Final Report

June 2019 – February 2020

Pilot studies on GP Crop yield estimation using Technology (Kharif 2019) using SENTINEL 2 Satellite data (in Andhra Pradesh, Telangana and Odisha States (Five Districts)) for Groundnut, Chickpea, Maize and Rice

Submitted to

Mahalanobis National Crop Forecast Center

INTERNATIONAL CROPS RESEARCH INSTITUTE FOR THE SEMI-ARID TROPICS

Pilot studies on GP Crop yield estimation using Technology (Kharif 2019) using SENTINEL- 2 satellite data (in Andhra Pradesh, Telangana and Odisha States (Five Districts)) for Groundnut, Chickpea, Maize and Rice

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Submitted to

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Project Start : June 2019

Project Completion : February 2020

Executive Summary

The Government of India plans to optimize Crop Cutting Experiments (CCEs) using different technologies including satellite derived metrics on crop performance and spatial variability to guide the selection and number of ground data sites. This requires the development of an approach for different crops for the different agro-climatic regions of India. The present study plans to develop an approach for following crops viz., Groundnut, Chickpea, Rice and Maize. The above crops will be studied in five districts of three states viz. Andhra Pradesh, Telangana and Odisha. The study will use comprehensive and existing environmental, weather and management data along with satellite derived crop spatial data. This information will be modelled using statistical optimization techniques to assess the optimal numbers of CCE's that can be undertaken.

The project will be executed by ICRISAT in partnership with Mahalonobis National Crop Forecasting Center (Ministry of Agriculture, India)

Objectives:

1. Crop extent mapping (Major Crops) for the study districts
2. Conduct and assess crops cutting experiments using spatial statistical optimising technique for major crops of *kharif* season in the study districts.
3. Crop yield estimation based on simulation models

Target Areas

Anantapur, Krishna and Kurnool Districts in Andhra Pradesh, Mahbubnagar District in Telangana State and Puri District in Odisha State will be under taken for the system productivity enhancements.

ICRISAT: Project implementation, monitoring, coordination and reporting, and NARS capacity enhancement.

Cropping pattern mapping - Methodology

The process began with mapping land use/land cover using spectral matching techniques on Sentinel-2 time series data.

Six bands of Sentinel-2 data at 10 m resolution were obtained for the five districts– Mahabubnagar, Krishna, Puri, Kurnool and Anantapur Districts – for kharif season (i.e. June to January). For each month, images with minimum cloud cover were used. Sentinel-2 datasets are available in the public domain and are pre-calibrated (https://earthexplorer.usgs.gov/). The large swath width of 290 km and a revisit time of 2-3 days at mid-latitudes because of the two-satellite constellation of Sentinel-2 makes it attractive for mapping large crop areas. The list of Sentinel-2 bands used in the present study is given in table 1. Twenty-four bands (six bands from each of the Sentinel-2 images of the four months) were stacked and used for classification.

Table 1: Sentinel-2 bands used for classification, and their spatial resolutions

Band	Resolution (m)
Band 2 - Blue	10
Band 3 - Green	10
Band 4 - Red	10
Band 8 - NIR	10
Band 11 - SWIR 1	20
Band 12 - SWIR 2	20

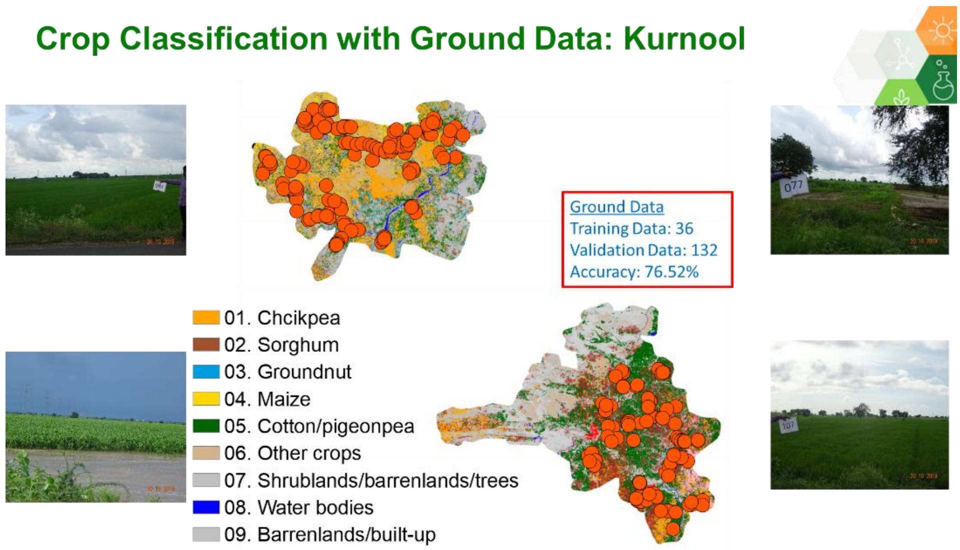
Unsupervised classification was used to generate initial classes. The unsupervised ISOCLASS cluster algorithm (ISODATA in ERDAS Imagine 2016TM) run on the 24-band stack generated an initial 160 classes, with a maximum of 60 iterations and convergence threshold of 0.99. Though ground survey data was available at the time of image classification, unsupervised classification was used in order to capture the complete effect of all wavelengths over a large area. Use of unsupervised techniques is recommended for large areas that cover a wide and unknown range of vegetation types, and where landscape heterogeneity complicates identification of homogeneous training sites1. Identification of training sites is particularly problematic for small, heterogeneous irrigated areas.

Land use/land cover classes were identified based on temporal signatures along with ground survey data. We observed crop growth stages including length of growing periods (LGPs) and cropping pattern from temporal signatures, such as (a) onset of cropping season (e.g., monsoon and winter); (b) duration of cropping season such as monsoon and winter; (c) magnitude of crops during different seasons and years (e.g., water stress and normal years); and (d) end of cropping season.

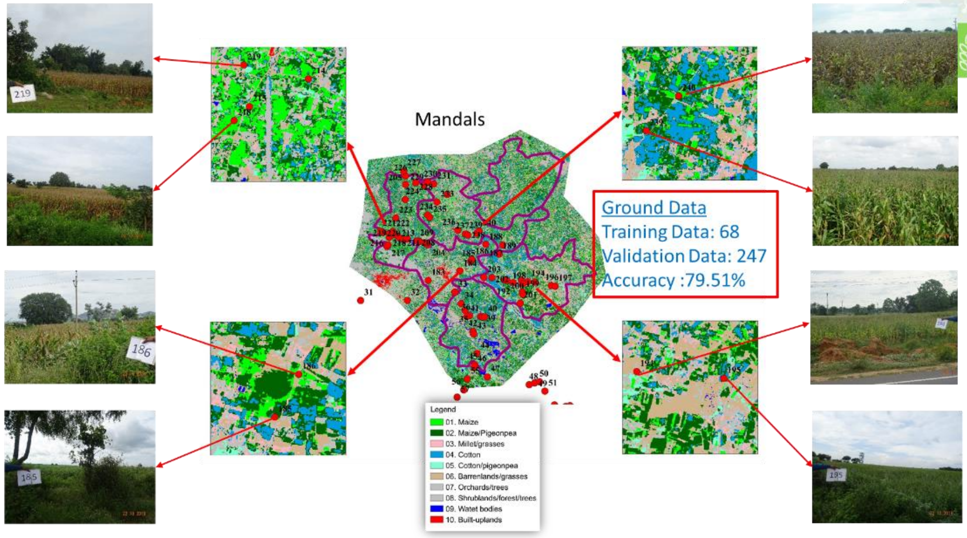
The process of labelling and class identification was done based on spectral matching techniques (SMTs) [1-3]. Initially, 70 classes from the unsupervised classification were grouped based on spectral similarity or closeness of class signatures. Each group of classes was matched with ideal spectral signatures and ground survey data, and assigned class names. Classes with similar time series and land cover were merged into a single class, and classes showing significant mixing, e.g., homogeneous irrigated areas and forest, were masked and reclassified using the same ISOCLASS algorithm. This resulted in following classes for each district. While class aggregation could have been performed statistically using a Euclidean or other distance measure, we employed a user-intensive method that incorporates both ground survey data and high resolution imagery in order to avoid lumping classes that might be spectrally similar but have distinct land cover [4,5]. The signatures of some classes differed in only one or two months, which would have caused the classes to be merged if an automated similarity index were used.

