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Rice yield estimation through semi-physical model: A case study in Mahabubnagar District, Telangana

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Abstract
The study was conducted in Mahabubnagar district, Telangana, during *kharif*, 2024, where accurate rice yield estimation is crucial for food security planning and agricultural management, particularly under diverse agro-climatic conditions and fragmented landholdings. A semi-physical model (SPM) was adopted, integrating multi-source datasets: Sentinel-1 synthetic aperture radar (SAR) and Sentinel-2 NDVI for rice area mapping, meteorological inputs (rainfall, temperature, solar radiation), and physiological crop parameters. Sentinel-1A backscatter data were processed using temporal filtering and supervised machine learning (Random Forest) classification, combined with Sentinel-2A/2B optical data, to delineate rice cultivation areas with an accuracy of 98.33% and a kappa coefficient of 0.97 during the *kharif* season, showing only a 0.76% deviation from district statistics.

Rice yield estimation was driven by net primary productivity (NPP), derived from meteorological and crop growth parameters, then converted to grain yield using a crop-specific harvest index. Calibration and validation with ground-truth field survey data yielded strong predictive performance ($R^2 = 0.79$, RMSE = 1159 kg ha^{-1}, nRMSE = 24.19%), demonstrating the model's effectiveness in capturing spatial and temporal yield variations at the regional scale.

Keywords: Sentinel-1A, random forest, crop area estimation, yield estimation, semi physical model

1. Introduction

Rice is the principal staple crop in India, playing a central role in national food security and rural livelihoods. Yield estimation at regional scales is essential for crop insurance, procurement planning and food supply management. In districts like Mahabubnagar, Telangana, where rice is cultivated under diverse irrigation and soil conditions, traditional crop cutting experiments (CCEs) are often insufficient due to logistical challenges and limited spatial coverage (Dwivedi *et al.*, 2019) [3]. To overcome these limitations, remote sensing and modelling-based approaches are increasingly being used for yield estimation.

Semi-physical models have emerged as a promising approach that balances empirical and process-based techniques. These models simulate net primary productivity (NPP) by incorporating physiological parameters such as photosynthetically active radiation (PAR), radiation use efficiency (RUE) and temperature stress functions. The resulting NPP is converted to crop yield using crop-specific harvest index (HI) values (Monteith, 1972; Field *et al.*, 1995) [10, 4]. Unlike fully mechanistic crop models, semi-physical model require fewer inputs while still capturing key biological processes, making them well-suited for large-scale, data-sparse regions.

The use of remote sensing, especially the combination of Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 optical sensors, enables accurate crop area delineation and monitoring. Sentinel-1 SAR data provide robust, cloud-penetrating imagery critical during the monsoon (*kharif*) season, while Sentinel-2 imagery captures vegetation indices such as NDVI that correlate with chlorophyll content, canopy structure and biomass (Veloso *et al.*, 2017; Pazhanivelan *et al.*, 2022) [17, 13]. Integration of these sensors allows for improved spatial mapping of paddy fields, even in fragmented and mixed cropping landscapes (Mansaray *et al.*,2019) [9].

Several studies have demonstrated the value of such approaches in India and globally. Jain *et al.* (2016) used MODIS-based NDVI time-series and semi-empirical models for large-scale rice yield prediction in eastern India. Dwivedi *et al*. (2019) [3] combined crop growth simulation and remote sensing to estimate rice yield in the Indo-Gangetic plains. Pazhanivelan *et al*. (2022) [13] illustrated how the fusion of Sentinel-1 and Sentinel-2 improved crop area and yield estimation in Tamil Nadu. These studies reinforce the reliability and scalability of combining physiological modelling with satellite observations for operational crop monitoring.

This study aims to apply a semi-physical model for rice yield estimation in Mahabubnagar district, integrating Sentinel-1 and Sentinel-2 data for accurate rice area mapping. The model uses PAR-based NPP estimation, calibrated with meteorological inputs and field-measured yield data. The overarching goal is to provide a scalable, cost-effective and timely yield estimation framework for district-level agricultural monitoring in India.

2. Study area

Rice is the major crop predominantly cultivated in Mahabubnagar district of Telangana state. The study area is Mahabubnagar district of Telangana covering 16.737509° N latitude, 78.008125° E with altitude of 490 m which is shown in Fig 1.

Mahabubnagar district in Telangana is predominantly covered by two major soil types: red sandy soils (Alfisols) and black cotton soils (Vertisols). Alfisols, found mainly in upland areas, are well-drained but low in organic matter and water-holding capacity, making them suitable for rainfed crops like groundnut, millets, and pulses. In contrast, Vertisols are deep, clay-rich soils with high fertility and moisture retention, ideal for crops such as cotton and paddy, though they pose challenges due to their swelling and cracking nature. The region receives an average annual rainfall of 600 to 750 mm, primarily during the southwest monsoon season from June to September, which plays a crucial role in sustaining agriculture. However, the reliance on monsoonal rains also makes farming in the district vulnerable to rainfall variability and dry spells, particularly in rainfed areas.

