

CROP SIMULATION MODEL, REMOTE SENSING, GIS AND THEIR INTEGRATION FOR YIELD MONITORING

Abstract

Numerous weathers, soil, and management factors that differ greatly in area and time considerably affect crop growth and productivity. Farmers can establish site-specific crop management practices while also learning useful information about their fields and crops through yield monitoring. The revealing of regional and temporal variability in crop yields is one of the key advantages of the yield monitoring system. The yield maps that are the end result of monitoring have a significant influence on the decision-making process. Mechanistic crop growth simulation models are helpful for predicting agricultural yield because they define crop development processes and quantify the impact of weather, soil, and management factors on crop growth and yield. Getting the spatial information on model input parameters, however, is the main obstacle to their application at the regional level. Data from remote sensing (RS), collected repeatedly over agricultural land, is useful for identifying and mapping crops as well as gauging crop vigour. In order to model and track crop growth at the regional level with inputs from remote sensing, crop simulation models (CSM) that have been successful in field-scale applications are being modified in a GIS framework with RS data. As a result, assessments are vulnerable to local soil variability, seasonal weather conditions, and crop management techniques. The leaf area index (LAI), crop phenology, crop distribution, and crop environment can all be learned from the RS data. This data is integrated with CSM in a variety of methods, including direct variable forcing, parameter re-calibration, and the use of simulation-observation discrepancies in a variable for yield monitoring correction.

Keywords: Yield monitoring, crop simulation model, remote sensing, GIS, Yield monitoring scenario in India.

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I. CONCEPT OF YIELD MONITORING

For a rising population to have enough food, crop yield monitoring is crucial. A component of precision agriculture called yield monitoring aids in giving farmers the information they need to make informed decisions about their fields. Farmers can learn useful information about their fields and crops through yield monitoring while also establishing site-specific crop management practices. The identification of regional and temporal variability in crop yields is one of the key advantages of the yield monitoring system. The yield maps that are the end result of monitoring have a significant influence on the decision-making process. Therefore, timely and accurate yield monitoring and estimating at a regional level is crucial for maintaining national food security and promoting sustainable agricultural growth.

II. CHRONOLOGICAL ADVANCEMENTS IN YIELD MONITORING

Initially, to simulate crop growth dynamics including LAI, canopy cover (CC), and the total dry biomass, mathematical formula-defined crop models are employed [1]. These models provide yield estimations and indicators of crop growth status, driven by dynamical elements such as the environment, management, and soil conditions [2]. By supplying more relevant information, which would enhance model calibration and parameterization and boost the simulation accuracy at a regional scale, this uncertainty of crop models was minimised. In order to improve yield predictions, new methodologies or procedures can be used to effectively and efficiently integrate observable data into crop models [3]. The rapid development of remote sensing technology has made it possible to acquire timely crop growth status information during the growing season at the regional to global scale [4]. By making more use of these in crop models, this uncertainty can be minimised. For example, LAI [5], the percentage of photosynthetically active absorption (FPAR) [6], chlorophyll content [7], evapotranspiration [8], and soil moisture have all been estimated using remote sensing at various geographical resolutions [9]. To estimate biophysical and biochemical parameters from vegetative indicators, numerous techniques have been developed [10]. Recently, it has been thought that using remote sensing data in crop models is a good way to keep track on crop development and yield [11].

III. CROP GROWTH MODEL FOR YIELD MONITORING

Crop simulation models (CSMs) mimic how changes in the growing environment affect plant growth and development on a daily basis. They are based on real plant processes. A CSM is a straightforward illustration of a crop that serves as an explanation. Phenology, photosynthesis, dry matter generation, and dry matter partitioning are the main processes that are modeled in simulation models intended for potential production. Modules for phyllochron, branching pattern, and probable flowers/grain filling sites are among those targeting crop-specific behaviour. Models of soil water balance, crop uptake and transpiration, and nitrogen transformations in soil, uptake, and remobilization inside plants, respectively, are incorporated to model the reaction of crop to environments with limited access to food and water. Weed and pest impact models are being developed and included in the advanced generation of crop simulation models.

