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Advancements in remote sensing based crop yield modelling in India

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ABSTRACT

Crop yield prediction at regional levels is an essential task for the decision-makers for rapid decision making. Pre-harvest prediction of a crop yield can prevent a disastrous situation and help decision-makers to apply more reliable and accurate strategies regarding food security. With the advent in digital world, various advanced techniques are employed for crop yield prediction. Remote Sensing (RS) data with its capability to provide the synoptic view of the Earth's surface, has numerous returns in the area of crop monitoring and yield prediction. This study provides as a review for the advanced techniques for crop yield prediction in India with RS data as a base. The advanced techniques like RS based statistical yield modelling, machine learning based yield modelling, semi-physical yield modelling are described in the current study. The assessment of the studies related to integration of RS data in crop simulation model is also described in a section. All the techniques involved in the current study show significant improvements in crop yield prediction, enabling the development of new agricultural applications in India.

Keywords: Crop yield, Remote Sensing, Machine learning, Semi-physical model, Assimilation

Agriculture holds profound significance in Indian society, acting as a vital pillar of the nation's socio-economic framework, providing employment opportunities, ensuring food security, bolstering national self-reliance, and contributing to the overall welfare. Given India's recent status as the most populated country in the world, the importance and necessity of agriculture have significantly increased, making the agriculture production crucial for maintaining sustainable balance. Moreover, the indispensable need for timely and reliable information on crop yield is widely acknowledged, playing a crucial role in the tactical and strategic decision-making process among diverse stakeholders in the agricultural domain. These stakeholders include producers, processors, resource managers, marketing entities, financial institutions and government bodies. Accurate crop yield prediction can help the farmers on what to grow and when to grow.

Remote sensing (RS) encompasses a diverse set of techniques that utilize space-based technologies, such as satellites, and ground-based observations at varying altitudes to monitor and assess Earth's resources with greater precision and accuracy. RS technology emerges as an exceptional tool for acquiring repetitive and synoptic observations on the spectral behaviour of the object under consideration, In the context of evolving global market economies, the value of reliable agricultural information has escalated even further. Utilizing RS technology opens up a plethora of applications, encompassing crop area assessment, crop yield forecasting, drought assessment, crop stress assessment, monitoring and managing range and irrigated lands (Sahai & Dadhwal, 1990).

The application of RS data in agriculture has been a primary area of interest ever since the advent of satellite remote sensing. One of the pioneering programs, LACIE (Large Area Crop Inventory Experiment) led by MacDonald & Hall in 1980, initiated a global wave of research on crop mapping, yield estimation, condition assessment, and monitoring. Weiss *et al*. (2020) conducted a comprehensive review of RS applications in agriculture, covering various aspects like land use monitoring, precision farming, and ecosystem services at local to global scales. Furthermore, they identified potential areas for future research. The international community is actively collaborating through cooperative programs such as GEOGLAM to align with the United Nations' sustainability development goals (SDGs) as outlined by Whitcraft *et al*. (2019).

The agriculture application of RS technology in India

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dates back to the year 1969, when under the collaboration of USA and France pioneering work on detection of coconut root wilt disease in Kerala was conducted using aerial platforms. The results of which were presented in the International Astra nautical Federation Congress in Germany in 1970 (Dakshinamurthy *et al*., 1971). Since then, the advancements in RS application of agriculture in India are phenomenal. Until 1982, aerial photography was frequently used for agricultural land use and crop inventory, with major studies covering crops like wheat in Punjab (Dhanju and Shankarnarayana, 1978), groundnut in Andhra Pradesh (Sahai *et al*., 1977), rice and sugarcane in Karnataka and Kerala (Ayyangar *et al*., 1980; Sahai *et al*., 1985).

The work on crop yield prediction and forecasting in India commenced with the launch of the 'Indian Remote Sensing (IRS) Utilization Programme' in 1983, as reported by Navalgund and Kasturirangan (1983). This program encompassed projects focused on crop stress detection and crop yield modeling as preparatory activities for the launch of the IRS satellite (IRS-1A) in 1988. Consequently, a significant number of studies were conducted between 1983 and 1995, utilizing Landsat and IRS series satellites, namely IRS-1A, IRS-1B, and IRS P2, to monitor and assess major crops such as wheat and other crops (Sahai and Dadhwal, 1990).

