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Regional Rice Yield Estimation by Integration of Spatial Technologies and Crop model

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Abstract
This study investigates how spatial technologies like remote sensing and GIS (Geographic Information System) integrated with a crop growth model to estimate paddy rice yields. Two approaches were used to estimate rice yield one is from remote sensing images and another from soil, climate layers of GIS, linked to the crop model. Oryza2000 model was used as a crop model to link with these technologies. Results show that yield estimated from these two approaches were closed to the reported values from department of Agriculture, Andhra Pradesh, India and yield estimated from remote sensing is more precise than GIS layers. This underscores the potential value of remote sensing, GIS and crop model for yield estimation. The successful application of methodology used in our study to other areas will depend on number of factors including the secondary data estimates, distribution of different crops grown in that area, crop condition at the time of satellite overpass and land scene anomalies.

Keywords: *rice, yield estimation, remote sensing, GIS, Oryza2000 model, NDVI*

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INTRODUCTION
Paddy fields account for over 11% of global crop land area [1]. The major rice-producing countries of Asia account for over half of the world's population and rice represents over 35% of their daily caloric intake (FAO, 2004). Among the rice growing countries in the world, India stands first in rice area, (44.00 million hectares) and second in production (95.97 million tons) in 2007. The challenges posed by global climate change like decreasing water and energy availability for agriculture and increasing demands for biofuels will further exacerbate constraints on food production [2, 3]. Agricultural water use (in the form of irrigation withdrawals) accounted for ~70% of global fresh water withdrawals [4], and the majority of Asian rice agriculture is irrigated [5, 6]. Due to wide spread cultivation of rice across the world a number of unique farming methods such as irrigated, rainfed, deepwater, semi-deep water, upland and hills etc., have evolved based on farming type, single crop and multi-crop system based on crop management, and wet and dry seasons based on seasonality. Monitoring and mapping of paddy rice agriculture in a timely and efficient manner is very important for agricultural and environmental sustainability, food and water security, and greenhouse gas emissions [7].

Monitoring agricultural crop production during the growing season and estimating the potential crop yields are both important for the assessment of seasonal production [8]. Accurate real time estimation of crop yield in provincial and national level is very important for government agencies. In the past, the standard yield estimation is based on crop cuttings at randomly sampled ground plots during harvest [9], or by using meteorological regression models [10]. Crop simulation models can help to develop appropriate crop management practices and develop decision support systems, explore effects of climatic change, and make yield predictions [11, 12]. Several comprehensive mechanistic and process based rice models, such as SIMRIW [13], CERES- RICE [14], Oryza1 for potential production [15], Oryza_W for water limited production [16], and Oryza2000 [17] are available. These models require numerous inputs that are specific to the crop, soil characteristics, management practices, and local climatic conditions. Use of these models for predicting crop yields at regional scale is very difficult as fewer inputs required for the model at regional scale are available. However, satellite remote sensing technology has been shown to be capable of providing certain crop characteristics and a real-time snapshot of changes in conditions affected by weather related events. Growth models simulate biophysical processes in the soil-crop atmospheric system to provide a continuous description of growth and development. Combining such a growth model with input parameters derived from remotely sensed data provides spatial integrity as well as a real-time “calibration” to simulations of model parameters [18–24]. GIS based agricultural decision making system is a cost-effective tool to disseminate expert agricultural knowledge to the farming community in order to improve crop productivity and it enables the scientists to provide location-specific expert advice in a personalized and timely manner. Several researchers have demonstrated the strength of linking GIS and crop simulation models [25, 26]. Remote sensing and GIS can be used to derive some of the important inputs required for the growth models [27]. The objective of this study was to test the applicability of integrated remote sensing data, crop growth model and GIS to predict yield at regional scale. Rice yield was estimated using two approaches one is from remote sensing images and another from soil, climate layers of GIS, linked to the crop model Oryza 2000.

METHODOLOGY

Study Area

A predominantly irrigated rice growing region, Miryalaguda (region) geographically located at 16°52'19"N 79°33'46"E with an altitude of 126 msl in Nalgonda district of Andhra Pradesh State (Figure 1) was selected to develop and evaluate different components of the system. Miryalguda is famous for the paddy cultivation and it is listed among the top five paddy markets in Andhra Pradesh. The average rainfall is 736 mm and 71% of the annual rainfall is received during south west monsoon (June to September). This region experiences hot and dry weather throughout the year except during the south west monsoon season. Soils are mainly 'red earth's' comprising loamy sands, sandy loams and sandy clay loams.

