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# Yield Estimation of Paddy and Maize Crops in Mahabubabad District Using Sentinel-2 Data with a Hybrid Convolutional Neural Network-Lstm Model

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## ABSTRACT
*Estimating crop yield during the early growing season is important for agricultural planning and food security, particularly in semi-arid regions where climate variability plays an important role in influencing crop production. In this study, a novel deep learning framework that combines multi-temporal Sentinel-2 imagery is developed for estimating the paddy and maize yields during the early growth stages for Mahabubabad district, Telangana. The methodological framework involves Convolutional Neural Networks (CNN) to extract spatial features and Long Short-Term Memory (LSTM) networks to analyze temporal patterns, combined with an attention mechanism to identify key phenological stages. The model is trained with 874 field polygons of field data, spectral and phenological information from multi-temporal Sentinel-2 during 2023-24. Hybrid CNN-LSTM architecture results demonstrate that the yield prediction achieved an $R^2$ of 0.87 for paddy and 0.84 for maize at the maturity phase, which is higher compared to traditional machine learning approaches. Temporal analysis indicates that prediction accuracy varies considerably during different phenological stages, with the best performance at 45–60 days before harvest. The developed model exhibited good early-season prediction ability with highest accuracy during the reproductive phase of paddy and maize crops. Overall, the proposed methodology offers a scalable framework for early-season yield estimation in semi-arid climates.*

***Keywords:*** *Deep learning; Yield prediction; Sentinel-2; Semi-arid agriculture; CNN-LSTM;*

## 1. INTRODUCTION
Yield prediction in the early growing season is essential for agricultural planning and food security, especially in semi-arid regions, where climate variability and water scarcity significantly impact crop production (Brown & de Beurs, 2008; Quader et al., 2023; Vicente-Serrano et al., 2006). Predicting yields with accuracy at preliminary growth periods allows timely interventions in agricultural management, an efficient allocation of resources, and informed decision-making on food security strategies. Crop yield estimation in early growth stages is challenging in semi-arid agriculture regions (Jaafar & Ahmad, 2015; Zere et al., 2005). Paddy and Maize are important staple crops for many southern states in India (Sivasankari & Vasanthi, 2020). Conventional yield estimation techniques require extensive past data and often cannot adjust to the variability (Patel et al., 2020). Remote sensing plays a vital role in forecasting the yield for several crops (Guo et al., 2006; Pinter et al., 2003). Numerous studies have attempted to estimate yield have made use of various remote sensing data and derived indices such as NDVI, NDWI from crop spectral responses (Ghazaryan et al., 2020; Huang et al., 2014). However, many of the previous remote sensing-based studies for yield prediction of maize and paddy crops in semi-arid regions have not included crop phenology and environmental parameter interactions (Ji et al., 2021). In case of paddy, moisture stress during sensitive growth stages predominantly determines its yield potential, whereas maize shows variable responses with a change in moisture availability at different phenological stages (Gardner et al., 1986; Park et al., 1999). In addition to this inherent uncertainty, crop-specific responses in various wavelength ranges add significant volatility to early-season yield forecasts, especially in semi-arid climates where climate variability drives yield volatility (Brown & de Beurs, 2008).

The growing availability of high-resolution satellite imagery (e.g. from Sentinel-2) have paved the way for the development of various machine learning models for yield estimation of paddy and maize crops (Christianson, 2023; Guruprasad et al., 2019; Zhang et al., 2021). Despite the advancement of remote sensing technology and advances in artificial intelligence based predictive models, there exist research gaps in early-season yield predictions for semi-arid regions (Jaafar & Ahmad, 2015). Existing methods based on regular machine learning models such as random forests, support vector machines, etc., mainly focus on spectral information, disregarding the significance of spatial information in crop yields formation (Harshith et al., 2023; Khade et al., 2022; Mahore & Gadge, 2023). Such operational yield prediction models have a limited integration of multi-source data such as satellite-based imagery, soil properties and meteorological variables. Additionally, existing studies lack insights on the temporal evolution of yield formation dynamics across growth stages in changing environmental settings (Rogachev & Simonov, 2022; Priyanka et al., 2019). In this regard, the advancements in deep learning architectures (e.g. convolutional neural networks) create exciting opportunities to enhance early-season yield prediction (Chang et al., 2021; Kaur et al., 2022; Khaki & Wang, 2019). However, there is a need for systematic investigation regarding the utility of environmental variables in deep learning models and their performance across different crop types and growing seasons particularly in semi-arid regions. Therefore, this study aims at following main objectives:

