# Crop yield assessment at Gram Panchayat level using technology

INTERNATIONAL CROPS RESEARCH INSTITUTE FOR THE SEMI-ARID TROPICS

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Rabi – 2022-23

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| Project PI | : | Dr Murali Krishna Gumma |
| Project Start | : | December 2022 |
| Project Completion | : | June 2023 |

INTERNATIONAL CROPS RESEARCH INSTITUTE FOR THE SEMI-ARID TROPICS

2023

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# Contents

# 1. Executive Summary

*The Government of India plans to optimize Crop Cutting Experiments (CCEs) and Gram Panchayat crop yield estimations using different technologies including satellite derived metrics and crop modelling techniques. The present study for Rabi season (2022-23) aims to crop yield estimations for non-cereal crops in 10 districts of five states viz. Chhattisgarh, Gujarat, Madhya Pradesh, and Rajasthan. 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 and DSSAT crop modelling to assess the yield estimations.*

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

# 2. Objectives

1. Crop extent mapping for the study districts
2. Conduct and assess crops cutting experiments using spatial statistical optimising technique for crop of *Rabi* season in the respective study districts.
3. Crop yield estimation based on DSSAT crop simulations.

# 3. Data & Methods

The work has been divided into four components to execute the study

1. Ground Data Collection
2. Crop Classification
3. CCE collection
4. Crop Simulation Model (CSM)
5. Integration of Remote Sensing with CSM

## 3.1 Ground Data Collection

Ground data were collected based on preliminary crop classification and near real-time satellite imagery, i.e., Sentinel-2 false color composites with tracking GPS using image processing software along with Bhuvan Fasal Application and iCrops mobile application. The ground data was collected in a 90 m * 90 m homogenous plots and recorded information like location, LULC categories, crop type and cropping pattern, methods of irrigation, farmers' interviews (wherever possible), etc. Crop name and location data were collected at each point to validate crop type classification. Two independent datasets were collected: one for training and another for validation.

Ground data collection has completed in all districts including the later provided districts. But later MNCFC given instructions to do study in only 15 districts. So, we have carrying out further study based on MNCFC instructions.

A minimum of 300 ground samples were collected in every district covering all land use and land cover using BHUVAN Application and also our own mobile application "iCrops". The database and credentials has already shared with concern person of MNCFC to view real time data.

Overall 6098 points were collected in provided districts as shown in Annexure 1.

## 3.2 Crop classification

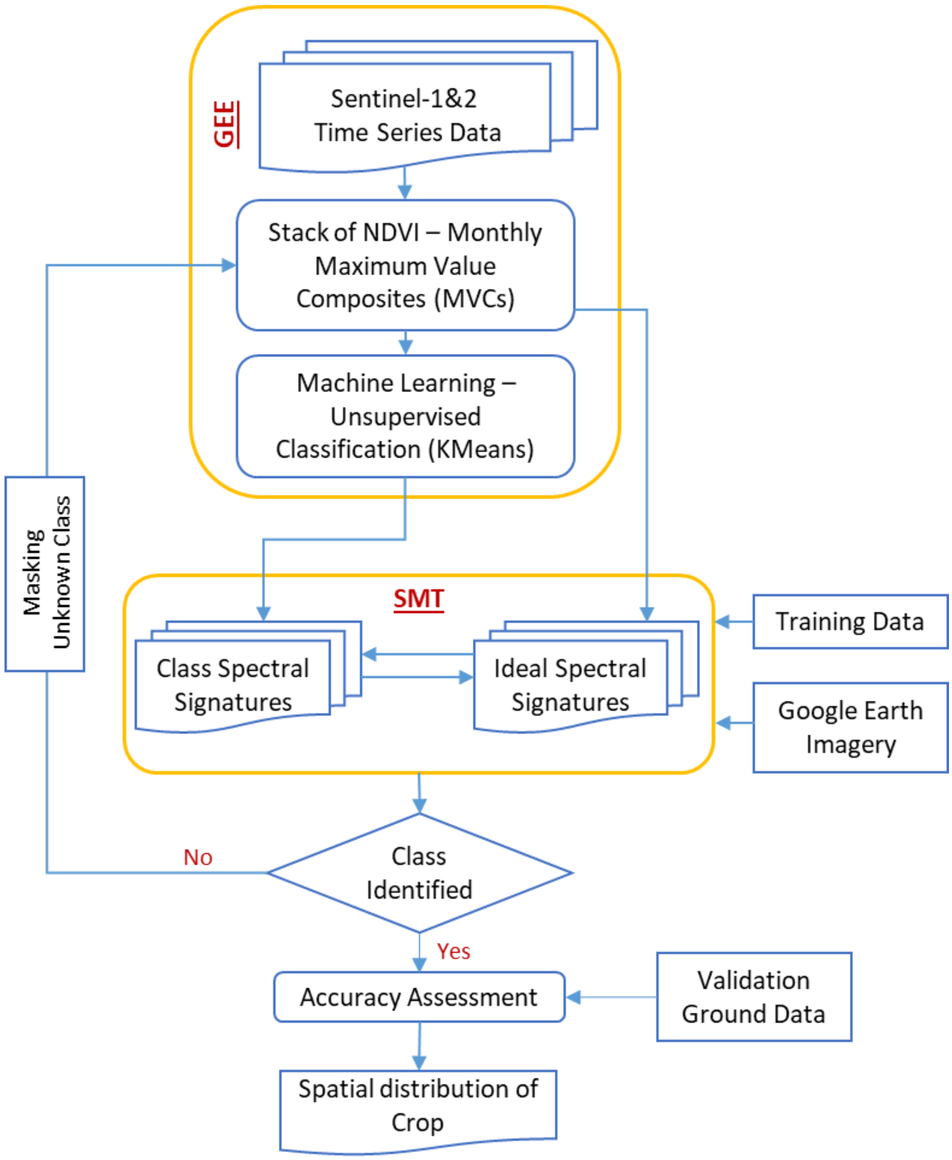



**Figure 1:** The methodology followed for crop type classification

The crop type classification was carried out using sentinel 1 and sentinel -2 satellite time series data with the help of ground data (Figure 1) (Gumma, Thenkabail, et al., 2022). The stacked image downloaded from GEE consists of every 30 days for entire Kharif season. Unsupervised classification was used to generate initial classes. The unsupervised ISOCLASS cluster algorithm (ISODATA in ERDAS Imagine 2018) run on the stack generated an initial 40 classes, with a maximum of 40 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 sites. 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(Gumma, Thenkabail, Teluguntla, & Whitbread, 2018).

