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Spatial wheat yield prediction using crop simulation model, GIS, remote sensing and ground observed data

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ABSTRACT

A study was conducted with a broad objective of developing and demonstrating a methodology for crop growth monitoring and yield forecasting which can provide periodical crop growth assessment with spatial information. The procedure was developed to generate grid-weather, link the point based simulation model WOFOST (World Food Studies) to spatial inputs like crop, soil and weather and predict wheat yield at grid and administrative scale. Two approaches were adopted to predict wheat yield; a) the regression approach, in which simulated potential yields were regressed with final estimated yields by Directorate of Economics and Statistics (DES) for each of the six major wheat growing states and b) forcing approach in which LAI for each grid (25km x 25km) derived from remote sensing was forced into the simulation model to divert the simulation output and final grain yield into right direction. The deviations between the estimated state yield and reported yield were more in case of the forcing (0.7 – 25.4 %) as compared to regression approach (0.5 – 9.2 %). However, the spatial variability at grid level was explained more in case of forcing approach. Results indicated that regression approach is suitable for in season yield forecasting at state level and forcing approach is better for spatial crop condition assessment and crop growth monitoring.

Key words: Wheat yield, crop simulation, WOFOST model, LAI, remote sensing

Accurate regional wheat yield assessment is very important for national food security and decision-making. Among various approaches of yield assessment, crop modelling is the ultimate tool for yield prediction. For large area yield modelling input data is required at spatial level, for which ground observation is not sufficient and collection through ground observation is very much time and labour consuming. Remote sensing provides observations over large area at regular intervals, thus making it useful in large-scale crop modelling (Moulin *et al*., 1998; Reynolds *et al*., 2000). Use of satellite-based inputs highly simplifies the process considering the amount of time and labour that regional level data collection requires. A number of studies have been carried out using remote sensing based regression models for regional or countrywide predictions (Rasmussen, 1998; Dabrawoska *et al.*, 2002). Doraiswamy *et al.* (2005) used remote sensing inputs in a crop model for regional yield assessment and the findings indicate that with the selection of an appropriate crop model and careful application of input information derived from satellite-based observations, regional crop yield assessments using remote sensing can be highly beneficial. Dadhwal and Ray (2000) reported use of such regression models for district level yield forecasting in India. However, the regression-based models are highly variable and do not consistently provide adequate accuracy for larger areas since they are empirical in nature (Moulin *et al.*, 1998). The variables used in the regression models to increase the accuracy (or the R-square) cannot be of global application as such variables differ from region to region. Other methods used by some researchers are based on application of Montieth-based models that employ Photosynthetically Active Radiation (PAR) and Absorbed Photosynthetically Active Radiation (APAR) parameters to estimate yield (Bastiaanssen and Ali, 2003). These methods do not use meteorological inputs and are mostly based upon the ability of plants to utilize the solar radiation for photosynthesis. Therefore, these models are not appropriate for and have not been adapted to all kind of regional application, especially in rain-fed condition. Hence, most suitable crop prediction models for regional application, which may be adapted to incorporate information from remote-sensing based observations, are mechanistic models that relate physiological growth stage to environmental variables to obtain the model output. Sehgal (2001) described the modification of the WTGROWS for using RS data. The WTGROWS model has been linked spatially as well as with RS inputs on phenology for determining district-wise sowing date from WiFS profiles and using it for spatial simulation of wheat growth (Sehgal *et al*., 2002). Among mechanistic models, some require very detailed field level information that cannot be estimated for regional level modelling purposes. In this context, the WOFOST (WOrld FOod STudies) model (van Diepen et. al., 1989) holds promise, as even though it is a mechanistic model the inputs required for running the model are very simple. However as the model is point based, its spatial application requires spatial database generation (both agro-meteorological and biophysical) and linking of the spatial database to the WOFOST application program. Assimilation of remote sensing data in crop model can be done in two different ways. One is use of agro-meteorological input parameter in the model directly and the second is coupling of one of the state variable derived from remote sensing in the model through forcing. Among different state variables governing grain yield, LAI is the one of the important variable explaining the ability of the crop to intercept solar energy and in understanding the impact of crop management practices and hence in regulating the grain yield.

