**Title:**

**Crop Simulation Model, Remote Sensing, GIS and their integration for Yield Monitoring**

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**Abstract**

Crop growth and productivity are determined by a large number of weather, soil and management variables, which vary significantly across space and time. Yield monitoring allows farmers to gain valuable information about their fields and crops and at the same time develop site-specific crop management. One of the main benefits of the yield monitoring system is revealing the spatial and temporal variability in crop yields. 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. As RS data and techniques have improved, the initial efforts that directly related RS-derived vegetation indices (VI) to crop yield have been replaced by approaches that involve retrieved biophysical quantities from RS data. 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. This makes assessments sensitive to seasonal weather factors, local soil variability, and crop management practises. 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.

**Concept of yield monitoring**

For a rising population to have enough food, crop yield monitoring is crucial. Yield monitoring is an aspect of precision agriculture that helps to provide farmers with adequate information to make educated decision about their field. 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, for national food security and sustainable agricultural growth, timely and accurate yield monitoring and estimation at a regional level is essential.

**Chronological advancements in yield monitoring**

Initially, crop models defined by mathematical formulas are used to simulate crop growth dynamics, including LAI, canopy cover (CC), and the accumulated dry biomass (Curry, 1971). These models, which are driven by dynamical factors including the climate, management, and soil conditions, provide yield estimates and indicators of crop growth status (Launay and Guerif, 2005). But when crop growth models are used in vast agricultural regions, the uncertainties with respect to spatial spread of crop attributes, beginning conditions, soil properties, and field management approaches might impair the estimation accuracy of crop output (Hansen and Jones, 2000). 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 (Curnel *et al.,* 2011). The rapid development of remote sensing technology that has made it possible to acquire timely crop growth status information during the growing season at the regional to global scale, it is one of the most accurate data sources that can be used in crop models to estimate crop yields using data assimilation techniques (Jarlan *et al.,* 2008). By making more use of these crop models, this uncertainty can be minimised. For example, LAI (Aasen *et al.,* 2015), the percentage of photosynthetically active absorption (FPAR) (Baret *et al*., 2007), chlorophyll content (Jin *et al*., 2012), evapotranspiration (Mutiga *et al*., 2010), and soil moisture have all been estimated using remote sensing at various geographical resolutions (Hasan *et al*., 2014). To estimate biophysical and biochemical parameters from vegetative indicators, numerous techniques have been developed (Huang *et al*., 2015). 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 (Li *et al.,* 2014).

**Crop growth model for yield monitoring**

Crop simulations models are based on physical plant processes and simulate the effects of change in growing environment on plant growth and development on a daily basis. A crop simulation model 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 modelled in simulation models intended for potential production. Modules for phyllochron, branching pattern, and probable flowers/grain filling sites are among those targeting crop-specific behavior. 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. According to laws based on an understanding of the physical, chemical, and biological processes that take place during crop growth, their value is dependent on the state and driving variables.

The Decision Support System for Agrotechnology Transfer (DSSAT), a computer software programme that integrates 11 crop simulation models (CERES cereal, CROPGRO legume, and other models) with a standardized input and output, was created as part of the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) project. It has been tested and used in a number of nations. In India, the use of the CERES-Wheat component of DSSAT for predicting regional wheat yields was shown (Nain *et al.,* 2004).

**Basic Steps in crop growth simulation modelling**

1. Define goals: Agriculture system
2. Define system and its boundaries: Crop model
3. Define key variables in system:
	* 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

**Remote sensing for yield monitoring**

Remote sensing (RS) is the practice of deriving information about the Earth’s land and water surfaces using images acquired from an overhead perspective, using electromagnetic radiation in one or more regions of the electromagnetic spectrum, reflected or emitted from the Earth surfaces (Campbell, 2006). We remotely gather data using a variety of sensors that may be processed to learn more about the thing, places, or phenomena being studied. Data can be collected in a variety of ways, for as by changes in force distributions, acoustic wave distributions, or electromagnetic energy distributions.

Optical remote sensing uses visible, near infrared, and short-wave infrared sensors to create images of the Earth's surface by detecting the solar energy reflected in these wavelengths from targets on the ground. At these visible and infrared wavelengths, different materials reflect and absorb radiation in different ways. Targets can thus be distinguished from one another based on the spectral reflectance characteristics visible in the remotely sensed photographs. Panchromatic imaging systems (such as IKONOS pan and SPOT HRV-Pan), multispectral imaging systems (such as Landsat MSS, Landsat ETM, Spot HRV-XS, and Ikonos MS), super spectral imaging systems (such as Modis & Meris), and hyperspectral imaging systems (i.e. Hyperion on EO1 satellite) are the various categories into which optical RS systems fall.