The process of labelling and class identification was done based on spectral matching techniques (SMTs) (Gumma, Amede, et al., 2022; Gumma, Tummala, et al., 2022)[1]. Initially, 40 classes from the unsupervised classification were grouped based on spectral similarity or closeness of class signatures(Panjala, Gumma, & Teluguntla, 2022). 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. 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(Gumma, Nelson, & Yamano, 2019; Gumma, Thenkabail, Deevi, et al., 2018; Gumma, Thenkabail, Teluguntla, et al., 2018; Gumma, Thenkabail, Teluguntla, & Whitbread, 2019; Gumma, Tsusaka, et al., 2019).

The spatial distribution of crop classification is shown in Annexure 3 and respective accuracy of crop classification is shown in Annexure 1.

## 3.3 CCE Collection

[1] Gumma, M.K., Thenkabail, P.S., Panjala, P., Teluguntla, P., Yamano, T. and Mohammed, I., 2022. Multiple agricultural cropland products of South Asia developed using Landsat-8 30 m and MODIS 250 m data using machine learning on the Google Earth Engine (GEE) cloud and spectral matching techniques (SMTs) in support of food and water security. *GIScience & Remote Sensing*, *59*(1), pp.1048-1077.

**CCE's Data Optimisation:** The optimisation of CCE's were carried out using following methodology(Panjala, Gumma, Ajeigbe, et al., 2022) (Figure 2). The process begins with collection of sentinel 2 NDVI Maximum data (available), climate data and soil map.

The NDVI data with crop mask and respective climate and soil data were combined into homogenous stratum and collected random points using stratified sampling. By multiple regression techniques, the number of samples were reduced into half of random samples.

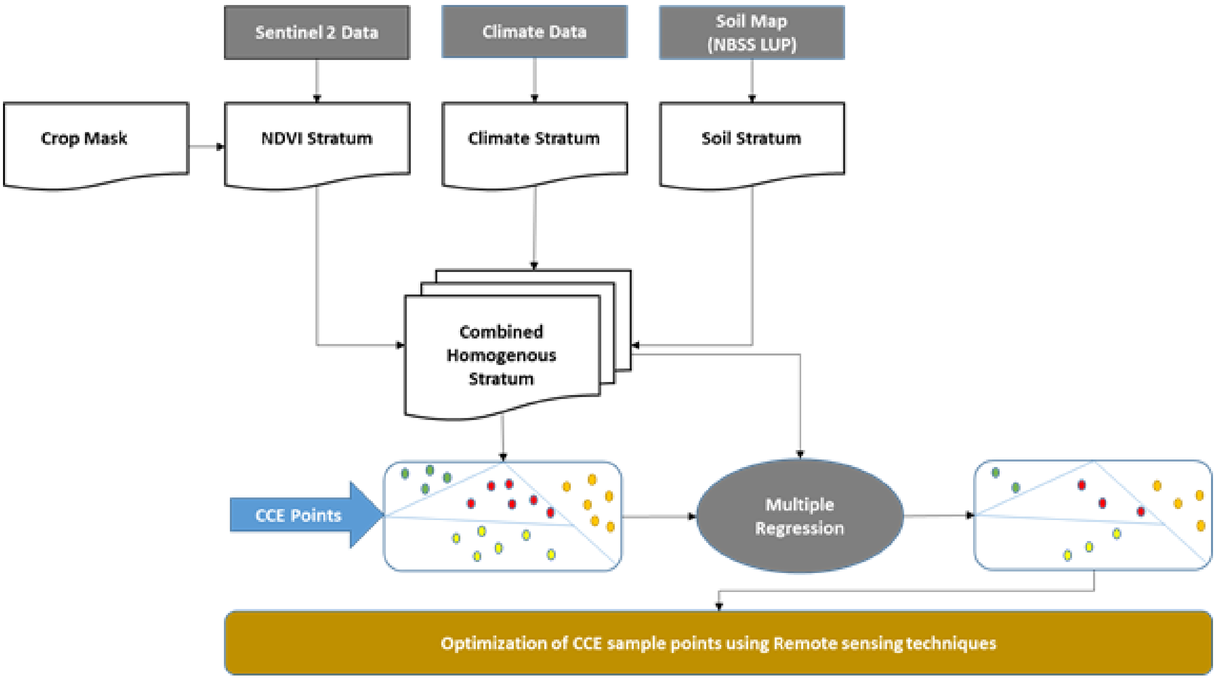



**Figure 2:** Optimisation of Crop Cutting Experiments using remote sensing techniques

Using above optimization, we instructed our field staff to collect the possible samples.

**CCE's Data Collection:**

Based on spatial map of Crop extent, optimization and Leaf Area Index (LAI) of crop in their respective areas, the selection of CCE's were shortlisted. LAI indirectly shows the health of the crop, which helps in locating the good crop fields as well as adverse fields for collection of CCE's.

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

The total number of 160 samples were collected for each district (Annexure 2).

## 3.4 Leaf Area Index

This study used MODIS derived LAI and also sentinel -2 derived LAI index.

- Based on the fact that the spectral response of leaves is unique compared to that of other parts of the plant.
- 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 Sentinel 2-derived Soil Adjusted Vegetation Index (SAVI). According to METRIC model,

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

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

$$SAVI = \frac{(1 + L)\ (B8 - B4)}{L + B8 + B4}$$

Where L is a soil factor, taken to be 0.1, B8 in the spectral reflectance in band 8 (Near Infrared) and B4 is the spectral reflectance in band 4 (Red).