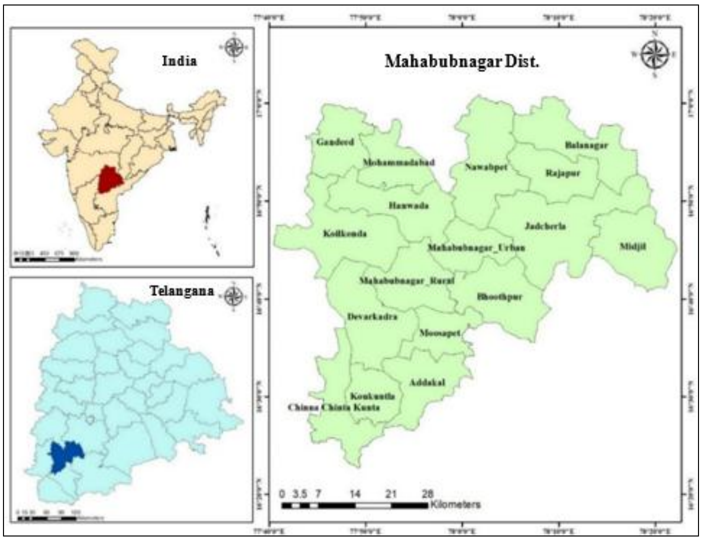

Fig 1: Study area is Mahabubnagar district, Telangana state, India.

3. Data used

The basic input data required for model development are photosynthetically active radiation (PAR), fraction of absorbed photo synthetically active radiation (faPAR), temperature stress, water scalar and harvest Index (HI) data will be used for yield estimation. Details of data product, satellite and sources are given below in Table 1.

Table 1: Details of data product, satellite and source taken for semi physical model

Data / Product	Satellite/ Ground	Sensor	Resolution	Source
Daily integrated Insolation (PAR)	INSAT 3D	Imager	4 km	MOSDAC
8-days composite faPAR	Terra Sentinel 3	MODIS OLCI	0.5 km 0.3 km	NASA-EARTHDATA ESA
8-days composite surface reflectance	Terra Sentinel 2	MODIS MSI	0.5 km 10-20 km	NASA-EARTHDATA ESA
Crop Mask	Sentinel 1 Sentinel 2	SAR MSI	20 m 10 m	Downloaded satellite data from Copernicus and developed crop mask
Crop Sowing Date	Ground Data	-	Mandal level	Farmer interview during the field visit
Harvest Index	Ground CCE data	-	Mandal level	Crop cutting experiment conducted
Daily Tmin and Tmax	Gridded data	-	10 km Grid	NASA Power

4. Methodology

4.1 Downloading and pre-processing of Sentinel -1A SAR data

The Sentinel-1A satellite images covering the study area were obtained from the European Space Agency's (ESA) Copernicus Data Space Ecosystem. Multi-temporal images collected between June and November, 2024 were pre-processed using SNAP software.

4.1.1 Pre-processing of Sentinel -1A SAR data

The SNAP software is utilized to pre-process Sentinel-1A satellite SAR data. Due to the large volume of Sentinel SAR data, extensive processing is required to eliminate noise and correct errors, thereby enhancing data quality. The pre-processing workflow includes radiometric calibration, speckle filtering (using the Refined Lee filter) and terrain correction.

Batch processing was employed to pre-process the satellite data using the Batch Processing Module within SNAP's Graphical Builder. Radiometric calibration was performed to generate sigma naught (σ°) images. To reduce speckle noise, the Lee Sigma filter with a 5x5 kernel was applied. Range Doppler Terrain correction was conducted using SRTM DEM to correct for geometric distortions due to topography. Finally, the processed data were converted from linear scale to decibels (dB).

4.2 Computation of NDVI

NDVI was computed from the Sentinel - 2A/2B optical data for the month of September, October and November, 2025. The formula for NDVI is given below:

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + \mathrm{RED})}$$

4.3 Crop area estimation using supervised machine learning algorithm

Crop area was mapped using a supervised machine learning algorithm (Random Forest) applied to multi-source remote sensing datasets. Synthetic Aperture Radar (SAR) imagery from Sentinel-1A (VV & VH polarizations) was employed to capture key surface properties, including vegetation structure, soil moisture and surface roughness. These SAR datasets were further enhanced by incorporating optical data from Sentinel-2A and 2B platforms. A total of 15 layers were stacked six images of VV polarization, six images of VH polarization and three NDVI from September, October and November month.

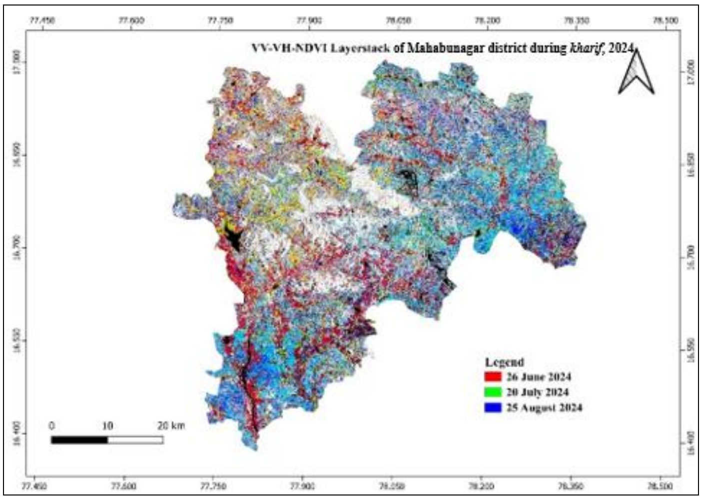

Fig 3: VV, VH and NDVI layer-stacked image for Mahabubnagar district *kharif*, 2024