1. Develop and validate a deep learning architecture that integrates multi-temporal Sentinel-2 satellite imagery to perform early-season yield prediction of paddy and maize crops.
2. Determine the best prediction window and gain insights into how the prediction accuracy changes across the different growth stages.

The study is implemented over Mahabubabad district in Telangana, which is a semi-arid region. With field observation and satellite imagery and environmental variables dataset developed for the 2023-24 growing season, the research examines the potential of deep learning frame work i.e., convolutional neural networks for estimating the yield of maize and paddy crops.

## 2. STUDY AREA & DATA SETS

### 2.1 Study Area:

Mahabubabad district, located in Telangana, India, lies between 17°36′ to 18°00′ N latitude and 79°30′ to 80°15′ E longitude, covering an area of 2,569 km² as shown in Figure 1. The terrain is predominantly flat, with elevations ranging from 200 to 500 meters above mean sea level. The region is characterized by black cotton soils and red sandy loams, which significantly influence local agricultural practices and crop yields. It experiences a semi-arid climate with three distinct seasons: summer (March–May), monsoon (June–September), and winter (October–February). The average annual rainfall is approximately 900 mm, primarily received during the southwest monsoon. Temperatures range from 45°C in summer to 15°C in winter.

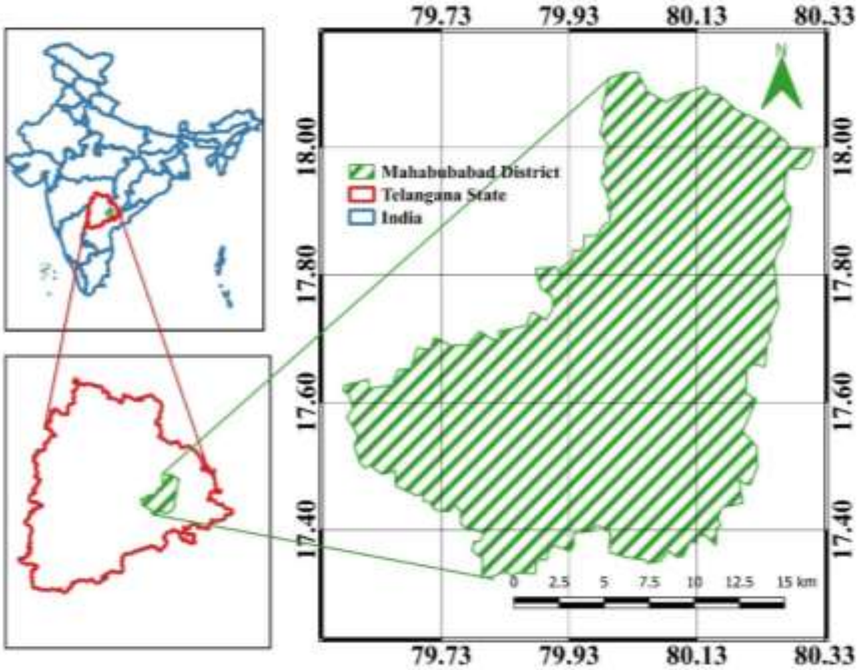


**Figure 1.** Study area map.

Kharif (June-November) and Rabi (December-March) are the two main cropping periods in the district. Paddy cultivation is predominant in Kharif and is facilitated by monsoon, maize is sown in Kharif and Rabi season depending on the availability of irrigation water. Agriculture landscape is comprised primarily with small to medium land holdings ranging from 0.5 to 2 hectares.

