IMPACT OF POST EMERGENCE HERBICIDES ON WEED DYNAMICS, YIELD AND NUTRIENT UPTAKE OF MAIZE: A COMPARATIVE EVALUATION OF LINEAR AND MACHINE LEARNING APPROACH

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ABSTRACT

Effective weed management is essential for improving maize (*Zea mays* L.) productivity through the identification of selective and efficient post-emergence herbicides. Field experiments were conducted during 2019–2021 at the farmer field to evaluate weed control efficacy, weed dynamics, and maize yield under four herbicide treatments i.e. T_1: Weedy check, T_2: Tembotrione (42% S.C.) 287.5 mL ha^{-1} [25 DAS (days after sowing)], T_3: Topramezone (33.6% S.C.) 100 mL ha^{-1} (25 DAS) and T_4: Halosulfuron Methyl (75% WG) 90 g ha^{-1} (25 DAS) with data averaged across five locations for four treatments each year. The resulting dataset comprised 12 treatments-year observations with 11 agronomic variables. The machine-learning analyses were conducted as an initial exploratory assessment. Using chronological validation, 2019–2020 observations were used for training and 2021 observations for independent testing (66:34 split). Among the evaluated treatments, application of tembotrione proved the greatest broad-spectrum weed suppression and produced the highest grain yield **(**8,936 kg ha^{-1}), compared with the untreated control **(**3,897–4,324 kg ha^{-1}). Spearman correlation analysis revealed strong positive associations between grain yield and nutrient uptake of maize ($\rho = 0.916$) and strong negative associations with the weed index ($\rho = -0.909$) and broadleaf weed density ($\rho = -0.825$). These predictive modeling using linear regression (LR), random forest (RF), and XGBoost was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). Within the constraints of the small dataset, LR achieved the best predictive performance ($R^2 = 0.949$, RMSE = 379.58, MAE = 327.96). Ridge Regression with SHAP analysis identified total nutrient input (total NPK; +408.95) as the strongest predictor of maize yield while year had the lowest contribution (+192.78). These findings demonstrate that effective broad-spectrum weed management enhances maize productivity, while the modelling provides preliminary insights into weed control, soil fertility and yield relationships.

Keywords: Linear regression, maize yield, random forest, SHAP analysis, weed density, weed management, XGBoost

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INTRODUCTION

Maize (*Zea mays* L.) is globally most popular and leading cereal crop after rice and wheat it was more nutritious food to the human beings as well as livestock. Similarly, across the globe maize products were used as raw material in ethanol and other industries. India shares in production 42-43 million tonnes from 10.74 m ha during 2024-25. The average productivity of maize (3.54 t ha^{-1}) in India, which is lower than global average productivity (4.9 t ha^{-1}) hence there was need to improve the package of practices pertaining to weed management (APEDA, 2024-25). Among the major constraints to maize production, weed interference is one of the most important factors limiting productivity. Six to seven weeks (up to 45 DAS) are most critical for weed growth depending on severity of weed infestation, the yield may reduce by 15 to even 50% (Rapado-Rincón, 2025). There was need timely weed management in maize to get maximum yield and efficient utilization of natural resources without weed competition (Gower *et al*., 2003; Knight *et al*., 2017). The grain yield of maize was influenced by uptake of nutrients through reduced the weed population per unit area (Pandey *et al*., 2001; Gharde *et al*., 2018).

Although integrated weed management is considered the most effective strategy, labour shortages, increasing production costs, and limited adoption of intercultural operations have increased farmers' reliance on post-emergence herbicides. More than 100 weed species belonging to 66 genera and 24 plant families have been reported in Indian maize fields, whereas many commercially available herbicides provide only narrow-spectrum weed control (Patel *et al*., 2006). Topramezone and tembotrione herbicides were inhibits the enzyme activity through its broad-spectrum systemic activity

against all the weeds. Similarly, these two systemic herbicides were target the weeds, initially scoring effect on weeds and later leads to discolouration of leaves and damage the internal tissues of weeds (Williams *et al*., 2011; Swetha *et al*., 2015; Yadav *et al*., 2017).

However, comparative information on the field performance of these herbicides with respect to weed suppression, nutrient uptake, and grain yield under Indian production conditions remains limited. In this context there was need to identify and evolve best suitable post emergence herbicides for effective control of weeds and increased the productivity of maize. The data revealed the performance of herbicides in the experimental sites on weed dynamics, nutrient uptake and yield of maize was positive approach. The efficacy of herbicide reduces the weed density and increased the weed control efficiency up to 40-45 DAS.

Data-driven modeling approaches can complement field observations by identifying influential agronomic variables and exploring their relationships with crop productivity.

Conventional statistical methods, such as linear regression (LR), together with machine learning techniques including Random Forest (RF) and Extreme Gradient Boosting (XGBoost), have increasingly been used for crop yield prediction. However, comparative evaluation of these modelling approaches for predicting field-generated weed management outcomes has remained limited, particularly when weed-related variables are involved and model interpretation is supported by explainable artificial intelligence techniques such as SHAP (SHapley Additive exPlanations) (Rizvi *et al*., 2024; Wang *et al*., 2024; Taremwa *et al*., 2025).

Currently available studies have primarily focused on regional yield prediction using remote sensing, climatic variables, or individual machine learning models (Zhu *et al*., 2021; Rani *et al*., 2023; Ingale Jagruti *et al*., 2025), with less emphasis on integrating field-based herbicide evaluation and weed-related variables within an interpretable modelling framework.

Thus, the current study was undertaken with the aim of comparatively evaluating three models, viz., linear regression (LR), random forest (RF), and extreme gradient boosting (XGBoost), for predicting maize yield using agronomic and weed-related variables, with SHAP analysis employed to provide interpretable insights into the relative importance of these variables, and (ii) evaluating the effectiveness of selected post-emergence herbicides for weed control, nutrient uptake, and grain yield of maize under field conditions.

MATERIALS AND METHODS

The field trial was conducted during the Rabi seasons of 2019, 2020, and 2021 at five farmer fields in Khammam district with similar soil and crop management practices. For each treatment, observations from the five locations were averaged within each year to obtain representative treatment-level values for subsequent machine learning analysis. This data aggregation was adopted to minimize site-specific variability and focus on overall treatment performance. The experiment was laid out in RBD design comprising four treatments mean with every year considered as replication. Herbicides were applied uniformly in a randomized plots (5 x 6 m^2) with the help of knapsack sprayer. Soils of the experimental fields was sandy clay loam in texture, on an average the range of organic carbon (OC) was medium 0.58 to 0.64% (Walkley and Black 1934), low in available nitrogen 232.8 to 248.4 kg ha^{-1} (Subbiah and Asija,1956), high in available phosphorus was 38.6 to 46.5 kg ha^{-1} (Olsen *et al*., 1954), and medium in available potassium was148.4 to176.6 kg ha^{-1} (Jackson, 1973). Soil reaction was in mild alkaline (pH 7.4-7.8).

