



Early-Season Crop Yield Prediction Using Multi-Sensor Data Fusion: A Review of Emerging Techniques

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Abstract. Crop yield prediction contributes significantly in food security and managing agricultural resources. For larger field area it is practically impossible for field based observations for crop yield estimation. From the last few years remote sensing and geographic information system proves to be prominent in crop yield prediction for large scale area. This review article offers systematic review of multi sensor fusion method for crop yield prediction in early season of crop. This review paper is structured according PRISMA framework to study different satellite imagery with different sensors like Sentinel-2A, Landsat etc. Also focuses on climatic measures and soil data for understanding crop dynamics related to crop yield. Diverse fusion level strategies for fusions like data level fusion, feature level fusion and model level fusion are studied. Also, machine learning techniques like random forest, support vector machine, long short term memory (LSTM) techniques are identified which show good results. Temporal analysis with vegetation indices like NDVI, EVI, SAVI etc. highlights the potential crop yield prediction in the early season. Also, future scope highlights the need of fusion approach in crop yield estimation. In summary this systematic review address different data fusion methods and scalable modeling techniques with future scope.

Keywords: Crop Yield Prediction, NDVI, DL, Data Fusion.

1 Introduction

Modern precision agriculture is based on crop yield prediction, providing farmers, policymakers, and agribusiness stakeholders with information that enables them to make informed decisions [1]. Historically, yield estimation was based on field surveys, past

history and statistical models that were not very spatial and time sensitive. As the need for food rises with the rising population and climate variability, there is an urgent need to have accurate, scalable and early prediction procedures [2]. Precision agriculture is an integration of the latest technologies to track the status of crops and optimize inputs to make yield prediction more objectively and effective [3].

Crop yield prediction in early season has become a very important aspect since stakeholders are able to make proactive decisions prior to harvesting. Early predictions aid in the scheduling of irrigation, fertilizer, supply chain logistics and market plans [4]. Early forecasts also aid in risk management, as they determine the possible yield losses in case of bad weather, pests, or diseases. Nevertheless, early growth stages are not easy to predict yield because of the few observable crop traits and high uncertainty, and it is necessary to use sophisticated analytical methods [5].

Remote sensing technologies have transformed the agricultural monitoring by offering non-destructive, continuous, and large-scale monitoring of crop conditions. Multi-spectral satellite data like Sentinel and Landsat can be used to calculate vegetation indices like NDVI and EVI, which are directly related to crop health and biomass [6]. Simultaneously, Geographic Information Systems (GIS) are used to store, process and analyze georeferenced data efficiently. Remote sensing and GIS integration makes it easy to map crop variability, track growth patterns, and evaluate environmental conditions that affect yield [7].

The ability of crop yield prediction systems has been further improved in recent years with the creation of multi-sensor data fusion techniques. Multi-sensor fusion involves a combination of different data sources, including optical imagery, Synthetic Aperture Radar (SAR), weather data and soil information, and offers a more detailed view of the state of crops [8]. Such integration can address the shortcomings of single data sources, including cloud cover problems with optical imagery or lack of spectral detail in SAR data. State-of-the-art machine learning and deep learning methods have also been instrumental in their successful combination to enhance prediction accuracy through the combination of these heterogeneous datasets [9].

This paper incorporates novel approach for comprehensive analysis of crop yield prediction based on multi sensor data fusion approach. This review focuses on different fusion level approach like data level fusion, feature level fusion and multi model fusion for crop yield estimation. It also highlights the role of ML and DL based models such as SVM, CNN and LSTM in handling heterogeneous multi temporal datasets. The main aim of this review paper is to critically review and synthesize existing literature on multi-sensor fusion techniques in the early season prediction of crop yields with reference to remote sensing and GIS. In this study we have followed a systematic literature review with PRISMA framework for various data sources, methodologies and modeling frameworks employed in literature, define the main challenges and limitations in the research, and outline the new trends and directions.