Fig. 1: *The location of Miryalaguda, Nalgonda District in Andhra Pradesh (AP), India.*

Crop Growth Model and Data Sets

Oryza2000 model was selected for this study. The model was tested for mid duration varieties (120–130 days duration) and the input parameters are dates of sowing, transplanting, panicle initiation, flowering and maturity. Meteorological inputs to the model like sunshine hours, maximum and minimum temperatures, vapour pressure and precipitation, for Nalgonda district were obtained from Department of Economics and Statistics, Hyderabad, Andhra Pradesh. Data pertaining to the fertilizer and irrigation application were obtained from the annual Production Oriented Surveys (POS) conducted by the Directorate of Rice Research under All India Coordinated Rice Improvement Project. Diffuse ($E_{c,dif}$) and direct ($E_{c,dir}$) radiation, Global incident short wave radiation(G), Incident Photosynthetically Active Radiation (IPAR), Leaf Area Index (LAI) were derived from the model for the respective sowing dates. Fraction of absorbed PAR was derived from the remote sensing data.

Yield Estimation by Satellite Image and Crop Model

During crop growing period of Nalgonda district, Indian Remote Sensing (IRS-1D) digital data from Linear Imaging Self Scanning Sensor (LISS–III) (path 101/60 14 November 2004) was chosen (Figure 2) for this study and the image was processed with ERDAS image 8.6 package. The satellite image was registered and polyconic projection was applied uniformly to all the datasets with latitude/longitude information in degrees. A block level map of Nalgonda district was extracted from the topo sheet of AP and boundary of this map was used to extract Nalgonda district from the satellite imageries. Nalgonda block level map was digitized and polygons of these blocks were converted into Area of Interests (AOI) to use further to extract block level subsets. Miryalaguda block image was extracted by using its AOI.

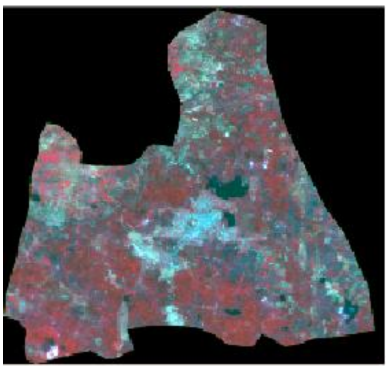

Fig. 2: IRS 1D LISSIII Image of Miryalaguda Block of Nalgonda District.

From the satellite image Normalized Difference Vegetation Index (NDVI) was derived from spectral reflectance values in near infra-red (NIR) and Red(R) bands of the image. NDVI is calculated as follows:

$$NDVI = (NIR–R)/(NIR + R)$$

Yield was estimated using a simple model derived from [28, 29].

$$Yield = APAR * \acute{\varepsilon} * HI/(1–m_{oi}) \quad (1)$$

$\acute{\varepsilon}$ is light use efficiency in units of g biomass (MJ PAR^{-1}), and HI is the harvest index. In this case, as in most studies, HI and $\acute{\varepsilon}$ refers only to above ground biomass and does not include roots. m_{oi} is the moisture content of product during harvest. The $\acute{\varepsilon}$ was taken as 2.5 and Harvest index at HI = 0.5 and moisture content (m_{oi}) as 10%. Measurements of APAR (MJ from 400–700 nm) estimated as the product of incident photo synthetically active radiation (IPAR) and the fraction of PAR absorbed by the canopy (fAPAR), summed over the growing season.

$$APAR = \sum(IPAR * fAPAR) \quad \Delta t \quad (2)$$

$$APAR= G* E_c * fAPAR$$

$$APAR=G*fAPAR*(E_{c,dif}+ E_{c,dir})$$

G= Global incident short wave radiation (MJ m^{-2} day^{-1}); E_c = Climatic efficiency: $E_{c,dif}$–Diffuse and $E_{c,dir}$ –Direct) (400–700 nm) in the short wave radiation (300–3000 nm) where G and E_c are daily values, the total in case of G and average in case of E_c and fAPAR. Climatic efficiency varies mainly with atmospheric conditions [30], but also with the solar elevation, geographical location and the time (hour, day or month) [31].These values were obtained from the model.