The experiment comprised with the following treatments-T_1: Weedy check, T_2: Tembotrine (42% S.C.) 287.5 ml ha^{-1} (25 DAS), T_3: Topramezone (33.6% S.C.) 100 ml ha^{-1} (25 DAS) and T_4: Halosulfuron Methyl (75% WG) 90 g ha^{-1} (25 DAS). All the herbicides were applied alone and uniformly in the experimental fields with the help of knapsack sprayer.

The maize variety DHM-117 was sown at a spacing of 60 × 20 cm between rows and plants. The recommended doses of inorganic fertilizers were given at the rate of 200:60:50 kg N, P_2O_5 and K_2O ha^{-1} in the form of urea, di-ammonium phosphate (DAP) and muriate of potash (MOP). The nitrogen was given in three equal splits *i.e*., at basal, knee heigh stage and remaining at silky stage while P_2O_5 applied at basal as single dose and K_2O was applied 50% as basal doses and remaining 50% at silky stage as well as all the recommended agronomic and plant protection measures were adopted to raise crop.

Observation recorded on the following aspects- weed density (individual category wise) at 40 DAS (m^{-2} area) estimated through dividing the total number of weeds counted in a sample area by the total number or size of those sample units these were subjected to square root transformation to normalize their distribution, Weed Control Efficiency (WCE) is calculated as the percentage reduction in weed count or dry weight in a treated plot compared to an untreated control plot at harvest, grain yield (kg ha^{-1}) estimated through divide the total weight of the harvested grain (kg or tonnes) by the total harvested land area in hectares.

The weed control efficiency (WCE) was calculated using the formula and expressed in percentage.

$$\text{Weed Control Efficiency} = \frac{\text{DWC - DWT}}{\text{DWC}} \times 100 \quad \ldots (1)$$

Where;
DWC = Dry weight of weeds in un-weeded plot
DWT = Dry weight of weeds in weed control treatment plot
The Weed Index (WI) was calculated using the formula and expressed in percentage.

$$WI = \frac{X - Y}{X} \times 100 \quad \ldots (2)$$

Where;
X =Crop/seed yield from the weed-free plot
Y = Crop/seed yield from the treated plot

A separate weed-free reference plot was maintained adjacent to the experimental plots to obtain the reference grain yield for Weed Index (WI) calculation. The yield from this plot was used only for WI estimation and was not included in the statistical comparison of treatments (T_1–T_4).

The nutrient uptake was calculated using the formula and expressed in kg/ha.

$$\text{Nutrient uptake (kg ha}^{-1}\text{)} = \frac{\text{Nutrient concentration (\%)} \times \text{Dry matter Yield (kg ha}^{-1}\text{)}}{100} \times 100 \quad \ldots (3)$$

Development of Predictive Machine Learning Models: Crop growth models are widely used to estimate crop yields, optimize farm management, assess the impacts of climate change on crops, and support food security planning (Nagata *et al*., 2025; Yusara *et al*., 2025). Early crop yield models often excluded important biophysical factors, such as weeds, pests, water stress, and management variability, leading to inaccurate estimates of yield gaps-the difference between actual and potential yield. AgMIP addresses this limitation by improving crop models to better represent yield gaps, which are often mis-estimated owing to inadequate consideration of pests and diseases, farmer management differences, rainfall variability, and nutrient limitations beyond nitrogen (Rosenzweig *et al*., 2013).

There is growing interest in machine learning (ML) models such as linear regression, random forest and XGBoost for real-time maize monitoring and yield prediction using low-cost, publicly available remote sensing data. ML effectively captures complex patterns in large agricultural datasets, making it well suited for modeling both linear and nonlinear relationships in farming systems to improve prediction accuracy (Taremwa *et al*., 2025).

A dataset of 12 treatment-year combinations (four treatments × three years) across 11 agronomic variables was utilized. Following a chronological validation strategy, eight samples (2019–2020) were allocated for model training, and four samples (2021) were reserved for testing.

Linear regression: Linear Regression (LR) was employed to model the relationship between crop yield ((Y)) and explanatory variables such as weed density and weed control efficiency (Xi). Prior to model development, key assumptions linearity, homoscedasticity, independence, and normality of residuals were verified (Montgomery, 2021). The model is expressed as:

$$Y=\beta 0+\beta 1X1+\beta 2X2+\cdots+\beta nXn+\epsilon \quad \ldots (4)$$

where (Y) denotes crop yield, (Xi) represent input variables, (β_i) are regression coefficients, and **(ε)** is the error term.

Random forest: Random Forest (RF) was used as an ensemble learning algorithm in order to enhance the accuracy of prediction and avoid over-fitting. In this context, the RF model was developed through bootstrap aggregation, which involved the generation of multiple samples from the training dataset with replacement. A random set of variables was used at each split in order to achieve diversity in tree generation. Trees were grown for the largest size possible without pruning (Breiman, 2001).

XGBoost (Extreme Gradient Boosting): XGBoost was used as a gradient boosting method for modeling complex and non-linear relationships. This algorithm creates trees incrementally such that each next tree corrects the error of the previous tree. XGBoost maximizes an objective function that combines loss and complexity of the model: $\mathbf{Obj(\theta) = L(\theta) + \Omega(\theta)}$

The machine learning algorithm was optimized by employing gradient descent, incorporating inherent components like regularization, tree pruning, and handling missing data (Chen & Guestrin, 2016).

Validation and testing: The whole database was built with the use of the integration of all variables that are associated with treatment of maize grain yield. The database consisted of important factors like weed density and weed control efficiency. The database was split into two parts, 66% for training and 34% for testing. The training dataset was used to build the model, and the testing dataset was used for independent evaluation of model performance. This partitioning

enables effective detection of overfitting, wherein a model may perform well on training data but fail to generalize to unseen observations (Linxinzhi, 2021; Tirink, 2025).

Model performance evaluation: The predictive accuracy of the Linear Regression, Random Forest (RF), and XGBoost models was evaluated using the following statistical metrics (Equations 5–7) (Mamić *et al*., 2023; Tirink, 2025).

1. **Root mean square error (RMSE):** RMSE measures the average magnitude of the error. It is the square root of the average of squared differences between prediction and actual observation. It gives a relatively high weight to large errors.

$$\text{Root Mean Squar Error (RMSE)} = \sqrt{\frac{1}{n}\,_{i=1}^{n}\Sigma(y_i - \hat{y}_i)^2} \qquad \ldots\ldots (5)$$

2. Mean absolute error (MAE): MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It is the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight.

$$\text{Mean Absolute Error (MAE)} = \frac{1}{n}\Sigma_{i=1}^{n}\mathrm{I}y_i - \widehat{y_i}\mathrm{I} \qquad \ldots\ldots (6)$$

3. Coefficient of determination (R^2): R^2 indicates how well the independent variables explain the variability of the dependent variable. An R^2 value of 1.0 indicates that the model perfectly predicts the target variable.

$$\text{Coefficient of Determination } (R^2) = 1 - \frac{\Sigma(y_i - \hat{y})^2}{\Sigma(y_i - \bar{y})^2} \qquad \ldots\ldots (7)$$

Where

n: Total number of sample observations

y_i: Observed value (or actual value) of the dependent variable for the i^{th} observation.

