CROP GROWTH AND PRODUCTIVITY MONITORING AND SIMULATION USING REMOTE SENSING AND GIS

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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. Remote Sensing (RS) data, acquired repetitively over agricultural land help in identification and mapping of crops and also in assessing 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have improved, the initial efforts that directly related RS-derived vegetation indices (VI) to crop yield have been replaced by approaches that involve retrieved biophysical quantities from RS data. Thus, crop simulation models (CSM) that have been successful in field-scale applications are being adapted in a GIS framework to model and monitor crop growth with remote sensing inputs making assessments sensitive to seasonal weather factors, local variability and crop management signals. The RS data can provide information of crop environment, crop distribution, leaf area index (LAI), and crop phenology. This information is integrated in CSM, in a number of ways such as use as direct forcing variable, use for re-calibrating specific parameters, or use simulation-observation differences in a variable to correct yield prediction. A number of case studies that demonstrated such use of RS data and demonstrated applications of CSM-RS linkage are presented.

INTRODUCTION

Crop growth and yield are determined by a number of factors such as genetic potential of crop cultivar, soil, weather, cultivation practices (date of sowing, amount of irrigation and fertilizer) and biotic stresses. However, generally for a given area, year-to-year yield variability has been mostly modeled

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through weather as a predictor using either empirical or crop simulation approach. With the launch and continuous availability of multi-spectral (visible, near-infrared) sensors on polar orbiting earth observation satellites (Landsat, SPOT, IRS, etc) remote sensing (RS) data has become an important tool for yield modeling. RS data provide timely, accurate, synoptic and objective estimation of crop growing conditions or crop growth for developing yield models and issuing yield forecasts at a range of spatial scales. RS data have certain advantage over meteorological observations for yield modeling, such as dense observational coverage, direct viewing of the crop and ability to capture effect of non-meteorological factors. Recent developments in GIS technology allow capture, storage and retrieval and visualization and modeling of geographically linked data. An integration of the three technologies, viz., crop simulation models, RS data and GIS can provide an excellent solution to monitoring and modeling of crop at a range of spatial scales.

In this paper an attempt is made to introduce a basic framework and indicate through specific case studies, (a) how RS data are useful in estimating crop parameters like LAI, (b) introduce crop simulation models, (c) how GIS tools are used for crop monitoring with RS data and interfaced with models, and (d) how RS-derived parameters, crop simulation models and GIS are useful for crop productivity modeling. Details on some of the above topics can be obtained from recent reviews, such as Moulin *et al.* (1998), Dadhwal (1999), Hartkamp *et al.* (1999), Dadhwal and Ray (2000), Maracchi *et al.* (2000) and Dadhwal *et al.* (2003).

LAI estimation using RS-data

The leaf area index (LAI), defined, as the total one-sided leaf area per unit ground area, is one of the most important parameters characterizing a canopy. Because LAI most directly quantifies the plant canopy structure, it is highly related to a variety of canopy processes, such as evapotranspiration, light interception, photosynthesis, respiration and leaf litterfall. RS-based LAI estimation would greatly aid the application of LAI as input to models of photosynthesis, crop growth and yield simulation models, evapotranspiration, estimation of net primary productivity and vegetation/ biosphere functioning models for large areas. A number of techniques for space borne remote sensing data have been developed/tested, ranging from regression models to canopy reflectance model inversions with varying successes, which include (1) statistical models that relate LAI to band radiance (Badhwar *et al.*, 1986) or develop LAI-vegetation index relation (Chen and Cihlar, 1996 and Myneni *et al.*, 1997), (2) biophysical models like Price (1993), and (3) inversion of canopy reflectance using numerical model or LUT based model (Gao and Lesht, 1997, Qiu *et al.*, 1998, and Knyazighin *et al.*, 1998).

Myneni *et al.* (1997) developed a simple approach for estimating global LAI from atmospherically corrected NDVI using NOAA-AVHRR data. One- or three-dimensional radiative transfer models were used to derive land cover-specific NDVI-LAI relations of the form

$$LAI = a \times \exp(b \times NDVI + c)$$

where, coefficients a and c are determined by vegetation type and soil.

Chen *et al.* (2002) have described relations using NOAA-AVHRR simple NIR/Red ratio (SR). These equations are vegetation type dependent and are being used to generate Canada wide 1 km LAI maps every 10/11 day. The equations are summarized in Table-1 and require a background SR that is season dependent as an additional input. In case of another high repetivity coarse resolution sensor, VEGETATION onboard SPOT satellite, use of SWIR channel is made to compute a new vegetation index, namely Reduced Simple Ratio (RSR). RSR reduces between vegetation and understory/background effects, thus making possible use of simplified equations for retrieval of LAI (Table-1).

Table 1. Equations for obtaining regional LAI products from atmospherically corrected data from NOAA-AVHRR and SPOT-VEGETATION (Chen *et al.*, 2002)

Sensor	Vegetation Type	Model
NOAA-AVHRR	Coniferous forest	LAI = (SR – Bc)/ 1.153
	Deciduous forest	LAI = -4.1xln[(16-SR)/(16-Bd)]
	Mixed forest	LAI = -4.45 x ln[(14.5 – SR)/(14-Bm)]
	Other (crops, scrub etc.)	LAI = -1.6 x ln{14.5 – SR) / 13.5]
SPOT-VEGETATION		LAI = RSR/1.242
		LAI = -3.86 ln (1-RSR/9.5)
		LAI = -2.93 ln (1-RSR/9.3)
		LAI = RSR / 1.3

Bc, Bd, Bm are background NDVI for coniferous, deciduous and mixed forests, respectively.

Using MODIS data, onboard TERRA (launched in Dec. 1999), it is now possible to obtain operationally generated eight-day composite 'LAI product', at a spatial resolution of 1km, which incorporates model and look-up-table based LAI retrieval algorithms (Knyazighin *et al.*, 1999) as a part of MODLAND. However, there is a need to validate this product, before it can be utilized in operational applications. Pandya *et al.* (2003) describe results of a study to develop small area LAI maps using IRS-LISS-III data using field sampling and regression approach and using the generated maps to validate MODIS LAI product. The atmospheric measurements of aerosol optical thickness and water vapour content were performed concurrently with the LAI measurements at the time of satellite acquisition and were used to convert digital numbers into the ground reflectance. These images were geo-referenced and the fields within the region of interest, where LAI measurements carried out were identified on images. Using NDVI of these fields, empirical models based on site-specific NDVI-LAI relation were developed (Figure 1) and used to generate LAI maps for each acquisition and study site. The LAI images were aggregated to 1km spatial resolution and compared with MODIS LAI product and results indicated significant positive correlation between LAI derived from LISS-III data and MODIS data albeit with a positive bias, in the MODIS product (Figure 2).

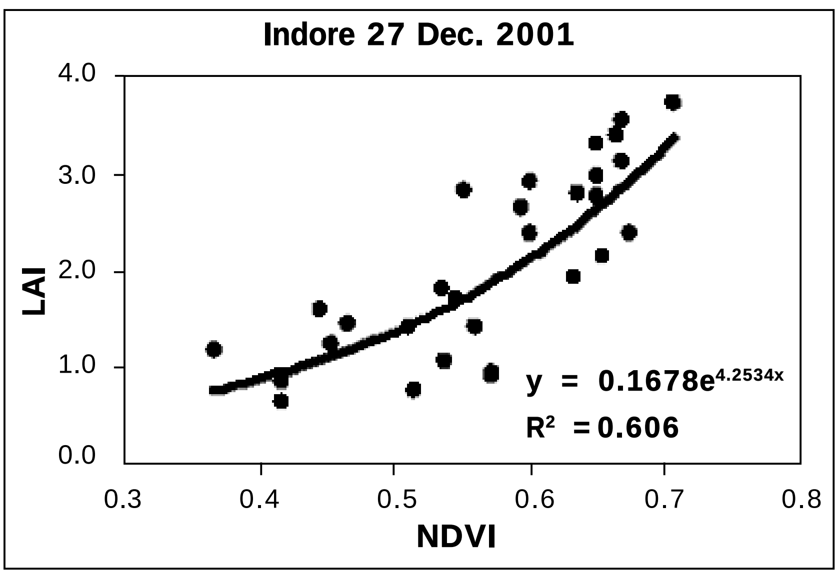


Figure 1: Relationship of ground measured LAI on wheat fields with IRS LISS-III derived NDVI at Indore (Madhya Pradesh, India) (Pandya *et al.*, 2003)

