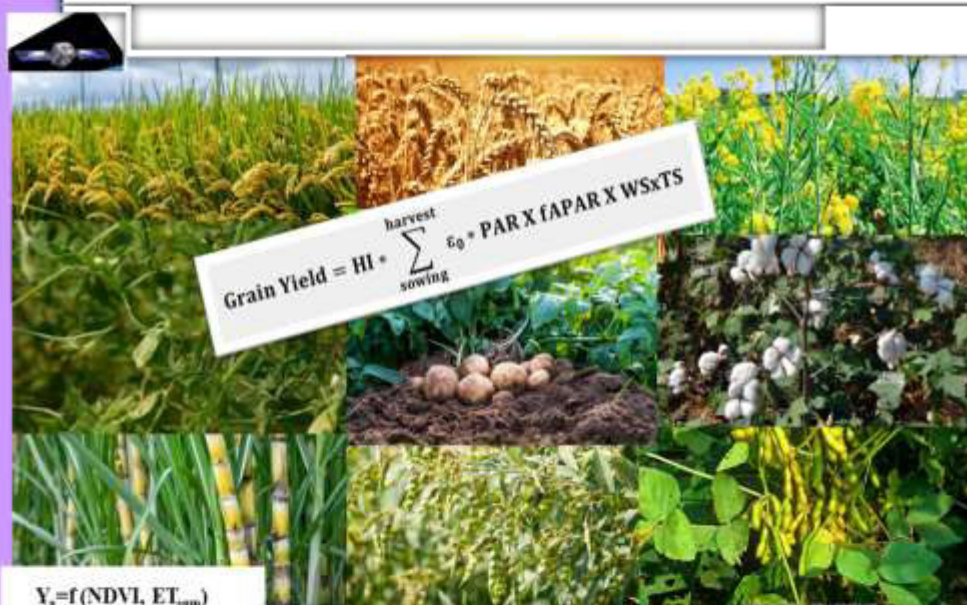




NATIONAL SYSTEM FOR CROP YIELD ESTIMATION with SEMI-PHYSICAL MODEL

Technical Manual



$$Y_s = f(NDVI, ET_{min})$$

$$Y_s/Y_m = K_y * (1 - ET/ET_0)$$

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NATIONAL SYSTEM FOR CROP YIELD ESTIMATION with SEMI- PHYSICAL MODEL

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Abbreviations and Symbols

Abbreviations

Sl no	Abbreviation/short form	Expanded form
1	VI	Vegetation index
2	AI	Artificial Intelligence
3	ML	Machine Learning (ML)
4	CSM	Crop Simulation Model
5	DSSAT	Decision Support System for Agro-technology Transfer
6	CropSyst	Cropping System Simulation
7	InfoCrop	Information on Crops
8	WOFOST	World FOod STudies
9	PAR	Photosynthetically Active Radiation
10	(RUE _{max})	Maximum radiation use efficiency
11	fAPAR	Fraction of PAR absorbed by the plant
12	PEM	Production Efficiency Models
13	EWT	Equivalent Water Thickness
14	NDVI	Normalized Deviation Vegetation Index
15	SAVI	Soil Adjusted Vegetation Index
16	EVI	Enhanced Vegetation Index
17	LAI	Leaf Area Index
18	NIR	Near InfraRed
19	SWIR	Short Wave InfraRed
20	LSWI	Land Surface Water Index
21	LSWI _{max}	Maximum LSWI over a spatial domain
22	WS	Water Scalar
23	TS (t)	Temperature Scalar
24	VGT	Vegetation (SPOT satellite sensor)
25	MNCFC	Mahalanobis national Crop Forecasting Centre
26	MoAFW	Ministry of Agriculture and Farmers Welfare
27	SOI	Survey of India

Symbols

Sl no.	Symbols	Meaning
1	T_n	Daily Minimum Temperature
2	T_x	Daily Maximum Temperature
3	T_{Av}	Daily mean Temperature
4	T_{min}	Minimum temperature required to start plant metabolic activity
5	T_{max}	Maximum threshold temperature above which plant metabolic activity ceases
6	T_{opt}	Optimum temperature for plant metabolic activity
8	TDB_a	Total Actual Dry Biomass
11	ΔDM_a	Actual dry biomass over a defined period
12	K_c	Extinction Coefficient
13	ρ	Surface Reflectance
15	TBD_a_month	Total actual dry biomass over a month
16	Y_a	Actual yield
20	HI	Harvest Index
22	r	Correlation Coefficient
23	RD	Relative Deviation
24	$RMSE$	Root Mean Square Error
25	MAE	Mean Absolute Error
26	IoA	Index of Agreement
27	R^2	Coefficient of determination