Due to Coarse resolution of MODIS, the study uses LAI derived from Sentinel 2. Compared both values and used the optimised values.

**LAI values were extracted for every CCE location and validated against the DSSAT crop model LAI**

## 3.5 Classification using Planet High resolution satellite data

We have used high resolution planet data in some part of study districts to do crop classification with high accuracy and also identifying the other LULC from crop pixels. This study adopted the resolution merge i.e. available Sentinel-2 data with Planet data and carried classification. The maps of classification are shown in Annexure 3.

# 4. Crop Simulation Model

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

### 4.1 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 parameterization 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 parameterization of the crop growth model and augment simulation with the use of remotely sensed observations.

## 4.2 Methodology

The methodology **(Fig 3)** includes crop model data mainly soil, weather and crop management data and its integration with remote sensing data(Gumma, Kadiyala, et al., 2022).

### 4.2.1 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 blocks 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.

### 4.2.2 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.

### 4.2.3 Weather data

The weather data such as daily maximum temperature, minimum temperature, rainfall and solar radiation data was collected from Automatic Weather Stations (AWS) stations of respective state authorities. If AWS data not available, NASA power data was used for analysis.

### 4.2.4 The Cropping System Model

The Cropping System Model (CSM)– crop growth models as provided in the Decision Support System for Agro technology 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 and MODIS LAI 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 parameterization 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.

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

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

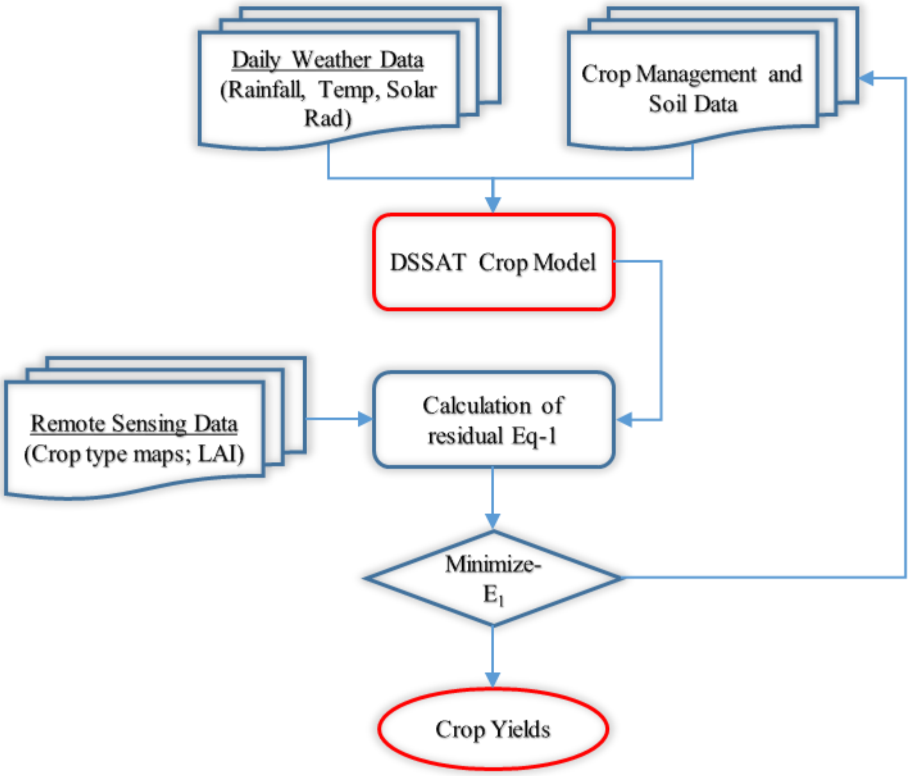



**Figure 3.** General methodology of the data assimilation approach integrating remote sensing data with crop growth models for crop yield estimation

## 4.3 Assimilation of Remote Sensing Data into Crop Growth Model for Yield Estimation

Remote sensing data assimilation methods with various levels of complexity have been tried, either by directly using remote sensing satellite data in simulation models (Doraiswamy, Moulin, Cook, & Stern, 2003; Olioso et al., 2005), by updating state variables or by re-parameterization of the model using remote sensing satellite data (Fang, Liang, & Hoogenboom, 2011; Jin et al., 2017)., we used the technique of re-parameterization of crop simulation models through several iterations using remotely sensed LAI estimates; this technique is supposed to best integrate crop growth conditions. The data assimilation approach helps with initializing parameters of the crop growth model and improve simulations with the help of remotely sensed satellite observations. The optimization process starts with initial model parameterization by adjusting the free parameters so that the model-simulated LAI is in agreement with the Sentinel-2 LAI observations (Eq. 1). The simulated LAI values depend on the values of the free variables (e.g., planting date, nitrogen dose, soil profile parameters) that are generated by minimizing the value of the following cost function. The remote sensing LAI data were collected for six times during the crop growth period.

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

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

Using a cost function measuring the distance between the simulated state variables and observed ones, the method employed automatically adjusts the set of model input parameters until the difference between the Sentinel 2 LAI and the crop model-simulated LAI is minimized. Finally, using this optimization algorithm, crop yields were predicted at each CCE location by obtaining a new set of parameters or initial values and allowing a simulation that resembles better observations. The technique we used was a frequently applied re-calibration methodology that enabled us to estimate the yields of respective successfully and compare them with observed yields with significant accuracy at each CCE location. The data assimilation approach proved to be reliable and shows great potential in providing yield prediction data at the village level. In this study, since LAI is the only link between the crop growth model and remotely sensed data, the accuracy of the model and final predictions with optimized datasets depends on the quality of remotely sensed LAI data

### 4.3.1 Calibration of DSSAT and Validation of yield data at GP level

DSSAT crop models require genetic coefficients, which are cultivar specific for describing processes related to growth and development and grain production. These coefficients allow the model to simulate performance of diverse genotypes under different soil, weather and management conditions. The model was calibrated using field measured values of weather parameters, crop management and soil properties during the cropping season. In our previous studies as a part of Agricultural Model Intercomparision and Improvement Project (AgMIP) phase I & II, we have calibrated growth model for various cultivars of different duration.

