

Smart Precision Agriculture Monitoring using Drones and IoT Network (Indian Institute of Technology Hyderabad, India)

DST-JST funded Indo-Japan Project – DSFS – Data Sciences Farming Sciences – Data sciences based farming support system for sustainable crop production under climate change

Indian Institutes:

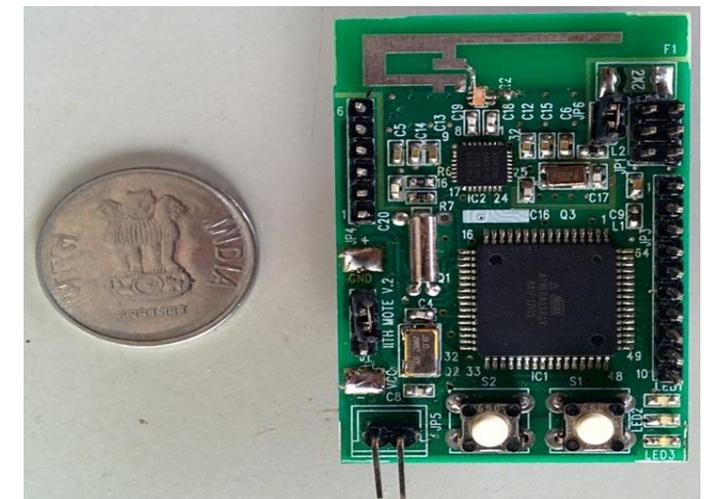
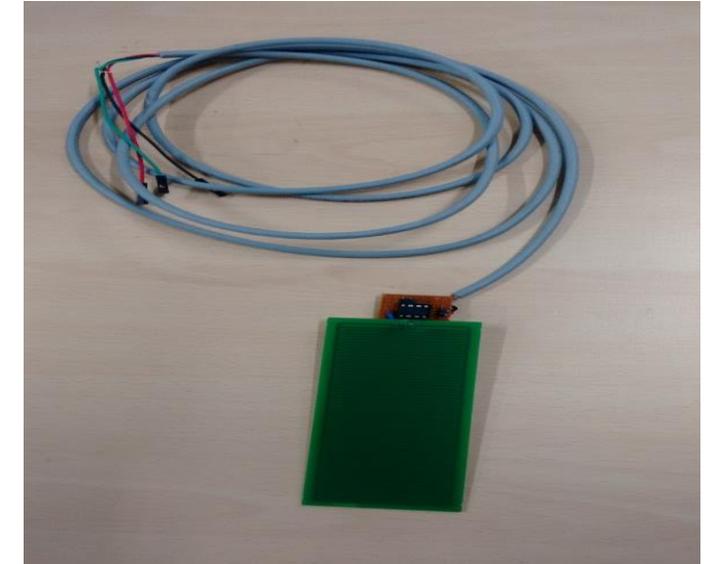
IIT Hyderabad, IIT Bombay, IIIT Hyderabad, PJTSAU

Japan Institute:

University of Tokyo

IoT Network for Smart Agriculture

- We have deployed IoT network in Maize and Rice fields.
- We are monitoring:
 - ❑ **Soil Parameters:** Soil Moisture and Soil Temperature
 - ❑ **Environmental Parameters:** Ambient Temperature, Humidity, Light Intensity and CO2 concentration.
- We have in-house developed **IITH mote** as a sensor node and the sink.
- To upload the data from sink, we have interfaced **Intel Edison board** and **4G modem** with IITH mote (the sink).
- We have developed a soil moisture sensor in our WiNet Lab IITH.
- We are using sensor for:
 - ✓ Light Intensity **BH1750**
 - ✓ Humidity and Ambient Temperature: **DHT11**
 - ✓ CO2 concentration: **Figaro's CDM4161A**
 - ✓ Soil Temperature: **Thermister – 10kΩ**
 - ✓ Soil Moisture: **In-house developed**