1. Introduction

Accurate and timely assessment of crop yield is required for different purposes. Policy makers require the information on crop production at relatively large scale like district, state and country for making import-export decision, while they require information at finer scale like gram panchayat, taluka or block for insurance settlement. Farm scale information is required for increasing the farm productivity through proper decision making on managing the farm level problems. Traditionally, these yield estimation are being carried out through ground survey, which are time and labour consuming and involves human error. Moreover, yield estimation prior to harvest is not possible with this method. Periodical estimation of crop biomass also indicates the health status and probable yield of the crop. This periodical information gathering on crop growth over a large area throughout the crop season became possible through space based observation over the cropped area. Information on crop growth over a large area at different spatial scale can be derived through the data from different satellite sensors working at different spectral bandwidths and spatial resolution. Hence, at Space Applications Centre, ISRO many research studies have been carried out to develop crop yield prediction approach using remotely sensed data from various sensors based on their availability. These approaches of crop yield prediction included five major categories such as 1. Statistical models with spectral vegetation index and/or weather variables; 2. Crop Simulation Models (CSM) with assimilation of remotely sensed data; 3. Semi-Physical Models (SPM) with remotely sensed input; 4. Agrometeorological Yield Models (AYM) with agromet indicators from satellite data; and 5. AI/ML yield models with inputs from satellite data. Each approach has some benefits as well as limitations in their application for large area multi-scale crop yield estimation prior to harvest.

Statistical models, both linear and nonlinear (AI/ML) methods are computationally efficient for large-scale mapping but can suffer from potential bias, especially when synthetic samples are not adequately representative of real-world conditions (Kanga and Özdoğanb, 2019). The mechanistic and dynamic crop growth simulation models (CSM) can describe the response of plants to their environment both physiologically and quantitatively. Many CSMs have been successfully used to simulate crop yield in India like DSSAT (Timsina et al., 2008, Singh et al., 2017); CropSyst (Singh et al., 2008); InfoCrop (Aggarwal et al., 2006,); ORYZA (Yadav et al., 2011). At SAC, WTGROWS, DSSAT and WOFOST models were tested and evaluated for wheat yield estimation at 25 and 5km grid size with the use of inputs from both space (solar radiation, planting date, LAI) and ground observation (interpolated temperature and rainfall, crop coefficient, soil properties) (Tripathy et. al 2013). These mechanistic approaches can be very accurate,

provided they are properly calibrated, but are the most computationally demanding, making their use for macro-scale applications difficult unless several simplifying assumptions are made (Grassini et al., 2015).

The semi-physical model considers the major physiological process of dry matter production, these are relatively easy to parameterize and can be run efficiently over large areas (Marshall et al., 2018). Semi-physical models for computing crop yield are based on the light use efficiency of crop (the major parameter for photosynthesis and dry matter accumulation). These are intermediate to the empirical and simulation models and are comparatively compatible to the RS based input. Here the dry matter accumulation in crop is assumed to be a function of the photosynthetically active solar radiation (PAR) and the fraction of PAR absorbed by the crop (fAPAR) (Monteith, 1977). At SAC, this semi-physical approach has been revised and tested for yield estimation of 9 crops- rice, wheat, maize, rabi pulse-gram, soybean, rapeseed and mustard, groundnut, cotton, and Jute (Tripathy et al., 2014, Tripathy, et, al., 2017, Tripathy et al., 2022) at district and state level. Availability of the new satellite sensors with spatial resolutions of 10m or finer have opened up new possibilities for farm level monitoring of crops. The semi-physical model has been tested for estimating yield at gram panchayat (GP) level using these fine resolution data for three different crops, rice, wheat and cotton (Tripathy, et. al., 2022) and soybean (paper under review). The semi-physical model could able to estimate yield of all those targeted crop at district and state level with acceptable accuracy (95% at state and >80% at district level). Multi-scale (state, district, tehsil, GP) yield estimation has been demonstrated for rice, wheat, cotton and soybean in a few selected districts of major growing states using the semi-physical model (Fig 1). The successful modification of semi-physical model for yield estimation at Gram Panchayat scale resulted in its implementation for crop insurance settlement purpose under YESTECH program of PMFBY for rice and wheat crops initiated in the year 2023-24 (Fig 2). This semi-physical model also has been used to generate the yield proxy for site selection for Crop Cutting Experiment (CCE) under the Smart Sampling Technique program of PMFBY which was implemented during 2019-20 and 2020-21 for rice, wheat, mustard and rabi sorghum in 10 states (Fig 3). The precision, scalability and the achievable accuracy level by the semi-physical model (SPM), paved the way towards development of a National system for crop yield forecasting at district and state level using semi-physical model.

