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**RESEARCH PAPER**

# Validation of leaf area index of maize for graded levels of fertilizers using conventional and artificial intelligence techniques

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**Abstract:** A field experiment was conducted at MARS, Dharwad during *kharif*, 2023-24 for validation of leaf area index of maize for graded levels of fertilizers using conventional and artificial intelligence techniques. The results showed that application of 150 per cent RDF recorded significantly higher grain yield (75.64 q $ha^{-1}$) and stover yield (96.18 q $ha^{-1}$) of maize than 50 per cent RDF (38.69 q $ha^{-1}$ and 55.71 q $ha^{-1}$, respectively) and it was on par with 100 per cent RDF (72.77 q $ha^{-1}$ and 94.64 q $ha^{-1}$, respectively). Among the subplots (Methods of LAI estimation) there was no significant difference. Among interactions, 150 per cent RDF + LAI estimation by artificial intelligence (AI) method showed significantly higher grain yield (75.70 q $ha^{-1}$) and stover yield (96.26 q $ha^{-1}$) than control. Among the different methods of LAI estimation, AI method showed least deviation (1.02-14.77%) particularly at grain filling (1.02%) followed by silking stage (2.9%) and maximum deviation (46.1-58.0%) was observed with disc method at all the growth stages. Among machine learning models, random forest model outperformed other models with $R^2$ (0.67-0.94) and RMSE (0.02-0.26) at all the growth stages (Knee high stage, tasseling stage, siliking stage and grain filling stage) compared to other models.

**Key words:** Artificial intelligence, Leaf area index, RDF, Machine learning models

## Introduction

Maize (*Zea mays* L.), known as the "queen of cereals," is highly versatile due to its adaptability to diverse agro-climatic conditions and its superior genetic potential for high yields compared to other cereals. It is extensively used for food, feed and various industrial applications, including starch, sweeteners and biofuel production. A critical factor in enhancing maize yield is the monitoring of crop growth. A key parameter for assessing crop growth is the Leaf Area Index (LAI), which reflects crop growth, photosynthesis, yield potential and is widely used for evaluating canopy structure (Gao *et al.,* 2012). Direct LAI measurement is accurate but time-consuming and impractical for large-scale applications (Araus and Cairns, 2014). Indirect methods, like the Licor LAI-2000 plant canopy analyzer, offer a non-destructive and efficient alternative by estimating LAI through gap fraction analysis. Recent advances in remote sensing and artificial intelligence (AI), particularly through UAV-based imaging, have enabled more precise and cost-effective LAI estimation, especially when integrated with RGB imagery. Hence, the present study focuses on the estimation of LAI by integrating AI with UAV technology, utilizing RGB imagery to assess LAI across varying fertilizer levels and growth stages of maize. Nutrient management in maize is equally important because maize is a crop with high nutrient demand, so effective nutrient management is vital for achieving optimal productivity. LAI is being influenced by several factors irrespective of crops. Nutrient plays an important role in growth and yield. Graded levels of fertilizer have been used in the present investigation to create variation in growth parameter visa-vis leaf area of maize at different growth stages with the objectives of validation of leaf area index using conventional and artificial intelligence techniques and to study the response of maize to growth and yield parameters to graded levels of fertilizers.

## Material and methods

A field study was conducted during *kharif* 2023 at Main Agricultural Research Station, UAS, Dharwad. Soil type was medium black clay (*Vertisol*). The soil was slightly alkaline in pH (7.53) and it was low in available nitrogen, medium in available phosphorus with high available potassium. The hybrid used for the study was NK 6668 Plus. Maize was sown on 18 August 2023 with the spacing of 60 x 20 cm using seed rate of 22.5 kg $ha^{-1}$. There were sixteen treatments laid out in split plot design comprised of three fertility levels as main plot (50, 100 and 150 per cent RDF) and five methods of estimation of LAI as subplot [length × breadth method, disc method, leaf area meter, canopy analyser and artificial intelligence (AI)] with fifteen treatment combinations and one control.

Leaf Area Index (LAI) was recorded at V8, VT, R1 and R3 using five methods, including three direct and two indirect methods.

