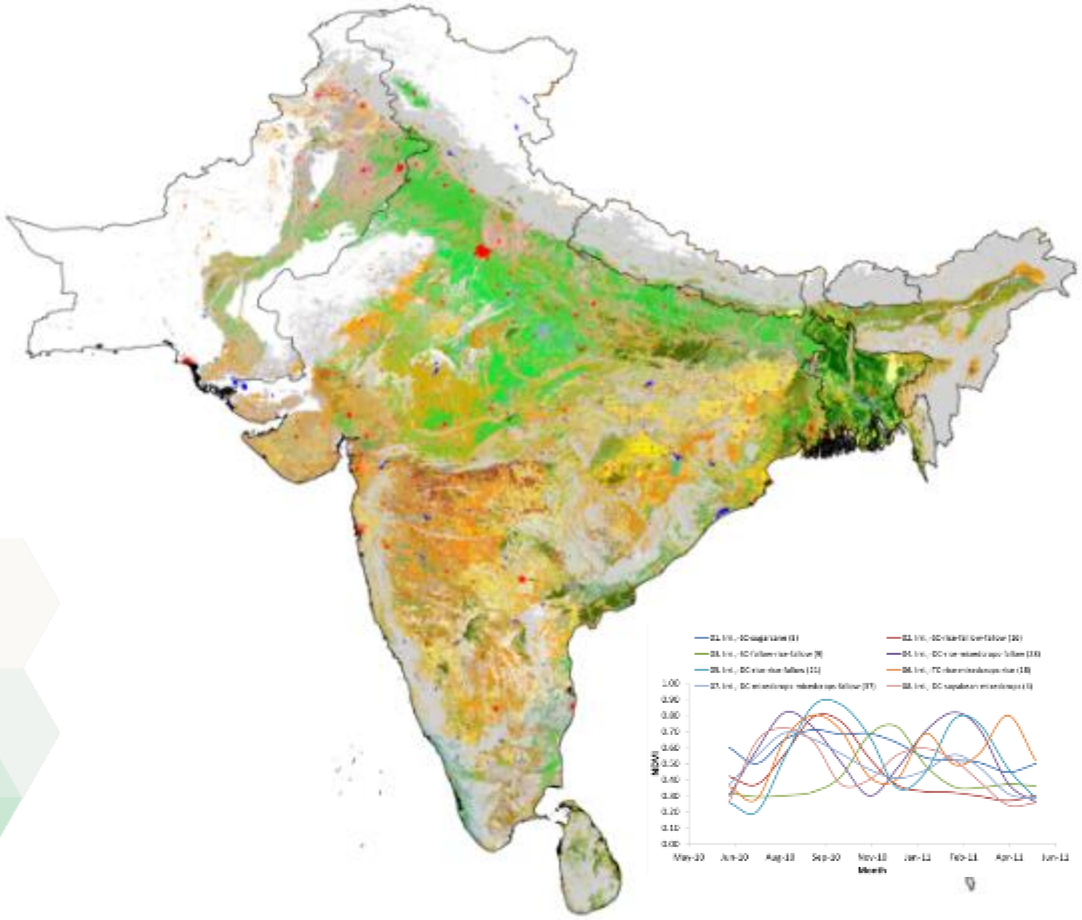
Monitoring croplands using remote sensing data, ground data and Machine learning algorithms



Murali Krishna Gumma and Team

RS/GIS Lab, SACSA

ISD,ICRISAT

<u>BIG Data</u>

05th November, 2020

INTERNATIONAL CROPS RESEARCH INSTITUTE FOR THE SEMI-ARID TROPICS

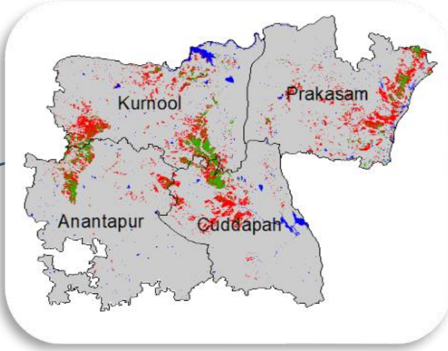
USGS science for a changing world

Google

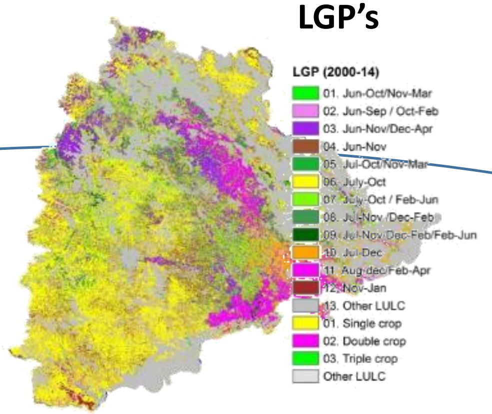
Geospatial products and contribution to Agriculture research

Crop type / Cropping pattern

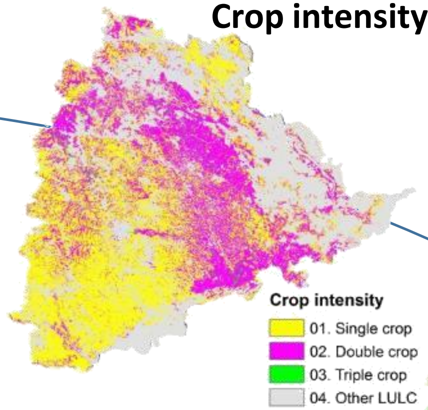
Land use changes



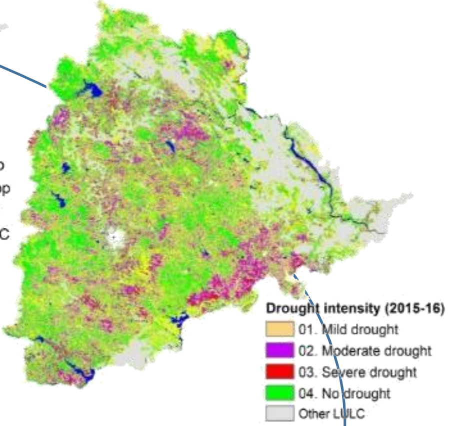
LGP's



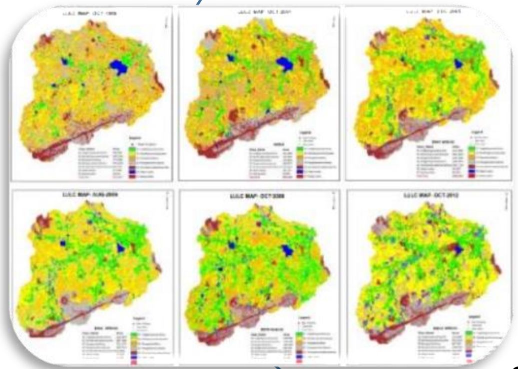
Crop intensity



Abiotic stresses



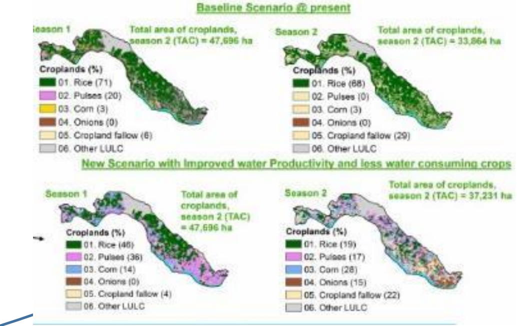
Tracking adoption of NRM Technologies



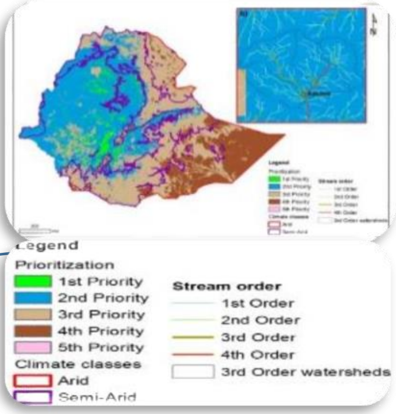
End Uses

→ Adaptation Strategies
→ Shift in climate tolerance crops
→ Quantitative crop damage
→ Optimizing Irrigation Scheduling
→ Crop Insurance
→ Policy makers
→ Agricultural expansion
→ food security
→ Farmer's Resilience
→ Risk Management

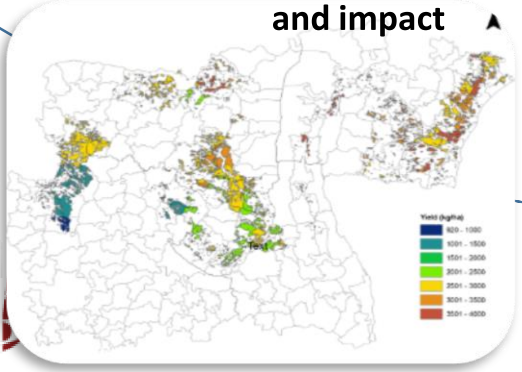
Water productivity



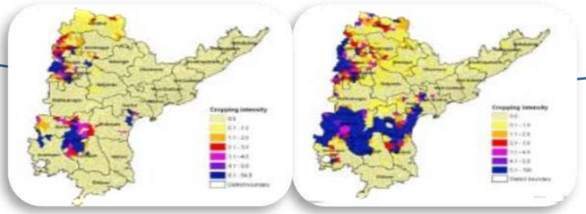
Spatial modelling (Prioritization)



Simulated yield estimations and impact



Impact assessment



Overview of the Presentation

Ground and Secondary Data

Plays a vital role in Classification and also for Validating the map with stats and ground data

Ground Data and Ancillary Data

Traditional Methodology

Downloading of Satellite Images, Pre-processing, Processing using Software. High Time Consuming

Existing Methodology

Machine Learning Algorithms

Processing is carried out in Cloud Eg: GEE, very Time Efficient. No need of downloading satellite images

Machine Learning Algorithms

Semi-Automated Techniques

Taking advantages of both Traditional and Machine Learning, and improving Classification Accuracy

Semi-Automated Techniques

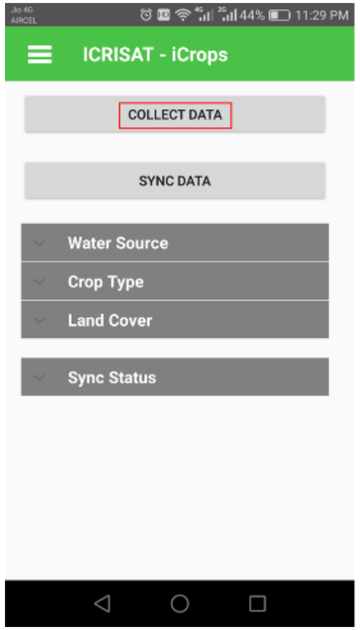
Geo-Spatial Products

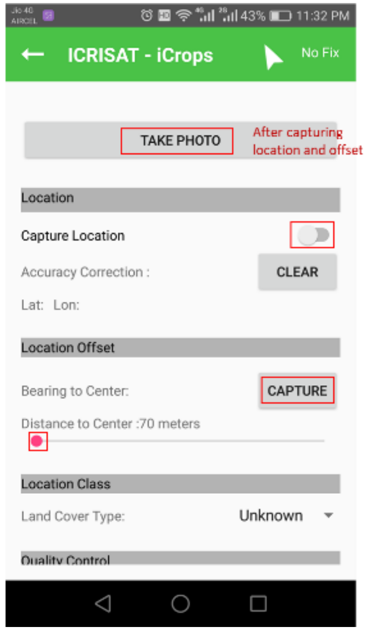
Eg: Rice Fallows for Short Duration Crops, Watershed Prioritization and its impacts

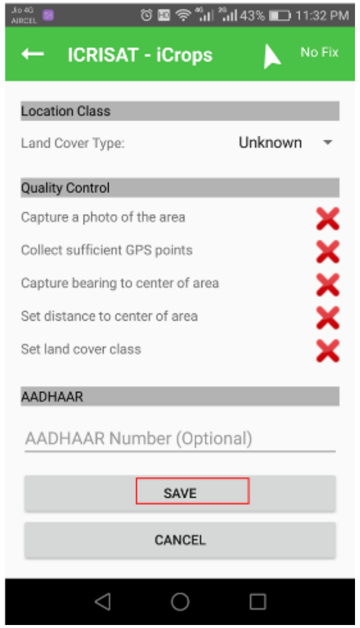
Geo-Spatial Products for Decision Making

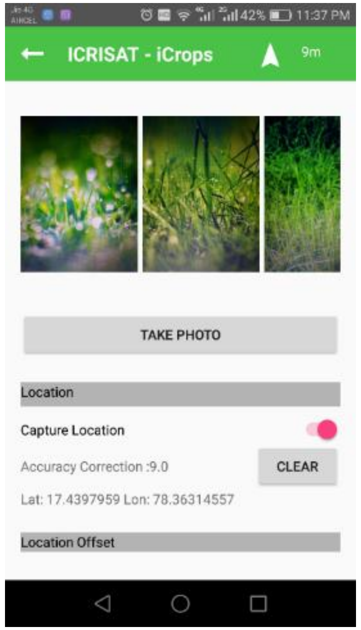
iCrops – Mobile Application for Ground Data Collection

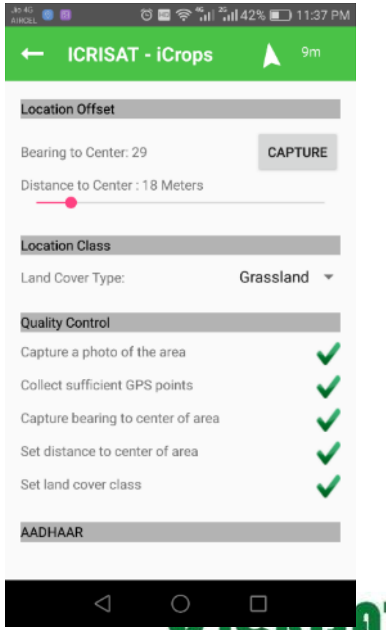
- Android mobile application
- Capture geo-tag photo's with necessary Information like Crop Type, Water Source and Land Cover
- Data can be used for training and validation
- Able to view the collected data in Map
- Collected data will be freely delivered

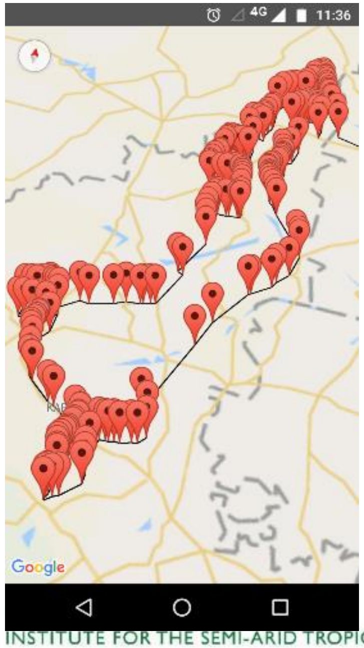












iCrops –Sample Images











Images are

- Geo tagged
- With Lat & Long Stamp on it

iCrops – Database

maps.icrisat.org/icrops/index.php

ICRISAT CROPS DATA COLLECTION

Welcome Admin!

Name: Admin admin

Email: admin@gmail.com

Phone: 9933882233

I-CROPS Data synchtonization Results | MAP Plotting DATA

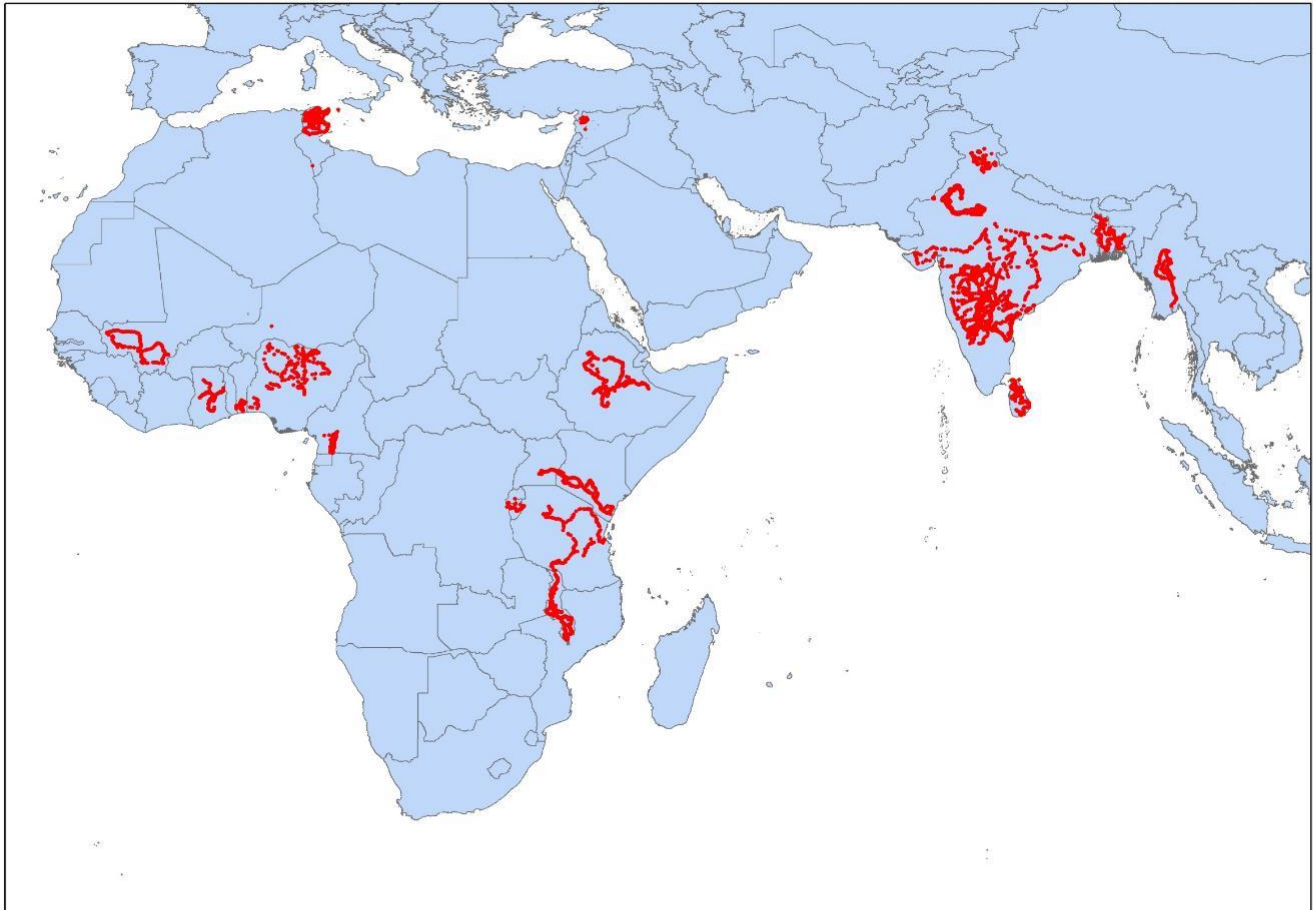
Id	Lat	Lon	Bearing	Distance	LandType	WaterSource	CropIntensity	PrimaryCrop	SeconderyCrop	ImageRefOne	ImageRefTwo	
0	17.439777135054452	78.36348612147358	6	19	Grassland							
a.whitbread@cgiar.org20170812_154646430	17.51170027377286	78.27815683331067	146	25	Builtup					a.whitbread%40cgiar.org20170812_154541990.jpg	null	
almoham800@gmail.com20170906_132728688	27.73284408421402	30.840993281453898	0	91	Forest					almoham800%40gmail.com20170906_132723970.jpg	null	
asdf@dfs.com20170527_182322563	17.438982214184136	78.36364839575381	156	99	Grassland					asdf%40dfs.com20170527_182259910.jpg	null	
asdf@dfs.com20170527_182711836	17.439263237192215	78.3636683484251	154	73	Cropland	Irrigated	Single	Rice	Barley	asdf%40dfs.com20170527_182615998.jpg	null	
balaswamymech.swamy1@gmail.com20170516_075214989	17.440406759799284	78.3626725061389	314	93	Builtup					balaswamymech.swamy1%40gmail.com20170516_075026754.jpg	null	
chowan851@gmail.com20170906_163757695	17.33897567240888	77.89453404000004	0	150	Shrub					chowan851%40gmail.com20170906_163532266.jpg	null	
chowan851@gmail.com20170915_071236108	17.533353380401476	77.55059415999999	0	25	Cropland	Unknown	Unknown	Unknown	Unknown	chowan851%40gmail.com20170915_071035877.jpg	chowan851%40gmail.com20170915_071051728.jpg	cho
cool20170430_111250090	17.43996452435708	78.3635633262164	33	36	Grassland							
cool20170430_125546191	17.44040885769702	78.36330603650464	358	85	Cropland	Rainfed	Double	Barley		cool20170430_125508158.jpg	cool20170430_125524895.jpg	
cool20170430_130235976	17.440378112821822	78.36287566263442	325	93	Cropland	Rainfed	Triple	Pigeonpea		cool20170430_130215596.jpg	null	
cool20170430_130408212	17.44056492584227	78.36357071838495	17	102	Cropland	Rainfed	Double	Chickpea		cool20170430_130352257.jpg	null	
cool20170430_130629252	17.440190044705943	78.36287127895591	321	78	Cropland	Rainfed	Double	Pigeonpea	Chickpea	cool20170430_130611965.jpg	null	
dahirurd@hotmail.com20170712_093759369	11.911905560258504	8.520821178449417	147	51	Cropland	Rainfed	Double	SoyaBean	Maize(Corn)	dahirurd%40hotmail.com20170712_093234193.jpg	null	
dahirurd@hotmail.com20170712_111716471	11.660005500081443	8.41553064084754	293	51	Cropland	Rainfed	Single	Rice	Unknown	dahirurd%40hotmail.com20170712_111520815.jpg	null	

Home | Download .CSV File | Add User | Refresh | Change Password | Logout

- **Real time Sync of Data into Server**
- **Data can be downloaded in .csv format.**

ICRISAT
INTERNATIONAL CROPS RESEARCH INSTITUTE FOR THE SEMI-ARID TROPICS

Ground Data Collected

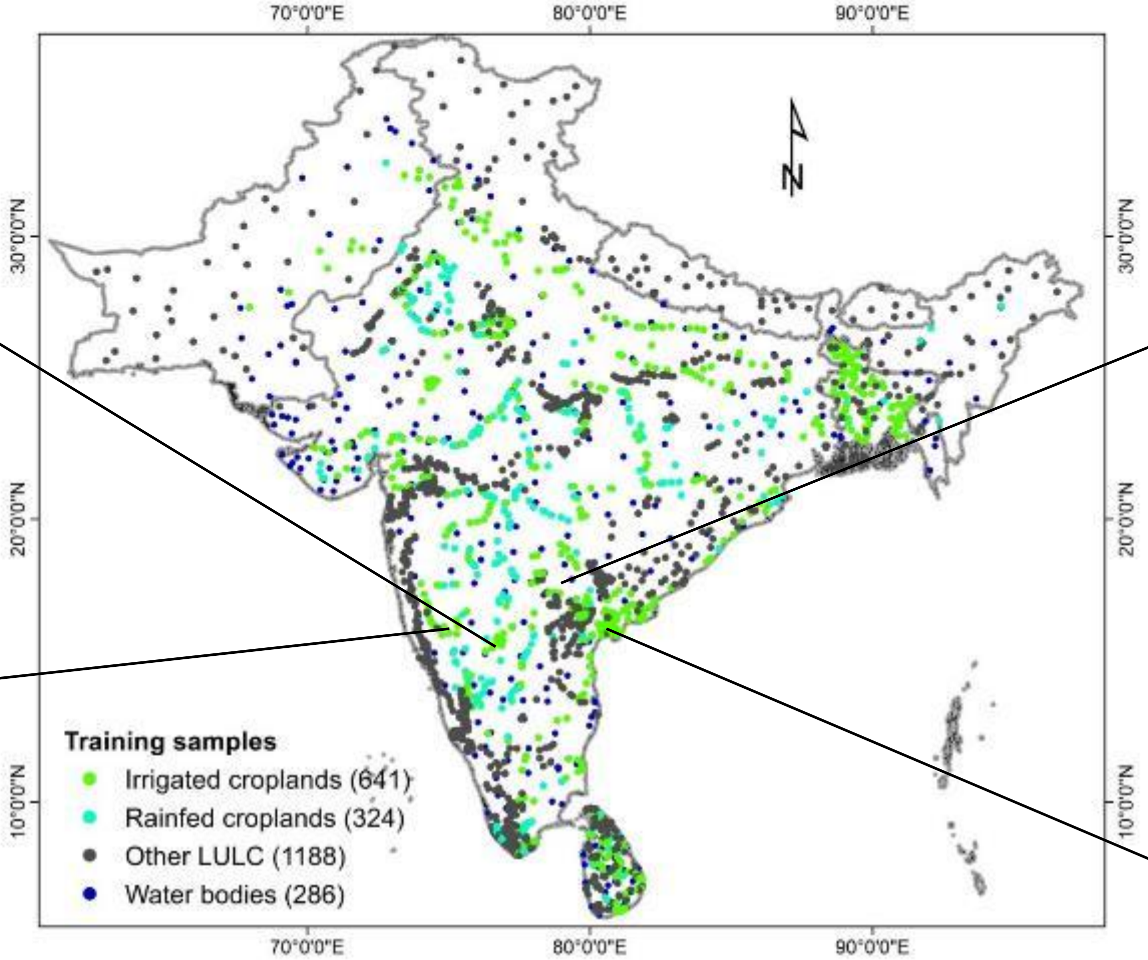


So far, we have collected Ground data in countries of

- South Asia
- East Africa
- West Africa

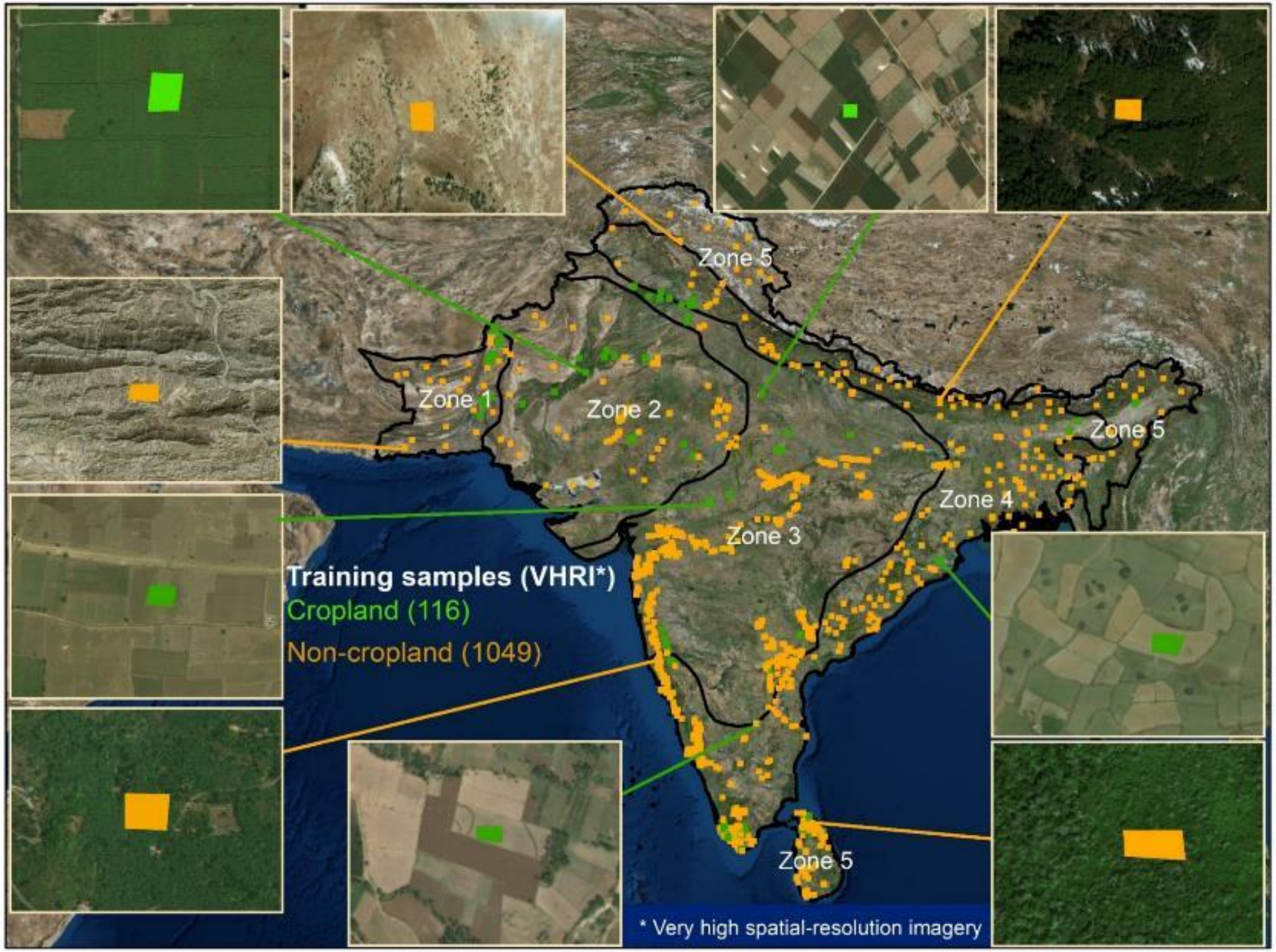
Ground data for South Asia

- Ground samples collected across South Asia using various sources

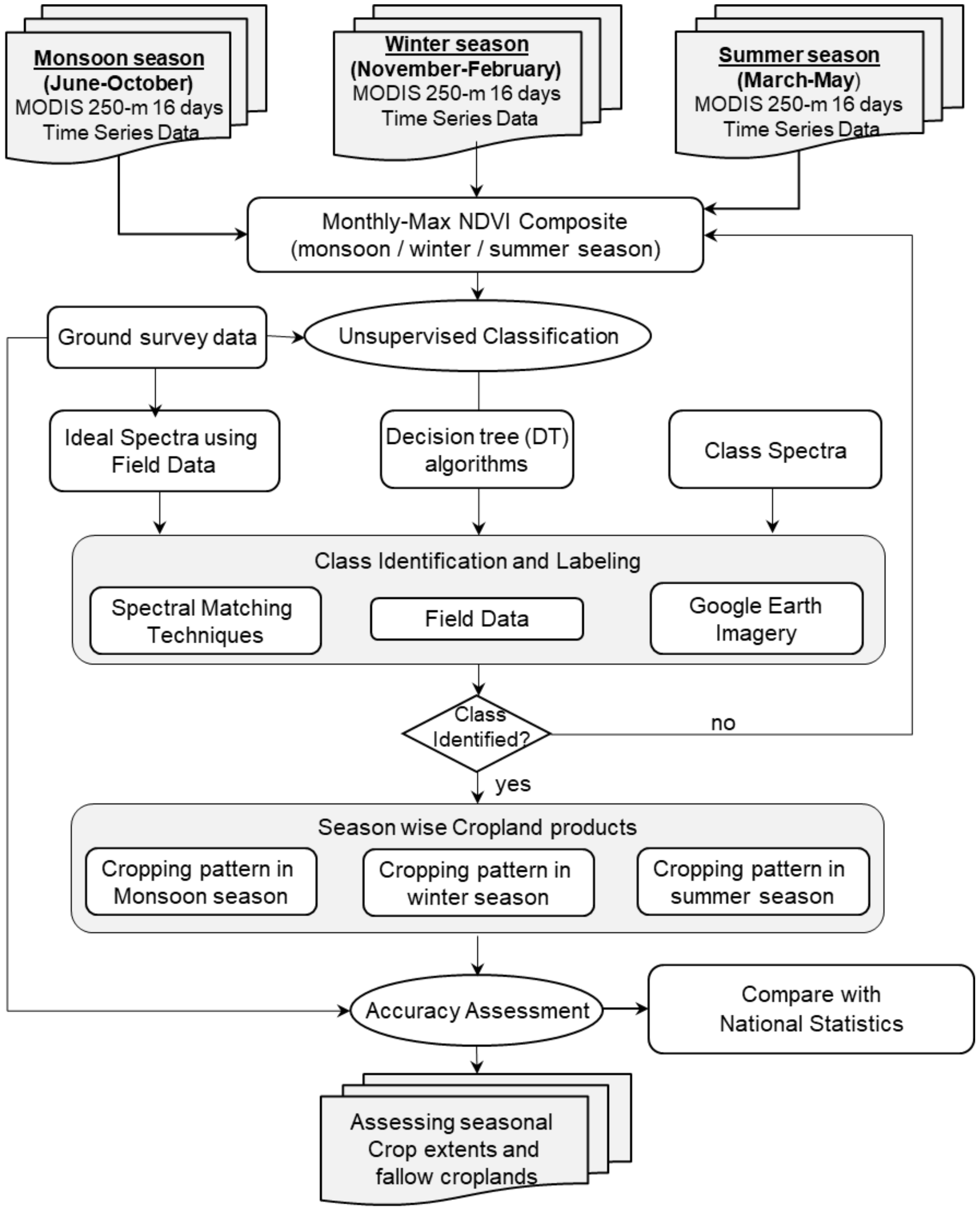


Samples collection using Google Earth VHRI

- Collecting ground data using visual interpretation of Google earth Imagery
- Identification of croplands and Non-croplands