Fraction of absorbed photosynthetically active radiation (fAPAR) was calculated from the NDVI image by the following model [32].

$$fAPAR=((NDVI–NDVI_{min})(fAPAR_{max}–fAPAR_{min})/(NDVI_{max}–NDVI_{min}))+fAPAR_{min} \quad (3)$$

Where, $NDVI_{min}$, $NDVI_{max}$ correspond to 2nd and 98th percentile of NDVI for the entire region and $fAPAR_{max}$ and $fAPAR_{min}$ are defined as 0.95 and 0.01. Further, fAPAR was calculated for the date when image was acquired (14 November 2004) using Eq. (3). The linear relationship between fAPAR and LAI was used for calculating fAPAR for the entire growing season. Yield was estimated by using the equation 1 and this raster image was converted to vector to find out pixel wise yield.

Yield Estimation by GIS Layers and Crop Model

Spatial databases were designed to store and manage information on, soil series and climate using Geographic Information System (GIS). Two spatial data layers were used. Soil data overlaid with the climatic data layer to form simulation mapping unit (SMU) for simulating rice yield. All soil related data were extracted from soil maps obtained from National Agricultural Research Management (NAARM), Hyderabad).

Soil Layer

A spatial database was designed to store and manage soil data at the series level. The spatial data are stored as Arc/Info coverage and other soil tables were generated in MS Access. Among soil attributes, soil texture, field capacity, available water capacity (AWC) and soil depth are important attributes for estimating water balance for rice field. Field capacities (FC) entered by the user for different textures of soil map. Depending on the unique values of depth, texture and AWC soil groups were created. A structure of soil database is shown in Figure 3.

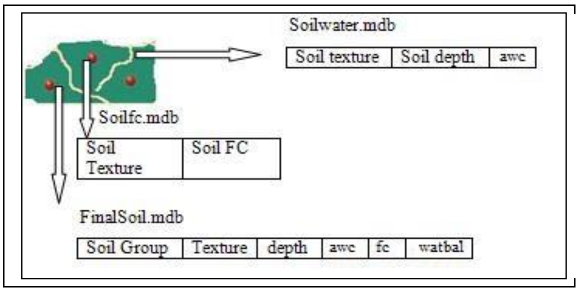

Fig. 3: *Relational Tables of Soil.*

Spatial Interpolation of Rainfall

Daily rainfall is required as a climatic data input for Oryza2000 model. There are 59 rainguage stations (each mandal as rainguage station) in Nalgonda. These stations were first taken as point coverage in ArcGIS. Thiessen method of spatial interpolation was used within ArcGIS (Figure 4) for all 59 rainguage stations and extracted polygons of Miryalaguda mandal.