As, the model was run at CCE plot level, the observed yield of every CCE collected was validated against the crop model yield generated by re-parameterization of the model free variables using remote sensing LAI data. The respective crop yields depend mainly on crop management practices followed mainly nitrogen amount and time of application, irrigation application rates, cultivar duration etc., The village mean yield was calculated with collected CCE yield and corresponding simulated yields.

As some times models may underestimate LAI as seen in several published literature and hence we re-parameterized the crop growth model variables using LAI developed from remote sensing data at regular intervals during crop growth period. However, the accuracy issues for remote sensing LAI may be possible due to due to cloud conditions and varying spectral indices. Further improvements of the Sentinel-derived LAI and vegetation index products are necessary, especially during the beginning of the growing season and continued data during the crop growth period. There is also an immediate need to further invest in studying relationship between remote sensing derived LAI product and field LAI observations across locations to understand the accuracy of remote sensing LAI predictions

The spatial distribution of gram panchayat level yields is shown in Annexure 4 and relevant statistics are shown in Annexure 2 for respective districts.

# 5. Future Work and Issues

**Future Improvements:**

- Improvements in LAI predictions
- Use of remote sensing derived dry matter production and other indices in addition to LAI to re-parameterization of model free variables for improving accuracy of predictions
- Exploring the possibility of establishing a good network of AWS stations for accurate location specific daily weather data for better prediction of crop yields

**Issues Facing:**

1. Not availability of Weather related data in some districts; and coarse resolution of soil data

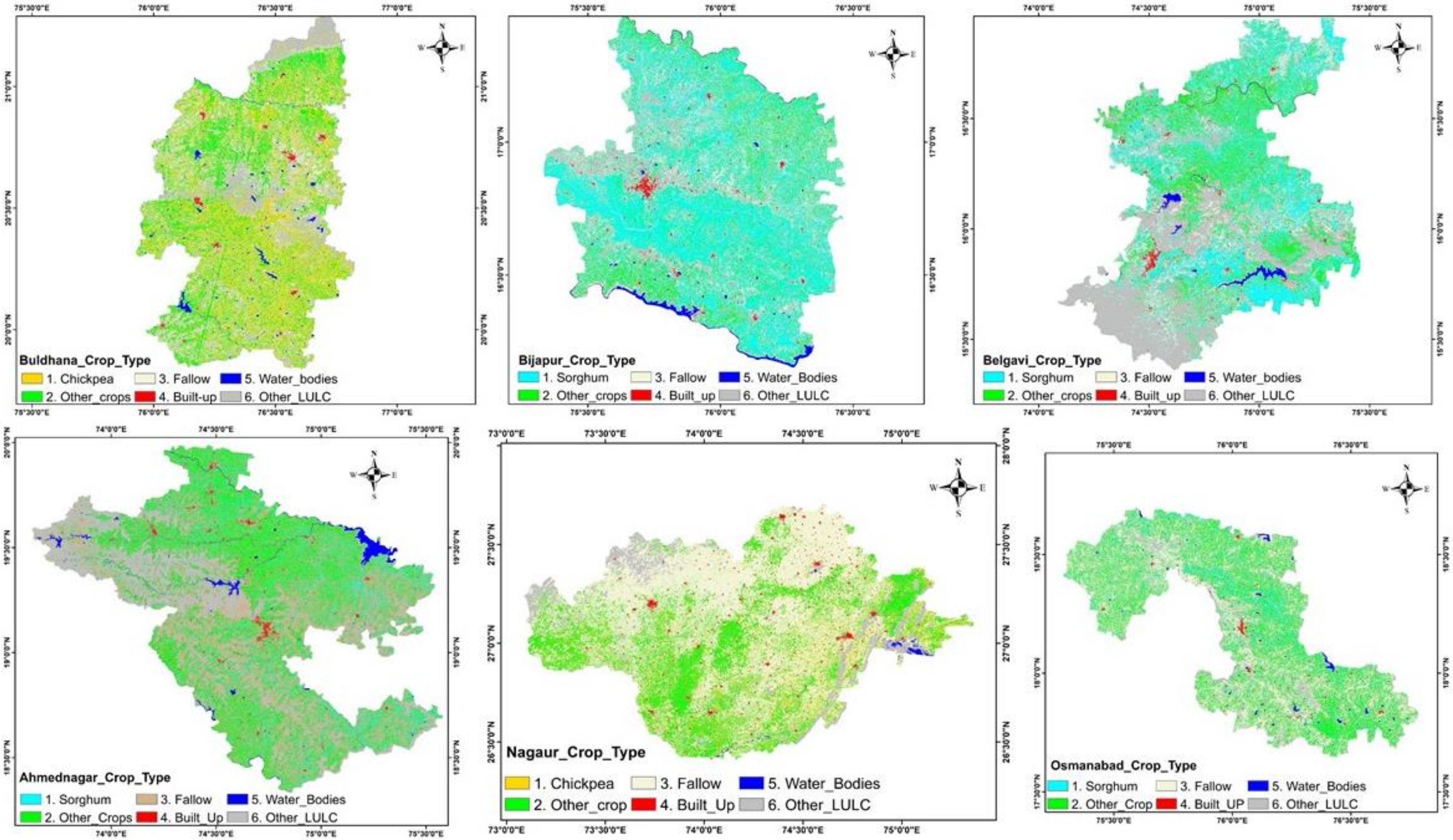
**<u>Annexure –1 :</u> Ground Data – Crop Classification Accuracies**