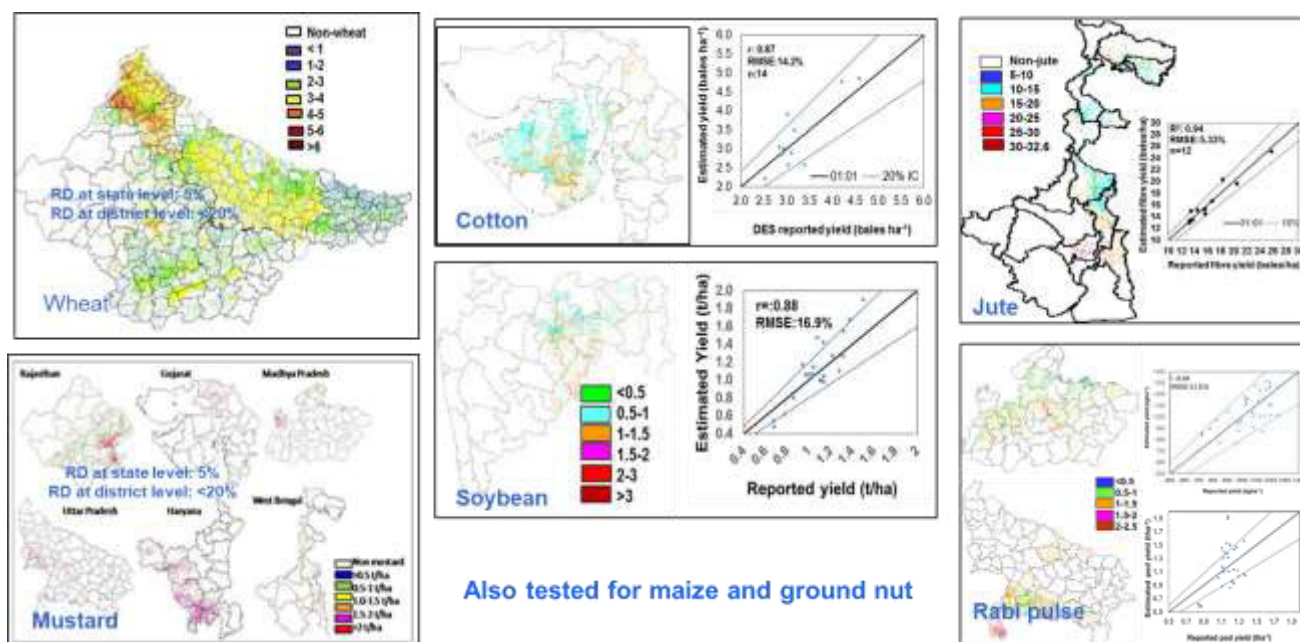


Fig 1 Yield estimation of 6 crops with RS based semi-physical model at district and state level

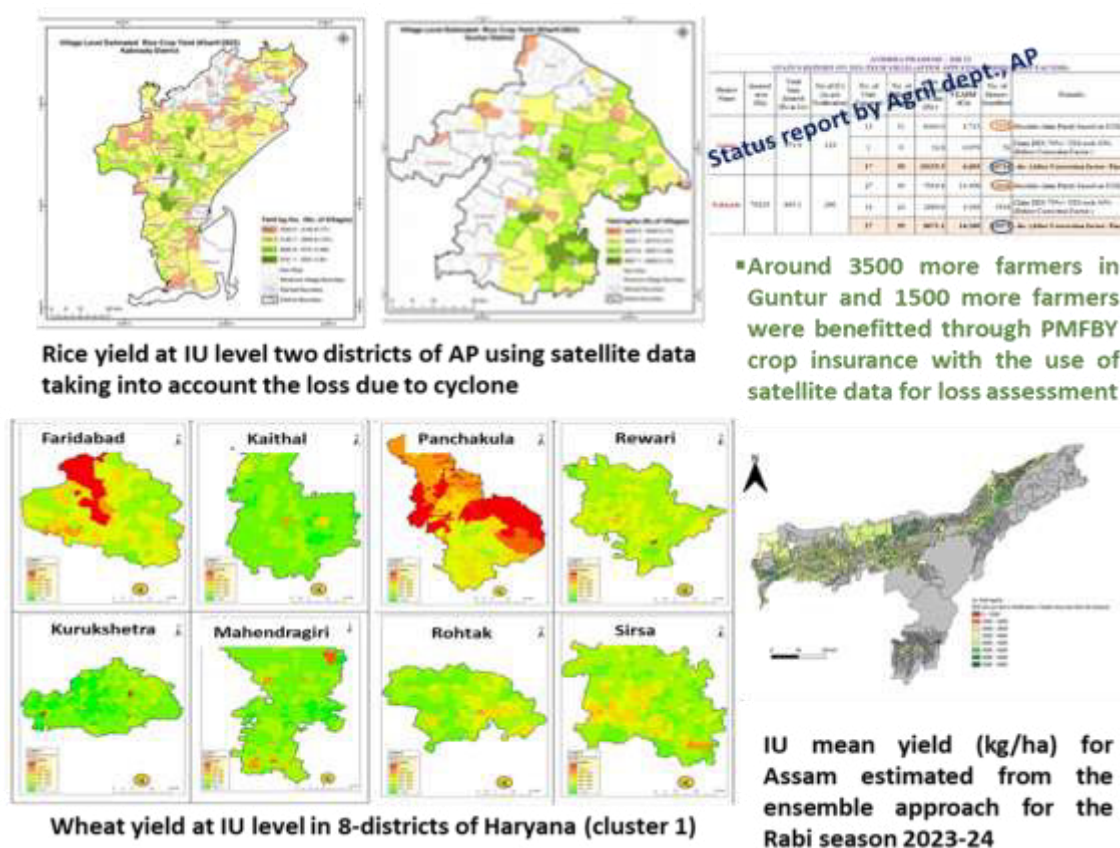


Fig 2 Application of fine-scaled semi-physical model for yield estimation of rice and wheat at Insurance unit for PMFBY