Following are the crop type classification images:

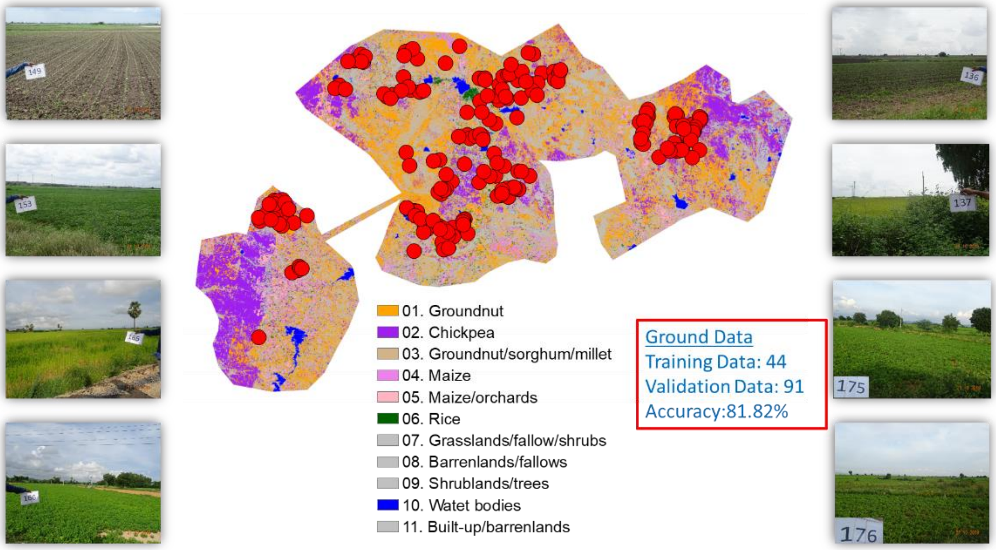
1. **Completed crop type classification in Mahabubnagar, Krishna, Puri, Kurnool and Anantapur Districts.**



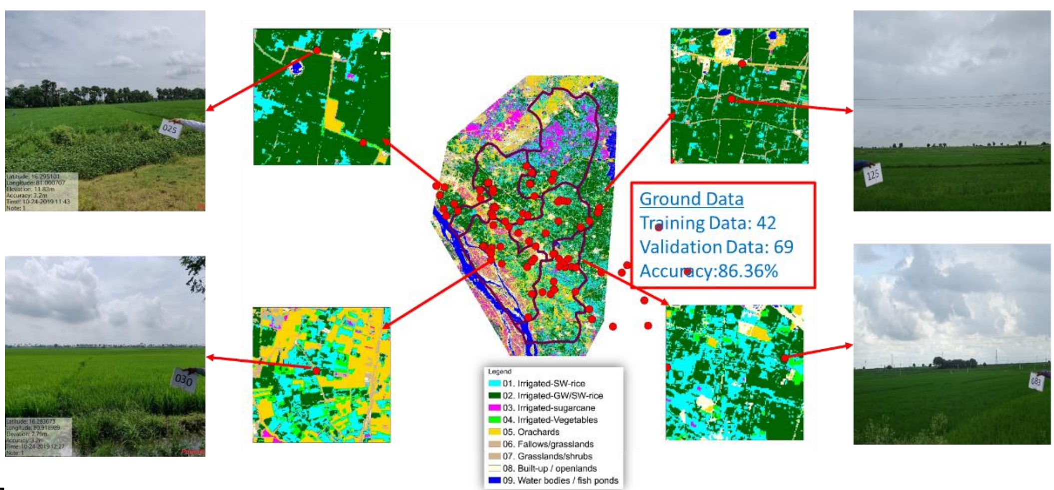
Crop Classification with Ground Data: Mahbubnagar



Crop Classification with Ground Data: Anantapur



Crop Classification with Ground Data: Krishna District



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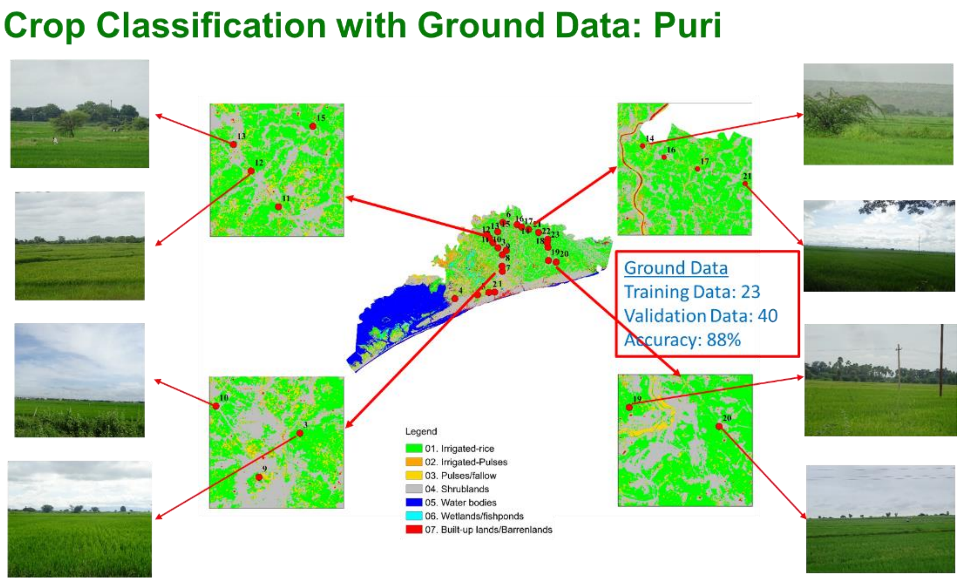


CCE's Data Collection:

Based on spatial map of Crop extent, Length of growing periods (LGP) and Leaf Area Index(LAI) of study crops in their respective areas, the selection of CCE's were shortlisted. With the help of crop extent map based on previously collected ground data gives an idea of crop locations, LGP shows the stages of crop like Start of Season (SOS), Peak of Season(POS) and End of Season(EOS) helps in identifying the harvesting stage of crop. LAI indirectly shows the health of the crop, which helps in locating the good crop fields for collection of CCE's.

Based upon the methodology from previous project, CCE's optimization was carried out in GP level.

The following protocol was followed in collecting CCE's

- Selecting five mandals in a district based on preliminary crop classification maps
- Selecting 10 Gram Panchayats (GP) in a Mandal
- Collecting 5 CCE samples in a Gram Panchayat

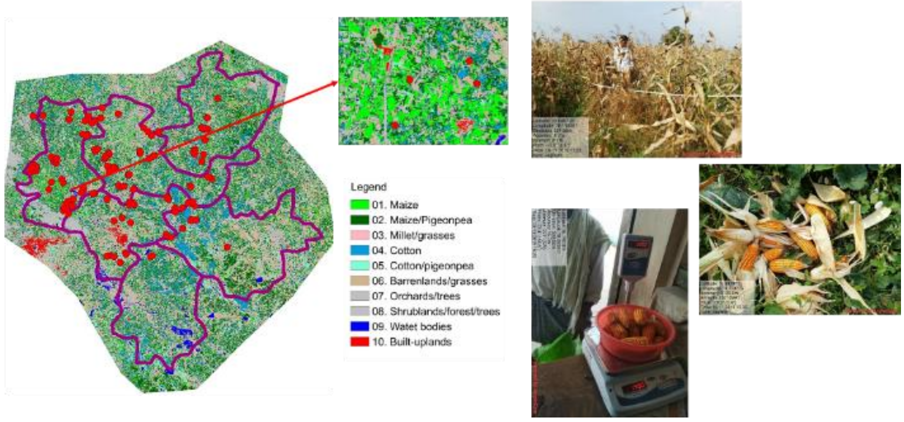
Number of CCE Samples in a District = 5 Mandals * 10 Gram Panchayats * 5 CCE samples = 250 samples per district

The CCE's was carried out by selecting 5m X 5m plot of field, manually harvested and weighted as shown in following images.

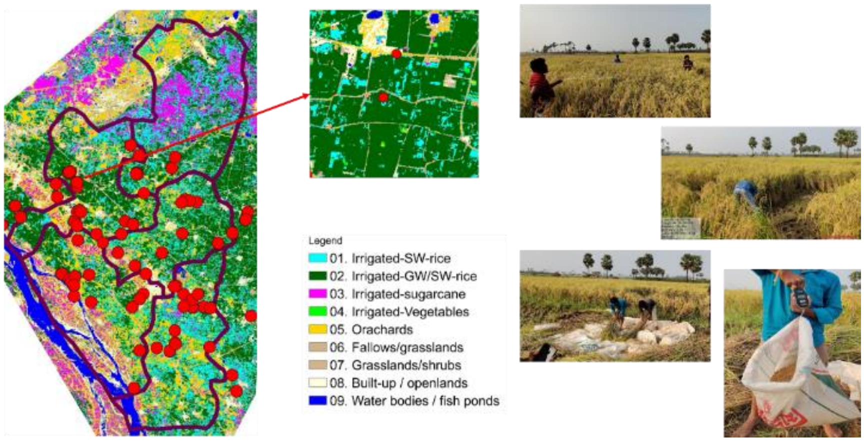
The below are the CCE's points with sample images in Mahabubnagar, Krishna, Puri, Kurnool and Anantapur Districts.