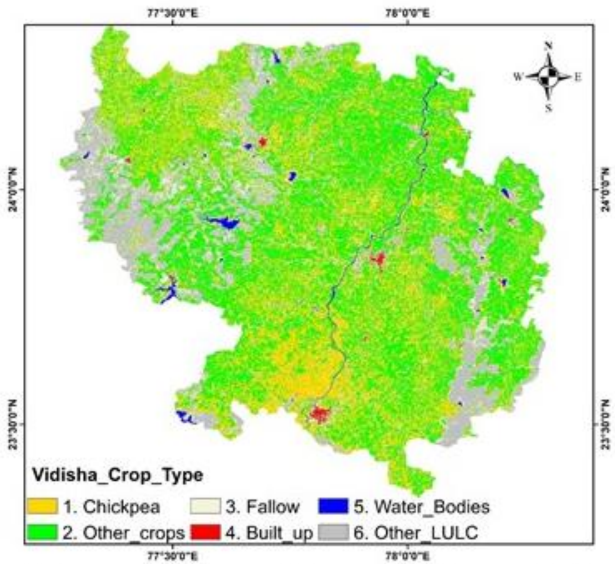
| S. No | State | District | Crop | GT | Validation Points | Crop classification | Accuracy |
|---|---|---|---|---|---|---|---|
| 1 | Chhattisgarh | Rajnandgaon | Bengal Gram | 322 | 559 | ☑ | 81.41% |
| 2 | Karnataka | Raichur | Bengal Gram | 207 | 1060 | ☑ | 80.66% |
| 3 | Karnataka | Vijayapura | Sorghum | 200 | 563 | ☑ | 76.38% |
| 4 | Karnataka | Belagavi | Sorghum | 238 | 361 | ☑ | 78.95% |
| 5 | Madhya Pradesh | Vidisha | Bengal Gram | 183 | 353 | ☑ | 80.17% |
| 6 | Maharashtra | Osmanabad | Bengal Gram | 185 | 694 | ☑ | 72.33% |
| 7 | Maharashtra | Buldhana | Bengal Gram | 325 | 491 | ☑ | 76.99% |
| 8 | Maharashtra | Solapur | Sorghum | 279 | 993 | ☑ | 78.05% |
| 9 | Maharashtra | Ahmednagar | Sorghum | 281 | 762 | ☑ | 87.27% |
| 10 | Rajasthan | Nagaur | Bengal Gram | 253 | 369 | ☑ | 80.76% |
| Total | | | | 2473 | 6205 | | |

**Annexure – 2 :** CCE – Yield Estimation -Accuracy

| S. No | State | District | Crop | CCE | Soil Data | Weather Data | Yield Validation $R^2$ |
|---|---|---|---|---|---|---|---|
| 1 | Chhattisgarh | Rajnandgaon | Bengal Gram | 160 | ☑ | ☑ | 0.66 |
| 2 | Karnataka | Raichur | Bengal Gram | 167 | ☑ | ☑ | 0.64 |
| 3 | Karnataka | Vijayapura | Sorghum | 160 | ☑ | ☑ | 0.66 |
| 4 | Karnataka | Belagavi | Sorghum | 164 | ☑ | ☑ | 0.70 |
| 5 | Madhya Pradesh | Vidisha | Bengal Gram | 160 | ☑ | ☑ | 0.61 |
| 6 | Maharashtra | Osmanabad | Bengal Gram | 160 | ☑ | ☑ | 0.67 |
| 7 | Maharashtra | Buldhana | Bengal Gram | 164 | ☑ | ☑ | 0.68 |
| 8 | Maharashtra | Solapur | Sorghum | 162 | ☑ | ☑ | 0.69 |
| 9 | Maharashtra | Ahmednagar | Sorghum | 172 | ☑ | ☑ | 0.65 |
| 10 | Rajasthan | Nagaur | Bengal Gram |  | ☑ | ☑ | Excluded |
| | | Total | | 1469 | | | |