India's agriculture scenario is characterized by smallholder farming with diverse crops, climates, cultural practices, and socio-economic conditions, making the implementation of remote sensing techniques challenging due to the presence of small fields and significant variability in crops, cultivars, and management practices. The research community is actively working to address these challenges. Recent developments in the field of remote sensing technology, including high-resolution and open-access data, processed multi-date datasets, integration of remote sensing data in crop simulation modeling, machine learning techniques, and the utilization of smartphones for field data collection, are some of the factors driving research advancements. This review incorporates numerous studies that highlight the progress and advancements of remote sensing techniques in crop yield estimation in India.

STATISTICAL CROP YIELD MODELLING

Regional scale crop yield estimation

Various advanced statistical yield modelling approaches being developed for yield prediction of agricultural crops recently. Gontia and Tiwari, (2011) developed a statistical model based on IRS P6 and WiFS dataset for wheat yield simulation in West Bengal. Soil Adjusted Vegetation Index (SAVI) based model was found effective for yield estimation, with an R^2 of 0.92. Dubey *et al*. (2018) developed the Vegetation Condition Index (VCI) based stepwise regression model for sugarcane yield estimation over 53 sugarcane growing districts in 5 states of India. Similarly, Chakraborty *et al*. (2018) developed a RS based-statistical yield model to predict wheat yield in Ganganagar, Hanumangarh and Alwar regions of Rajasthan. They found Vegetation Health Index (VHI) as the most effective variable for crop yield prediction in comparison to Temperature Condition Index (TCI) and Vegetation Condition Index (VCI).

Moreover, coarse resolution satellite data and derived agrometeorological products from geostationary satellites (e.g. INSAT-3D, MSG-SEVIR) are now employed to develop capabilities of regional crop yield prediction. Various satellite based agrometeorological indicators like evapotranspiration (ET), rainfall and soil moisture have been used to explore possibilities of water-production functions in agrometeorological yield modelling. The bivariate regression model based on ET and Normalized Difference Vegetation Index (NDVI) representing the water relation and the spectral behavior of sugarcane crop was found to be the best (r = 0.79) having RMSE of 7.9% in terms of consistency and performances as compared to univariate models that account only spectral behaviour or only water relations (Tripathy *et al*., 2023). It is also observed that inclusion of crop yield response factor and relative ET in water-production function found to be more effective than ET alone in predicting sugarcane yield over Uttar Pradesh, India (Tripathy *et al*., 2023). Air temperature is one of the crucial ''input'' in crop production. Notably, night-time temperature have been identified as a critical determinant in crop yield modelling as reported by Dadhwal *et al*. (2023). The authors developed an empirical statistical model that integrated two key variables: the MODIS – Enhanced Vegetation Index (EVI) and a high-resolution temperature dataset provided by the National Centre for Medium Range Weather Forecasting (NCMRWF). This model was meticulously designed to predict long-term (2001 – 2019) wheat yield at the district level within the Punjab region. The yield model with night-term temperature as one of the predictor along with EVI and average temperature yielded a substantial R^2 of 0.71.

High-resolution or field-scale yield estimation

Besides regional scale yield prediction or estimation, few attempts were also noticed to map field-scale crop yields with either high-resolution satellite imageries or drone-based image acquisitions. Verma *et al*. (2020) evaluated the capability of LISS-IV for sugarcane yield estimation. This study aims to explore the feasibility of estimating sugarcane plant yield through an empirical relationship derived from leaf area index (LAI) and farm-scale sugarcane plant yield. Ground measurements of sugarcane LAI were obtained using the Accupar LP-80 Ceptometer instrument. A strong exponential relationship (R^2 = 0.861) was observed between the ground-measured LAI and the NDVI obtained from the LISS-IV sensor. To develop the yield model, regression analysis was performed using plot-wise yield data and LISS-IV LAI data. This empirical yield model was found to provide a reasonably fair indication (R^2 = 0.714) of the expected yield of sugarcane in advance. Pandey *et al*. (2019) estimated sugarcane yield using Landsat satellite data in Sugarcane mill area in Saharanpur. Yield models were based on multi-date normalized difference vegetation index (NDVI) from Landsat. Stepwise linear regression (SLR), multiple linear regression (MLR) and random forest techniques were followed for yield estimation. The yield models for ratoon cane and planted cane demonstrated significant explanatory power for yield variations, with coefficient of determination (R^2) values of 0.83 and 0.69, respectively. Similarly, predictive functions were established for village-level yield estimates using a monthly composite dataset, yielding R^2 values of 0.83 (P=0.00001) for stepwise regression, 0.792 (P=0.00081) for Multi-Linear Regression (MLR), and 0.466