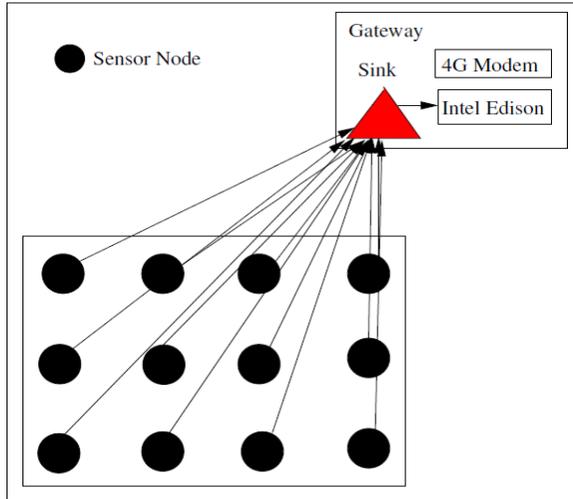


IoT Network Deployment in PJTSAU Fields

Online Agri_Data



http://iot.iith.ac.in:8084/IOT/agri_index.jsp



Sensor Node

Node_id	Type	Soil moisture	Soil Temp.	Ambient Temp.	Humidity	Light Intensity	CO2
99	Sink	NA	NA	NA	NA	NA	Yes
10	Sensor node	Yes	Yes	Yes	Yes	Yes	NA
20	Sensor node	Yes	Yes	Yes	Yes	NA	NA
30	Sensor Node	Yes	Yes	Yes	Yes	NA	NA
40	Sensor node	Yes	Yes	Yes	Yes	NA	NA
50	Sensor node	Yes	Yes	Yes	Yes	NA	NA
60	Sensor node	Yes	Yes	Yes	Yes	NA	NA
70	Sensor node	Yes	Yes	Yes	Yes	NA	NA
80	Sensor node	Yes	Yes	Yes	Yes	NA	NA



Maize Field



Rice Field

Development and Calibration of Soil Moisture Sensor



Proposed Sensor Probe



Calibration @ Lab

Performance Analysis

Capacitance in different materials

Probe Type	Air _{cap} (pF)	Water _{cap} (pF)	S (pF / % VWC)
IDT	58.326	1416.56	13.57
CPC	12.5	1429	14.165
Our Sensor	16.9	1782	17.651

Penetration Depth

Probe Type	Penetration Depth (mm)
IDT	5
CPC	20
Our Sensor	22

Our sensor probe cost Rs. 550 /- which is cheaper than commercially available sensor probe.

Soil Moisture Calibration

Calibration in Real Field

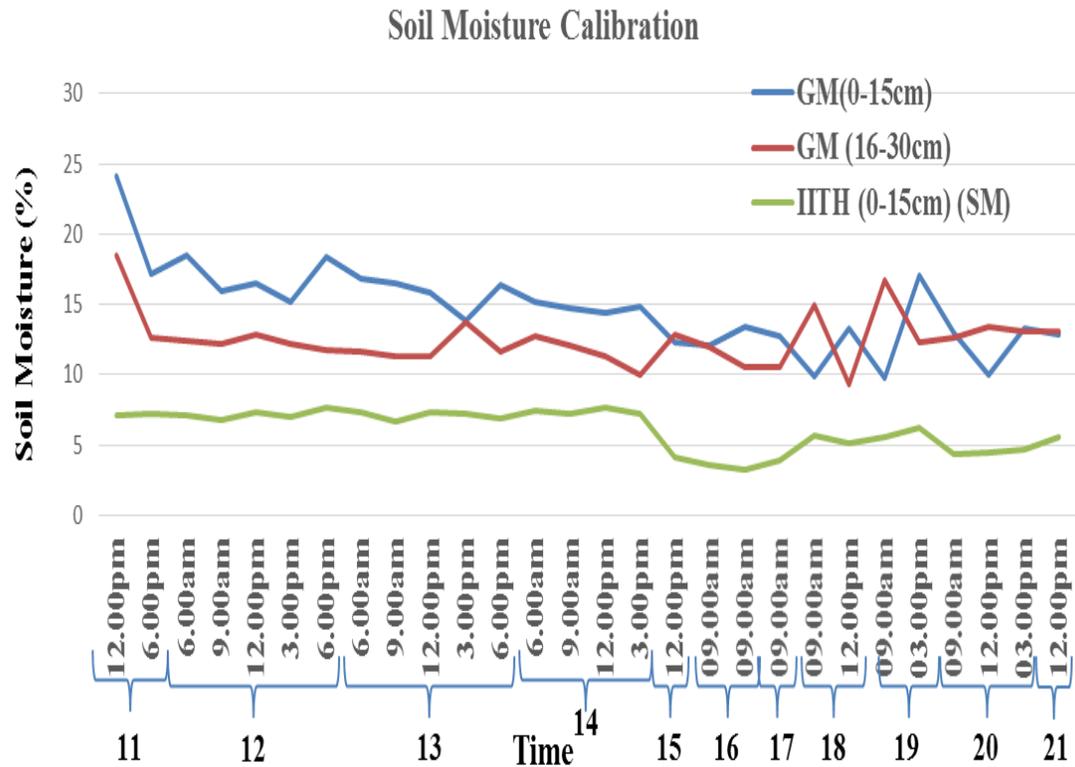
- Calibration done using gravimetric method