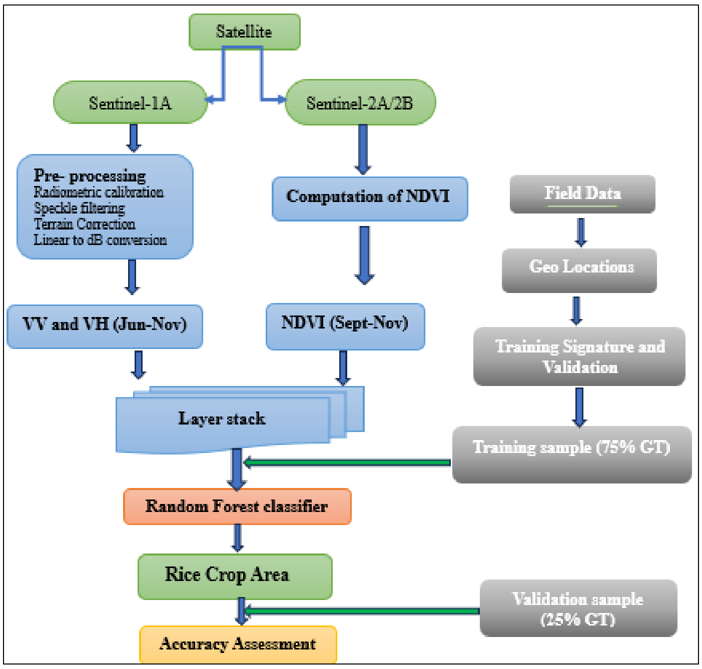

Fig 2: Flow chat for SAR data processing and crop area estimation

Supervised machine learning using the Random Forest (RF) algorithm was implemented in ArcMap 10.5 with threshold values derived from temporal backscatter signatures and texture metrics to classify land cover types such as cropland, water bodies, urban areas, and natural vegetation (e.g., scrub and forest). These decision rules effectively captured crop-specific spatial and temporal patterns, enabling accurate identification of agricultural areas.

To improve classification accuracy and validate initial results, the RF model was further trained using ground-truth data combined with multi-temporal SAR and optical imagery. This approach facilitated more precise mapping and delineation of crop zones across the study region.

4.4 Yield Estimation

A semi-physical model is a hybrid modelling approach that combines fundamental physical principles with empirical data or observed relationships to simulate real-world processes more accurately. Unlike pure empirical models that rely solely on statistical correlations, semi-physical models incorporate known physical laws such as radiation use, energy balance, or crop growth dynamics and enhance them through calibration with observed data. This approach offers a balance between theoretical understanding and practical applicability, making it especially useful in crop yield estimation. Each component of the semi physical model is described below.

Photosynthetically Active Radiation (PAR)

Photosynthetically Active Radiation (PAR) refers to the portion of electromagnetic radiation that green plants utilize as an energy source for photosynthesis ($MJm^{-2}\ d^{-1}$). PAR was generated for the study area from INSAT 3DR INSOLATION data retrieved from MOSDAC data portal. After downloading the insolation data PAR was calculated using the formula:

PAR = Daily Surface Insolation × 0.48

The daily data was combined to prepare 8-day composites of PAR by summing up the daily insolation for the entire crop growth period in the study area.

Fraction of Photosynthetically Active Radiation

The fAPAR represents fraction of solar radiation absorbed by active, green leaves for photosynthesis, focusing solely on the living components of the canopy. It indicates the vegetation canopy's ability to absorb energy and serves as a key physiological indicator of vegetation structure, as well as related material and energy exchange processes. This parameter plays a crucial role in estimating plant biomass. MODIS15A2H data have been downloaded. The 8-day composites of fAPAR were generated for the study region after multiplying with the scale factor and extracting the sub dataset.

Water Stress (WS)

The land surface water index (LSWI) was employed in modelling to capture canopy water stress, helping to reflect the impact of moisture stress on plants. It was calculated using reflectance values from the Near-Infrared (NIR) and Short-Wave Infrared (SWIR) bands, especially around the 2120 nm wavelength. LSWI is particularly responsive to the presence of vegetation water content and underlying soil background.

$$LSWI = \frac{NIR - SWIR}{NIR + SWIR}$$

The calculated LSWI was subsequently used to determine the water stress scalar following the equation provided by Xiao *et al.* (2005) [18].

Water Stress (Water Scalar) = 1+LSWI/1-$LSWI_{max}$

This calculation for Water Stress was performed for the entire crop growth period across the study area.

Temperature Stress (TS)
Daily temperature records for the crop growing season were obtained from the NASA POWER web portal. Air temperature, maximum temperature and minimum temperature at 2 m height (°C) were used to generate 8-day composite temperature stress datasets aligned with the corresponding Julian dates. Temperature stress was then computed using the equation proposed by Raich *et al.* (1991) [15].

$$\text{Temperature stress} = \frac{[(T-Tmin)(T-Tmax)]}{(T-Tmin)(T-Tmax)-(T-Topt)^2}$$

Where, T = the daily mean temperature (°C); Tmin = minimum temperature for photosynthesis (°C); Tmax = maximum temperature for photosynthesis (°C); Topt = optimal temperature for photosynthesis (°C), Topt was taken as 30°C (optimum temperature for rice crop). Jha *et al.*, 2022 [7] used 30°C as optimum temperature for rice yield estimation using semi physical model.