Traditional Methods for classification



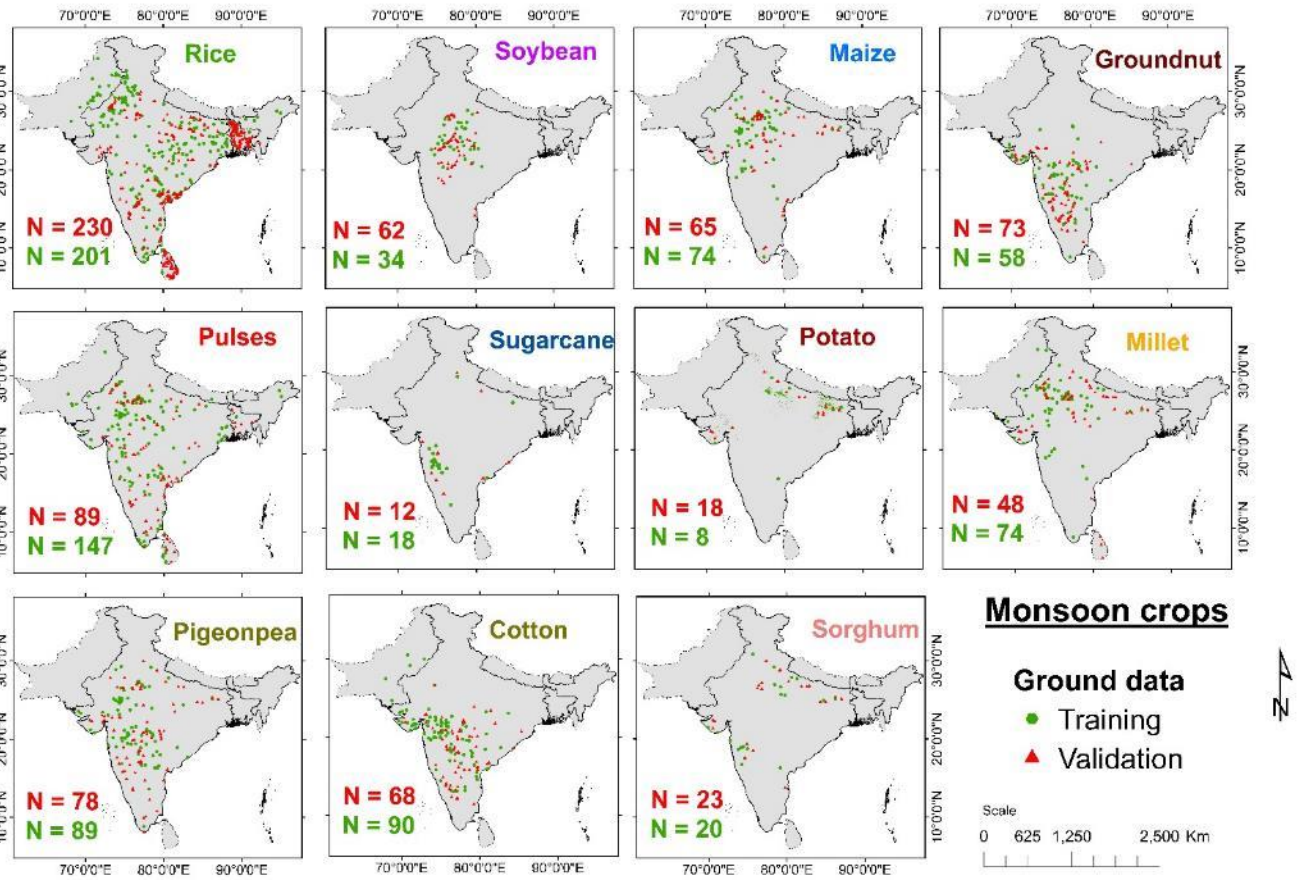
Major Steps of Methodology:

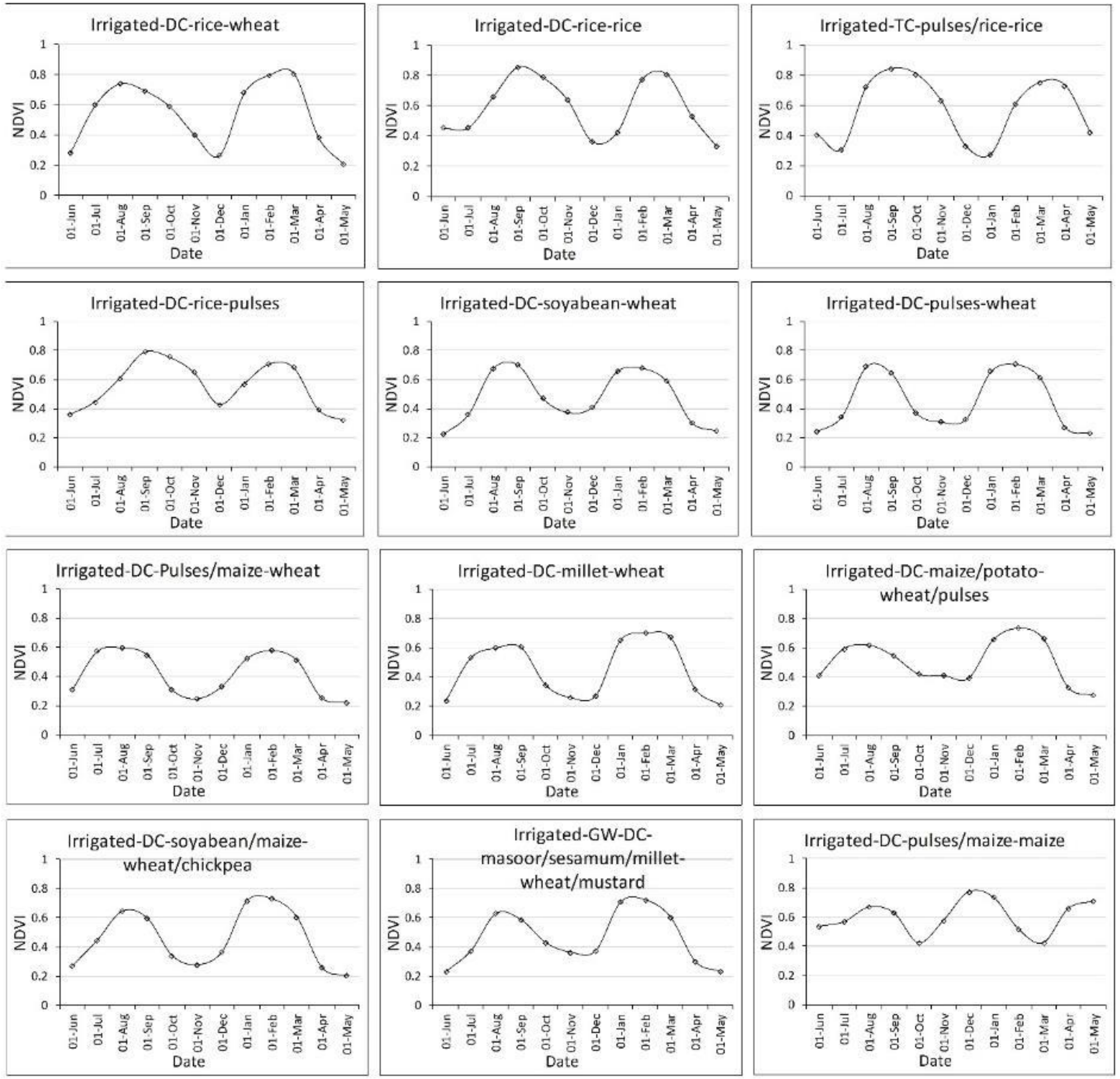
- NDVI images for every month
- Stacking of season wise NDVI images
- Applying unsupervised classification on stacked image
- Using Methods like Decision Trees algorithms and Spectral Matching Techniques with the help of Ground Data for Classification

Limitations:

- Satellite Data should be downloaded, requires high bandwidth data
- Pre-Processing and Processing will be carried out using Software, requires high end computers
- High Time Consuming

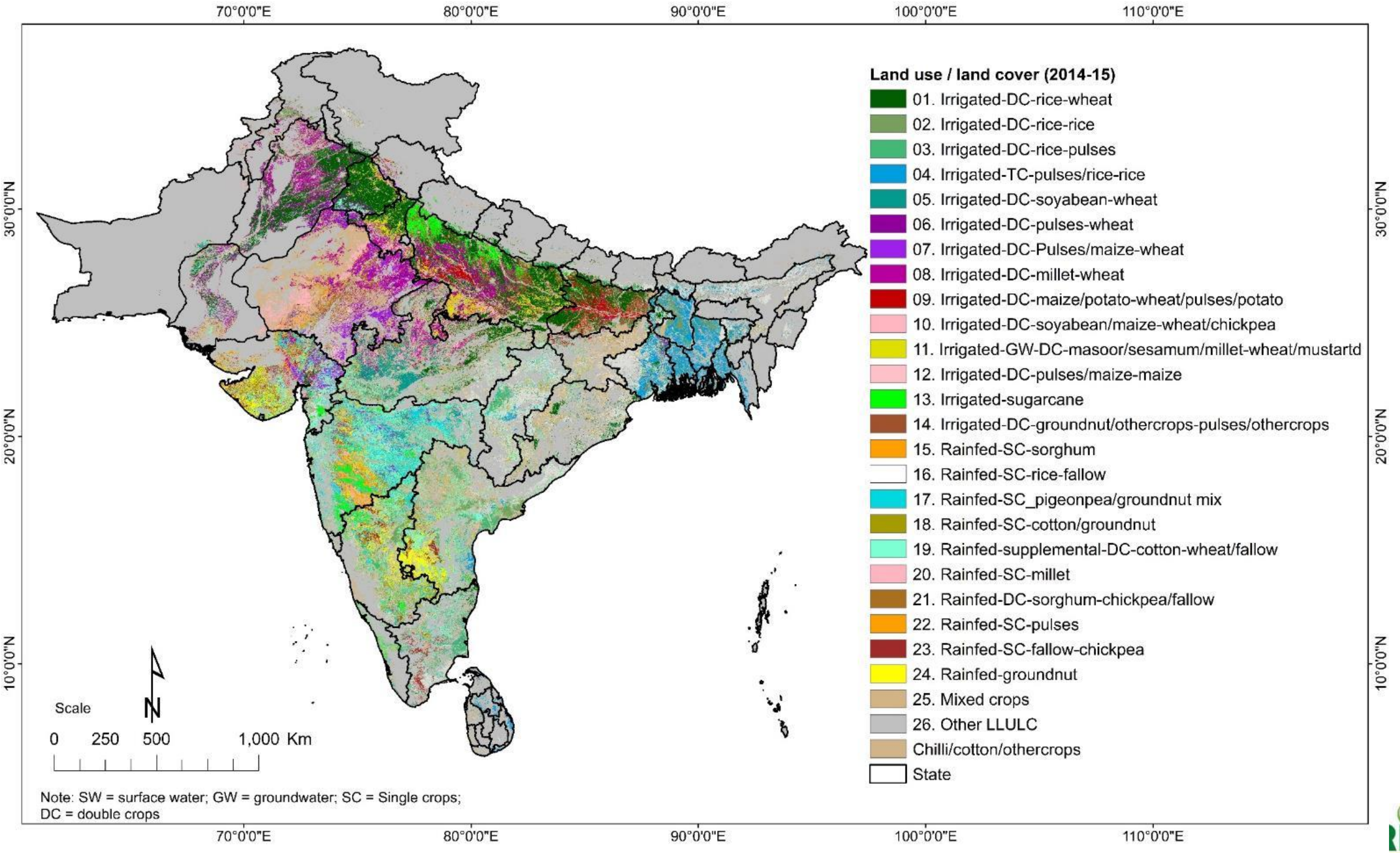
Ground data and Ideal spectra signatures





Gumma et al (prep)

Crop type Map of 2014-2015



- Major crop types as well as cropping patterns were identified for the crop year 2014-15

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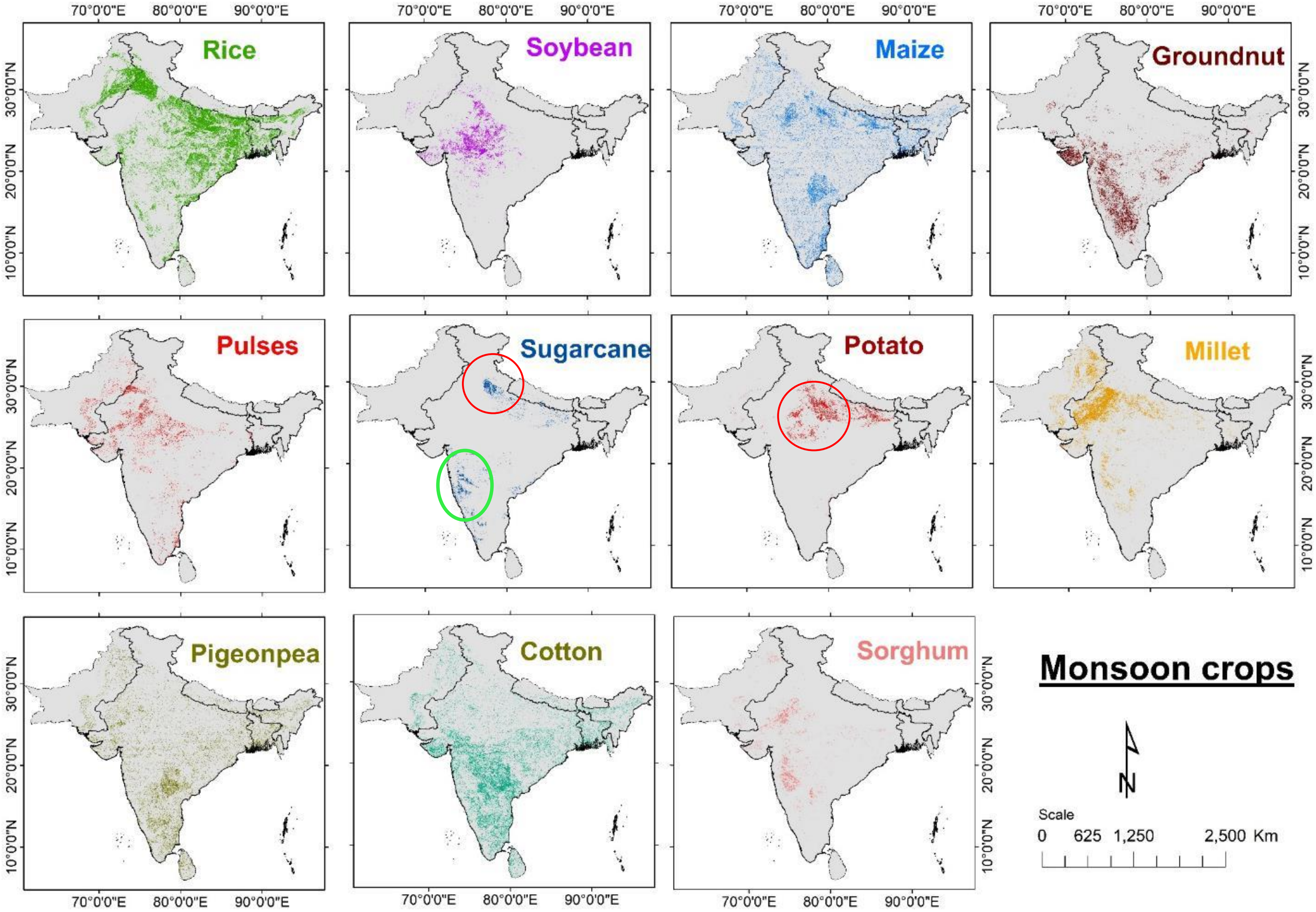
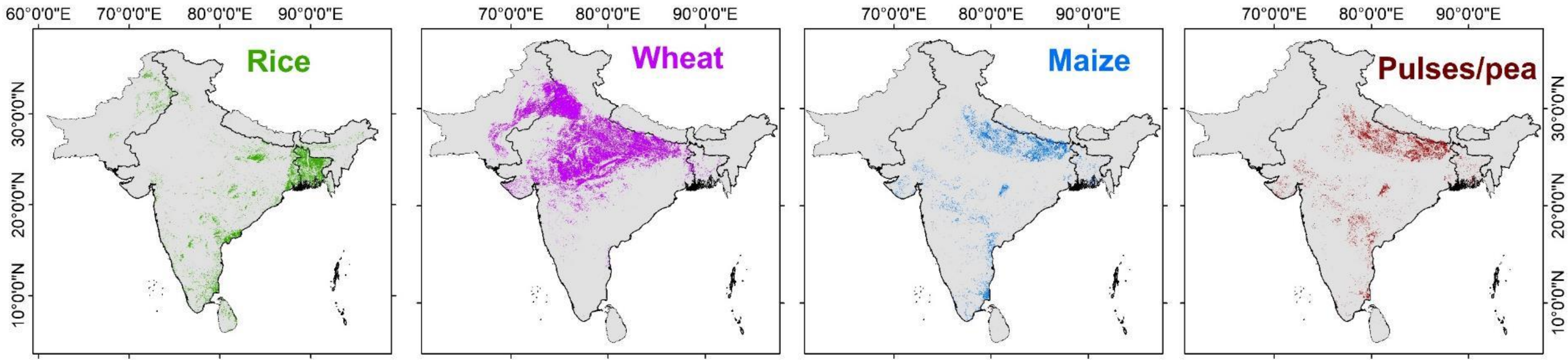
Cropping type Map – Monsoon - 2014-2015

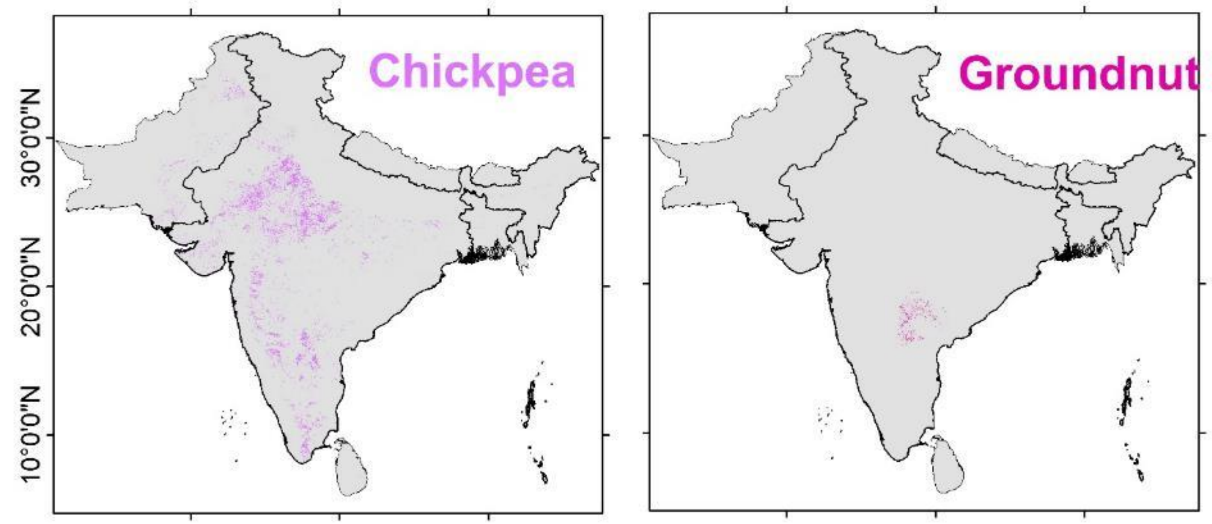


- Spatial distribution of Major crops during Monsoon season

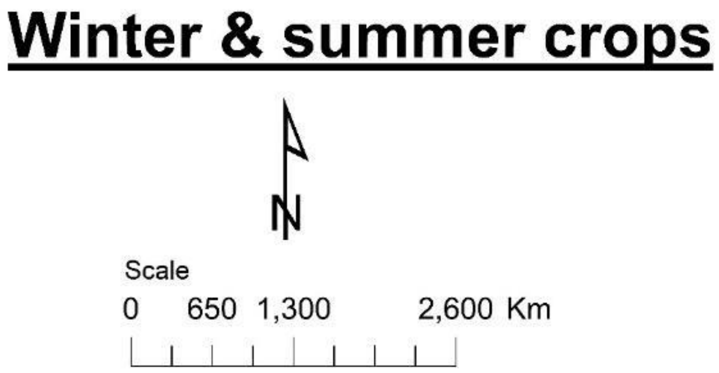
Gumma et al (prep)

Crop Type Map – Winter/Summer -2014-15



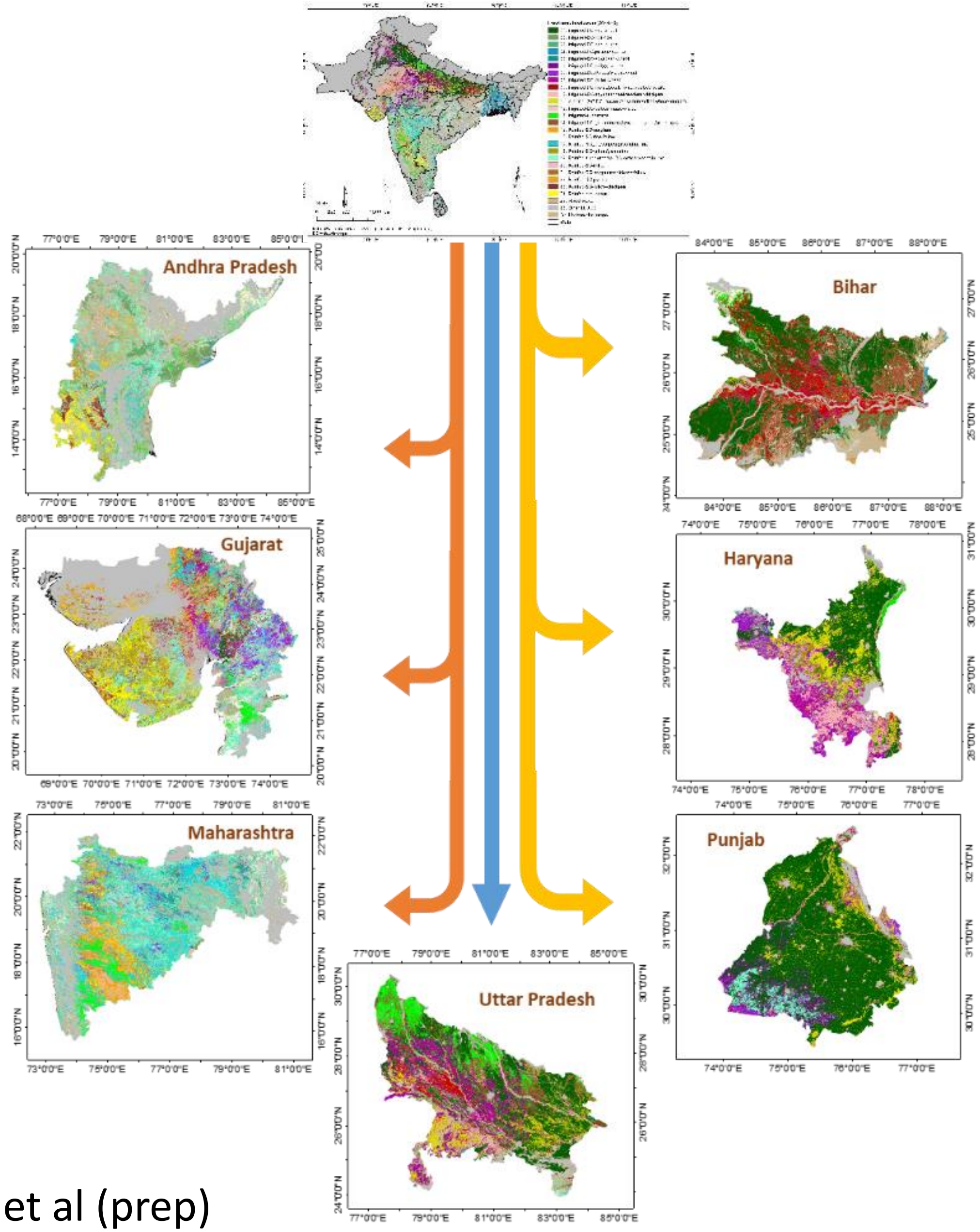


- Spatial distribution of major crops during winter and summer seasons

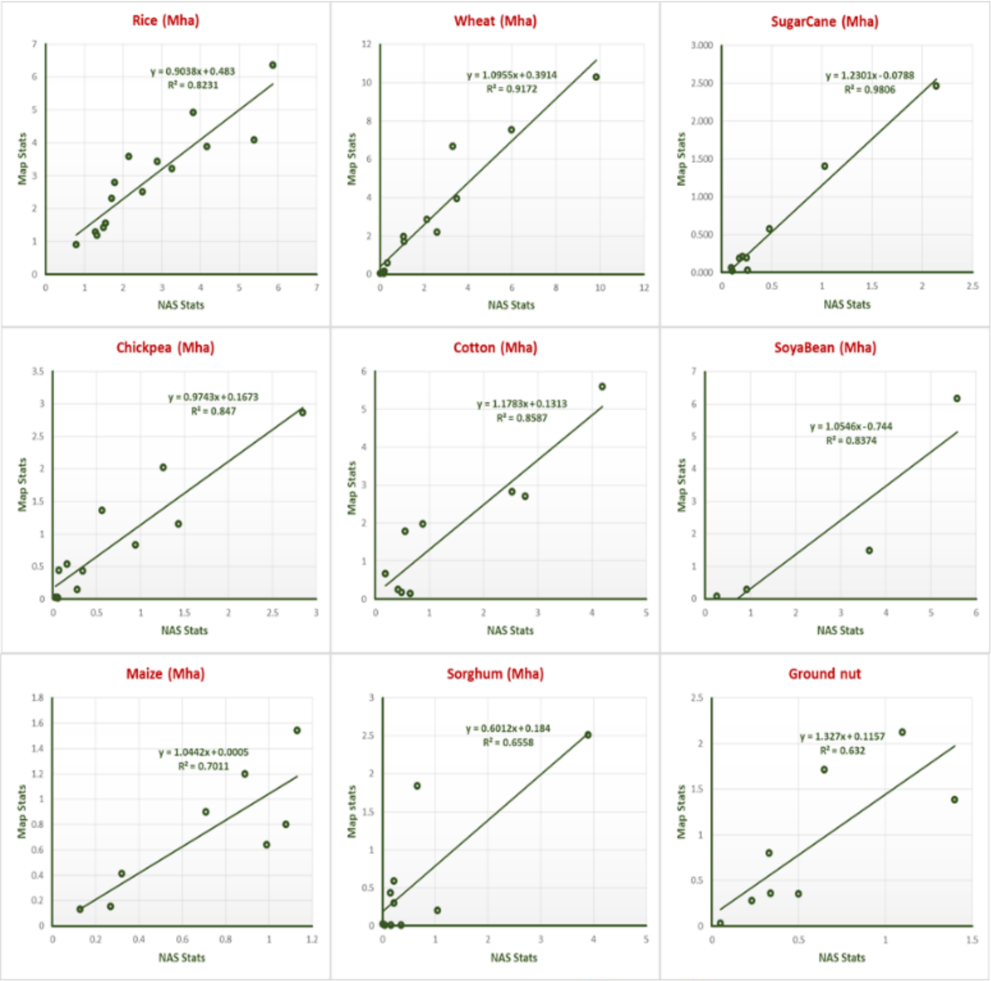


Gumma et al (prep)

