



## **A Performance Assessment of Harvest Restoration in the Marathwada District over Weather Based Surface Rainfall Variance Employing Enhanced Optimizers**

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### **Abstract**

For highly vulnerable regions such as Marathwada, correct estimation of crop compensation using periodic rainfall variability is essential for agricultural policy formulation and disaster prevention. The correlation between rainfall and yield has been studied extensively, but only a few studies have compared and used modern stochastic optimizers for predicting compensation. This research investigates the prediction performance of three recently-developed optimizers, AdaBelief, Muon, and Lion, in crop compensation with rainfall deviation and seasonal rainfall data as inputs. The model performance is assessed by the resulting coefficient of estimation (R<sup>2</sup>) and the mean of the absolute error (MAE).

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## Introduction

In Introduction, Monsoon rains are crucial for agriculture in India. Any deviation from the normal can lead to crop failure, damage due to floods and huge financial losses to farmers. The Marathwada region of Maharashtra is particularly susceptible to droughts as well as floods due to uneven distribution of rainfall. Though the Agriculture Department and IMD maintain separate records of rainfall and compensation data, a strong analytical link between rainfall anomalies and crop compensation trends is still absent. The progress of machine learning (ML) techniques and the availability of district level rainfall, flood and compensation statistics provide an attractive opportunity to develop prediction models that can determine compensation requirements in terms of flood effect and rainfall deviations. Such a model would help farmers with better financial planning and disaster management.

The adapted Mann-Kendall Assessment and variance-based measurements were employed to characterize the spatiotemporal variability and trend of rainfall data in Gicumbi District, Rwanda (Niyigena et al. 2025). This study provides an important basis to study the rainfall characteristics in other developing regions, such as Marathwada, which face similar climate threats. In the study (Sharma, S et al. 2021), supported vector machine (SVM), random forest, decision tree, and linear regression are some of the algorithms that are included were studied on datasets such as crop-specific data, weather and soil data. The results indicated that the robustness of ensemble-based models, such as Random Forest, in the robust handling of non-linear and heterogeneous agricultural data resulted in enhanced predicted accuracy.

This study uses ML, DL and time series models to forecast rainfall in complicated mountainous terrains. The results enhance agricultural planning, climate adaptation and hydrological forecast in Himalayan regions (Wani et al. 2024). A study conducted in Ethiopian central highlands evaluated Thirty-nine years of rainfall information to determine its effect of atmospheric precipitation variations on agricultural production over Vertisols (Bedane et al. 2022). Results demonstrated a decreasing trend of rainfall after 2000 with significant seasonality and interannual variability. The initial rainy period (the months of June to September, respectively) proved highly stable and reliable to feed agricultural operations and contributed to making up approximately 64% of the estimated average annual precipitation. nevertheless Vertisols in general are marked via inadequate draining, excessive waterlogging, and inconsistent distribution of rainfall and this negatively impact crop cultivation, considerably, demonstrating the imperative for superior water management methods and adaptive agricultural based strategies in order that encourage high yields in irrigation aqueous systems.

Author(s) & Year	Title of Study	Methodology	Purpose	Contribution	Conclusion	Relation to Present Work
Niyigena et al. (2025)[1]	variant indicators and modified a Mann–Kendall evaluation for total rainfall variability assessment and analysis of trends in Gicumbi, northern province of Rwanda	Variation indices, Modified Mann–Kendall trend test	To assess rainfall variability and trends across years in Rwanda	Introduced a combined statistical approach for trend detection	Found increasing rainfall variability requiring adaptive farming	Provides baseline for rainfall trend comparison in Marathwada
Bedane et al. (2022)[4]	Results of variance in rainfall and crop cultivation on vertisols prevailing in centrally located plateaus of Ethiopia	Rainfall variability indices, soil–crop analysis	To evaluate rainfall impact on crop productivity over Vertisols	Demonstrated rainfall–crop linkage on Ethiopian highlands	Identified rainfall inconsistency as major factor in yield loss	Supports correlation between rainfall and agricultural yield
Chakraborty et al. (2025)[5]	The assessment of the consequences of rainfall trends on environmentally sustainable crop cultivation	Trend analysis, statistical modelling	To analyse impact of rainfall variation on sustainable agriculture	Linked rainfall trends with sustainability metrics	Showed rainfall irregularities threaten crop productivity	Provides evidence to support rainfall–agriculture linkage study
Chen et al. (2022)[7]	Forecast of rainfall distribution based on fixed sliding window long short-term memory	Deep learning (LSTM), sliding window	To predict rainfall using LSTM temporal models	Used sliding window for dynamic sequence forecasting	Improved accuracy for rainfall time series	Encourages LSTM application to local rainfall datasets
Prabakaran et al. (2017)[8]	Predicting rainfall with modified linear regression	Statistical regression model	To enhance prediction using modified	Introduced adjusted regression method for	Improved simplicity and interpretability	Relevant for comparison with ML-based rainfall