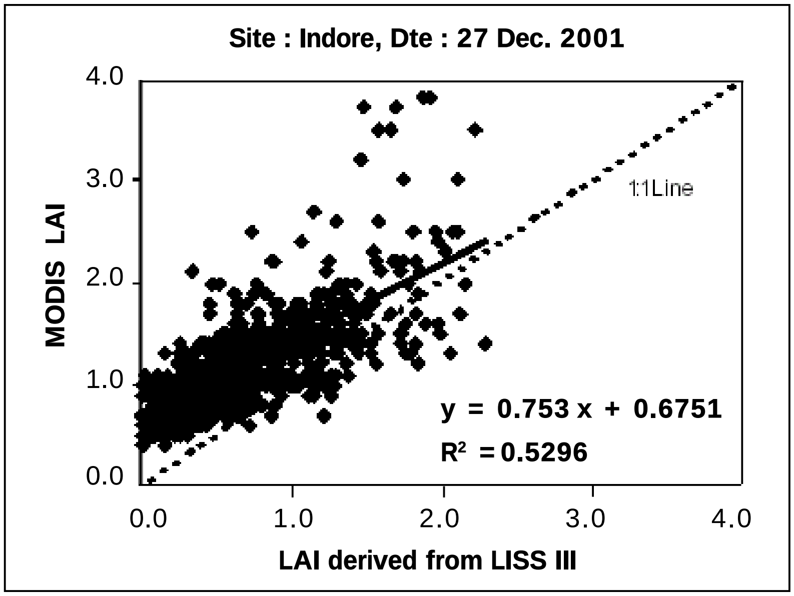


Figure 2: Comparison between LISS-III derived LAI and MODIS LAI at Indore (MP, India) (source: Pandya *et al.*, 2003)

Rastogi *et al.* (2000) tested Price model on farmers fields during 1996-97 season in Karnal (Haryana, India) and 1997-98 in Delhi using IRS LISS-III data and estimated wheat attenuation coefficients. The root mean square error (RMSE) between RS estimates and ground measured LAI ranged between 0.78-0.87 when LAI was in the range of 1-4, while for higher LAI range (4-6), the RMSE varied from 1.25 to 1.5 in two sites. Such errors can severely reduce utility of a model using field-level LAI as input.

Crop simulation models

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 simple representation of a crop and is explanatory in nature. The processes essentially modeled are phenology, photosynthesis and dry matter production, dry matter partitioning, in simulation models aimed at potential production. Those aiming at crop-specific behaviour include modules for phyllochron, branching pattern and potential flowers/ grain filling sites. The response to water and nutrition limited environment is added by introducing models of soil water balance and uptake and transpiration by crop, and nitrogen transformations in soil, uptake and remobilization within plant, respectively. Models of effects of weeds and pests are being developed and could be available in new generation of crop simulation models.

In dynamic crop simulation models, three categories of variables recognized are, state, rate and driving variables. The state variables are quantities like biomass, amount of nitrogen in soil, plant, soil water content, which can be measured at specific times. Driving variables, or forcing functions, characterize the effect of the environment on the system at its boundaries, and their values must be monitored continuously, e.g., meteorological variables. Each state variable is associated with rate variables that characterize their rate of change at a certain instant as a result of specific processes. These variables represent flow of material or biomass between state variables. Their value depends on the state and driving variables according to rules that are based on knowledge of the physical, chemical and biological processes that take place during crop growth.

Under the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) project a computer software package called the Decision Support System for Agrotechnology Transfer (DSSAT) was developed which integrates 11 crop simulation models (CERES cereal, CROPGRO legume and other models) with a standardized input and output (Jones, 1993) and has been evaluated/ used in a number of countries. Use of CERES-Wheat included in DSSAT for regional wheat yield prediction has been demonstrated recently in India (Nain *et al.*, 2004).

GIS AND ITS USE FOR CROP MONITORING

Introduction to GIS

Burrough and McDonnell (1998) has defined GIS as a powerful set of tools for collecting, storing, retrieving at will, transforming and displaying spatial data from the real world for a particular set of purposes. The three major components of GIS are (i) computer hardware, (ii) computer software and (ii) digital geographic data. The information stored within a GIS is of two distinct categories. The spatially referenced information that can be represented by points, lines, and polygons, that are referenced to a geographic coordinate system and is usually stored in either raster (grid-cell) or vector (arc-node) digital format. The second category of information stored in a GIS is attribute data or information describing the characteristics of the spatial feature.

Using RS & GIS for crop monitoring

The use of GIS along with RS data for crop monitoring is an established approach in all phases of the activity, namely preparatory, analysis and output. In the preparatory phase GIS is used for (a) stratification/zonation using one or more input layers (climate, soil, physiolgraphy, crop dominance etc.), or (b) preparing input data (weather, soil and collateral data) which is available in different formats to a common format. In the analysis phase use of GIS is mainly through operations on raster layers of NDVI or computing VI profiles within specified administrative boundaries. The final output phase also involves GIS for aggregation and display of outputs for defined regions (e.g., administrative regions) and creating map output products with required data integration through overlays.

Wade *et al.* (1994) described efforts within National Agricultural Statistics Service (NASS) of U.S. Department of Agriculture (USDA) of using NOAA AVHRR NDVI for crop monitoring and assessment of damage due to flood and drought by providing analysts a set of map products. Combining satellite data in a GIS can enhance the AVHRR NDVI composite imagery by overlaying State and county boundaries. The use of raster-based (grid-cell) capabilities of ARC/INFO (GRID) for the generation of difference image helps compare a season with previous year or average of a number of years. Overlaying a crop mask helps in highlighting only effects on crops. Application of frost isolines is made to help analysts to locate average dates of the first frost for possible crop damage. Generation and overlay of contours of precipitation data generated using TIN function of ARC/INFO also is an aid to interpreting NDVI difference image.

Interfacing crop simulation models to GIS

Crop simulation models, when run with input data from a specific field/ site, produce a point output. The scope of applicability of these simulation models can be extended to a broader scale by providing spatially varying inputs (soil, weather, crop management) and policy combining their capabilities with a Geographic Information System (GIS). The main purpose of interfacing models and GIS is to carry out spatial and temporal analysis simultaneously as region-scale crop behaviour has a spatial dimension and simulation models produce a temporal output. The GIS can help in spatially visualizing the results as well as their interpretation by spatial analysis of model results.

While GIS and modeling tools have existed for so long, the integration, including the conceptual framework is being given attention only recently. Hartkamp *et al.* (1999) have reviewed GIS and agronomic modeling and suggested that 'interface' and 'interfacing' be used as umbrella words for simultaneously using GIS and modeling tools, and 'linking', 'combining' and 'integrating' as suitable terminology for degree of interfacing. These correspond to loose, tight and embedded coupling, respectively, as used by Burrough (1996) and Tim (1996). While there is a continuum between linking and combining, the terms are explained below:

(a) Linking: Simple linkage strategies use GIS for spatially displaying model outputs. A simple approach is interpolation of model outputs. An advanced strategy is to use GIS functions (interpolation, overlay, slope, etc.) to produce a database containing inputs of the model and model outputs are also exported to the same database. Communication between GIS and model is through identifiers of grid cells or polygons in input and output files, which are transferred in ascii or biary format between GIS and model (Figure 3a). Such an approach is not able to utilize full potential of the system and suffers from limitation due to (a) dependence on formats of GIS and model, (b) incompatibility of operating environments and (c) not fully utilizing the capabilities of GIS.