2 Recent approach for Crop Yield Prediction

Recent studies show the increasing significance of remote sensing via satellite in crop monitoring and yield prediction. One of the authors conducted a study that suggested a

field-scale approach that involves the use of Sentinel-2 vegetation indices to identify the most favorable time window to use in prediction of yields. In the study, it was highlighted that temporal analysis of vegetation indices in a GIS setting can be applied to greatly enhance the accuracy of prediction by reducing external variability (e.g. soil and microclimate variations). The research emphasized the need to have a spatially explicit analysis in which GIS is very crucial to handle and analyze the field level variability to have a more accurate estimate of yield [10].

Author is another significant contribution that created a yield forecasting framework based on Sentinel-2 time-series data with deep learning methods. The research employed the combination of time-series of vegetation index with field data to simulate the dynamics of crop growth and yield forecasting. The authors showed that the inclusion of the temporal satellite data can greatly improve the performance of the model, especially when it is processed in the geospatial frameworks to manage the spatial variability. The paper supports the importance of GIS in the organization of multi-temporal data and its analysis in crop observation and yield forecasting [11].

Another author did a more recent study on interpretable machine learning of wheat yield estimation with time-series remote sensing data. The study combined vegetation indices like NDVI and EVI with meteorological variables to enhance better prediction. The research revealed that the integration of remote sensation data with environmental parameters in a GIS based analysis platform results in more effective yield estimation models. It also emphasized the value of monitoring of crop growth over time as well as integration of spatial data to predict early in the season [12].

2.1 Multi-Sensor Data Fusion Techniques

Multi-sensor data fusion is the fusion of information of various sources to come up with a more reliable, precise and holistic information regarding crop monitoring and yield forecasting. In precision agriculture, it allows combining heterogeneous data like satellite images, UAV measurements, and environmental parameters and avoids the shortcomings of univariate data [13].

Based on the level at which integration occurs, data fusion can be categorized into three main types. Data-level fusion (early fusion) is where raw data of various sensors is directly fused without processing, retaining as much information as possible but necessitating delicate preprocessing and alignment [14]. Intermediate fusion (feature-level fusion) involves the combination of extracted features, including vegetation indices, texture, or temporal measures, which makes it more robust and computationally efficient. Decision-level fusion (late fusion) uses the results of several models or classifiers, improving prediction accuracy using ensemble methods [15].

Different combinations of fusions are popular in the agricultural practice. Optical and SAR data integration enhances monitoring during cloud cover and both spectral and structural crop data are captured. Integration of satellite and UAV data makes it possible to analyze data on a multi-scale by merging the large-scale coverage with high-resolution information. Moreover, remote sensing data can be complemented by weather and soil data to improve the performance of the model by introducing environmental and physiological conditions on crop growth [16].

We have studied multiple research papers based on fusion type which are summarize in table 1, table 2 and in table 3 respectively.

Table 1. Data Level Fusion

Crop Type	Sensor/Satellite	Fusion Approach	Techniques Used	Result	Reference
Field Pea	UAS multi-spectral + high-resolution satellite imagery	Data-level fusion (image fusion + feature fusion)	Random Forest, pan-sharpening, intensity-hue-saturation (IHS), additive wavelet luminance proportional (AWLP)	Multi-scale and multi-temporal fusion improved yield prediction. Pan-sharpened imagery achieved better performance than original imagery. Key indices: GNDVI and TTVI.	[17]
Wheat	UAV RGB, multispectral, thermal infrared	Multi-sensor data fusion	Cubist, SVM, DNN, Ridge Regression, Random Forest, Ensemble Learning	Multi-sensor fusion outperformed single-sensor models. Ensemble learning achieved highest accuracy ($R^2 = 0.692$, RMSE = 0.916 t ha ⁻¹).	[18]
Cotton, Gram, Groundnut, Maize, Moong, Paddy, Sugarcane, Wheat	IoT multi-sensor agri-cultural data	Multisensor data fusion	J48 Decision Tree, Hoeffding Tree, Random Forest	Random Forest achieved best classification with lowest RMSE (13%). Fusion improved crop recommendation accuracy and environmental monitoring.	[19]
Wheat (Above-ground Biomass)	UAV multi-spectral, RGB, thermal infrared	Multimodal data fusion	Random Forest Regression (RFR), PLSR, MLR	Multimodal fusion using vegetation, thermal, and structural parameters achieved highest accuracy ($R^2 = 0.897$) compared to single-modal data.	[20]