### Direct methods

**Length × Breadth Method:** Index leaf lamina was measured for length (base to tip) and breadth (widest point).

The leaf area was calculated using the formula:

Leaf Area= Length × Breadth × 0.75

Then, LAI is calculated by dividing the leaf area per plant by land area occupied by single plant (Watson, 1947).

$$\text{LAI}= \frac{\text{Leaf area per plant (cm}^2)}{\text{Ground area (cm}^{2)}}$$

**Disc Method:** Leaves were harvested and fifty discs of known diameter were cut using a cork borer. The discs and remaining leaf material were dried at 65°C until constant weight obtained. (Vivekananda *et al*., 1972).

$$LA = \frac{Wa \times A}{W_d}$$

Where,

LA = Leaf area (dm²)

$W_a$ = Weight of all leaves (including 50 discs in g)

$W_d$ = Weight of 50 discs (g)

A = Area of 50 disc (dm²)

Then, LAI is calculated by dividing the leaf area per plant by land area occupied by single plant (Watson, 1947).

**Leaf area meter:** BioVis PSM-L300 (IDS uEye-XS software) was used. Leaves were cleaned and placed on a conveyor belt for scanning. The device captured images and the software calculated leaf area based on RGB color intensity data.

**Indirect methods**

**LAI-2200C Plant canopy analyzer:** This optical sensor measured light transmission through the canopy at various zenith angles (0°, 15°, 30°, 45° and 60°). Above-canopy readings established a baseline, followed by below-canopy readings taken along a diagonal transect to capture canopy variability. The analyzer calculated LAI directly from light transmission data.

**AI: UAV-Based RGB images:** Phantom UAV equipped with an RGB camera was used. The UAV captured 15-second video segments from a height of 15 meters. Videos were recorded at a resolution of 1920 x 1080 pixels during early morning 7 to 8 AM. Post-flight, video files were processed to extract individual plot frames, resized to 128 x 128 pixels. The three vegetation indices namely Excess Green Index (ExG), Green Leaf Index (GLI) and Red Green Blue Vegetation Index (RGBVI) were derived from cropped images to assess their correlation with LAI for machine learning model training.

**Model training and evaluation**

Machine learning models, including Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN) and Decision Tree (DT) were trained on the selected vegetation indices. Model performance was evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and $R^2$ Score.

**Validation**

The accuracy of LAI measurements from each method was validated against the Length × Breadth method by calculating percentage deviation:

$$\text{Percentage deviation} = \frac{|(LAI_{Method} - LAI_{l \times b})|}{|LAI_{l \times b}|} \times 100$$

Where,

Low deviations indicated reliable methods, while high deviations suggested potential inaccuracies.

**Results and discussion**

**Performance evaluation of model accuracy**

Based on the highest correlation rankings from the grey correlation analysis, the first three vegetation indices were selected *i.e.,* Excess Green Index (E x G), Green Leaf Index (GLI) and Red-Green-Blue Vegetation Index (RGBVI) which showed strong correlation with LAI as shown in Table 1. The high correlation of E x G (0.88), GLI (0.88) and RGBVI (0.87) with LAI resulted from their ability to detect green vegetation. ExG effectively distinguished plants by highlighting green light reflection, which was closely linked to LAI. Similarly, GLI focused on the green spectrum relative to red and blue, reducing sensitivity to lighting changes and enhancing its correlation. RGBVI strengthened its association with LAI by emphasizing plant greenness and minimizing interference from non-plant elements.

The random forest model significantly outperformed other models throughout different growth stages. At knee-high stage, it recorded the Mean Absolute Error (MAE) of 0.02, Root Mean Squared Error (RMSE) of 0.03 and high Coefficient of Determination ($R^2$) of 0.67. The ensemble nature of random forests enabled it to average out multiple decision trees, mitigating overfitting and enhancing predictive accuracy (Breiman, 2001). The decision tree model followed with a close MAE of 0.01 and $R^2$ of 0.59, implying reliable predictions though with less robustness compared to the ensemble approach. The Support Vector Machine (SVM) model exhibited a poor fit with a negative $R^2$ of -0.03 at this stage due to its sensitivity to noise and linear assumptions (Wang, 2023). Meanwhile, the K-Nearest Neighbors (KNN) model offered moderate performance with $R^2$ of 0.38, yet its local data reliance limited its predictive capabilities.