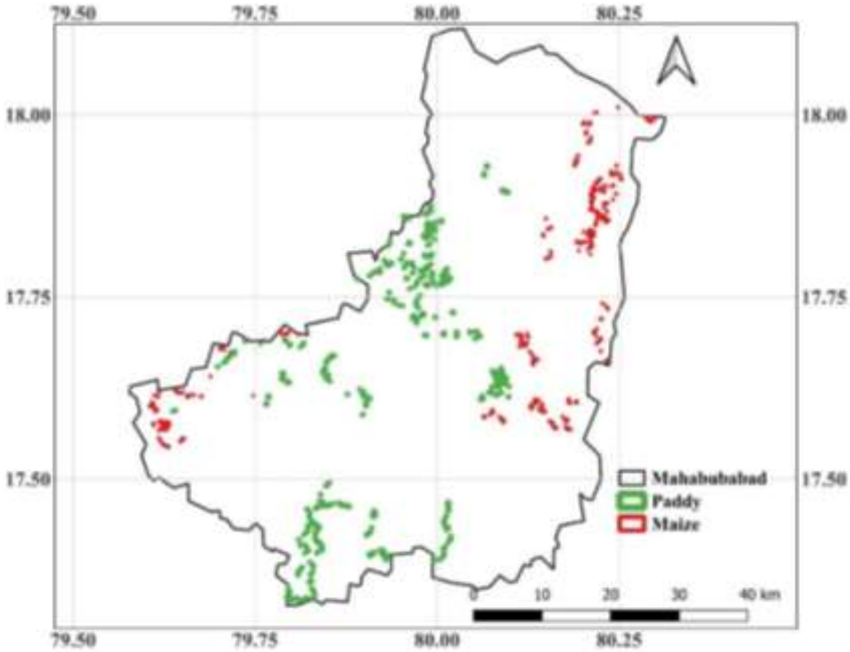


**Figure 2.** Field observations of paddy and maize crops.

**2.2 Datasets:**

This study employs different datasets that included satellite imagery, field measurements, and environmental variables from the 2023-24 agricultural season. The key components of data are:

### 2.2.1. Field Data

The study is based on a reliable field dataset of 874 agricultural fields in Mahabubabad district (see in Figure 2) for the cropping seasons of 2023-24. This dataset comprised 554 and 320 fields/samples of paddy rice (yielding 3.5-6.2 tonnes/ha) and maize (yielding 4.2-7.8 tonnes/ha), respectively. Crop phenological stages were systematically recorded throughout the growing period using remotely sensed data, ensuring temporal alignment with key developmental phases. This dataset is used as a ground truth for both training and evaluating the CNN-LSTM model for crop yield prediction.

### 2.2.2. Satellite Data

This study utilized Sentinel-2 multi-spectral imagery (10 m resolution) to monitor crop dynamics in the 2023–24 agricultural year. A total of ten cloud-free (<10% cloud cover) images were selected, evenly distributed across the Kharif (June–November) and Rabi (December–March) seasons to capture key phenological stages of paddy and maize. The selected scenes (See in Table 1) covered the entire cropping cycle to ensure comprehensive temporal representation. The selected imagery forms the basis for further pre-processing and analysis described in the methodology section.

**Table 1.** Sentinel-2 Image acquisition details and crop season

| Acquisition Date | Cloud Cover (%) | Season |
|---|---|---|
| 15-06-2023 | 5.2 | Kharif |
| 20-07-2023 | 8.4 | Kharif |
| 25-08-2023 | 12.1 | Kharif |
| 30-09-2023 | 3.5 | Kharif |
| 15-12-2023 | 2.1 | Rabi |
| 20-01-2024 | 4.3 | Rabi |
| 25-02-2024 | 6.7 | Rabi |
| 15-03-2024 | 3.2 | Rabi |
| 30-03-2024 | 4.8 | Rabi |
| 15-04-2024 | 2.8 | Rabi |