## Annexure 3: Spatial Distribution of Crop Type

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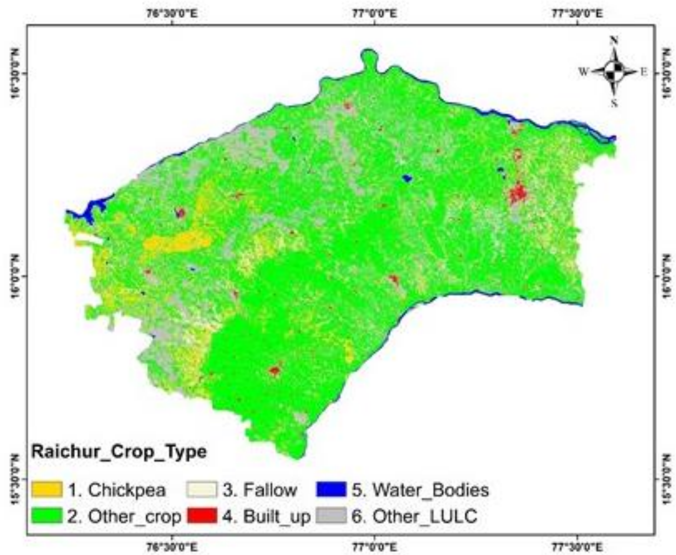
2. Other_crops
3. Fallow
4. Built_up
5. Water_Bodies
6. Other_LULC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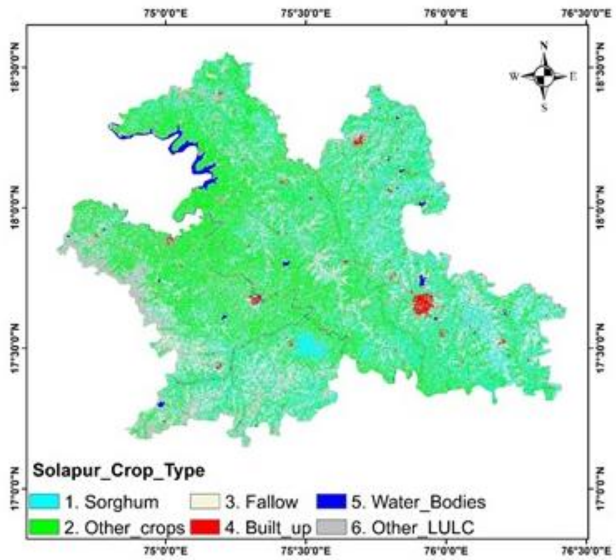
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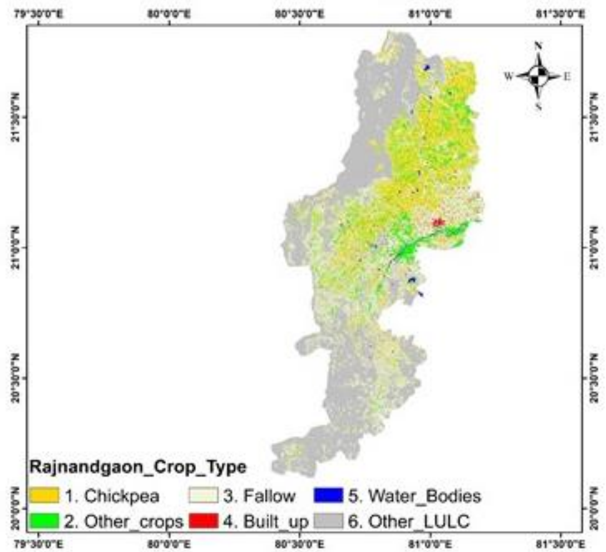
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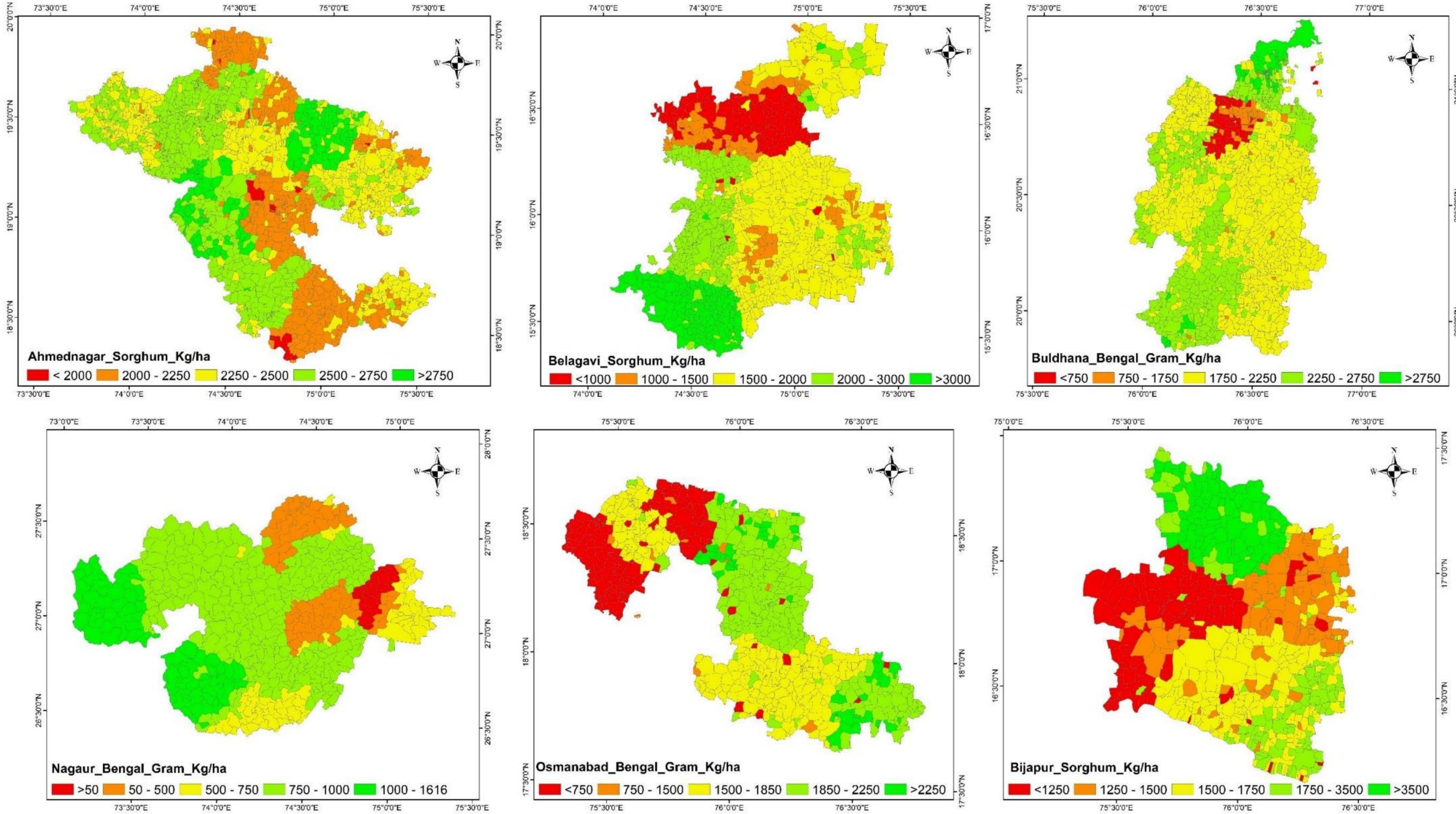
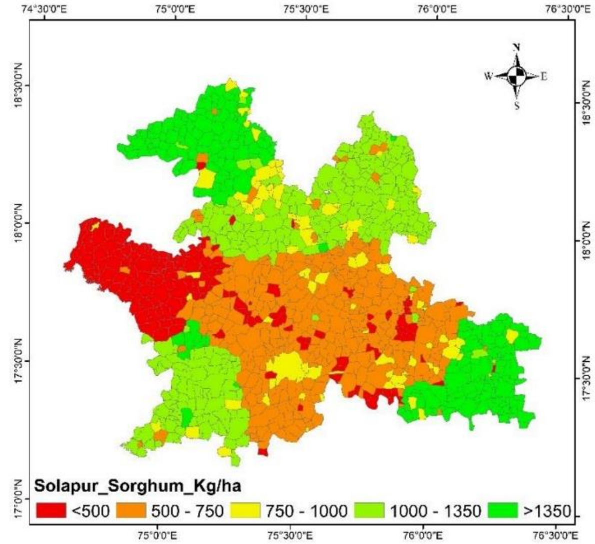
## Annexure 4: Spatial Distribution of GP level Yield Estimations