Radiation Use Efficiency (RUE)
RUE, indicates how efficiently a crop converts absorbed radiation into dry matter, varies by variety and growth stage. The RUE was calculated with the CCE data using the following formula:

$$\text{RUE } (gMJ^{-1}) = \text{Biomass } (gm^{-2}) \,/\, \text{PAR } (MJm^{-2}day^{-1})$$

Net Primary Product (NPP)
The NPP is the dry matter accumulated in plant over a period of time ($gm^{-2}d^{-1}$) in semi physical model was determined by the total amount of photosynthetically active radiation (PAR) and the plant's capacity to absorb this radiation (fAPAR) and convert it into dry matter through Radiation Use Efficiency (RUE). RUE represents how effectively a plant transforms absorbed radiation into biomass. The overall biomass is estimated using the following formula:

$$NPP(Biomass) = RUEmax \times \sum_{Sowing}^{Harvest} (PAR \times fAPAR \times WS \times TS)$$

The NPP was calculated for 8-day composite corresponding to the Julian dates of other datasets and then all the NPP was summed up to get the final NPP(Biomass). Once, the crop biomass was estimated the crop yield was estimated using the harvest index obtained during the crop cutting experiment.

$$HI = \frac{Grain\ Weight(kg/ha)}{Straw\ Weight\ (kg/ha)}$$

Finally, the yield is calculated for the study area by multiplying the net primary product with the harvest index.

$$Yield\ (kg/ha) = NPP(Biomass) \times HI$$

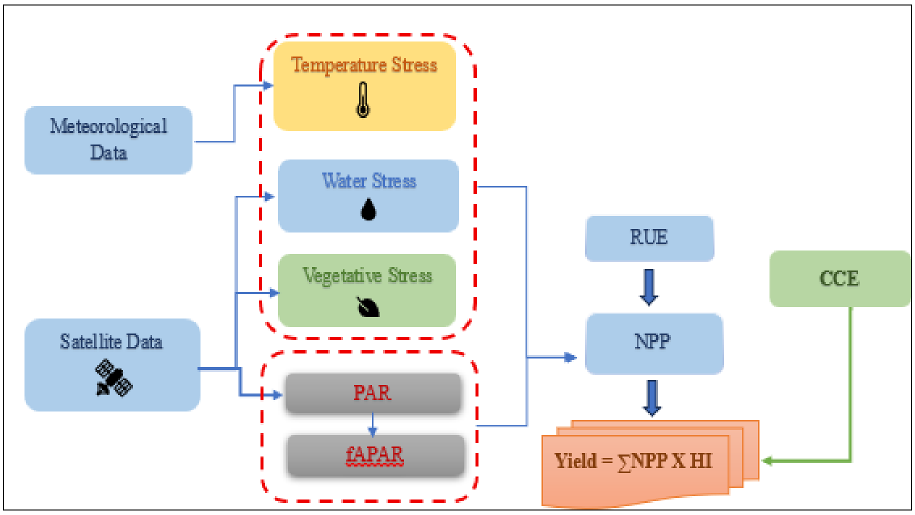

Fig 4: Methodology adopted for Yield Estimation using semi physical model

Validation
The yield estimates from this model were evaluated by comparing the estimated *kharif* rice yield with the crop cutting experiments.

Results and Discussion
Crop Area Estimation
In Mahabubnagar district, crop area was estimated for the *kharif* season, 2024 using time-series C-band SAR and optical data. This included dual-polarization backscatter measurements (VV and VH) from Sentinel-1A along with NDVI derived from Sentinel-2A/2B MSI imagery. The ground truth points were collected during the field survey and those points were used to extract the SAR backscatter (dB) values during the crop growth period. The temporal crop signatures were then generated for each training site by extracting the mean dB values of rice crop at the field level, corresponding to different crop management stages initial land preparation, sowing, peak vegetative growth, reproductive phase and final harvest. These signatures were then analysed to discriminate the crop.
During the initial transplanting phase of the rice crop, the backscatter values were at their lowest, with VH ranging between -21.43 and -20.42 dB, mainly due to the waterlogged conditions of the fields. As the crop progressed to the maximum tillering stage, these values rose markedly, corresponding to the increase in biomass, with VH values spanning from -18.46 to -15.84 dB. By the maturity stage, backscatter values decreased again, indicating a reduction in canopy moisture and structural alterations, with VH values between -17.63 and -16.56 dB. Similar patterns were observed by Bharothu *et al.* (2025) [2].

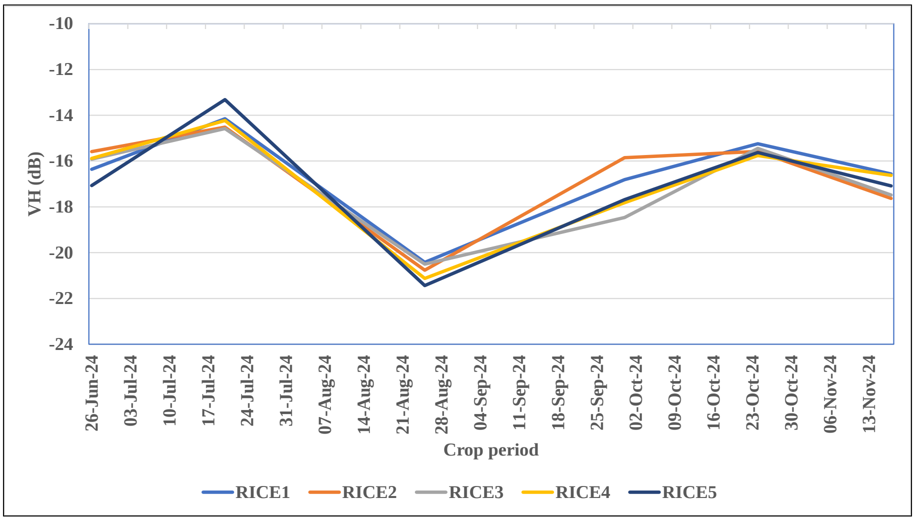

Fig 7: Time-series of VH temporal profiles for rice crop

The rice acreage map has been generated with supervised classification. From classification of satellite data, it was found that the estimated and reported area of rice was found to be 76,577 ha and 75,993 ha, respectively in the *kharif* season 2024. Thus, the estimated area is 0.76% higher than the actual area. The overall accuracy and kappa coefficient were 98.33% and 0.97 respectively.