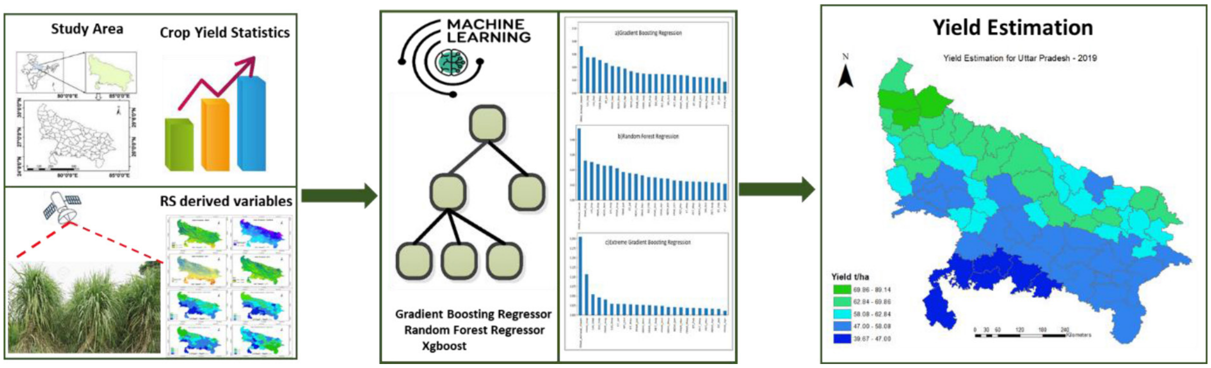

Fig. 1: Schematic representation machine learning for crop yield prediction

(P=0.038) for Random Forest Regression. Kumar *et al.* (2022) have developed empirical models for sugarcane yield prediction in four factory mill areas located in Gujarat and Maharashtra. Their yield model utilized LISS-III based NDVI and water scalar. The simple structured model has proven its ability to effectively predict sugarcane yield two months before harvest. The utilization of Sentinel series, renowned for their high spatial resolution and open accessibility, has demonstrated their efficacy in yield estimation at the field level. Kumar *et al.* (2022) harnessed the seasonal maximum NDVI derived from Sentinel-2 data to forecast maize yield, achieving a remarkable R^2 value of 0.87.

Furthermore, rapid development of near-ground remote sensing from Unmanned Aerial Vehicle (UAV) offering newer dimensions to map crop yields at field-scale and providing technological solutions to crop management and smart-farming. Multispectral camera mounted on UAV can provides various chlorophyll related spectral vegetation indices to map accurately within field variability of crop parameters e.g. Chlorophyll content (Chl), leaf area index (LAI), crop coefficient (Kc) over agricultural crops (Khose *et al.*, 2022; Shanmugapriya *et al.*, 2022; Palanisamy *et al.*, 2023). An Empirical or statistical model developed by relating crop yield against UAV based spectral vegetation indices directly or crop characteristics like Chl and LAI enables within-field yield estimation (Shanmugapriya *et al.*, 2022). This kind of remote sensing finally support adoption of wide-spread application of unmanned aerial vehicle (UAV) based imageries in precision agriculture and farmer-centric agricultural solutions.

CROP YIELD PREDICTION MODELS USING MACHINE LEARNING ALGORITHMS

Crop yield procedures and processes are complex, non-linear, and influenced by a wide range of factors (Dash *et al.*, 2018; Whetton *et al.*, 2017; Wieder *et al.*, 2018). Traditional stepwise calculations or exact equations often fail to model these intricate systems, especially with diverse, ambiguous, or incomplete data. However, recent studies suggest that machine learning algorithms offer promising potential to capture and forecast agricultural outcomes effectively (Johnson *et al.*, 2016; Cai *et al.*, 2018; Pantazi *et al.*, 2016).