$\hat{y}$: Predicted value generated by the regression model (3-model) for the i^{th} observation.

$\bar{y}$: Mean (average) value of all the observed values.

Software and statistical anaysis: The data from the four herbicide treatments were analyzed using a Randomized Complete Block Design (RCBD), with the three experimental years (2019–2021) serving as temporal blocks (replications). A one-way ANOVA—partitioning variance into Treatment (DF=3), Block (DF=2), and Error (DF=6)—was conducted to evaluate main treatment effects on weed density, weed control efficiency, nutrient uptake, weed index, and grain yield. For effects yielding a significant F-value ($p \leq 0.05$), Tukey's Honest Significant Difference (HSD) test ($\alpha = 0.05$) was applied to separate treatment means.

The proposed approach was implemented using the python programming language (v3.x). Most components were developed from scratch by the authors, while selected open-source implementations were also utilized. Data orchestration and preprocessing were performed using the Pandas and NumPy libraries. The machine learning models-linear regression, random forest, and XGBoost-were developed using the Scikit-learn and XGBoost frameworks. Furthermore, SHAP (SHapley Additive exPlanations) ridge regression was utilized to conduct feature importance analysis and provide model interpretability (Mokhtar *et al*. 2022).

RESULTS

The effects of weed density, weed control efficiency and weed index on maize grain yield were analysed using machine learning models to identify the best-fitting approach. SHAP analysis was employed to interpret model behaviour and identify key variables influencing predictions. Spearman rank correlation was used to assess relationships between weed parameters and yield attributes. Bar charts showed the effect of treatments on maize grain yield, whereas horizontal bar charts showed the effect of each variable on yield response. The findings are presented below.

Predictive accuracy of linear regression, random forest, and XGBoost models for grain yield: The predictive performance of three models, namely linear regression (LR), random forest (RF), and XGBoost, was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). The findings represent exploratory evidence of the relationships among the evaluated variables. In the present database, all three models have R^2 values that exceed 0.80 (Fig.1). Among them, LR showed the best performance, with an R^2 of 0.949, RMSE of 379.58, and MAE of 327.96 (Table 1). RF ranked second, with an R^2 of 0.874, RMSE of 595.51, and MAE of 593.70, whereas XGBoost showed comparatively lower performance (R^2 = 0.807, RMSE = 736.45, MAE = 711.31). These results suggest that, for the present dataset**,** LR captured the observed relationships more effectively than RF and XGBoost. As the independent test set included four 2021 treatment observations evaluated using 11 agronomic

parameters, the reported performance should be interpreted. Validation using larger, independent datasets is needed to confirm model performance and generalizability.

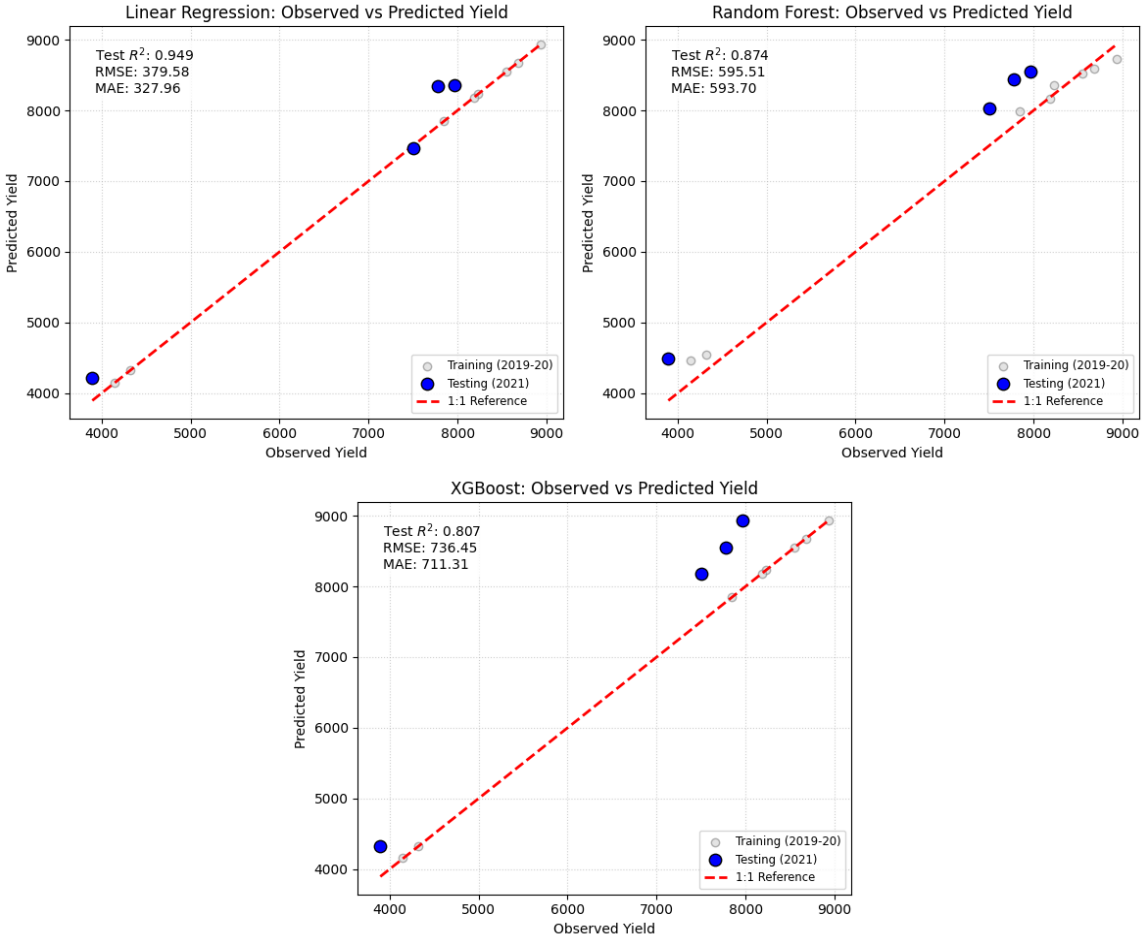

Fig. 1: Comparison of machine learning models for grain yield kg ha^{-1} (top) prediction using observed vs. predicted scatter plots with a 1:1 reference line.