Similarly, Bharothu *et al.* (2025) [2] mapped *kharif*-season cotton, rice, and maize in two mandals of Nagarkurnool district, Telangana, using Sentinel-1A SAR data (June-December 2023). The Random Forest classifier with VH polarization delivered the highest performance, achieving 94.44% overall accuracy (kappa 0.91) and closely matching official crop area records. Comparable results were also found by Neelima *et al.* (2022) [11] and Bhargav *et al.* (2022) [1].

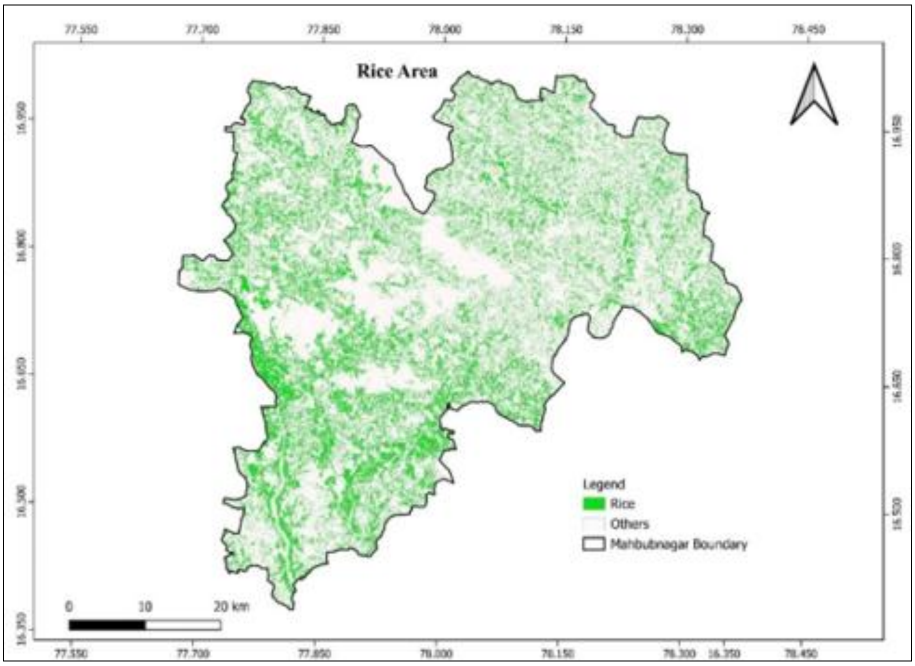

Fig 6: Rice area map of Mahabubnagar district during *kharif*, 2024

Yield Estimation by Using a Semi-Physical Model (SPM)

In this model the yield was estimated using PAR, fAPAR, water stress and temperature stress were used as a component that were affecting the yield of rice crop. PAR was downloaded from the MOSDAC portal INSAT 3DR satellite data and insolation was converted to PAR by multiplying with 0.48 and then 8-day composites were generated. PAR, which plants absorb to drive photosynthesis, serves as a key indicator of crop growth throughout different stages (Kshetrimayum *et al.*, 2024) [8].

PAR values in the study area ranged from 8.2 to 81.1 MJm^{-2}, with the highest values in October 2024 (73.34 to 81.1 MJm^{-2}) and the lowest in November 2024 (8.2 to 8.6 MJm^{-2}), likely due to decreased solar radiation. Similar results have been found by Dwivedi *et al.*, 2019 [3] assessed SPM for rice yield estimation for during *kharif*, 2018 and found out that the PAR values ranged from 34 to 189 MJm^{-2} during August across India.

fAPAR represents the actual fraction of PAR absorbed by crops and provides near real-time insights into crop health and development during the growing season. The fAPAR ranged between 0.2 to 1 in the study area. For water stress satellite data MODIS MOD09A1 dataset (8-day composite) was downloaded and then LSWI was computed. From the LSWI water stress was computed for the entire crop growth period across the study area and its value ranged from 0.3 to 0.8. Jha *et al.* (2022) [7] assessed a semi-physical model for estimating rice yield and reported the water stress values varied between 0.679 and 1.

Temperature stress in 8-day composites was computed from the temperature data acquired from the NASA power and its value ranges from 1: no stress to 0: maximum stress Tripathy *et al.* (2014) [16]. In the study area, temperature stress values ranged from 0.87 to 0.99. No significant temperature stress was recorded in June 2024 (0.99), whereas the highest stress occurred in August 2024 (0.87).

Net Primary Productivity (NPP) is influenced by multiple factors, including Photosynthetically Active Radiation (PAR), the fraction of PAR absorbed by vegetation (fAPAR), Radiation Use Efficiency (RUE) and the effects of water and temperature stress. In the present context, estimation of rice yield is strongly dependent on the availability of PAR and the crop's RUE. While PAR drives photosynthesis, RUE determines how effectively that energy is utilized for biomass formation. Variability in these parameters accounts for the yield differences observed at the mandal level. NPP happens to be a profound parameter from the perspective of yield for any crop (Tripathy *et al*. 2014) [16].

