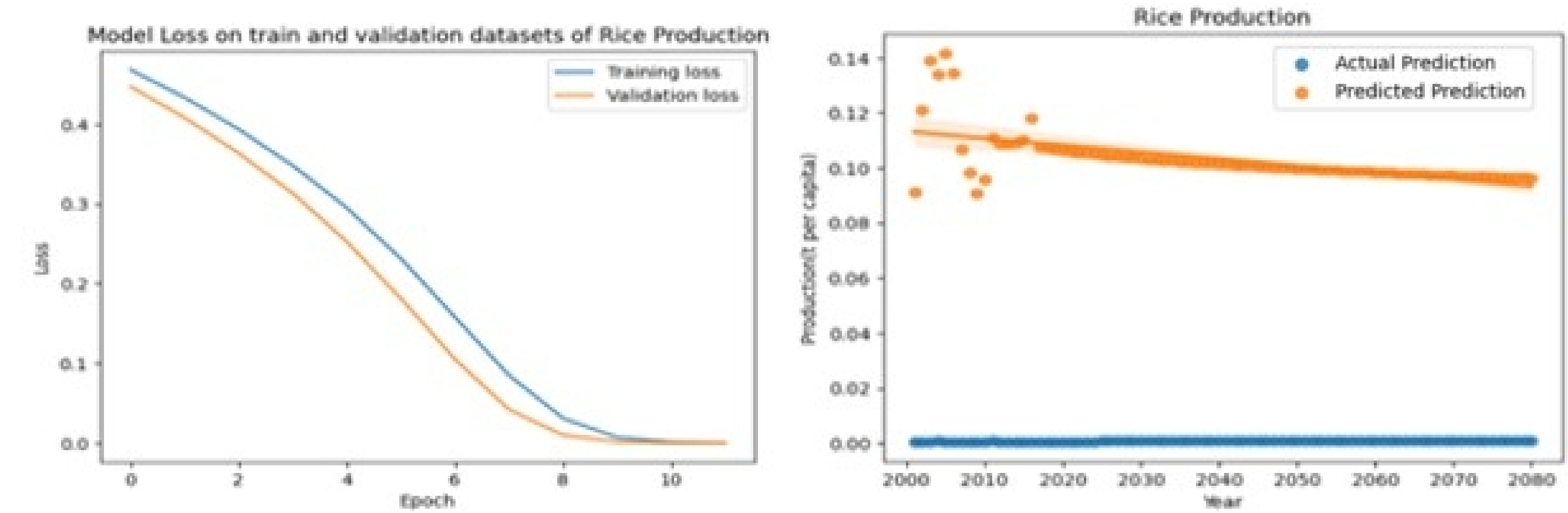


## Train Score: 0.0227 RMSE



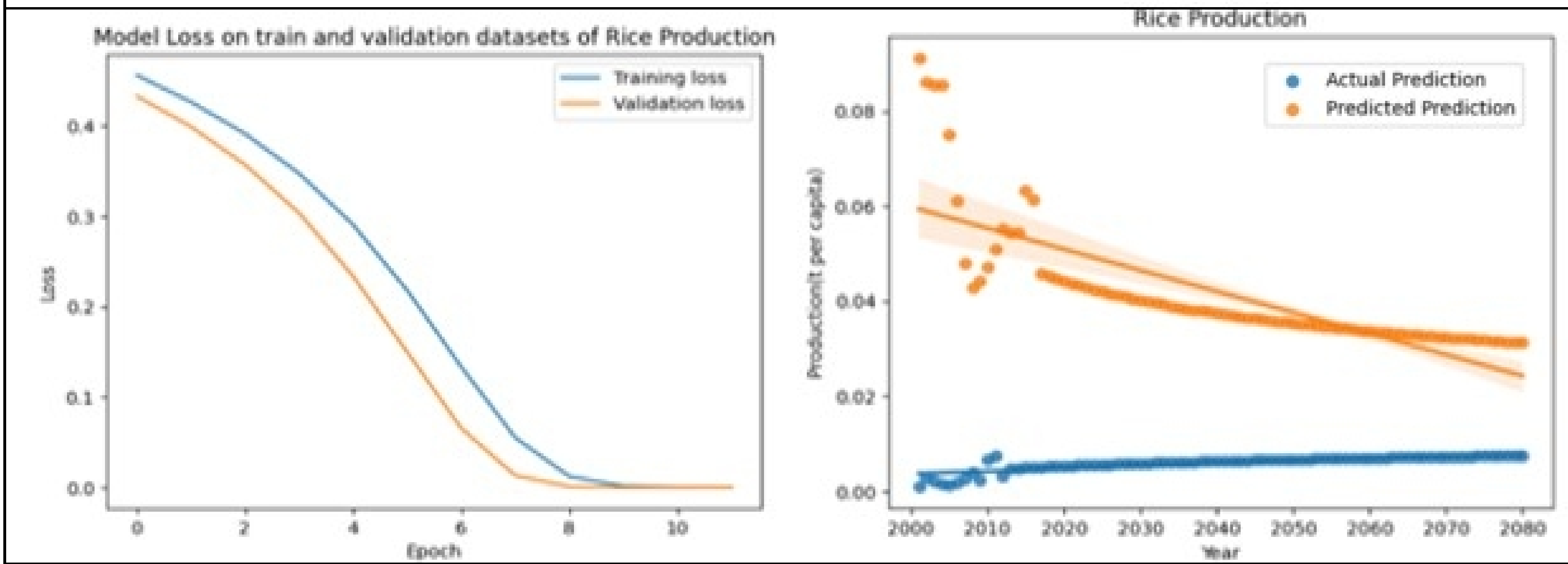

# 2. THANE

## Train Score: 0.1102 RMSE