Machine learning (ML), a subset of Artificial Intelligence (AI) dedicated to learning from data, offers a practical and effective means of enhancing crop yield prediction through the analysis of various features. By identifying patterns and correlations and extracting knowledge from datasets, ML models can make informed predictions based on historical experiences. During the training phase, these models are fed long term, where the outcomes are represented, allowing them to learn from past examples. The model's parameters are then determined based on this historical data. Subsequently, during the testing phase, a separate portion of the historical data, not used for training, is employed to evaluate the performance of the model. The schematic representation of ML based crop yield modelling is illustrated in Fig. 1

Prasad *et al.* (2020) developed a random forest (RF) based yield model to predict regional cotton yield in 5 districts of Maharashtra. The model was capable to integrate and process a large number of inputs as derived from different satellite modalities. The model overfitting was avoided with maintaining high precision in the model. Furthermore, the efficacy of machine learning techniques has demonstrated significant superiority over multiple linear regression, as evidenced by Palakuru *et al.* (2020) in the case of rice crop and Gupta *et al.* (2022) in the context of wheat crop.

Nihar *et al.* (2022) utilized the four machine learning algorithms like Support Vector Regressor (SVR), Gradient Boosting Regressor (GBR), Xgboost (XGB) and RF for regional sugarcane yield forecasting in Uttar Pradesh. MODIS data products over a period of 18-year period were used to train the machine learning models. The study demonstrated moderate accuracy and was employed to estimate the sugarcane crop yield for the year 2019. The GBR algorithm achieved the highest R^2 value of 0.66 and an RMSE of 7.15 t ha^{-1}, utilizing seven variables and 24 features. The XGB model closely followed with an R^2 of 0.65 and an RMSE of 7.20 t ha^{-1}. Among the features, FPAR-based features showed the most significant contribution to the model, followed by LAI and NDVI features. Krupavathi *et al.* (2022) proposed a field-scale sugarcane yield model using artificial neural network (ANN) technique. They utilized various variables for yield prediction, including multi-date Landsat-8 derived NDVI, APAR, canopy surface temperature and crop water stress index (CWSI). The statistical analysis recommends the reliability of ANN model for sugarcane yield prediction. Rakhee *et al.* (2022) presented a unique approach for rice yield prediction. The authors introduced particle swarm optimization (PSO) technique and finally predicted through Bayesian Neural Network (BNN) model.