The present study was carried out with a broad objective of developing and demonstrating a methodology for crop growth monitoring and yield forecasting which can provide periodical crop growth assessment with spatial information. To develop the procedure to generate grid-weather, link the point based simulation model WOFOST to spatial inputs like crop, soil and weather and predict wheat yield at grid and administrative scale. The evaluation of two different approaches; the forcing approach (forcing of RS derived LAI into the model) and the regression approach (using historical yield) for spatial wheat yield forecasting.

METHODOLOGY

Study area

The study is confined to six major wheat-growing states of India viz. Punjab, Haryana, Uttar Pradesh (UP), Bihar, Rajasthan and Madhya Pradesh (MP). The six major states cover about 86.5 percent area and 92 percent production of wheat in India (Oza *et al*., 2006). The aerial extent is from 32^o 15' N to 20^o 55' N latitude in north-south direction and from 69^o 30' E to 88^o 15' E longitude in east-west direction.

Preparation of data on GIS framework

For spatial scale implementation of WOFOST model, the study area was divided into number of equal area grid cells (25 km x 25 km size) inside which the soil, weather and crop were assumed to be homogenous. Albers Conical Equal Area projection was used for this purpose that preserves the original shape of the country and maintains equal area of the grids. Total number of grids falling under six wheat-growing states were about 1430 grids. District and state boundaries were overlaid over the grids to aggregate the outputs at required administrative units.

Description of WOFOST Model

WOFOST calculates first the instantaneous photosynthesis at three depths in the canopy for three times in a day, which is subsequently integrated over the depth of the canopy and over the light period, to arrive at daily total canopy photosynthesis. After subtracting maintenance respiration, assimilates are partitioned into roots, stems, leaves and grains as a function of the development stage, which is calculated by integrating the daily development rate, described as a function of temperature and photoperiod. Assimilates are then converted into structural plant material taking into account growth respiration. Aboveground dry matter accumulation and its distribution over leaves, stems and grains are simulated from sowing to maturity on the basis of physiological processes as determined by the crop response to daily weather.

Spatial weather data generation

The daily data viz. minimum and maximum temperature, rainfall, dew point temperature, wind speed of 199 weather stations of IMD were used for this purpose. Solar radiation was estimated using Hargreaves formula (Hargreaves *et al*., 1985) from maximum and minimum temperature and local Hargreaves coefficients (Tripathy *et al*., 2008). The missing values in the observed station data were replaced through temporal and spatial interpolation using available surrounding information. The daily and weekly climatic normals were also considered for interpolation of missing weather parameters like wind speed and early morning vapour pressure. The station data were interpolated at 25 km grid level using Thin Plate Spline (TPS) interpolation technique (Hutchinson and Gessler, 1994). As the incorporation of a continuous spatially varying elevation is a critical factor in the accuracy of minimum and maximum temperature surfaces, the values were adjusted with the elevation of a station and median elevation of a grid to which temperature data are to be interpolated. Grid-wise median elevation map was generated using Shuttle Radar Terrain Mapper (SRTM) data available at 1km x 1km raster image. A separate lapse rate for minimum and maximum temperature was used for temperature interpolation (Chaudhari *et al*., 2005, Tripathy *et al*., 2006) to get the grid wise weather data. The example of resultant interpolated temperature surfaces for maximum and minimum temperatures of January 1, 2007 is shown in Fig. 1.

Soil Parameters: Texture, soil moisture constants, Hydraulic conductivity at different suction, Saturated Hydraulic conductivity, and percolation rate. FAO soil map (1:5,000,000) was used and grid-wise soil files prepared using different soil textural classes were integrated with the crop simulation model – WOFOST.