Calibration in Lab

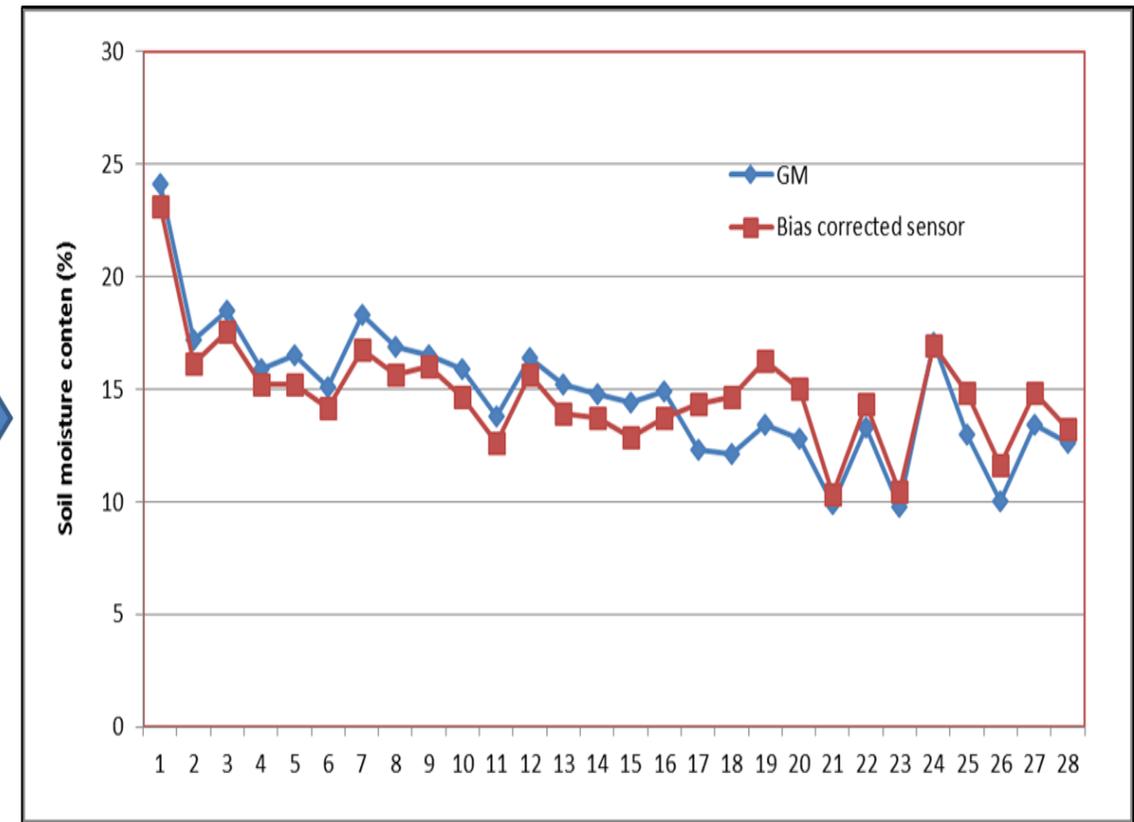


Result of Calibration in Real Field

➤ After bias correction the sensor closely following the trend

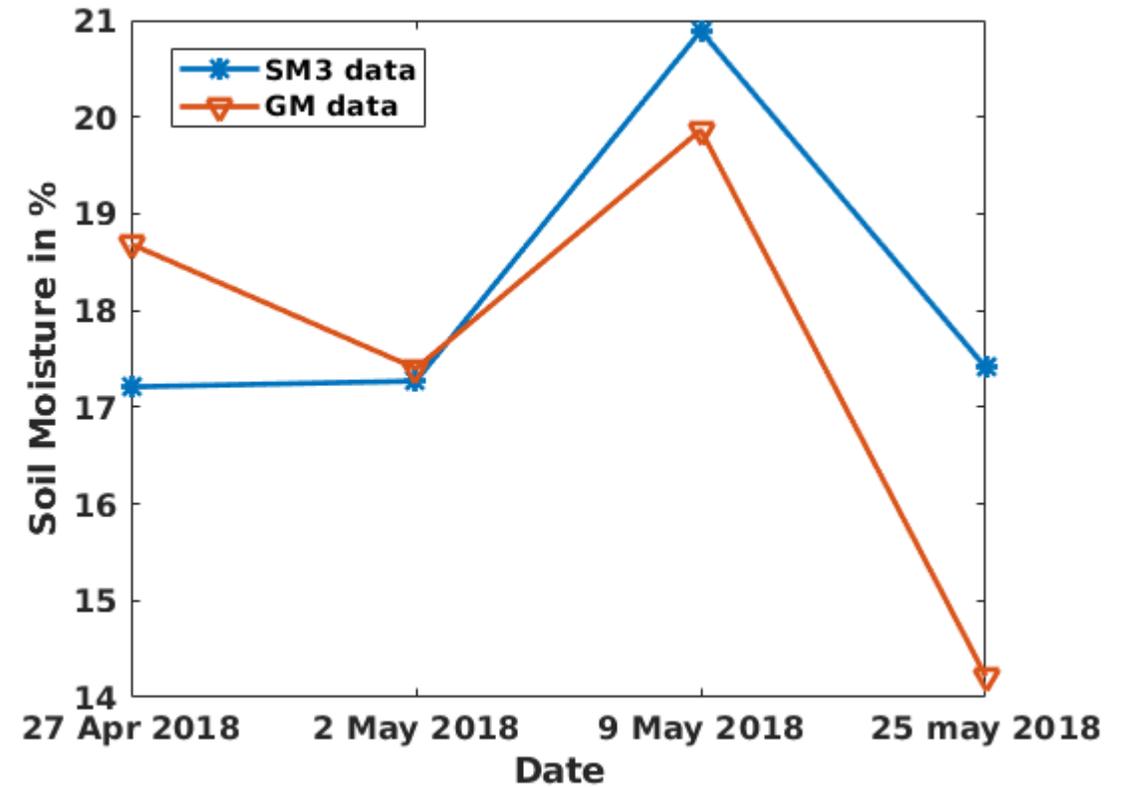