2. **Completed CCE's Data collection for Mahabubnagar, Krishna, Puri, Kurnool and Anantapur Districts.**

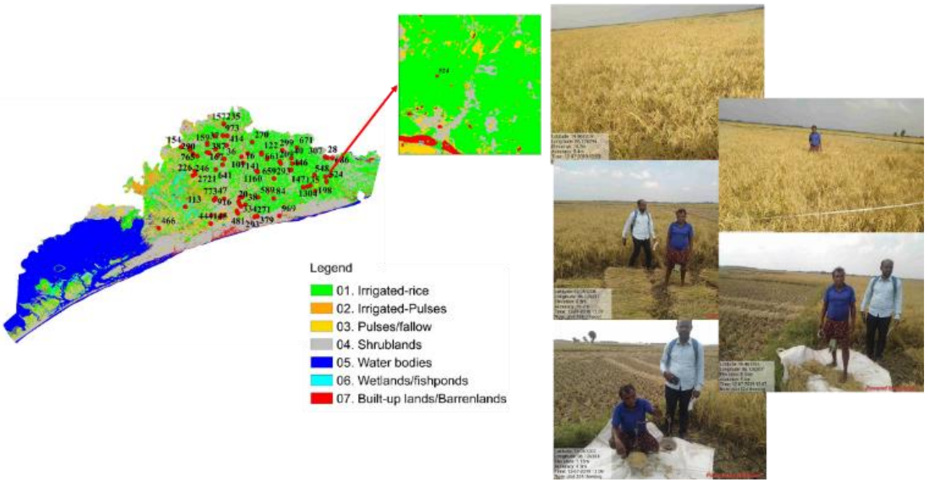
CCEs with crop Classification : Mahbubnagar



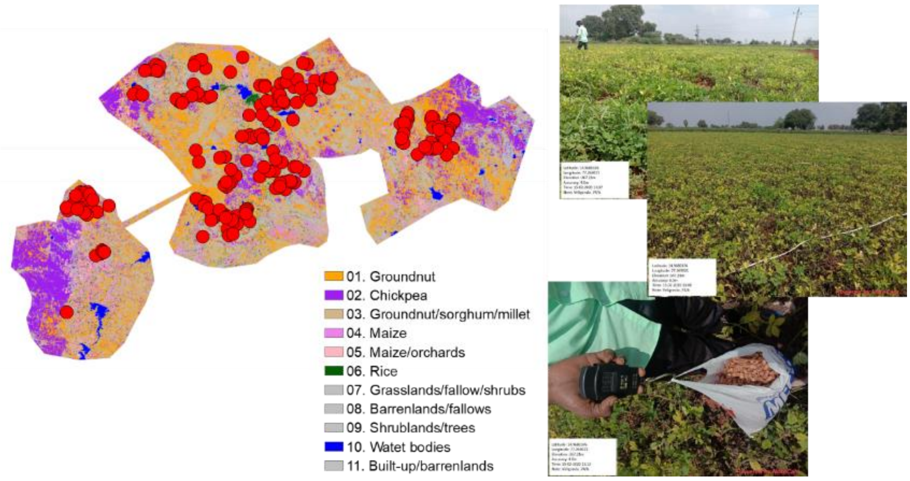
CCEs with crop Classification : Krishna



Puri District



Anantapur District



Kurnool District

5. Leaf Area Index

- Based on the fact that the spectral response of leaves is unique compared to that of other parts of the plant [6,7].
- Vegetation indices – NDVI, EVI, SAVI, etc. – have shown high positive correlation to LAI.
- With a limited field data consisting of LAI values at few locations, regression equations can be arrived at, relating LAI to spectral vegetation indices.
- METRIC (Measuring Evapotranspiration at high Resolution with Internalized Calibration) model has developed a relation between LAI and Landsat-derived Soil Adjusted Vegetation Index (SAVI). According to METRIC model,

$$LAI = \frac{-\ln\left(\frac{0.69 - SAVI}{0.59}\right)}{0.91}$$

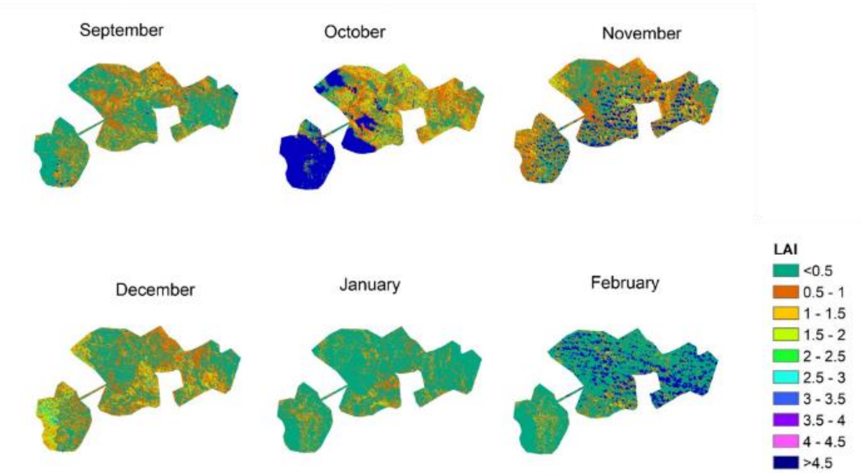
For Landsat-8 images used in this study, SAVI is computed from the formula:

$$SAVI = \frac{(1 + L)\,(B5 - B4)}{L + B5 + B4}$$

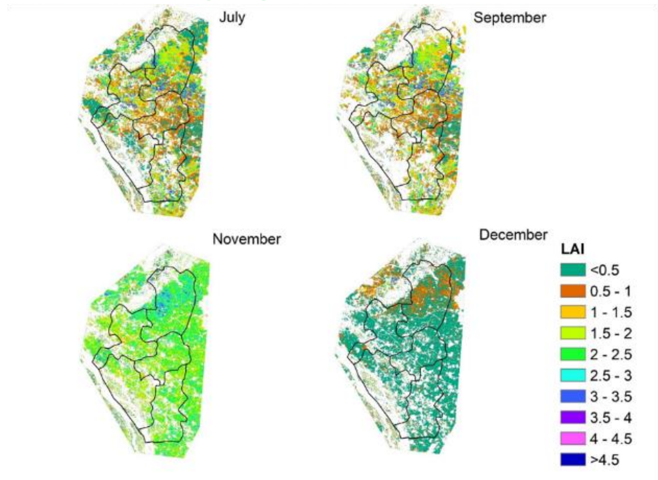
Where L is a soil factor, taken to be 0.1, B5 in the spectral reflectance in band 5 (Near Infrared) and B4 is the spectral reflectance in band 4 (Red).

LAI was calculated for study area

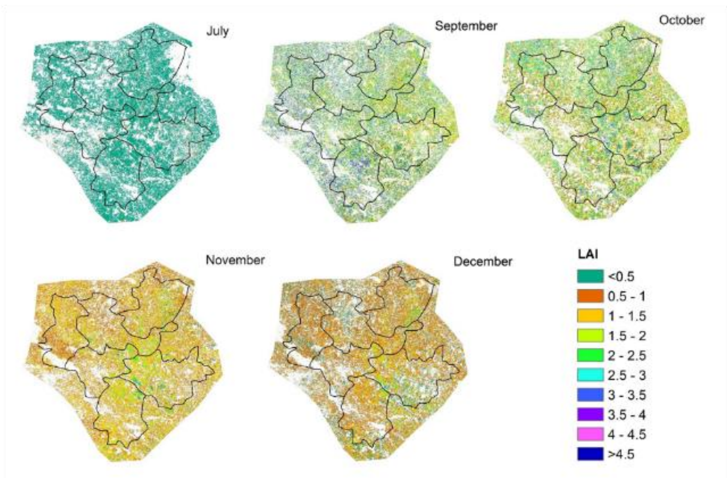
Leaf area index (LAI): Anantapur



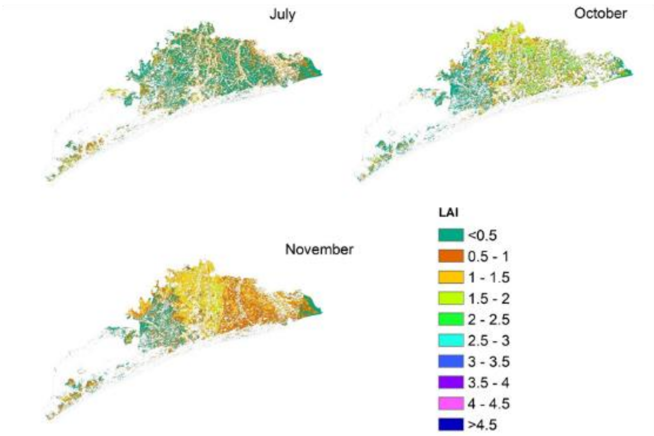
Leaf area index (LAI): Krishna district



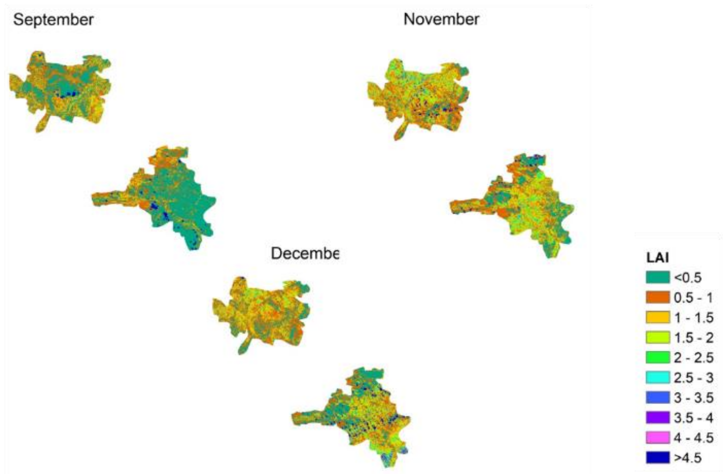
Leaf area index (LAI): Mahbubnagar



Leaf area index (LAI): Puri district



Leaf area index (LAI): Kurnool



Most of the crops contains LAI less than 3.

Integration of remote sensing LAI products with crop simulation models for better crop yield estimation

1. Introduction

Timely and accurate prediction of crop yield is important for agricultural land management and policy making. Several studies have demonstrated the utilization of satellite data in crop yield estimation. However, majority of studies used methods of empirical nature and they work only for specific locations, crops, cultivars and for a particular crop growth stage. Cropping system models and remote sensing tools are two different methodologies often used to answer some of the agronomic questions at various levels such as field and regional scales. Several researchers used these technologies independently however information derived from remote sensing is used to update cropping systems model simulations in recent times as both these technologies are complementary.