(b) Combining: Combining also involves processing data in a GIS and displaying model results, however, the model is configured with GIS and data are exchanged automatically. This is done with facilities in GIS package of macro language, interface programmes, libraries of user callable routines (Figure 3b). This requires more complex programming and data management than simple linking. Example of combining is AEGIS (Agricultural and Environmental GIS) with ArcView (Engel *et al.*, 1997).

(c) Integrating: Integration implies incorporating one system into the other. Either a model is embedded in GIS or a GIS system is included in a modeling system. This allows automatic use of relational database and statistical packages (Figure 3c). This requires considerable expertise, effort and understanding of the two tools.

Calixte *et al.* (1992) developed a regional agricultural decision support system, known as Agricultural and Environmental Geographic information System (AEGIS) that uses the DSSAT capabilities within ARC/INFO GIS for regional planning and productivity analysis. AEGIS allows the user to select

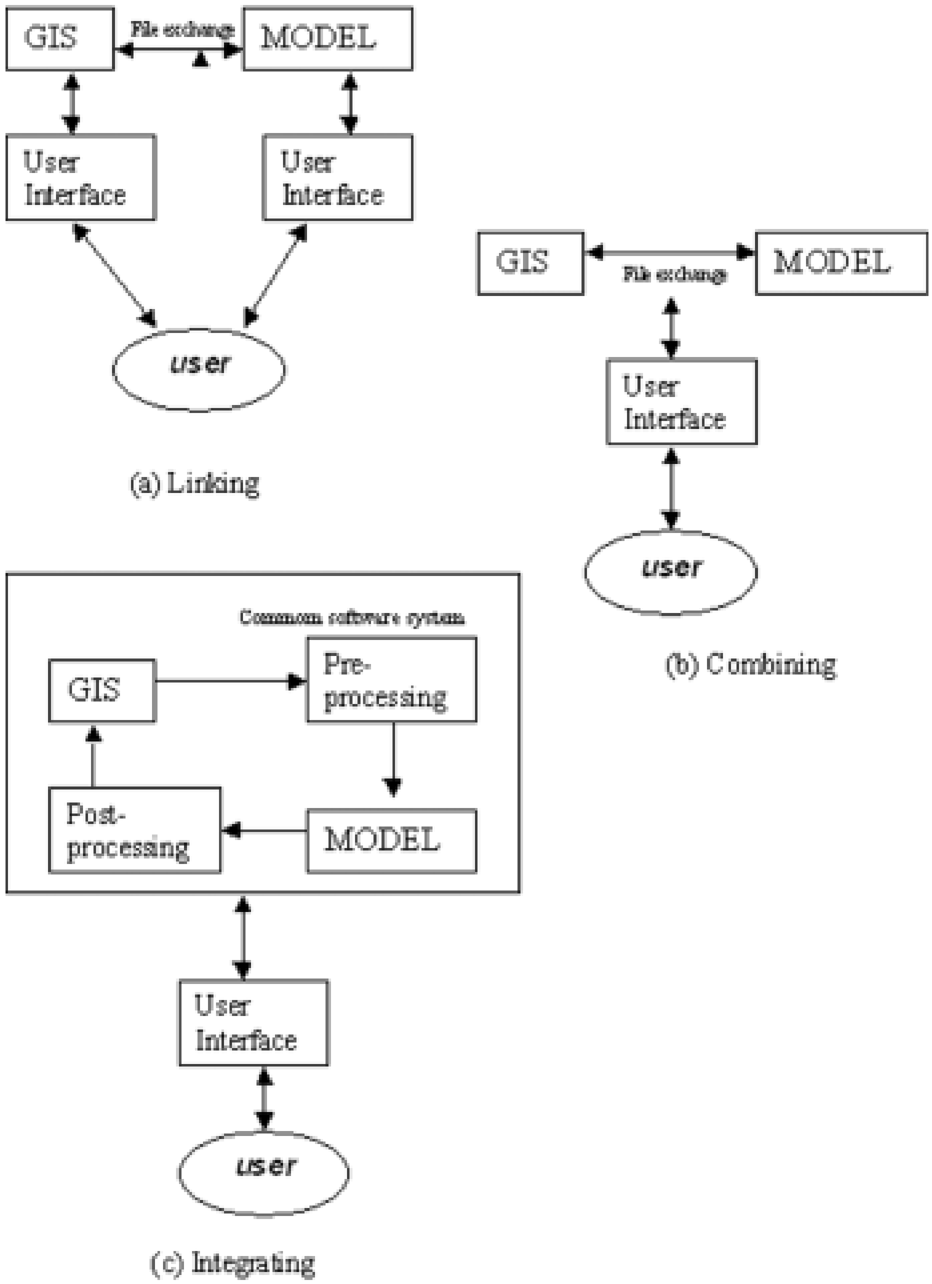


Figure 3: Organizational structure for (a) linking, (b) combining and (c) integrating GIS and crop models (Hartkamp *et al.*, 1999)

various combinations of crop management practices over space and evaluate potential crop production. 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. Thornton *et al.* (1997a) developed spatial analysis software for the most recent release of the DSSAT, Version 3.1. This software standardized the links between crop models and GIS software and this allowed developers to make use of whatever GIS software is most suitable for a particular purpose, while ensuring that basic links to the DSSAT system and the crop models are the same. The spatial analysis software has two modules: (i) a geostatistical module to interpolate maps and produce probability surfaces from a network of data points, and (ii) a utility that calculates agronomic and economic output statistics from model simulations and maps the results as polygons. Another effort is development of a SPATIAL-EPIC linked to Arc/Info (Satya *et al.*, 1998).

Demonstrated applications of CSM interfaced with GIS

Current wide range of applications of interfacing of GIS and modelling are reviewed by Hartkamp *et al.* (1999) and covers spatial yield calculation (regional and global), precision farming, climate change studies, and agro-ecological zonation, etc.

CGMS (Crop Growth Monitoring System) of MARS (Monitoring Agriculture with Remote Sensing)

This project of European Union uses WOFOST model and Arc/Info for operational yield forecasting of important crops (Meyer-Roux and Vossen, 1994). The Crop Growth Monitoring System (CGMS) of the MARS integrates crop growth modelling (WOFOST), relational batabase ORACLE and GIS (ARC/INFO) with system analytical part for yield forecasting (Bouman *et al.*, 1997). There are databases on soil, weather, crop, and yield statistics that cover the whole of EU. The system-analytical part consists of three modules: agrometeorological module, a crop growth module and a statistical module. The meteorological module takes care of the processing of daily meteorological data that are received in real time to a regular grid of 50x50 km for use as input by crop growth model or for assessment of 'alarm' conditions. The crop growth module consists of the dynamic simulation model WOFOST in which crop growth is calculated and crop indicators are generated for two production levels: potential and water-limited. In CGMS, WOFOST is run on a daily bases for each so-called 'simulation unit', i.e. a unique combination of weather, soil, and crop (mapping) units. In the statistical module, crop indicators (total above ground dry weight and dry weight storage organs) calculated with WOFOST are related to historical yield statistics through regression analysis in combination with a time-trend, for at least 15 years of simulated and historical data (Vossen, 1995). The resulting regression equations per crop per region are used to make actual yield forecast. CGMS generates on a 10 day and monthly basis three types of output on current cropping season: (i) Maps of accumulated daily weather variables on 50x50 km grid to detect any abnormalities, e.g. drought, frost, (ii) Maps of agricultural quality indicators based on comparison of simulated crop indicators with their long-term means, (iii) Maps and tables of yield forecasts.

Precision Farming

Han *et al.* (1995) developed an interface between PC ARC/INFO GIS and SIMPOTATO simulation model to study potato yield and N leaching distribution for site-specific crop management (precision farming) in a 50 ha field. The GIS input layers, corresponding to important distributed input parameters for the model, were irrigated water/N layer, soil texture layers and initial soil N layers. For each unique sub-area stored in the GIS database, the interface program extracts the attribute codes of that sub-area from the GIS database, converts the attribute codes to the input parameters of the SIMPOTATO and sends them to the model. After running the model, the interface program retrieves the output data (potato yield and N leaching), converts them to the attribute codes and stores the output data in the GIS database.