In contrast, radar (Radio Detection and Ranging) sensors work in the electromagnetic spectrum's microwave region, which is outside of the visible and thermal infrared range. 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 portion of the electromagnetic spectrum. The longer wavelengths of a radar imaging system, in contrast to optical sensors, are unaffected by cloud cover or haze, allowing data collecting irrespective of atmospheric conditions. According to their design parameters, radar systems transmit microwave signals at particular wavelengths or frequencies.

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.

**Types of crop yield prediction through remote sensing**

1. **Empirical models with remotely sensed input**
2. Vegetation indices
3. Spectral profile characteristics of crop growth
4. **Assimilation of remotely sensed data in crop simulation model**
5. Biophysical parameter ( LAI, fAPAR, Chlorophyll content, Nitrogen content)
6. 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. The reflectance between 800 and 1300 nm was found to be at its maximum because of internal reflection, regulated by the internal 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 remote sensing observations, vegetation indices (VIs), which are mathematical combinations or ratios of canopy reflectance primarily in the red, green, and infrared spectral bands, are used. According to research by Zhou *et al*. (2017), the normalized difference red edge index (NDRE) at heading stage accounted for 88% of the variation in wheat grain production. Dempewolf *et al*. (2013) predicted wheat yield for 36 Punjab districts using the normalized difference vegetation index (NDVI), wide dynamic range vegetation index (WDRVI), and vegetation condition index (VCI). As RS data and techniques have advanced, the original efforts that directly linked RS-derived VIs to crop output have been supplanted by methods involving recovered biophysical quantities from RS data. Biomass is a crucial indicator for yield monitoring since it can reveal plant growth status. Utilizing parametric empirical correlations between in situ measurements of the aforementioned factors and vegetation indices, LAI and above-ground biomass have been estimated from remote sensing data. According to Gerighausen *et al.* (2016), who investigated the predictive power of partial least squares regression (PLSR) for dry matter retrieval from hyperspectral (EnMAP), superspectral (Sentinel-2), and multispectral (Landsat 8, RapidEye) remote sensing data based on field reflectance measurements, the global PLSR models' R2 ranged from 0.76 to 0.87.

**2. Linking crop simulation models to RS inputs**

Richardson et al. (1982) first suggested the use of remote sensing data to increase the precision of crop models. They advised employing spectrally calculated LAI as an independent check to the model's computation for the model's re-initialization or as a direct input to the physiological crop model. 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 remote sensing offers a multispectral evaluation of the current state of the crops in a specific area. The different ways to combine a crop model with remote sensing observations (radiometric or satellite data) were initially described by Maas (1988) and this classification scheme was revised by Delecolle *et al.* (1992) and by Moulin *et al.* (1998). Six methods of remote sensing data integration into the models have been identified:

(a) the direct use of a driving variable estimated from RS data in the model

(b) the updating of a state variable of the model (e.g., LAI) derived from RS (‘forcing’ strategy);

(c) the re-initialization of the model

(d) the re-calibration of the model

(e) Re-parameterization using coupled crop simulation models and canopy radiation models

(f) the corrective method

**(a) Direct use of driving variable**

The driving variables of the crop simulation models are weather inputs, which include daily observations of the highest and lowest temperatures, solar radiation, relative humidity, and wind speed as a minimum subset. 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. Maas (1988) estimated the ratio of daily absorbed PAR (Q) to integrated daily PAR (R) from radiometric NDVI and generated daily values of Q/R by linear interpolation between NDVI measurements for use as driving variable in a simplified maize growth model. The model overestimated the above-ground biomass at anthesis by 6.2%. In Burkina Faso, Thornton *et al.* (1997) employed METEOSAT-based decadal (10-day) rainfall utilising cold cloud duration as input to CERES-Millet to anticipate provincial millet yields midway through crop duration to within 15% of their final values.

**(b) Forcing strategy**

The forcing technique entails using remote sensing data to update at least one state variable in the model. LAI has been the most commonly updated state variable. Figure 1 illustrates the idea of a straightforward crop simulation model and how it is modified for RS-derived LAI forcing.

According to Maas (1988), the forcing could either be performed solely on the day of the RS observation or the daily LAI profile may be produced using a straightforward parametric model (Delecolle and Guerif, 1988).

**(c) Re-initialization strategy**

The re-initialization method makes use of the fact that state variable initial conditions have an impact on model performance. To reduce the disparity between a derived state variable or radiometric signal and its simulation, it entails adjusting the initial condition of the state variable. A reduction of an error function between remotely observed LAI values and simulated LAI values during simulation can be used to alter the initial value of LAI (L0) at emergence (Maas, 1988). Results from updating (forcing) were identical to those from re-initialization using one observation. However, as additional observations were employed, the stability of the model estimates gained by re-initialization grew.