Table 1. Grey Correlation Analysis between the LAI and Vegetation indices

| Vegetation indices | Grey correlation analysis |
|---|---|
| ExG | 0.88 |
| GLI | 0.88 |
| VIG | 0.79 |
| RGBVI | 0.87 |
| GNDVI | 0.80 |
| ERVI | 0.82 |
| BRRI | 0.76 |
| EXR | 0.71 |
| EXB | 0.73 |
| CIVE | 0.65 |
| VARI | 0.78 |
| MGRVI | 0.80 |

ExG: Excess Green Index, GLI: Green Leaf Index, VIG: Vegetative Index Green, RGBVI: Red Green Blue Vegetation Index, GNDVI: Green Normalized Difference Vegetation Index, ERVI: Enhanced Red-Blue Vegetation Index, BRRI: Blue Red Ratio Index, ExR: Excess Red Index, ExB: Excess Blue Index, CIVE: Color Index of Vegetation Extraction, VARI: Visible Atmospherically Resistant Index, MGRVI: Modified Green Red Vegetation Index.

Table 2. Performance evaluation of machine learning models

| Growth stages | Models | MAE | RMSE | $R^2$ |
|---|---|---|---|---|
| Knee-high | Random Forest | 0.02 | 0.03 | 0.67 |
| | Decision Tree | 0.01 | 0.03 | 0.59 |
| | SVM | 0.04 | 0.05 | -0.03 |
| | KNN | 0.03 | 0.04 | 0.38 |
| Tasseling | Random Forest | 0.11 | 0.26 | 0.85 |
| | Decision Tree | 0.09 | 0.30 | 0.80 |
| | SVM | 0.38 | 0.55 | 0.32 |
| | KNN | 0.16 | 0.32 | 0.77 |
| Silking | Random Forest | 0.13 | 0.25 | 0.87 |
| | Decision Tree | 0.10 | 0.25 | 0.81 |
| | KNN | 0.17 | 0.34 | 0.76 |
| | SVM | 0.42 | 0.69 | 0.01 |
| Grain filling | Random Forest | 0.12 | 0.19 | 0.94 |
| | Decision Tree | 0.11 | 0.21 | 0.92 |
| | KNN | 0.29 | 0.46 | 0.64 |
| | SVM | 0.48 | 0.64 | 0.29 |
| Overall | Random Forest | 0.17 | 0.33 | 0.97 |
| | Decision Tree | 0.16 | 0.40 | 0.96 |
| | KNN | 0.22 | 0.42 | 0.96 |
| | SVM | 0.73 | 0.91 | 0.79 |

MAE: Mean absolute error, RMSE: Root mean square error, $R^2$: Coefficient of determination,
SVM: Support Vector Machine, KNN: K-Nearest Neighbour

As the growth progressed to the tasseling stage, the random forest continued its dominance, achieving an MAE of 0.11 and $R^2$ of 0.85. The decision tree closely followed, while SVM and KNN underperformed with SVM recorded MAE of 0.38 and $R^2$ of 0.32 and KNN recording the highest MAE of 0.16.

At the silking stage, the random forest model continued to give good performance, with MAE of 0.13, RMSE of 0.25 and high $R^2$ of 0.87. The reasons for its strong performance included its use of random feature selection during training, enabling it to focus on the most predictive features of the data. The decision tree model also performed well, but it was more prone to model noise due to its simplistic nature compared to random forests. Both KNN and SVM models exhibited poor performance, KNN showed a higher MAE of 0.17 and the SVM model had the highest MAE of 0.42 and a very low $R^2$ of 0.01, suggesting that it could not capture the complexities of the data.

By the grain-filling stage, the random forest model continued to display its predictive strength, ultimately achieving MAE of 0.12 and the highest $R^2$ of 0.94. The decision tree model also performed well, but KNN found difficult with a higher MAE of 0.29, indicating the challenges it faced in more varied datasets. The recurrent under performance of SVM showed its inability to effectively model the complexities inherent in the datasets compared to ensemble methods.

**Validation of leaf area index of maize**

The disc method significantly underestimated the leaf area index (LAI) across all growth stages, with deviations 25.54-58.00 per cent. This underestimation arose from its reliance on weight-to-area conversion, which failed to account for variations in leaf thickness and moisture content, especially if the midrib was excluded. In contrast, the length × breadth (l × b) method provided a more accurate estimation by including the entire leaf structure and using a correction factor for irregular shapes.