Agro-ecological Zonation

Aggarwal (1993) used WTGROWS to simulate potential and water-limited wheat yields for 219 weather locations spread all over the country. The district boundaries (as polygons) and model input parameters of soil, weather stations and agro-ecological regions were stored in ARC/INFO GIS. The model outputs of potential and rainfed productivity were stored in GIS as polygon attribute data. Based on potential and rainfed productivity, the districts were classified into 10 iso-yield zones and represented as map using GIS.

Evaluating Agricultural land use options

Aggarwal *et al.* (1998) studied the agricultural land use option for the state of Haryana using symphonic use of expert knowledge, simulation modelling, GIS and optimization techniques. The study area was divided into agro-ecological land units by overlaying maps of soil, soil organic carbon and climatic normal rainfall in raster GIS IDRISI. The original soil mapping units based on 19 soil properties were reclassified based on soil texture, level and extent of salinity and sodicity, slope and ground water depth. The organic carbon and normal rainfall maps were generated by inverse square interpolation of observed data points followed by segmentation. The CSM for specific crops have been linked to GIS layers of administrative boundaries, physiographic features, climate, soil and agroclimatic zones and GCM outputs to study effect of future climatic changes on crop potential / productivity (Bacsi *et al.*, 1991; Carter and Saarikko, 1996).

LINKING CROP SIMULATION MODELS TO RS INPUTS & GIS

The use of remotely sensed information to improve crop model accuracy was proposed as early as two decades ago by Wiegand *et al.* (1979) and Richardson *et al.* (1982). They suggested using spectrally derived LAI either as direct input to physiological crop model or as an independent check to model calculation for its re-initialization. The main advantage of using remotely sensed information is that it provides a quantification of the actual state of crop for large area using less labour and material intensive methods than *in situ* sampling. While crop models provide a continuous estimate of growth over time, remote sensing provides a multispectral assessment of instantaneous crop condition with in a given area (Delecolle *et al.*, 1992).

The different ways to combine a crop model with remote sensing observations (radiometric or satellite data) were initially described by Maas (1988a) and this classification scheme was revised by Delecolle *et al.* (1992) and by Moulin *et al.* (1998). Five 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, i.e., the adjustment of an initial condition to obtain a simulation in agreement with the RS derived observations;

(d) the re-calibration of the model, i.e., the adjustment of model parameters to obtain a simulation in agreement with the remotely-sensed derived observations, also called 're-parameterization' strategy;

(e) the corrective method, i.e., a relationship is developed between error in some intermediate variable as estimated from remotely sensed measurement and error in final yield. This relationship may be applied to a case in which final yield is not known.

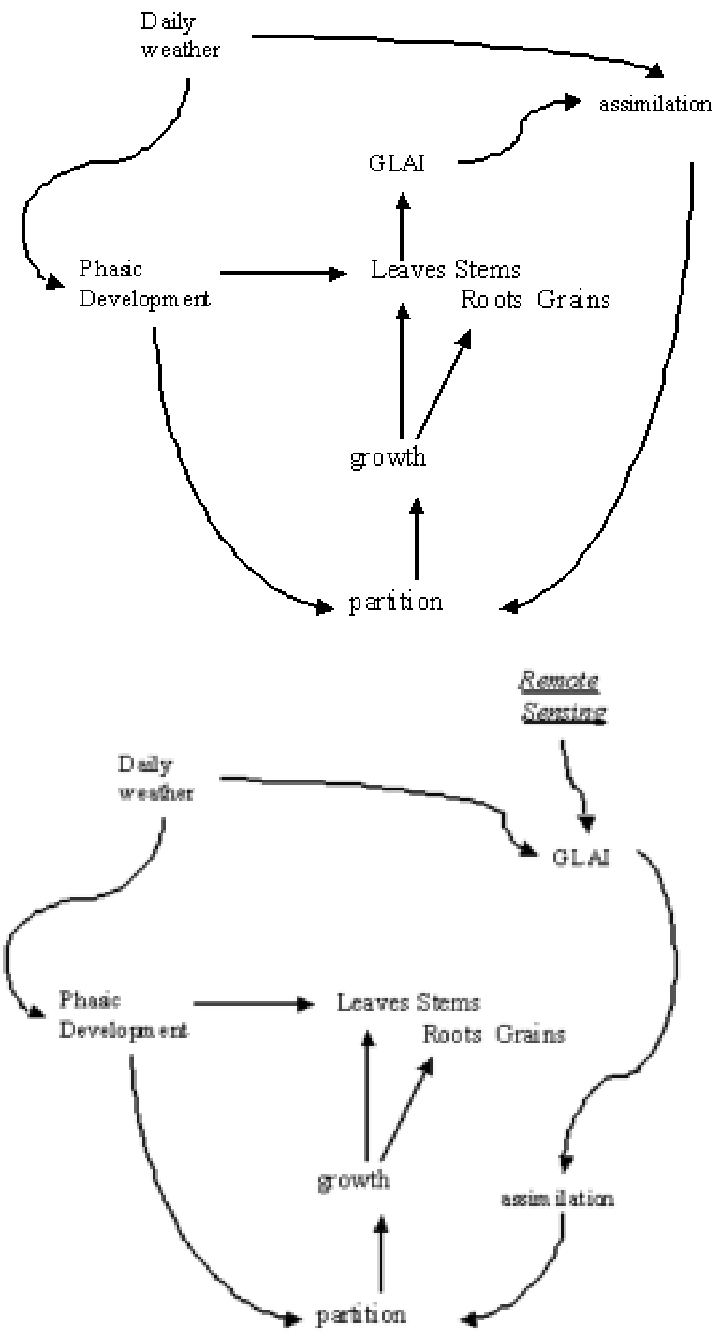
Direct use of driving variable

The driving variables of crop simulation models are weather inputs comprising daily observations of maximum and minimum temperature, solar radiation, relative humidity, and wind speed as a minimal subset. In a recent review on this subject, Moulin *et al.* (1998) cited inadequate availability of RS-derived parameters, due to cloud cover problem and intrinsic properties of sensors and platforms, as a major drawback, for adoption of this approach. However, this is a promising area, given the sparse distribution of weather observational network and recent progress in deriving some of these variables from sensors in space. Rainfall, solar radiation and intercepted/absorbed PAR have received maximum attention.

Maas (1988a) 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 showed an overestimation of 6.2% in above ground biomass at anthesis. METEOSAT based decadal (10-day) rainfall using cold cloud duration has been used as input to CERES-Millet in Burkina Faso by Thornton *et al.* (1997b) to forecast provincial millet yields halfway through crop duration to within 15% of their final values.

Forcing strategy

The forcing strategy consists of updating at least one state variable in the model using remote sensing data. LAI has been the most commonly updated state variable. The concept of a simple crop simulation model and its modification for RS-derived LAI forcing is illustrated in Figure 4. Some examples of forcing spectrally derived LAI in crop simulation models are summarized in Table-2. The forcing could either be done only on day of RS observation (Maas, 1988a) or daily LAI profile is generated using some simple parametric model for use (Delecolle and Guerif, 1988).