Table 2. Feature Level Fusion

Crop Type	Sensor/Satellite	Fusion Approach	Techniques Used	Result	Reference
Winter Wheat & Corn	Sentinel-2 multi-source remote sensing imagery	Feature-level fusion	Relief FRFE, contextual semantic feature aggregation, spatial channel attention, hierarchical refinement strategy	Reduced 224 features to 31 optimal features. Achieved high classification accuracy (95.76% for winter wheat, 93.44% for corn). Improved small fragmented plot extraction.	[21]
Winter Wheat	Traditional remote sensing variables (EVI, LAI), SIF, climate data	Feature-level fusion	BO-CNN-BiLSTM, Bayesian Optimization, 1D-CNN, BiLSTM	Fusion of TS, SIF, and climate data achieved highest accuracy ($R^2 = 0.81$, RMSE = 616.99 kg/ha). Effective 25 days before harvest.	[20]
Soybean, Wheat, Corn	Meteorological time series + static soil data	Feature-level fusion	Multi-head self-attention network, clustering, attribute selection	Integration of meteorological and soil features improved multi-stage and in-season yield prediction performance over existing models.	[22]
Wheat	Climate, NDVI, soil, and spatial datasets from GEE	Feature-level fusion	Random Forest, SVM, LASSO	Fusion of climate, NDVI, soil, and spatial data improved prediction accuracy ($R^2 = 0.74-0.88$). RF achieved best performance ($R^2 = 0.88$).	[23]

Table 3. Decision Level Fusion

Crop Type	Sensor/Satellite	Fusion Approach	Techniques Used	Result	Reference
Wheat	UAV RGB, multi-spectral, thermal infrared	Decision-level fusion (ensemble learning)	Ensemble learning combining Cubist, SVM, DNN, RR	Ensemble learning improved prediction accuracy beyond individual ML models (R^2 up to 0.692).	[18]

Soybean, Wheat, Rapeseed	Sentinel-2, weather, soil, topo- graphic data	Multi- model gated fu- sion	Multi-modal Gated Fu- sion (MMGF), modality en- coders, gated unit	MMGF outperformed conventional models with sub-field predic- tion $R^2 = 0.68$ and field-level $R^2 \approx 0.80$. Adaptive weights im- proved multimodal contribution learning.	[24]
Corn	MODIS NDVI and EVI	Multi- stream deep learning fusion	MSDNN, DNN, SVR, RFR	Multi-stream DNN achieved best county- level prediction accu- racy ($R^2 = 0.86$). Demonstrated effec- tive early-season pre- diction.	[25]

All in all, multi-sensor data fusion has a number of benefits namely, enhanced prediction accuracy, enhanced spatial and temporal coverage, greater robustness to various conditions and greater ability to make decisions. With these advantages, it is an important element in the creation of sound early-season crop yield forecasting systems.

3 **Methodology**

For systematic review we used A PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to identify, screen and select relevant research articles for crop yield prediction using multi fusion remote sensing approach. Among the research papers 27 papers are practical work oriented based on different crops like sugarcane, rice and corn. Remaining 7 selected papers are review papers and among all 34 research papers only 1 paper is conference proceeding. Research papers were collected from major sources including “IEEE Explorer, Science Direct, MDPI, Springer, Taylor & Francis, and Google Scholar. Also using keywords such as “crop yield prediction”, “data fusion”, “feature fusion”, “SAR-optical fusion”, “remote sensing”, “UAV”, and “machine learning”. Duplicate and irrelevant studies were removed through title, abstract, and full-text screening. Finally, 34 relevant studies published between 2023 and 2026 were selected for detailed review and comparative analysis. The figure 1 shows pictorial representation of PRISMA framework.