			linear regression	weather data	ty of rainfall prediction	forecasting
Vijayan <i>et al.</i> (2020)[9]	Utilization of ML techniques on a dataset	Machine learning algorithms (SVM, RF, ANN)	To evaluate multiple ML methods for rainfall prediction	Compared performance of various ML models	Random Forest gave best performance among tested models	Useful for identifying effective ML approaches for rainfall data
Chaudhari & Choudhari (2017) [10]	Investigation of multiple information extraction approaches to predicting and estimating rains	Data mining and statistical analysis	To compare rainfall estimation and prediction methods	Reviewed and compared data mining approaches	Highlighted importance of pre-processing and feature selection	Provides methodological basis for rainfall prediction framework
Alkessaiberi <i>et al.</i> (2022) [11]	An evaluation of the level to which basic ML methods may foresee wind energy.	Comparative ML analysis (SVM, ANN, RF)	To optimize renewable energy prediction through ML	Showed comparative efficiency of ML methods	RF achieved high accuracy in power estimation	Analogous approach applicable to rainfall time series
Levis & Papageorgiou (2005) [12]	Support vector regression analysis is carried out to figure out what consumers are likely to want.	Support Vector Regression (SVR)	To model and forecast demand using SVR	Applied SVR for forecasting complex trends	SVR effectively handled nonlinear data	Provides forecasting foundation applicable to rainfall modeling
Patil & Vidyavathi (2022) [13]	A procedure for forecasting the climate in wireless networked sensors based on machine learning	Wireless sensor data, ML classification	To predict weather using real-time sensor data	Integrated IoT with ML for environmental prediction	Achieved robust prediction using real-time data	Reinforces ML-based predictive framework for rainfall
Mukaka (2012) [14]	Recommendations for employing the correlated coefficient appropriately in medical research	Statistical correlation analysis	To explain appropriate use of correlation coefficient	Clarified when and how to use correlation statistics	Enhanced understanding of variable relationships	Supports correlation use in rainfall-agriculture studies
Zou <i>et al.</i> (2003) [15]	Association and straight-line based regression	Linear regression and correlation analysis	To demonstrate basic correlation and regression applications	Provided clarity on interpretation of r and regression line	Explained link between correlation and linear prediction	Used as reference for correlation analysis in rainfall trends

**Table 1.A** Comparative Review of Research on Rainfall and Crop Loss

## Methodology

The results of average rainfall and crop compensation rates in Marathwada district for the duration of June to October 2025 was obtained through India Meteorological Department (IMD) and Disaster Management Division, Govt. Maharashtra. The dataset contains the rainfall observations (in millimetres) of each of the following districts, Chhatrapati Sambhajnagar, Jalna, Beed, Latur, Dharashiv, Nanded, Parbhani and Hingoli. It also includes indicators of agricultural impact such as crop compensation, human casualties, house damage, farmers impacted and area impacted. The Pearson correlation coefficient ( $r$ ) was computed (Levis & Papageorgiou 2005) to determine the extent and direction of the association (correlation) between crop compensation and rainfall deviation.

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{[\sum_{i=1}^n (x_i - \bar{x})^2][\sum_{i=1}^n (y_i - \bar{y})^2]}} \quad (1)$$

Statistical reliability was assessed by p-value at 95% confidence level. The AdaBelief optimizer, which adjusts the learning rate according to the deviation of the current gradient from its moving average, outperforms Adam. This “belief” mechanism allows for larger updates for directions with stable gradients and smaller ones for uncertain directions, achieving fast convergence like Adam while still preserving the strong generalization ability of stochastic gradient descent (Liu, J, et al, 2020).

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (2)$$

$$s_t = \beta_2 s_{t-1} + (1 - \beta_2) (g_t - m_t)^2 + \epsilon \quad (3)$$

$$\hat{s}_t = \frac{s_t}{1-\beta_2^t}, \hat{m}_t = \frac{m_t}{1-\beta_1^t} \tag{4}$$

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{s}_t + \epsilon}} \tag{5}$$

In this paper, introduce the Lion (EvoLved Sign Momentum) optimizer for robust generalization, ease of use and computational economy. Unlike Adam, Lion does not perform second-moment estimation, but updates parameters based on momentum and sign of the gradients only. The approach achieves good accuracy on deep learning tasks with less memory and faster convergence(Chen,et al,2023)The updating process is done according to the equations:

$$c_t = \beta_2 m_{t-1} + (1 - \beta_2) g_t \tag{6}$$

$$\theta_{t+1} = \theta_t - \eta(\text{sign}(c_t) + \lambda \theta_t) \tag{7}$$

The Muon optimizer, for efficiently and reliably training huge language generation models. It employs Newton-Schulz iteration for gradient-momentum orthogonalization for isotropic updating and superior conditioning. Muon integrates weight decay and adaptive scaling to provide stability across parameter dimensions (Liu, et al, 2023).