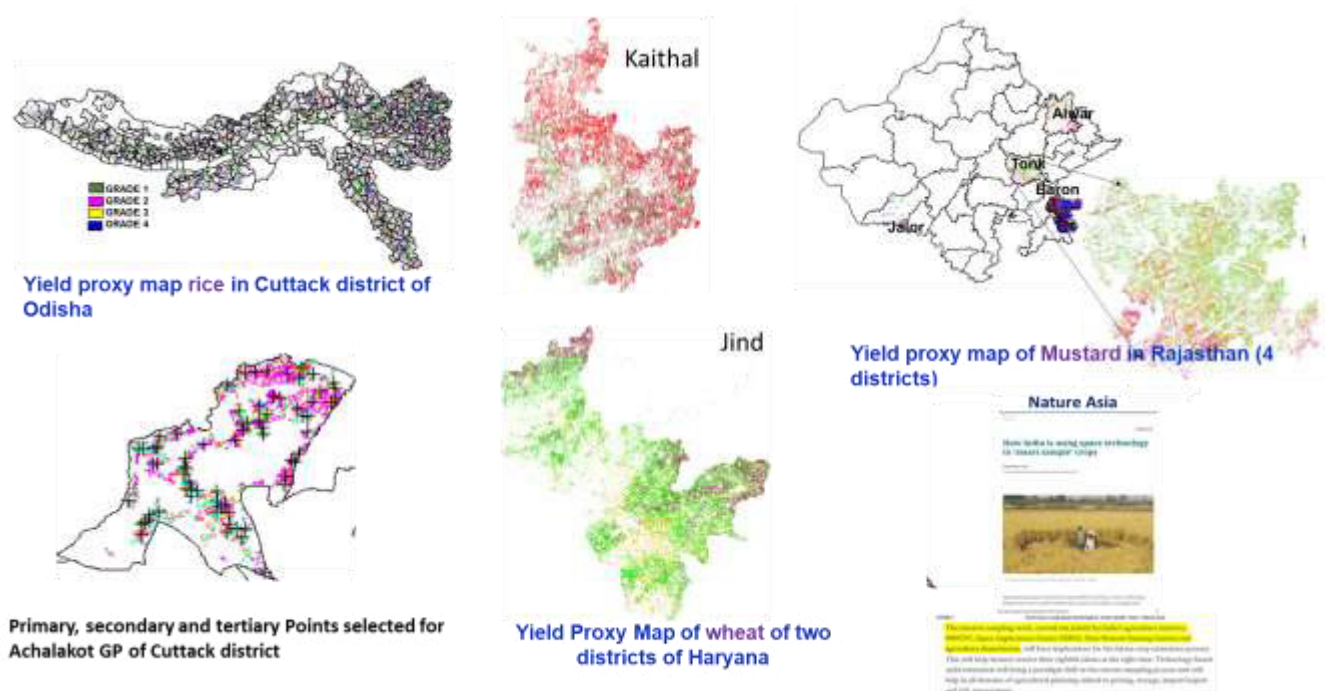


Fig 3. Semi-physical Model for Generating yield proxy for Smart Sampling

The web portal based geospatial crop yield estimation system is planned to be developed for operational implementation of the semi-physical model to estimate yield of 6 crops (Transplanted Rice, Soybean, Cotton, Wheat, Mustard and Gram) out of the total 10 targeted crops under FASAL 2.0 program of MoA&FW. The system will be operational at KRISHI-DSS of MoA&FW as well as VEDAS portal of SAC, ISRO. This will generate the planting date, periodical biomass and yield of the targeted crops of India at district and state level automatically at defined time interval. Many users from the agricultural department and MoA &FW (with/without much expertise in crop modeling and remote sensing data handling) can effectively use it for estimating and/or forecasting yield of different crops at different spatial scale and temporal domain. Three new crops (Arhar, Lentil and Potato) will be added to the system after demonstrating the same model for yield estimation.

2. Input Data

The base data required for the semi-physical model and the source for acquisition is given in Table 1.

Table 1 : Base data requirement and their source for acquiring

Data /Product	Satellite/Sensor/ ground	Resolution (km)	Source	Period of data
Daily Insolation	INSAT-3DR	4	www.mosdac.gov.in	Current season - from planting to date of prediction Past season - three years temporal average
fAPAR (8-days composite)	Terra- MODIS	0.05	https://lpdaac.usgs.gov	
Surface reflectance (RED, NIR, SWIR at around 1.6µm)	Terra- MODIS	0.05	https://lpdaac.usgs.gov	
NDVI (16 days composite)	Terra- MODIS	0.025	https://lpdaac.usgs.gov	Current season - 15 days prior to planting date as per previous year to date of prediction
Crop mask (past and current season)	RS2- AWiFS/MODIS/Sentinel1-SAR and 2-MSI	0.056, 0.025, 0.001	MNCFC, New Delhi	Static (Once for a crop season)
Daily Tmin and Tmax	IMD/ERA 5	Station	www.imd.gov.in	Current season - from planting to date of prediction Past season - three years temporal average
Crop duration and HI	LUT	Crop wise and district wise	Annexure 1	static
RUE max	LUT	Crop wise	Annexure 1	static
Temperature thresholds (Tmax, Tmin, Topt)	LUT	Crop wise	Annexure 1	static
Days to emerge	LUT	Crop wise	Annexure 1	static