**(d) Re-calibration/re-parameterization strategy**

This method makes the assumption that the model is formally adequate but has to be re-calibrated. This is accomplished by reducing the error between the state variable derived by RS and the model's simulation of it. This renders a method which is susceptible to mistakes made when obtaining state variables from RS data. The the choice of parameter to adjust and the quantity of observations used in analysis depend critically on the model structure. Maas (1988) used remotely sensed GLAI measurements to show how the maize model needed to be re-calibrated. As the number of parameters in the multidimensional re-parameterization process increased, more consistent estimates of LAI and biomass at anthesis were found, according to a multi-dimensional error function reduction technique.

**(e) Re-parameterization using coupled crop simulation models and canopy radiation models**

Instead of obtaining canopy parameters from radiometric data, crop models can directly use it while being re-initialized and re-parameterized (Moulin *et al.,* 1998). In this method, a radiative transfer reflectance model is coupled to a crop production model to simulate the temporal behaviour of canopy surface reflectance, which may be compared to satellite-observed canopy reflectance. The minimising of discrepancies between the simulated and observed reflectance values is accomplished by modifying beginning circumstances or model parameters.

**(f) Corrective approach**

A correlation is established between the inaccuracy in the ultimate yield and the error in some intermediate variable as assessed via remotely sensed measurement. In a situation where the final yield is unknown, this connection may be used. This method was utilised by Sehgal *et al.* (2005) to create the wheat yield maps for farmers' fields during rabi 1998–1999 in Alipur block (Delhi).

**GIS, remote sensing and crop simulation model for yield monitoring**

Geographic information system (GIS) is a potent set of tools for gathering, storing, accessing at will, altering, and displaying spatial data from the actual world for a specific set of uses (Burrough and McDonnell, 1998). Digital geographic data, computer software, and computer hardware are the three main elements 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 crop monitoring during all stages of the activity, including planning, analysis, and output. In the planning stage, GIS is utilised for either (a) stratification or zonation using one or more input layers (climate, soil, physiography, crop dominance, *etc.*), or (b) converting input data (weather, soil, and collateral data) that are available in various formats to a standard 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 used in the final output phase to aggregate and display outputs for specified regions (such as administrative regions) and to create map output products with the necessary data integration through overlays.

Wade *et al*. (1994) described the efforts within the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture (USDA) to use NOAA AVHRR NDVI for crop monitoring and evaluation of damage due to flood and drought by providing analysts with a set of map products. Combining satellite data in a GIS can improve the AVHRR NDVI composite imagery by superimposing State and county boundaries. It is possible to compare a season to a prior year or the average of several years by using the raster-based (grid-cell) capabilities of ARC/INFO (GRID). A crop mask that is overlaid aids in highlighting only effects on crops. To assist analysts in locating typical first frost dates for potential crop damage, frost isolines are applied. A tool for understanding NDVI difference images is the generation and overlay of precipitation data contours created using ARC/TIN INFO's function.

**Interfacing crop simulation models to GIS**

Crop simulation models, when run with input data from a specific field/ site, generate a point output. By supplying geographically variable inputs (soil, weather, crop management), and then combining their capabilities with a GIS, these simulation models' range of applicability can be expanded to a larger scale. Since region-scale crop behaviour has a geographical dimension and simulation models generate a temporal output, the major goal of integrating models and GIS is to perform simultaneous spatial and temporal analysis. The spatial visualization of the results and their understanding through spatial analysis of model results can both be aided by GIS.

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, Hartkamp *et al*. (1999) 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.

**(a) 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 2a). 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.

**(b) Combining:** Combining also entails showing model outputs and processing data on a GIS, but the model is set up with GIS and data are shared automatically. This is accomplished using the GIS package's macro language, interface programmes, and user callable procedure libraries (Figure 2b). 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 (Engel *et al*., 1997).

**(c) 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 Agricultural and Environmental Geographic Information System (AEGIS), created by Calixte et al. in 1992, is a regional agricultural decision support system that employs the DSSAT capabilities of ARC/INFO GIS for regional planning and productivity analysis. AEGIS enables the user to choose different spatially distributed crop management practise combinations and assess the prospective crop yield. Engel *et al.* (1997) modified the AEGIS into AEGIS/WIN (AEGIS for Windows) written in Avenue, an object-oriented macro scripting language, which links the DSSAT (Version 3) with the geographical mapping tool ArcView-2.

**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 (Economic Survey 2014-15). 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). (National Crime Records Bureau statistics, 2015). 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). Crop cutting is done in the field by designating a certain area, harvesting the crop there, and then weighing the harvest. 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. Satyukt analytics, an expert in remote sensing is capable of monitoring crop health and other parameters responsible for the spatial variation of crop yield.



Figure 1. Changes in model parameters before and after forcing of LAI (Wlv, Wst and TAGP implies weight of leaves, stem and total above-ground production, respectively)

GIS

MODEL

User

Interface

File exchange

1. Combining

GIS

MODEL

User

Interface

User

Interface

File exchange

1. Linking

GIS

MODEL

Pre-

processing

Pre-

processing

User

Interface

1. Integrating

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

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