Crop coefficients: crop phenology (Temperature sum requirement from sowing to emergence, from emergence to anthesis and from anthesis to maturity); crop morphology (LAI at emergence, relative growth rate of LAI, specific leaf

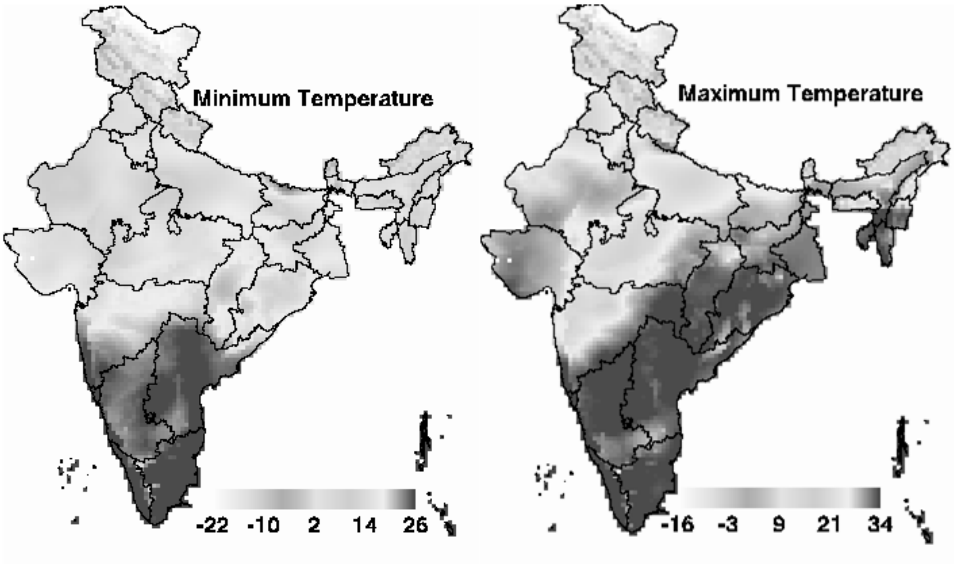

Fig. 1: Interpolated temperatures using TPS method at 25 km grid size (Jan1, 2007)

Table 1: Crop coefficients used in WOFOST model for yield simulation of different varieties in different states

State	Variety	Coefficients for different crop parameters									
		TSum1	TSum2	TSum3	RGRLAI	EFFTB	KDIFTB	CVL	CVO	CVR	CVS
Bihar and UP	HD2733	120	1188	1017	0.0080	0.60	0.5	0.685	0.709	0.694	0.662
Haryana and Punjab	PBW343	125	1181	810	0.0060	0.60	0.5	0.685	0.679	0.694	0.625
MP	Malvasakti	117	947	770	0.0084	0.58	0.5	0.600	0.661	0.694	0.602
Rajasthan	Raj3765	95	809	614	0.0082	0.55	0.5	0.720	0.709	0.694	0.662

TSUM1: Temperature sum from sowing to emergence [cel d]; TSUM2: temperature sum from emergence to anthesis [cel d]; TSUM3: temperature sum from anthesis to maturity [cel d]; RGRLAI: maximum relative increase in LAI [ha ha^{-1} d^{-1}]; KDIFTB: extinction coefficient for diffuse visible light [-]; EFFTB: light-use efficiency single leaf [kg ha^{-1} hr^{-1} j^{-1} m^2 s]; CVL, CVO, CVR and CVS are efficiency of conversion into leaves, storage org.; roots and into stems, respectively [kg kg^{-1}].

area); crop physiology (extinction coefficient, Light use efficiency, conversion efficiency for leaf, stem, root and storage organ, partitioning coefficients for root, stem, leaf and storage organ)

Calibrated crop coefficient of one major wheat variety for each of the six major states was used for yield prediction of the respective state (Table 1).

Spatial implementation of model

The spatial implementation of point based WOFOST model necessitated the linkage of the model with the crop, soil and weather parameters of each grid to the WOFOST model. An interface module was written in FORTRAN to link grid-wise data for soil, crop and weather to WOFOST executable module. The potential yield map was generated from the output file using ENVI-IDL software.

Approaches of yield estimation

Two approaches were tried and compared for multi-scale yield estimation using crop simulation. In one approach the LAI derived from RS data was forced in the WOFOST model and other approach is the regression approach based on historical yield data. The details of both the approaches are given below.