3. Methodology for generating input parameter and intermediate output

The input parameter for the semi-physical model are

- Crop mask
- Planting date or start of the season
- Crop proportion under each planning date class

- Harvest date or End of the Season
- Periodical PAR
- Periodical FAPAR
- Periodical WS
- Periodical TS
- Maximum Radiation Use Efficiency
- Harvest Index

The intermediate output from this model are

- Periodical and seasonal APARsum
- Periodical Biomass
- Final biomass

3.1 Methodology for Estimating start of season (planting date t1) and End-of season

Planting date of a crop for each pixel resolution is determined using the time series NDVI for a period starting from the 15 days prior to the date of normal planting date and 15 days after the time of peak crop season. For kharif crops, 15 May to 15 October while for rabi crops 1 Oct to 30 Jan next year will be the approximate period for time-series NDVI. Schematic diagram for generating planting date in wheat is given in fig 4.

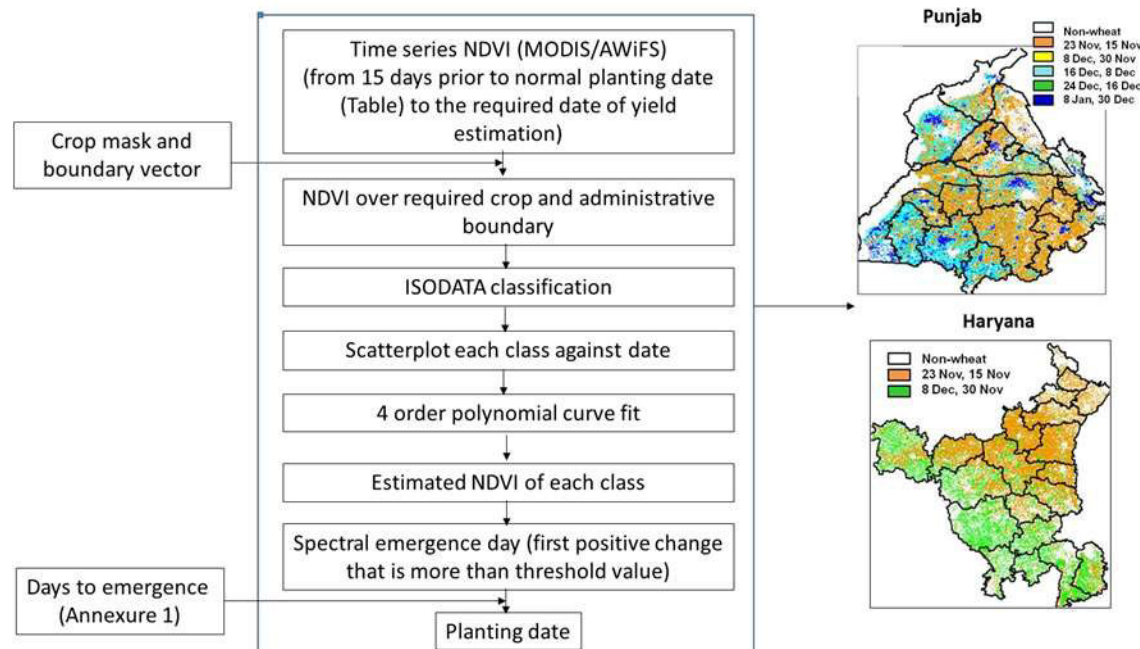


Fig 4 Methodology for generating planting date or start of season (SOS)

The crop mask and the boundary of the administrative unit is overlaid to get the NDVI specific to that crop and area. ISODATA unsupervised classification scheme was used to generate different classes of planting date over the required administrative area (here district). The smoothed NDVI was generated using the higher order polynomial curve for each class. From the smoothed curve of NDVI, the inflection point was identified where NDVI starts increasing. This date on which first positive change occurs is identified as spectral emergence date (SED). The days to emergence (annexure 1) is subtracted from SED to get the planting date, which is the date for start of season or SOS).

Crop duration (annexure 1) for each crop and state will be given as Look Up Table (LUT) and used for computing the end of season (EOS) or harvest date

$$\text{EOS (Pf)} = \text{Start of season} + \text{crop duration} \quad \text{---- (1)}$$

The planting date and the proportion of crop pixels under each planting date class inside the desired administrative boundary (here it is district or state) is derived considering only the crop pixels.

3.2 Periodical PAR

PAR (Photosynthetically Active Radiation) is the fraction of the total incident solar radiation or daily global surface insolation (INS) that comes from the visible range (0.4-0.7 μm) of the EM spectrum that is useful for photosynthesis. Therefore,

PAR on a given day (t),

$$\text{PAR (t)} = f * \text{INS(t)} \quad \text{----- (2)}$$

(f is the fraction of the total incident solar radiation or daily global surface insolation (INS) that comes from the visible range of the EM spectrum, here we have generalized this fraction to be 0.5 for Indian region). Here, PAR and INS on a given day are in MJ/day.