State, rate, and driving factors are the three categories of variables identified in dynamic crop simulation models. Quantities that can be measured at certain times include

biomass, soil nitrogen content, plant water content, and soil water content are considered as state variables. Driving variables, also known as driving functions, describe how the environment affects the system at its limits. Their values need to be continuously tracked, for example, meteorological variables. Each state variable has a set of rate variables that describe the rate of change for each state at any given time as a result of particular activities. These variables depict the movement of biomass or material between state variables. In India, the use of the CERES-Wheat component of DSSAT for predicting regional wheat yields was shown [12].

Basic Steps in crop growth simulation modeling

1. Define goals: Agriculture system
2. Define system and its boundaries: Crop model
3. Define key variables:
 - State variables
 - Rate variables
 - Driving variables
 - Auxiliary variables
4. Quantify relationships (Evaluation)
5. Calibration/verification
6. Validation
7. Sensitivity analysis
8. Use of model in decision support

IV. REMOTE SENSING FOR YIELD MONITORING

Remote sensing (RS) is a technique of gathering information about the Earth's land and sea surfaces by receiving the radiation, reflected or emitted from the Earth's surface [13]. We remotely gather data using a variety of sensors that may be processed to learn more about the thing, places, or phenomena being studied.

Optical remote sensing uses VIS, IR, and SWIR sensors to create images of the Earth's surface. At these visible and infrared wavelengths, different material reflects and absorbs radiation in different ways. Targets can thus be distinguished from one another based on the spectral reflectance characteristics visible in the remotely sensed photographs.

Table 1: Various categories of optical RS

Imaging system	Example
Panchromatic	IKONOS pan, SPOT HRV-Pan
Multispectral	Landsat MSS, Spot HRV-XS, IKONOS-MS
Super spectral	MODIS, MERIS
Hyperspectral	Hyperion on EO1 satellite

In contrast, RADAR sensors work in the electromagnetic spectrum's microwave region. Synthetic Aperture Radar (SAR) sensors have grown in significance as a source of data for monitoring and managing natural resources and agriculture. For example, RISAT-1, RADARSAT, Sentinel uses microwave radiation. Signal penetration inside of vegetation and

soil targets is improved while operating in the microwave region. The longer wavelengths of a radar imaging system, as opposed to optical sensors, are unaffected by cloud cover or haze, allowing data collecting irrespective of atmospheric conditions.

In order to identify and distinguish the majority of the main crop varieties and circumstances, optical RS has been employed to monitor the situation of global agricultural production. However, using this technology for crop monitoring in agricultural areas with regular cloud cover can be problematic. Radar RS data, on the other hand, are sensitive to vegetation biomass and structure, making these sensors a desirable choice for crop monitoring. Radar data and wavelengths in the visible and infrared light both offer complementing information about various target characteristics. Intense research efforts are being made to apply RS technology as a result of the synergy between data from optical and SAR sensors. When combined, optical and radar data offer an important source of information for agricultural applications.

Methods of crop yield prediction through remote sensing

1. Empirical models with remotely sensed input

- Vegetation index
- Crop spectral signature

2. Integration of remotely sensed data in crop simulation model

- Biophysical parameter (Example: LAI)
- Agro-meteorological parameter (Insolation, LST, Rainfall, AET/PET, Soil Moisture)

1. Empirical models with remotely sensed input: RS data collected repeatedly over agricultural land aid in crop identification, mapping, and crop vigour assessment. The presence and concentration of photosynthetic pigments had an impact on the reflectance between 350 and 700 nm. The chlorophyll absorption band caused the dips in reflectance at 450 and 680 nm. It was discovered that the reflectance between 800 and 1300 nm was at its highest which is controlled by the interior structure of leaves. Due to the water absorption band, dips in the plant reflectance curve were seen around 1300 and 1900 nm. In order to identify functional correlations between crop features and RS observations, vegetation indices (VIs), which are mathematical combinations of canopy reflectance primarily in the red, green, and infrared spectral bands, are used. NDVI is the widely used VI for the yield monitoring. According to research by Reference [14], the normalized difference red edge (NDRE) at heading stage accounted for 88% variation in the wheat grain production. Biomass is a crucial indicator for yield monitoring since it can reveal plant growth status. LAI and above-ground biomass can be calculated from RS data using parametric empirical correlations between in situ observations of the aforementioned components and vegetation indices.