The leaf area meter delivered precise and consistent measurements with deviations of 0.4 to 17.1 per cent, utilizing direct scanning for accurate quantification without indirect assumptions. Canopy analyzers, however, underestimated LAI due to assumptions about light absorption and the random distribution of leaves, failing to account for clumping and orientation. AI method, particularly with the Random Forest model, showed minimal deviation of 1.02 to 14.7 per cent by effectively handling data variability through an ensemble of decision trees, enhancing accuracy and robustness in LAI estimation across different growth stages in maize.

**Effect of graded levels of fertilizers on growth and yield parameters**

Significantly higher grain and stover yield was obtained with the application of 150 per cent RDF (75.64 and 96.18 q $ha^{-1}$ respectively) as compared to 50 per cent (38.69 and 55.71 q $ha^{-1}$ respectively) and remained on par with 100 per cent RDF (72.77 and 94.64 q $ha^{-}$ respectively). The increase in maize grain yield with 150 per cent RDF was to the tune of 3.93 and 95.57 per cent over 100 and 50 per cent RDF respectively (Table 3). When the moisture is not limiting factor maize responds to higher levels of fertilizer and produces maximum yield. Increased yield observed with the application of 150 per cent RDF could be attributed to improved nutrient availability and a more conducive rhizosphere environment, which enhances the yield. Similar findings were reported by Awadalla *et al.* (2018) who

Table 3. Per cent variation in LAI of maize by all methods of estimation from l × b method

| Fertilizer levels | Methods | Knee-high stage | Tasseling stage | Silking stage | Grain filling stage |
|---|---|---|---|---|---|
| 50% RDF | Disc method | 46.1 | 53.3 | 55.6 | 58.0 |
| | Leaf area meter | 17.1 | 11.21 | 5.71 | 5.4 |
| | Canopy analyzer | 39.5 | 10.3 | 15.6 | 14.1 |
| | AI method | 25.0 | 17.76 | 6.23 | 3.7 |
| 100% RDF | Disc method | 47.1 | 53.6 | 46.94 | 52.1 |
| | Leaf area meter | 5.9 | 5.5 | 3.3 | 5.0 |
| | Canopy analyzer | 38.8 | 6.2 | 25.42 | 30.7 |
| | AI method | 16.5 | 3.1 | 2.2 | 0.6 |
| 150% RDF | Disc method | 42.0 | 40.6 | 24.54 | 42.4 |
| | Leaf area meter | 3.4 | 0.4 | 0.18 | 1.6 |
| | Canopy analyzer | 21.6 | 6.4 | 21.79 | 30.0 |
| | AI method | 14.77 | 3.40 | 2.9 | 1.02 |

noted that highest dose of NPK fertilizers increased grain yield by approximately 14.4 per cent compared to the lowest dose.

The main purpose of agronomic practices is to optimize the leaf area index (LAI) to ensure maximum crop productivity. Significantly higher LAI at 65 DAS was observed under 150 per cent RDF (5.00) compared to 50 per cent (3.40) and was on par with 100 per cent RDF (4.55). The increase in LAI with 150 per cent RDF ranged from 1.21 to 3.32 per cent over 100 per cent and 36.89 to 58.49 per cent over 50 per cent RDF. The higher LAI with 150 per cent RDF was attributed to higher leaf area per plant and the number of leaves per plant. Shivay *et al.* (2002) also found improvement in leaf area index with increasing levels of nitrogen. Similar results were also reported by Karki *et al.* (2005) and Arunkumar *et al.* (2007).

**Effect of methods of estimation of LAI on growth and yield of maize**

The methods used to estimate the LAI did not record significant variation in grain yield and stover yield of maize.

LAI of maize significantly influenced by methods of estimation of LAI of maize at all the growth stages of maize. At the knee-high stage, the l × b method recorded the higher LAI (0.83), which was significantly higher than the all other methods but remained on par with LAI estimation by leaf area meter (0.78). The precision of the l × b method in estimating detailed leaf dimensions and applying a correction factor led to a more accurate estimation of LAI.