3.3 Periodical FAPAR

FAPAR is the fractional absorbed PAR. This is derived from the surface PAR balance equation:

$$f\text{APAR} = 1 - t_{\text{PAR}} - r_{\text{PAR}} \quad \text{----- (3)}$$

The t_{PAR} is the transmitted PAR fraction through the crop canopy and constitutes the major portion of PAR balance. r_{PAR} is the reflected PAR fraction from crop canopy and soil which ultimately depends on land surface PAR albedo within 0.4 to 0.7 μm .

$$t_{PAR} = PAR_{trans}/PAR_i = \text{EXP}(-Kc.LAI) \text{ ----- (4)}$$

PAR_{trans} and PAR_i are transmitted PAR through canopy and incident PAR on the top of canopy, respectively. The Kc is canopy extinction coefficient. LAI is Leaf Area Index.

Since LAI depends on spectral response of canopy, it has been found that fAPAR is linearly correlated with spectral vegetation index (VI) such as NDVI, SAVI or EVI (Myneni and Williams, 1994; Boschetti et. al., 2011). In the semi-physical model, we use the fAPAR as a product; however, the option for using a linear function of NDVI to derive fAPAR needs to be kept in the algorithm flow.

Therefore,

$$fAPAR(t) = m \cdot NDVI(t) + c \text{ ----- (5)}$$

Where, m and c are slope and intercept of the linear function, respectively. These will vary from sensor to sensor based on spatial resolution and should be made available in advance from experimental data.

As FAPAR is available as a product, we have used the product from MODIS at 500m resolution.

3.4 Water Scalar (WS)

We derive water scalar from an index called Land Surface Water Index (LSWI) (Xiao et al., 2002c, 2004) derived from the surface reflectance at NIR (0.78–0.89 μm) and SWIR (1.58–1.75 μm) spectral bands. Previous studies reported that the SWIR band (1.6 μm) is sensitive to land (canopy-soil cover complex) surface water content (Tucker, 1980, Xiao et al., 2004). A number of studies have suggested that a combination of NIR and SWIR bands have the potential for retrieving leaf and canopy water content (EWT, gcm^{-2}), based on LANDSAT image data (Hunt & Rock, 1989), hyper-spectral image data (Gao, 1996; Serrano et al., 2000b) and VGT data (Ceccato et al., 2001, 2002a,b).

$$LSWI = (\rho_{NIR} - \rho_{SWIR}) / (\rho_{NIR} + \rho_{SWIR}) \text{ ----- (6)}$$

The water scalar (WS) for a given period, p , is computed as:

$$WS(p) = (1 + LSWI(p)) / (1 + LSWI_{max}) \quad \text{----- (7)}$$

LSWI_{max} is the spatial maximum within each administrative unit (as required by the user) on a particular day. This is done to normalize and scale the LSWI over the crop pixels in that administrative unit. As the range of LSWI varies from -1 to +1, 1 is added to avoid the negative value. As such, the water scalar remains between zero and one.

Mean WS over the District or state was used as the WS of the respective district or state.

3.5 Temperature Scalar (WS)

TS (t) for a given day (t) is expressed using the equation (Raich et al., 1991):

$$TS(t) = \frac{(T_{Av}(t) - T_{min})(T_{Av}(t) - T_{max})}{[(T_{Av}(t) - T_{min})(T_{Av}(t) - T_{max}) - (T_{Av}(t) - T_{opt})^2]} \quad \text{----- (8)}$$

Where, T_{min}, T_{max} and T_{opt} are minimum, maximum and optimal cardinal temperatures for photosynthesis or growth for a crop type or crop group or vegetation class, respectively. T_{Av}(t) is the daily mean air temperature at 2m height for a given day (t) which is computed from the average ((T_n+T_x)/2) of daily minimum (T_n) and maximum (T_x) air temperatures. The T_{min}, T_{max} and T_{opt} for each crop are given in Annexure 1. If daily mean temperature is above T_{max} or below T_{min}, TS is set to be zero.

From the research studies, we found that for the kharif season crops in India, the temperature stress Ts is negligible and hence the TS nears to one throughout the season. Thus, we use TS only for rabi-season crops.