Forcing approach

In this approach, the value of state variable, here LAI,

Table 2: Regression coefficients used for yield estimation of six major wheat-growing states

State	b0	b1	b2	R^2
Bihar	-6.63	1.5E-04	3.9E-03	0.31
Haryana	-39.03	9.0E-05	2.2E-02	0.51
MP	-24.94	1.8E-04	1.3E-02	0.43
Punjab	5.03	1.7E-04	1.6E-02	0.53
Rajasthan	-97.92	2.5E-04	4.9E-02	0.64
UP	-58.04	8.0E-05	3.0E-02	0.65

b0: intercept; b1: coefficient for simulated yield; b2: coefficient for time trend; R^2: coefficient of determination

at a given time step of growth simulation is corrected by its observed value (from remote sensing data). As the corrected value of the state variable determines the rate of growth of the state variables at next time step, the model then steers on a correct growth path and ultimately results in grain yield closer to the actual value. Among different state variables governing grain yield, LAI is most important in explaining the ability of the crop to intercept solar energy and in understanding the impact of crop management practices (Chen and Cihlar, 1996). Hence, here the most important biophysical parameter LAI estimated using an empirical relationship between field observed LAI and NDVI (Normalized Difference Vegetation Index) generated from remote sensing at approximately peak vegetative growth (Nigam *et al*., 2007) was forced to the crop simulation model for predicting crop yield at spatial scale.

It was observed that by updating only one state variable (here LAI), model behaviour became unpredictable. It may be due to the fact that unless all model state variables are updated on the day of observation, model may show inconsistencies in simulation, as pointed by Maas (1988). Hence, along with the LAI other related state variables like periodical biomass of each plant part were also adjusted in proportion to the adjustment made in LAI as calculated from remote sensing data. A correction factor (CF) was calculated as the ratio of this LAI to the model computed LAI for the observed date.

For this approach, the WOFOST model was run at each grid using grid-wise weather, soil, and crop data to generate different output up to the date for which LAI from remote sensing was derived. Then the simulated state variables (LAI, Specific leaf weight, stem weight, etc.) were corrected using the CF to get the final yield at grid level. Aggregation was done at state level based on the grid-wise crop fraction obtained through RS data analysis (Anonymous, 2007).

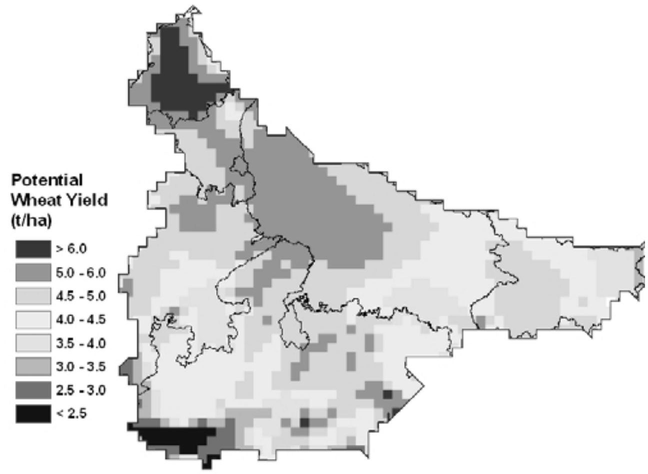

Fig. 2: Potential wheat yield (t ha^{-1}) simulated by WOFOST model for 2006-07

Regression approach

In the other approach, a combination of a linear time trend and crop growth simulation results are used to account for the trend in yield series and weather variability, respectively. It can be described as:

$$\hat{Y}_T = b_0 + b_1 S_T + b_2 T$$

Where, v_T and S_T are estimated yield and simulated yield or predictors (t/ha), respectively in year T, and b_0, b_1 and b_2 are regression constants.

The regression coefficients for each state were derived using the DES reported yield for last 10 years (1995-2004) and simulated yield for that period. The simulated grain yield of the current season was used as predictor for current season yield prediction. The coefficients are given in Table 2.

Comparison of two approaches

Both the approaches were compared for the applicability of in-season multiple forecasting as well as the capability in capturing spatial yield variation. For assessing the accuracy of yield estimation, the yield reported by DES at state level was used and the absolute deviation from the reported yield was calculated.