At tasseling stage, the l × b method continued to show a higher LAI (4.06), which was significantly greater than the LAI obtained by the canopy analyzer (3.85) and the disc method (2.13). The superiority of this method was due to its ability to accurately account for leaf area variations. However, the LAI values from the l × b method were on par with those from the leaf area meter (4.20) and AI method (4.06), suggesting that these methods were all effective in capturing the true leaf area during tasseling stage of maize growth.

During silking stage, the AI method recorded the significantly higher LAI (4.93), than the LAI obtained by the canopy analyzer (3.85) and the disc method (2.90). This was mainly because AI-based methods can analyze complex leaf structures and variations, providing a more accurate estimation. The LAI from the AI method was on par with those obtained from the l × b method (4.93) and leaf area meter (4.91) and canopy analyzer.

At grain filling stage, the AI method again recorded the highest LAI (4.50), which was significantly higher than the LAI recorded by the canopy analyzer (3.27) and the disc method (2.20). The AI-based method's ability to handle complex canopy structures at grain filling stage is likely the reason for its superior performance. However, the LAI from the AI method was on par with the l × b method (4.42) and the leaf area meter (4.24).

**Interaction effects of graded levels of fertilizers and methods of estimation of LAI on growth and yield parameters**

There was a significant influence of fertilizer levels and methods of estimation of LAI on growth and yield of maize.

Table 4. Leaf area index of maize as influenced by graded levels of fertilizers and methods of estimation of leaf area index (LAI)

| Treatments | Leaf area index | | | |
|---|---|---|---|---|
| | V8(Knee-high stage) | VT(Tasseling stage) | R1(Silking stage) | R3(Grain filling stage) |
| Main plot (Fertilizer levels) | | | | |
| $F_1$ | $0.57^{b}$ | $2.87^{b}$ | $3.40^{b}$ | $3.07^{b}$ |
| $F_2$ | $0.66^{ab}$ | $3.93^{a}$ | $4.55^{a}$ | $3.92^{a}$ |
| $F_3$ | $0.75^{a}$ | $4.26^{a}$ | $5.00^{a}$ | $4.19^{a}$ |
| S.Em± | 0.01 | 0.06 | 0.10 | 0.05 |
| Sub plot (Different methods of estimation of leaf area index) | | | | |
| $L_1$ | $0.83^{a}$ | $4.15^{a}$ | $4.93^{a}$ | $4.42^{a}$ |
| $L_2$ | $0.46^{d}$ | $2.13^{c}$ | $2.90^{c}$ | $2.20^{c}$ |
| $L_3$ | $0.78^{a}$ | $4.20^{a}$ | $4.91^{a}$ | $4.24^{a}$ |
| $L_4$ | $0.56^{c}$ | $3.85^{b}$ | $3.85^{b}$ | $3.27^{b}$ |
| $L_5$ | $0.68^{b}$ | $4.06^{a}$ | $4.99^{a}$ | $4.50^{a}$ |
| S.Em± | 0.01 | 0.04 | 0.09 | 0.07 |
| Interaction (Fertilizer levels × Different methods of estimation of leaf area index) | | | | |
| $F_1L_1$ | $0.76^{de}$ | $3.21^{e}$ | $3.85^{b}$ | $3.55^{d}$ |
| $F_1L_2$ | $0.41^{k}$ | $1.50^{h}$ | $1.71^{d}$ | $1.49^{h}$ |
| $F_1L_3$ | $0.63^{g}$ | $3.57^{d}$ | $4.07^{b}$ | $3.36^{de}$ |
| $F_1L_4$ | $0.46^{jk}$ | $2.88^{f}$ | $3.25^{c}$ | $3.05^{ef}$ |
| $F_1L_5$ | $0.57^{h}$ | $3.78^{d}$ | $4.09^{b}$ | $3.68^{c}$ |
| $F_2L_1$ | $0.85^{bc}$ | $4.55^{ab}$ | $5.39^{a}$ | $4.76^{ab}$ |
| $F_2L_2$ | $0.45^{k}$ | $2.11^{g}$ | $2.86^{c}$ | $2.28^{g}$ |
| $F_2L_3$ | $0.80^{cd}$ | $4.30^{c}$ | $5.21^{a}$ | $4.52^{b}$ |
| $F_2L_4$ | $0.52^{hi}$ | $4.27^{c}$ | $4.02^{b}$ | $3.30^{de}$ |
| $F_2L_5$ | $0.71^{ef}$ | $4.41^{bc}$ | $5.27^{a}$ | $4.73^{ab}$ |
| $F_3L_1$ | $0.88^{ab}$ | $4.70^{a}$ | $5.46^{a}$ | $4.93^{a}$ |
| $F_3L_2$ | $0.51^{ij}$ | $2.79^{f}$ | $4.12^{b}$ | $2.84^{f}$ |
| $F_3L_3$ | $0.91^{a}$ | $4.72^{a}$ | $5.45^{a}$ | $4.85^{ab}$ |
| $F_3L_4$ | $0.69^{f}$ | $4.40^{bc}$ | $4.27^{b}$ | $3.45^{d}$ |
| $F_3L_5$ | $0.75^{de}$ | $4.54^{ab}$ | $5.62^{a}$ | $4.88^{a}$ |
| S.Em± | 0.02 | 0.06 | 0.15 | 0.12 |
| Control | | | | |
| Without fertilizer | 0.65 | 2.63 | 3.42 | 2.65 |
| S.Em± | 0.02 | 0.15 | 0.18 | 0.15 |
| CD at 5% | 0.05 | 0.42 | 0.53 | 0.43 |