Major crop extents - state wise



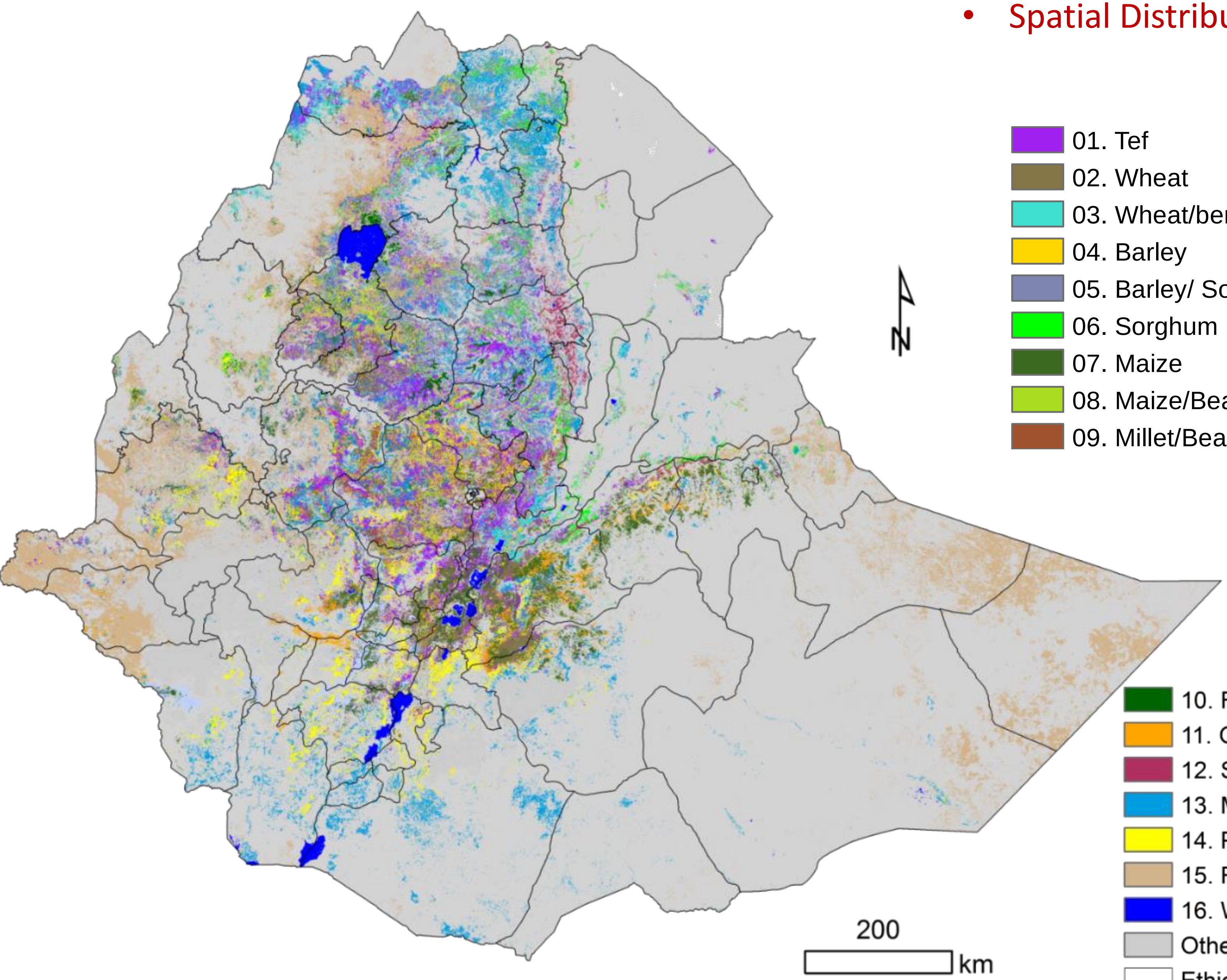
- Correlated the Map statistics with National Agricultural statistics for major crop growing states
- Achieved significant correlation with crop statistics



Gumma et al (prep)

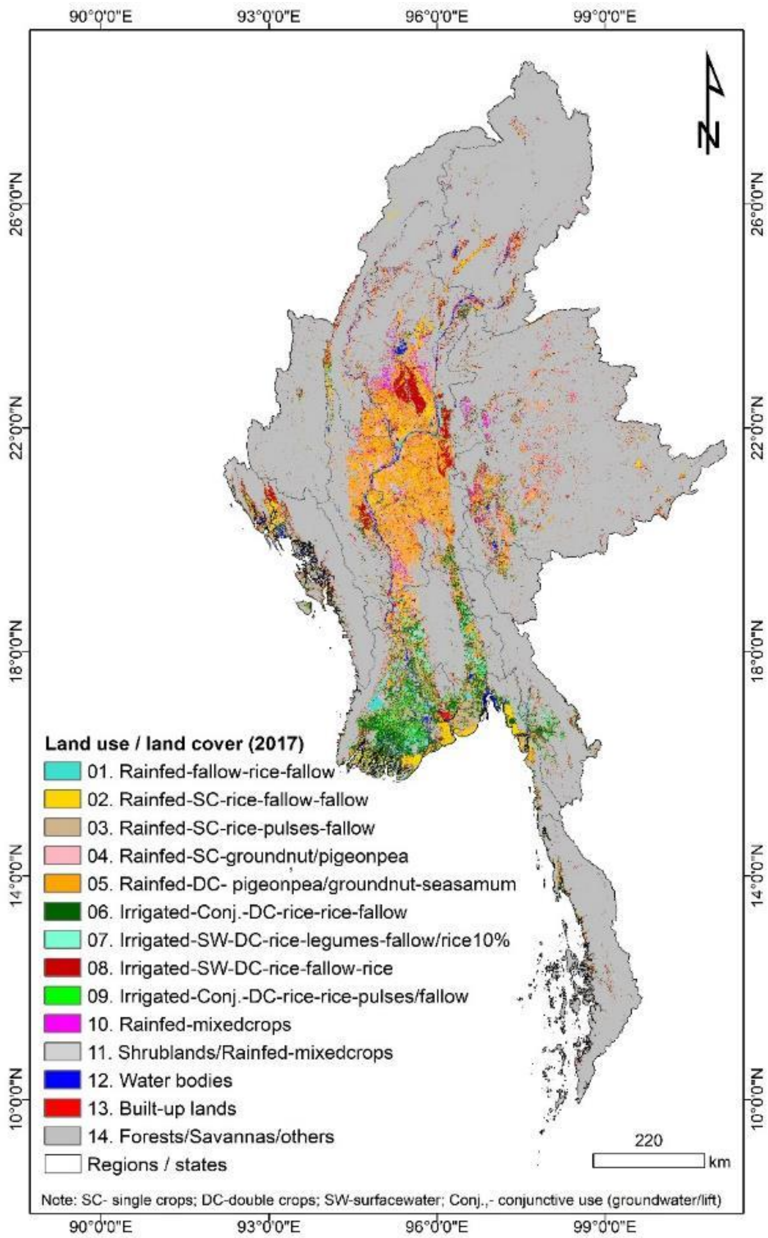
Cropping type Map – Ethiopia (2014)

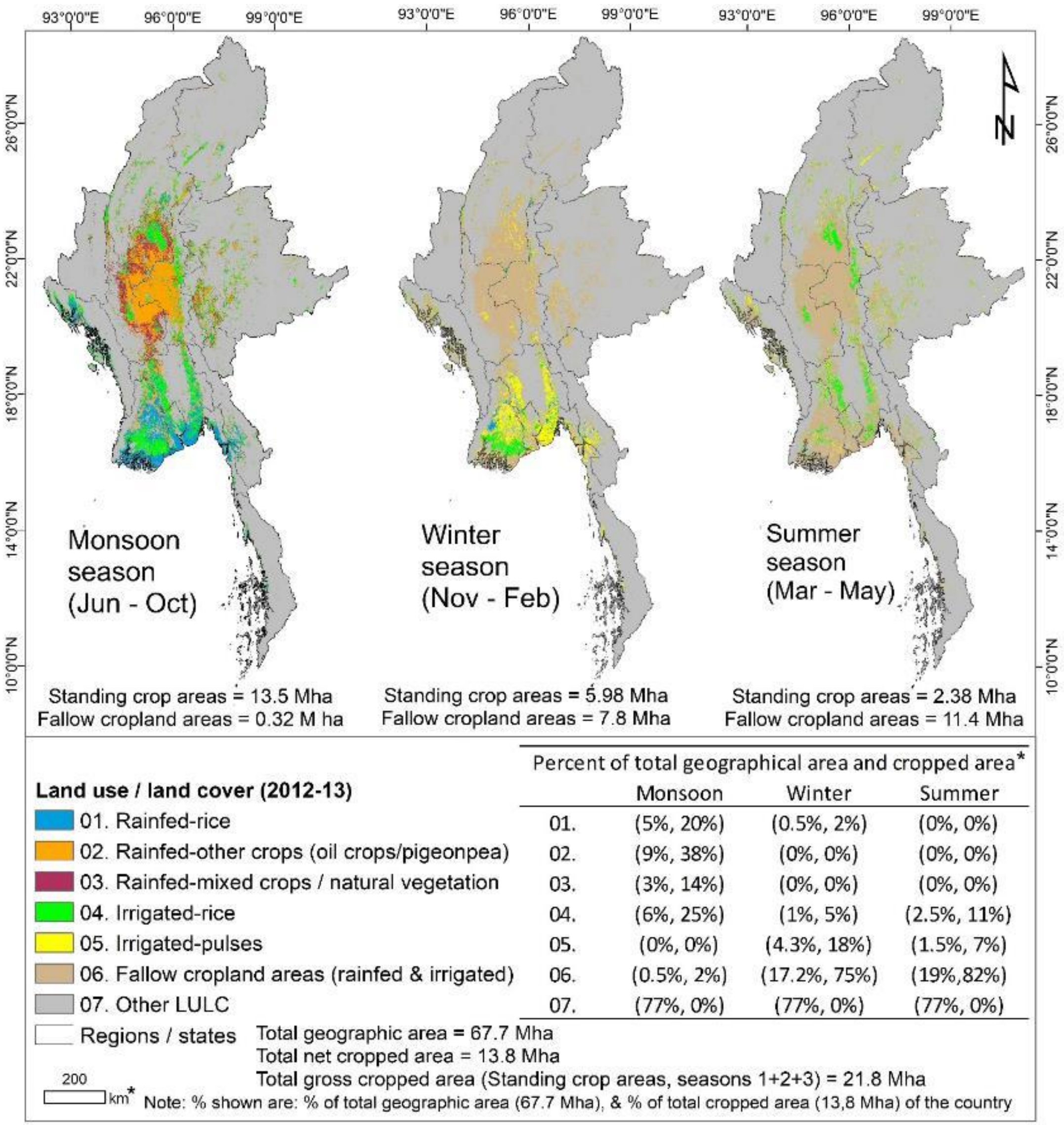
- Spatial Distribution of crops in Ethiopia



Land use / land cover	Area (ha)
01. Tef	39,83,045
02. Wheat	5,39,519
03. Wheat / Faba bean	13,10,152
04. Barely	8,49,443
05. Barely / Sorghum	16,82,131
06. Sorghum	8,58,706
07. Maize	25,36,256
08. Maize / Legumes	4,17,684
09. Millet / Beans	3,50,367
10. Rice	1,57,956

Mapping cropping systems in Myanmar

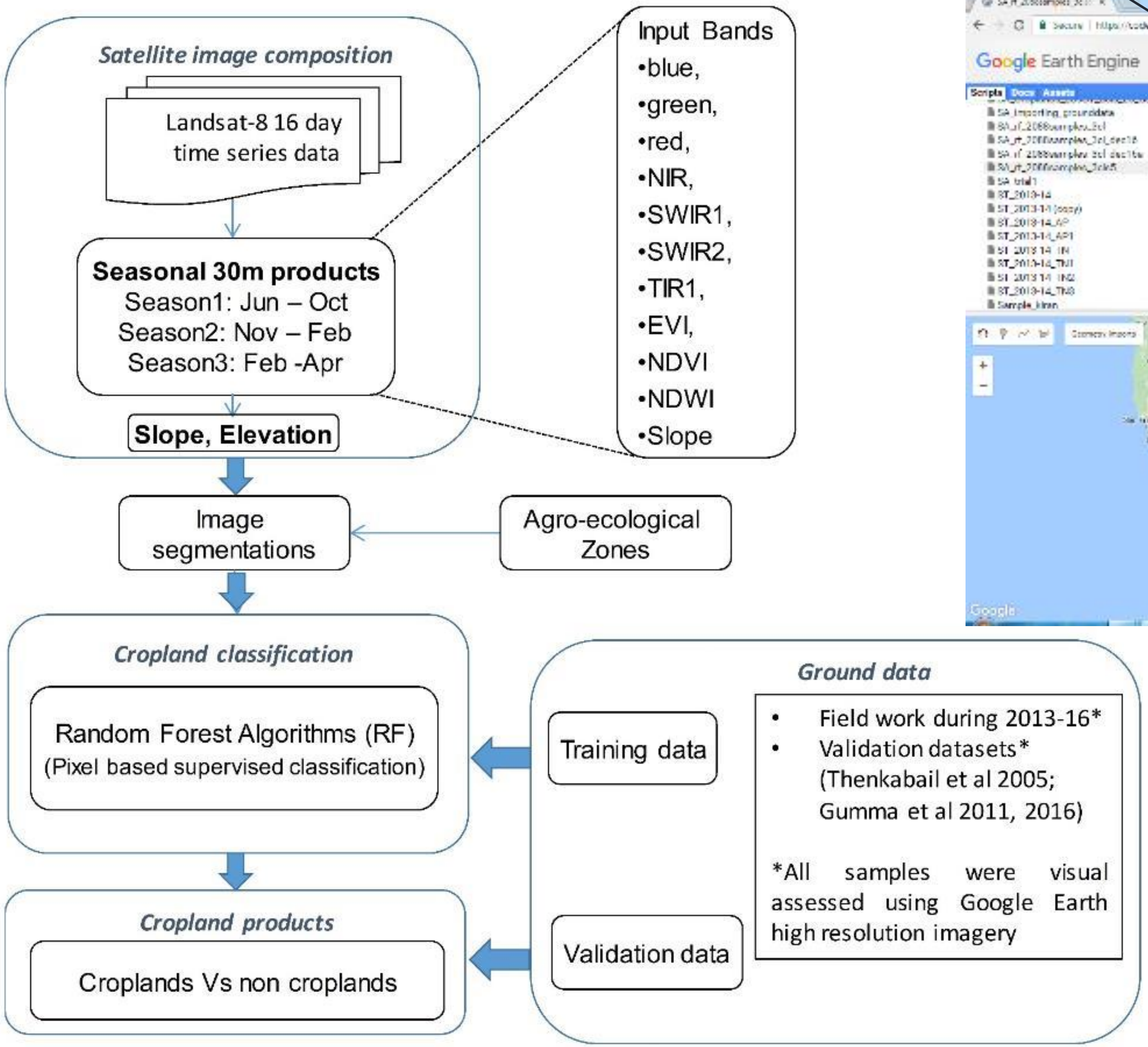


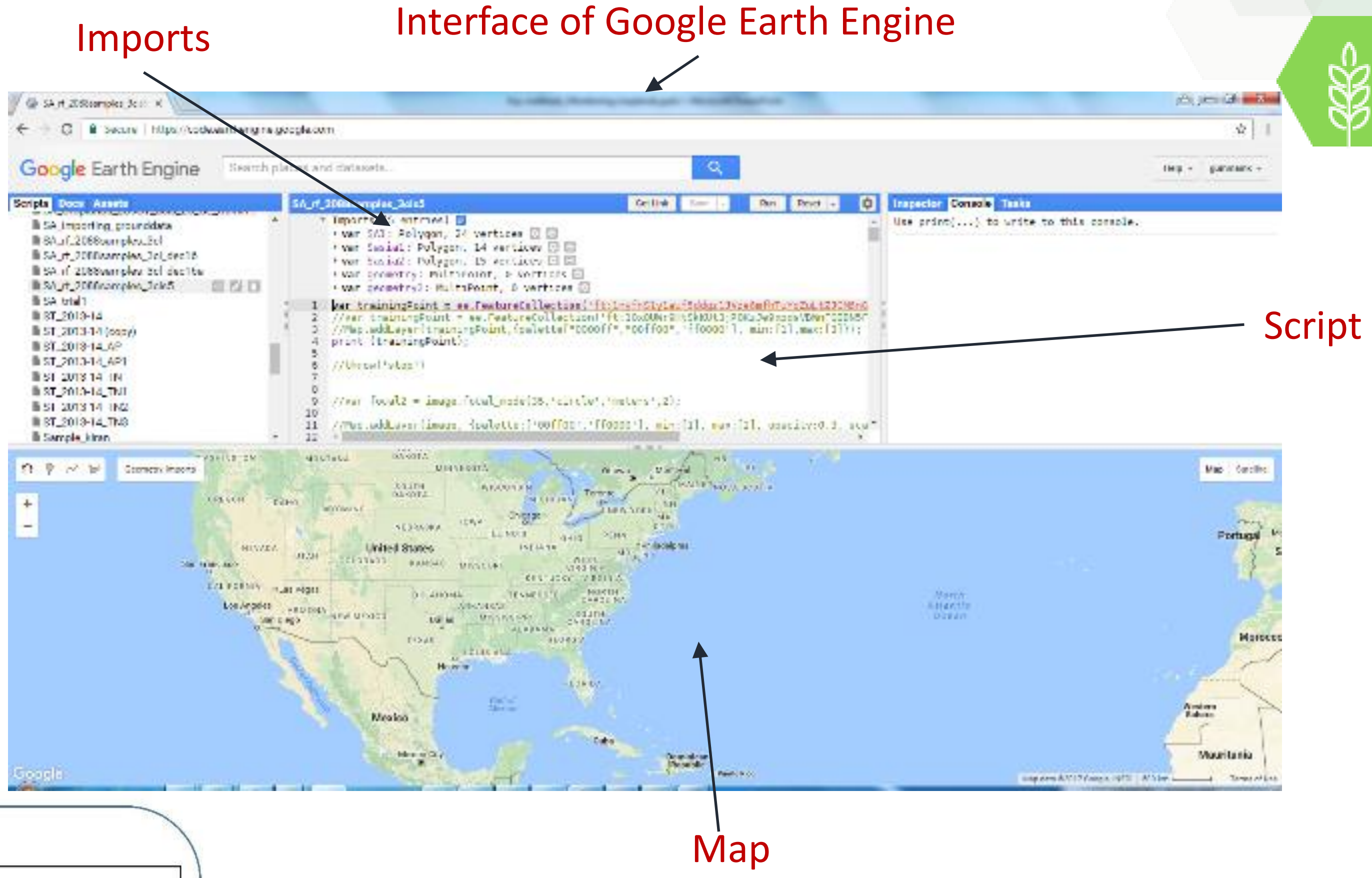


- Spatial distribution of LULC and Major crop types in Myanmar for year 2017
- Spatial distribution of Standing and Fallow cropland areas for all seasons in crop year 2012-13

Gumma, M.K, Thenkabail, P.S, Deevi, K, Irshad, A.M, Teluguntla P.G, Oliphant A, Jun X, Tin A, and Whitbread A.M. (2019). **Mapping Cropland Fallow Areas in Myanmar to Scale Up Sustainable Intensification of Pulse Crops in the Farming System**. ***GIScience and Remote sensing***. DOI:10.1080/15481603.2018.1482855

Machine learning: Google Earth Engine (GEE)



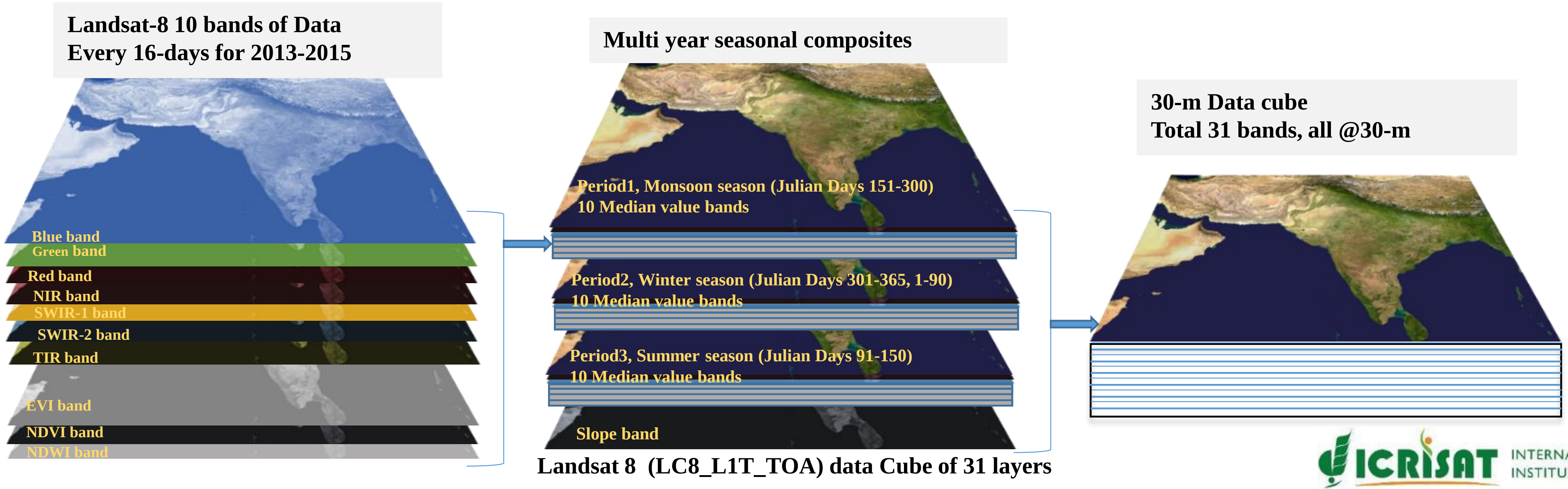


- Importing datasets through import section
- Collecting training samples using Map
- Writing related code in Script and running ML algorithm

(Gumma et al., 2020)

Implementation of Random Forest

1. Create image composite
2. Select training samples
3. Extract band values for each pixel within training data
4. Set random forest variables in GEE and run model on image composite and training data band values
5. Load classified image in GEE gauge approximate accuracy and visual correctness
6. Adjust number and location of training samples based on previous map



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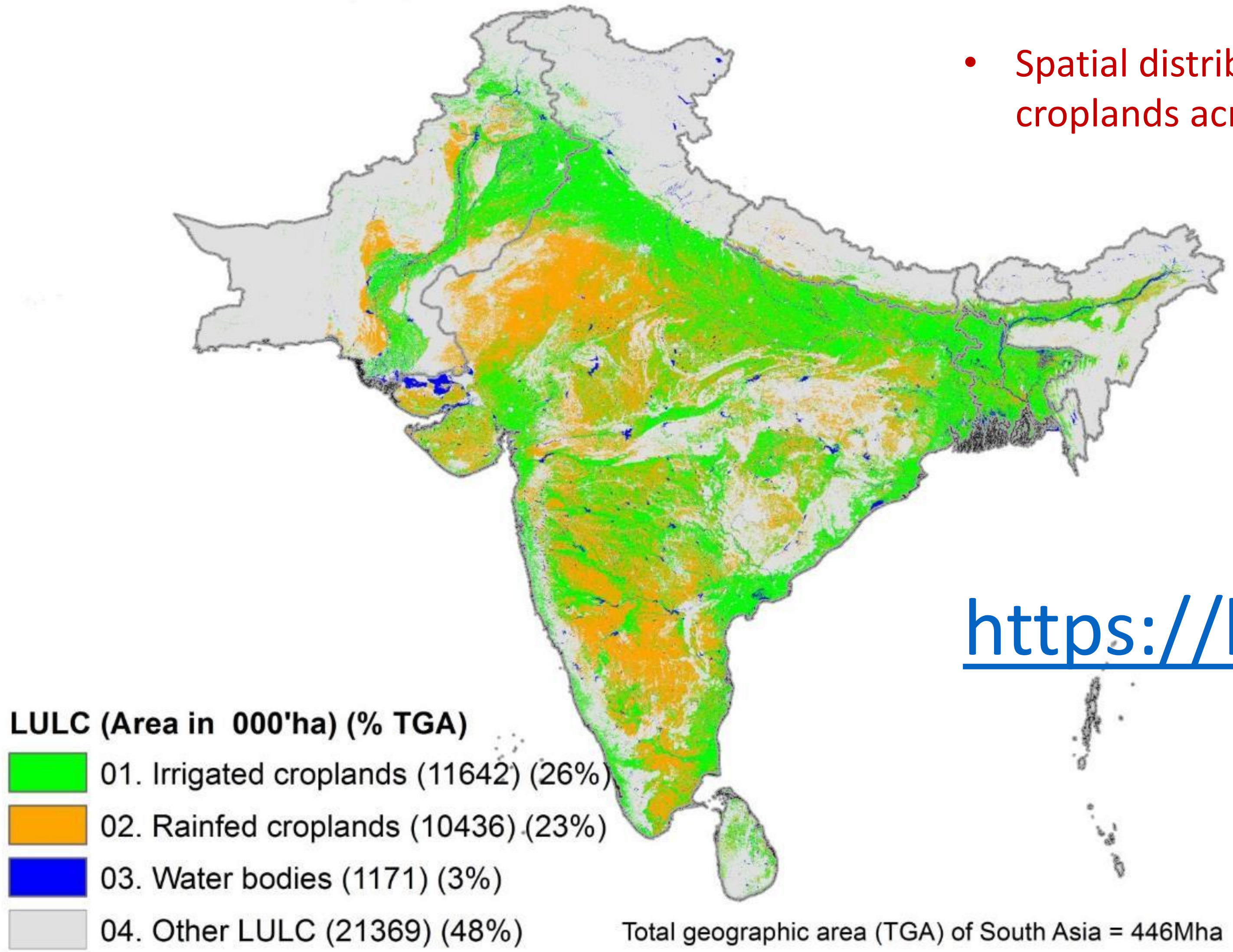
Irrigated Vs Rainfed cropland @ 30m: South Asia

- Spatial distribution of Irrigated and Rainfed croplands across South Asia



<u>Sample size = 2634</u>
Irrigated croplands = 1099
Rainfed= 651
Non croplands = 884

https://lpdaac.usgs.gov/node/1280

(Gumma et al., 2020)

Methodology

Google Earth Engine

Ground truth data
Points are converted to polygons

Satellite data
All available S1 images from June to October 2020

Satellite data
All available S2 images from June to October 2020

Pre-processing
- Filtering and computation of monthly median images
- Computation of band ratio VV/VH for each month