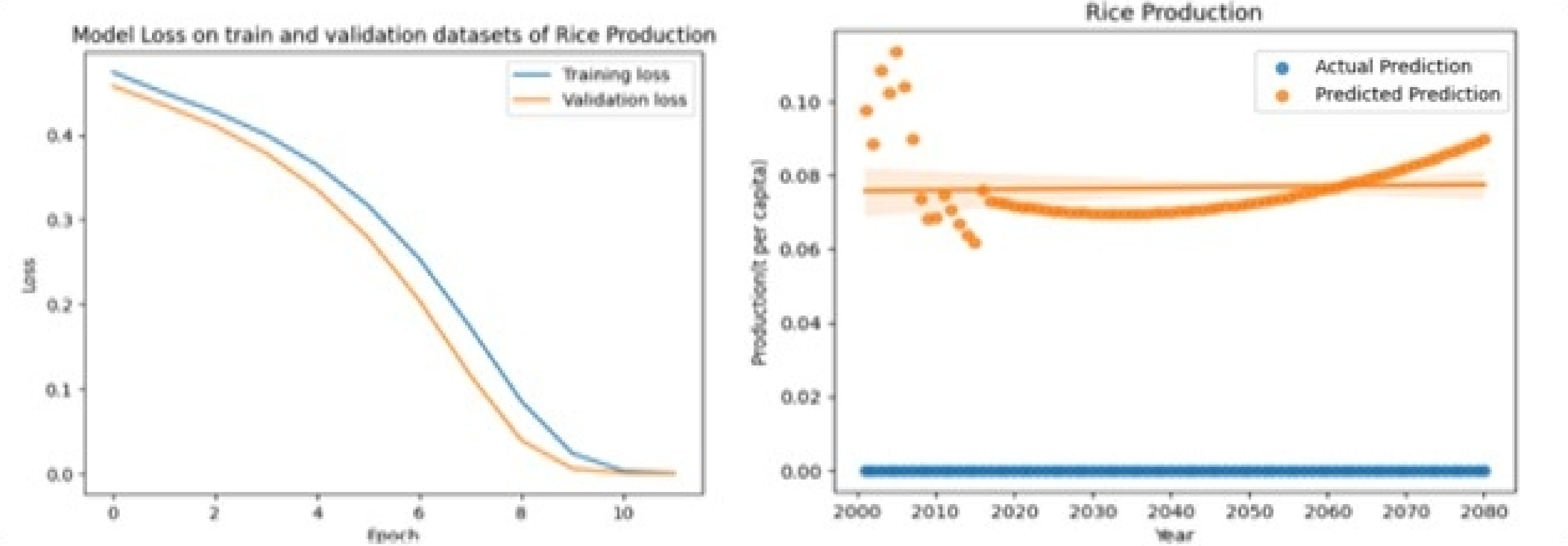

# 3. SURAT

## Train Score: 0.0529 RMSE




Figure

| **4. RATNAGIRI** |
| --- |
| **Train Score: 0.0792 RMSE** |




Figure