Keeping in view the complimentary nature of these technologies several researchers started integration of remote sensing data with crop growth simulation models found to be a promising option for crop growth monitoring and yield estimation. However, each technology has its own advantages limitations. For example use of remote sensing as a temporal crop analysis tool is limited due to availability of cloud free time-series remote sensing data and difficulties in accurate LAI estimation from remotely sensed data.

Similarly cropping systems models are often limited by data availability such as information on cultivar, management, soil, and meteorological inputs for spatial simulations. Uncertainties associated with spatial simulations can be reduced by periodically readjusting the simulation using spatial information from remote sensing images.

Several remote sensing data assimilation methods at various complexity levels were tried mostly either by directly using remote sensing data in the simulation models, updating the state variables or re parametrization of the model using remote sensing data in recent years.

In this study, we used the technique of re- parameterization of crop simulation models based on the several iterations using remote sensing input such as leaf area index(LAI) as it is supposed to be the highest degree of integration. The essence of the data assimilation approach is to improve the initial parametrization of the crop growth model and augment simulation with the use of remotely sensed observations.

2. Methodology

2.1. Data collection

Crop Cutting Experiments (CCE) is an assessment method employed by governments to estimate the crop yield in the region given cultivation cycle. The traditional method of CCE is based on the yield component method where sample locations are selected based on a random sampling of the total area under study. In the current analysis, we identified few mandals in Krishna, Anantapur and Kurnool districts in Andhra Pradesh, Puri district in Odisha and Mahabubnagar in Telangana to test the methodology. Data assimilation from remote sensing products such as leaf are index (LAI) in to cropping system models to predict crop yield in CCE sites. We have collected GPS location, date of sowing, irrigated vs rainfed and other management details from CCE location if available.

2.2. Soil data

Biophysical crop simulation models normally require profile-wise soil data. For each CCE location, soil inputs to the model were obtained from a set of soil profile data available from ICRISAT data repository and NBSSLUP data bases. We also used certain parameters in soil as free variable. Soil physical and chemical properties such as texture, hydraulic parameters, bulk density, organic matter and available N were extracted for each location based on the available soil profile data. Additional soil parameters such as soil albedo, drainage constant, and runoff curve number were estimated based on soil texture and converted using the generic soil database available in the DSSAT-models.

2.3. Weather data

The weather data such as daily maximum temperature, minimum temperature, rainfall and solar radiation data was collected from Andhra Pradesh and Telangana State Development Planning Society (APSDPS & TSDPS) automatic weather station network across the testing sites.

2.4. The Cropping System Model

The Cropping System Model (CSM)–Crop Environment Resource Synthesis (CERES)–Rice, Maize crop growth model. CROPGRO -Chickpea growth simulation model and PEANUTGRO-Groundnut model as provided in the Decision Support System for Agrotechnology Transfer (DSSAT) were used for yield simulations. Crop models require various input data such as crop characteristics, soil condition, management practice and daily weather information were prepared in advance. Using these input data, daily crop biophysical information (e.g. LAI) was generated by the crop growth model. The simulated LAI were compared with the corresponding Sentinel 2 products, and residuals between the simulated and Sentinel 2 LAI were minimized by adjusting the free input parameters, finally with the optimized set of input parameters, the model was executed to update the crop yield prediction.

The optimization process starts from an initial parametrization and adjusts the free parameters in order that the model given LAI with simulation is in agreement with the Sentinel 2
observations. The simulated LAI values depend on the values of the free variables (e.g. planting date, nitrogen dose, soil profile parameters) that are estimated by minimizing the cost function as shown below.

$$= \frac{1}{m}\sum_{i=1}^{m} \mathrm{abs}\left[(\mathrm{LAI})_{\mathrm{S}}(t_i) - (\mathrm{LAI})_{\mathrm{M}}(t_i)\right] / (\mathrm{LAI})_{\mathrm{M}}(t_i)$$

where LAIS (ti), LAIM (ti) are the simulated and measured LAI at time ti, respectively.

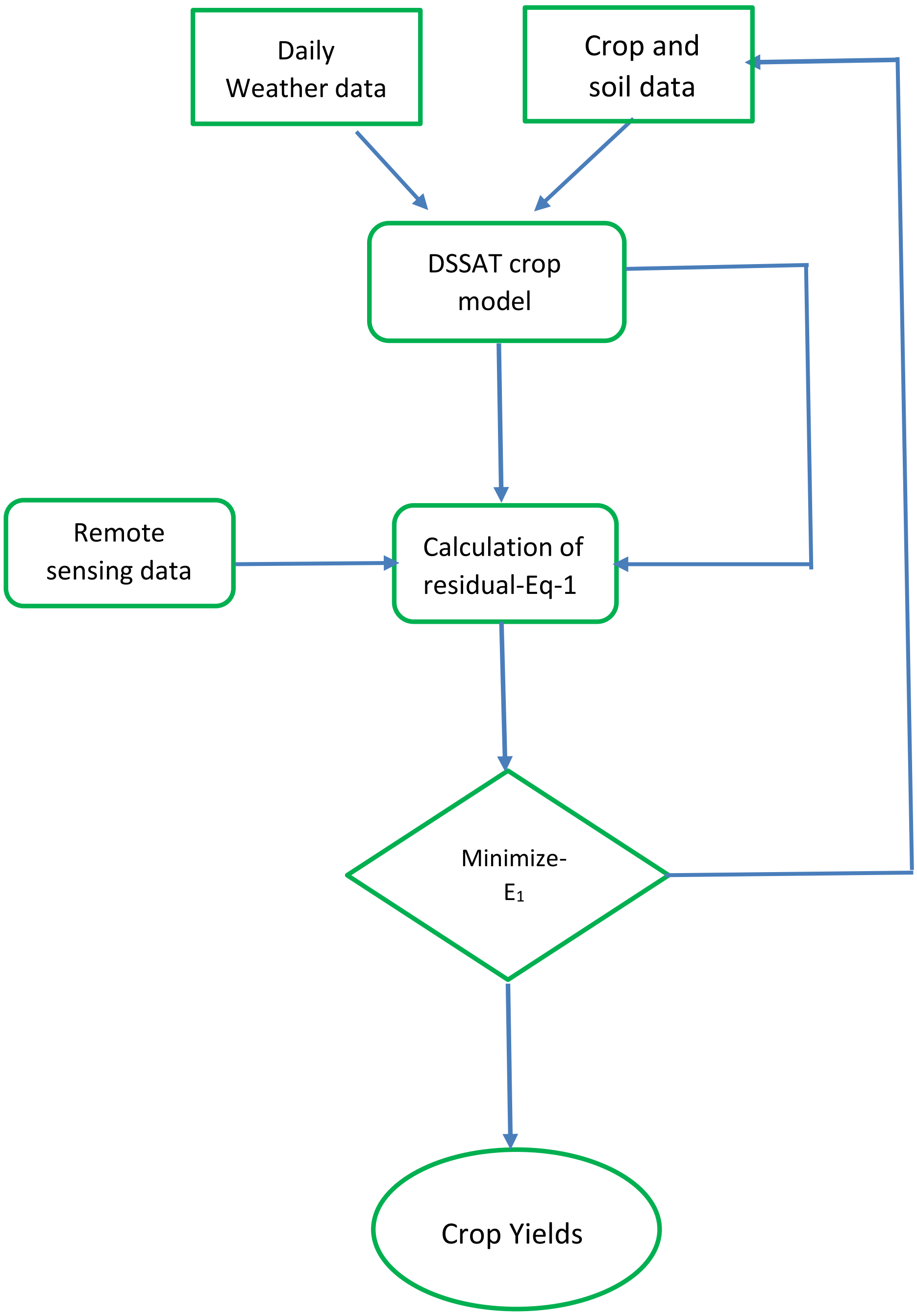


Figure 1. General methodology of the data assimilation approach integrating remote sensing data with crop growth models for crop yield estimation

3.0. Study sites

3.1. Location 1- Puri district, Odisha

Puri district is a coastal district on the eastern part of Odisha, India, covering an area of 348 thousand hectares and situated in East and South Eastern Coastal Plain Zone of Odisha. The district is blessed with sandy-clay-loam, silty-loam, Loam, clay-loam and clayey soil in varied agro-eco system. The district has 11 blocks namely Astarang, Brahmagiri, Delang, Gop, kakatpur, Kanas, Krushnaprasad, Nimapada, Pipili, Puri and Satyabadi. The mean annual rainfall and rainy days are 1491 mm 57 days respectively. Paddy, green gram, black gram, horse gram and groundnut are grown in the District.

In the current study we selected the blocks of Delang, Gop, Puri, Nimapada and Pipilli. The data was collected from 131 CCE location on paddy. Daily weather data required for this study were collected at block level from the Govt. of Odisha. Soil properties data were collected NBSSLUP data sets.

Variables such as the cultivar type, planting date, flood depth, planting population and nursery age, nitrogen application rates were found to be very important for the execution of the CSM–CERES–Rice model. The nursery age, soil types across the blocks, plant population, nursery age, nitrogen application does and time were kept as free parameters.

CSM–CERES–Rice- model simulates growth, development and yield of rice under different weather, soil and management conditions. The CSM–CERES–Rice model used in this study was one of several models in the Decision Support System for Agrotechnology Transfer package.