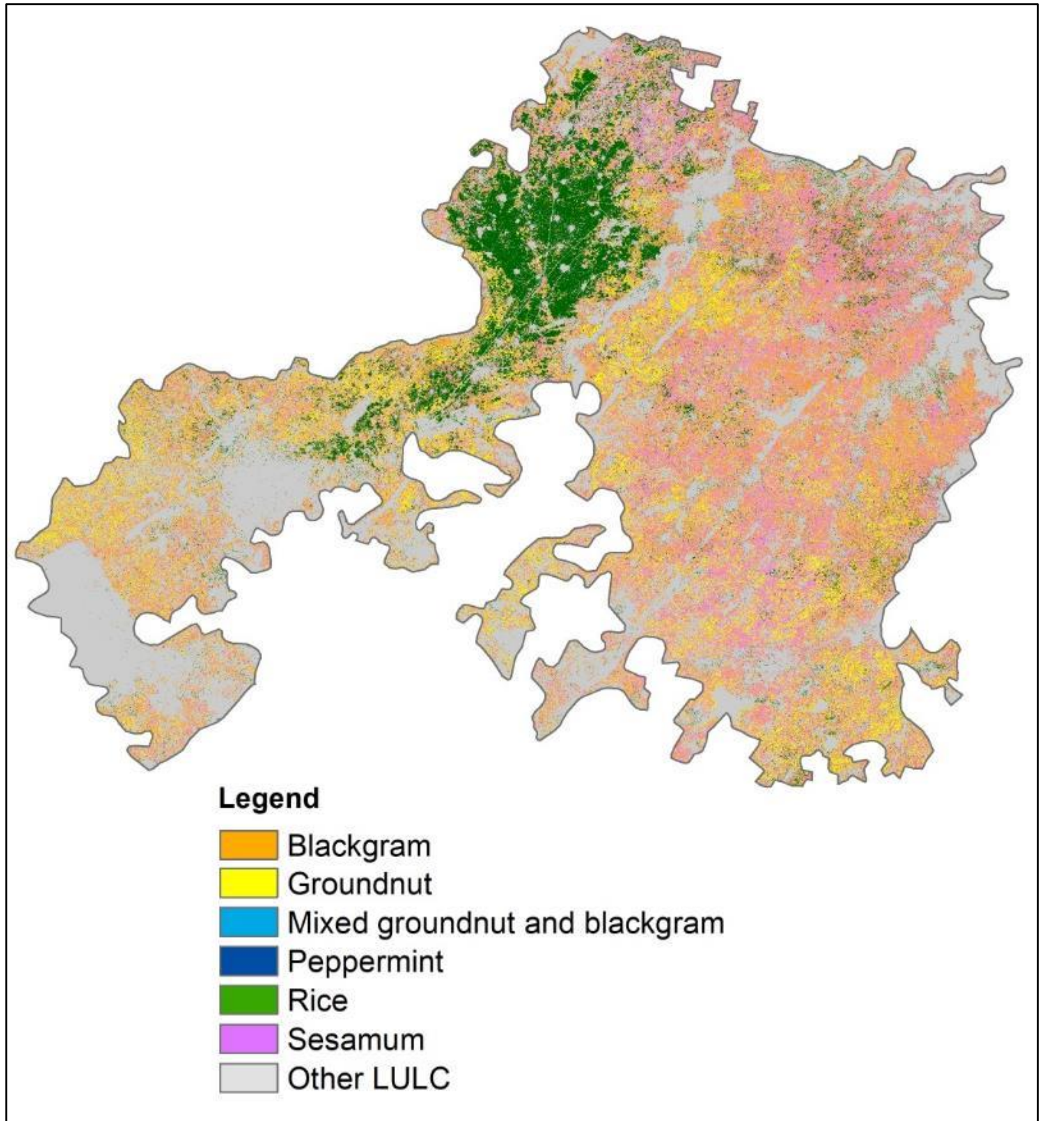
Pre-processing
- Cloud filtering
- Computation of monthly maximum NDVI composites

Classification
- Stacking of layers – bands and band ratios
- Training using ground truth data
- Random Forest classifier

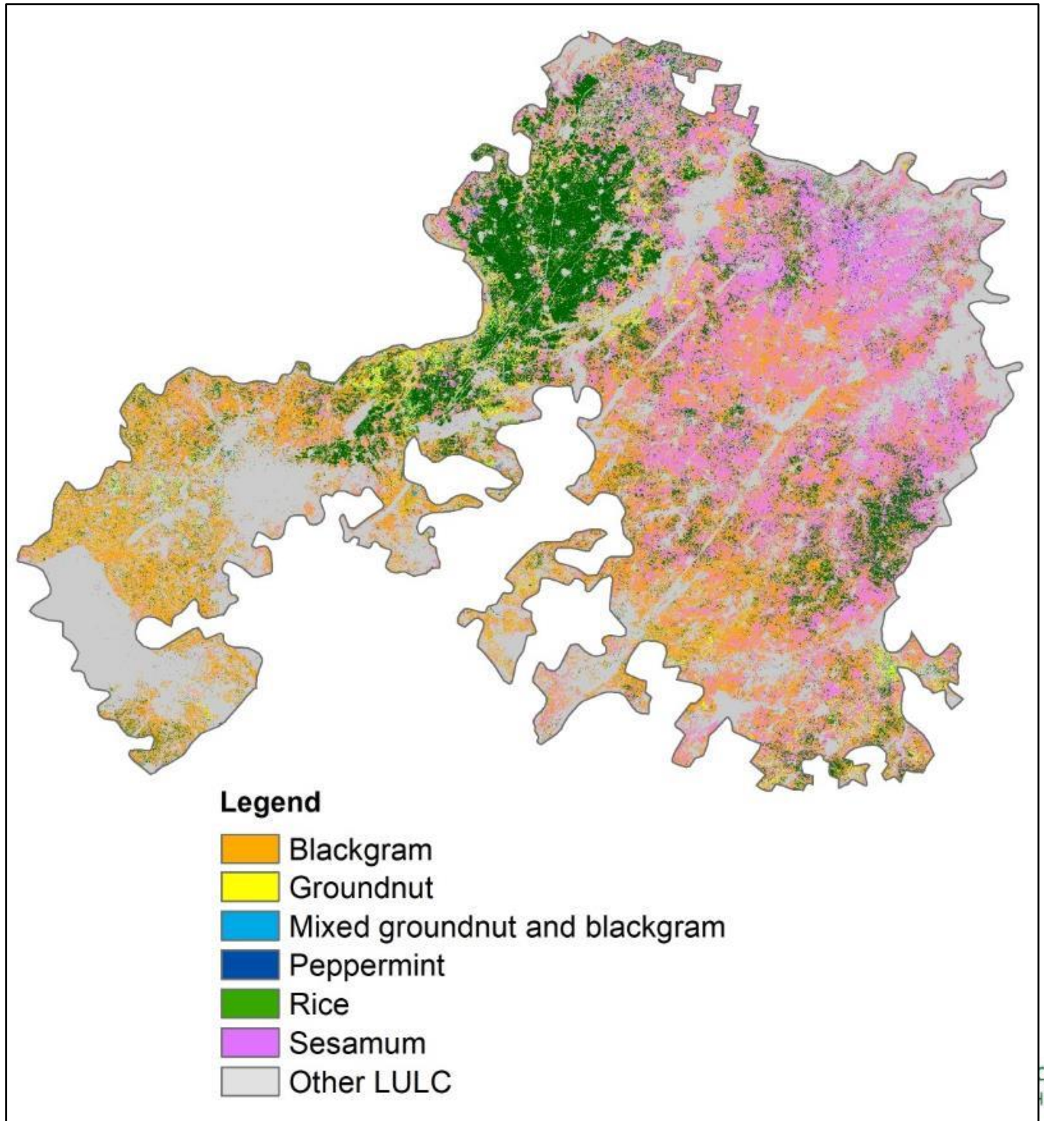
Output
Crop type map of Jhansi for Kharif 2020

Crop Classification using Sentinel 1 and 2

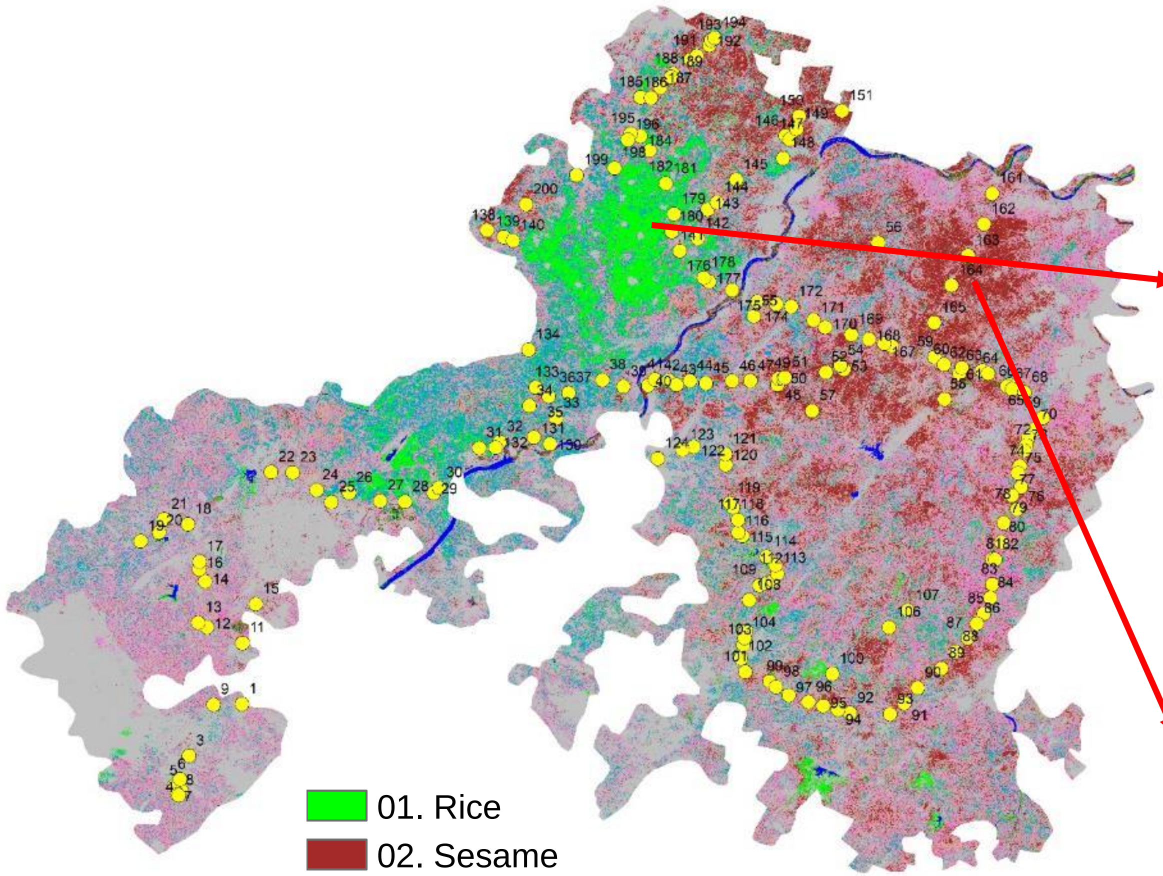
Kharif crop type map- Jhansi district
Mapped using S1 data only



Kharif crop type map- Jhansi district
Mapped using S1 and S2 data



Crop Type Mapping (Kharif 2020) – Jhansi

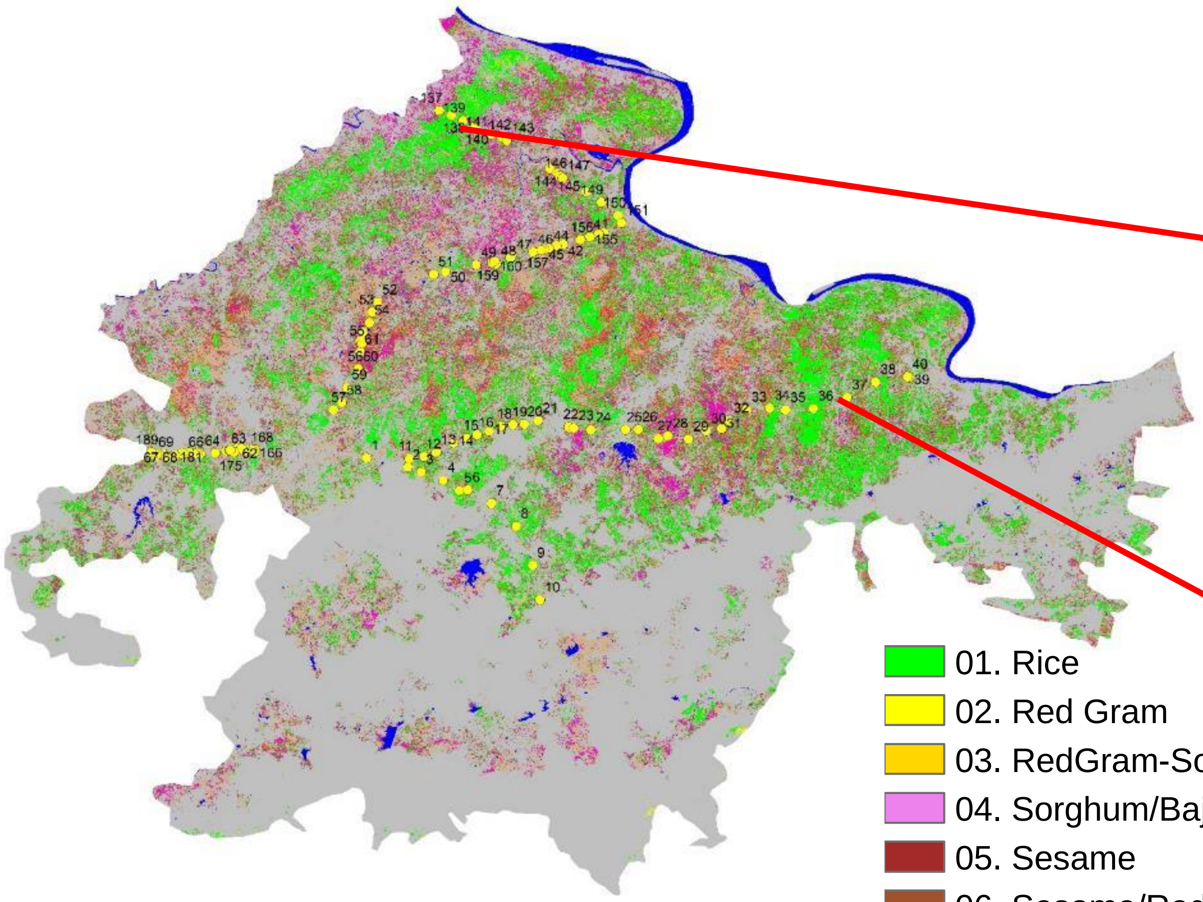


01. Rice
02. Sesame
03. Sesame/Blackgram
04. Groundnut
05. Groundnut/Blackgram
06. Other/Mixed Crops
07. Shrubs
08. Barren/Builtup
09. WaterBodies

Overall Accuracy : 85.54%
Kappa Co-efficient : 0.8102

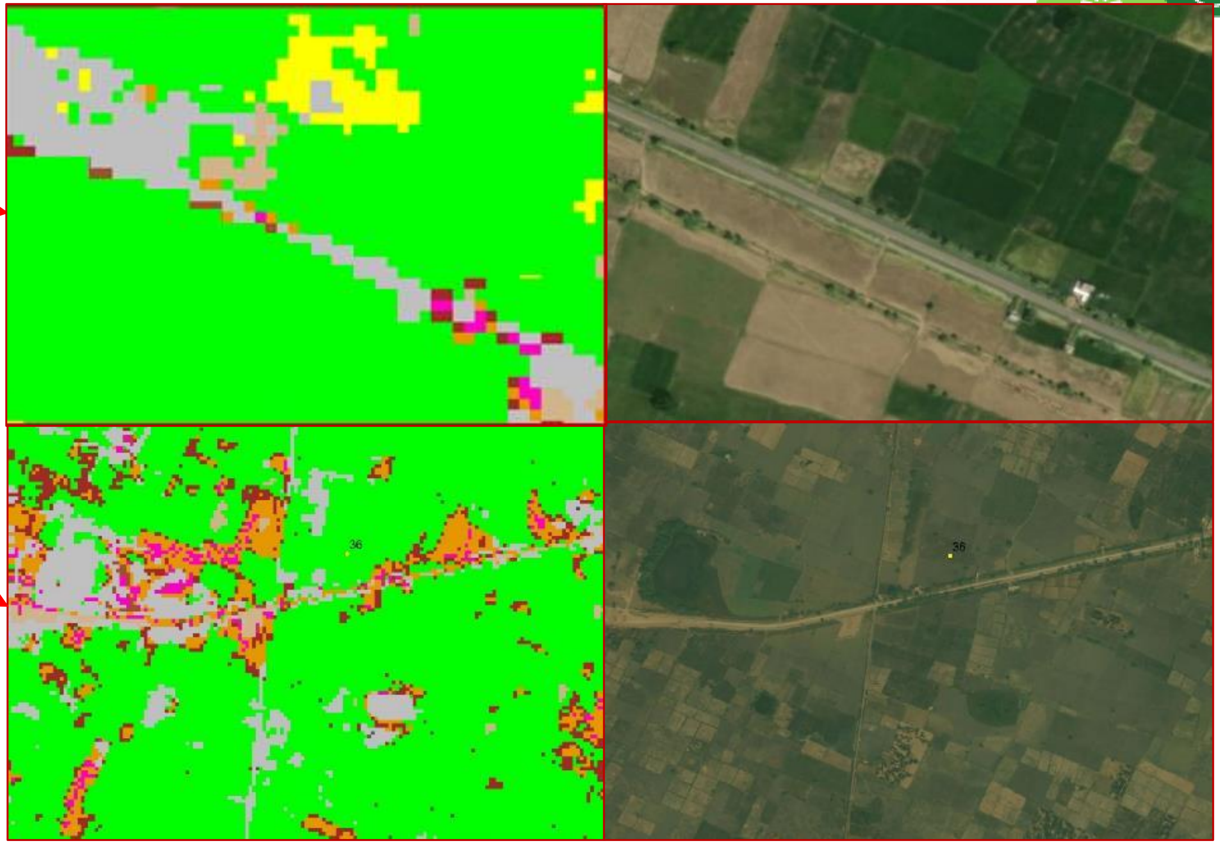
Class	Reference Totals	Classified Totals	Number Correct	Producer's	User's
01. Rice	18	17	16	88.89%	94.12%
02. Sesame	29	25	23	79.31%	92.00%
03. Sesame/Blackgram	64	67	56	87.50%	83.58%
04. Groundnut	25	25	19	76.00%	76.00%
05. Groundnut/BlackGram	23	25	22	95.65%	88.00%
06. Other/Mixed	7	7	6	85.71%	85.71%
		Kappa Co-effiecient	0.8102	Overall Accuracy	85.54%

Crop Type Mapping (Kharif 2020) – Chitrakoot



01. Rice
02. Red Gram
03. RedGram-Sorg
04. Sorghum/Bajr
05. Sesame
06. Sesame/RedGr
07. Baresoil/fal
08. Shrubs/grass
09. Forests/tree
10. WaterBodies

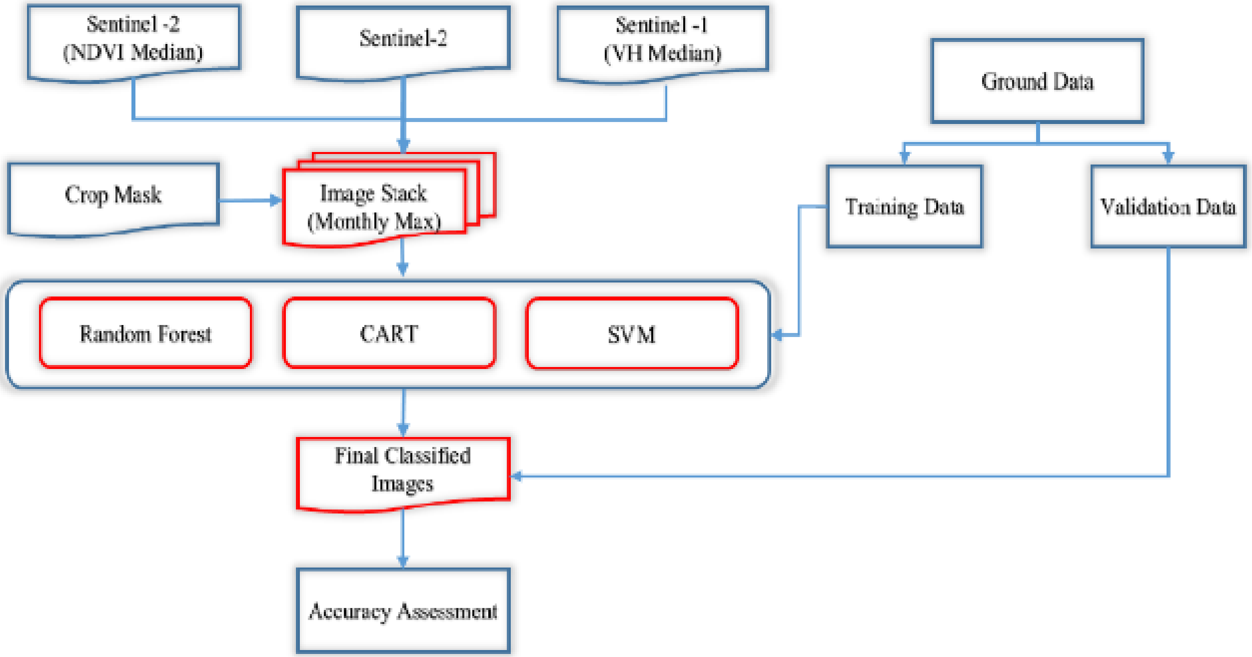
Overall Accuracy : 87.5%
Kappa Co-efficient : 0.828

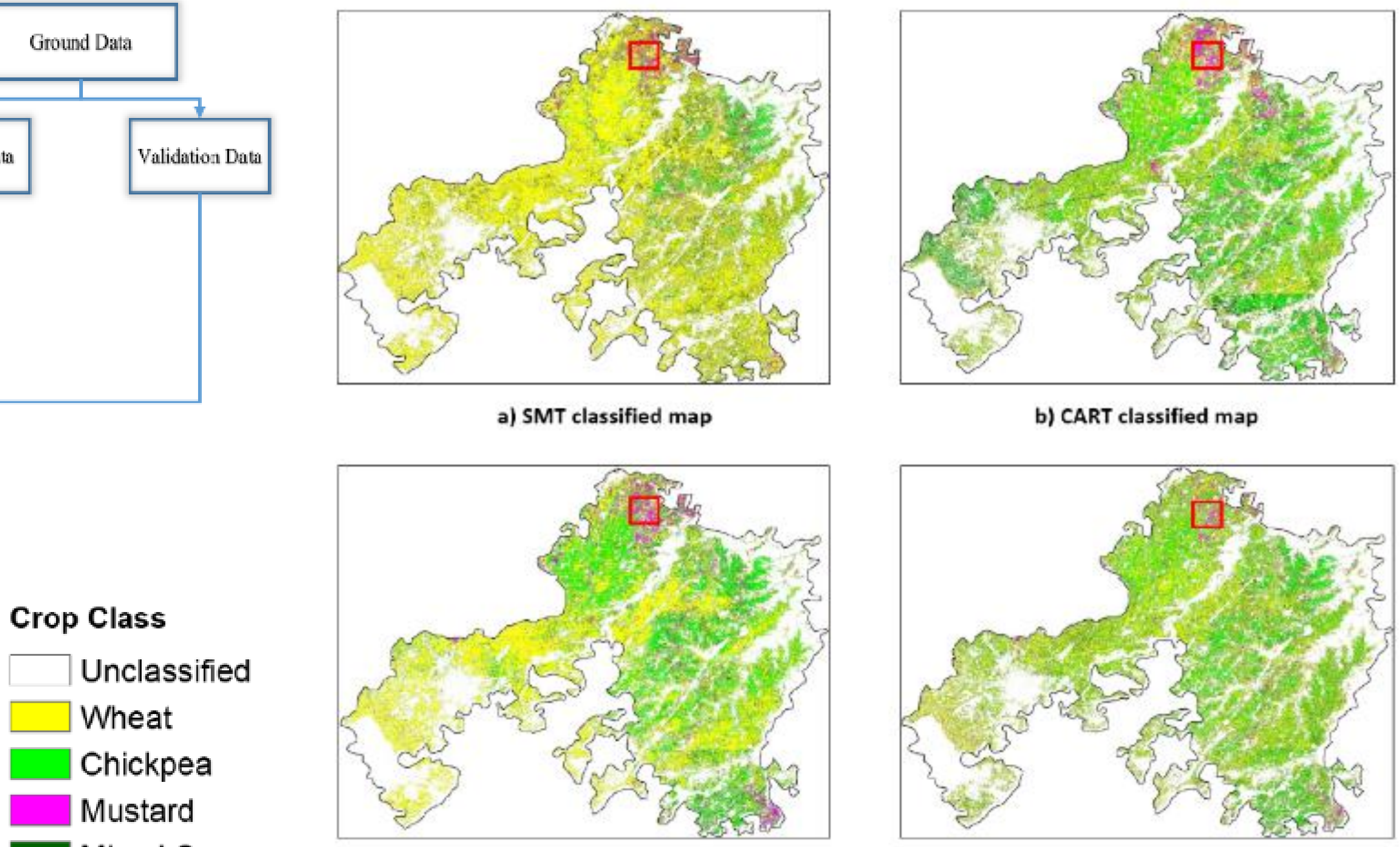


Class	Reference Totals	Classified Totals	Number Correct	Producer's	User's
01. Rice	21	21	20	95.24%	95.24%
03. RedGram-Sorghum	14	15	13	92.86%	86.67%
04. Sorghum/Bajra	12	12	9	75.00%	75.00%
06. Sesame/RedGram	7	8	7	100.00%	87.50%
		Kappa Co-effiecient	0.8284	Overall Accuracy	87.50%

Crop type mapping (Rabi) using different Machine Learning algorithms

Methodology





a) SMT classified map

b) CART classified map

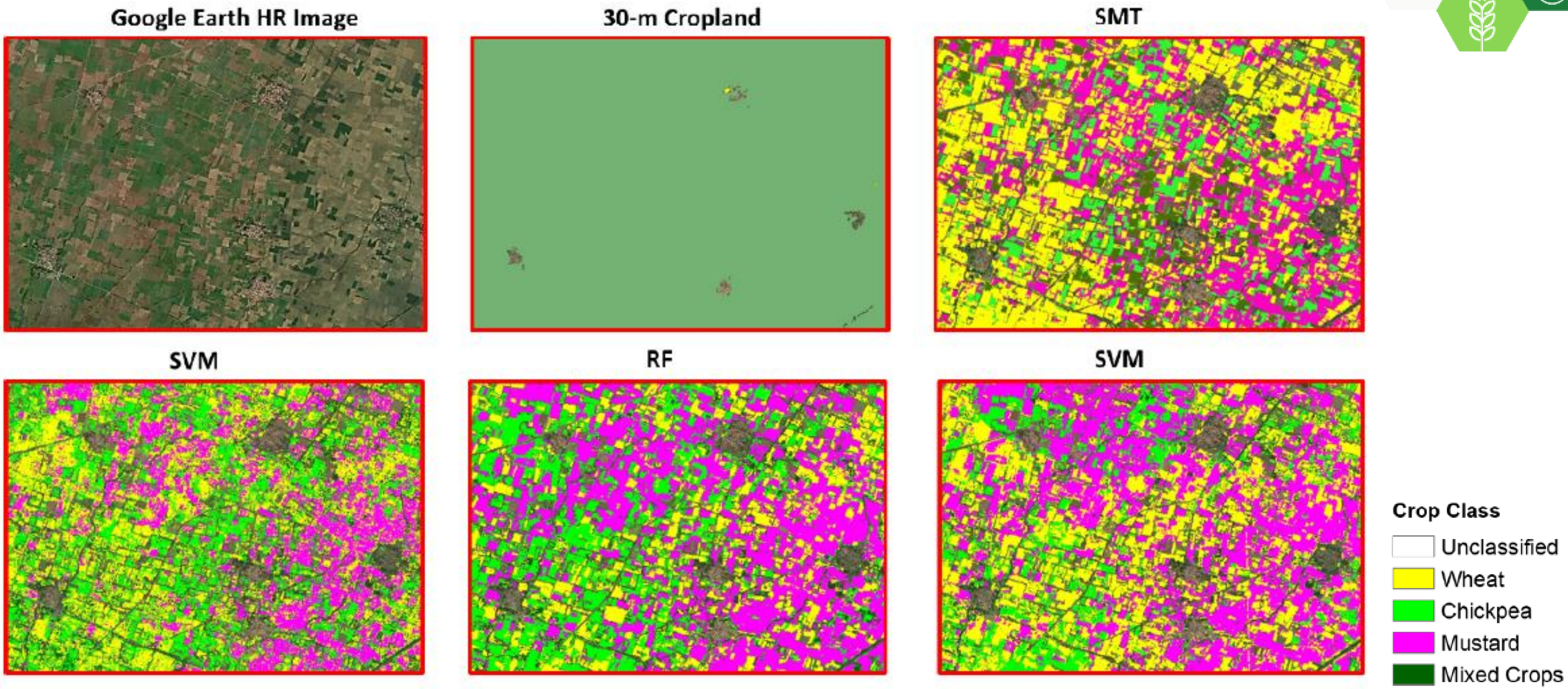
c) RF classified map

d) SVM classified map

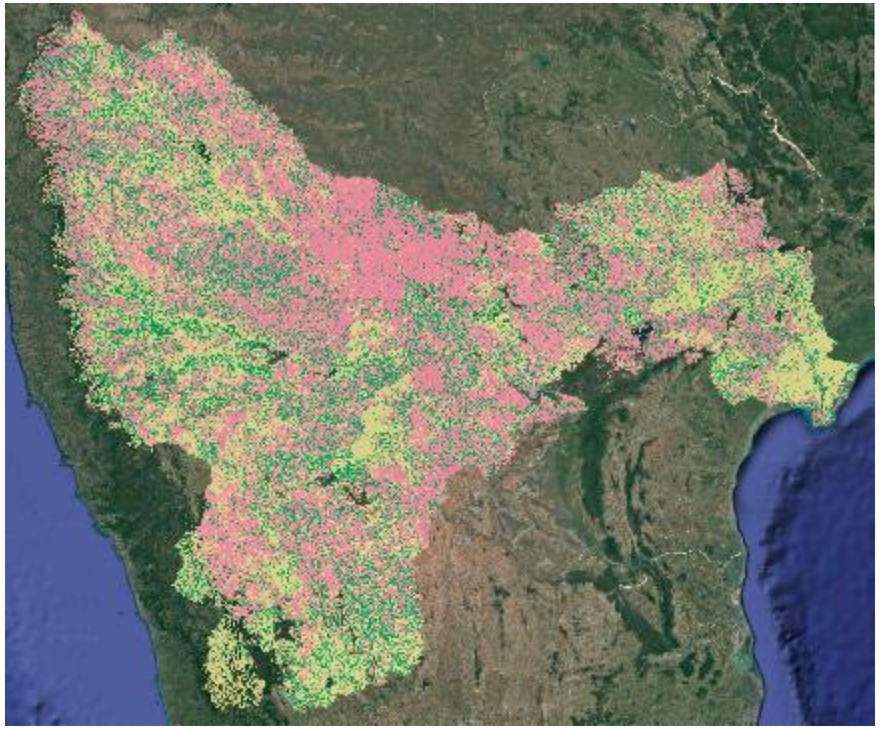
- Conducted crop type classification using different machine learning algorithms with Sentinel 2 imagery and Ground data
- Identified the advantages of each algorithms