2. Integration of RS inputs in crop simulation models: Reference [15] first suggested the use of RS data to increase the precision of crop models. They suggested using spectrally calculated LAI as a direct input to the physiological crop model or as an independent

check to the model's computation for the model's re-initialization. The fundamental benefit of employing remotely sensed data is that it allows for a measurement of the real state of the crop over a vast region using less labor- and resource-intensive techniques than in situ sampling. Crop models offer a continuous estimate of growth through time, whereas RS offers a multispectral evaluation of the current state of the crops in a specific area. There are different ways to incorporate remote sensing data into the models:

- Direct use of a driving variable estimated from RS
- Updating of a state variable derived from RS ('forcing' strategy);
- Re-initialization of the model
- Re-calibration of the model
- Re-parameterization using coupled crop simulation models and canopy radiation models
- Corrective method

Direct use of driving variable: The driving variables of CSMs are weather inputs, which comprise daily observations of the maximum and minimum temperatures, solar radiation (SR), relative humidity (RH) and wind speed etc. An important disadvantage to using this strategy is the insufficient availability of RS-derived metrics caused by the cloud cover issue and inherent characteristics of sensors and platforms. In order to predict provincial millet yields halfway through the crop duration to within 15% of their ultimate values, reference [16] used METEOSAT-based decadal (10-day) rainfall using cloud duration as input to CERES-Millet.

Forcing strategy: The forcing technique entails using remote sensing data to update at least one state variable in the model. The most often updated state variable is LAI. Figure 1 illustrates the idea of a straightforward crop simulation model and how it is modified for RS-derived LAI forcing. Reference [17] said that the forcing might be carried out either on the daily LAI profile or just on the day of the RS observation.

Re-initialization strategy: The re-initialization method makes use of the fact that state variable initial conditions have an impact on model performance. It entails adjusting the initial condition of the state variable. The starting value of LAI (L_0) during emergence can be changed to reduce the error function between remotely observed LAI values and simulated LAI values throughout simulation [17]. Results from updating (forcing) were identical to those from re-initialization using one observation.

Re-calibration/re-parameterization strategy: This method makes the assumption that the model is formally adequate but has to be re-calibrated. By lowering the error between the state variable calculated by RS and the model's simulation of it, this is achieved. This renders a method which is susceptible to mistakes made when obtaining state variables from RS data. The choice of parameter to adjust and the quantity of observations used in analysis depend critically on the model structure. Reference [17] used remotely sensed green LAI (GLAI) measurements to show how the maize model needed to be re-calibrated. With the increase in number of parameters, more reliable estimates of LAI and biomass at anthesis were found, according to a multi-dimensional error function reduction technique.

Re-parameterization: Instead of obtaining canopy parameters from radiometric data, crop models can directly use it while being re-initialized and re-parameterized [18]. To simulate the temporal behaviour of canopy surface reflectance, which can be compared to satellite-observed canopy reflectance, a radiative transfer reflectance model is coupled to a crop production model in this method.

Corrective approach: A correlation is established between the inaccuracy in the ultimate yield and the error in some intermediate variable as accessed via RS measurement. In a situation where the final yield is unknown, this connection may be used. Reference [19] used this technique to produce wheat yield maps for farmer fields during rabi 1998-1999 in Alipur block (Delhi).

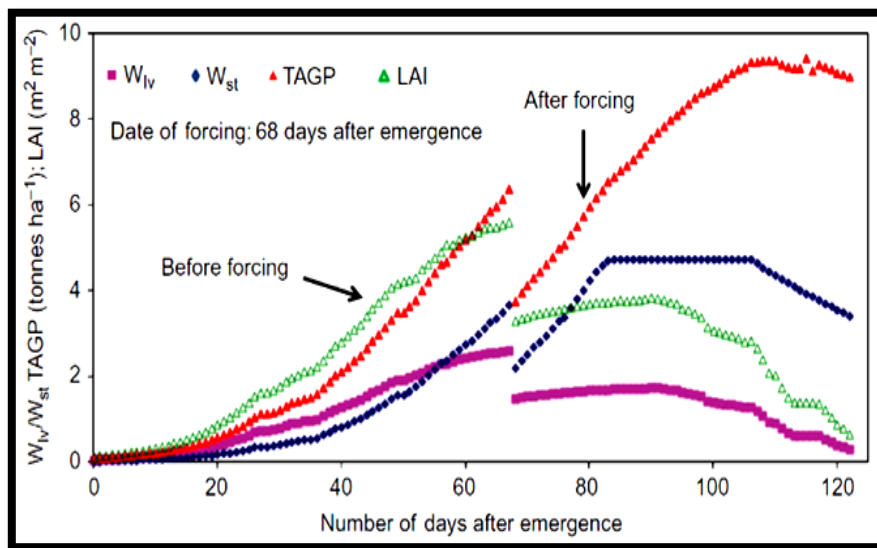


Figure 1: Forcing strategy of LAI (W_{lv} , W_{st} and TAGP implies weight of leaves, stem and total above-ground production, respectively)