The CSM–CERES–Rice model simulates phenological development, vegetative and reproductive plant development stages, partitioning of assimilates, growth of leaves and stems, senescence, biomass accumulation and root system dynamics [7-9]. It has been used to predict grain yield of rice is influenced strongly by cultivar characteristics, soil and weather conditions, and crop management. The input parameters for the crop growth model include soil types, planting dates, planting rates and local weather data. The initial conditions required for model were assume by discussing with local CCE farmers and experts. Input data, such as crop characteristics, soil condition, management practices and weather information were prepared in advance and model was calibrated for different duration cultivars.

A list of free variables shown in Table 1. were used and crop biophysical information (e.g. LAI, biomass, yields) was generated by the crop growth model for the locations where CCE were conducted. The simulated vegetation indices and LAI were compared with the corresponding Sentinel 2 products, and residuals between the simulated and Sentinel 2 LAI were minimized by adjusting the input parameters. With the optimized set of input parameters, the model was executed to update the crop yield prediction.

Table 1. Free parameters and their range used in the crop growth model

Variable	Range
Crop Growth Model – CERES Rice	
Cultivars	6 cultivars of three different duration (short, medium and long)
Planting date	July 2nd week to August 2 week
Plant Population	20-44 plants/m2
Nursery age	20-45 days
Nitrogen fertilizer application rate	30-240 kg/ha
Soil types	12 types

The optimization process starts from an initial parametrization and adjusting the free parameters in the crop yield model in order that the model gives LAI simulation (Figure 2.) in agreement with the Sentinel 2 observations (Figure 3.). The parameters are adjusted sequentially based on the cost function value.

3.1.1. Results

A comparison of the estimated rice yield and CCE collected yield data for selected locations in five blocks of Puri district were presented in Figure 4 and the model statistics were also presented in the table 2.

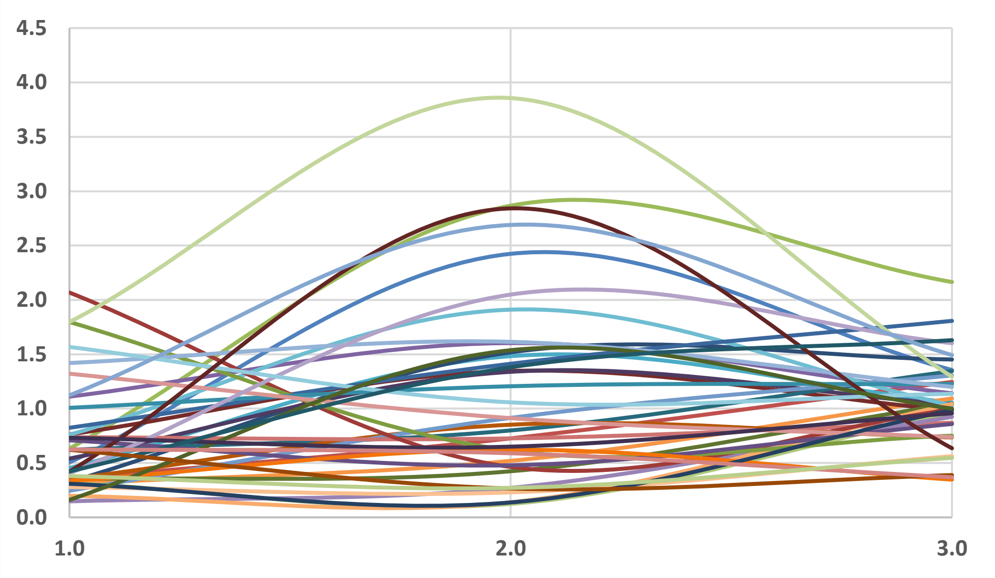


Figure 2. LAI for rice in Puri districts as per remote sensing data

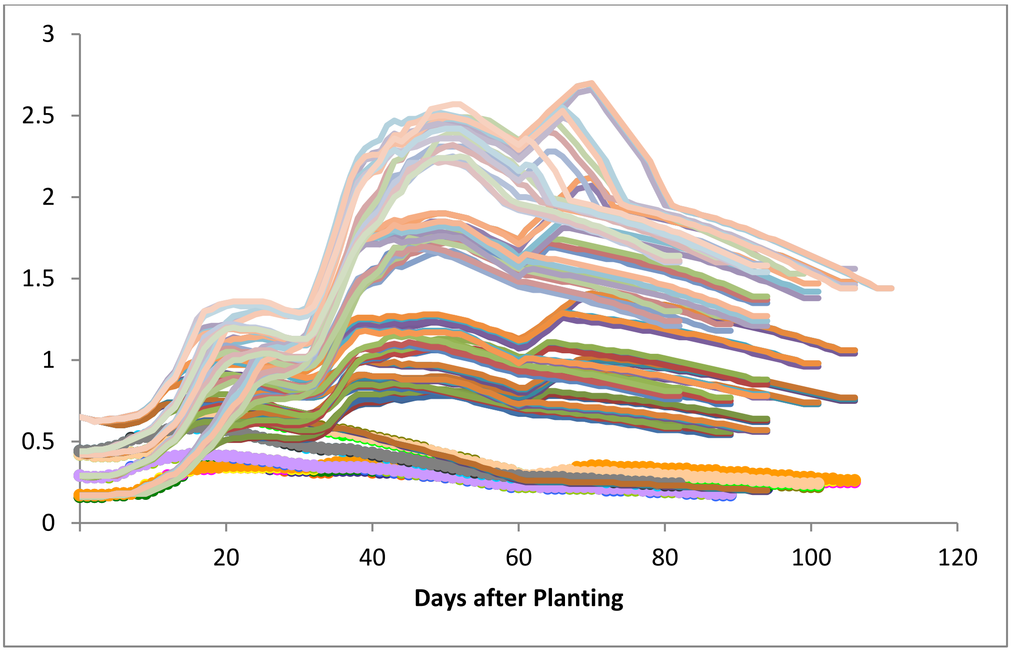


Figure 3. LAI for rice crop generated through the CSM–CERES–Rice model for one location in Puri district

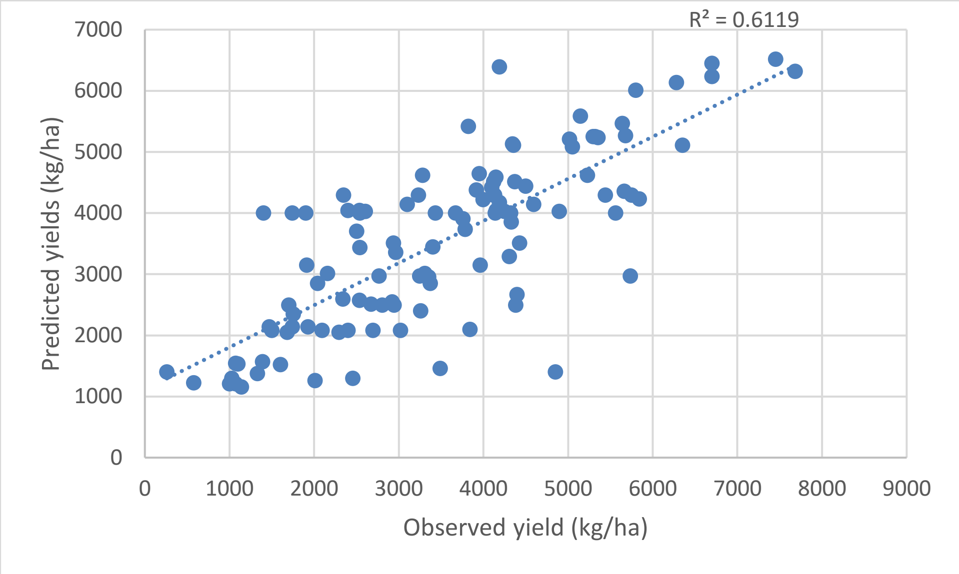


Figure 4. Comparison of the estimated rice yields with CCE actual yields in Puri district, Odisha

Table 2. Descriptive statistics showing the performance of CERES-Rice model assimilated with remote sensing LAI data

Variable	CCE locations	Observed	Simulated	RMSE	RRMSE	MAE	MF
Rice yields (kg/ha)	131	3543	3650	989	0.28	722	0.60

RMSE: Root mean squared error, NRMSE: Relative root mean squared error, MAE: Mean absolute error, MF: Modeling efficiency

3.2. Location 2- Krishna district of Andhra Pradesh

Krishna district of Andhra Pradesh is under Eastern Coastal plane, hot, sub-humid to semi-arid eco region. Tropical climate conditions with extreme hot summer and cold winter prevail in this District. There are four types of soils in this district viz., black cotton soils (57.6%), Sandy clay loams (22.3%) and Red loamy soils (19.4%) and sandy soils (0.7%). The sandy soils form a fringe along the cost. The belt cotton soil is the most extensive and occurs in almost all the Mandals. The sandy clay loams are formed along rivers and streams. The red loamy soils in the district are suitable for cultivation and as a result 72 per cent of the area has been brought under the plough. The alluvial soils are mainly suitable for the paddy, sugarcane and the upland areas are mainly suitable for dry and horticulture crops

Paddy is major crop grown in this region with an area of 2.45 lakh hectares in 2018-19. With the production was 14.2 lakh metric tons. The district average yield was recorded around 6.125 t/ha with maximum yield of 6.5 t/ha deltaic area and 6.1t/ha in the coastal belt.