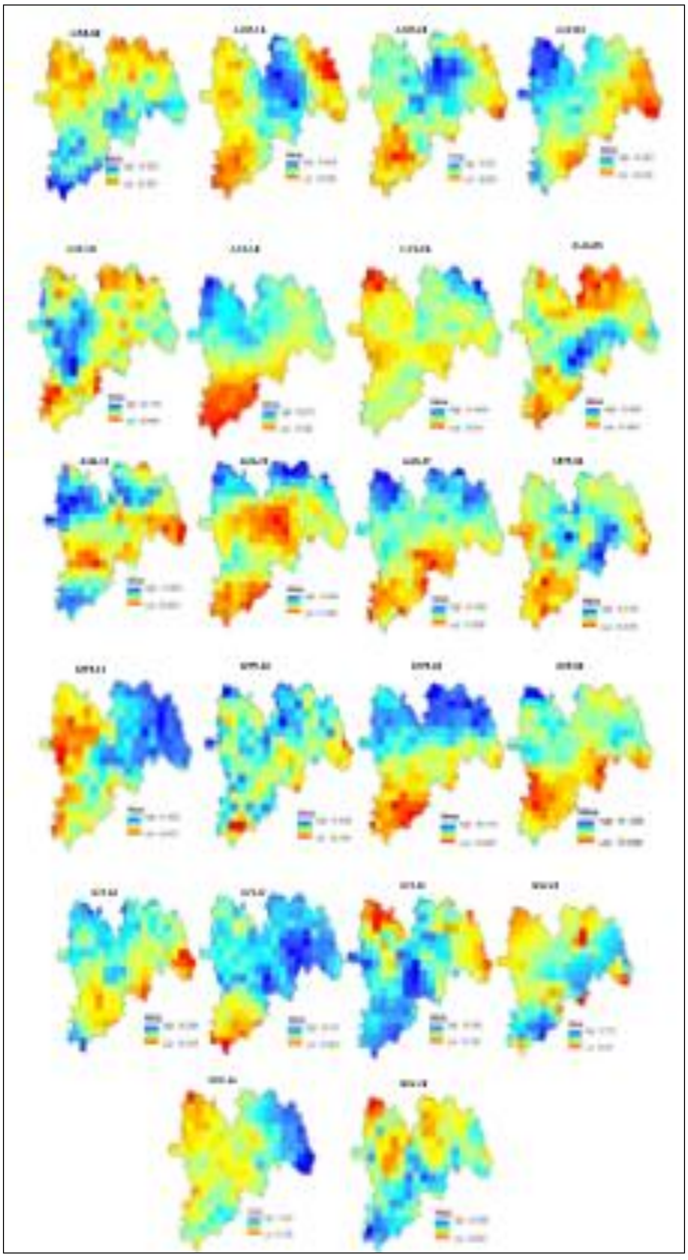

Fig 8: 8-day composite PAR maps for Mahabubnagar district during *kharif*, 2024

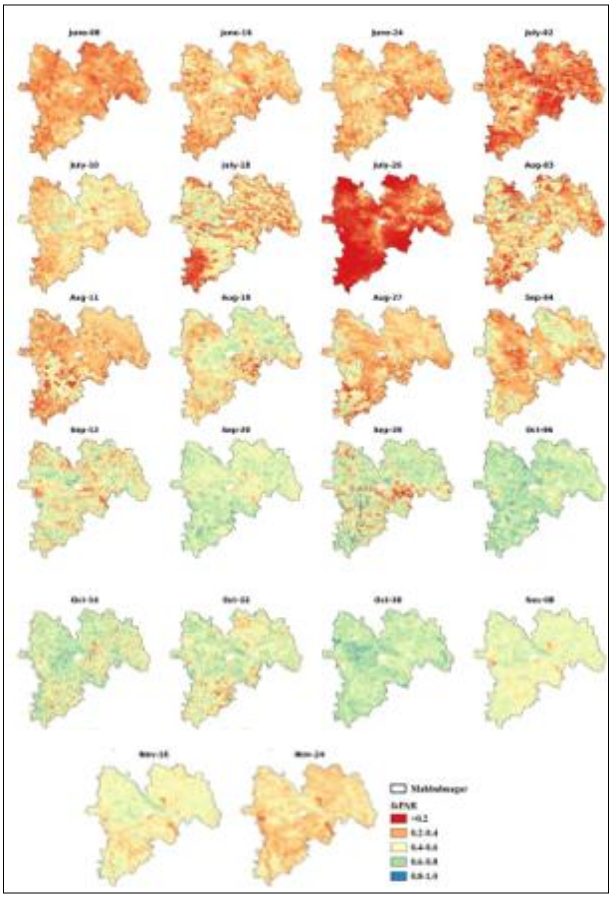

Fig 9: 8-day composite fAPAR for Mahabubnagar district during *kharif*, 2024

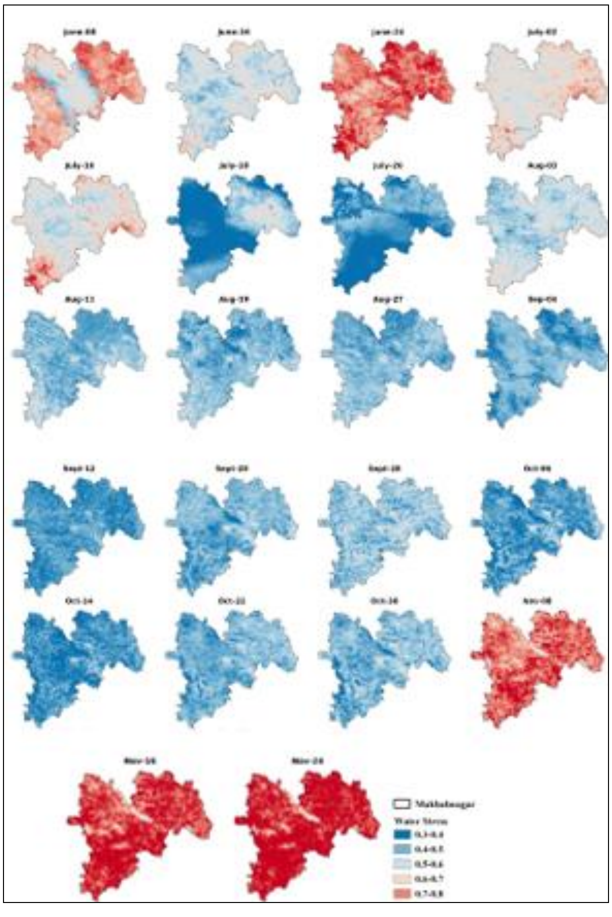

Fig 10: 8-day composites of water stress for Mahabubnagar district during *kharif*, 2024

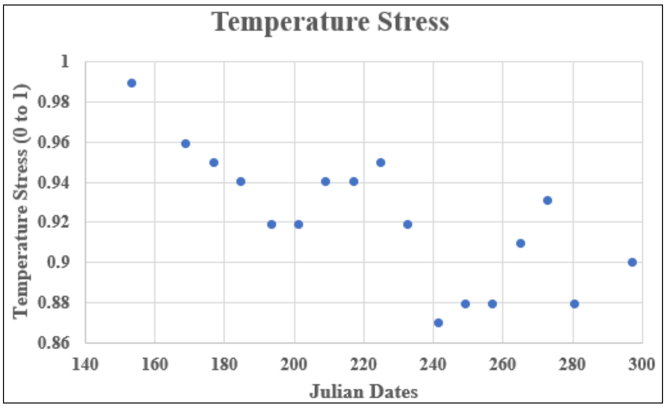

Fig 7: Temperature Stress in Mahabubnagar district during *kharif*, 2024