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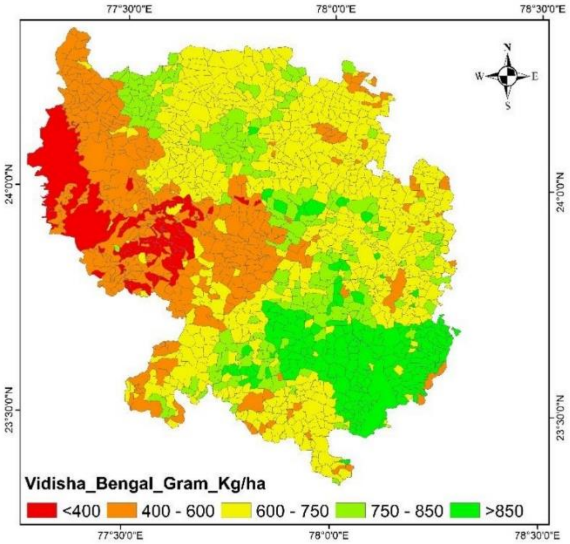
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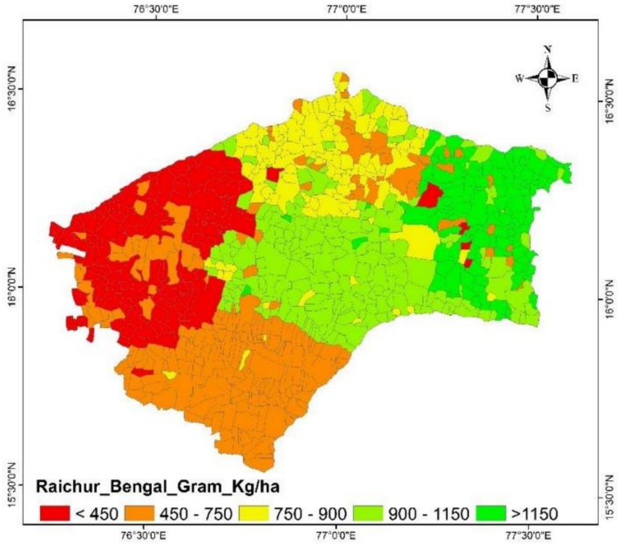
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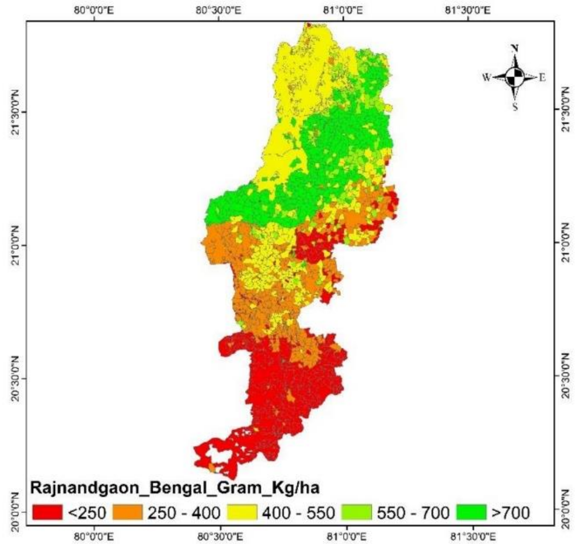
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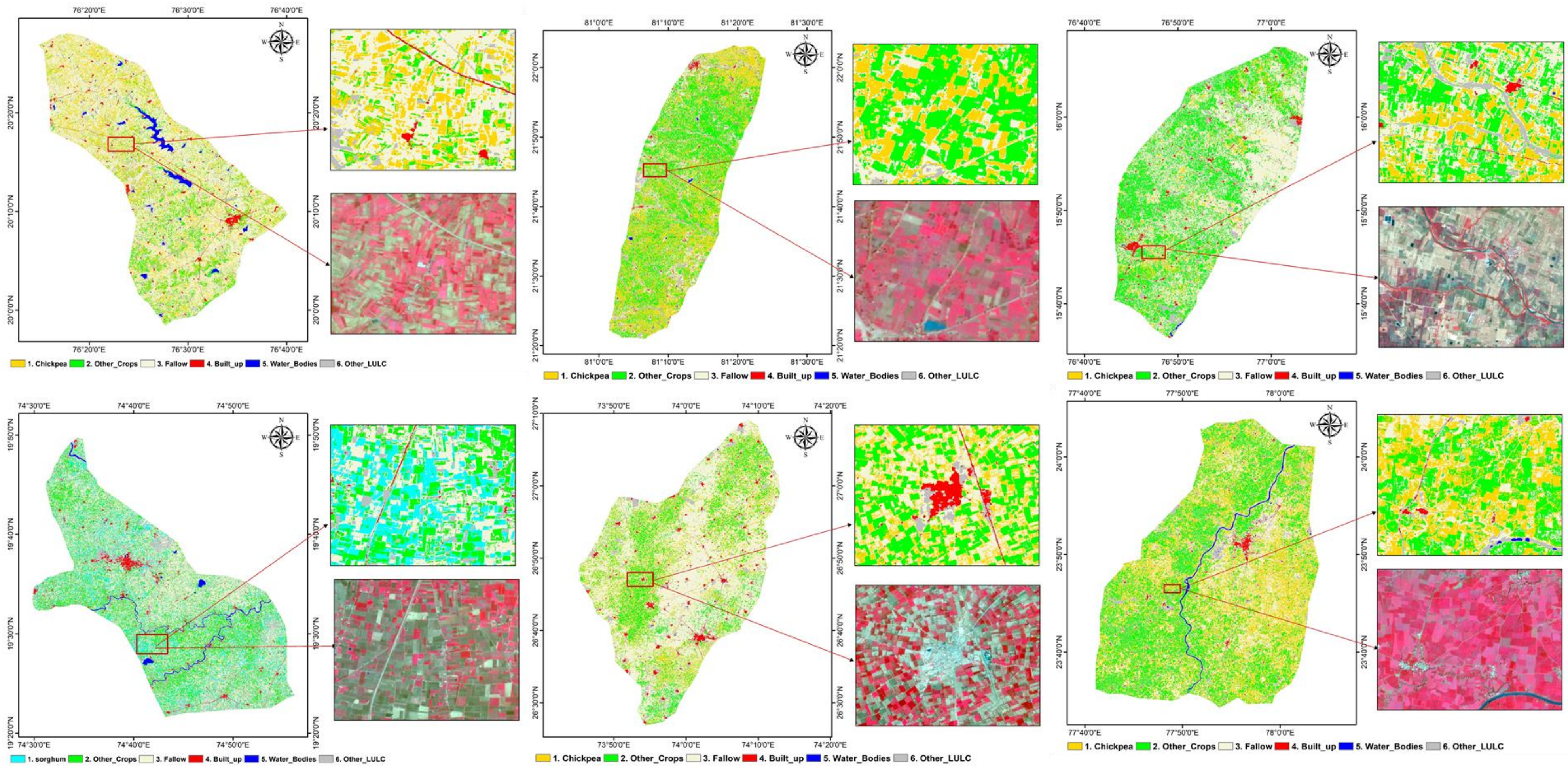
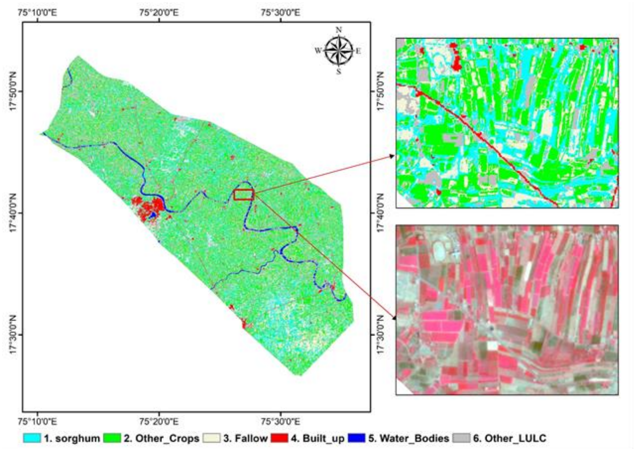
## Annexure 3: Classified images using Planet Data