RESULTS AND DISCUSSION

Potential yield

Potential yield indicated the effect of weather parameters on yield. Wheat yield is mainly affected by

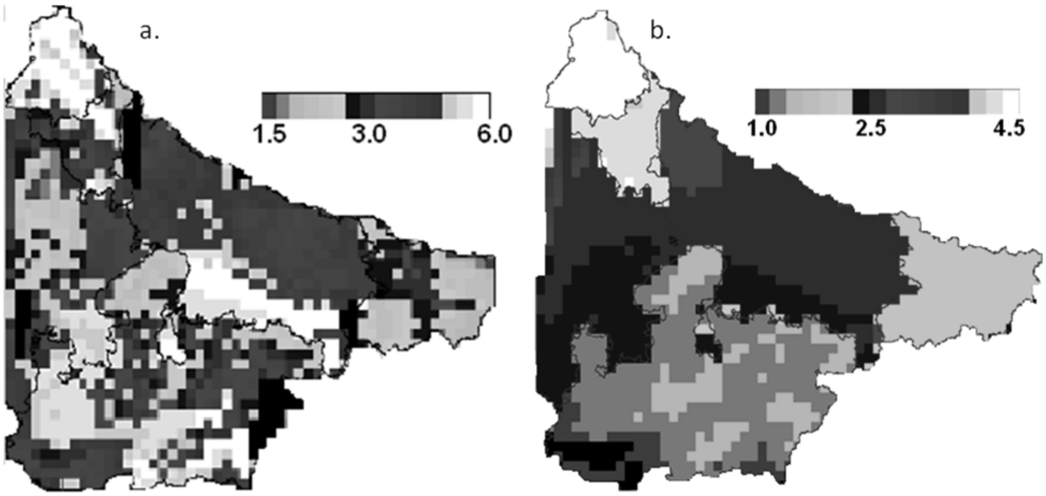

Fig. 3: Wheat yield (t ha^{-1}) estimated by a. forcing approach and b. regression approach

Table 3: Absolute deviation (t ha^{-1}) of estimated yield from DES reported yield

State	Reported yield (t ha^{-1})	Estimated yield (t ha^{-1})		Absolute deviation (t ha^{-1})	
		Forcing approach	Regression approach	Forcing approach	Regression approach
Punjab	4.42	4.39	4.13	0.03	0.29
Haryana	3.85	3.71	3.83	0.14	0.02
UP	2.78	3.50	2.58	0.72	0.20
Bihar	1.87	1.53	2.02	0.34	0.15
Rajasthan	2.29	2.56	2.50	0.27	0.21
MP	1.52	2.90	1.54	1.38	0.02

temperature (both minimum and maximum) and solar radiation. As expected, potential yield increased at high latitude where low temperature prevails compared to low latitude where high temperature prevails. The states like Punjab, Haryana and Northern Uttar Pradesh show higher yield. Lowest yield was simulated in Madhya Pradesh state (Fig. 2). It varied from 1.80 t ha^{-1} in the southern part of MP and Rajasthan to 7.30 t ha^{-1} in northern parts of Punjab.

Simulated yield through forcing approach

For all grids wheat yield was estimated using three dates of sowing (normal, one week before and one week after the normal). The weighted average of the yield of one grid for these three dates (50 % of normal date, 25 % of the pre-normal date and 25% of the post normal date) was taken as actual yield of that grid. Grid-wise yield map for the six states is given in Fig. 3a. The state level average yield varied from 1.53 t ha^{-1} in Bihar to 4.39 t ha^{-1} in Punjab. Grid-wise variation in yield was more in this approach as compared to regression approach (Fig. 3a). In Punjab, the yield varied from 1.0 t ha^{-1} to 6.78 t ha^{-1} with state average of 4.39 t ha^{-1}. Same pattern of variability was also observed in other states also. The estimated yield using this approach was closer to the reported yield for the states like Punjab and Haryana (Table 3). However, the model over estimated the yield in the states of MP and UP while under estimated for Bihar.