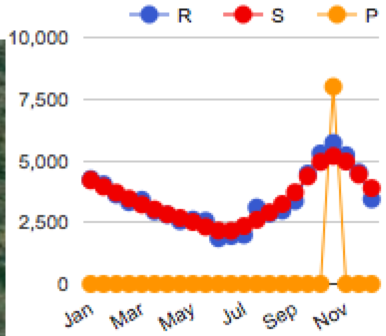
Crop type mapping using different Machine Learning algorithms

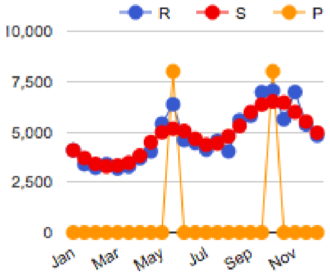
- Field level distribution of Croplands in 10m * 10m resolution

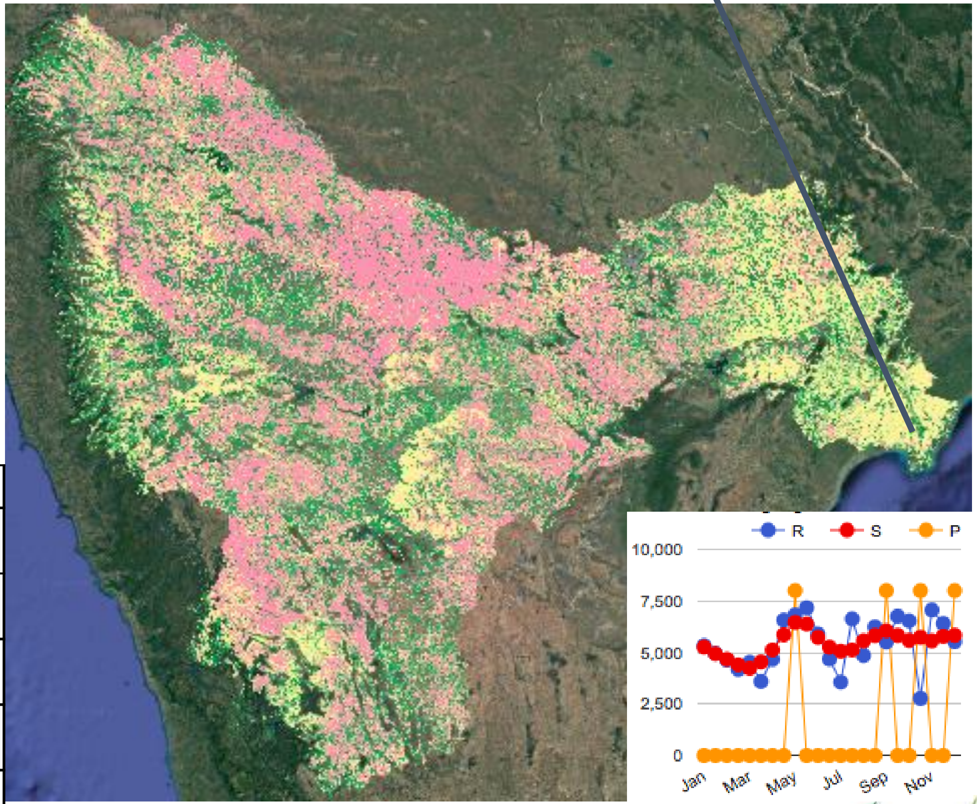


Crop intensity@ 30m: Krishna basin







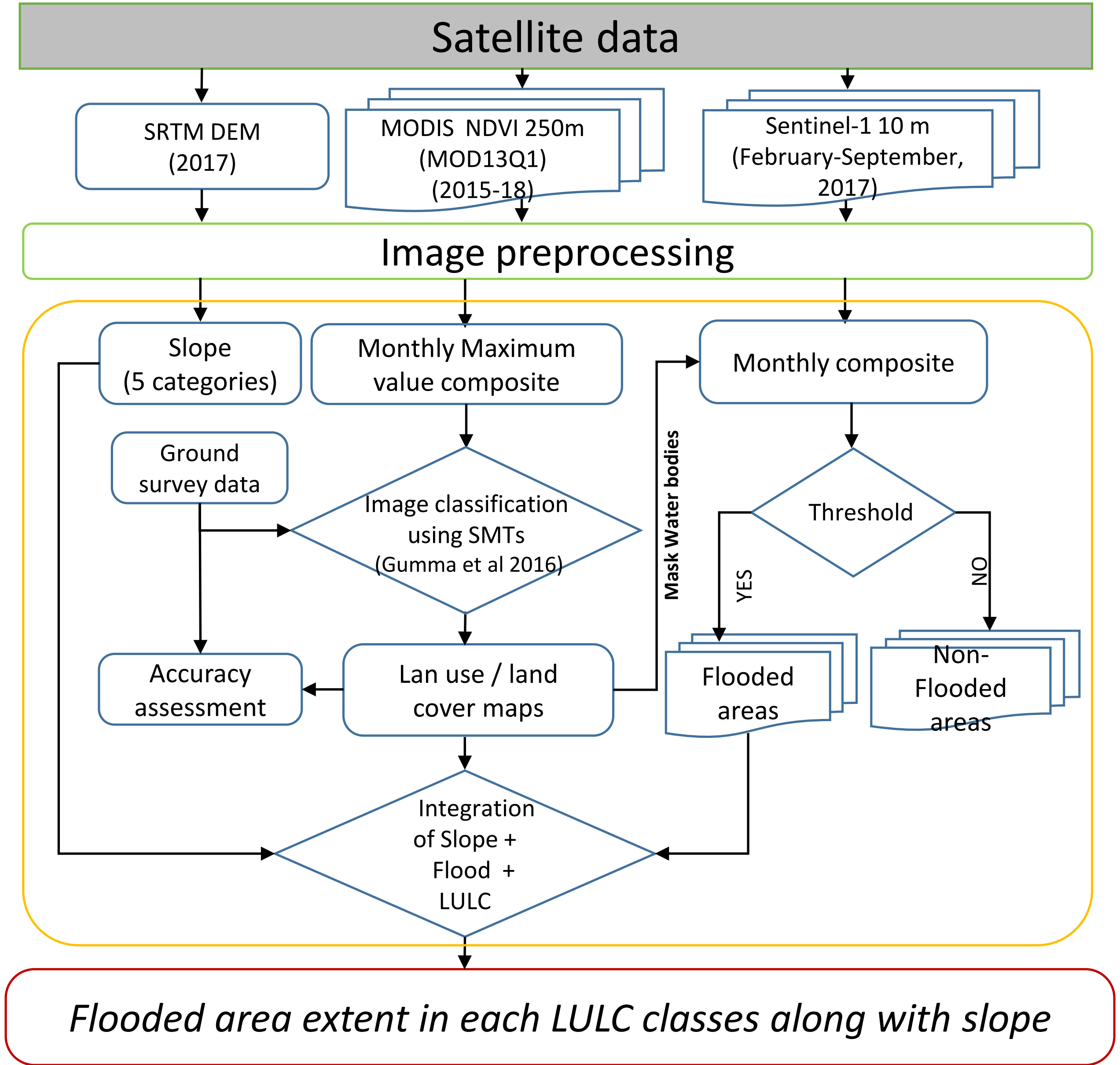


Krishna Crop Area (30-m, Mha)		
Class	GFSAD30	Gumma, 2011
1 - Single	13.75	12.70
2 - Double	3.82	4.30
3 - Continuous	0.42	0.17
Total	17.99	17.17

- Calculate spectral values
- Generate spectral profiles
- Identify vegetation peaks of spectral profiles
- Classify as cropping intensity map

Flood based farming systems

Methodology for mapping LULC and Flood areas in Afar region



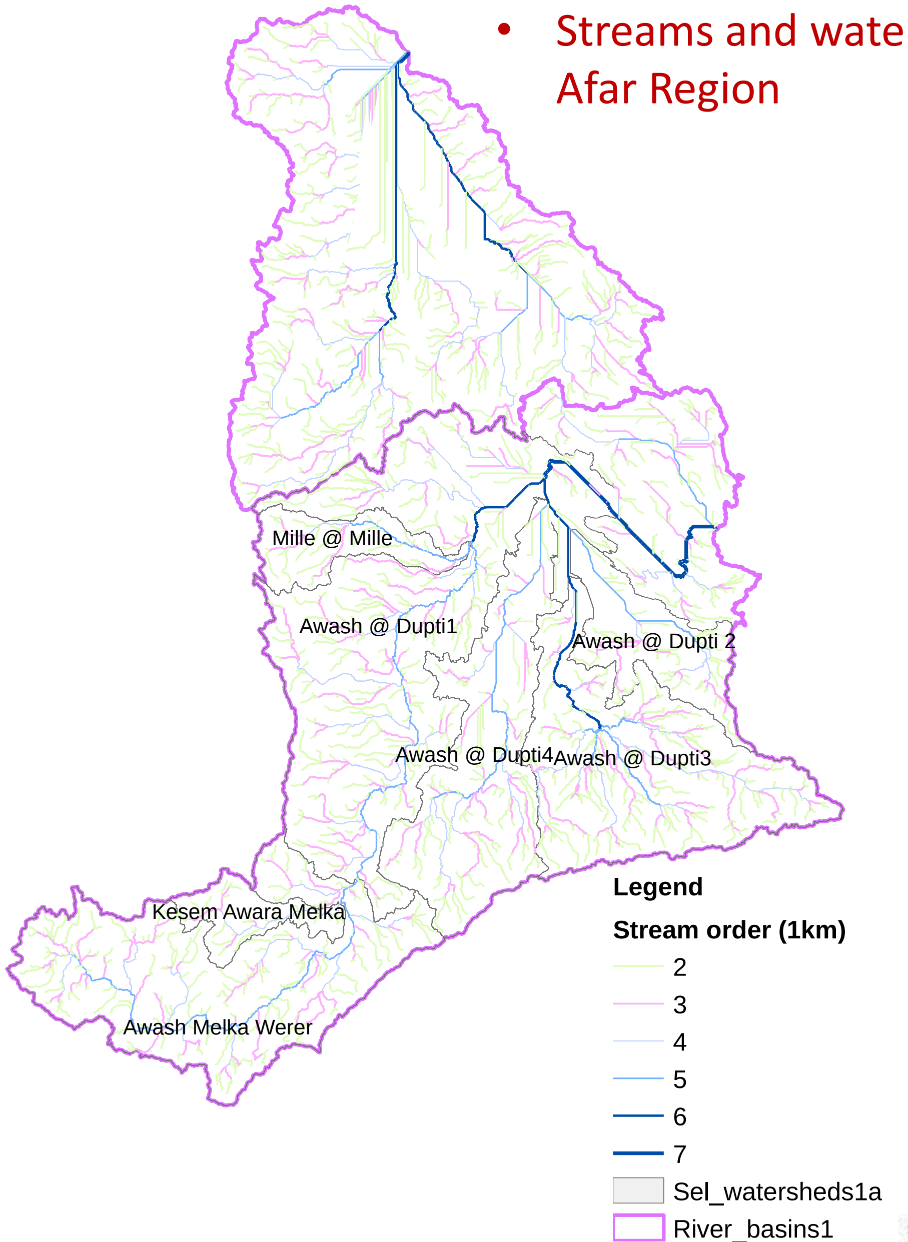
Imagery	Units	Band width nm3 / Range	Potential application
MODIS data sets			
250m 16 days NDVI	NDVI	-1 to +1	Vegetation conditions
250m 16 days EVI	EVI	-1 to +1	Canopy structural variations
250m 16 days red reflectance (Band 1)	Reflectance	620-670	Absolute Land Cover Transformation, Vegetation Chlorophyll
250m 16 days NIR reflectance (Band 2)	Reflectance	841-876	Cloud Amount, Vegetation Land Cover Transformation
250m 16 days blue reflectance (Band 3)	Reflectance	459-479	Soil/Vegetation Differences
250m 16 days MIR reflectance (Band 7)	Reflectance	2105-2155	Cloud Properties, Land Properties
SRTM	90 meters		Extraction of slope
Sentinel-1	10 meters	SAR	Flood mapping

- Methodology for mapping LULC and flood areas in Afar region of Ethiopia using various datasets

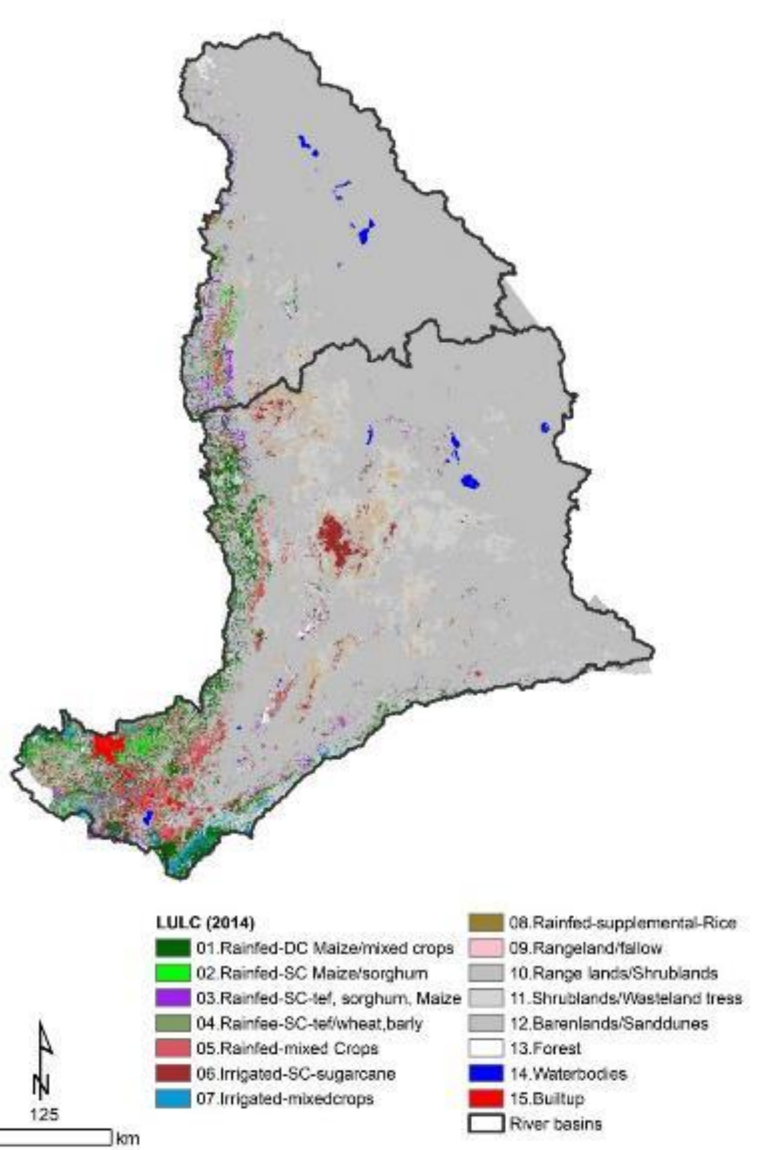
(Gumma et al., 2020)

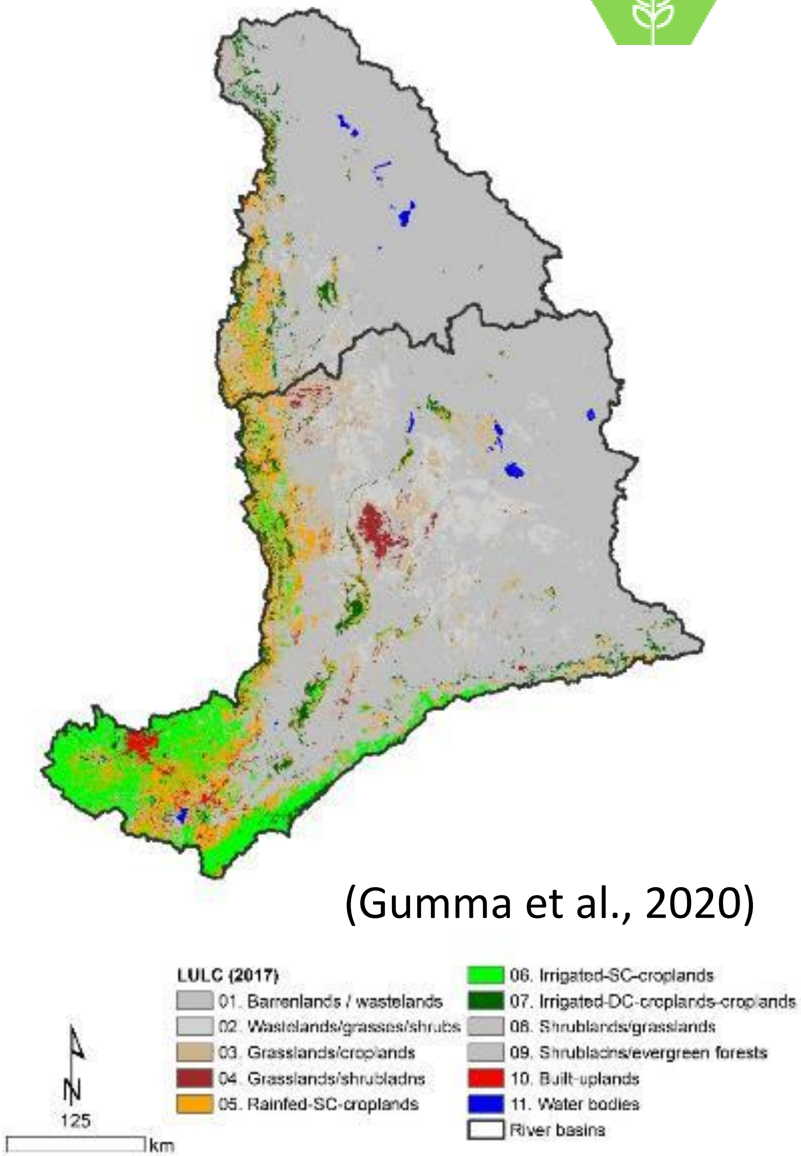
Land use changes: Afar region

- Streams and watersheds in Afar Region



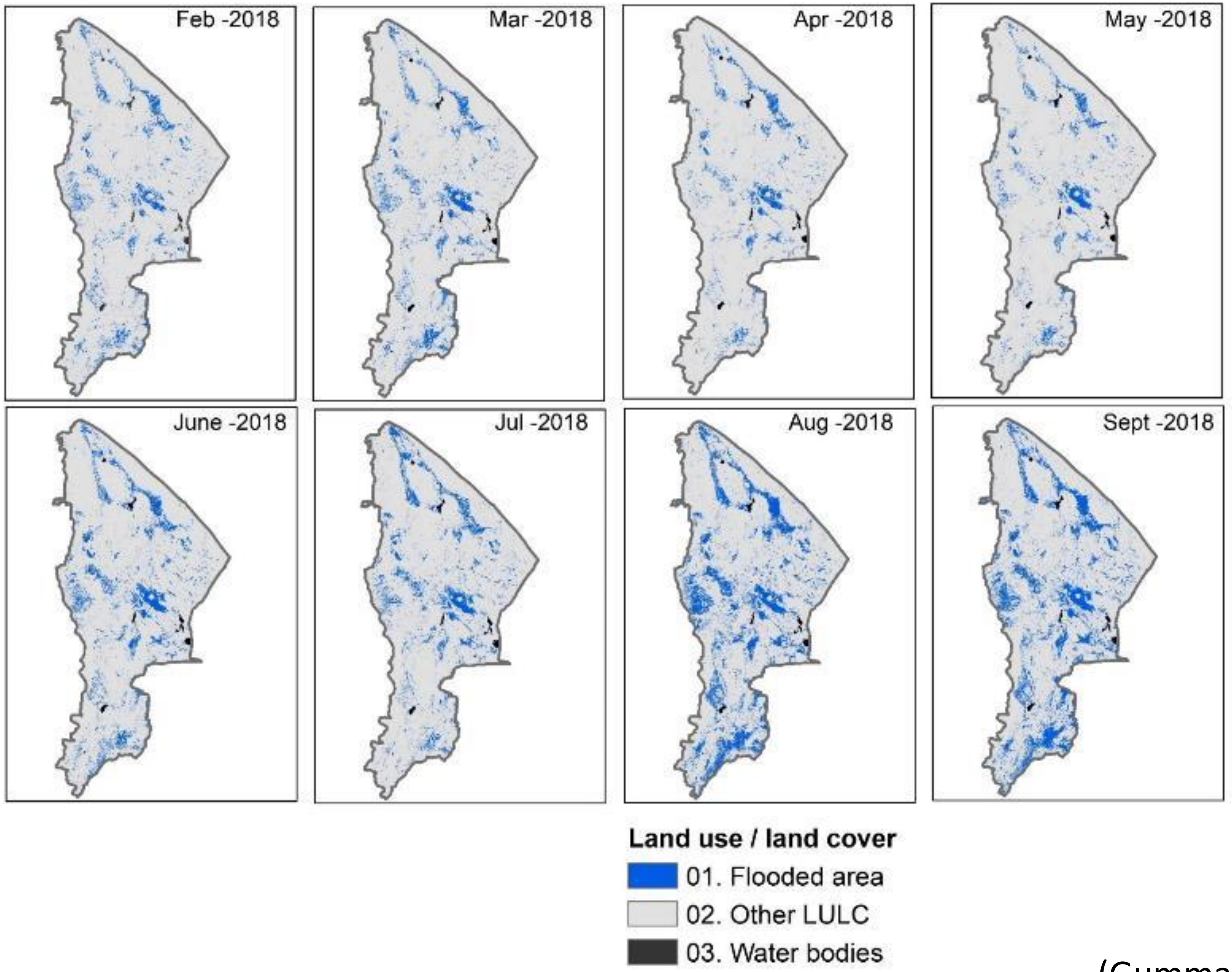
- LULC changes between 2014 and 2017





(Gumma et al., 2020)

Flooded area in each month of the **Belg** and **Meher** seasons :**2018**

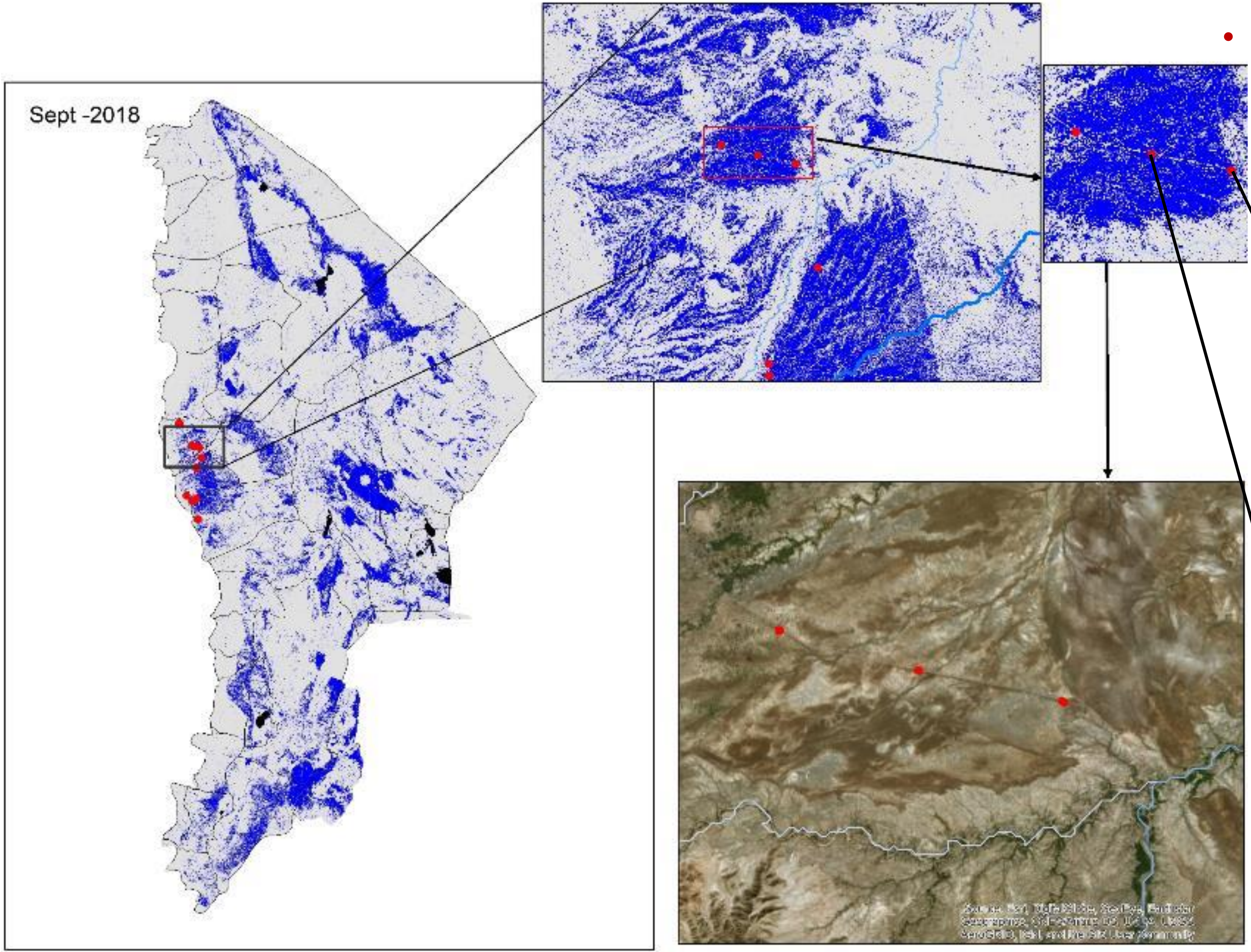


Month	Area in 000'ha		
	01. Flooded area	02. Other LULC	% flooded
Feb-18	657	8780	7%
Mar-18	731	8705	8%
Apr-18	553	8883	6%
May-18	570	8867	6%
Jun-18	951	8486	10%
Jul-18	887	8549	9%
Aug-18	1660	7776	18%
Sep-18	1592	7844	17%

- Monthly wise Flooded area of Afar region
- Calculated percent of area under flood

(Gumma et al., 2020)

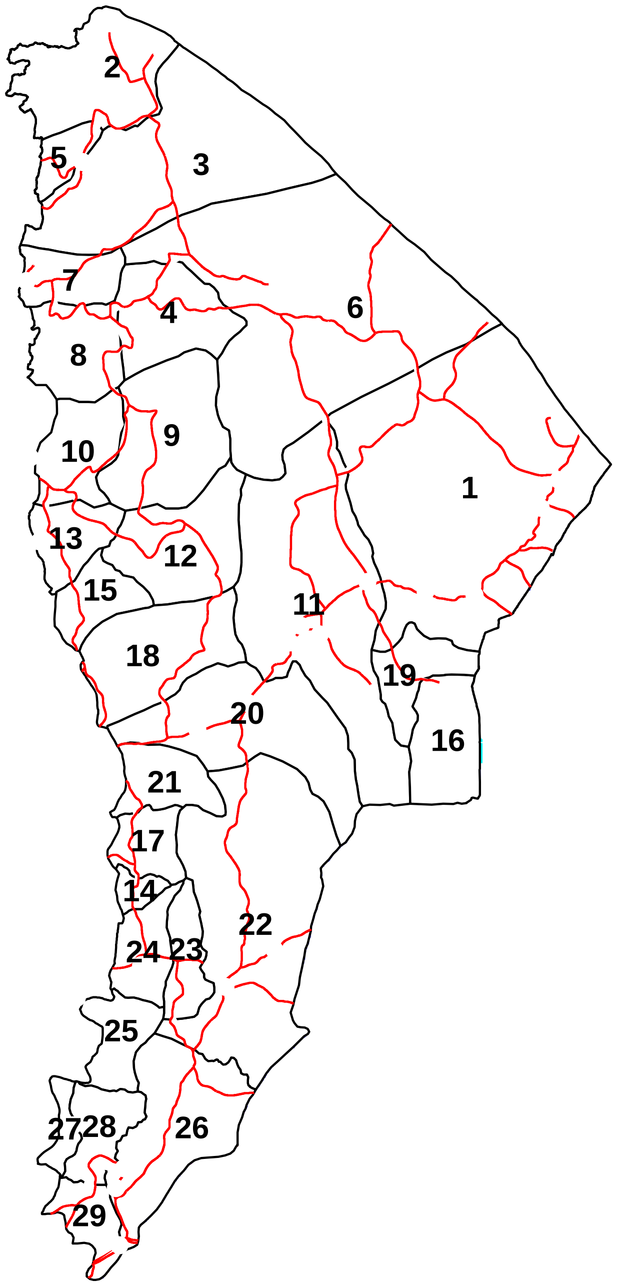
Flood analysis using Sentinel-1: Sept 2018