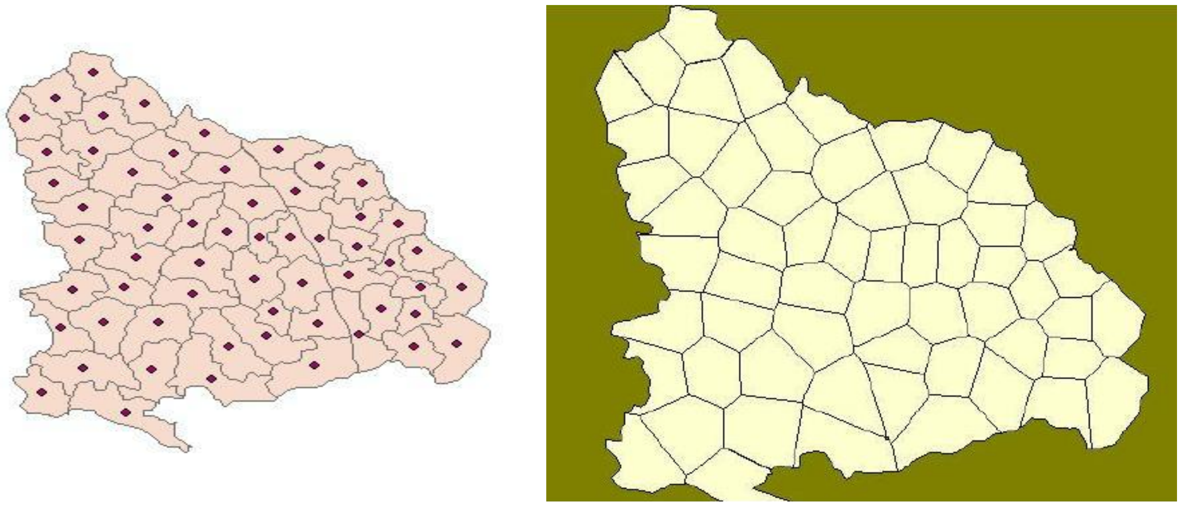

Fig. 4: *Rainguage Stations and Thiessen Polygons of Nalgonda District.*

Comparison of Satellite Image Derived Rice Crop Yield with GIS Estimated Yield

Rice yield was estimated from NDVI approach and using absorbed photo synthetically active radiation (APAR) through remote sensing. The remote sensing yield image was overlaid with soil layer and soil group wise yields were extracted by attribute queries in ARCGIS. Similarly rainfall and soil overlaid map was used as inputs to Oryza2000 model to estimate soil group wise yields. Soil group wise attributes such as soil field capacity, available water capacity and soil depth were taken from the overlaid layer. Block wise rainfall was used as input weather data to Oryza2000 model. The yields estimated by the two methods were compared and percentage differences were calculated.

RESULTS AND DISCUSSION

Yield Estimation by Satellite Image and Crop Model

NDVI has been considered to be a useful way for crop yield assessment models using various approaches from simple integration to more complicated transformation. NDVI reflects vegetation greenness, thus it indicates levels of healthiness in the vegetation development. Although vegetation development of crop fields may differ from those of natural vegetation because of human influences involved such as irrigation, use of fertilizer and pesticides, NDVI is considered as a valuable source of information for the crop conditions (Prasad et al. 2006). In the present study rice yields were calculated for NDVI method for each polygon and the estimated yields were grouped into low (<2 t/ha), medium (2–3 t/ha) and high (>4 t/ha) levels (Figure 5). It was observed that more rice pixels were found in high yield level (55%) followed by low yield level (28%). The yield estimated from NDVI method is 5.03 t/ha which is close to the reported yield (5.05 t/ha) level of crop cutting experiments conducted by Department of Agriculture, Andhra Pradesh, India (Table 1).

Table 1: *Calculations of Yield Estimates for Miryalaguda and Comparison with Crop Cutting Experiment Values.*

Method	**APAR (Mj/sq.m)**	**APAR* *e***	**Estimated Yield (t/ha)**	**Reported yield from crop cutting experiments**
NDVI	215.21	538.02	5.03	**5.05 t/ha**

NDVI: Normalised Difference Vegetation Index; APAR: Absorbed Photosynthetically Active Radiation; e: Light Use Efficiency; HI: Harvest Index; m_{oi} :Moisture content; E_c : Climatic Efficiency

Seasonal accumulated NDVI values are correlated well with the reported crop yields in semi-arid regions [33]. The production of crop and prediction of crop yield have direct impact on year-to-year national and international economies and play an important role in the food management [34]. The NDVI data have been used extensively in vegetation monitoring, crop yield assessment and forecasting [35–38]. The most accurate estimates of yield were reported by using fAPAR-NDVI [39, 40]. Xin Du et al. (2009) [41] estimated winter wheat yield with the NDVI calculated from remote sensing data and found that the precision of the yield prediction using NDVI was better than with predicting using fixed HI. These results suggest that yield can be accurately estimated with a single image provided that the image is acquired towards the middle of growing season when most canopies are fully developed. Simulations reveal that over 50 percent of rice planted areas in Miryalaguda yielded higher than 5 tons/ha (Figure 5).