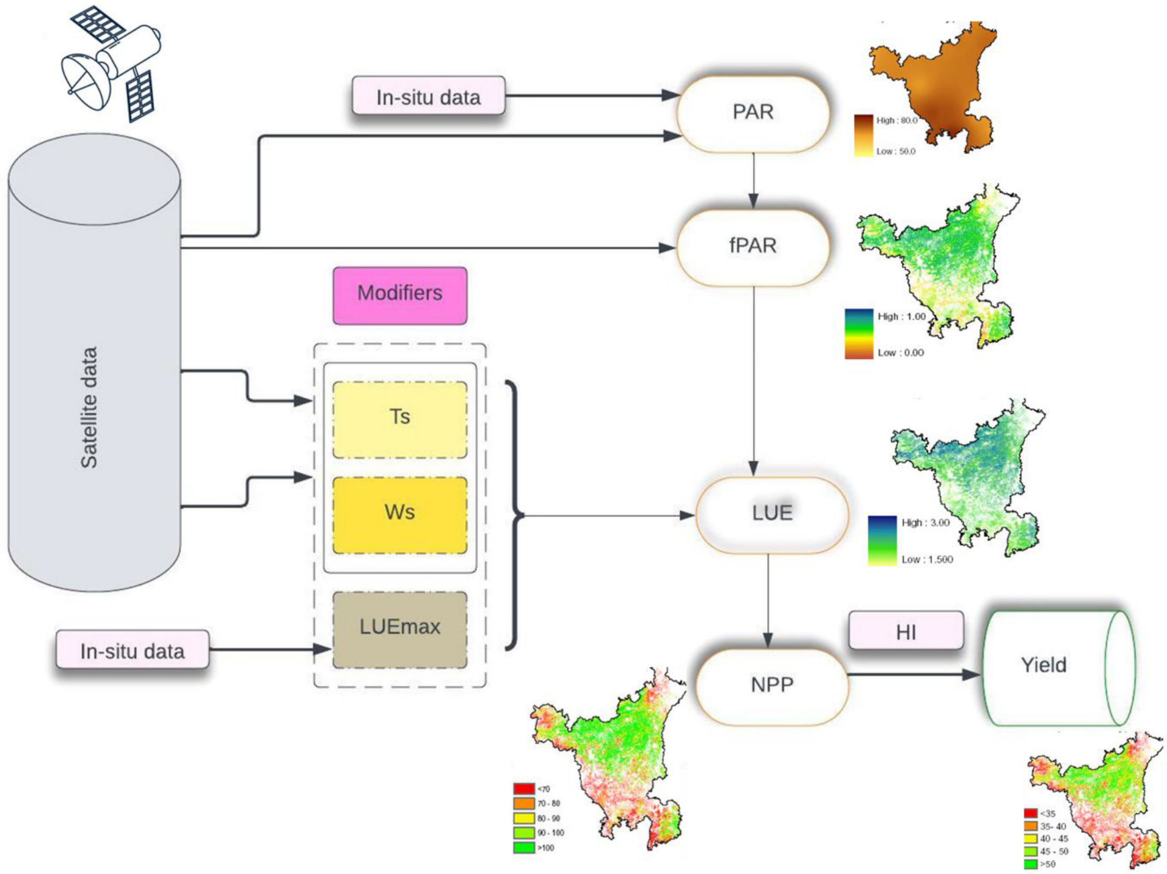

Fig. 2 : Schematic representation of semi-physical (LUE based) model

Agriculture in India relies heavily on monsoons, which can lead to cloud cover and hinder the use of optical data for crop yield predictions, especially during the Kharif season. Therefore, the utilization of microwave datasets along with optical dataset for yield prediction becomes crucial. Pazhanivelan *et al*. (2019) successfully employed the high resolution (3m) COSMO Skymed and TerraSAR X SAR imageries to track rice growth and estimate yield in Tamil Nadu. Yield simulation accuracy levels of 87% at district level and 85 – 96% at the block level demonstrated the suitability of high resolution satellite imagery for rice yield estimation. In another study by Das *et al*. (2023) described a ML based sugarcane yield prediction model using Sentinel 2 and Sentinel 1 dataset. They estimated pre-harvest sugarcane production of four sugar mills in Gujarat and Maharashtra, India for proper planning about intra or inter-regional sugarcane trading. ML algorithms employed in the study include Bayesian Inference, ensemble models such as bagging and boosting. The models developed at the village cluster level, exhibited good prediction accuracies at least 1-2 months before harvesting.

SEMI-PHYSICAL RS-BASED MODEL FOR CROP YIELD PREDICTION

Semi-physical models for crop yield estimation refer to the models that combine both physical and empirical component to predict crop yields. These models take advantage of both the underlying physiological processes of crops and the relationships between crop yields and various environmental factors. Light use efficiency/radiation use efficiency (LUE/RUE) and water use efficiency (WUE) are some of the commonly employed models for crop yield estimation. The LUE model works on the principle developed by Monteith (1972) and Field *et al*. (1995). The schematic representation of LUE based model is illustrated in Fig. 2.

The ratio of cumulative biomass to absorbed photosynthetically active radiation (APAR) is expressed as LUE expressed in g MJ^{-1} (Monteith 1972, Monteith, 1977). The cumulative biomass is gross primary productivity (GPP) up to the physiological maturity. Crop yield is generally estimated based on the product of biomass and harvest index (HI) (Sinclair and Horie, 1989). Hence, a simple GPP model can be adapted to crop yield prediction using Monteith's logic of LUE. The maximum LUE/RUE (LUE_{max}) is the key parameter in the model which is further constrained by water and temperature scalars. Crop yield is generally estimated from the product of above ground biomass (AGB) at physiological maturity and harvest index (*HI*) (Sinclair and Horie, 1989). The AGB is gross primary productivity (*GPP*) upto physiological maturity. A simple *GPP* model was adapted following the Monteith›s (Monteith, 1972) resource capture and crop yield principle. For accurate crop yield prediction, the accurate inputs of LUE_{max} and HI is required. The values of LUE_{max} and HI for different crops are tabulated in Table 1.