Table 1: Performance comparison of machine learning models for grain yield (kg ha^{-1}) prediction

Model	R² Score	RMSE	MAE
Linear Regression	0.949	379.58	327.96
Random Forest	0.874	595.51	593.70
XGBoost	0.807	736.45	711.31

SHAP feature impact summary (beeswarm plot) and global feature importance on maize yield: To evaluate the contribution of agronomic variables to maize yield prediction, the best-performing Ridge Regression was interpreted using SHAP (SHapley Additive exPlanations), presented as a feature impact beeswarm plot (Fig. 3a) and a global feature importance bar plot (Fig. 3b). The overall feature importance ranking, based on the mean absolute SHAP values, indicated that nutrient availability and weed-related variables were the dominant drivers of maize yield (Fig. 3b). Among all predictors, total uptake of N, P and K exhibited the highest predictive importance (mean SHAP = +408.95), followed by total_WD (+396.59), WI (+359.32), and total_WCE **(%)** (+329.04). In contrast, year had the lowest contribution (+192.78), indicating that seasonal variability had only a minor influence on model predictions.

The SHAP beeswarm plot clearly illustrates the magnitude and direction of feature effects on maize yield (Fig. 3a). Since Ridge Regression was used for regularization, SHAP values were distributed smoothly and had stability in distribution to address multicollinearity among the features relating to nutrients and weeds. Total uptake of N, P, and K had the most positive effects on maize yield such that high nutrient uptake (represented by red points) resulted in the

prediction of yield up to +500 kg ha^{-1}, whereas low nutrient uptake (represented by blue points) led to the prediction of yield reduction by −800 kg ha^{-1}. On the other hand, total WD and WI had very negative impacts on yield since high WD and WI caused reduction of yield prediction by up to −800 kg ha^{-1} because of competition between the two plants. In addition, total WCE (%) positively impacted SHAP value distribution, which indicated that good weed control improved the production of maize. The year feature remained clustered around the zero SHAP value.

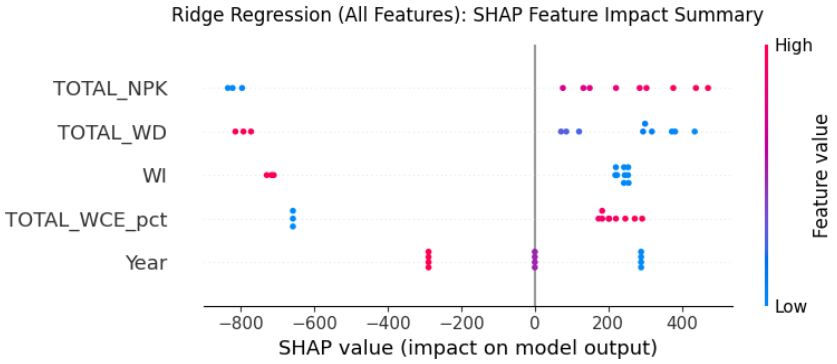

Fig. 3a: SHAP feature impact summary (beeswarm plot) illustrating influence of management inputs on maize yield.

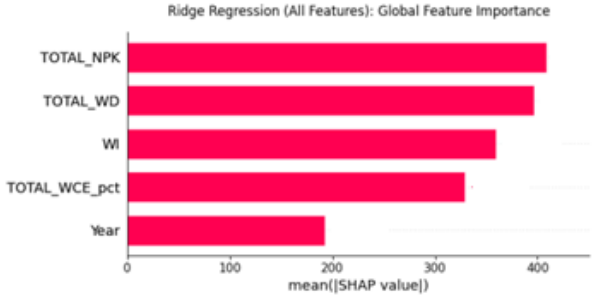

Fig. 3b: Global feature importance of agronomic predictors on maize yield based on regularized Ridge Regression.

In conclusion, the analysis done using regularized SHAP showed that the key determinants of maize productivity include balanced application of nutrients and effective weed control; Ridge Regression made it possible to get stable results free from multicollinearity problems.

Spearman rank correlation analysis of weed metrics, nutrients, and yield: The Spearman rank correlation test was carried out to analysed the monotonic association of weed indices, primary soil nutrients, and crop productivity (Fig. 4a). As seen from the correlation coefficients (ρ) in Table 2, there is an accurate value and direction of association of the variables ranked in order of their strongest positive and the strongest negative association with maize yield. It can be observed that primary macronutrients are dominantly associated with maize yield positively, with Phosphorus (P), Nitrogen (N), and Potassium (K) uptake showing the exact high level of correlation coefficient (ρ = 0.916). This shows that nutrient availability played the main role in the crop productivity. As for the weed control, weed control efficiency (WCE) indices were highly correlated with yield; namely, WCE of grasses (WCE_G, ρ = 0.866) and WCE of broadleaf weeds (WCE_B, ρ = 0.847) indicated that effective control of these weeds had a great effect on crop performance. However, WCE of sedges (WCE_S) showed a relatively weak positive correlation coefficient (ρ = 0.433), which corresponds to the minor role of sedges in the trial.

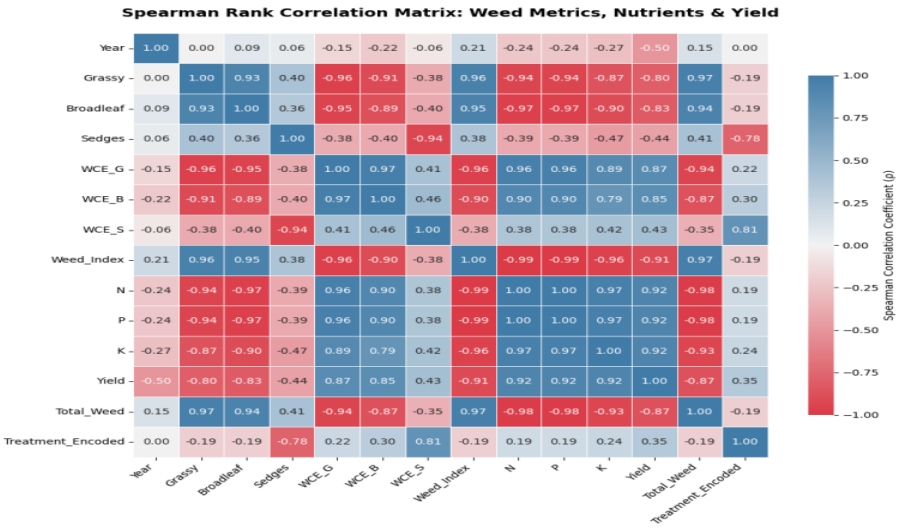

Fig. 4: Spearman rank correlation matrix heatmap among weed metrics, soil nutrients, and maize yield: Regarding weed pressure, high negative correlations were recorded for all the weed density indexes, which confirmed that higher weed competition greatly decreases crop production. In this regard, the general weed index showed a high negative correlation with the yield (ρ = -0.909), followed by the total weed density (ρ = -0.874). Of the various types of weeds, broadleaf weed (ρ = -0.825) and grassy weed (ρ = -0.804) had highly disruptive suppressive effect on maize yield.