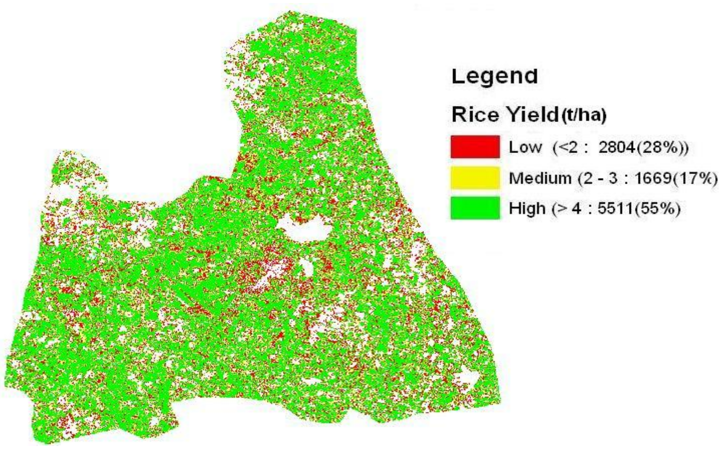

Fig. 5: *Miryalaguda Block – Rice Yield Map as Estimated by using NDVI Method.*

Being predominantly irrigated area, the crop was not expected to be exposed to water stress during the crop growth period. The absence of major pest and diseases did not resulted in major variation in fAPAR and light use efficiency. Another important issue for any approach based on satellite reflectance measurements is persistent cloud cover during the growing season [42]. The cloud cover was not a major concern for our study. However, images captured from any crop growing period can be used in the modeling frame work developed. Important crop characters like light use efficiency (ἑ) and HI were obtained from the reported values in the literature and from the on-farm experiments conducted at Directorate of Rice Research, Hyderabad. Variability in these parameters can influence the overall yield as a result of annual changes in practices, cultivars or environmental conditions. The modeling approach followed in the present investigation can be easily extended to other crops as well as other regions for estimating the yield.

Yield Estimation by GIS Layers and Crop Model

Rice yield was estimated by Oryza2000 model linked to soil and weather layers using GIS. Soil field capacities, available water capacity and depth data were obtained from soil map Nalgonda district. Nalgonda soils were divided into 31 soil groups and Miryalaguda block was extracted from Nalgonda soil layer. There were five soil groups in Miryalaguda block (Figure 6) and five thiessen polygons generated for this block. Overlay of block, thiessen and soil contains 12 combinations of soil and thiessen polygons (Figure 7).

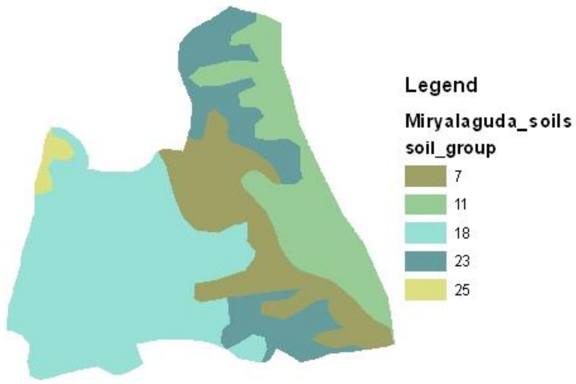

Fig. 6: *Soil Groups in Miryalaguda Block.*

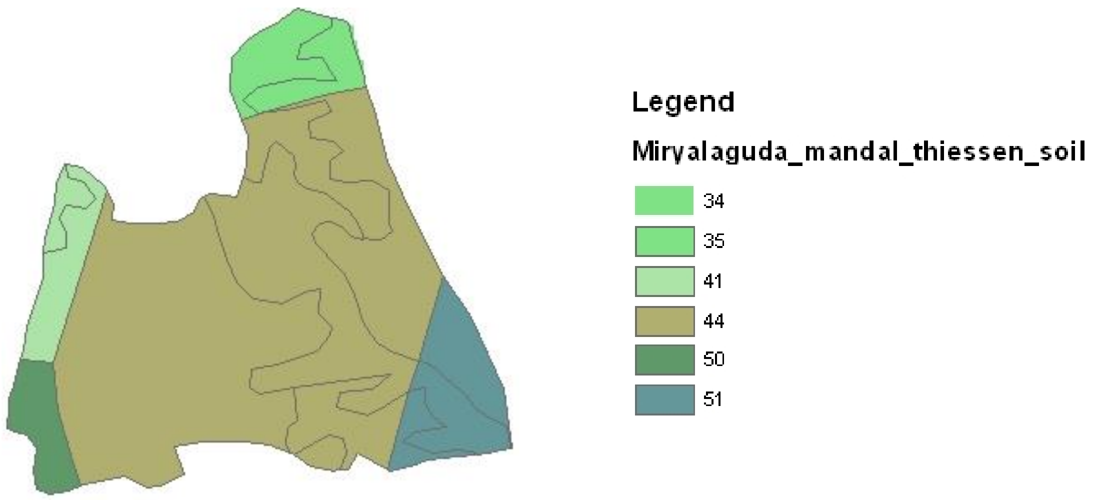

Fig. 7: *Overlay of Block, Soil and Thiessen Polygons of Miryalaguda Block.*

Rice yield was estimated for each soil group (Table 2). The estimated yield varied from 4.05 t/ha to 4.65 t/ha. There is slight variation in rice yields among soil groups which can be attributed to the differences in the rainfall and soil characteristics. Average yield estimated from this approach was 4.36 t/ha which was 15% lower than the yield recorded from crop cutting experiments (5.05 t/ha) conducted by Department of Agriculture, Andhra Pradesh, India. As reported in production oriented survey of DRR, the average yields in command areas were reported to be 5–6 t/ha which are similar to the yield estimated from the model.