Table 1: LUE_{max} and HI values used in LUE model for different crops

Crop	LUE_{max} ($g\ MJ^{-1}$)	HI	References
Cotton	1.53	0.07, 0.12	Prasad *et al.,* (2022)
Wheat	2.02	0.24	Bhattacharya *et al.,* (2011)
Wheat	-	0.24	Dhakore *et al.,* (2011)
Wheat, cotton, rice	Wheat: 3, Rice: 2.2, Cotton: 1.8	-	Tripathy *et al.,* (2022)
Sugarcane	3.22	0.8	Chaurasiya *et al.,* (2017)
Sugarcane	3.22	0.88	Nihar *et al.,* (2023)
C3, C4	C3: 1.388 C4: 1.588	Sugarcane: 0.69, Wheat: 0.6, Cotton: 0.28, Mustard: 0.3, Groundnut: 0.3, Winter rice:0.37, Monsoon Maize: 0.29	Gangopadhyay *et al.,* (2022)

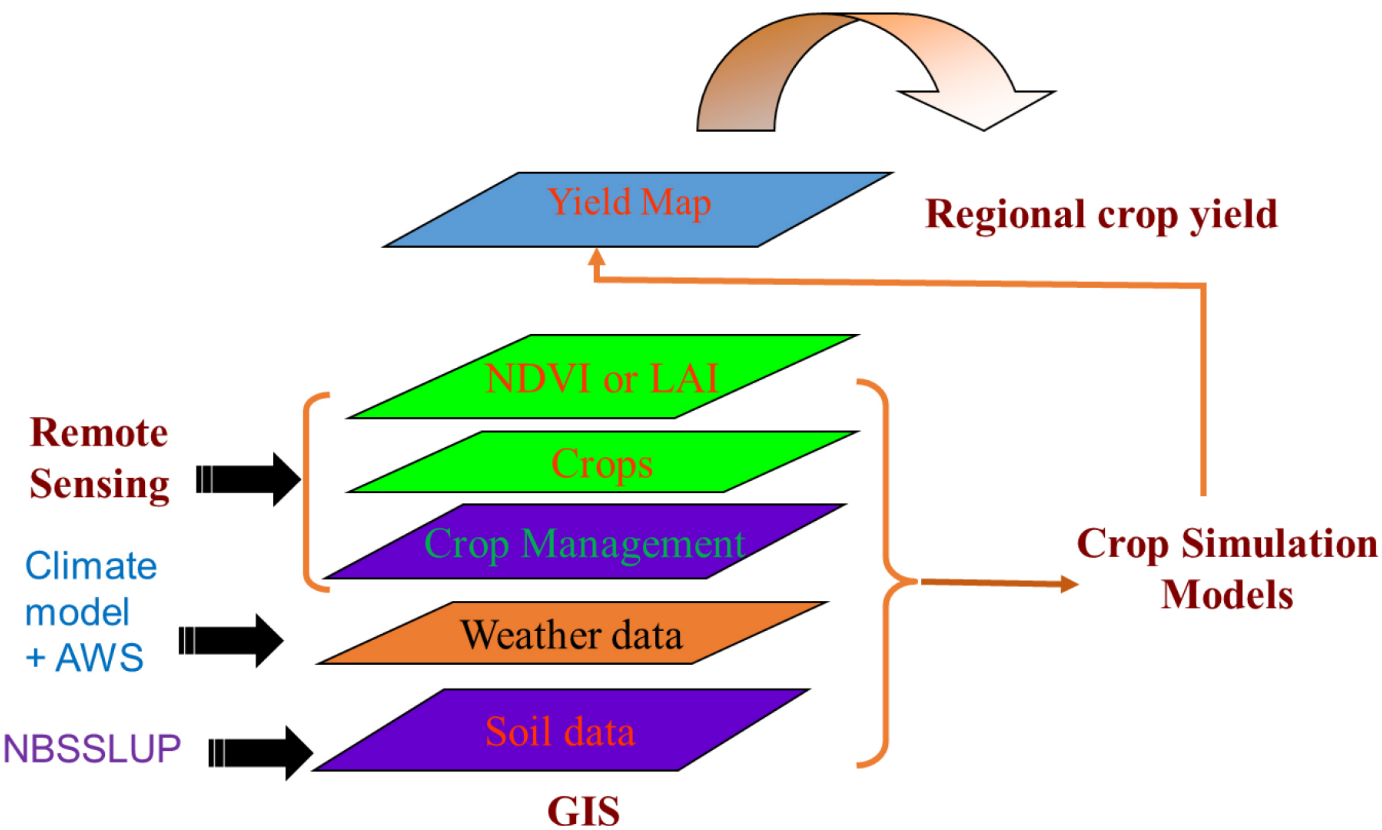

Fig. 3 : Schematic representation of integration of remote sensing data (viz., LAI, NDVI), climate model based data, spatial soil data in crop simulation model for regional crop yield estimation