First, for this approach, the LAI estimated using RS data is the main driving force to convert potential to actual simulated yield, there for any error in LAI estimation leads to errors in simulated yield. Here, LAI estimated at grid level using empirical equations developed at state level, was used to enforce the model output to right direction. The LAI estimation itself is a topic of wide discussion and many issues involved beginning from the approach of estimation to up-scaling from field to satellite resolution and again to grid level aggregation. Second, the normal dates of sowing collected through literature and survey shows the wide range from region to region and grid to grid even within the grid. The coefficients used for single variety and single date as appropriate with fixed weightages for prior and after dates are not sufficient for the states having vast area and diversity like UP, MP and Bihar that led to yield anomaly in these states (Table 3). Any error in either of two or in both leads to wrong CF computation and finally to grain yield. Other possible sources of error may be error in estimation of solar radiation and error in interpolation of weather data. The approach has good strength to predict yield at grid level provided with grid level date of sowing using periodical RS data, better LAI estimation using radiation transfer models and daily insolation estimated from satellite data.

Simulated yield through regression approach

The final yield of each grid falling in a state was estimated using the model for that state and spatial yield map was generated for all the six states (Fig. 3b). The yield in Punjab varied from 3.87 t ha^{-1} to 4.22 t ha^{-1}. The state average was 0.29-t ha^{-1}more than that reported by DES (Table 3). In Haryana the yield varied from 3.75 to 3.95 t ha^{-1} with a state average of 3.83 t ha^{-1} (0.02 t ha^{-1} more). In MP, it varied from 1.55 to 1.77 t ha^{-1} with the state average of 1.54 t ha^{-1} (absolute deviation of 0.02 t ha^{-1} from reported yield). For UP state average was 0.20 t ha^{-1} less than that of the reported yield with yield varied from 2.30 to 2.76 t ha^{-1}. In Bihar the spatial variability was very less (2.00 to 2.04 t ha^{-1}) with a state average of 2.02 t ha^{-1} that is 0.20 t ha^{-1} more than that of reported yield (Table 3). For six major wheat-growing states the yield varied from 1.46 t ha^{-1} to 4.22 t ha^{-1} (Fig. 3b).

Comparison of two approaches

Both approaches were compared on the basis of their capability to forecast yield at different crop growth stages, to capture the spatial variability and the level of accuracy as compared to reported yield. As the forcing approach requires peak LAI value for better prediction, forecasting at early growth stage is difficult with this approach. The results indicated that the absolute deviation between the estimated state yield and the reported yield was more in case of the forcing than that with the regression except for Punjab (Table 3). Hence, regression approach is suitable for yield forecasting for in season crop yield forecasting at state level. The spatial variability at grid level was more in case of forcing approach as compared to the regression approach (Fig. 3). This is because the historical yield was available only at district or state level and not per grid, hence the same prediction equation was used for all grids of a particular state to estimate grid level yield while in the forcing approach LAI values were derived for each grid and used to estimate the final yield. Hence, for spatial crop growth monitoring forcing approach can be used.

CONCLUSIONS

The study demonstrated the methodology for in-season crop yield forecasting at spatial scale with the use of dynamic simulation model-WOFOST and RS derived crop parameters like crop fraction, LAI etc. It was found that the regression approach would be more suitable for within season yield forecasting at district or state level while the forcing approach can be applied for finding out the spatial variability of yield using LAI derived from RS data. However, use of RS derived LAI improved the spatial yield estimation, and hence, can be used successfully for relative crop condition monitoring. There is need to calibrate major 2-3 varieties per state to represent the vast variability in states like UP, MP, Bihar and Rajasthan. The study suggests future research for improving the LAI estimation at grid level which can improve the accuracy of regional yield prediction using LAI forcing with more spatial variability. The approach has good strength to predict yield in future with grid level date of sowing using periodical RS data, better LAI estimation using radiation transfer models and daily insolation estimated from satellite data. This study suggests use of weather data from remote sensing and automatic weather stations for more accurate regional yield prediction, which can provide real data at different spatial level and hence can reduce the error relating to interpolation.

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