- Flood areas with ground Photographs

Flood analysis using Sentinel-1: August 2018

- District level flood analysis
- Calculated district wise area under flood

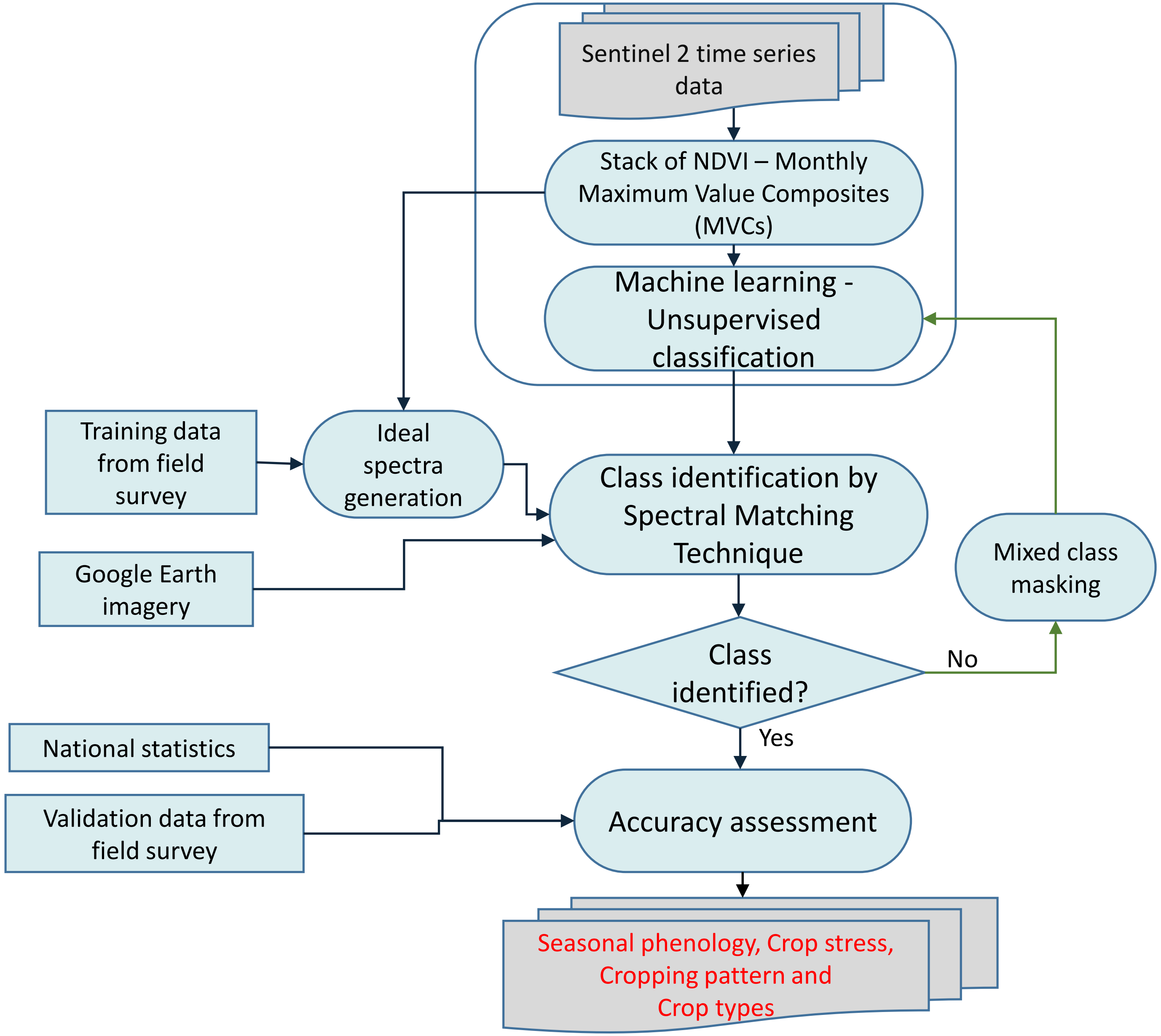


Slope-Flood analysis

- 01. Flood & <2% slope
- 02. Flood & 2 - 3% slope
- 03. Flood & >3% slope
- 04. Other
- 05. Waterbodies
- Districts
- Afar roads

Unique ID	District	Area (ha)				
		01. Flood & <2% slope	02. Flood & 2 - 3% slope	03. Flood & >3% slope	04. Other	05. Waterbodies
1	ELIDAR	147658	5554	14646	1216412	0
2	DALLOL	66827	979	18013	258237	0
3	BERAHLE	97483	1381	10661	618653	3106
4	EREBTI	22743	1042	2883	219005	0
5	KONEBA	339	397	3420	63385	0
6	AFDERA	269475	9862	8415	1028648	10325
7	ABALA	5138	581	4777	117733	0
8	MEGALE	16877	1919	5984	172003	0
9	TERU	67445	1593	1853	294841	0
10	YALO	13725	950	6758	160550	0
11	DUBTI	210609	5606	6589	641962	2231
12	HABRU	100154	2664	2673	195973	0
13	GULINA	28635	959	840	102118	0
14	ARTUMA	1876	20	58	35460	0
15	EWA	55378	325	37	64755	0
16	AFAMBO	40480	303	598	142741	20156
17	DEWE	9482	53	77	96353	0
18	CHIFRA	59924	776	464	267944	0
19	AYSAITA	16851	146	1199	115945	2964
20	MILLE	88708	1116	1513	381141	4165
21	TELALAK	11129	424	110	127437	0
22	GEWANE	127045	2210	3411	731651	436
23	BURE_MUDAY	24795	204	1	77964	7407
24	FURSI	19649	122	88	108495	0
25	SIMUROBI_G	2104	120	251	122264	0
26	AMIBARA	89529	1354	856	298385	1440
27	ARGOBA_SPE	378	97	410	46206	0
28	DULECHA	11522	749	135	112956	653
29	AWASH_FENT	14618	887	522	88145	0
	Total area	1620575	42394	97244	7907362	52883

Method and approach of semi-automated Techniques



Taking Advantages of Both Machine Learning and Traditional Methods.

With Machine learning algorithms

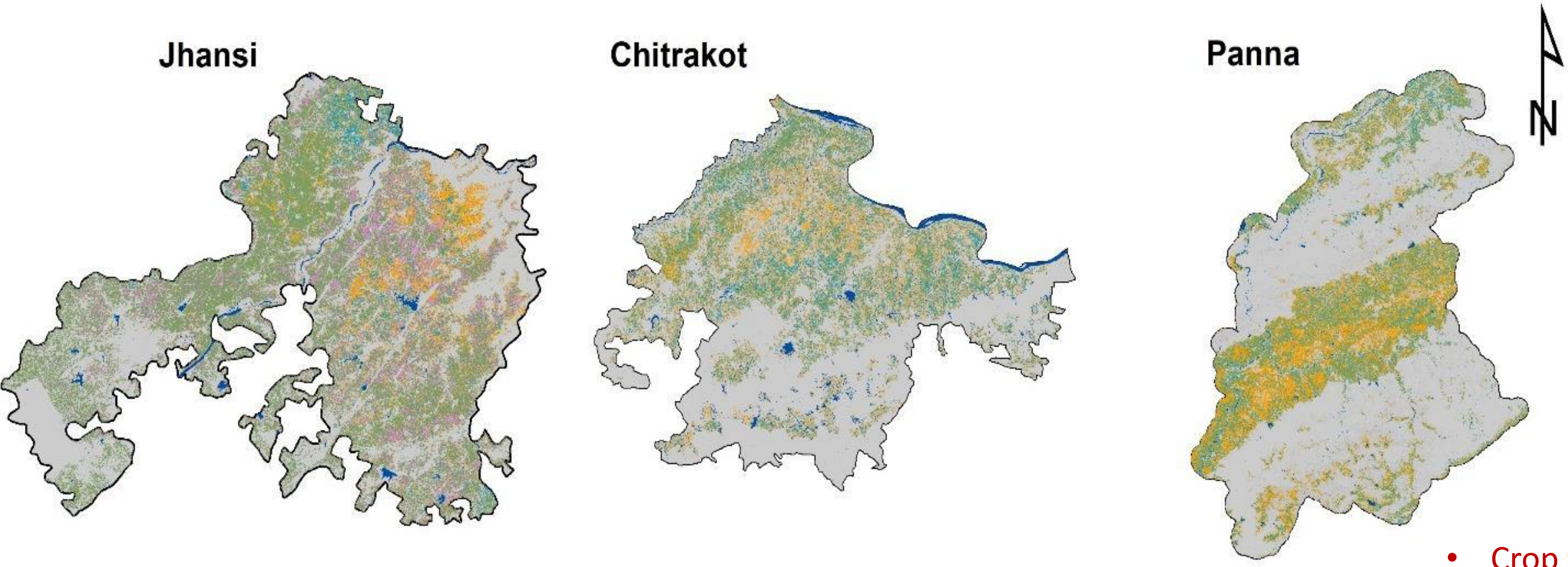
- Stacking of Satellite Images
- Classification of Stacked Image

With Spectral Matching Techniques

- Improving Classification

➢ **Semi-Automated Techniques produce better outputs than Machine Learning Algorithms**

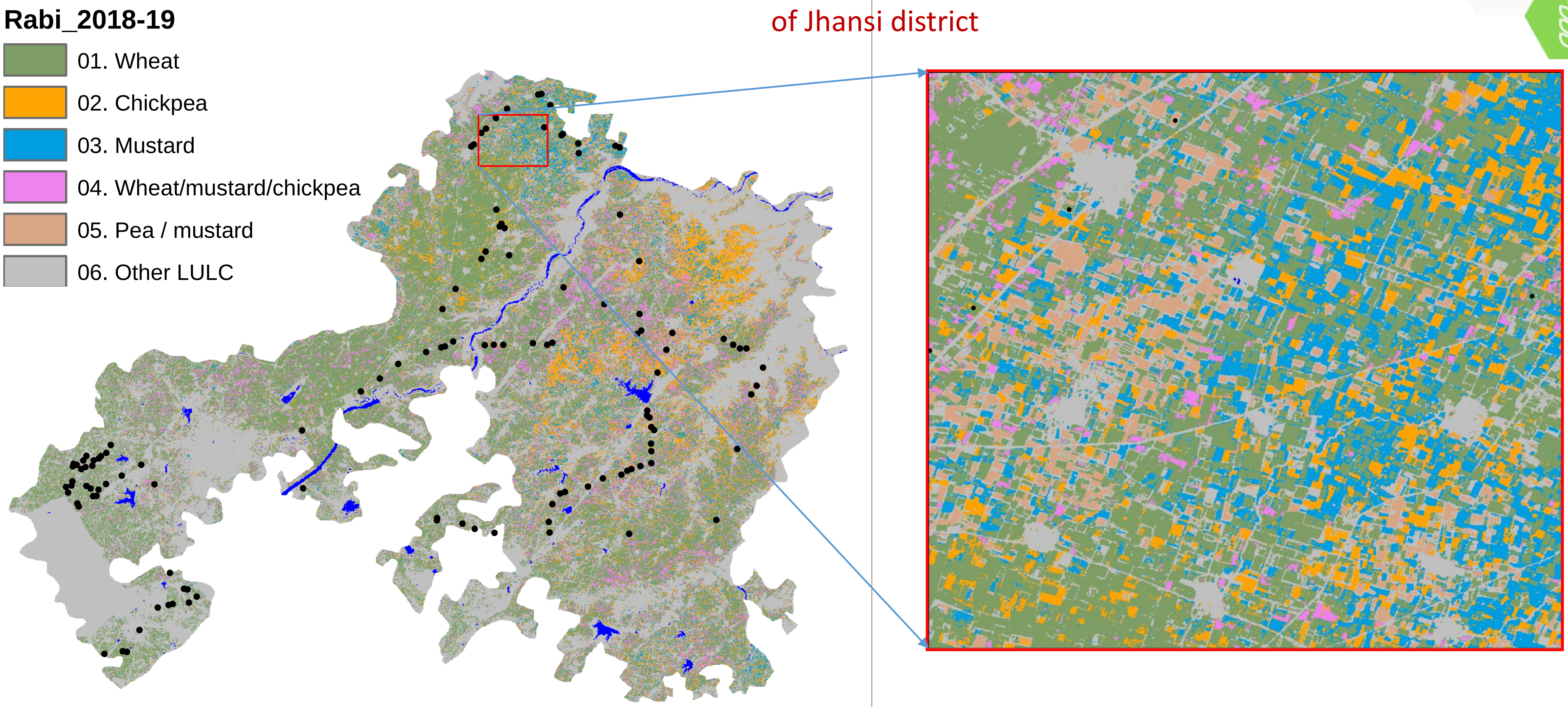
Cropping pattern during Rabi season (2018-2019)



- Crop type map for Jhansi, Chitrakoot and Panna districts using Sentinel -2 10m data

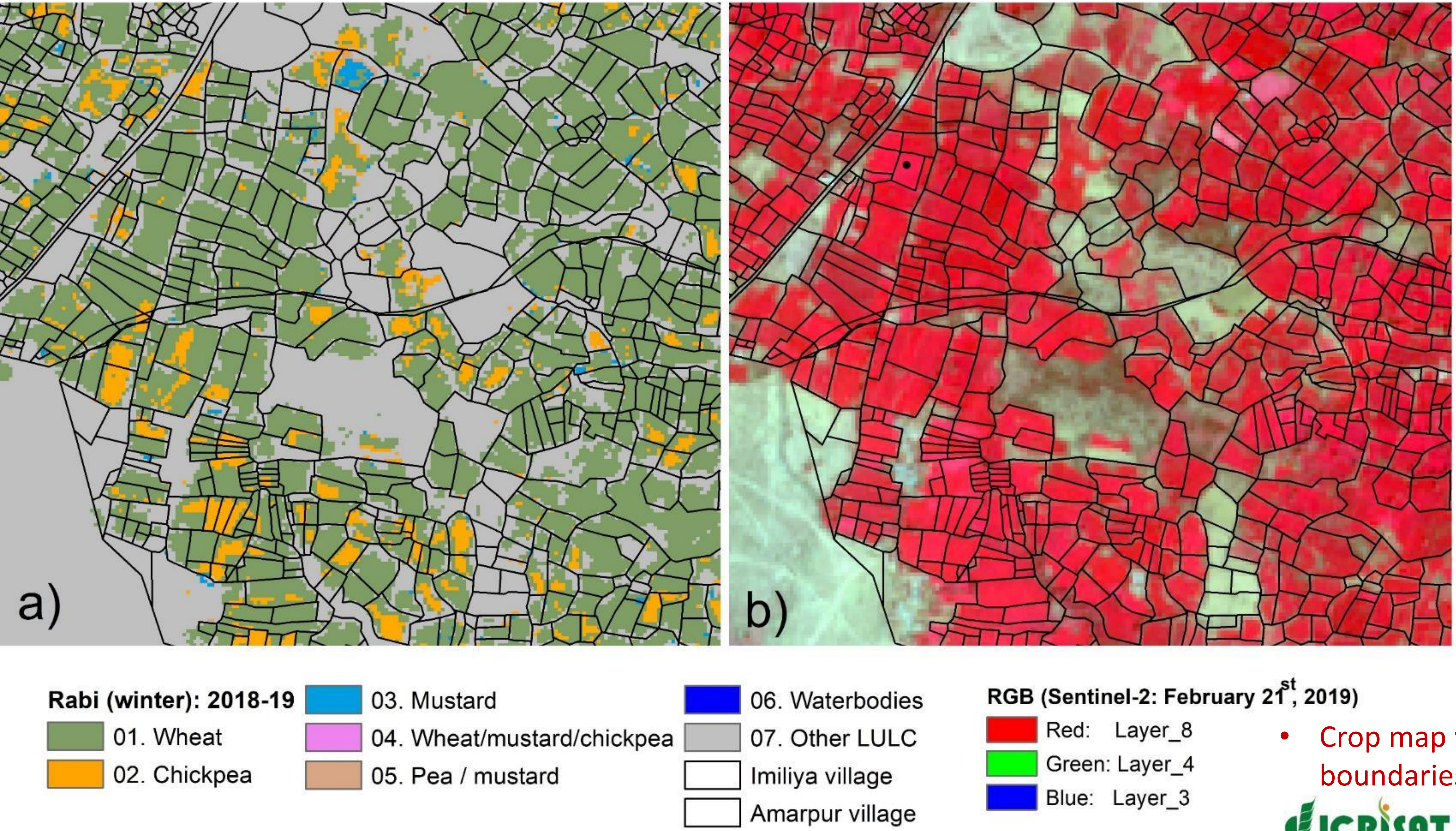
Cropping pattern during rabi season in Jhansi: Sentinel-2

- Field level view of spatial distribution of croplands of Jhansi district



Gumma et. al (2020)

Cropping pattern during rabi season in Jhansi: Sentinel-2



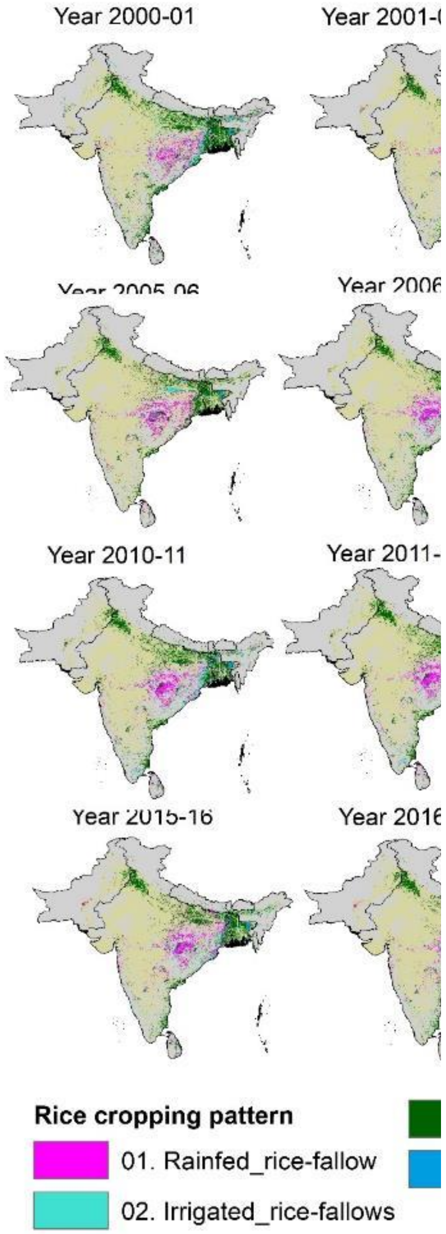
- Crop map with Plot boundaries at village level

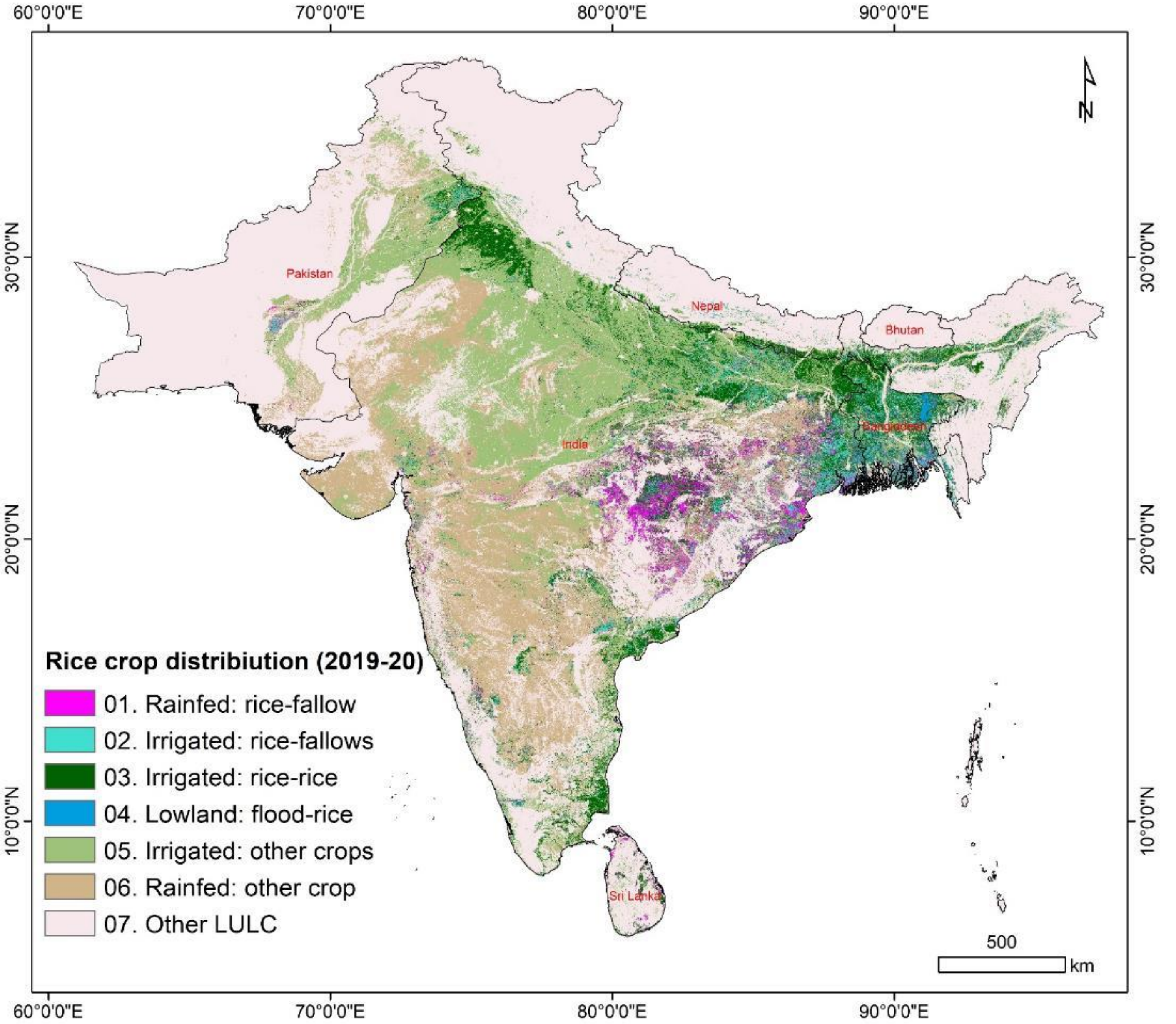
Geospatial products –Decision Making

Utilization of Geospatial products for decision making

- Assessing potential areas for short duration legumes
- Assessing watershed impacts
- Watershed prioritization

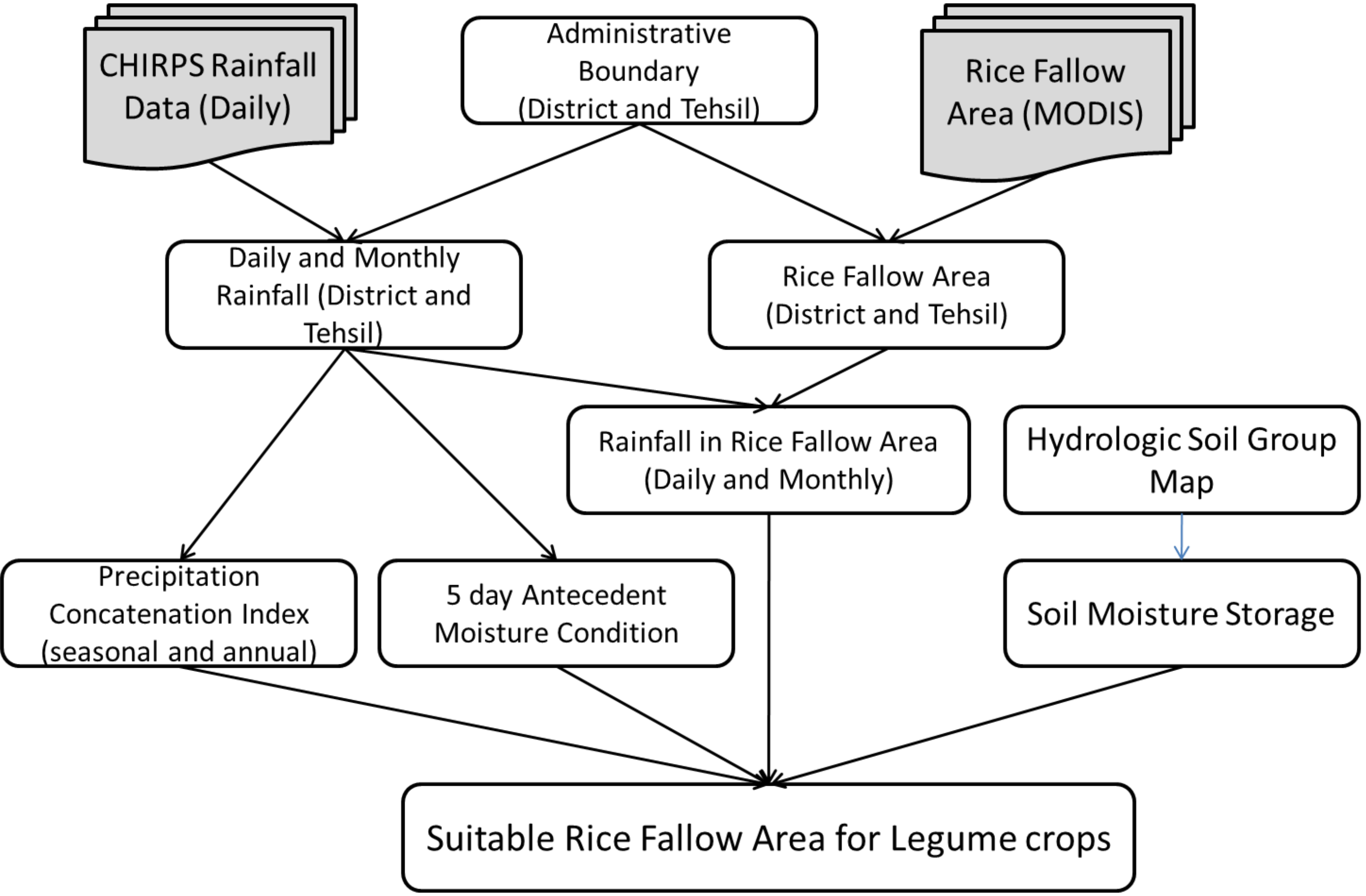
Rice Fallows during 2000-2020





- Identification of Rice Fallows for intensification of Short duration legumes

Methodology for Suitable Rice Fallow Area for Legume Crops



Input Data

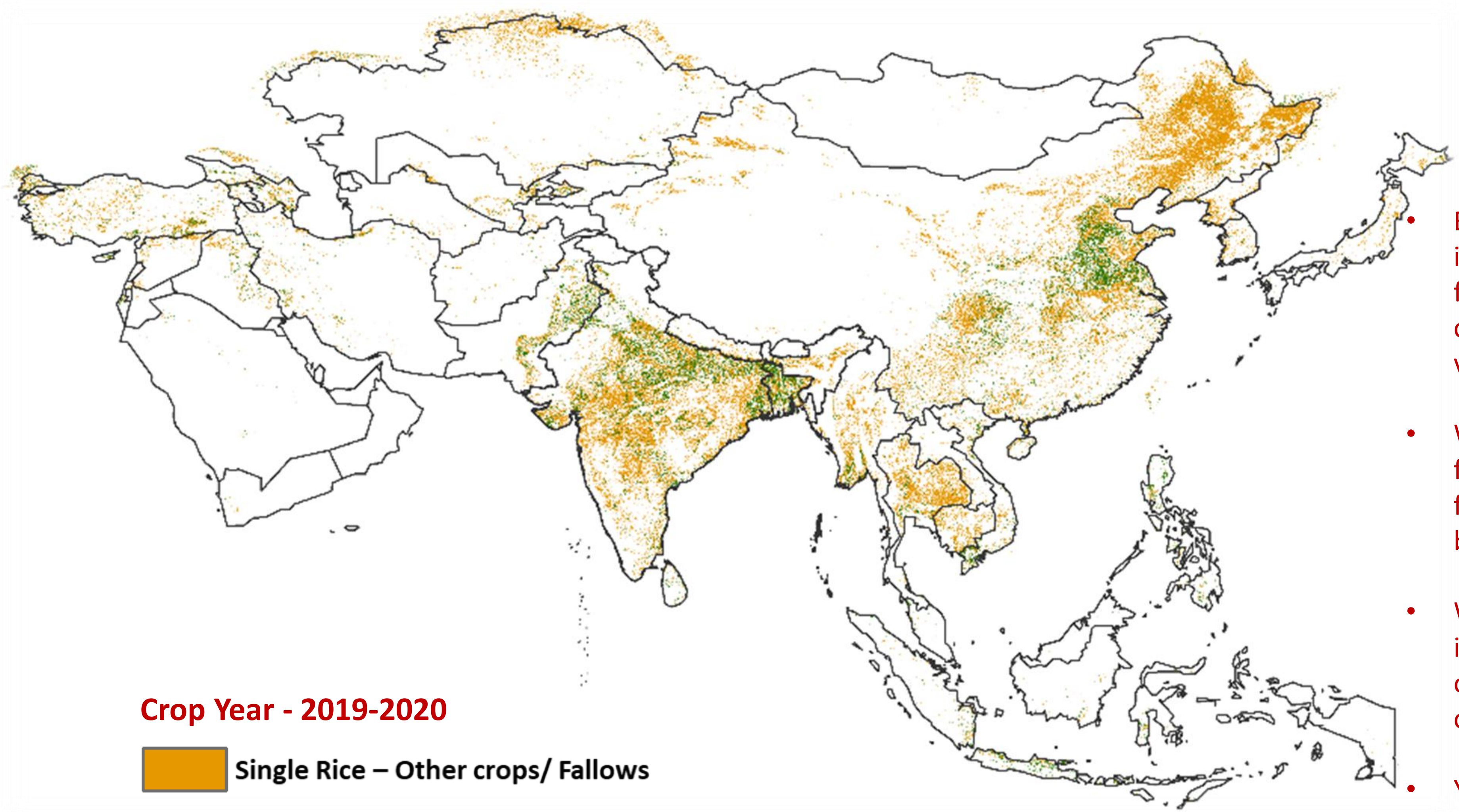
1. CHIRPS daily Rainfall data (2010-2011)
2. Rice Fallow areas using MODIS data (2010-2011)
3. Global Hydrologic Soil Groups