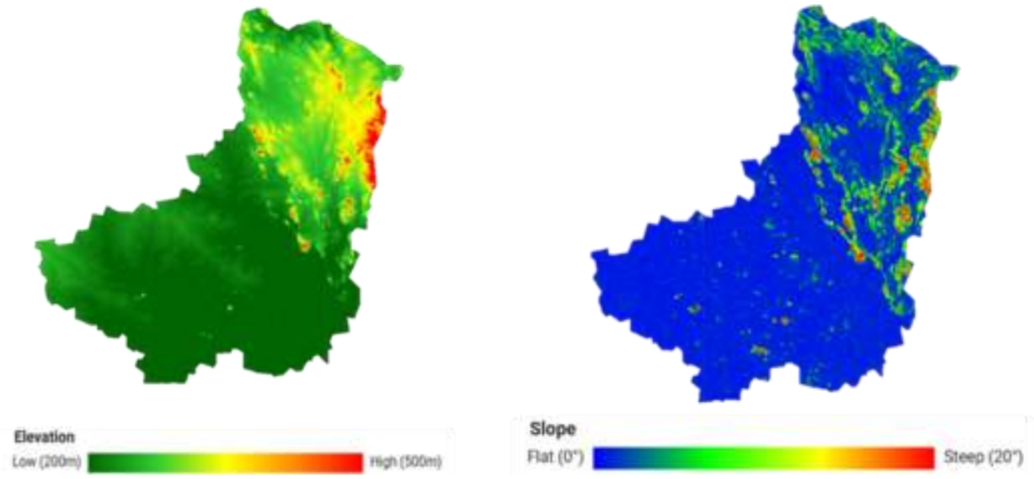


**Figure 3.** Topographical elevation and slope of Mahabubabad district

### 2.2.3. Topographical variables

In addition to Sentinel-2 data, the methodology integrates different topographical variables for improving the yield prediction. Topographical elevation and slope are extracted from SRTM digital elevation model (DEM) data at 30 m spatial resolution for topographic characterization of Mahabubabad district as depicted in the Figure 3. These topographic attributes are important as they control the distribution of soil moisture, patterns of runoff, and microclimatological regimes in the study region, all of which affects the growth and productivity of crops.

## 3. METHODOLOGY

### 3.1 Data Preparation:

This methodology commences with the complete preprocessing of Sentinel-2 imagery (radiometric calibration, and atmospheric correction performed by the Sen2Cor processor). Rigorous quality control and preprocessing were applied to all datasets to ensure consistency across different data and enhance the overall accuracy. In this regard, all spatial data were reprojected to a common projection system (UTM Zone 44N). To match spatial resolution across the dataset, the 20m resolution bands, elevation and slope are resampled to 10m using bilinear interpolation. Atmospheric and radiometric corrections of Sentinel-2 Level-2A imagery was performed using Sen2Cor processor. These radiometrically corrected images were clipped to the study area and temporally stacked. The stacked imagery consists of following bands to capture the temporal crop dynamics effectively: Band 2 (Blue, 490 nm), Band 3 (Green, 560 nm), Band 4 (Red, 665 nm), Band 5 (Red Edge 1, 705 nm), Band 6 (Red Edge 2, 740 nm), Band 7 (Red Edge 3, 783 nm), Band 8 (NIR, 842 nm), and Band 8A (Narrow NIR, 865 nm). These bands were chosen due to their sensitivity to vegetation structure and health, allowing the derivation of key vegetation indices such as NDVI, EVI, and Red Edge NDVI. The calculation of these vegetation indices (VIs) are critical for crop yield quantification. Maximum NDVI and EVI are indices of plant health, and the normalised difference water index (NDWI) provides information about water status of crops. The red-edge posture position (REP) indices are calculated to express the variation of the chlorophyll content. The spatiotemporal data set from Sentinel-2 was used for derivation of the spectral signatures and vegetation indices. The field data, temporal data set and derived information collectively were used as the inputs to the CNN-LSTM model for prediction of the yield.

### 3.2 Deep Learning Architecture:

The Deep learning framework proposed here integrates CNNs for spatial feature extraction and LSTMs for temporal pattern analysis. The CNN part employs a ResNet50 architecture adjusted, pretrained using ImageNet and fine-tuned for agricultural purposes. This network has five followed convolutional blocks with residual connections, followed by global average pooling to extract the spatial features of the satellite images. The LSTM network reads the temporal sequences of spatial features extracted by the CNN. The architecture consists of three bidirectional LSTM layers, each with 256 units, enabling the model to learn temporal features in the crop growth over time in both forward and backward directions. To prevent overfitting, dropout layers (rate=0.3) are used between the LSTM layers. An attention mechanism is added after the LSTM layers using self-attention to find and weigh the importance of different temporal features for prediction output.