(a)

(b)

Figure 4: (a) Simple schematic of a crop simulation model. (b). Modified structure of crop simulation model with RS-based LAI forcing (Delecolle and Guerif, 1988)

Table 2. Selected case studies on use of RS-derived LAI for forcing crop simulation models

Crop	Model	LAI estimation & interfacing	Evaluation of performance	Reference
Maize	-	Ground NDVI-LAI on obs. Dates	AGDM estimation improved	[1]
Wheat	AFRCWHEAT	SPOT/HRV LAI-WDVI relation: Daily interpolated LAI	Yield RMSE decreased	[2]
Wheat	SUCROS	LAI-WDVI	Biomass at harvest	[3]

[1] Maas, 1988a; [2] Delecolle and Guerif, 1988; [3] Bouman, 1995

Re-initialization strategy

The re-initialization method takes advantage of the dependence of model performance on state variable initial condition. It involves adjustment of initial condition of state variable so as to minimize the difference between a derived state variable or the radiometric signal and its simulation. Maas (1988a) in his simplified maize model adjusted the initial value of LAI (L0) at emergence based on the minimization of an error function between remotely sensed LAI values and simulated LAI values during the course of simulation. Re-initialization using one observation produced results similar to updating (forcing). However, the stability of model estimates obtained through re-initialization increased as more observations were used. The observation at 51 days after emergence, which caused a 42% error using updating, resulted in less than a 3% error using re-initialization. Maas (1988b) demonstrated a similar study for sorghum using satellite observations. The simulation model was developed and verified using 10 fields in Central Texas in 1976 and the re-initialization approach was validated for the 37 fields in South Texas using Landsat MSS data and agronomic observations. Without using the initialization procedure, the average yield for the 37 fields was underestimated by 30%. Use of satellite derived green LAI data to initialize the same simulations resulted in a 2% overestimation of average yield.

Re-calibration/re-parameterization strategy

In this approach it is assumed that model is formally adequate but requires re-calibration. This is achieved by minimizing error between RS-derived state variable and its simulation by the model. This makes such an approach sensitive to errors in deriving state variables from RS data. In this case also, the state variable matched is LAI. However, depending on the model structure, which parameter to tune and number of observations used in analysis is critical.

Maas (1988a) demonstrated the re-calibration for maize model with remotely sensed GLAI observations. A multi-dimensional error function minimization procedure was used which indicated more consistent estimates of LAI and biomass at anthesis as the number of parameters increased in multi-dimensional re-parameterization.

Delecolle *et al.* (1992) illustrated the use of re-calibration for rice crop using GRAMI model. Values of one to four parameters in the GRAMI model were re-calibrated to match the simulated LAI profile to observed LAI values. The results showed that improvement in simulated LAI profile by re-calibration depends largely on the number and timing of LAI observations. Clevers and Leeuwen (1996) used ground and airborne radiometric measurements over sugar beet fields to calibrate the SUCROS model. They derived LAI from measurements in optical and microwave wavebands. The adjusted parameters and initial conditions were sowing date, a growth rate, light use efficiency and maximum leaf area. The results showed that re-calibration with both optical and microwave observations estimated yield better than optical data alone. In the absence of optical remote sensing data, radar data yielded a significant improvement in yield estimation with the case of no remotely observed observations. Inoue *et al.* (1998) related paddy vegetation indices to the fraction of absorbed photosynthetically active radiation (fAPAR) as exponential equations with different parameters for the periods before and after heading. A real time recalibration module based on a simplex algorithm was developed and proved effective in linking remotely sensed fAPAR with a simple rice growth model.

Re-parameterization using Coupled Crop Simulation Models and Canopy-radiation Models

The re-initialization and re-parameterization of crop models can also make direct use of radiometric information instead of deriving canopy parameters from them (Moulin *et al.*, 1998). In this strategy, coupling a radiative transfer reflectance model to the crop production model reproduces the temporal behaviour of canopy surface reflectance, which can be compared with canopy reflectance observed from satellite. Adjusting initial conditions or model parameters carries out the minimization of differences between the simulated and observed reflectance values.

Such an approach has been used by Clevers *et al.* (1994) and Guerif and Duke (1998) for sugarbeet. The LAI simulated by SUCROS on dates of spectral observations was passed on to PROSPECT-SAIL and SAIL model, respectively, and parameters of SUCROS model adjusted to minimize differences between observed WDVI and simulated WDVI. The re-parameterization of SUCROS reduced yield prediction errors. This approach was extended to microwave RS by Bouman *et al.* (1999) who simulated radar backscatter of agricultural crops (sugar beet, potato, winter wheat) by integrating LAI and leaf moisture from SUCROS with top soil moisture content by soil water balance model (SAHEL) and radar backscatter model (CLOUD).

Since canopy-radiation models such as SAIL have parameters in addition to LAI, their uncertainty could affect the results from this approach. Moulin and Guerif (1999) concluded that the error in canopy reflectance estimates as a result of omitting data on canopy leaf angle and soil reflectance, two parameters in SAIL model, is so large that direct use of simulated canopy reflectance in simulation models for yield prediction is severely affected. However, the use of vegetation indices drastically reduced the errors linked to crop structure (NDVI) and to soil reflectance (TSAVI).

Corrective approach

Sehgal *et al.* (2001b) used this strategy for generating the wheat yield maps for farmers' fields during rabi 1998-99 in Alipur block (Delhi). The RS inputs as estimated LAI were linked to wheat simulation model WTGROWS for yield mapping and results were validated with yield observations on farmers' fields. Biometric relation of grain yield and leaf area index (LAI) is derived from simulation model by running model for a combination of input resources, management practices and soil types occurring in the area. Then this biometric relationship is applied to all the crop fields of the study area for which the LAI is computed from remote sensing data. The WTGROWS simulated grain yield for the combination of inputs showed yields varying between 1.1 and 4.9 t ha^{-1}. The corresponding range of simulated LAI on 27 Jan 1999 was 0.6 to 4.2. The regression equation fitted between simulated LAI on 27th Julian day (i.e. 27-January-99) and simulated grain yield showed saturating logarithmic nature with a R^2 value of 0.81. The relationship is given below:

$$\text{Yield (kg/ha)} = 1571.2 * \ln(\text{LAI}) + 2033.6 \qquad \text{...[2]}$$

This empirical biometric relation was applied to the LAI map of the wheat pixels and grain yield map for farmer's fields of Alipur block, Delhi, was generated. The predicted yields ranged from 2.1 to 4.8 tha^{-1}. The comparison of predicted grain yield and observed yield for the 22 farmers' fields showed high correlation coefficient of 0.8 and a root mean square error (RMSE) of 597 kg ha^{-1} which was 17 per cent of the observed mean yield (Figure 5).

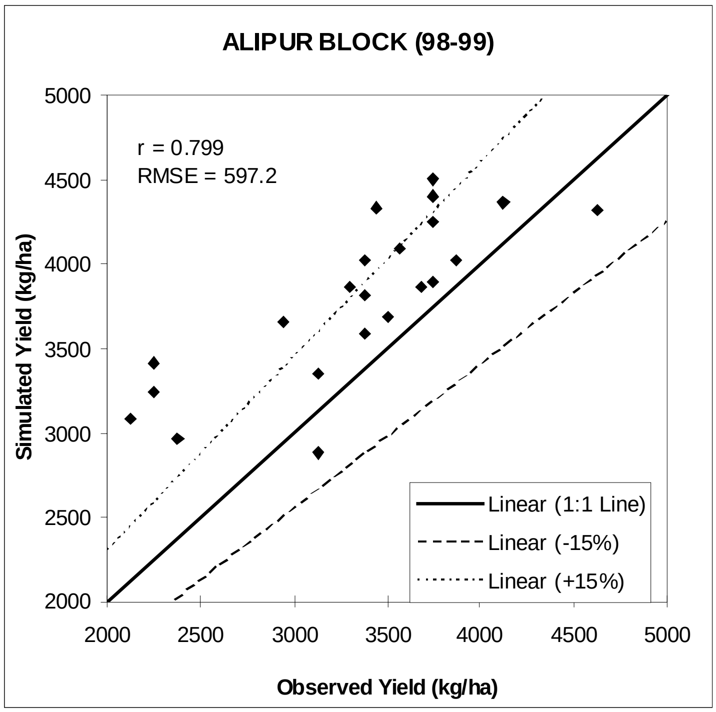


Figure 5: Comparison of predicted grain yield by modified corrective approach and observed values for 22 farmers' fields. The 1:1 line and its ±15 per cent band lines are also shown (Sehgal *et al.*, 2001b)

Development of a RS-based CGMS for wheat in India

Sehgal *et al.* (2001a) reported the development of a prototype Crop Growth Monitoring System (CGMS) for wheat using WTGROWS simulation model on a 5'x5' grid in GIS environment for generating daily crop growth maps and predicting district-wise grain yield. The inputs used were RS based wheat distribution map, daily weather surfaces, soil properties map and crop management input databases in a GIS environment and analysis for wheat season of 1996-97 was carried out. The inputs, their processing in GIS and framework for CGMS are summarized in Figure 6. The grid-wise final simulated grain yields are shown in Figure 7. The figure clearly indicates spatial patterns in yield variability. The high grain yields in Kurukshetra and Karnal and low yields in Bhiwani, Rohtak, Yamunanagar and Ambala are brought out clearly. The comparison of simulated grain yields aggregated at district level and estimates by the State Department of Agriculture is shown in Figure 8. In general, the model simulated yields were higher than observed. This could be due to a number of yield reducing factors such as pest, weed, soil constraints, which operate in field but are not considered by the model. The model predicted yields were within ±10% of reported yields in 12 out 16 districts. The RMSE of 335.4 kg ha^{-1}, which is less than 10 per cent of the State mean yield, was obtained. Only in two districts, Mahendragarh and Bhiwani, the simulated district yields were lower than observed yields while for Kaithal, Karnal, Ambala and Yamunanagar, the simulated yields were higher than observed yields by more than 10 per cent.