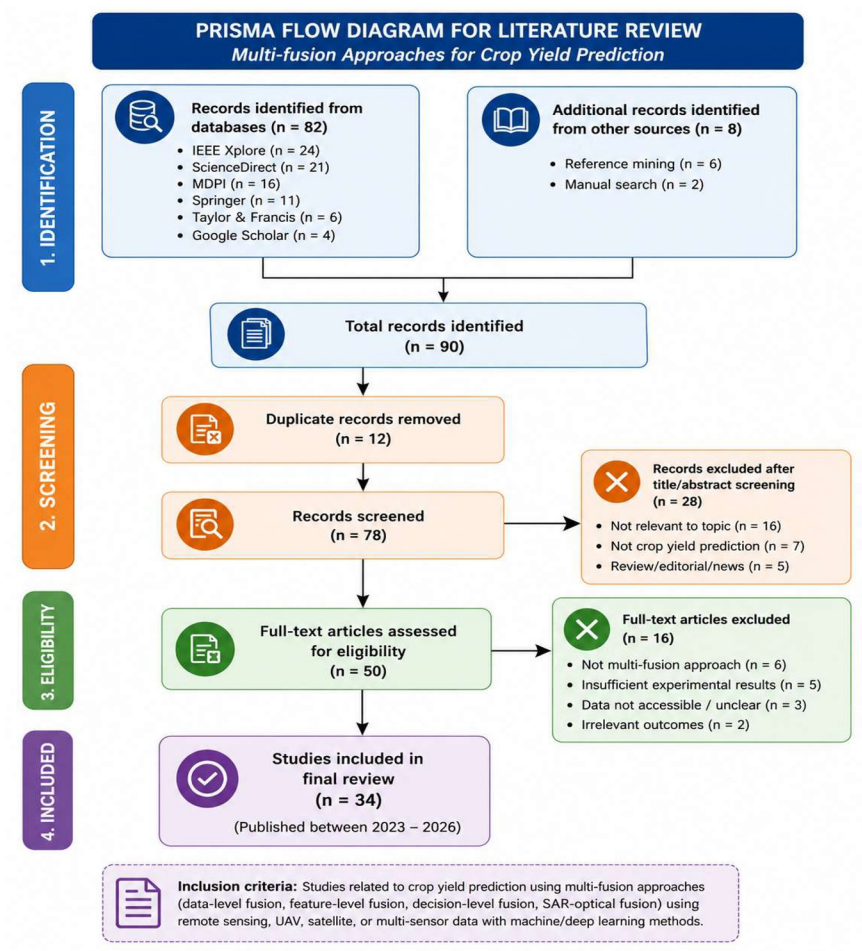


Fig. 1. PRISMA Framework

According to literature survey we identified methodology prescribed in figure 2, for early season crop yield prediction where remote sensing data and GIS plays a vital role.

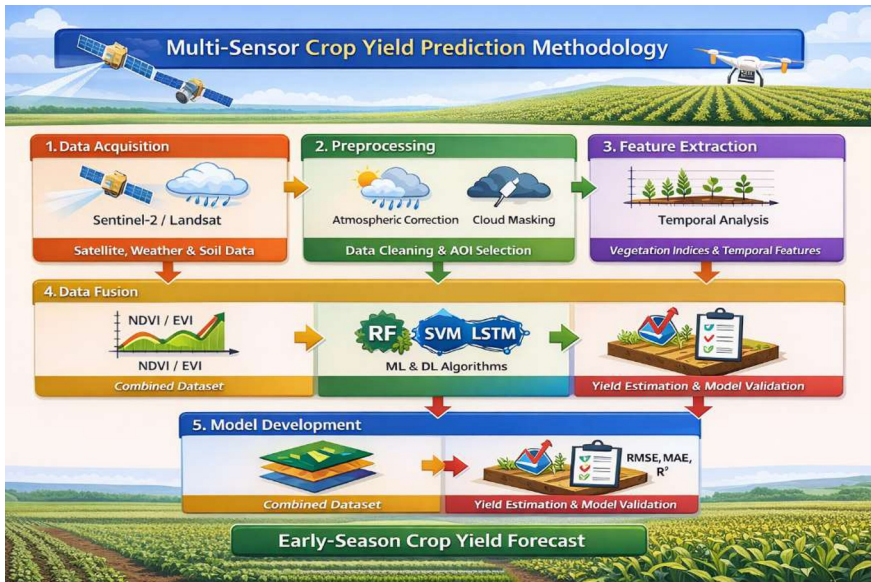


Fig. 2. Proposed Methodology

3.1 Data Acquisition

The initial one is to gather multi-source data that is needed to conduct crop tracking and predict yield. Sentinel-2 and Landsat satellite data are obtained to obtain high-resolution multispectral image to analyze crop conditions over time. Also among the remote sensing data, there is also weather data such as temperature, rainfall and humidity provided by meteorological sources to capture the environmental factors affecting crop growth. Field level variability is also represented by soil data, including soil moisture, soil texture and soil nutrient content. The combination of these datasets also provides a holistic coverage of factors influencing crop yield [26].