To integrate the spatial and temporal information effectively, a feature fusion layer is introduced. This layer concatenates the spatial features extracted by the CNN with the temporal features processed by the LSTM-attention module. The combined feature vector is then passed through fully connected layers to generate the final yield prediction.

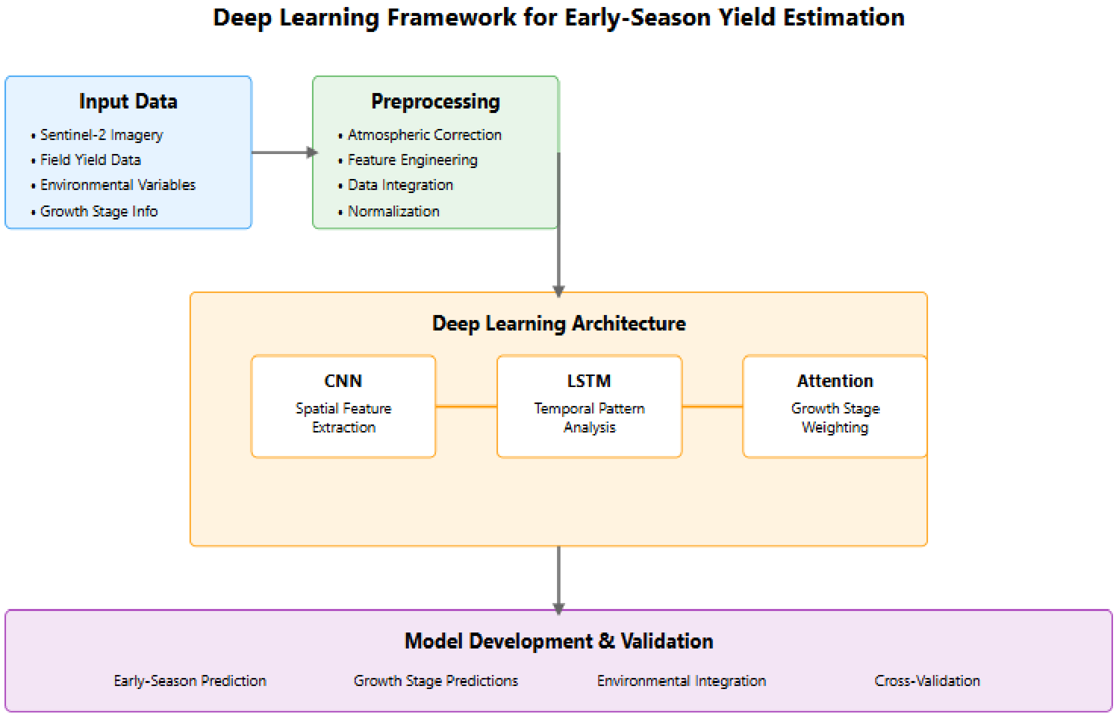


**Figure 4.** Flow chart representing the methodology.

### 3.3 Model Development:

An early-season prediction framework is adopted in this approach. Towards this, the model runs on a progressive updating approach by incrementally adding new satellite observations for the determination of crop yield. Therefore, the model is trained on different temporal windows to measure prediction accuracy over different growth stages. The data was time-split with 70% used for training, 15% for validation and 15% for testing, preserving the spatial and temporal distribution of samples across splits. Separate layers for continuous and categorical environmental variables were used, followed by subsequent fusion of these features with the spectral features. A multi-task learning approach is adopted which facilitates growth stage-specific predictions. Therefore, the developed model in this study predicts the final yield and intermediate estimates in parallel, where the information on growth stages is used as auxiliary data. The code implementation of the whole methodology is developed in Python, TensorFlow is used for deep learning implementation, while scikit-learn is used for preprocessing and validation. Early stopping mechanism is used to avoid overfitting, and learning rate, other parameters are optimized using hyperparameter tuning for convergence of the model.