3.6 Intermediate output- (Periodical and seasonal APAR and above-ground dry biomass)

The algorithm uses a semi physical model that temporally integrates crop biomass as a function of RUE_{max}, PAR, fAPAR, water scalar (WS) and temperature stress (TS). The model is based on the concept that the biomass produced by a crop is a function of the ability to use the intercepted PAR for converting the radiation into dry matter (RUE_{max}) and the amount of total intercepted PAR (APAR). The intercepted PAR depends on incoming solar radiation in the photosynthetically active region of the solar spectrum (0.4-0.7µm) (PAR) and the crop's PAR absorption capacity measured by the fAPAR which is the fraction of absorbed PAR to incident

PAR ($0 \leq fAPAR \leq 1$) and is quantified from remote sensing using NDVI (Baret and Guyot, 1991). The vegetation index (VI) and greenness are linearly related to PAR absorption rate of crop canopies and hence, crop-absorbed PAR can be estimated from remotely sensed VI or greenness and PAR observed at ground stations. This has been utilized for many crops to remotely estimate yields with satisfactory results (Asrar et al., 1985; Wiegand et al., 1989; Wiegand & Richardson, 1990). These studies used maximum RUE for estimating the potential or unstressed biomass. However, in reality the radiation conversion efficiency is affected by nitrogen deficiency (Sinclair & Horie, 1989) and water stress, similarly the harvest index is influenced by water or temperature stress during reproductive and grain-filling stages. Thus, if these stress factors are not considered then the yield estimated will be far from the actual crop yield especially in a country like India where the yield gap from the potential is large due to these stresses. Hence, the stress components should be included as scalars for converting potential biomass to actual biomass and hence actual yield. Here, we use only water (WS) and temperature scalars (TS) as the nutrient stress (mainly nitrogen) is accounted by fAPAR (NDVI).

The transformation of PAR and fAPAR into total absorbed PAR (APAR) and dry matter (ΔDM) or net carbon accumulation on a given day or over a period (p) under unstressed condition at potential (pot) or maximum production condition is expressed as:

$$APAR(p) = (\sum_{t=t_1}^p PAR(t)) * fAPAR(p) \text{ ----- (9)}$$

$$\Delta DM_p(p) = APAR(p) * RUE_{max} * 10 \text{ ----- (10)}$$

Where, ΔDM : dry matter accumulation ($gm^{-2}d^{-1}$) in plant for a given period, p, which is determined by compositing period of input data. Here, t_1 is the planting date in terms of calendar day, which is determined 1 month after middle of the season. The multiplicative factor 10 is to convert $g m^{-2}$ to $t ha^{-1}$

The RUE_{max} is maximum radiation use efficiency that indicates the amount of dry matter produce per unit MJ of APAR. This is a crop genetic parameter and taken from published literature for each of the targeted crop, The range of RUE_{max} for each crop is given in annexure 1. With the use of RUE_{max} we convert the total intercepted PAR in the canopy (APAR) into dry biomass. RUE_{max} varies with crop type or cultivar of a crop. This is assumed to be constant for a crop type throughout growing period and is specified as global constant.

Under stressed conditions, the equation 10 becomes,

$$\Delta DM_a(p) = APAR(p) * RUE_{max} * WS(p) * TS(p) * 10 \text{ ----- (11)}$$

Here, WS (p) is water scalar (0 to 1) for canopy-soil cover complex and TS(p) is temperature scalar (0 to 1) for a given period or compositing period, p.

The WS (p) and TS(p) is the mean of daily values for a given period equivalent to compositing period, p

The seasonal dry matter accumulated over the period from p1 to pf is computed as total dry above-ground biomass (TDB_a).

$$TDB_a = \sum_{p=p1}^{pf} \Delta DM_a(p) \text{ ----- (12)}$$

Where, p1 is the starting period corresponding to the start of simulation and pf is the end of season corresponding to the crop maturity as per the crop duration.

In addition to the final biomass, periodical biomass is an output of this approach. Periodical biomass product (monthly) is computed as

$$TDB_{a_month} = \sum_{p=p1}^{np} \Delta DM_a \text{ ----- (13)}$$

Where, n is the number of p periods in a given month; p1 is the starting period corresponding to planting date

4. Yield Estimation

Actual yield (Y_a) is estimated as the fraction of total biomass that is converted to economic plant part. Hence,

$$Y_a = HI * TDB_a \text{ ----- (14)}$$

Where, HI is the harvest index denoting the ratio of weight of economic plant part to the weight of total dry biomass. Range of HI for different crops is given in annexure 1. Yield is expressed in kg/ha unit rounded up to nearest whole number

5 Validation and Error computation

Validation can be carried out for estimated actual yield (Y_a) using the reference yield, which is to be given by user. Model validation, in its simplest form, is a comparison between simulated and observed values. Beyond comparisons, there are several statistical measures available to

evaluate the association between predicted and observed values, among them are the correlation coefficient (r) and its square, the coefficient of determination (R^2). Wilmot (1982) has pointed out that the main problem with this analysis is that the magnitudes of r and R^2 are not consistently related to the accuracy of prediction where accuracy is defined as the degree to which model predictions approach the magnitudes of their observed counterparts. Further, as R^2 often is unrelated to the sizes of the difference between observed and predicted values, high or statistically significant R^2 may be misleading. Hence, two different groups of test criteria, called summary measures and difference measures have been used to evaluate the performance evaluation of the two models. While summary measures describe the quality of simulation, difference measures try to locate and quantify errors. Summary measures include the mean of observed values ($\bar{O}$) and predicted values ($\bar{P}$), the standard deviations of observations (S_o) and the predictions (S_p), the intercept (a) and slope (b) of the least-squares regression ($P_i = a + bO_i$). The difference measures include the mean absolute error (MAE) and the root mean square error (RMSE). Here three statistical indicators can be generated-

$$1. \text{ Pearson correlation Coefficient } (r) = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n \sum x^2 - (\sum x)^2][n \sum y^2 - (\sum y)^2]}} \text{ ----- (15)}$$