Table 2: Spearman rank correlation coefficients (ρ) and ranking of features with maize yield

Rank	Feature	Correlation with Maize Yield (ρ)
1	P	0.916
2	N	0.916
3	K	0.916
4	WCE_G	0.866
5	WCE_B	0.847
6	WCE_S	0.433
7	Treatment Encoded	0.345
8	Sedges	-0.441
9	Year	-0.503
10	Grassy	-0.804
11	Broadleaf	-0.825
12	Total_Weed	-0.874
13	Weed_Index	-0.909

In contrast, sedges showed a comparatively lower, moderate negative correlation (ρ = -0.441), indicating they were significantly less competitive than broadleaf and grassy species under these experimental conditions. In general, the study shows that reducing the total weed load, particularly broadleaf and grassy weeds, by ensuring effective weed management, is equally important in increasing the maize production potential as maintaining optimum N, P, and K nutrient absorption levels.

Evaluation of weed metrics, nutrient uptake and yield dynamics under different treatments: In order to fully assess the effects of various weed management systems (T_1-T_4) on crop performance, weed pressure, weed control effectiveness and nutrient uptake patterns have been assessed under four different criteria (Fig. 5a-d and Table 3).

The analysis of weed population patterns revealed a number of differences in weed community structures among the treatments (Fig. 5a). The weed community comprised of grasses density (GD) and sedges density (SD) was quite low in most treatment plots, apart from treatment T_1 where both the weed communities attained their highest mean density levels of 5.82 ± 0.19 and 5.23 ± 0.16, respectively. On the other hand, broadleaf density (BD) was always higher

in comparison to other weed density classes, recording its highest value of 6.83 ± 0.19 in treatment T_1 and significantly high in treatment T_4 (4.53 ± 0.06).

Table 3: Effect of treatments on weed density, weed control efficiency, nutrient uptake, weed index and grain yield.

Treatment	Total Weed Density (m^2)	Mean WCE (%)	Total Nutrient Uptake (kg ha^{-1})	Weed Index (%)	Grain Yield (kg ha^{-1})
T1	17.88^a	0.00^c	61.60^d	62.93^a	4122.00^b
T2	6.95^d	63.76^b	148.73^a	1.52^c	8481.33^a
T3	7.80^c	62.57^b	137.63^b	2.21^c	8228.67^a
T4	9.75^b	68.80^a	127.10^c	3.61^b	7843.33^a
F-Value	1,745.33	3,561.68	4,648.24	33,690.70	807.64
p-value	≤ 0.001	≤ 0.001	≤ 0.001	≤ 0.001	≤ 0.001

Means with different letters in a column are significantly different ($p \leq 0.05$).

Conversely, treatments T_2 and T_3 exhibited the highest weed suppressive efficacy, maintaining uniformly low weed densities across all three weed categories. In general, the above results reveal that the weed pressure was more severe for the treatment T_1, and that the broadleaf weeds were the major weed pressure in the experimental field.

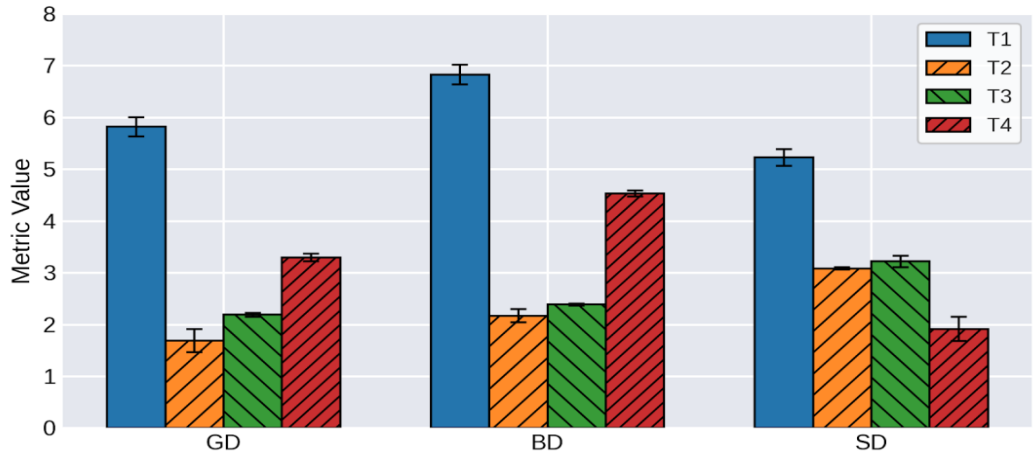

Fig. 5a: Effect of herbicides on weed density (weeds m^{-2}) at 40 DAS in maize

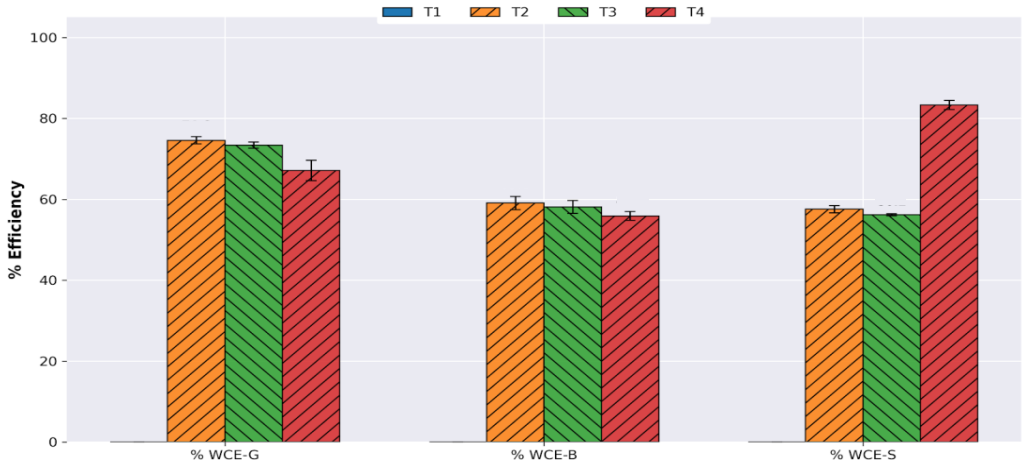

Fig. 5b: Effect of herbicides on weed control efficiency (%) at harvest (Grasses, Broad leaf weeds and Sedges) in maize