$F_1$: 50% RDF (50: 25: 12.5 kg N: $P_2O_5$: $K_2O$ $ha^{-1}$)
$F_2$: 100% RDF (100: 50: 25 kg N: $P_2O_5$: $K_2O$ $ha^{-1}$)
$F_3$: 150% RDF (150: 75: 37.5 kg N: $P_2O_5$: $K_2O$ $ha^{-1}$)
$L_1$: LAI estimation by length x breadth x correction factor
$L_2$: LAI estimation by disc method
$L_3$: LAI estimation by Leaf area meter
$L_4$: LAI estimation by Leaf area index meter or Canopy analyzer.
$L_5$: LAI estimation by AI (RGB camera mounted UAV)
Control: Without fertilizer

The interaction effects of fertilizer levels and methods of LAI estimation on grain yield was significant. Application of 150 per cent RDF and LAI estimation by AI showed significantly higher yield (75.70 q $ha^{-1}$) than other treatment combinations and control (35.28 q $ha^{-1}$) as shown in the Table 4. However, it was on par with treatments like 150 per cent RDF with other four methods of estimation of LAI. 100 per cent RDF + with other five methods of estimation of LAI. This was mainly because, application of major nutrients synchronized with crop demand led to the synchrony in application and uptake, which improved photosynthesis. This led to higher growth attributes

Table 5. Yield parameters and economics of maize as influenced by graded levels of fertilizers and methods of estimation of leaf area index (LAI)