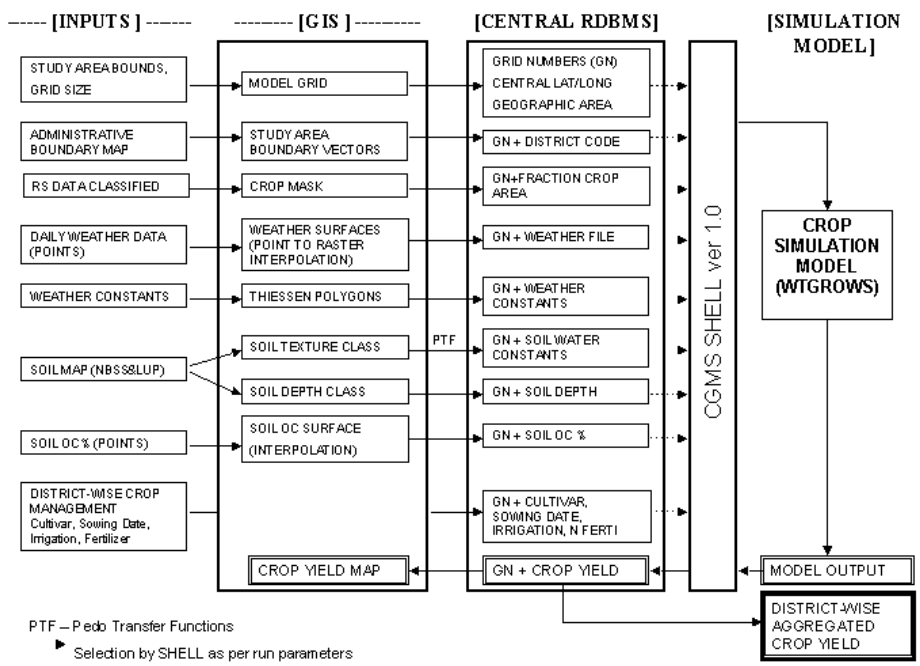


Figure 6. Schematic diagram of a crop growth monitoring system showing the linkages between inputs, spatial layers in GIS, and relational database to WTGROWS simulation model (Sehgal *et al.*, 2001a)

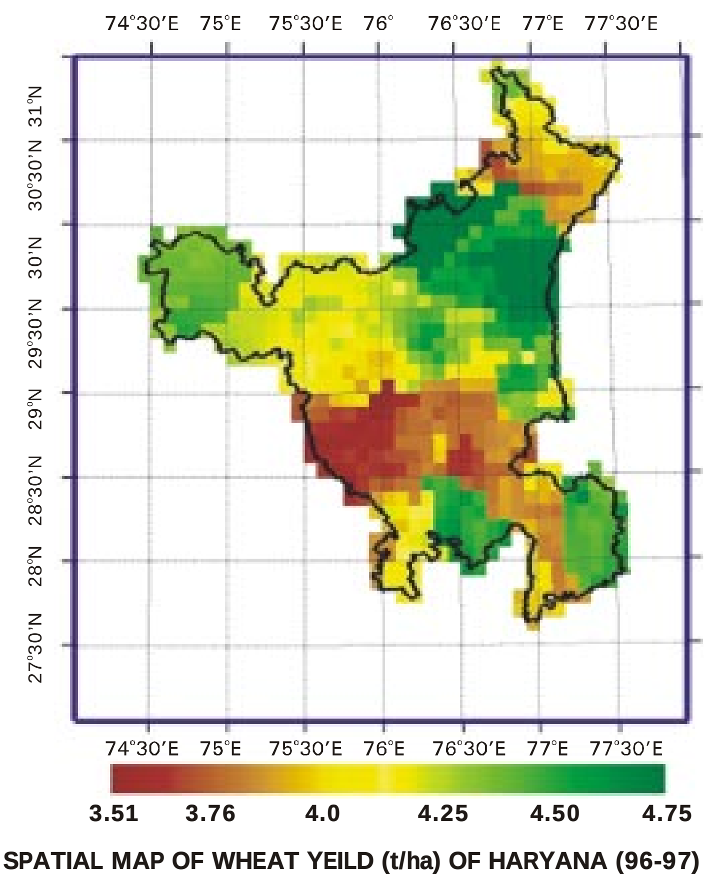


Figure 7: Grid-wise simulated wheat yields by WTGROWS simulation model for 1996-97 season in Haryana (Sehgal *et al.*, 2001a)

Sehgal *et al.* (2002) demonstrated a technique for estimating date of sowing (DOS) using RS-derived spectral-temporal crop growth profiles and CGMS simulation capability and evaluated the capability of CGMS for spatial yield mapping and district level yield prediction for Haryana State during 2000-01 crop season. The technique for estimating district-wise DOS matched the RS-derived date of peak NDVI (from multi-date WiFS sensor aboard IRS-1D satellite) to date of peak LAI simulated in CGMS for a range of plausible dates of sowing (Figure 9). The peak date of NDVI was computed by fitting Badhwar model to the multi-date NDVI values. The CGMS performance was evaluated by incorporating RS-derived date of sowing in predicting district level wheat yields with and without use of district-wise N fertilizer application

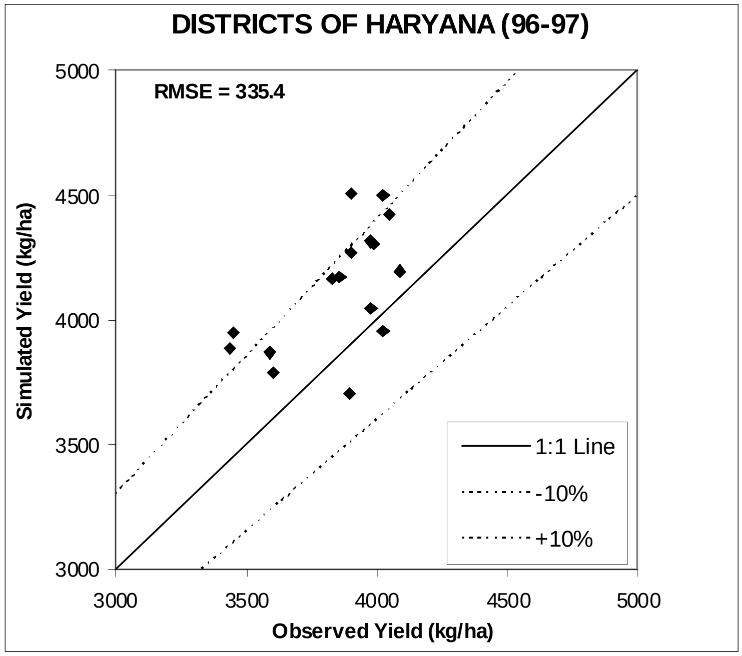


Figure 8: Comparison of simulated district wheat yields by CGMS with observed values reported by the State Department of Agriculture, Haryana , for 1996-97 season. The 1:1 line and its ±10 per cent band lines are also shown (Sehgal *et al.*, 2001a)

rate computed from district-wise fertilizer consumption statistics. The correlation between district yield simulated by CGMS and official State Department of Agriculture (SDA) estimates was only 0.163 when constant median/mean inputs of DOS, N fertilizer and irrigation application were specified for all the districts. The correlation increased to 0.52 when RS-CGMS-derived district-wise DOS was used as input and further increased to 0.74 when information from consumption statistics of N fertilizer use was additionally specified.