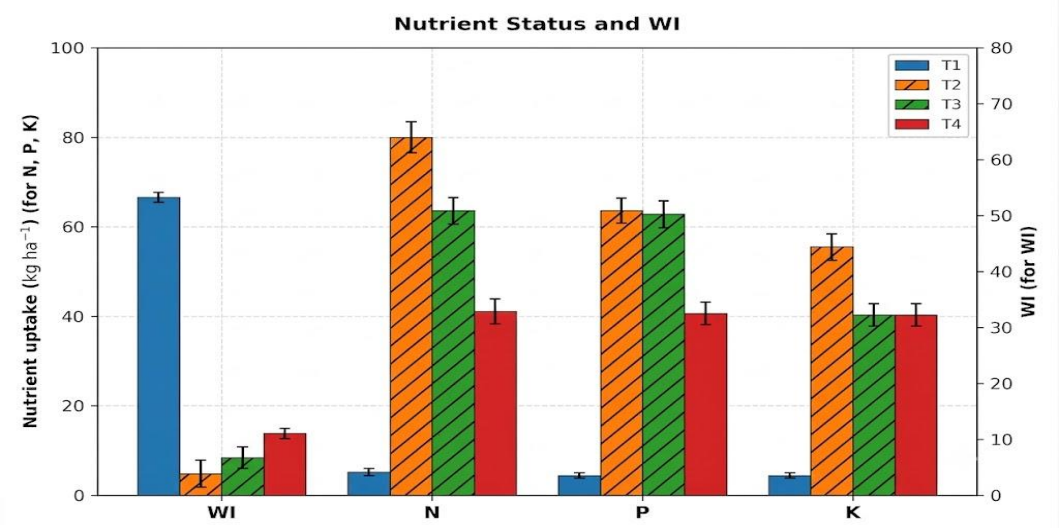

Fig. 5c: Effect of herbicides on weed index and nutrient uptake (kg ha^{-1}) at harvest in maize

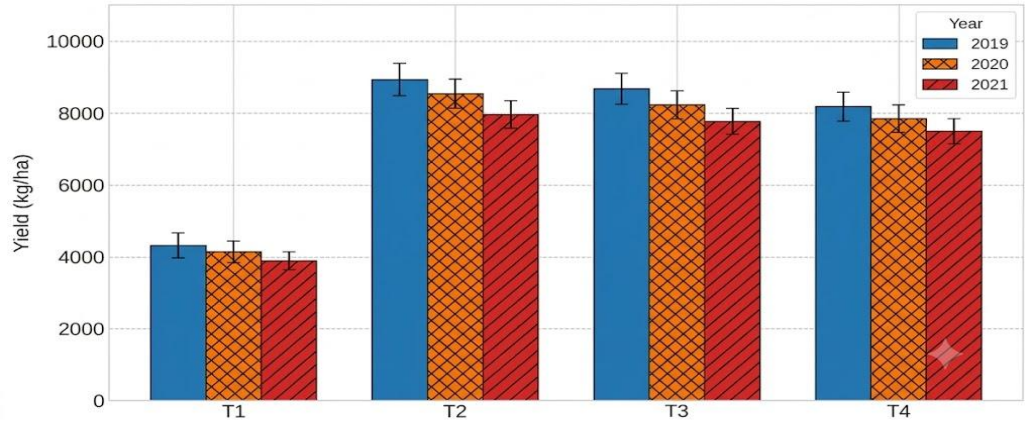

Fig. 5d: Effect of herbicides on grain yield of maize (kg ha^{-1})

The above-mentioned patterns of densities can be attributed to weed control efficiencies of each of the treatments. Complete elimination of grassy weeds occurred at very high efficiency levels for treatments T_2 and T_3, with % WCE-G holding very strong values between 73.4% and 74.6% for the herbicide treatments, although the efficiency value fell slightly to 67.2% for T_4. The management systems were also able to perform moderately and in an intermediate manner against broadleaf weeds, where % WCE-B held very steady values of 55.9% to 59.1% for all herbicide treatments. On the other hand, there was an evident split behaviour in terms of control efficiency of sedges (% WCE-S); where T_2 and T_3 had moderate efficiency of controlling sedges between 56.2% and 57.6%, while T_4 showed outstanding effectiveness of controlling sedges, with its maximum mean efficiency reaching up to 83.3%. Thus, sedges showed resistance to routine weed control methods (T_2 and T_3), but were exceptionally sensitive to T_4.

The change in weed indices had a direct impact on nutrient absorption by the plant (Fig. 5c). The total weed index (WI) reduced significantly in the treated blocks in comparison with the control, which showed that there was significant weed competition. The reduction in weed index enabled better absorption of nutrients by the crop. There was an increase in the nitrogen (N) absorption of up to 80 in the T_2 treated blocks, and then it became steady between 40 and 60 in other treatments. There was a similar pattern for the phosphorus (P) and Potassium (K), which was up to 60 and 55 respectively.

All of this led to the actual final yield in terms of the combination of the mentioned ecological and nutritional factors, which can be shown on the basis of the differences in grain yield in various treatment groups (Fig. 5d). The control groups without any weed management measures (T_1), which were monitored within all blocks, obviously showed high levels of stress due to weed competition and had the minimum yield of 3897 kg ha^{-1} – 4324 kg ha^{-1}. Application of weed management techniques brought about high yield increases. The best approach for weed control was the T_2

treatment, which brought about the maximum grain yield of 8936 kg ha^{-1} due to highly efficient weed reduction. The second highest yielding treatment was the T_3 treatment, with the yield of 7965 kg ha^{-1}. The T_4 treatment was found to provide the lowest yield among all treatment groups, which was 4998 kg ha^{-1}. Nevertheless, the T_4 treatment was still better than the baseline due to its selective nature, allowing partial weed survival.

DISCUSSION

The Indian agricultural sector faces numerous challenges, among which effective weed management is critical for sustaining crop production and productivity across the globe. Weeds pose a serious threat to crops by competing for essential resources such as nutrients, water, and sunlight, ultimately leading to a significant reduction in yield (Shorewala *et al*., 2021; Mishra *et al*., 2022). Studies on crop production indicate that weeds and pests together account for approximately 40% of yield losses.

The application of post emergence herbicides was significantly affected on the grain yield data are presented in Fig no 5c & d. The application of tembotrione 287.5 ml ha^{-1} at 25 DAS inhibits the activity of the 4 hydroxy-phenyl-pyruvate-dioxygenase enzymes. The formation of carotenoids (plant pigments) is disrupted by the blockage of the enzyme in weeds. Depletion of carotenoids deprives chlorophyll, where photosynthesis takes place of its protection against an overdose of light and these results in chlorophyll bleaching. The symptoms of action become visible fast and the full weed control effect is seen within a few days of application. The application of tembotrione 287.5 ml ha^{-1} creates and facilitate the weed free condition for uptake of more nutrients and moisture from the soil, during critical period of crop growth compared to rest of the herbicides up to 40 DAS, similar report was confirmed by (Shantveerayya and Agasimani 2012; Kumar *et al*., 2017). The data revealed that tembotrione and topramezone were found most suitable and most effective in order to reduce the weed density, there by weed control efficiency is more in all the years compared to other treatments (Hatti *et al*., 2014).

However, conventional weed control methods such as manual weeding and the use of specially designed mechanical weeders are often labour intensive and time-consuming (Shorewala *et al*., 2021; Rizvi *et al*., 2024; Mishra *et al*., 2025). To address these limitations, various treatment combinations have been explored in different studies, involving the integrated application herbicides, and irrigation over periods of two to four years, in order to evaluate their effectiveness in improving weed control and enhancing crop yield (Tong *et al* 2022; Rizvi *et al*., 2024). In recent times, prediction of crop yield has been one of the focal areas in agricultural science due to its significance in terms of economic development. Proper and timely predictions assist in the formulation of appropriate policies and proper agricultural decision-making (Wang *et al*., 2024).