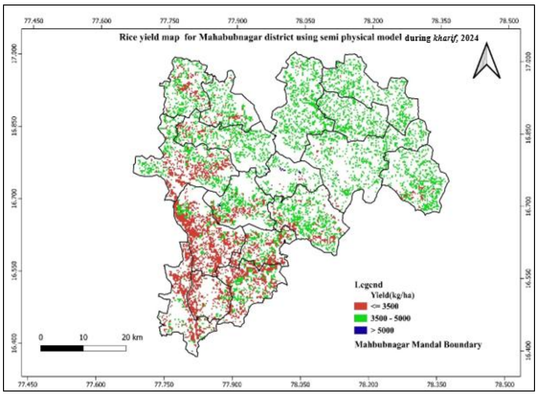

Fig 11: Rice crop yield map of Mahabubnagar district during *kharif*, 2024

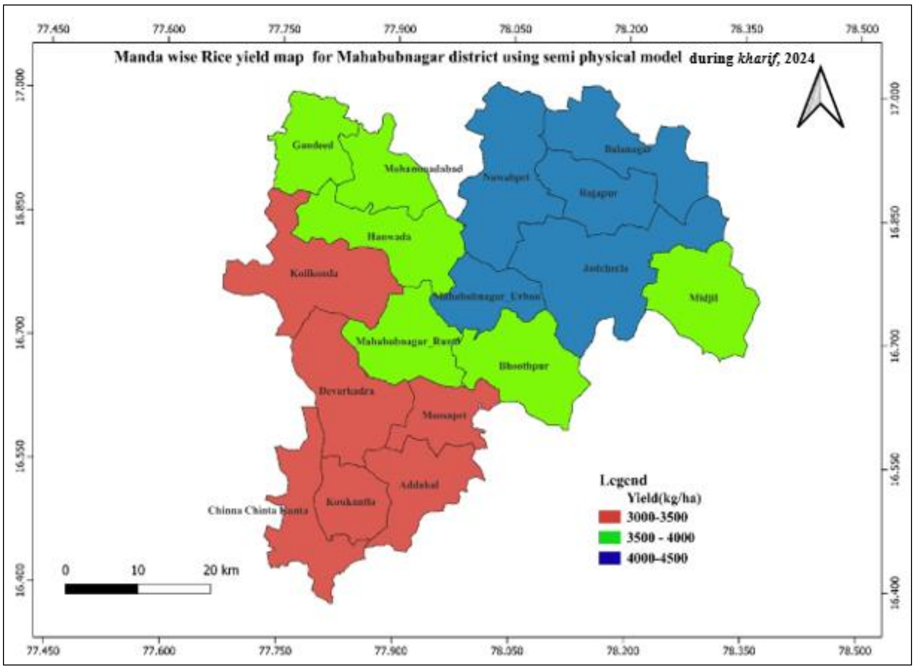

Fig 12: Mandal average yield of Mahabubnagar district during *kharif*, 2024

Validation of rice yield

The yield was validated with the yield from crop cutting experiment conducted during the season. A total of 20 CCE was conducted across three mandals i.e., Nawabpet, Koilkonda and Devarkadra and the mandal average yield was compared with the model yield.