Bhattacharya *et al.* (2011) developed a LUE based model for pre-harvest wheat yield prediction in Gujarat. The model was based on radiation use efficiency (RUE) and water use efficiency (WUE) approach. RUE require the inputs like PAR, FAPAR while WUE involve actual evapotranspiration, evaporative fraction as inputs. Among both the approaches, the RUE based approach produced better accuracy in wheat yield prediction with higher R^2 (0.92) and lower RMSE (390 kg Hac^{-1}). Dhakore *et al.* (2011) also employed the RUE and WUE approach for wheat yield prediction in Gujarat from 2003-2005. RUE approach was implemented within one of the LUE based model, namely Carnegie-Ames-Stanford Approach (CASA) model. The accuracy of RUE based model was found better with RMSE of 17.7 %. Chaurasiya *et al.* (2017) evaluated LUE model for sugarcane yield prediction in five districts of Uttar Pradesh. Tripathy *et al.* (2022) present a LUE based approach for yield prediction of rice in Cuttack, cotton in Rajkot, and wheat in Fatehabad and Indore by utilizing a multi-sensor data. This method combines geostationary INSAT data for insolation, high temporal MODIS data for phenology and fAPAR (fraction of absorbed photosynthetically active radiation), and Sentinel data for water scalar and crop mapping. Field observed biomass and grain yield from the crop cutting experiment was used to calculate the HI of the respective crop in the respective taluka (Table 1). The study demonstrated that high resolution remote sensing data has immense potential for finer scale yield estimation, which can further be aggregated at gram panchayat and taluka level with satisfactory results. Prasad *et al.* (2022) predicted cotton yield in Maharashtra using the LUE model utilizing the multi-sensor satellite data. The LUE model approach used observed minimum (0.07) and maximum (0.12) lint HI values for cotton yield prediction. The performance of LUE model with HI value of 0.07 was more accurate in terms of low RMSE value of 154 kg hac^{-1}. Gangopadhyay *et al.* (2022) utilized LUE model for yield estimation of C3 and C4 crops for whole India for two decades. Nihar *et al.* (2023) utilized LUE model for sugarcane yield estimation in UttarPradesh using Sentinel-1 and Sentinel-2 data.

INTEGRATION OF RS AND CROP SIMULATION MODELS

Crop growth simulation model (CGSM) describe process of crop growth and development as a function of weather, soil and crop management (Hoogenboom *et al.,* 2004; Jones *et al.,* 2003). CGSMs are extensively used to monitor crop growth and estimate yield. However, they have limitations of applicability at the regional scale due to two main reasons: (1) lack of extensive input data on management practices at the field scale, which requires significant resources to collect, and (2) challenges in validating modeling output regionally. Hence, forecasting yield at regional scale using CGSMs is a significant challenge. In this rescue, RS plays a pivotal role by offering real-time synoptic and repetitive coverage of a geographical area, making it ideal for monitoring crop growth, detecting abiotic stresses and issuing early warning at regional scales. Combining remote sensing data with crop models offers a promising solution for near real-time assessment of crop growth, addressing the shortcomings of each tool and providing both qualitative and quantitative information (Moulin *et al.,* 1988). The schematic representation of integration of remote sensing data into crop weather models is illustrated in Fig. 3.