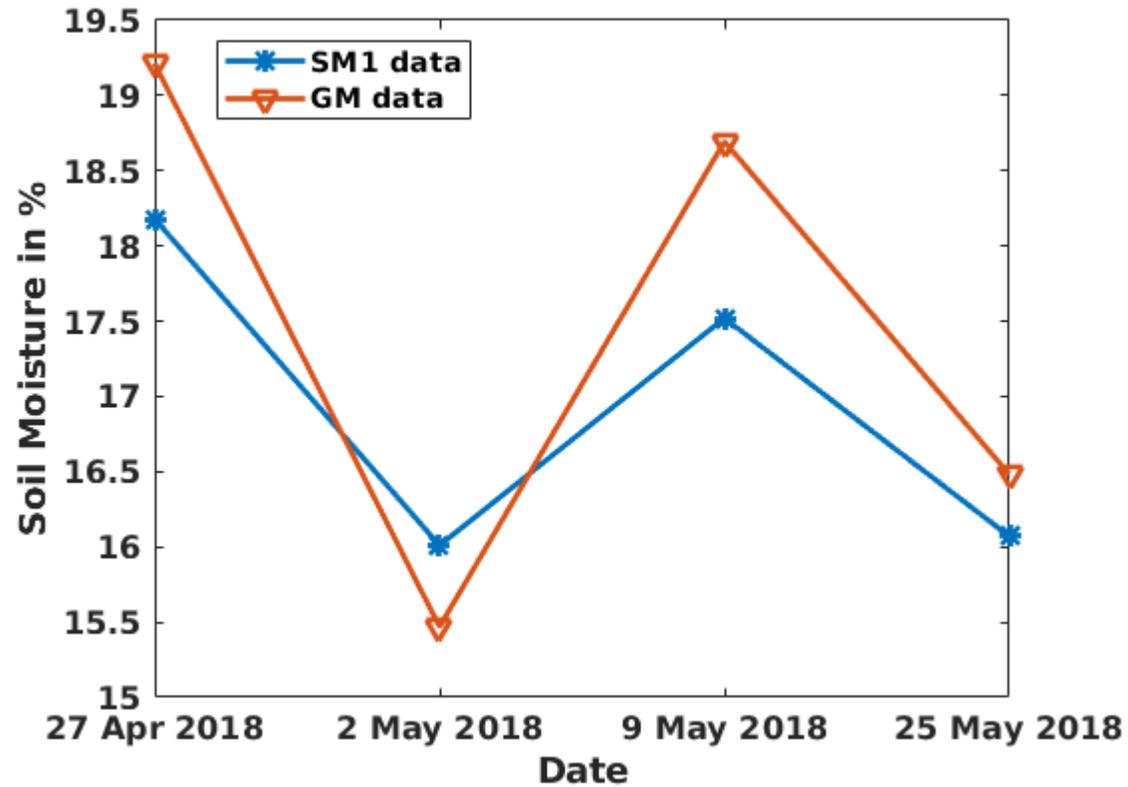


Bias Correction

Soil Moisture Probe on Paddy (Rice) Field

□ Our probe correctly capturing status the soil moisture on the field.