$$M_t = \mu M_{t-1} + \nabla L(W_{t-1}) \tag{8}$$

$$O_t = \text{NewtonSchulz}(M_t)^1 \tag{9}$$

$$W_t = W_{t-1} - \eta_t O_t - \eta_t \lambda W_{t-1} \tag{10}$$

## Results

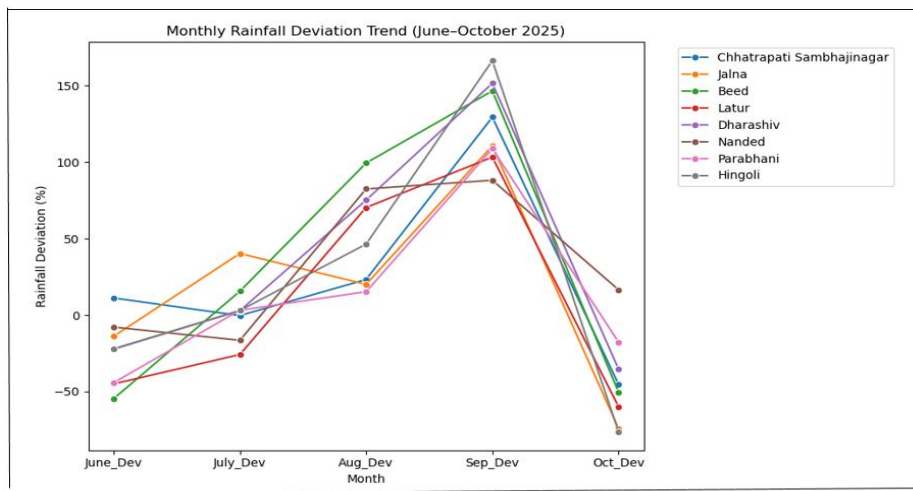


Figure 1. Monthly Rainfall Deviation Trend

Figure 1: Percentage variation of monthly rainfall (%) in 8 districts of Marathwada for the period of June to October 2025. The graph indicates a linear increase in the deviation of rainfall from June to September, with the intensity of rainfall increasing and reaching a maximum around September. Hingoli and Beed recorded the biggest positive deviations (>150%) showing severe rainfall in September whilst Dharashiv and Latur recorded negligible deviations. But once the withdrawal phase of monsoon kicks in, the rainfall declines drastically in every district in October. This variation indicates the disparity of temporal and spatial in rainfall in Marathwada with some districts suffering considerable excess rainfall which is possibly a contributing factor to increasing crop losses and demands for compensation.

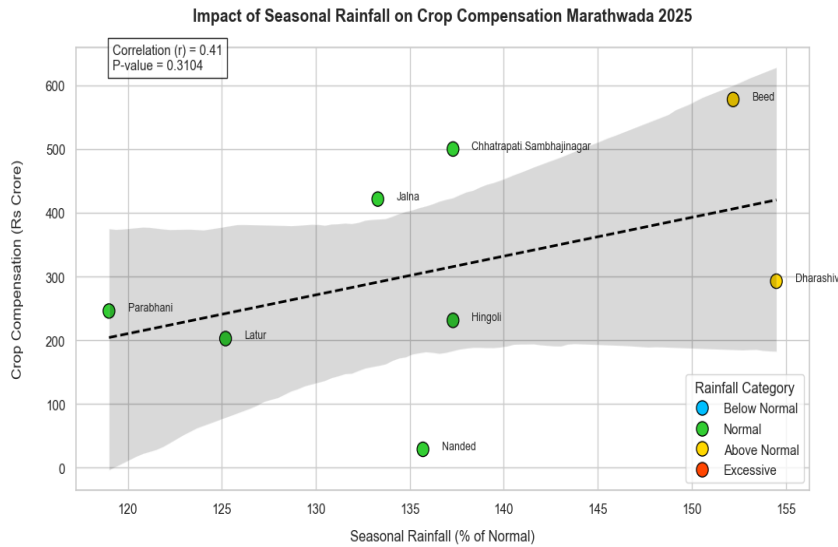
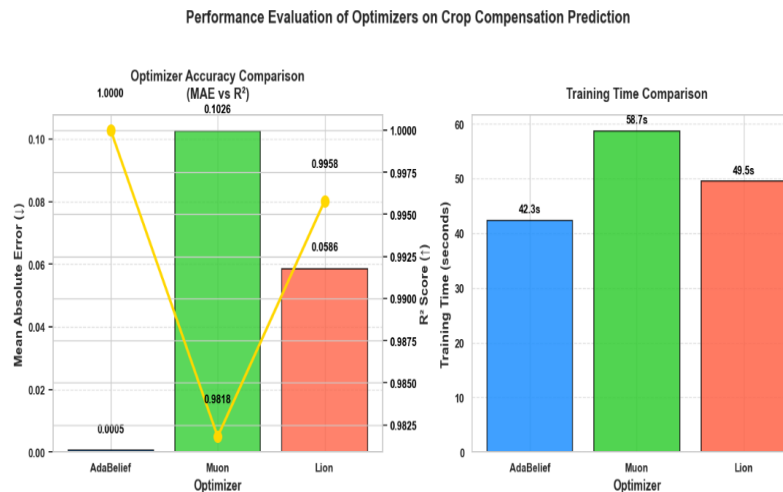