3.2 Preprocessing

Data must be preprocessed to guarantee the quality and consistency of data before the analysis. Satellite imagery undergoes atmospheric correction to eliminate atmospheric distortions that are created by atmospheric particles and improve reflectance accuracy. Cloud masking algorithms remove cloud-pixels, which may be counterproductive to analysis, particularly in optical imagery. Moreover, image clipping is carried out with the help of the Area of Interest (AOI), which is usually defined in GIS shape files in order to take only the agricultural land, which is of interest. These preprocessing measures increase reliability and usability of the data [27].

3.3 Feature Extraction

During this phase, significant features are extracted out of the processed data to reflect the state of crops. Multispectral bands can be used to measure crop health, biomass, and vigor by using vegetation indices: NDVI (Normalized Difference Vegetation Index) and EVI (Enhanced Vegetation Index). Temporal features are also obtained using a time-series data to obtain crop growth patterns over various phenological stages. These characteristics are important predictive modeling inputs [28].

3.4 Data Fusion

Data fusion entails the combination of two or more sources of data into one data set to enhance the analysis. Appropriate fusion methods (including feature-level fusion) are used to combine satellite-derived features, weather parameters and soil information. This combination assists in the capture of spatial and temporal variability in crop situations. Through data fusion, heterogeneous datasets are more robust and predictive, unlike single-source methods [29].

3.5 Model Development

Machine learning (ML) and deep learning (DL) models are trained to forecast the crop yield by relying on the obtained features. Algorithms like Support Vector machine (SVM) and random forest (RF) are applied due to their capability of dealing with non-linear relationships and high-dimensional data. Furthermore, to learn temporal dependencies in time-series data, deep learning networks, such as the Long Short-Term Memory (LSTM), are used. The models are optimized by training on past data then optimized to give the best predictive results [30].

3.6 Prediction & Validation

The study area is estimated to yield crops using trained models in the last stage. The model results are compared with the actual results of the observed yield to determine the model performance. The accuracy of the prediction is determined using various measures including the root mean square error (RMSE), the mean absolute error (MAE) and the coefficient of determination (R^2). This is necessary to guarantee reliability and applicability of the developed model to the real-life agricultural decision-making [31].

4 Result and Discussion

The extensive review of the chosen articles demonstrates that the use of multi-source data integration can substantially enhance the efficiency of crop yield prediction models. Remote sensing information (such as satellite imagery and UAV images), environmental factors (weather condition, rainfall and soil parameters) are constantly added to

improve prediction accuracy. Some of the research involving UAV-based RGB and multispectral imaging discovered that a combination of vegetation indices obtained using multiple sensors led to better model performance than a single-source data. For an instance, fused vegetation indices models resulted in better correlation coefficients and reduced errors in prediction, indicating the value of multi-sensor fusion in more effectively capturing crop variability [28].

Data level fusion methods are used to integrate raw data from several sensors, including UAV RGB, multispectral imaging, thermal imaging, and satellite-imaged data, for better accuracy in calculating crop yields. Research demonstrated that the use of multi-scale and multi-temporal data improves the prediction results than using a single data source. The author showed that fusion of satellite and UAV images using pan sharpening method boosted the estimation of the yield of field pea [17] and another author found that the fusion of multiple types of UAV images (multimodal fusion) improved the prediction accuracy of wheat biomass ($R^2 = 0.897$). In a similar fashion [20], one of the author reported that the combination of RGB, multispectral, and thermal UAV data in ensemble learning led to better wheat yield prediction ($R^2 = 0.692$). In fusion at the data level, however, the issues are those of heterogeneity of the sensors, spatial mismatch resolution, contamination by clouds, and increased computational complexity [18].