It is clear from the above studies that the potential of integrating crop simulation model, RS inputs and GIS has been well proven in a number of case studies. While techniques for geophysical and crop biophysical parameter retrieval are becoming available and producing products of required accuracy, the available crop simulation models need to be provided with GIS integration and iterative run options to benefit from this integration.

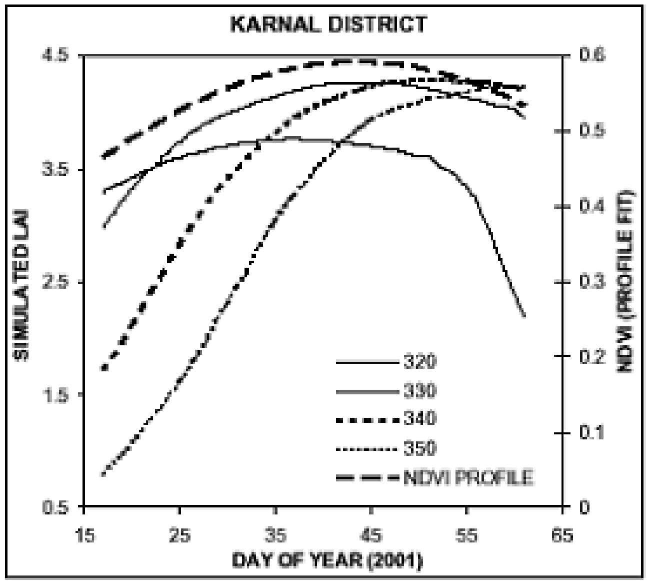


Figure 9: An illustration for obtaining date of sowing (DOS) for Karnal district by matching date of simulated LAI peak with date of fitted NDVI profile peak (Tmax). Different simulated LAI curves correspond to various dates of sowing (320 to 350) in year 2000 (Sehgal *et al.*, 2002)

CONCLUSIONS

Remote sensing data provide a complete and spatially dense observation of crop growth. This complements the information on daily weather parameters that influence crop growth. RS-crop simulation model linkage is a convenient vehicle to capture our understanding of crop management and weather with GIS providing a framework to process the diverse geographically linked data. Currently RS data can regularly provide information on regional crop distribution, crop phenology and leaf area index. This can be coupled to crop simulation models in a number of ways. These include, (a) direct use of RS inputs as forcing variable, (b) re-initializing or re-calibrating CSM so that its outputs of LAI match RS observations, and (c) using simulation model to estimate impact of variation in a state variable (e.g. LAI) and final yield and using CSM-RS differences to modeling yield predictions. These approaches have been demonstrated through case studies on wheat in India at different spatial scales (village, grid and district). CSM-RS linkage has a number of applications in regional crop forecasting, agro-ecological zonation, crop suitability and yield gap analysis and in precision agriculture.

In future the RS-CSM linkage will be broadened due to improvements in sensor capabilities (spatial resolution, hyper-spectral data) as well as retrieval of additional crop parameters like chlorophyll, leaf N and canopy water status. Thermal remote sensing can provide canopy temperatures and microwave data, the soil moisture. The improved characterization of crop and its growing environment would provide additional ways to modulate crop simulation towards capturing the spatial and temporal dimensions of crop growth variability.

REFERENCES

Aggarwal, P.K. 1993. Agro-ecological zoning using crop growth simulation models: characterization of wheat environments of India, pages 97-109. In: Systems Approaches for Agricultural Development, Vol. 2. (Penning de Vries, F.W.T., Teng, P. and Metselaar, K. eds.), Kluwer Academic Publishers, Dordrecht, The Netherlands.

Aggarwal, P.K., Kalra, N., Bandhyopadhyay, S.K., Pathak, H., Sehgal, V.K., Kaur, R., Rajput, T.B.S., Joshi, H.C., Choudhary, R. and Roetter, R. 1998. Exploring agricultural land use options for the State of Haryana: Biophysical modelling, pages 59-65. In: Exchange of methodologies in land use planning (Roetter, R., Hoanh, C.T., Luat, N.V., van lttersum, M.K. and van Laar, H.H. eds.), SysNet Research Paper Series No. 1, IRRI, Los Banos, Philippines.

Bacsi, Z., Thorton, P.K. and Dent, J.B. 1991. Impacts of future climate change on Hungarian crop production: An application of crop growth simulation models. Agric. Sys., 37: 435-450.

Badhwar, G. D., MacDonald, R.B., and Mehta, N.C. 1986. Satellite-derived LAI and vegetation maps as input to global cycle models-a hierarchical approach. Int. J. Remote Sensing, 7: 265-281.

Bouman, B.A.M. 1995. Crop modelling and remote sensing for yield prediction. Netherland J. Agric. Sci., 43: 143-161.

Bouman, B.A.M., van Dipen, C.A., Vossen, P. and van Der Wal, T. 1997. Simulation and systems analysis tools for crop yield forecasting, pages 325-340. In: Applications of Systems Approaches at the Farm and Regional Levels, Vol. 1. (Teng, P.S., Kropff, M.J., ten Berge, H.F.M., Dent, J.B., Lansigan, F.P. and van Laar, H.H. eds.), Kluwer Academic Publishers, Dordrecht, The Netherlands.

Bouman, B.A.M., van Kraalingen, D.W.G., Stol, W. and van Leeuwen, H.J.C. 1999. An ecological modeling approach to explain ERS SAR radar backscatter of agricultural crops. Remote Sens. Environ., 67: 137-146.

Burrough, P.A. and McDonnell, R.A. 1998. Principles of geographic information systems. Oxford University Press, Oxford, UK, pp. 10-16.

Burrough, P.A. 1996. Environmental modelling with geographical information system, pages 56-59. In: Models in Action, Quantitative Approaches in Systems Analysis (Stein, A., Penning de Vries, F.W.T. and Schotman, P.J. eds.), No 6, AB-DLO, Wageningen, The Netherlands.

Calixte, J.P., Beinroth, F.J., Jones, J.W. and Lai, H. 1992. Linking DSSAT to a geographic information system. Agrotechnology Transfer, 15: 1-7.

Carter, T.R. and Saariko, R.A. 1996. Estimating regional crop potential in Finland under a changing climate. Agric. For. Meteorol., 79: 301-313.

Chen, J.M. and Cihlar, J. 1996. Retrieving leaf area index of boreal conifer forests using Landsat TM images. Remote Sens.Environ., 55: 153-162.

Chen, J.M., Pavlic, G., Brown, L., Cihlar, J., Leblanc, S.G., White, H.P., Hall, R.J., Peddle, D.R., King, D.J., Trofymow, J.A., Swift, E., Van der Sanden, J., Pellikka, P.K.E. 2002. Derivation and validation of Canada-wide coarse-resolution leaf area index maps using high-resolution satellite imagery and ground measurements. Remote Sens. Environ., 80: 165-184.

Clevers, J.G.P.W., Buker, C., van Leeuwen, H.J.C. and Bouman, B.A.M. 1994. A framework for monitoring crop growth by combining directional and spectral remote sensing information. Remote Sens. Environ., 50: 161-170.

Clevers, J.G.P.W. and van Leeuwen, H.J.C. 1996. Combined use of optical and microwave remote sensing data for crop growth monitoring. Remote Sens. Environ., 56: 42 - 51.

Dadhwal, V.K. 1999. Remote Sensing and GIS for agricultural crop acreage and yield estimation. Internat. Arch. Photogramm. & Remote Sensing, XXXII, 7-W9, 58-67.