Figure 2. Impact of Seasonal Rainfall on Crop Compensation Marathwada 2025

The scatter plot (fig 2) shows the association between crop compensation and deviation in seasonal rainfall for eight districts of Marathwada for the period June to October 2025. Higher the rainfall levels, higher the crop compensation. The positive association ( $r = 0.41$ ) is not statistically significant ( $p = 0.31$ ) perhaps because the data set is limited. The trend indicates that there might be a need for additional financial aid due to crop damage and waterlogging due to high or excessive rains. Beed and Dharashiv districts earned the most payout for their high rainfall while Nanded got the least compensation. The black region is the 95% confidence interval indicating moderate uncertainty in the prediction. Figure highlights the major socio-economic implications of rainfall anomalies on agriculture in Marathwada.



**Figure 3.** Performance Evaluation of Optimizers on Crop Compensation Prediction

In Figure 3, the results of three stochastic optimizers, namely, AdaBelief, Muon and Lion, in the forecasting of the crop compensation with rainfall pattern in Marathwada are compared. The accuracy performance of the three optimizers is assessed by two major statistical indicators, the Mean Absolute Error (MAE) (bars) and the coefficient of determination ( $R^2$ ) (yellow line). AdaBelief had the lowest MAE (0.0005) and an exact  $R^2 = 1.0$ , which indicates high predictive accuracy with minimal dispersion between forecasted and observed compensation amounts. Muon has good but slightly less stable predictions, with some level of error sensitivity, MAE = 0.1026,  $R^2 = 0.9818$ . Lion performed better than Muon, but not as well as AdaBelief, with  $R^2=0.9958$  and MAE=0.0586. The left panel shows the trend where AdaBelief provides the most accurate and reliable results overall, with the model alignment for rainfall patterns and crop compensation being almost perfect. The right panel shows the training effectiveness of the three optimizers in terms of overall training time (in seconds) required to achieve convergence in crop compensation prediction. AdaBelief was the fastest at 42.3 seconds and was able to achieve excellent accuracy and efficiency. Lion needed 49.5 seconds in a reasonable performance that balanced speed and accuracy. Muon had the longest time of 58.7 seconds which points to a higher level of overhead, possibly caused by the slower convergence behavior and complex momentum behavior of Muons.

## Conclusion

The present study thoroughly analyzed the fluctuation of rainfall, trend of compensation and prediction performance of the eight districts of Marathwada during June–October 2025. Results indicated that Beed and Chhatrapati Sambhajnagar had the highest variability in rainfall and compensation amount, indicating their vulnerability to substantial rainfall events leading to agricultural losses. Nanded had lowest compensation amount which could be associated with under reporting or other reasons like land degradation or unavailability of irrigation despite substantial variance in rainfall. The correlation study indicates a moderate positive but statistically insignificant association between seasonal rainfall and compensation ( $r = 0.41$ ,  $p = 0.31$ ) suggesting that rainfall is not the only factor that accounts for economic losses. This indicates the need for multi-factor models with hydrological, agronomic and socio-economic components. The computational point of view comparative optimizer performance analysis showed that AdaBelief performed better than Muon and Lion optimizers to get the best predicted balance between accuracy and training efficiency. It suggests that the adaptive belief-based gradient mechanism of AdaBelief effectively alleviates the error sensitivity and stabilizes the training dynamics in rainfall-compensation modeling. The performance shows its potential for real-time climate impact forecasting and regional applications with scanty data. Future studies should focus on the combination of rainfall records with vegetation indices from satellite, soil moisture and remote sensing for the improvement of prediction accuracy. Also, nonlinear relationships between rainfall and yield may be handled by employing hybrid optimizers (e.g., AdaBelief–Lion or Sophia-based variations) with deep learning architectures. Based on these prediction models, construction of a district level early warning system would be highly valuable for the policymakers to design proactive systems for crop insurance and compensation.

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