(x and y are Y_a and Reference yield values, respectively)

$$2. \text{ Relative deviation (RD, \%)} = 100 * (YA - R) / R \text{ (R: reference yield) ----- (16)}$$

$$3. \text{ Root mean square error (RMSE Absolute)} = \left[n^{-1} \sum_{i=1}^n x(P_i - O_i)^2 \right]^{0.5} \text{ ----- (17)}$$

$$\text{RMSE (\%)} = 100 * (\text{RMSE Absolute} / \text{mean reference yield}) \text{ ----- (18)}$$

Where, n is the number of cases, P_i and O_i are YA and Reference yield value of i^{th} case, respectively. $P_i' = P_i - \bar{O}_i$, and $O_i' = O_i - \bar{O}_i$ ($\bar{O}_i$ is the mean of Reference yield value of all cases)

6. Flow chart for overall methodology of Semi-physical model

Figure 5 shows the flowchart of different steps for estimating crop yield

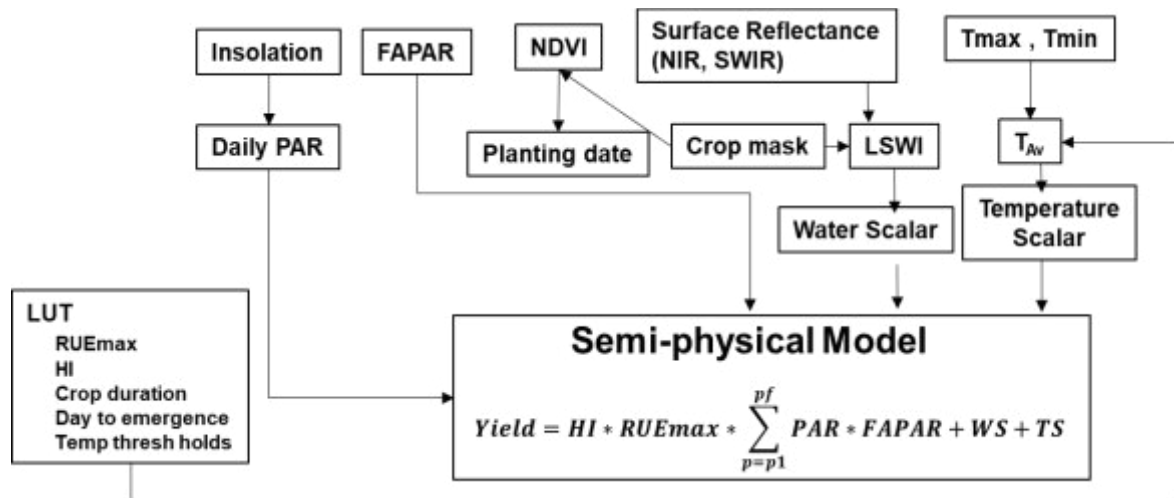


Fig 5: Flow chart for crop yield estimation using semi-physical approach

7. Conclusion and way forward

This technical manual gives a glimpse of the semi-physical model used for estimating crop yield through the web-portal system developed on the VEDAS web portal of Space Applications Centre, ISRO, Ahmedabad. This system has been developed under the FASAL 2 program of MoA&FW for National crop yield estimation of 10 crops (List shown in the user interface). The system is ready for generation of input parameters required for yield estimation of kharif rice and soybean. The following components are to be included in the system during the course of development of the full system for 10 crops.

1. Use of data from future remote sensing satellite
2. Inclusion of five new crops (wheat, rabi rice, mustard, cotton and gram)
3. Inclusion of new model for sugarcane
4. R&D for three new crops (potato, redgram and lentil) and subsequent inclusion in the system
5. Pre-harvest Forecast through new technique

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Annexure-1

Crop-wise days to emerge, crop duration, cardinal temperature, RUE max, harvest index and ginning percent for cotton

Sl no	Season	Crop	Days to emerge (days)	Duration (days)	Tmax degC	Tmin degC	TOpt	RUEmax Deg C	HI	Ginning Percent
1	Kharif	Transplanted Rice	7	120-150	NA			2.5-3.0	0.25-0.5 (rice)	
2	Kharif	Soybean	15-20	100-140	NA			1.8-2.4	0.18-0.35 (pod)	
3	Kharif	Cotton	10-15	140-180	NA			1.8-2.0	0.18-0.25 (seed)	25-40
4	Rabi	Wheat	10-20	120-150	35	6	25	3.0-3.5	0.3-0.6 (grain)	
5	Rabi	Mustard	10-15 days	130-150 days	35	6	25	2-2.5	0.18-0.35 (pod)	
6	Rabi	Gram	10-15 days	135-140 days	35	6	25	1.8-2.5	0.18-0.25 (seed)	