The data collected through evaluation becomes large and complicated in nature, thus making it difficult to perform temporal analysis and identify important factors affecting crop yield. Traditional techniques lack ability to recognize such relationships between variables. Artificial intelligence (AI), which comprises of machine learning, deep learning, and computer vision, is very helpful in analyzing complicated data sets (Mishra *et al*., 2022; Rizvi *et al*., 2024; Wang *et al*., 2024).

Moreover, results obtained from the current investigation are corroborated by the previous studies, which confirm that the use of linear regression models has become very popular for predicting crop yields because of their consideration of different biological and environmental factors. For example, the development of multiple linear regression models for the prediction of maize yield proved to be very accurate, having an R^2 value of 0.984 (Ingale Jagruti *et al*., 2025). At the same time, in the paper by (Zhu *et al*. 2021), the hierarchical linear model that incorporated Landsat 8 vegetation indices and weather data had an adjusted R^2 equal to 0.75. Moreover, mathematical models that relied on fruit characteristics for the estimation of baby corn yield showed extremely high accuracy, having correlation coefficients of 0.992 and 0.993 over two cropping seasons (Rani *et al*., 2023). Moreover, Shahhosseini *et al*., (2019) performed a comparison of linear models, such as LASSO and Ridge Regression, to the use of ensemble machine learning algorithms in pre-seasonal maize yield prediction. Linear correlation analysis was applied by (Cargnelutti *et al*., 2020) to explore relationships between maize architecture and grain yield and to find positive correlations of leaf number and area with productivity

In addition to high prediction accuracy, the use of AI models in farming has considerable economic and environmental benefits, especially through prompt weed removal, avoiding unnecessary application of inputs, and effective management. Therefore, these models will be crucial in the development of sustainable and precise agriculture in the future (Li *et al*., 2022).

Conclusion: Tembotrione application (287.5 mL ha^{-1} at 25 DAS) resulted in better weed management and maximum maize grain yield (8,936 kg ha^{-1}) as opposed to control treatments (3,897 to 4,324 kg ha^{-1}), whereas halosulfuron methyl application (90 g ha^{-1} at 25 DAS) controlled sedges successfully. The mode of action of tembotrione was inhibition of

enzyme activity, depletion of carotenoids, causing bleaching of chlorophyll, reduced weed population, and improved nutrient uptake in maize plants. Our results showed that linear regression appeared as the most accurate predictor for our small dataset (R^2 = 0.949) which suggests linear interactions for the particular experimental field. Nutrient uptake and weed control were established as key positive factors affecting yield whereas weed index proved to be a key negative factor predicting yield. Machine learning algorithms with SHAP and spearman correlation analysis could prove to be an effective approach for evaluation of weed dynamics and nutrient uptake effects on maize yield.

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Author's contribution: RS R Srinivasa Rao was done adaptive trial; JB Jambamma B was done conceptualization, methodology, and writing of original draft; SR, SRS Sravanthi & Srinivasa Reddy were done reference data collection, formal analysis, validation, and investigation; of trial data curation and visualization: Srinivasa Rao.

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REFERENCES

APEDA, (2024). APEDA Products 2024–25. Department of Commerce, Ministry of Commerce and Industry, Government of India.

Breiman, L. (2001). Random Forests. Mach. Learn. 45(1): 5–32. https://doi.org/10.1023/A:1010933404324

Cargnelutti Filho, A., D.L. Silveira, B.M. Alves, F. Carini, C.T. Bandeira and R.V. Pezzini (2020). Genetic variability and linear relationships between plant architecture and maize grain yield. Cienc. Rural. 50(10): e20190661. https://doi.org/10.1590/0103-8478cr20190661

Chen, T. and C. Guestrin (2016). XGBoost: A Scalable Tree Boosting System. Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discov. Data Min. pp. 785–794. https://doi.org/10.1145/2939672.2939785

Gharde, Y., P.K. Singh, R.P. Dubey and P.K. Gupta (2018). Assessment of yield and economic losses in agriculture due to weeds in India. Crop Prot. 107: 12–18. https://doi.org/10.1016/j.cropro.2018.01.007

Gower, S.A., M.M. Loux, J. Cardina, S. Kent Harrison, Paul L., Sprankle, Norman J., Probst, Thomas, T., Bauman, Wayne bugg, W., S. Curran, Randall, S. Currie, R. Gordon Harvey, William, G. Johnson, James, J. Kells, Micheal, D. K. Owen, David, L., Regehr, Charles, H., Slack, Marvin Spaur, Christy L., Sprague, Mark Vangessel, and Bryan G. Young (2003). Effect of postemergence glyphosate application timing on weed control and grain yield in glyphosate-resistant corn: results of a 2-yr multistate study. Weed Technol. 17: 821–828.

Hatti, V., M.T. Sanjay, T.V. Ramachandra Prasad, K.N. Kalyanamurthy, K. Basavaraj and M.K. Shruthi (2014). Effect of new herbicide molecules on yield, soil microbial biomass and their phytotoxicity on maize (*Zea mays* L.) under irrigated conditions. Bioscan. 9(3): 1127–1130.

Ingale Jagruti D., V.S. Goswammi and L. Kailas Vairal (2025). Crop yield prediction using linear regression: A case study on maize production. Int. J. Stat. Appl. Math. 10(12): 01–03. https://doi.org/10.22271/maths.2025.v10.i12a.2201

Jackson, M. L. (1973). Soil chemical Analysis. Prentice Hall India.

Knight, A.M., W.J. Everman, D.L. Jordan, R.W. Heiniger and T.J. Smyth (2017). Interactions of nitrogen source and rate and weed removal timing relative to nitrogen content in corn and weeds and corn grain yield. Int. Sch. Res. Notices. 2017: 8961367. https://doi.org/10.1155/2017/8961367

Kumar, A., M.C. Rana, N. Sharma and S.S. Rana (2017). Effect of post-emergence herbicide-tembotrine on yield, soil dehydrogenase activity and its phytotoxicity on maize (*Zea mays* L.) under mid hill conditions of Himachal Pradesh. Int. J. Curr. Microbiol. Appl. Sci. 6: 2297–2303. https://doi.org/10.20546/ijcmas.2017.603.263

Li, K.Y., R. Sampaio de Lima, N.G. Burnside, E. Vahtmäe, T. Kutser and K. Sepp (2022). Toward automated machine learning-based hyperspectral image analysis in crop yield and biomass estimation. Remote Sens. 14(5): 1114. https://doi.org/10.3390/rs14051114

Linxinzhi (2021). The application of machine learning models in the prediction of PM2.5/PM10 concentration. Proc. 4th Int. Conf. Comput. Manage. Bus. (ICCMB 2021). pp. 1–12. https://doi.org/10.1145/3450588.3450605