Outputs at District and Tehsil

1. Precipitation Concentration Index (Annual and Seasonal)
2. Antecedent Moisture Condition and Soil Moisture Storage
3. Suitable sites for Grain Legume Production

Gumma, HariPrasad et al..(Prep)

Mapping of Rice fallows for entire Asia using GEE



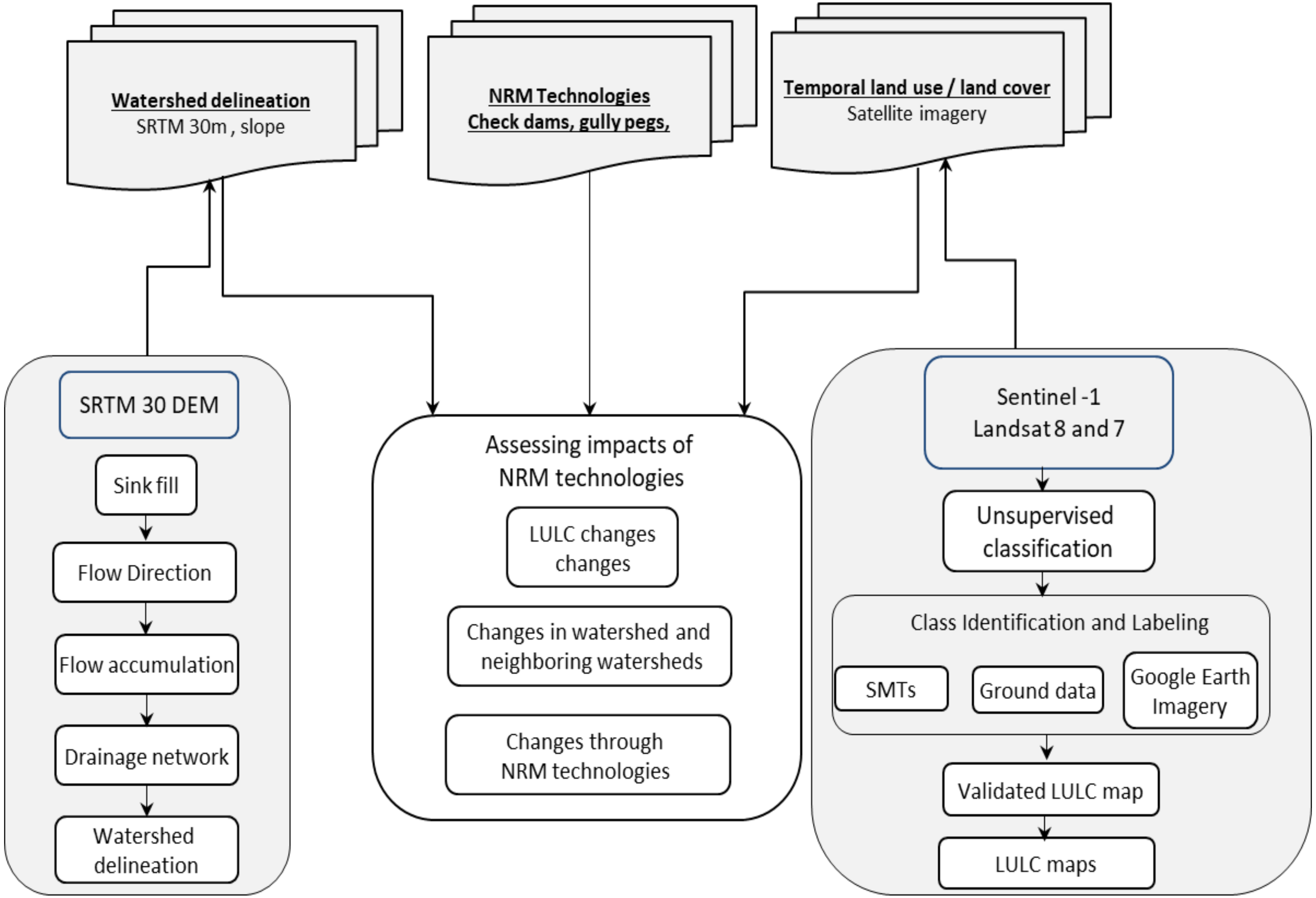
Crop Year - 2019-2020

Single Rice – Other crops/ Fallows

Rice –Rice/wheat

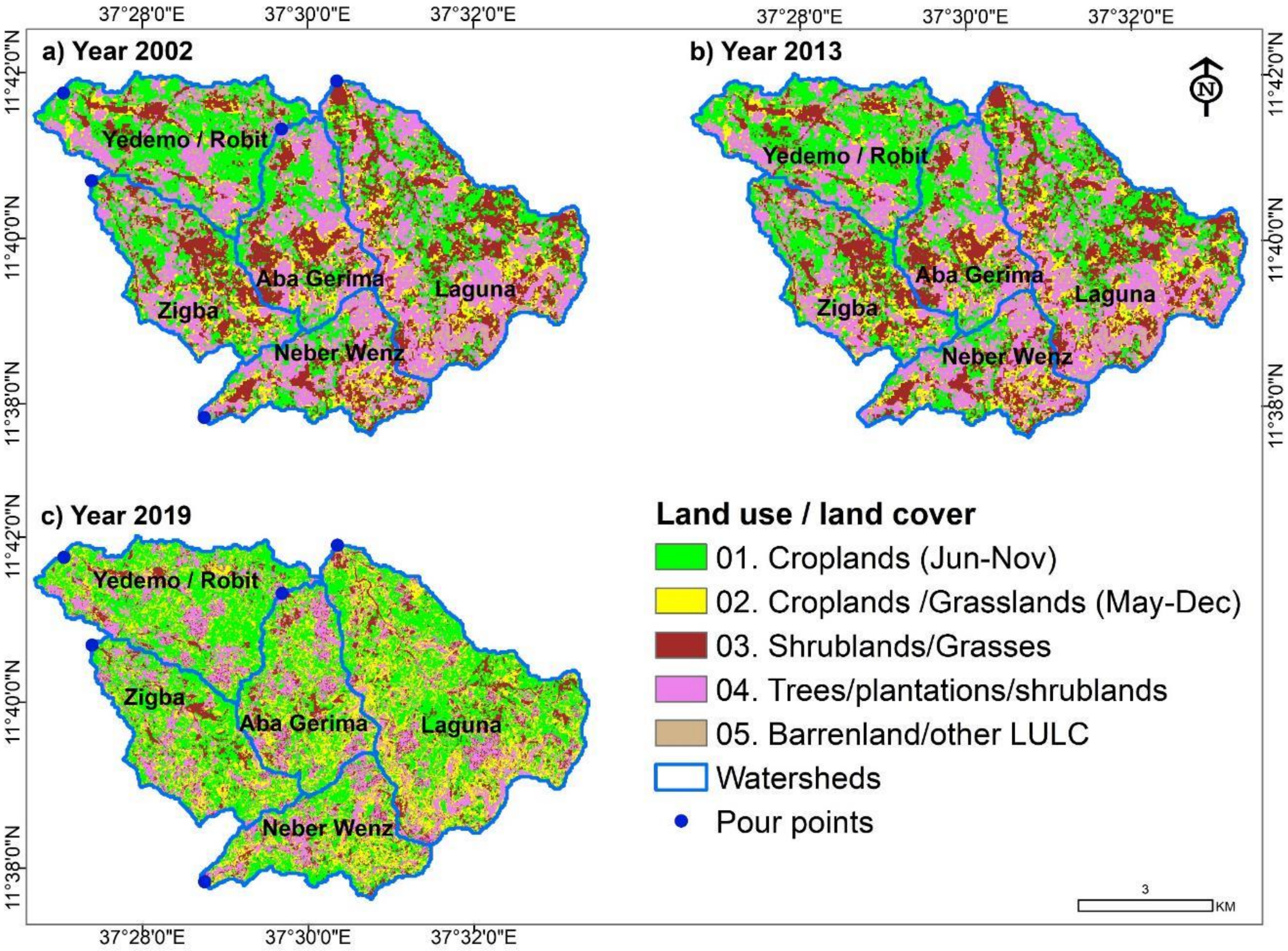
- Based on the methodology, We have identified rice fallows as well as rice followed by other crops and also changes in croplands classes to other classes and vice versa
- We have separated rice classes as Rice followed by other crops/ Fallows and Rice followed by Rice/ wheat/sugarcane for better understanding
- We are further improving the classes by integrating the present methodology with other techniques as well for better classification
- Yet to apply same methodology for other years and validate with respective countries statistics

Assessing impacts of watershed intervention



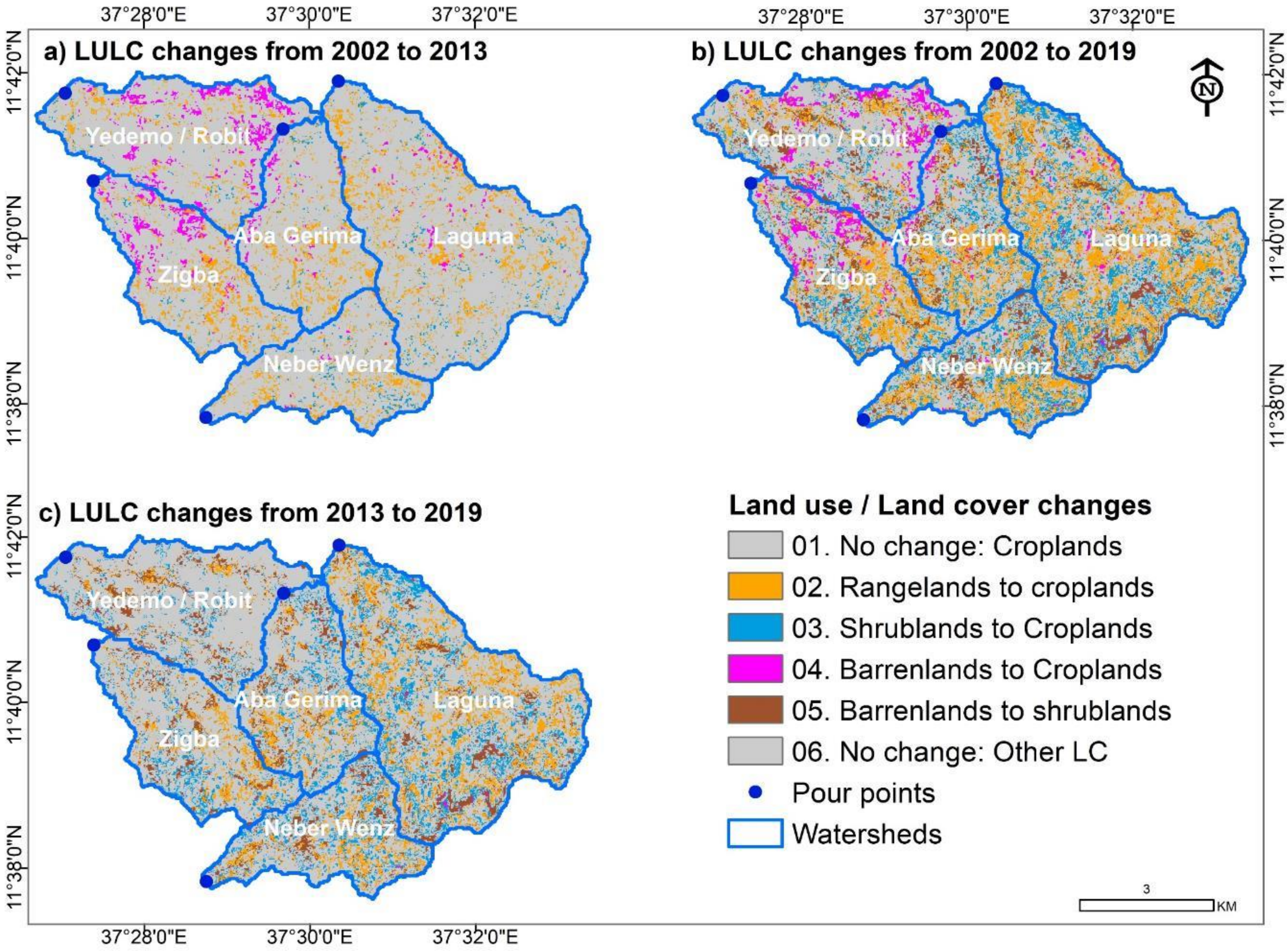
- Integrating NRM (watershed) with Remote sensing data for assessing impacts
- Identifying the changes in Model and Neighbouring watersheds

Spatial Distribution of Land Use Land Cover -2002, 2013 and 2019



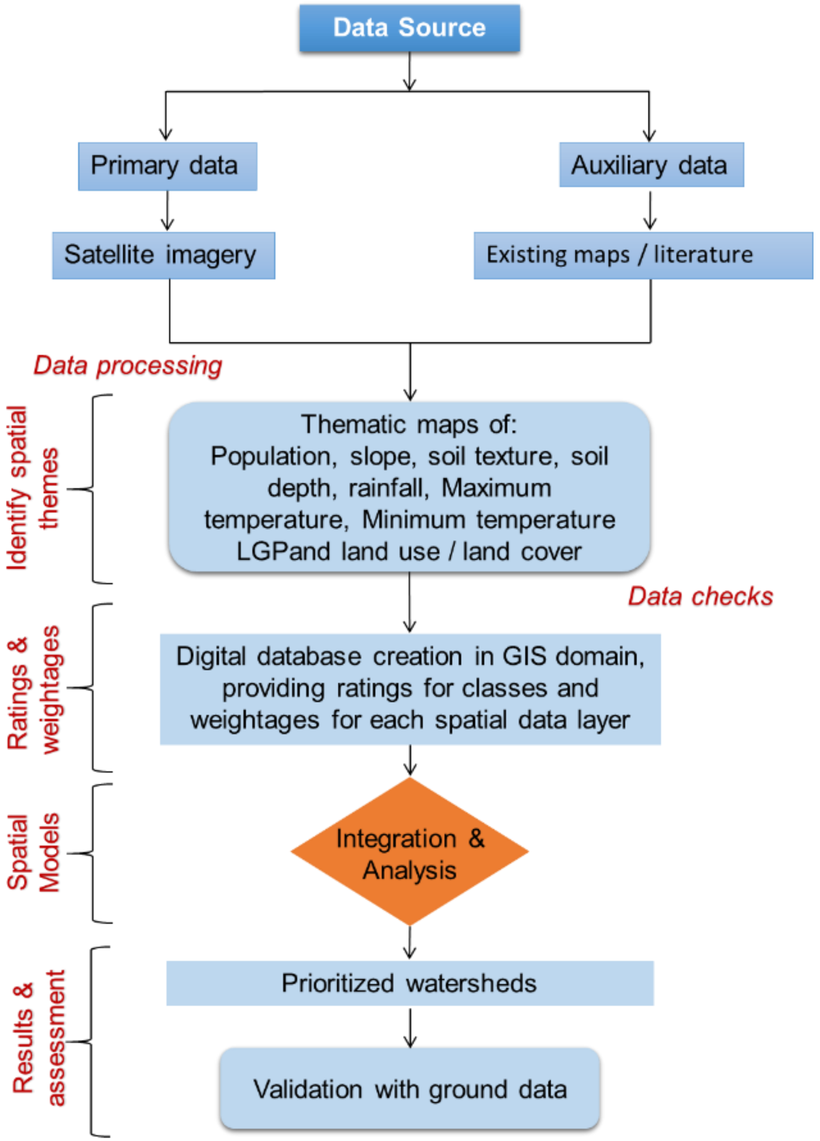
- This study was conducted on Aba Gerima Watershed, Ethiopia
- Identified Croplands and Barrens for the years 2002, 2013 and 2019

Land use / land cover changes in the study area



- Identified LULC changes for Model watershed and also Neighbouring watersheds
- Identified significant impact of watershed intervention in Neighbouring watersheds
- Agriculture productivity was increased
- Crop areas were expanded significantly

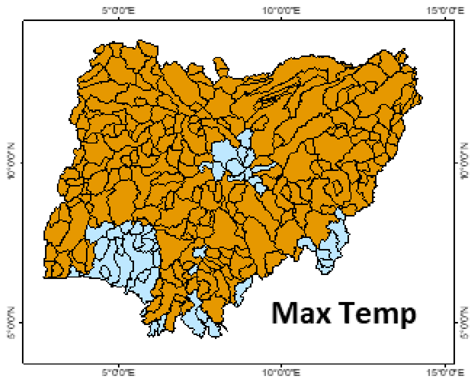
Prioritization of Watersheds across Nigeria

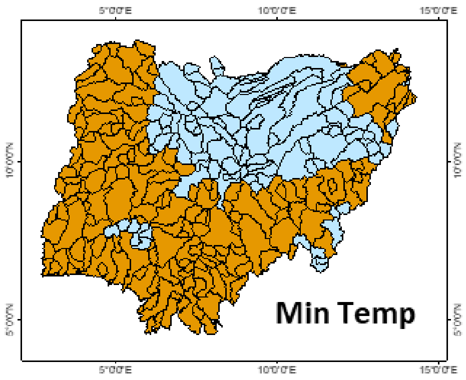


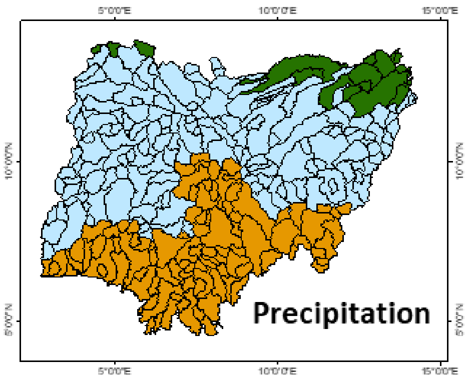
Using biophysical parameters and Machine learning algorithms for agricultural development planning

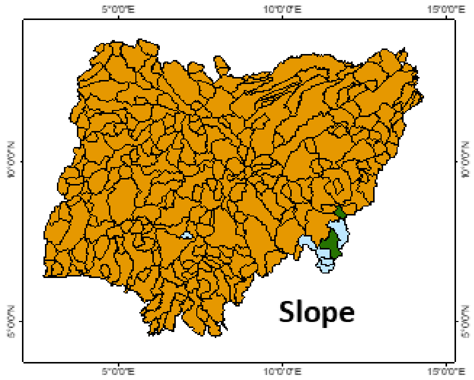
1. Identify critical spatial data layers needed for the Crop suitability model for different agro-ecological regions in Nigeria;
2. Provide the scores (1-4) to spatial data layers and for the weightages to spatial data layers based on expert knowledge;
3. Develop spatial model that will provide answers to relevant questions and identify best sites (e.g., Plantations) based on the spatial data layers and their weightages.

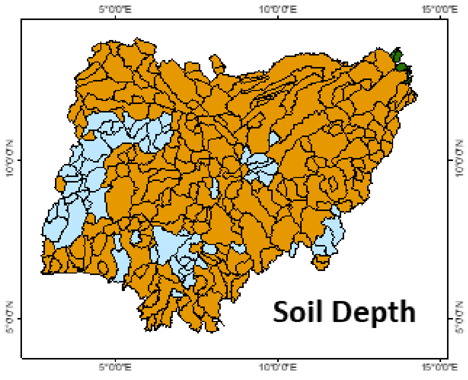
Prioritization of Watersheds across Nigeria

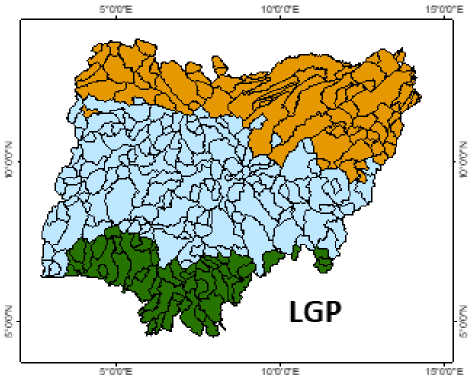


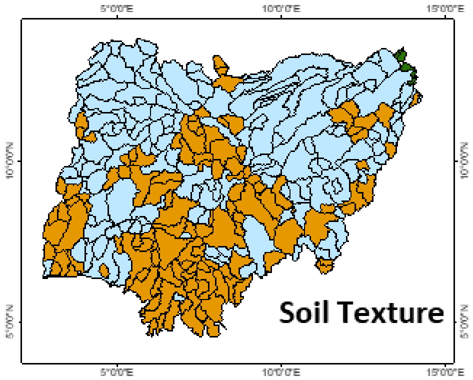






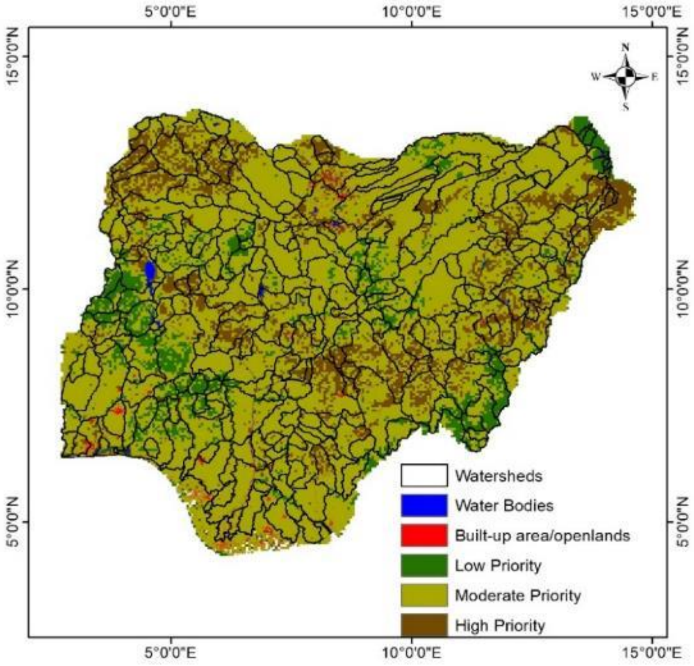




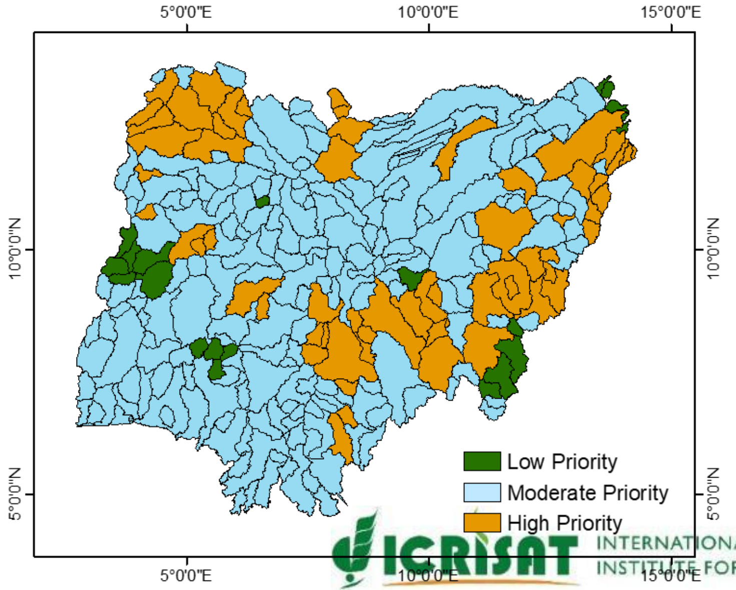


Watersheds - Priority level maps for all thematic layers

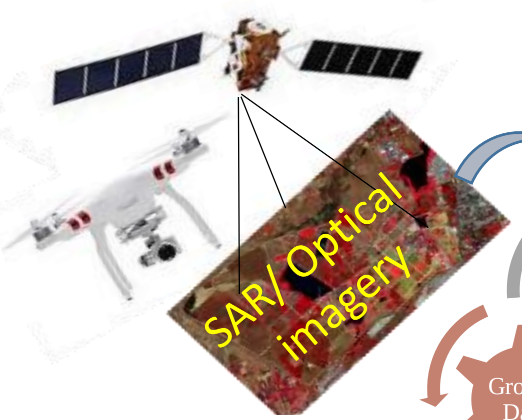
Low Priority
Medium Priority
High Priority

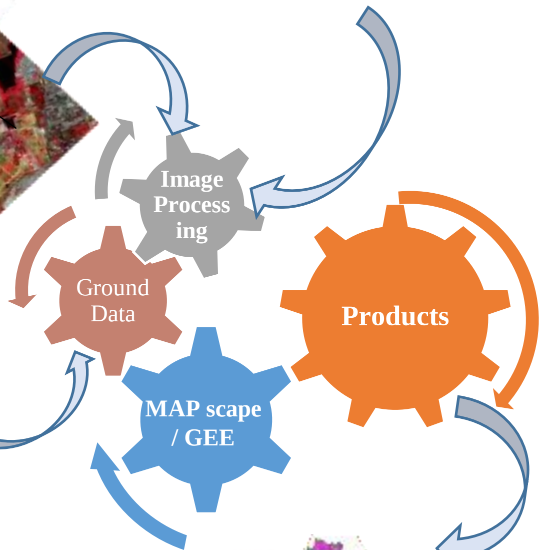


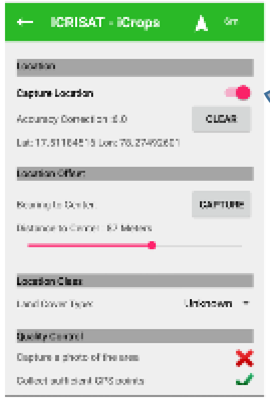
Final watershed Map with priorities

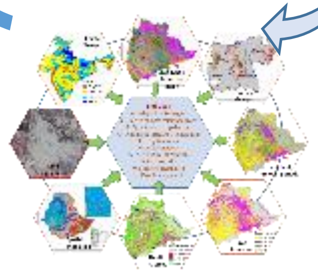


Agriculture Resilience: Linking Insurance and Technology with Climate Adapted Farming Systems









- Cropping pattern
- LGP (SoS, PoS, EoS)
- Water bodies
- Crop stress maps
- Soil properties

- Yield predictions
- Climate analysis
- Crop base advisories

1. Capacitating Farmer Collectives for risk mitigation and resilient communities
2. Developing innovative meso-level insurance products
3. Policy advocacy for main streaming remote sensing based risk assessment

Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

Swiss Agency for Development and Cooperation SDC

ICRISAT INTERNATIONAL CROPS RESEARCH INSTITUTE FOR THE SEMI-ARID TROPICS

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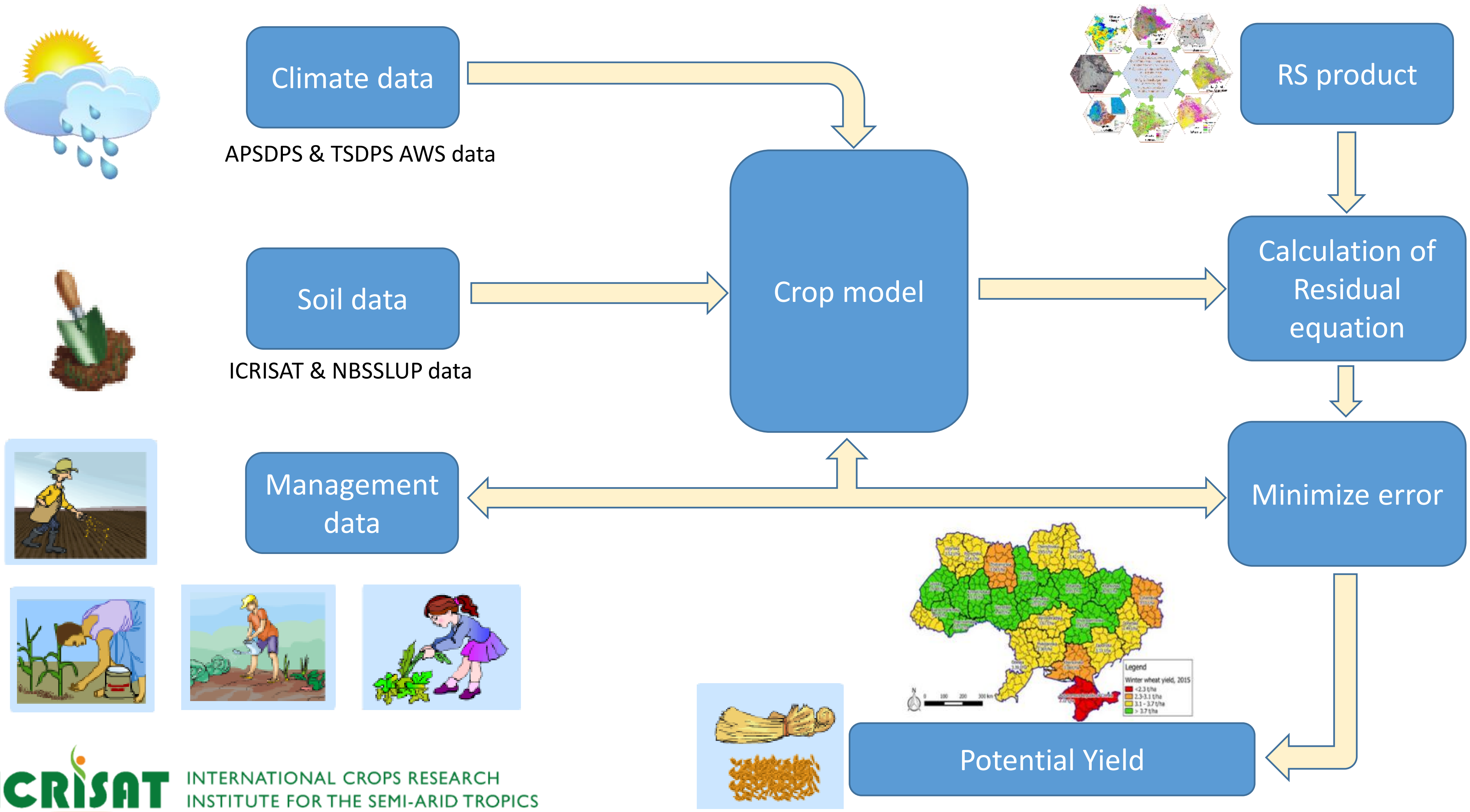
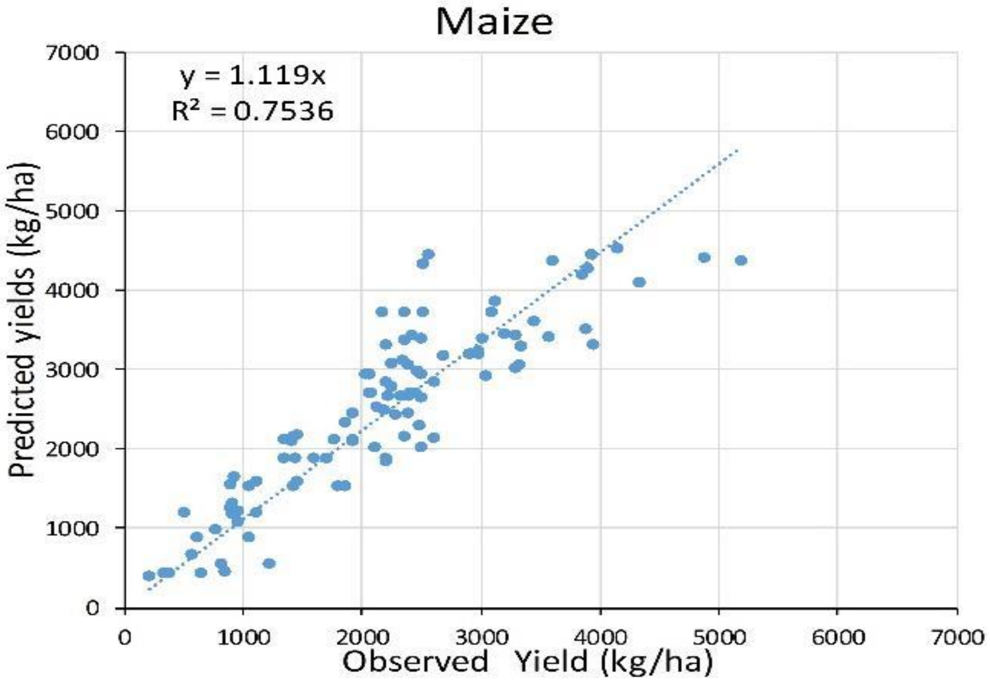
BASIX

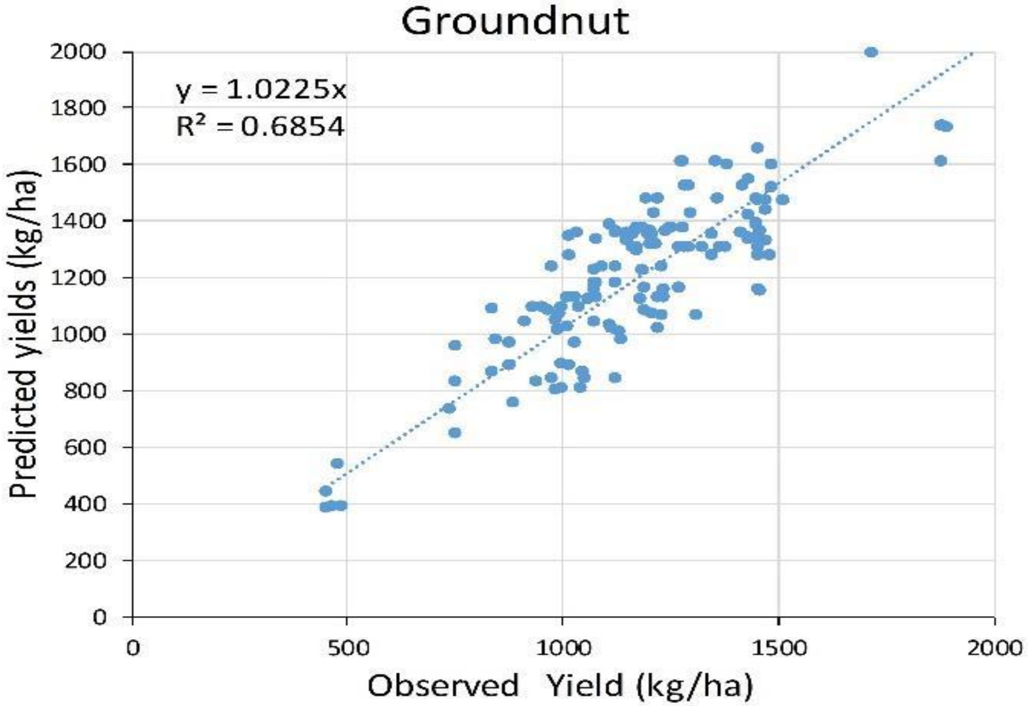
Earth Analytics India

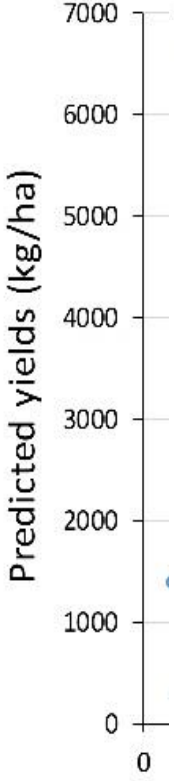
Integrating remote sensing data with crop growth models for crop yield estimation

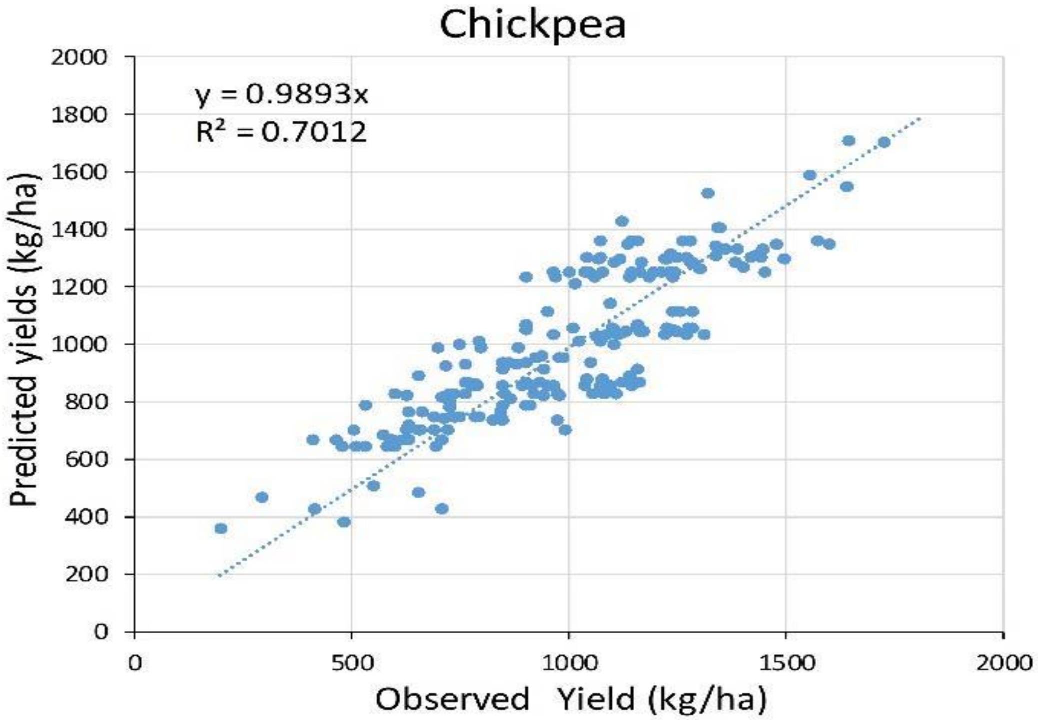


LAI from









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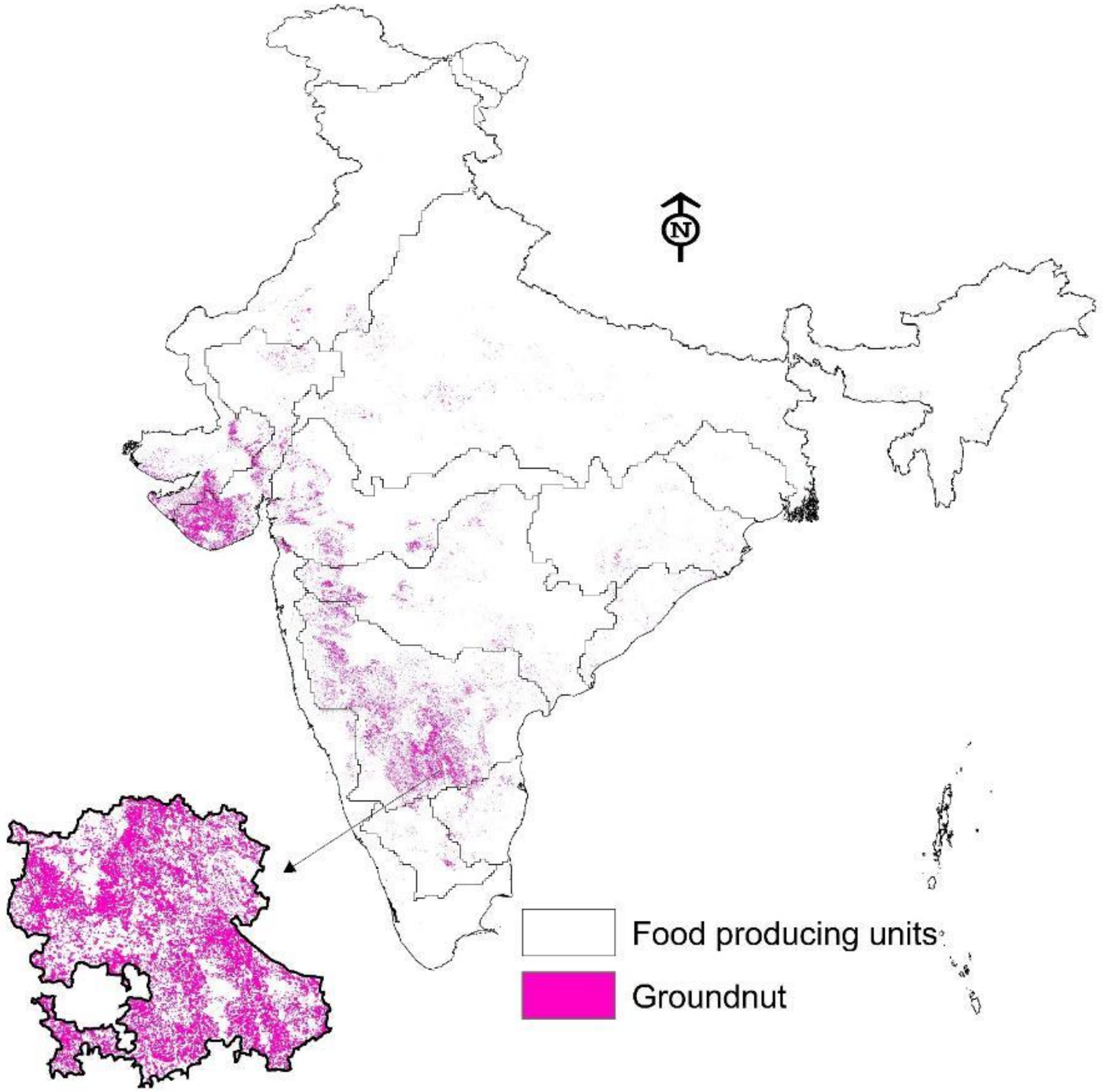
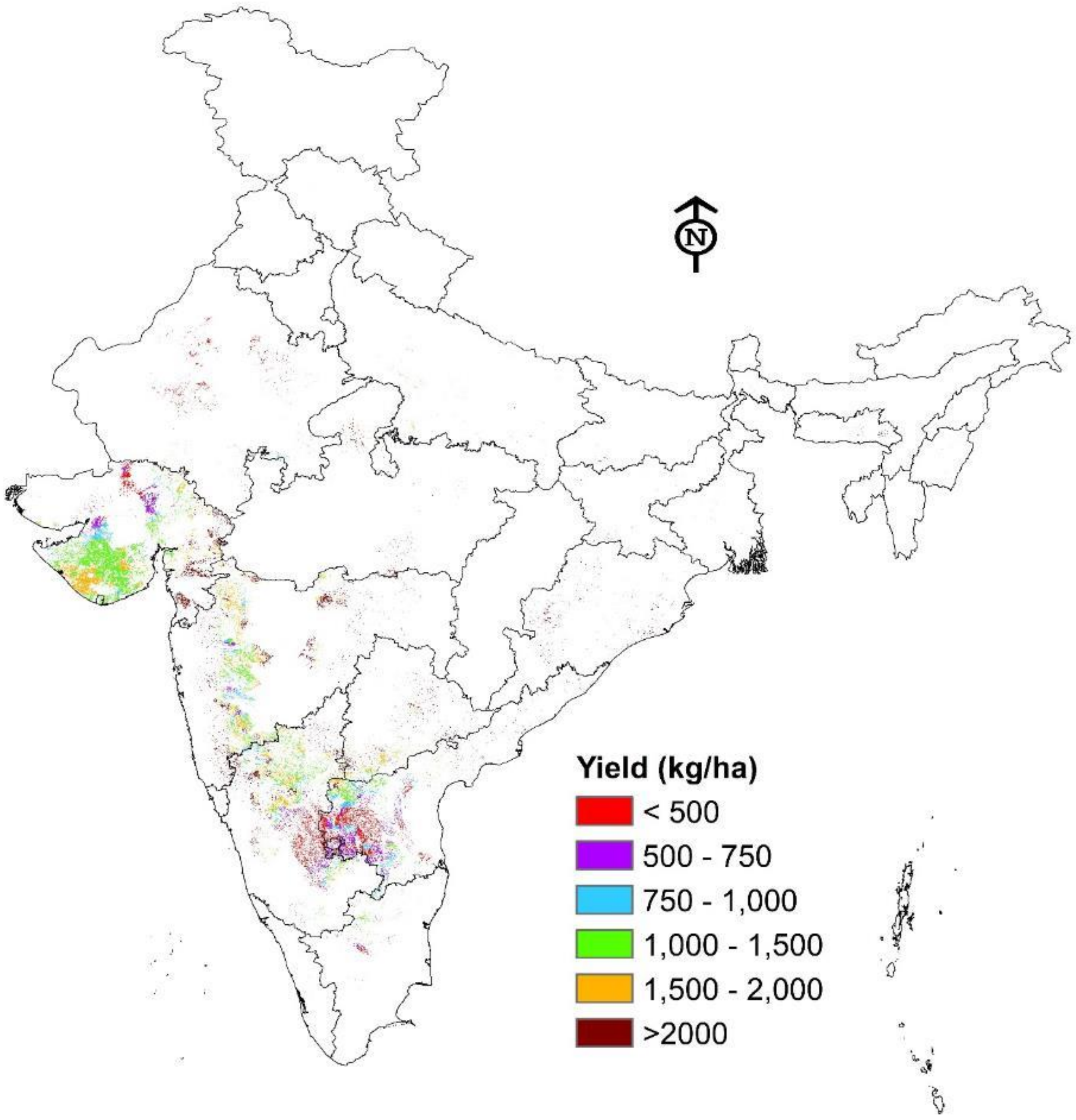
Yield assessment: Groundnut

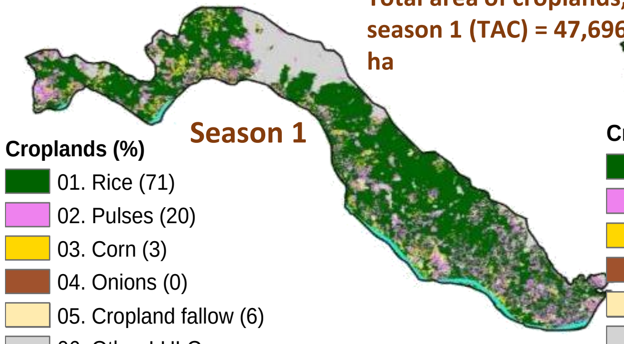




Dakshina et. al (review)

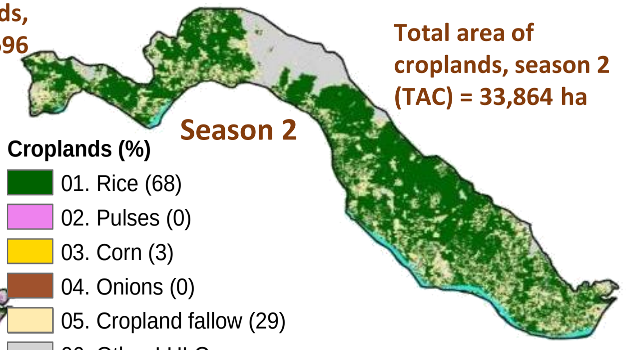
Performance measure and improve productivity: Kadam command area

Baseline Scenario @ present



Total area of croplands, season 1 (TAC) = 47,696 ha

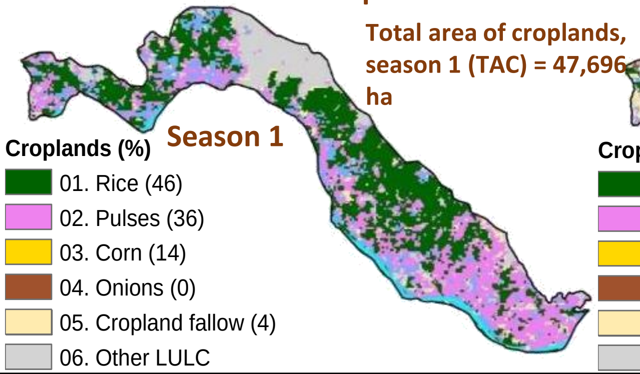
Croplands (%)
- 01. Rice (71)
- 02. Pulses (20)
- 03. Corn (3)
- 04. Onions (0)
- 05. Cropland fallow (6)
- 06. Other LULC



Total area of croplands, season 2 (TAC) = 33,864 ha

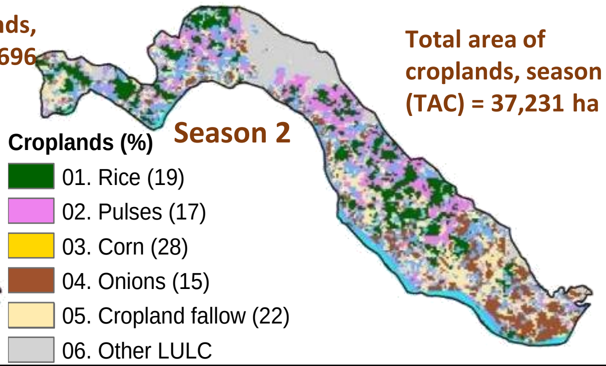
Croplands (%)
- 01. Rice (68)
- 02. Pulses (0)
- 03. Corn (3)
- 04. Onions (0)
- 05. Cropland fallow (29)
- 06. Other LULC

New Scenario with Improved water Productivity and less water consuming crops



Total area of croplands, season 1 (TAC) = 47,696 ha

Croplands (%)
- 01. Rice (46)
- 02. Pulses (36)
- 03. Corn (14)
- 04. Onions (0)
- 05. Cropland fallow (4)
- 06. Other LULC



Total area of croplands, season 2 (TAC) = 37,231 ha

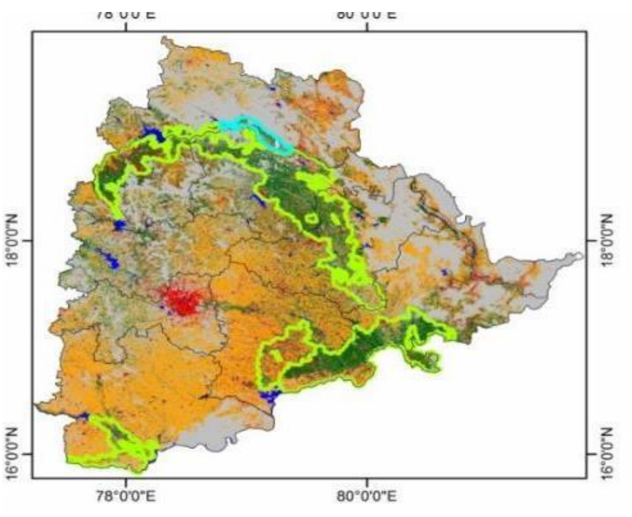
Croplands (%)
- 01. Rice (19)
- 02. Pulses (17)
- 03. Corn (28)
- 04. Onions (15)
- 05. Cropland fallow (22)
- 06. Other LULC

A. In existing cropping scenario high water consuming crop like rice dominates. Also water productivity of rice is poor.

B. So, we propose agriculture that is:

1. water-smart (replacing less water consuming, short duration crops like pulses in some rice areas, especially during season 2);
2. Nutrition rich (e.g., pulses);
3. Increased water productivity (improved "crop per drop" through better management);
4. Climate-smart (e.g., growing less water consuming second crop); and
5. Economic-smart (e.g., ensure farmers are not dependent on one crop markets)

……resulting in a saving of 120 billion liters of water in just 56,606 hectares resulting in "new water" that is used for creating new "water banks" [above-ground (surface water) and below-ground (ground water)].



(Thenkabail & Gumma et. al)

Table A. Kaddam water use in: (A) baseline scenario, and (B) New scenario of improved water productivity and re-allocation of crops

Crop type	Percent of total cropland area in season 1[A,C] (%)	Percent of total cropland area in season 2[A,C] (%)	Water used for producing 1 kg of grain[E,F] (liters)	Yield per hectares in (kg/hectare)	Total water used by all crops in 2 season (liters)
A. Baseline scenario: with business as usual crops at present during season 1 and\or 2					
Rice	71	68	3400	2500	483579280000
Pulses	20	0	1608	1320	20247524352
corn	3	3	1222	6500	19434932400
onions	0	0	345	19000	0
Cropland fallow	6	29	100	0	0
Total Area of croplands (hectares)	47696	33864			532,262 billion liters
Other land cover area (hectares)	8910	22742	Current water use		523 billion liters
Total area (croplands + non-croplands) (hectares)	56606	56606			
B. New scenario: with improved water productivity, re-allocation of less water consuming water-smart, econon					
Rice	46	19	2600	2400	1.81048E+11
Pulses	36	17	1608	1320	49879799165
corn	14	28	1222	6500	1.35842E+11
onions	0	15	345	19000	36607380750
Cropland fallow	4	22	100	0	0
Total Area of croplands (hectares)	47696	37231			403,377 billion liters
Other land use land cover area (hectares)	8910	19375	New reduced water use		403 billion liters
Total area (croplands + non-croplands) (hectares)	56606	56606			
Reduced water use in new scenario			Water Savings		120 billion liters

Gaps & Limitations

Satellite Data

- Optical data with Cloud cover during monsoon season
- Image classification with SAR images are not as good as Optical data because of high noise in SAR data
- Even in optical data, the indices are depend upon local agro-ecological conditions. So, standard algorithms are not applicable

Google Earth Engine

- Not able to standardize automated algorithms for Crop classification;
- Issue with precipitation indices;
- Classification using high resolution SAR data.
  - Crop type Classification techniques;
  - Object-based image analysis/classification techniques;
  - Classification computation time run out;
- Crop Phenology assessments methods like Dynamic Time wrapping methods, etc…whichever is possible.
- Prepare and edit Map composition/layout and export in high resolution jpeg or tiff format;
- Filtering /Smoothing of data : Methods to implement with GEE codes;

Downscaling techniques for the following coarse resolution data sets :

- Soil moisture datasets
- Climate data

Way forward!

- Suitable Rice Fallow Area for intensification of Legume Crops using GEE
- Improving crop water productivity
- Crop stress monitoring using GEE
- GP-level crop yield assessment using technology

Related publications

- Xiong, J., Thenkabail, P.S., Gumma, M.K., Teluguntla, P., Poehnelt, J., Congalton, R.G., Yadav, K., Thau, D., 2017a. Automated cropland mapping of continental Africa using Google Earth Engine cloud computing. ISPRS Journal of Photogrammetry and Remote Sensing 126, 225-244.
- Teluguntla, P., Thenkabail, P., Oliphant, A., Xiong, J., Gumma, M.K., Congalton, R.G., Yadav, K., Huete, A., 2018. A 30-m landsat-derived cropland extent product of Australia and China using random forest machine learning algorithm on Google Earth Engine cloud computing platform. ISPRS Journal of Photogrammetry and Remote Sensing 144, 325-340.
- Gumma, M.K., Thenkabail, P.S., Teluguntla, P.G., Oliphant, A., Xiong, J., Giri, C., Pyla, V., Dixit, S., Whitbread, A.M., 2020a. Agricultural cropland extent and areas of South Asia derived using Landsat satellite 30-m time-series big-data using random forest machine learning algorithms on the Google Earth Engine cloud. GIScience & Remote Sensing 57, 302-322.
- Gumma, M.K.; Amede, T.; Getnet, M.; Pinjarla, B.; Panjala, P.; Legesse, G.; Tilahun, G.; Van den Akker, E.; Berdel, W.; Keller, C. Assessing potential locations for flood-based farming using satellite imagery: A case study of afar region, ethiopia. *Renewable Agriculture and Food Systems* **2020**, 1-15.
- Gumma, M., Thenkabail, P., Teluguntla, P., Oliphant, A., Xiong, J., Congalton, R., Yadav, K., Smith, C., 2017. NASA Making Earth System Data Records for Use in Research Environments (MEaSUREs) Global Food Security-support Analysis Data (GFSAD) Cropland Extent 2015 South Asia, Afghanistan, Iran 30 m V001.
- Gumma, M.K., Tummala, K., Dixit, S., Collivignarelli, F., Holecz, F., Kolli, R.N., Whitbread, A.M., 2020b. Crop type identification and spatial mapping using Sentinel-2 satellite data with focus on field-level information. Geocarto International, 1-17.
- Gumma, M.K, Thenkabail, P.S, Teluguntla P.G, Mahesh R, Irshad, A.M, and Whitbread A.M. (2016). Mapping Rice Fallow Areas for Short Season Grain Legumes Intensification in South Asia using MODIS 250m Time-Series Data. International Journal of Digital Earth 9(10):981-1003
- Oliphant, A., Thenkabail, P., Teluguntla, P., Xiong, J., Congalton, R., Yadav, K., Massey, R., Gumma, M., Smith, C., 2017. NASA Making Earth System Data Records for Use in Research Environments (MEaSUREs) Global Food Security-support Analysis Data (GFSAD) Cropland Extent 2015 Southeast Asia 30 m V001.
- Oliphant, A.J., Thenkabail, P.S., Teluguntla, P., Xiong, J., Gumma, M.K., Congalton, R.G., Yadav, K., 2019. Mapping cropland extent of Southeast and Northeast Asia using multi-year time-series Landsat 30-m data using a random forest classifier on the Google Earth Engine Cloud. International Journal of Applied Earth Observation and Geoinformation 81, 110-124.
- Teluguntla, P., Thenkabail, P., Xiong, J., Gumma, M., Congalton, R., Oliphant, J., Sankey, T., Poehnelt, J., Yadav, K., Massey, R., 2017. NASA Making Earth System Data Records for Use in Research Environments (MEaSUREs) Global Food Security-support Analysis Data (GFSAD) Cropland Extent 2015 Australia, New Zealand, China, Mongolia 30 m V001.
- Xiong, J., Thenkabail, P.S., Tilton, J.C., Gumma, M.K., Teluguntla, P., Oliphant, A., Congalton, R.G., Yadav, K., Gorelick, N., 2017b. Nominal 30-m cropland extent map of continental Africa by integrating pixel-based and object-based algorithms using Sentinel-2 and Landsat-8 data on Google Earth Engine. Remote Sensing 9, 1065.

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Thank You

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