### 3.4 Validation of Model:

The validation strategy involves a cross-validation approach with both spatial and temporal folds during the model development to ensure model generalization and accuracy. Different performance metrics were used for the comparison and assessment of model's accuracy during different stages. These metrics include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-squared, which are calculated for each growth stage of each crop type. Additionally, CNN-LSTM model's performance was compared against other popular machine learning models i.e., random forest (RF) and support vector machine (SVM).

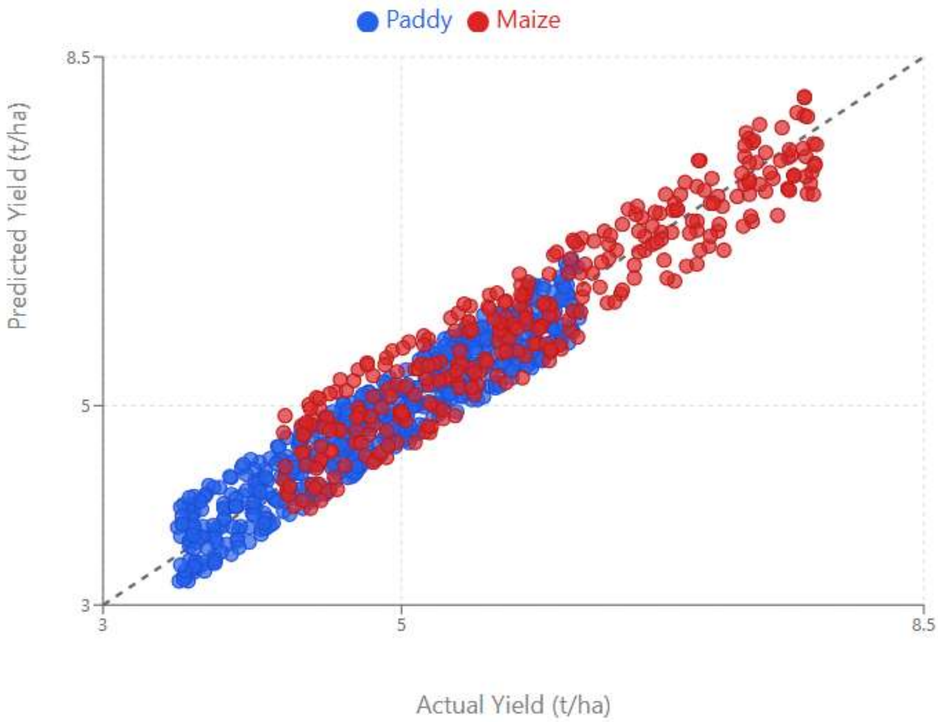


**Figure 5.** Paddy and Maize yield estimates from hybrid CNN-LSTM model

## 4. RESULTS AND DISCUSSION

### 4.1 Model Performance Analysis:

The hybrid CNN-LSTM based model with attention mechanism provides a promising performance in early-season yield prediction of paddy and maize crops. The results for paddy show an overall $R^2$ of 0.87 and RMSE of 0.42 tons/ha; while for maize an $R^2$ of 0.84 and RMSE of 0.56 tons/ha (See in Figure 5). The hybrid CNN-LSTM model results are further compared with classical machine learning models i.e., RF and SVM. The overall comparison results demonstrates that the proposed deep learning architecture outperforms the RF and SVM models.

CNN-LSTM model has a considerable improvement over classical machine learning methods (i.e., RF and SVM) for paddy and maize with reductions of approximately 23% and 18% in the RMSE, respectively. Followed by the hybrid CNN-LSTM model, random forest model has better performance with $R^2$ and RMSE of 0.72 and 0.58 tons/ha (See in Table 2). The results also indicate compared to Maize, the models have performed better for paddy. Further, it is observed that these improvements are most significant during early growth stages, indicating that the attention mechanism is able to successfully capture important phenological changes.