V. GIS, REMOTE SENSING AND CROP SIMULATION MODEL FOR YIELD MONITORING

Geographic information system (GIS), a powerful set of tools, can be used to collect, save, access at any time, modify, and display geographical data from the real world for a variety of purposes [20]. Digital geographic data, computer software, and computer hardware are the three main components of a GIS. On the other hand, RS data collected repeatedly over agricultural land aid in crop identification, mapping, and crop vigour assessment.

It is a well-established practice to employ GIS along with RS data for yield monitoring during all stages of the activity, including planning, analysis, and output. GIS is used during the planning phase to either (a) stratify or zone an area using input layers (climate, soil etc.), or (b) convert input data (weather, soil) into a common format. GIS is primarily used in the analysis phase to perform operations on NDVI raster layers or compute VI profiles within predetermined administrative borders. GIS is also utilised in the final output phase to aggregate and show results for specific regions and to produce map output products.

VI. INTERFACING CROP SIMULATION MODELS TO GIS

Crop simulation models, used with input data from a particular field or site, produce a point output. Geographically variable inputs (soil, weather, and crop management), when combined with a GIS, can be used to improve crop yields, these simulation models' range of applicability can be expanded to a larger scale. The main objective of integrating models and GIS is to carry out simultaneous spatial and temporal analysis because region-scale crop behaviour has a geographic component and simulation models produce a temporal output. Although GIS and modelling tools have been around for a while, integration and the conceptual framework have only recently received attention. In their evaluation of GIS and agronomic modelling, Reference [21] recommended using the terms "interface" and "interfacing" as catchall terms for using GIS and modelling tools at the same time, and linking, combining, and integrating as appropriate language for the degree of interfacing.

- 1. Combining:** Combining also entails showing model outputs and processing data on a GIS, nonetheless, the model is configured with GIS, and data are immediately exchanged. This is accomplished using the GIS package's macro language, interface programmes, and user callable procedure libraries (Figure 2a). This calls for more intricate data management and programming than just connecting. AEGIS (Agricultural and Environmental GIS) and ArcView are an example of how to combine.
- 2. Linking:** GIS is used in straightforward linkage schemes to geographically show model outcomes. Model output interpolation is a straightforward strategy. An advanced tactic is to create a database that contains the model's inputs and export the model's outputs to the same database using GIS tools (interpolation, overlay, slope, etc.). Grid cell or polygon identifiers in input and output files are used to transport data between the GIS and the model. These files are transferred in binary or ascii format (Figure 2b). Due to (a) dependence on GIS and model formats, (b) compatibility issues with operating systems, and (c) underutilization of GIS capabilities, such an approach is unable to fully leverage the potential of the system.
- 3. Integrating:** Integrating refers to the process of integrating two systems. A model is either integrated into a GIS system or a GIS system is integrated into a modelling system. This enables automatic usage of statistical software and relational databases (Figure 2c). This calls for a great deal of skill, work, and knowledge of the two tools. The AEGIS, created by Reference [22] enables the user to choose different spatially distributed crop management practise combinations and assess the prospective crop yield.