Table 3. Free parameters and their range used in the crop growth model

Variable	Range
Crop Growth Model – CERES Rice	
Cultivars	3 cultivars of three different duration (short, medium and long)
Planting date	July 2nd week to August 2 week
Plant Population	25-44 plants/m2
Nursery age	25-45 days
Nitrogen fertilizer application rate	60-240 kg/ha
Soil types	10 types

The optimization process starts from an initial parametrization and adjusting the free parameters as shown in Table 3 were tried in the crop yield model in order that the model LAI in agreement with the Sentinel 2 observations. A total of 121 locations of CCE data across five mandals (Kankipadu, Vuyyuru, Pamidimukkala, Penumaluru and Totlavallur) were collected. Daily weather data was collected from fifteen AWS stations available in these mandals.

Table 4. Descriptive statistics showing the performance of CERES-Rice model assimilated with remote sensing LAI data

Variable	CCE locations	Observed	Simulated	RMSE	RRMSE	MAE	MF
Rice yields (kg/ha)	121	5521	5254	583	0.10	437	0.3

RMSE: Root mean squared error, NRMSE: Relative root mean squared error, MAE: Mean absolute error, MF: Modeling efficiency

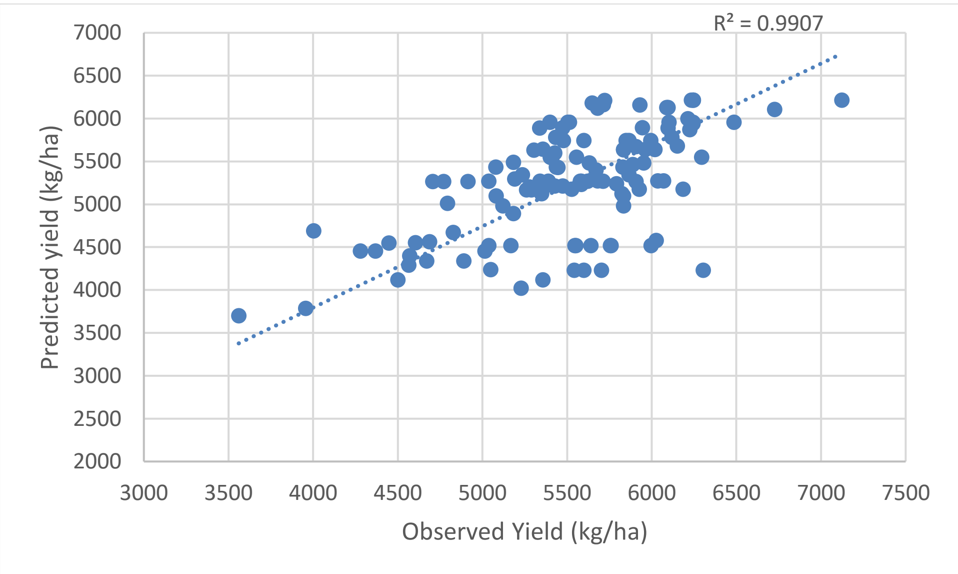


Figure 5. Comparison of the estimated rice yields with CCE actual yields in Krishna district, Andhra Pradesh

From the rice simulation it can be very clearly evident that models could simulate the rice yields (around 3 to 3.5 t/ha in Odisha and 5 to 5.5 t/ha in Krishna) moderately well across the two locations, however the accuracy was quite high with Puri locations, Availability more LAI data points from remote sensing methodology will help in improving the yield simulations.

3.3. Location 3- Maize in Mahabubnagar

The district is one of the most drought prone areas in Telangana and classified as rain shadow district. The average rainfall of Mahabubnagar district is 651 mm, most of it received during south west monsoon period (June – September). The dominant soil types of the selected mandals are sandy and loamy sand which has poor water retention capacity. Maize is an important crop in this region and mostly grown under rainfed conditions. Unfavorable weather conditions such as delayed monsoon, intermitted dry spells, erratic rainfall and prolonged droughts etc., are the major concern to the farmers in the district. For the current study 114 CCE location spread across five mandals (Balanagar, Rajapur, Mdijill, Jedcherla, Nawabpeta) were selected.

The rainfall data very crucial for the crop modeling simulation as this crop is mainly grown under rainfed conditions, hence daily weather data from 25 AWS locations were collected (source: TSDPS).

Table 5. Free parameters and their range used in the crop growth model

Variable	Range
Crop Growth Model – CERES Maize	
Planting date	**June 3rd week to July 3rd week**
Plant Population	**5.5 – 10 plants/m2**
Row spacing	**50-75 cm**
Nitrogen fertilizer application rate	**20-200 kg/ha**
Soil profile data	**28 soil profiles**

For maize simulations the optimization process starts from an initial parametrization and adjusting the free parameters as shown in the table were tried in the crop yield model in order that the model LAI in agreement with the Sentinel 2 observations. The optimization stated with soil types and later followed by other parameters such as planting date, nitrogen rate etc.,.

Table 6. Descriptive statistics showing the performance of CERES-Maize model assimilated with remote sensing LAI data

Variable	CCE locations	Observed	Simulated	RMSE	RRMSE	MAE	MF
Maize yields (kg/ha)	114	2245	2580	755	0.33	568	0.52

RMSE: Root mean squared error, NRMSE: Relative root mean squared error, MAE: Mean absolute error, MF: Modeling efficiency

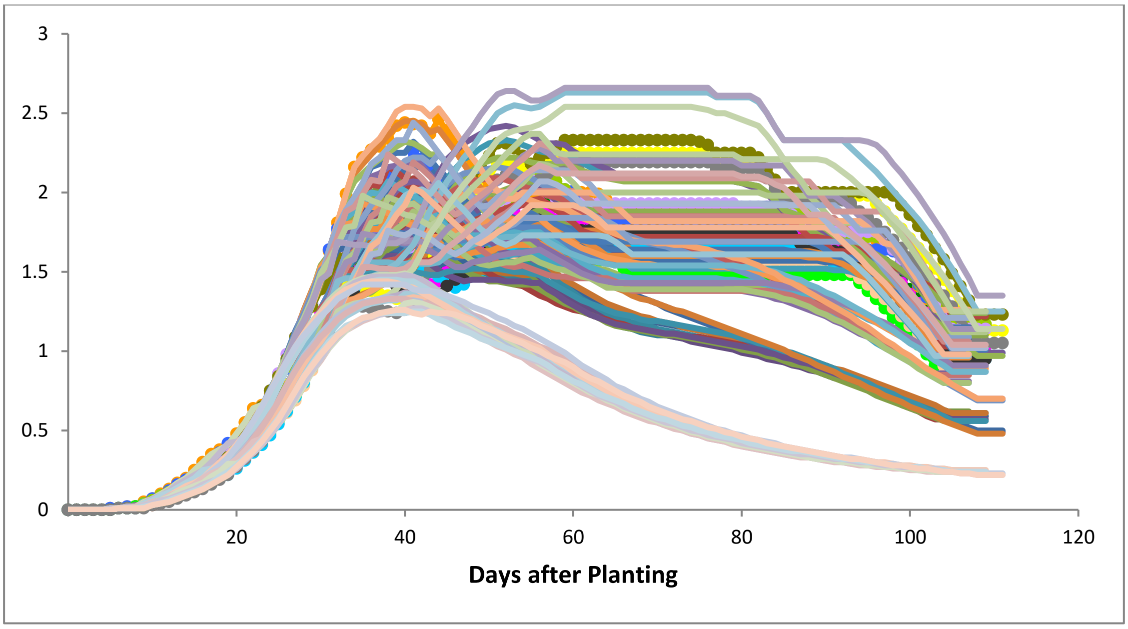


Figure 6. LAI for maize in Mahabubnagar districts as per remote sensing data

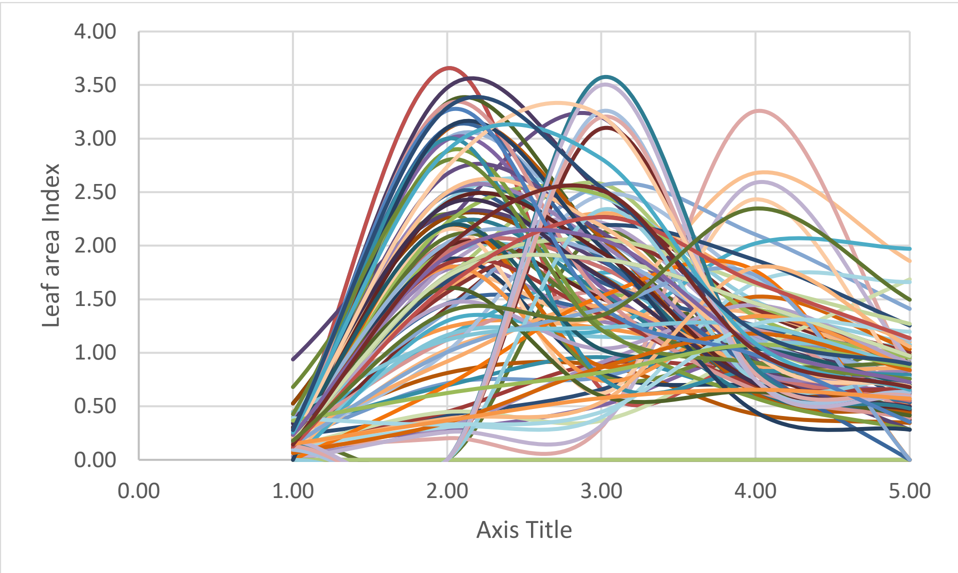


Figure 7. LAI for maize crop generated through the CSM–CERES–Mize model for one location in Mahabubnagar district