Crop biophysical parameters play a crucial role in crop simulation models, with leaf area index (LAI) and crop phenology being two common inputs (Sehgal *et al.,* 2005). As shown in the Fig. 2, phenology could be obtained through RS derived vegetation indices like NDVI. Crop Crop simulation model WOFOST have been integrated with RS derived LAI available at 25 km x 25 km for spatial wheat yield prediction (Chaudhari *et al.,* 2010). Mohite *et al.* (2019) successfully parameters derived from Syntehtic Aperture Radar (SAR) from Sentinel-1 satellite into a process-based Oryza crop growth simulation model for rice yield simulation in four districts of Andhra Pradesh. The study employed Sentinel-1 derived start of season and LAI look up table approach to reduce the computational complexity and CGSM time. The overall agreement between observed and simulated yield ranges from 83 – 89%. Through this study, the integration of RS based parameters in CGSM provides fairly accurate yield estimates. Similarly, Pazhanivelan *et al.* (2019) integrated SAR derived seasonal rice area, start of season and backscatter time series in Oryza model for rice yield simulation in Tamil Nadu. Advance assimilation techniques requires a lot of technical knowledge. Dhakar *et al.* (2022) utilized the ensemble Kalman filter assimilation technique to assimilate Sentinel-2A MSI derived LAI in InfoCrop model to improve the field level wheat yield production in Haryana.

Gumma *et al.* (2022) conducted a comprehensive multi-site study during the Kharif season, encompassing rice, groundnut, and maize crops. They utilized multi-date Sentinel-2 and Landsat-8 data to map a wide range of crops, including rice, groundnut, cotton, maize, pigeon pea, and millet, across the study area. To estimate yields, the researchers employed efficient VI-based stratification to identify fields for conducting crop cutting experiments. They assimilated multi-date LAI using LAI-SAVI empirical models into crop simulation models for rice and groundnut yield assessment. Through this approach, the study effectively captured yield variability in the farmer's fields, opening up possibilities for implementing RS-based crop insurance programs for Indian farmers. Milesi and Kukunuri (2022) have reported a successful application of the terrestrial observation and prediction system (TOPS) approach for crop yield estimation to support a crop insurance scheme at the gram panchayat level. They conducted a case study on pear millet in Faizabad district of Uttar Pradesh and rice in Kendujhar district of Odisha. Overcoming the challenge of crop discrimination and mapping during the monsoon season, they employed a combined use of SAR and optical data.

Integrated approaches having combination of geospatial data (remote sensing, soils, topography), climate models (WRF or RegCM) and crop simulation models for major staple crops like wheat and rice (DSSAT family) has been tested over Punjab and Haryana for advance lead-time crop yield predictions and developing early warning indicators of drought (Kirthigha and Patel, 2022; Rajasivaranjan *et al.,* 2023). Integrated climate-crop modelling of wheat inferred that wheat crop yield predicted 30-45 days in advance with more than 0.9 agreement index in spatially explicit manner. (Kirthigha and Patel, 2022; Rajasivaranjan *et al.,* 2023)

LIMITATIONS

Statistical regression yield models are the simple and straightforward models, and often require recalibration using new field measurements for new locations. Similarly, the accuracy of semi physical models are based on the parameterization of HI. It varies over time and even among cultivars and is a determining factor in the yield formation process. This suggests that the estimation of HI from satellite data needs to be further explored. In case of the ML based yield modelling, appropriate algorithms and feature engineering should be carefully compared and designed to improve the overall performance of the model (Wu *et al.,* 2023). The role of hyperspectral remote sensing and unmanned aerial vehicle is not explored for crop yield estimation in India. Moreover, there is a need to explore novel sensors for crop yield prediction, particularly focusing on geometric structures capable of simultaneous observations n optical, SAR, and thermal infrared bands with narrow spectra and multi-view azimuth angles. Such sensors would enable more precise measurements of phenotypic characteristics associated with the physiological processes of crops at the canopy, field, and regional levels.

CONCLUSIONS

The advanced technologies are being effectively used for crop yield prediction in India, drive by the availability of open-source satellite data like Landsat series, Sentinel series. The integration of ML techniques, spatial databases, crop simulation models further indicates for readiness to improve crop yield prediction using advanced technologies. However, current satellite-derived crop monitoring approaches still face challenges in providing near-real-time, reliable, and quantitative crop information despite the absence of data and processing constraints. To address these challenges, there is a need to explore satellite data for a better understanding of crop production determinants and to improve analytical capacities to translate metrics into useful knowledge for stakeholders. Moreover, to enhance automated crop yield monitoring, studies need to extend to more crops and regions while refining application system design for cost-efficiency and accuracy.

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