Mamić, L., M. Gašparović and G. Kaplan (2023). Developing PM2.5 and PM10 prediction models using open-source remote sensing data. Environ. Monit. Assess. 195(6): 644. https://doi.org/10.1007/s10661-023-11344-9

Mishra, A.M., M.P. Singh, P. Singh, M. Diwakar, I. Gupta and A. Bijalwan (2025). Hybrid deep learning model for density and growth rate estimation on weed image dataset. Sci. Rep. 15(1): 11330. https://doi.org/10.1038/s41598-025-86357-5

Mishra, A.M., S. Harnal, K. Mohiuddin, V. Gautam, O.A. Nasr, N. Goyal and A. Singh (2022). A deep learning-based novel approach for weed growth estimation. Intell. Autom. Soft Comput. 31(2): 1331–1348. https://doi:10.32604/iasc.2022.020174

Mokhtar, A., W. El-Ssawy, H. He, N. Al-Ansari, S.S. Sammen, Y. Gyasi-Agyei and M. Abuarab (2022). Using machine learning models to predict hydroponically grown lettuce yield. Front. Plant Sci. 13: 706042. https://doi.org/10.3389/fpls.2022.706042

Montgomery, D.C., E.A. Peck and G.G. Vining (2021). Introduction to Linear Regression Analysis. 6th ed. John Wiley & Sons.

Nagata, M., A. Yusara, T. Kato and Y. Masutomi (2025). Development of the global maize yield model MATCRO-Maize version 1.0. Geosci. Model Dev. 18(22): 8927–8948. https://doi.org/10.5194/gmd-18-8927-2025

Olsen, S.R., Cole, C.V., Watanabe, F.S. Dean LA. (1954). Estimation of Available Phosphorus in Soils by Extraction with Sodium Bicarbonate. Circular No. 939. Washington, DC: U.S. Department of Agriculture.

Pandey, A.K., V. Prakash, P. Singh, K. Prakash, R.D. Singh and V.P. Mani (2001). Integrated weed management in maize. Indian J. Agron. 46: 260–265.

Patel, V.J., P.N. Upadhyay, B. Patel and B.D. Patel (2006). Evaluation of herbicide mixtures for weed control in maize (*Zea mays* L.) under middle Gujarat conditions. J. Agric. Sci. 2(1): 81–86.

Rani, N., J.S. Bamel, S. Garg, A. Shukla, S.K. Pathak, R.N. Singh and K. Bamel (2023). Linear mathematical models for yield estimation of baby corn (*Zea mays* L.). Plant Sci. Today. 11(1): 166–175. https://doi.org/10.14719/pst.2618

Rapado-Rincon, D. (2025). Data association for building world models in agriculture. Ph.D. Thesis. Wageningen University, Wageningen, The Netherlands. https://doi.org/10.18174/681245

Rizvi, S.M.H., A. Naseer, S.U. Rehman, S. Akram and V. Gruhn (2024). Revolutionizing agriculture: Machine and deep learning solutions for enhanced crop quality and weed control. IEEE Access. 12: 11865–11878. https://doi.org/10.1109/ACCESS.2024.3357800

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., ... & Winter, J. M. (2013). The agricultural model intercomparison and improvement project (AgMIP): protocols and pilot studies. Agricultural and forest meteorology, 170(3), 166-182. https://doi.org/10.1016/j.agrformet.2012.09.011

Shahhosseini, M., R.A. Martinez-Feria, G. Hu and S.V. Archontoulis (2019). Maize yield and nitrate loss prediction with machine learning algorithms. Environ. Res. Lett. 14(12): 124026. https://doi.org/10.1088/1748-9326/ab5268

Shantveerayya Hawaldar and C.A. Agasimani (2012). Effect of herbicides on weed control and productivity of maize (*Zea mays* L.). Karnataka J. Agric. Sci. 25(1): 137–139.

Shorewala, S., A. Ashfaque, R. Sidharth and U. Verma (2021). Weed density and distribution estimation for precision agriculture using semi-supervised learning. IEEE Access. 9: 27971–27986. https://doi.org/10.1109/ACCESS.2021.3057912

Subbiah, B.V. Asija G.L. (1956). A rapid procedure for the estimation of available nitrogen in soils. Curr Scienc. 25:259–60.

Swetha, K., M. Madhavi, G. Pratibha and T. Ramprakash (2015). Weed management with new generation herbicides in maize. Indian J. Weed Sci. 47(4): 432–433.

Taremwa, D., E. Ahishakiye, A. Obbo, P.K. Kisozi and F. Kaggwa (2025). An Explainable Ensemble Model for ZARDI-Wise Maize Yield Prediction Using Climate Data in Uganda. https://doi.org/10.21203/rs.3.rs-7665531/v1

Tirink, S. (2025). Machine learning-based forecasting of air quality index under long-term environmental patterns: A comparative approach with XGBoost, LightGBM, and SVM. PLoS One. 20(10): e0334252. https://doi.org/10.1371/journal.pone.0334252

Tong, Y.S., T.H. Lee and K.S. Yen (2022). Deep learning for image-based plant growth monitoring: A review. Int. J. Eng. Technol. Innov. 12(3): 239–257.

Walkley, A. and Black I.A. (1934). An examination of the degtjareff method for determining soil organic matter, and a proposed modification of the chromic acid titration method. Soil Sci. 37:29–38. http://dx.doi.org/10.1097/00010694-193401000-00003

Wang, Y., Q. Zhang, F. Yu, N. Zhang, X. Zhang and Y. Li (2024). Progress in research on deep learning-based crop yield prediction. Agronomy. 14(10): 2264. https://doi.org/10.3390/agronomy14102264

Williams, M.M., R.A. Boydston, R.E. Peachey and D. Robinson (2011). Significance of atrazine as a tank-mix partner with tembotrione. Weed Technol. 25(3): 299–302. https://doi.org/10.1614/WT-D-10-00107.1

Yadav, T.K., R.S. Choudhary, G. Jat, D. Singh and N. Sharma (2017). Effect of weed management practices on yield attributes, yield and economics of maize (Zea mays L.). Chem. Sci. Rev. Lett. 6(23): 1452–1456.

Yusara, A., T. Kato, E.A. Ainsworth, R. Battisti, E. Kumagai, S. Nakano and Y. Masutomi (2025). Developing an eco-physiological process-based model of soybean growth and yield (MATCRO-Soy v. 1): model calibration and evaluation. Geosci. Model Dev. 18(22): 8801–8826. https://doi.org/10.5194/gmd-18-8801-2025

Zhu, B., S. Chen, Y. Cao, Z. Xu, Y. Yu and C. Han (2021). A regional maize yield hierarchical linear model combining Landsat 8 vegetative indices and meteorological data: Case study in Jilin Province. Remote Sens. 13(3): 356. https://doi.org/10.3390/rs13030356.