Dadhwal, V.K. and Ray, S.S. 2000. Crop Assessment using remote sensing – Part II: Crop condition and yield assessment. Indian J. Agric. Economics, 55 (2, Suppl.), 55-67.

Dadhwal, V.K., Sehgal, V.K., Singh, R.P. and Rajak, D.R. 2003. Wheat yield modeling using satellite remote sensing with weather data: Recent Indian experience. Mausum, 54(1): 253-262.

Delecolle, R. and Guerif, M. 1988. Introducing spectral data into a plant process model for improving its prediction ability. Proceedings of the 4th International Colloquium Signatures Spectrales d'Objects en Teledetection, 18-22 Jan, 1988, Aussois, France, pp. 125-127.

Delecolle, R., Maas, S.J., Guerif., M. and Baret, F. 1992. Remote sensing and crop production models: present trends. ISPRS J. Photogramm. Remote Sens., 47:145-161.

Engel, T., Hoogenboom, G., Jones, J.W. and Wilkens, P.W. 1997. AEGIS/WIN - a program for the application of crop simulation models across geographic areas. Agronomy J., 89: 919-928.

Gao, W. and Lesht, B.M. 1997. Model inversion of satellite measured reflectances to obtain surface biophysical and bi-directional reflectance characteristics of grassland. Remote Sens. Environ., 59: 461-471.

Guerif, M. and Duke, C. 1998. Calibration of SUCROS emergence and early growth module for sugar beet using optical remote sensing data assimilation. European J. Agronomy, 9: 127-136.

Han, S., Evans, R.G., Hodges, T. and Rawlins, S.L. 1995. Linking geographic information system with a potato simulation model for site-specific crop management. J. Environ. Qual., 24: 772-777.

Hartkamp, D.A., White, J.W. and Hoogenboom, G. 1999. Interfacing geographic information systems with agronomic modeling: A review. Agron. J., 91: 761-772.

Horie, T., Yajima, M. and Nakagawa, H. 1992. Yield forecasting. Agric. For. Meteorol., 40: 211-236.

Inoue, Y., Moran, M.S. and Horie, T. 1998. Analysis of spectral measurements in paddy field for predicting rice growth and yield based on a simple crop simulation model. Plant Production Sci., 1(4): 269-279.

Jones, J.W. 1993. Decision support systems for agricultural development, pages 459-471. In: *Systems Approaches for Agricultural Development*, Vol. 2. (Penning de Vries, F.W.T., Teng, P. and Metselaar, K. eds.), Kluwer Academic Publishers, Dordrecht, The Netherlands.

Knyazikhin, Y., Martonchik, J.V., Myneni, R.B., Diner, D.J. and Running, S.W. 1998. Synergistic algorithm for estimating vegetation canopy leaf area index and fraction of absorbed photosynthetically active radiation from MODIS and MISR data. J. Geophys. Res., 103: 32257-32275.

Maas, S.J. 1988a. Use of remotely sensed information in agricultural crop growth models. Ecol. Modelling, 41: 247-268.

Maas, S.J. 1988b. Using satellite data to improve model estimates of crop yield. Agron. J., 80: 655-662.

Maracchi, G., Perarnaud, V. and Kleschenko, A.D. 2000. Applications of geographical information systems and remote sensing in agrometeorology. *Agric. Forest Meteorol.*, 103: 119-136.

Meyer-Roux, J. and Vossen, P. 1994. The first phase of the MARS project, 1988-1993: overview, methods and results, pp. 33 – 85. In: Proceedings of the Conference on the MARS Project: Overview and Perspectives. Commission of the European Communities, Luxembourg.

Moulin, S. and Guerif, M. 1999. Impacts of model parameter uncertainties on crop reflectance estimates: a regional case study on wheat. Int. J. Remote Sens., 20(1): 213-218.

Moulin, S., Bondeau, A. and Delecolle, R. 1998. Combining agricultural crop models and satellite observations: from field to regional scales. Int. J. Remote Sens., 19(6): 1021-1036.

Myneni, R.B., Nemani, R.R. and Running, S.W. 1997. Estimation of global leaf area index and absorbed PAR using radiative transfer models. IEEE Trans. on Geosc. and Rem. Sensing, 35(6): 1380-1393.

Nain, A.S., Dadhwal, V.K. and Singh, T.P. 2004. Use of CERES-Wheat model for wheat yield forecast in central Indo-Gangetic plains of India. J. Agricultural Science (camb.), 142: 59-70.

Pandya, M.R., Chaudhari, K.N., Singh, R.P., Sehgal, V.K., Bairagi, G.D., Sharma, R. and Dadhwal, V.K. 2003. Leaf area index retrieval using IRS LISS-III sensor data and validation of MODIS LAI product over Madhya Pradesh. Current Science, 85(12): 1777-1782.

Price, J.C. 1993. Estimating leaf area index from satellite data. IEEE Trans. Geoscience Remote Sensing, 31: 727-734.

Qiu, J., Gao, W. and Lesht, B.M. 1998. Inverting optical reflectance to estimate surface properties of vegetation canopies. Int. J. Remote Sens., 19: 641-656.

Rastogi, A., Kalra, N., Agarwal, P.K., Sharma, S.K., Harit, R.C., Navalgund, R.R. and Dadhwal, V.K. 2000. Estimation of wheat leaf area index from satellite data using Price model. International J. Remote Sensing, 21(15): 2943- 2949.

Richardson, A.J., Wiegand, C.L., Arkin, G.F., Nixon, P.R. and Gerbermann, A.H. 1982. Remotely sensed spectral indicators of sorghum development and their use in growth modelling. Agric. Meteorol., 26: 11-23.

Satya, P., Shibasaki, R. and Ochi, S. 1998. Modelling Spatial Crop Production: A GIS approach. In: Proceedings of the 19th Asian Conference on Remote Sensing, 16-20 Nov., 1998, Manila, pp. A-9-1 – A-9-6.

Sehgal, V.K., Rajak, D.R. and Dadhwal, V.K. 2001a. Issues in linking remote sensing inputs in a crop growth monitoring system: results of a case study. In: Proc. of the ISRS National Symposium, Dec 11-13, 2001, Ahmedabad, India.

Sehgal, V.K., Sastri, C.V.S., Kalra, N. and Dadhwal, V.K. 2001b. Farm level yield mapping for precision crop management under Indian conditions using a simple approach of linking remote sensing information and crop simulation model. In: Proc. of the ISRS National Symposium, Dec 11-13, 2001, Ahmedabad, India.

Sehgal, V.K., Rajak, D.R., Chaudhary, K.N. and Dadhwal, V.K. 2002. Improved regional yield prediction by crop growth monitoring system using remote sensing derived crop phenology. Internat. Arch. Photogramm. Remote Sens. & Spatial Inf. Sci., 34 (7): 329-334.

Thornton, P.K., Bowen, W.T., Ravelo, A.C., Wilkens, P.W., Farmer, G., Brock, J. and Brink, J.E. 1997. Estimating millet production for famine early warning: an application of crop simulation modelling using satellite and ground-based data in Burkina Faso. Agric. For. Meteorol, 83: 95-112.

Tim, U.S. 1996. Coupling vadose zone models with GIS: Emerging trends and potential bottlenecks. J. Environ. Qual., 25: 535-544.

Vossen, P. 1995. Early assessment of national yields: the approach developed by the MARS-STAT project on behalf of European Commission, pages 327-347. In: Proceedings of the Seminar on Yield Forecasting, 24-27 Oct., 1995, Villerfranche-sur-Mer, France.

Wade, G., Mueller, R., Cook, P.W. and Doraiswamy, P.C. 1994. AVHRR Map products for Crop Condition Assessment: A Geographic Information Systems Approach. Photogrammetric Engineering & Remote Sensing, 60(9): 1145-1150.

Wiegand, C.L., Richardsons, A.J. and Kanemasu, E.T. 1979. Leaf area index estimates for wheat from LANDSAT and their implications for evapotranspiration and crop modeling. Agronomy J., 71: 336-342.