**Table 2.** Comparison of different models' overall accuracy

| Model | Paddy ($R^2$/RMSE) | Maize ($R^2$/RMSE) |
|---|---|---|
| CNN-LSTM+attention | 0.87/0.42 | 0.84/0.56 |
| Random Forest | 0.72/0.58 | 0.69/0.71 |
| SVM | 0.68/0.63 | 0.65/0.75 |

### 4.2 Temporal evaluation of accuracy:

The growing season of paddy and maize crops was divided into four different stages i.e., early vegetative, peak vegetative, reproductive and maturity. After that, the proposed hybrid CNN model is evaluated in each stage. The results depict that the performance of the hybrid CNN-LSTM model shows a distinct temporal pattern. The model's accuracy changes considerably in different phenological phases of the crop (See in Table 3). Predictions during early vegetative stages (30-45 days after sowing) yield moderate accuracies ($R^2$ = 0.71 for paddy and 0.68 for maize) but higher accuracies are observed in peak vegetative stage ($R^2$ = 0.83 for paddy and 0.79 for maize). Also, it was observed that model performance was highest during the reproductive stages, with $R^2$ values of 0.89 and 0.85 for paddy and maize, respectively. Whereas RMSE values during the reproductive stages are observed to be lowest with 0.47 tons/ha and 0.56 tons/ha respectively for paddy and maize crops.

**Table 3.** Growth Stage-wise Prediction Accuracy

| Growth stage | Paddy ($R^2$/RMSE in tons/ha) | Maize ($R^2$/RMSE in tons/ha) | Key period (DAS*) |
|---|---|---|---|
| Early vegetative | 0.71/0.67 | 0.68/0.78 | 30-45 |
| Peak vegetative | 0.83/0.52 | 0.79/0.65 | 45-60 |
| Reproductive | 0.89/0.47 | 0.85/0.56 | 60-90 |
| Maturity | 0.87/0.51 | 0.84/0.63 | 90-120 |
| *Note: DAS is Days after sowing | | | |

Model performance is highly dependent on crop establishment conditions during the vegetative stage. Predictions done early (30 days post sowing) provide moderate accuracy but quickly improves with crop growth. The crop yield prediction is observed to be highest during the reproductive stage indicating it as an optimal prediction window. In terms of crop calendars, the flowering period (65-75 days after sowing) appears to offer the most reliable yield indicators for paddy whereas maize has the best yield prediction potential during the grain filling stage (70-85 days after sowing). Prediction accuracy is highly impacted by phenological transitions. The attention mechanism adeptly adjusts to these transitions, as it fine-tunes feature importance weights based on growth stage progress to keep predictions stable.

## 5. SUMMARY, CONCLUSIONS AND FUTURE WORK

This study demonstrates the utility of a deep learning framework i.e., hybrid CNN-LSTM with attention mechanism in yield prediction of paddy and maize crops incorporating multi-temporal satellite imagery and auxiliary variables. By integrating CNN and the LSTM using an attention mechanism, the model depicts a considerable improvement in the prediction accuracy with $R^2$ values of 0.87 and 0.84 for paddy and maize respectively, far exceeding the performance of other techniques. The study identifies optimal temporal window i.e., during the reproductive phase for yield prediction, with model performance improving significantly at this phase. This is reflected in the attention mechanism, which identifies these critical periods as that of reproductive stage, where the prediction results for both crops also reach their peak. The proposed framework has shown yield predictions with high accuracy 45-60 days prior to harvest demonstrating its early-season forecasting ability.

The proposed framework in the study offers multiple methodological advances to remote sensing in agriculture. The hybrid architecture enables combining the spatial and temporal features for a better understanding of yield formation dynamics. Additionally, the attention mechanism's ability to identify and adjust weights helps to accurately model complex crop-environment conditions. Despite the advantages and improvements, there exist limitations which can be addressed in the future research. Field size variations, irrigation management practices, soil conditions, weather and climate information can affect the model's ability to accurately predict the crop yield. Though the model can be temporally transferable across growing seasons, but this will have to be validated after extreme weather is encountered in the future. Additionally, the computational complexity of the deep learning architecture would be a limitation for its large-scale operational implementation. In this regard, development of more efficient model architectures which allow for operational deployment at reduced cost shall be investigated. Additional data sources, such as high-resolution drone imagery, ground soil moisture measurements, irrigation data, etc., can enhance prediction accuracy during critical growth stages.

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