Feature level fusion consists of amalgamating the features of different features like vegetation parameters, climatic parameters, soil parameters, temporal crop parameters, etc., together and providing common framework to learning. One of the author discovered that multi-scale semantic feature fusion can greatly enhance the accuracy in the classification of corn and wheat during the winter season [21], while author devised a hybrid model called BO-CNN-BiLSTM, which combines SIF data, climate data, and traditional remote sensing variables to estimate winter wheat yield, with R^2 reaching 0.81 [20]. Soil data has also been shown to be beneficial in predicting multi-stage crop yields; the author also showed improved multi-stage crop yields using a combination of meteorological time-series and soil data, using a multi-head self-attention network [22]. Temporal analysis was considered to be of great importance since the growth dynamics of a crop changes during different phenological stages and arrival of multiple temporal observations enhanced the early season prediction accuracy. However, several important caveats still exist in relation to the transferability and robustness of models including feature redundancies, missing observations, overfitting and climatic uncertainties.

5 Future Work

Future studies on improving the strength and scalability of crop yield prediction models through incorporation of more diverse and high-resolution datasets should be undertaken. Integration of other sources of data including hyperspectral images, field sensors on IoT and real time weather data can also enhance the accuracy of the model and allow dynamic crop monitoring [32]. Furthermore, the creation of superior data fusion methods that can adequately integrate spatial, temporal and environmental information is

another area of concern. The use of more advanced deep learning models, like transformer-based models and attention mechanisms, is another promising direction as it would enable the better reflection of more intricate relationships in multi-source data. The models have the potential to enhance interpretability and gain better understanding of the factors that affect the yield of crops. Also, there should be an attempt to create lightweight and computationally efficient models that can be implemented in real-time agricultural decision support systems [33]. It is also necessary to increase the applicability of yield prediction models to new regions and crops. The next generation research needs to work on establishing generalized models which are capable of adapting to different agricultural environments with the least amount of retraining. The use of transfer learning and domain adaptation techniques can help address this challenge. Lastly, accessibility and quality of ground truth data is essential to validate models and increase their accuracy. The joint work of researchers, government departments and farmers can help to collect and share the data on a large scale [34].

Decision-level fusion fuses the output of a number of different machine learning and deep learning models to increase the model robustness and generalization capability. The author suggested an approach called Multi-modal Gated Fusion (MMGF) which adaptively weighted the multimodal data sources and eventually produced better crop yield prediction performance in the sub-fields [24]. In a similar fashion, another author proposed a multi-stream deep neural network with both the NDVI and EVI streams for better estimation of corn yield at the county level ($R^2 = 0.86$). No study concerning SAR-Optical fusion was done in the current dataset, but SAR-Optical fusion is considered very promising as SAR imagery can offer structural and moisture related information during cloudy conditions, which is limited for optical imagery [25]. Currently, however, potential operational use of advanced fusion-based crop yield prediction systems is limited by uncertainties involved in the quantification of crop yields, the computational burden, and reduced model generalization across different regions.

6 Conclusion

This study is the detailed critical review of RS, GIS and multi sensor fusion approach for crop yield prediction. We have followed systematic review approach with help of PRISMA framework. The study shows the substitution for traditional field survey approach for crop yield with advanced satellite based and other environmental based approach. The study identified overall methodology required for early season crop yield prediction with multi sensor approach. The analysis shows that remote sensing techniques provide timely and large scale data driven approach for understanding different crop conditions from different data sources. The aim of the study is to show overview of multi sensor data fusion approach for early season crop yield prediction illustrate convincingly. It also demonstrates weakness of some data sources can be surpass with help of SAR, Optical, soil data and climate data to understand crop dynamics. We also analyze fusion at data level, feature level and multi model level which shows prominent result. Form which some techniques are common for data level fusion and model level fusion. Despite there is tremendous developments, still there are some issues like data

availability, cloud interference in imagery, model generalization and need of precise ground truth data remains. Also, the differences in the model performance with respect to crops suggest that more flexible and scalable structures are required. These limitations are important to tackle to enhance the reliability and applicability of yield prediction systems. Also future studies give sophisticated approach to address these limitations.

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