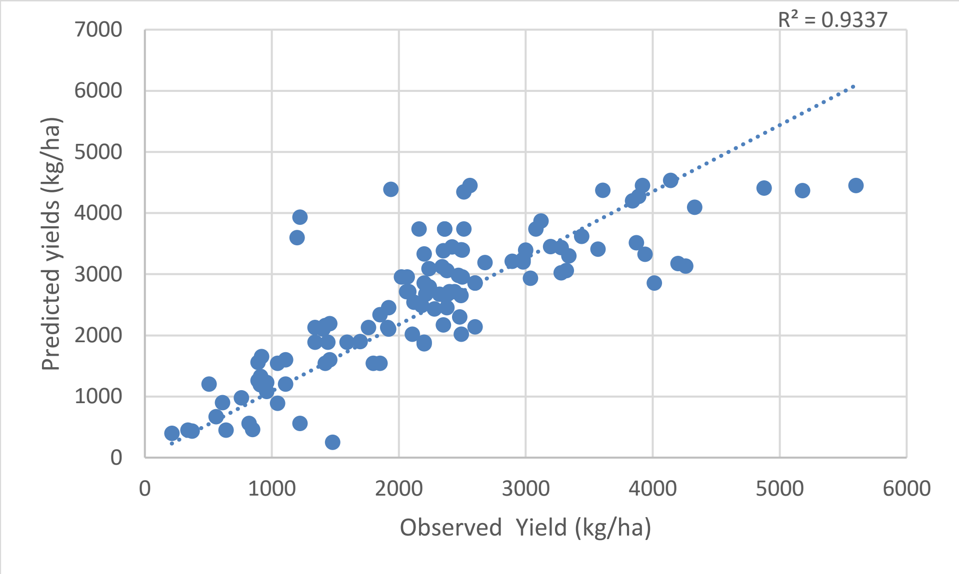


Figure 8. Comparison of the estimated maize yields with CCE actual yields in Mahabubnagar district, Telangana

3.4. Location 4- Groundnut in Anantapur

Groundnut is an important oilseed and food crop grown by small and marginal farmers in the district. Its yields have often been unpredictable due to low and erratic distribution of rainfall coupled with many other biotic factors. Average pod yield was observed to be 516 kg/ha and varies between a little over 200 kg/ha and 1200 kg/ha from year to year Anantapur district can be divided into four natural divisions based on soil types, elevation and rainfall, Northern region with 14 mandals (administrative unit), Central region with 24 mandals, Highland region with 12 mandals and Southern region with 13 mandals. Alfisols are the predominant soils (78% of the area), followed by Vertic Inceptisols (20%), and other soils are (2%). The soils based on soil texture can be classified as sandy loams (31%), clay (24%) loamy sands (14%), sandy clay loams (13%) and rocky lands.

In the present study we collected CCE data from 180 location spread across five mandals (Gooty, Guntakal, Yadiki, Pamidi, Uravakonda) and compared with simulated data.

Table 7. Free parameters and their range used in the crop growth model

Variable	Range
CROPGRO – Peanut Model	
Cultivars	**Four different cultivars**
Planting window	**July 2nd fortnight to Sep 1st fortnight**
Plant Population	**20 to 40 plants/m^2**
Soil profile data	**8 different soils**

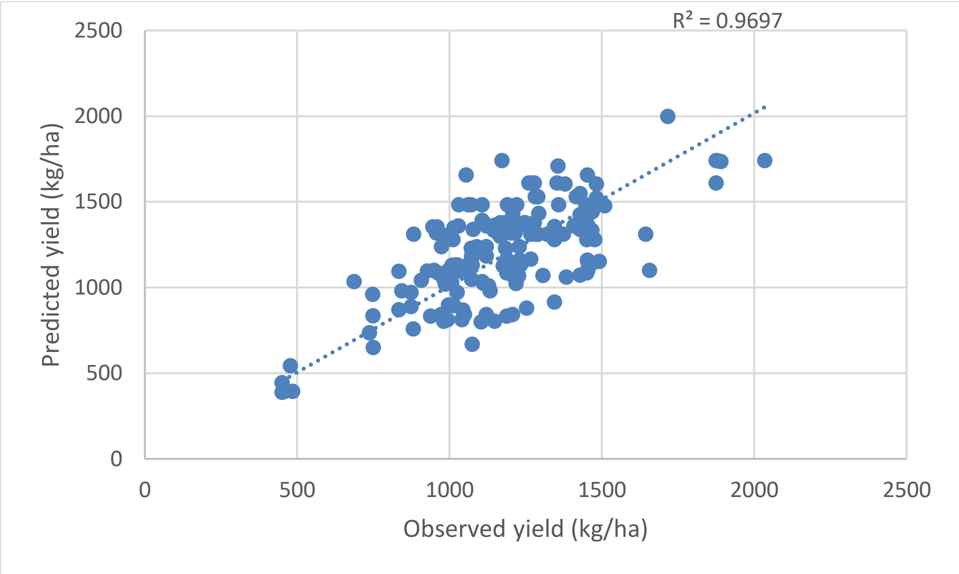


Figure 9. Comparison of the estimated groundnut yields with CCE actual yields in Anantapur district, Andhra Pradesh

Table 8. Descriptive statistics showing the performance of CROPGRO-Peanut model assimilated with remote sensing LAI data

Variable	CCE locations	Observed	Simulated	RMSE	RRMSE	MAE	MF
Groundnut yields (kg/ha)	180	1191	1290	218	0.18	178	0.30

RMSE: Root mean squared error, NRMSE: Relative root mean squared error, MAE: Mean absolute error, MF: Modeling efficiency

3.5. Location 5- Kurnool Chickpea

Kurnool district is in Andhra Pradesh located in the west-central part of the state and lies between the North latitudes of 140 54’ and 160 18’and East longitudes of 760 58’ and 790 34’. Of the total population of 4.04 million in the district, more than 70% lives in rural areas and are engaged in farming. The farmers cultivate crops in two seasons, namely the *kharif* season (rainy season – June to October) and the *rabi* season (post-rainy season – November to February). The major crops grown in the rainy season are paddy rice, cotton and pigeonpea; in the post-rainy season, chickpea, sorghum, and sunflower are the major crops. Due to dominant black soil in the district and constraints in cultivating during the rainy season, farmers keep the land fallow in the rainy season and cultivate crops in the post-rainy season using the residual moisture. ‘Fallow-chickpea’ is the dominant cropping system observed across Kurnool district. The soils in the district are characterized by low-to-medium fertility and yield gaps exist for the majority of crops. They are predominantly black cotton soils (Vertisols) of about 0.76 million hectares followed by red soils (0.2 million ha).

In the present study we have selected 226 CCE locations spread across five mandals (Banaganepalle, Gudur, Kalluru, Kodumuru and Koilkuntla) in the district. Daily weather data was collected from forty-two AWS stations located in the district.

Table 9. Free parameters and their range used in the crop growth model

Variable	Range
CROPGRO – Chickpea Model	
Cultivars	**Three different cultivars**
Planting window	**October 1st fortnight to November 1st fortnight**
Plant Population	**20 to 40 plants/m^2**
Soil profile data	**8 different soils**

Table 10. Descriptive statistics showing the performance of CROPGRO-chickpea model assimilated with remote sensing LAI data

Variable	CCE locations	Observed	Simulated	RMSE	RRMSE	MAE	MF
Chickpea yields (kg/ha)	226	997	1070	193	0.19	150	0.54

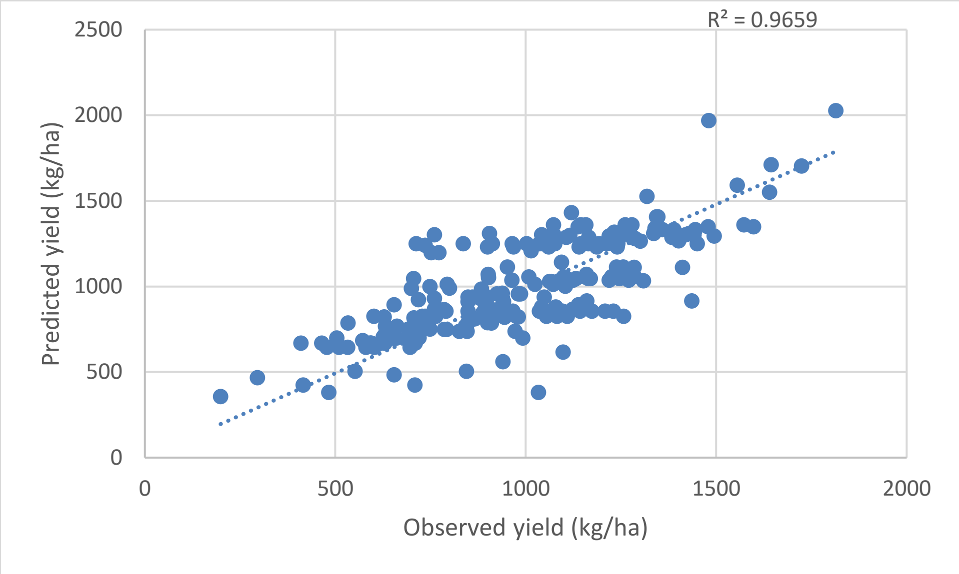


Figure 10. Comparison of the estimated chickpea yields with CCE actual yields in Kurnool district, Andhra Pradesh

The analysis of both group of CROPGRO models indicates theta the models can be effectively used with remote sensing assimilation data from yield prediction. Further improvements in yield prediction also needed by including other NDVI based products such as biomass, vegetative index etc.