| Treatments | Yield and yield attributes | | | |
|---|---|---|---|---|
| | Grain yield (q ha$^{-1}$) | Stover yield (q ha$^{-1}$) | Net return (₹ ha$^{-1}$) | B:C ratio |
| Main plot (Fertilizer levels) | | | | |
| $F_1$ | 38.69$^b$ | 55.71$^b$ | 32399$^b$ | 1.61$^b$ |
| $F_2$ | 72.77$^a$ | 94.64$^a$ | 104428$^a$ | 2.89$^a$ |
| $F_3$ | 75.64$^a$ | 96.18$^a$ | 108230$^a$ | 2.88$^a$ |
| S.Em± | 0.94 | 0.88 | 2013 | 0.04 |
| Sub plot (Different methods of estimation of leaf area index) | | | | |
| $L_1$ | 62.41$^a$ | 82.32$^a$ | 81782$^a$ | 2.46$^a$ |
| $L_2$ | 62.33$^a$ | 82.11$^a$ | 81598$^a$ | 2.46$^a$ |
| $L_3$ | 62.25$^a$ | 81.94$^a$ | 81416$^a$ | 2.46$^a$ |
| $L_4$ | 62.39$^a$ | 82.23$^a$ | 81744$^a$ | 2.46$^a$ |
| $L_5$ | 62.45$^a$ | 82.40$^a$ | 81890$^a$ | 2.47$^a$ |
| S.Em± | 0.53 | 0.58 | 963 | 0.02 |
| Interaction (Fertilizer levels × Different methods of estimation of leaf area index) | | | | |
| $F_1L_1$ | 38.76$^b$ | 55.81$^b$ | 32548$^b$ | 1.61$^b$ |
| $F_1L_2$ | 38.61$^b$ | 55.71$^b$ | 32233$^b$ | 1.61$^b$ |
| $F_1L_3$ | 38.50$^b$ | 55.67$^b$ | 31996$^b$ | 1.60$^b$ |
| $F_1L_4$ | 38.74$^b$ | 55.77$^b$ | 32519$^b$ | 1.61$^b$ |
| $F_1L_5$ | 38.82$^b$ | 55.92$^b$ | 32696$^b$ | 1.62$^b$ |
| $F_2L_1$ | 72.81$^a$ | 94.90$^a$ | 104526$^a$ | 2.89$^a$ |
| $F_2L_2$ | 72.76$^a$ | 94.40$^a$ | 104384$^a$ | 2.89$^a$ |
| $F_2L_3$ | 72.65$^a$ | 94.15$^a$ | 104142$^a$ | 2.89$^a$ |
| $F_2L_4$ | 72.79$^a$ | 94.76$^a$ | 104491$^a$ | 2.89$^a$ |
| $F_2L_5$ | 72.84$^a$ | 95.00$^a$ | 104598$^a$ | 2.89$^a$ |
| $F_3L_1$ | 75.65$^a$ | 96.25$^a$ | 108272$^a$ | 2.88$^a$ |
| $F_3L_2$ | 75.61$^a$ | 96.21$^a$ | 108176$^a$ | 2.88$^a$ |
| $F_3L_3$ | 75.59$^a$ | 96.00$^a$ | 108110$^a$ | 2.88$^a$ |
| $F_3L_4$ | 75.63$^a$ | 96.17$^a$ | 108221$^a$ | 2.88$^a$ |
| $F_3L_5$ | 75.70$^a$ | 96.26$^a$ | 108374$^a$ | 2.88$^a$ |
| S.Em± | 0.81 | 1.01 | 1668 | 0.04 |
| Control Without fertilizer | 35.28 | 52.34 | 28594 | 1.58 |
| S.Em± | 1.06 | 1.15 | 2230 | 0.04 |
| C.D at 5% | 3.05 | 3.32 | 6441 | 0.12 |

$F_1$: 50% RDF (50: 25: 12.5 kg N: $P_2O_5$: $K_2O$ ha$^{-1}$)
$F_2$: 100% RDF (100: 50: 25 kg N: $P_2O_5$: $K_2O$ ha$^{-1}$)
$F_3$: 150% RDF (150: 75: 37.5 kg N: $P_2O_5$: $K_2O$ ha$^{-1}$)
$L_1$: LAI estimation by length x breadth x correction factor
$L_2$: LAI estimation by disc method
$L_3$: LAI estimation by Leaf area meter
$L_4$: LAI estimation by Leaf area index meter or Canopy analyzer.
$L_5$: LAI estimation by AI (RGB camera mounted UAV)
Control: Without fertilizer

namely plant height and LAI. Adequate supply of nutrients under these treatments coupled with methods of estimation of LAI led to the maintenance of higher green leaf area per plant and translocation of assimilates towards reproductive parts resulted in higher grain and stover yield.

The interaction between fertilizer levels and LAI estimation methods had a significant impact on LAI at V8 stage. The combination of 150 per cent RDF and the leaf area meter resulted in the higher LAI (0.91), significantly higher than all other treatment combinations and the control (0.65). This higher LAI could be attributed to the optimal nutrient availability provided by 150 per cent RDF, which supports vigorous leaf growth, combined with the precise measurement capability of the leaf area meter. The LAI recorded by this combination was on par with the 150 per cent RDF + l × b method, indicating that both methods are effective when combined with levels of fertilizer levels.

At the VT stage, the combination of 150 per cent RDF and the leaf area meter again recorded the significantly higher LAI (4.72), than all other treatment combinations and the control (2.63). The superior performance of this combination could be attributed to the continued optimal nutrient availability provided by 150 per cent RDF, which promotes extensive leaf area development, along with the high accuracy of the leaf area meter in measuring the expanded canopy. The LAI from this combination was on par with the 150 per cent RDF + l × b method, 150 per cent RDF + AI combinations and 100 per cent RDF + l × b method suggesting that these methods also provide reliable LAI estimates when combined with high nutrient levels.