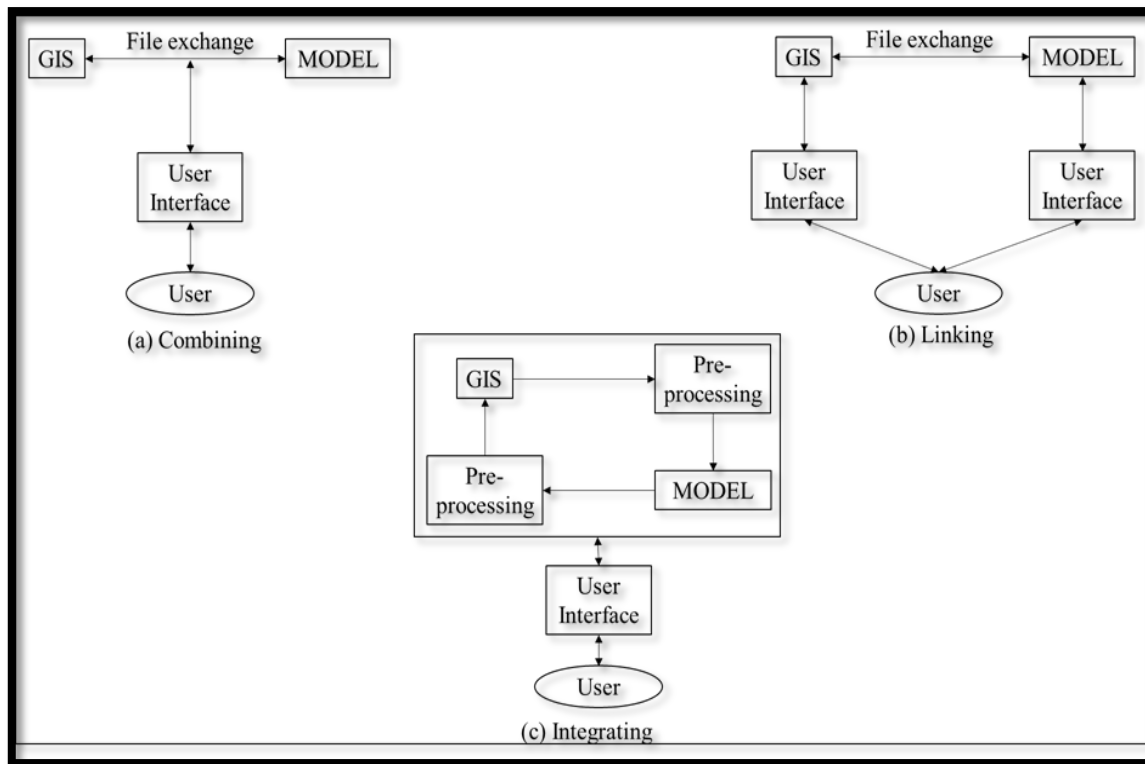


Figure 2: Organizational structure for (a) linking, (b) combining and (c) integrating GIS and crop models

VII. YIELD MONITORING SCENARIO IN INDIA

The outcome of agricultural production is quite uncertain. The risk associated with farm production is increased by hazards and unforeseen extreme weather events. Numerous dangers have a direct impact on the welfare and production choices of farmers. As an agrarian nation, 48.9% of Indians work in agriculture either directly or indirectly [23]. In 2015, 12,602 people in the farming industry (8,007 farmers and cultivators and 4,595 agricultural workers) died by suicide, making up 9.4% of all suicide victims in the nation (1,33,623) [24]. Numerous governmental and non-governmental organisations have been working to alleviate the financial loss that farmers have experienced as a result of these unforeseeable events. The Indian government's Pradhan Mantri Fasal Bima Yojana (PMFBY) programme is one of its initiatives. With the aim of protecting farmers against crop losses, this insurance programme was introduced in 2016. The programme was established to shield farmers from the production-related risks and to motivate them to increase their crop investments. In reality, though, insurance corporations profit more than farmers. This is primarily due to the approach taken to estimate yield and damage. In India, crop counts are calculated using enumeration, and crop yields are evaluated using a sample survey method called a crop cutting experiment (CCE). In the field, crop cutting is accomplished by establishing a designated area, harvesting the crop there, and then weighing the crop. 20% of districts are chosen annually to participate in these studies. Therefore, the spatial variation in yield caused by variations in the chemical and physical qualities of soil, which may be obvious within a field itself, would not be taken into consideration by this experiment. Additionally, there is no systematic mechanism of recording the outcomes of CCE studies.

By calculating the spatiotemporal variation of yield and crop acreage, the proper operation of this method (PMFBY) may be guaranteed. Manually carrying out these stages is laborious and time-consuming, and it may cause settlements to be delayed. With the development of remote sensing, it is now much easier to monitor crop health, crop yield, and other factors such as loss and risk associated with agricultural production in close to real-time. The crop health and other variables causing the spatial variance in agricultural output can be monitored by Satyukt Analytics, a RS expert.

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