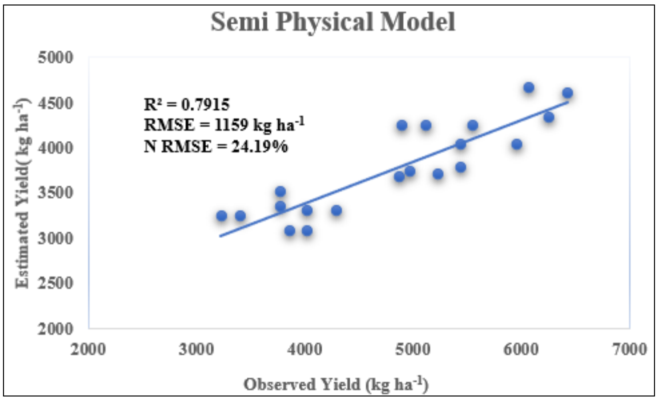

Fig 13: Comparison of rice crop observed and estimated yield

The model achieved a good predictive performance with an R^2 of 0.79, RMSE of 1159 kg ha^{-1} and nRMSE of 24.19% demonstrating its reliability in capturing spatial and temporal yield variations. The study demonstrates the model's potential to accurately estimate paddy yield at the mandal level. It also enables the generation of spatial yield maps for *kharif* rice. Similar results were found by Pazhanivelan *et al*. (2020) [13] estimated rice yield in Tamil Nadu's Cauvery delta for the 2020-2021 samba season using Sentinel-1A SAR data and a semi-physical model. Average yield was 3076 kg ha^{-1}, with Thanjavur recording the highest (3438 kg ha^{-1}). Yield estimates showed strong agreement with observed data ($R^2 = 0.78$, RMSE = 532.74 kg ha^{-1}, nRMSE = 14.52%). Comparable results were also found by Gumma *et al.* (2024) [5], Jha *et al*. (2022) [7], Tripathy *et al.* (2014) [16] and Dwivedi *et al*. (2019) [3].

A major share of this error can be traced to the coarse spatial resolution of the satellite imagery that supplies key biophysical inputs such as PAR and fAPAR. In Mahabubnagar, rice fields are typically small and fragmented, which poses a challenge when using satellite data with coarser resolutions. These pixels often cover more than one field or even different crops, resulting in mixed pixel effects. Similar results were found by Peng *et al.* (2014) [14]. This blending of spectral information masks the actual variability in plant density, nutrient levels, and crop condition across individual fields. As a result, the semi-physical model which relies on these satellite-derived data to estimate biomass and yield introduces a systematic bias. Areas with healthy, vigorous crops may be underestimated, while those under stress may be overestimated. This averaging effect increases the RMSE by distorting actual yield values, even though the overall spatial trend (as reflected by a high R^2) remains consistent.

Error is compounded by the model's simplified representation of water stress. Many semi-physical frameworks infer water limitations from meteorological water stress indices that ignore fine-scale irrigation patterns. In practice, farmers in the command areas partially or fully offset rainfall deficits through canal or tube-well irrigation, particularly during the sensitive reproductive window. If the model penalizes growth during periods when the crop was actually well watered or if the stress coincides with phenological stages that are inherently more tolerant, the simulated yield will be systematically depressed relative to CCE measurements.

Phenological mis-calibration and varietal specificity add a third layer of uncertainty. Growth-stage timing determines how strongly the crop responds to solar radiation and water deficits. When transplanting dates differ across villages or when short-duration varieties like RNR 15048 are widely used, relying solely on remote sensing without incorporating local phenology and variety-specific parameters can misrepresent stress periods and radiation-use efficiency and harvest index peaks. As a result, even an accurate satellite-based depiction of crop greenness may fail to translate into precise grain yield estimates. Similarly, Gumma *et al*. (2024) [5] found that semi physical model cannot adapt to dynamic and rapidly changing environmental conditions, potentially impacting their overall adaptability.

Conclusion

In this study, rice acreage map for Mahabubnagar district was generated by integrating microwave and optical remote sensing data from Sentinel-1A and Sentinel-2A/2B satellites. The area estimation exhibited a marginal overestimation of 0.76% compared to official statistics. Using the Monteith (1977) [10] approach, a semi-physical spectral yield model was applied to estimate the Net Primary Productivity (NPP) of kharif rice.

At the mandal level, the model achieved an RMSE of 1159 kg ha^{-1}, indicating a moderate deviation from crop-cutting experiment (CCE) yields. Results underscore that rice yield is primarily influenced by absorbed photosynthetically active radiation (APAR), with Radiation Use Efficiency (RUE) and Harvest Index (HI) derived from field measurements playing a significant role in overall productivity. The approach demonstrated the capability to provide kharif rice yield estimates by September with approximately 75% accuracy.

Observed discrepancies may be attributed to the coarse resolution of satellite imagery, which can mask field-scale variability in crop growth and management. Additionally, the model may have overestimated the effects of water stress by not fully accounting for supplemental irrigation or less sensitive crop stages. Future improvements should focus on integrating higher-resolution datasets, refining phenological calibration and incorporating local agronomic and irrigation practices to enhance yield estimation accuracy.

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