4.0. Challenges and improvements

This study indicates the importance of LAI in the data assimilation process and that the incorporation of LAI can improve crop yield prediction. However, the following points need to be considered to further improve the yield prediction.

1. Collection of cloud-free time-series remote sensing data during the cropping season (at least fortnightly if not weekly) for assimilation of data in crop models for improving modeling efficiency.
2. There is a need to study the relationship between remote sensing derived LAI product and final yields of various crops especially in rain-fed regions.
3. Further improvements of the Sentinel 2 -derived LAI and vegetation index products are necessary, especially during the beginning of the growing season and continuous data during the crop growth period.
4. The availability of location-specific weather data is the key for proper simulations with crop simulation models. In some states there exists a good network of AWS stations, however the majority of other locations this is major lacunae.

5.0 District level analysis of non-cereal crops

Primarily, the analysis was done to 3 to 5 mandals of selected districts. The selected non-cereals were Chickpea of Kurnool, Groundnut of Anantapur, and Maize of Mahabubnagar.

The analysis was further extended to the district level. The following are the village level analysis of entire district.

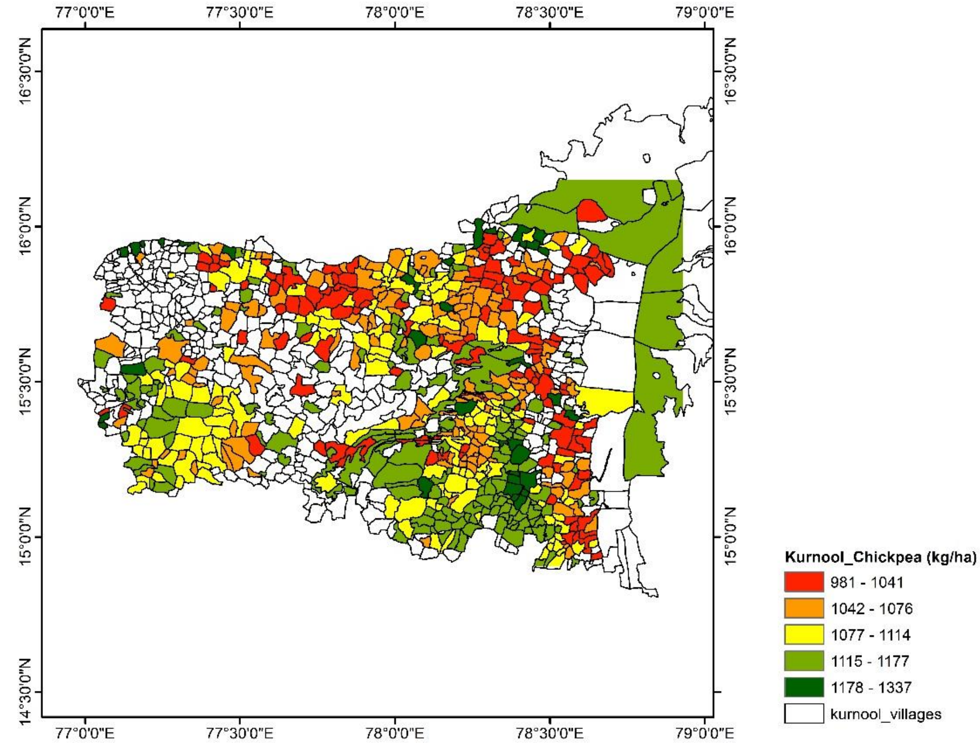


Figure 11: The spatial yield distribution of Chickpea of Kurnool district

The above map (fig 11) shows the spatial yield distribution of Chickpea of Kurnool district. The yield varies from 980 kg/ha to 1400 kg/ha. Some village has no chickpea cultivation. The village level mean yield was inserted as annexure_1.

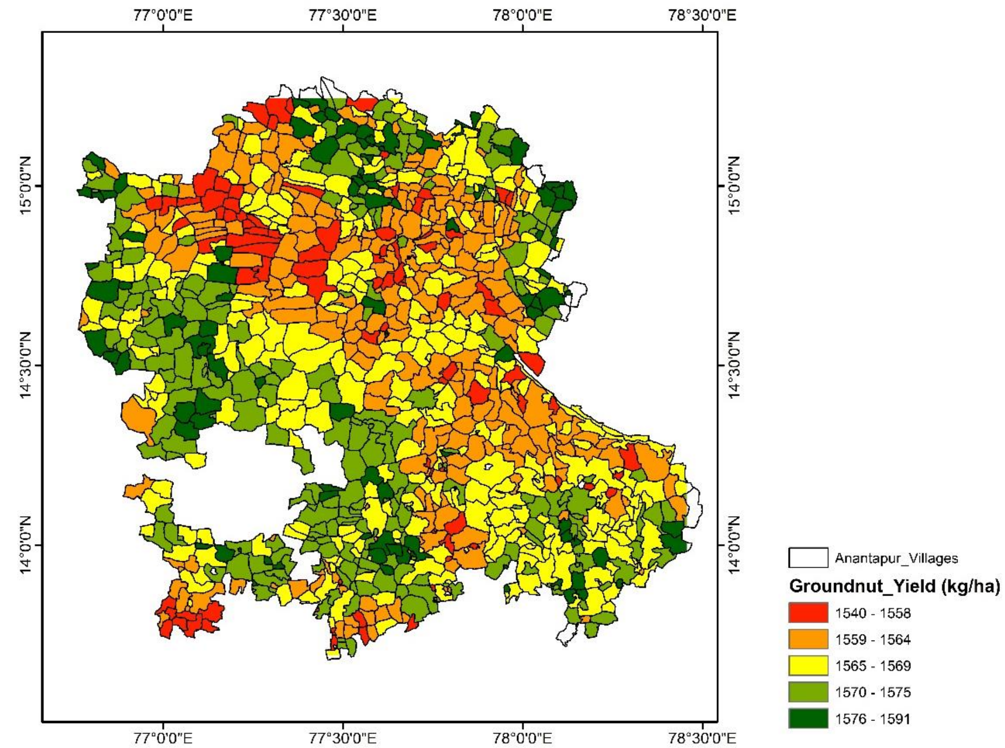


Figure 12: The spatial yield distribution of Groundnut of Anantapur district

The above map (fig 12) shows the spatial yield distribution of Groundnut of Anantapur district. The groundnut has a spread across the district. The yield varies from 1540 kg/ha to 1600 kg/ha. The village level mean yield was inserted as annexure_1.

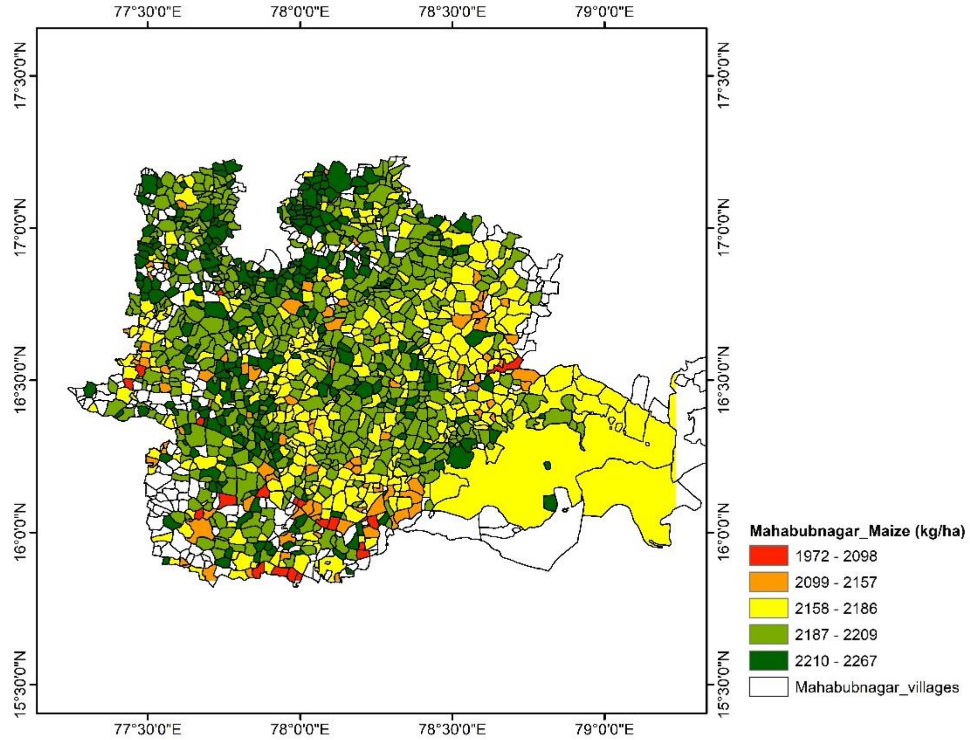


Figure 13: The spatial yield distribution of Maize of Mahabubnagar district

The above map (fig 13) shows the spatial yield distribution of Maize of Mahabubnagar district. The yield varies from 1900 kg/ha to 2300 kg/ha. There were few villages without maize cultivation. The village level mean yield was inserted as annexure_1.

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