During the R1 stage, the interaction of 150 per cent RDF with the AI method resulted in the highest LAI (5.62), significantly higher than all other treatment combinations and the control (3.42). The high LAI was likely due to the AI method's ability to accurately capture the complex leaf structures that developed during this critical reproductive stage, coupled with the nutrient-rich environment provided by 150 per cent RDF. The LAI from this combination was on par with other combinations, including 150 per cent RDF + length × breadth × correction factor, 150 per cent RDF + leaf area meter, 100 per cent RDF + AI, 100 per cent RDF + l × b method and 100 per cent + leaf area meter indicating that these methods also perform well when combined with sufficient nutrient levels.

At the R3 stage, the highest LAI (4.93) was recorded with the combination of 150 per cent RDF and the l × b method, significantly outperforming all other treatment combinations and the control (2.65). This superior LAI is likely due to its accuracy in estimation along with the continued benefits of the nutrient-rich 150 per cent RDF. The LAI from this combination was on par with the 150 per cent RDF + length × breadth × correction factor, 150 per cent RDF + leaf area meter, 100 per cent RDF + length × breadth × correction factor, 100per cent RDF + AI, showing that these methods also provide accurate LAI measurements when combined with varying levels of fertilizer, particularly those that are sufficiently high to support optimal leaf development.

## Economics

The results revealed that, fertilizer levels had a significant effect on economics of maize. Significantly higher net returns (₹ 108230 ha$^{-1}$) was recorded with application of 150 per cent as compared to 50 per cent RDF and on par with 100 per cent RDF (Table 5) . Significantly higher BC ratio (2.89) was recorded with the application of 100 per cent RDF than 50 per cent RDF and it was on par with 150 per cent RDF. This higher monetary returns and BC ratio were mainly attributed to higher grain and stover yield of maize. A steady and ample supply of nutrients throughout the crop growth period resulted in improved crop growth and yield. Sharma *et al.* (2018) also reported variations in gross returns, net returns, and the benefit-cost ratio across different fertilizer levels.

The methods used to estimate the Leaf Area Index (LAI) did not significantly influence the economics of maize.

Interaction of fertilizers levels and methods of estimation of LAI registered significant effect on economics of maize. Significant higher net returns (₹ 108374 ha$^{-1}$) was observed under 150 per cent RDF + LAI estimation by AI as compared to the rest of the treatment combinations and control (₹ 77928 ha$^{-1}$ and ₹ 28984 ha$^{-1}$ respectively). These findings were supported by Khalili *et al*. (2016), significantly higher net returns (₹ 1, 42,814) was observed when 240 kg N ha$^{-1}$ followed by 180 kg N ha$^{-1}$. Contradictorily, no fertilizer application resulted significantly the lowest net returns. This was primarily due to stress that inhibited plant growth and reduced maize yield, leading to lower monetary returns.

Significantly higher BC ratio was recorded with the application of 100 per cent RDF with all five methods of estimation of LAI (2.89) than all other treatment combinations and it was on par with 150 per cent (2.88) and lower B:C ratio were recorded under 50 per cent RDF with five methods of LAI estimation . The 100 per cent RDF with methods of estimation of LAI provided an optimal supply of essential nutrients, promoting plant growth and yield without incurring the higher costs associated with 150 per cent RDF. The optimal nutrient supply at 100 per cent RDF enhanced yield and economic efficiency, compensating for cultivation costs. Although 150 per cent RDF increased yields, the higher input costs slightly reduced its B:C ratio. In contrast, 50 per cent RDF led to reduced yields and lower returns, resulting in a lower B:C ratio.

## Conclusion

Destructive methods like the length × breadth × correction factor and leaf area meter methods provide precise and reliable estimates of leaf area index, making them suitable for validating other estimation techniques. Maize LAI can optimally estimated by using UAV derived RGB images with random forest model. Since higher accuracy of model and minimum deviation observed from tasseling (VT) and grain filling stage (R3), it can be concluded that R3 stage is the best stage to estimate LAI of maize. Application of 100 per cent RDF recorded higher grain yield, net returns and B:C ratio and it was on par with 150 per cent RDF.

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