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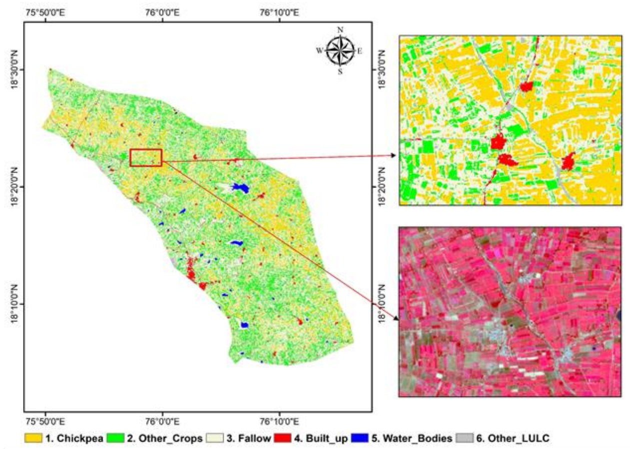
3. Fallow
4. Built_up
5. Water_Bodies
6. Other_LULC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3. Fallow
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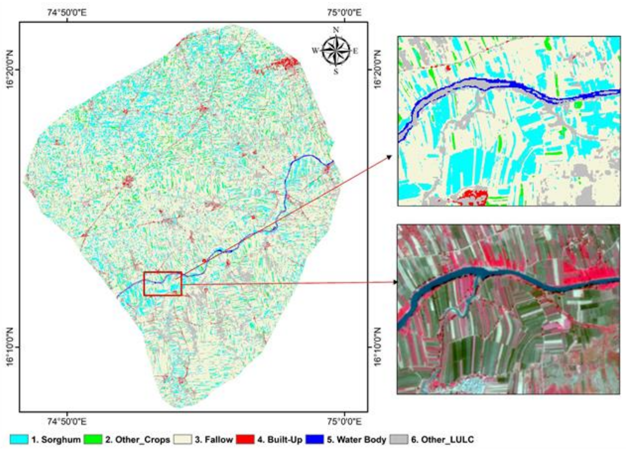
6. Other_LULC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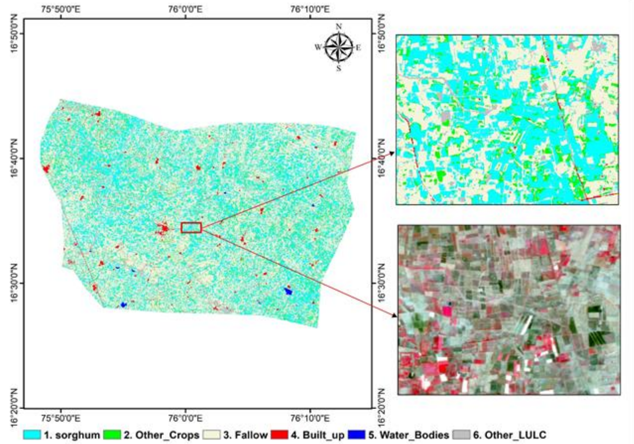
3. Fallow
4. Built-Up
5. Water Body
6. Other_LULC


1. sorghum
2. Other_Crops
3. Fallow
4. Built_up
5. Water_Bodies
6. Other_LULC

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