Table 2: *Rice Yield Estimated for Miryalaguda Block under Nitrogen and Water Limited Situation with 100 N and 20mm Irrigation with One Day Interval.*

S. No.	Soil group	Thiessen Id	Rice yield (t/ha)
1	11	34	4.058
2	18	41	4.542
3	23	44	4.239
4	18	44	4.655
5	7	44	4.555
6	23	44	4.239
7	25	44	4.654
8	11	44	4.502
9	18	50	4.530
10	23	51	3.206
11	7	51	4.317
12	11	51	4.235
		Average	**4.364**

District level weather data and block wise rainfall data were used for yield prediction (Department of Economics and Statistics, Hyderabad, Andhra Pradesh). The data on area under different rice varieties is not available either at district or block level which influenced the accuracy of yield prediction at block level. Availability of this data will possibly improve simulation results. Baker *et al*. (1992) [43] showed that the canopy dark respiration rate of rice reached maximum 30 to 50 days after planting, followed by a gradual decline with time until the end of the growing season, similar to photosynthesis [44]. Such studies need to be extended for rice varieties varying in durations and morphology. Accurate quantification of some these processes for groups of popular rice varieties grown in the target area in relation to development stages will improve the accuracy of yield prediction.

Comparing Satellite Image Derived Rice Crop Yields with GIS Derived Yield

In this study, crop yield was estimated for the Miryalaguda block using two methods (i) Remote sensing (ii) GIS linking to Oryza2000 model. Soil group wise yields for Miryalaguda block estimated from remote sensing and by GIS are given in the Table 3. The yields estimated through remote sensing were relatively higher than the yields estimated from GIS. However, only marginal differences were observed when the yields were estimated soil group wise. Three groups exhibited less than 20% difference. There is 15% variation in the average yields at block level between these two approaches.

The results presented here also emphasize the effects of soil and climate on rice yield. The combinations of soil and climate groups exhibited variation in rice yields (Table 3). There is nearly 20% difference between the lowest and highest yield estimated from different soil groups by the model. This is nearly 26% with remote sensing yields. Lobell (2005a and b) [42, 45] reported that the average difference between the best and poorly fertilized soils is approximately 18% with respect to estimation of wheat yield and concluded that management interactions with soil type and climate changes were also important for understanding yields.

Table 3: *Comparison of Remote Sensing and GIS Yields of Miryalaguda Block during 2004-05, Wet Season.*

Soil group	Estimated yield from Remote sensing (t/ha)	Estimated yield from GIS (t/ha)	Percentage difference (%)
7	5.47	4.44	23.31
11	5.73	4.27	34.30
18	4.73	4.58	3.43
23	4.55	3.89	16.87
25	4.67	4.65	0.28
Average	**5.03**	**4.36**	**15.23**

In addition to soil and climate, management practices also contribute to yield variation. Variability in crop yields between fields is a ubiquitous feature of agricultural landscapes, and often manifests itself in a significant gap between average yields and those achieved on the highest yielding lands. Narrowing this yield gap will play a critical role in raising food production in step with continued growth in demand, especially as the genetic yield potential ceiling for many major crops fails to increase at historical rates [46]. Recent developments in remote sensing have shown great promise for quantifying yield variations both within and between fields [47, 48]. Remote sensing provides quick estimates of yield variations among individual fields, in non-climatic factors at the pixel level [42].

SUMMARY AND CONCLUSIONS

Application of crop models and remote sensing imagery are commonly used to assess crop area and production. Several studies have been done in India on crop area and yield estimation using remote sensing, which require extensive ground truth data. Processing of remote sensing data with minimal ground truth information can reduce both time and energy for crop yield estimation. Remote sensing and GIS approaches used in this study successfully estimated rice yield despite the lack of year specific calibrations. This underscores the potential value of remote sensing, GIS and crop model for yield estimation. The successful application of methodology used in our study to other areas will depend on number of factors including the secondary data estimates, distribution of different crops grown in that area, crop condition at the time of satellite overpass and Land scene anomalies.

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