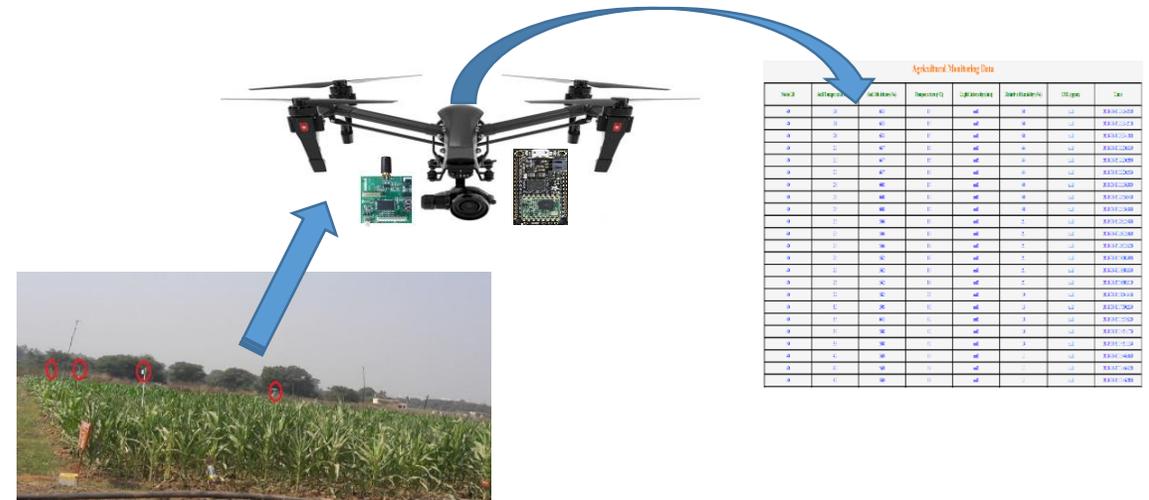
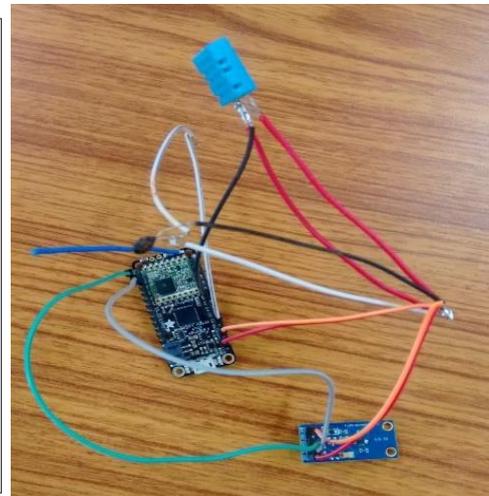
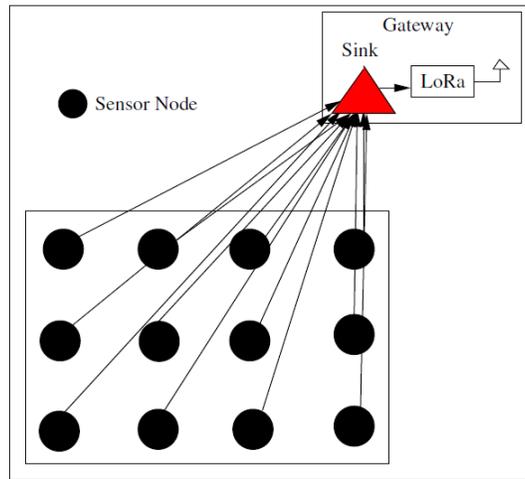


Ongoing Work:

❑ We will replace gateway and will make it based on Raspberry pi and 4G Dongle based.

❑ We will deploy LoRa based sensor nodes.

❑ Drone/Mobile Sink based data Gathering



Precision Agriculture using Drone with different sensors

High Throughput Phenotyping - Drones

Drone Image Processing

□ Drone can be a key factor

- ✓ To accelerate the process of phenotyping
- ✓ Optimize the use of agronomic inputs like: water, fertilizers, pesticides etc.
- ✓ Along with RGB, Multispectral images helps to generate quantitative information of crop.

□ We have

- ✓ Paddy rice of 216 breeds(varieties)
- ✓ Maize crop with different treatment
 - Three different date of sowing
 - Three different nitrogen treatment
 - Three different irrigation

➤ Phenotyping Using Drone Images

objective is to

- Estimate the canopy coverage, plant height, and growth rate of rice.
- Count the number of filled and unfilled spikelets of rice.

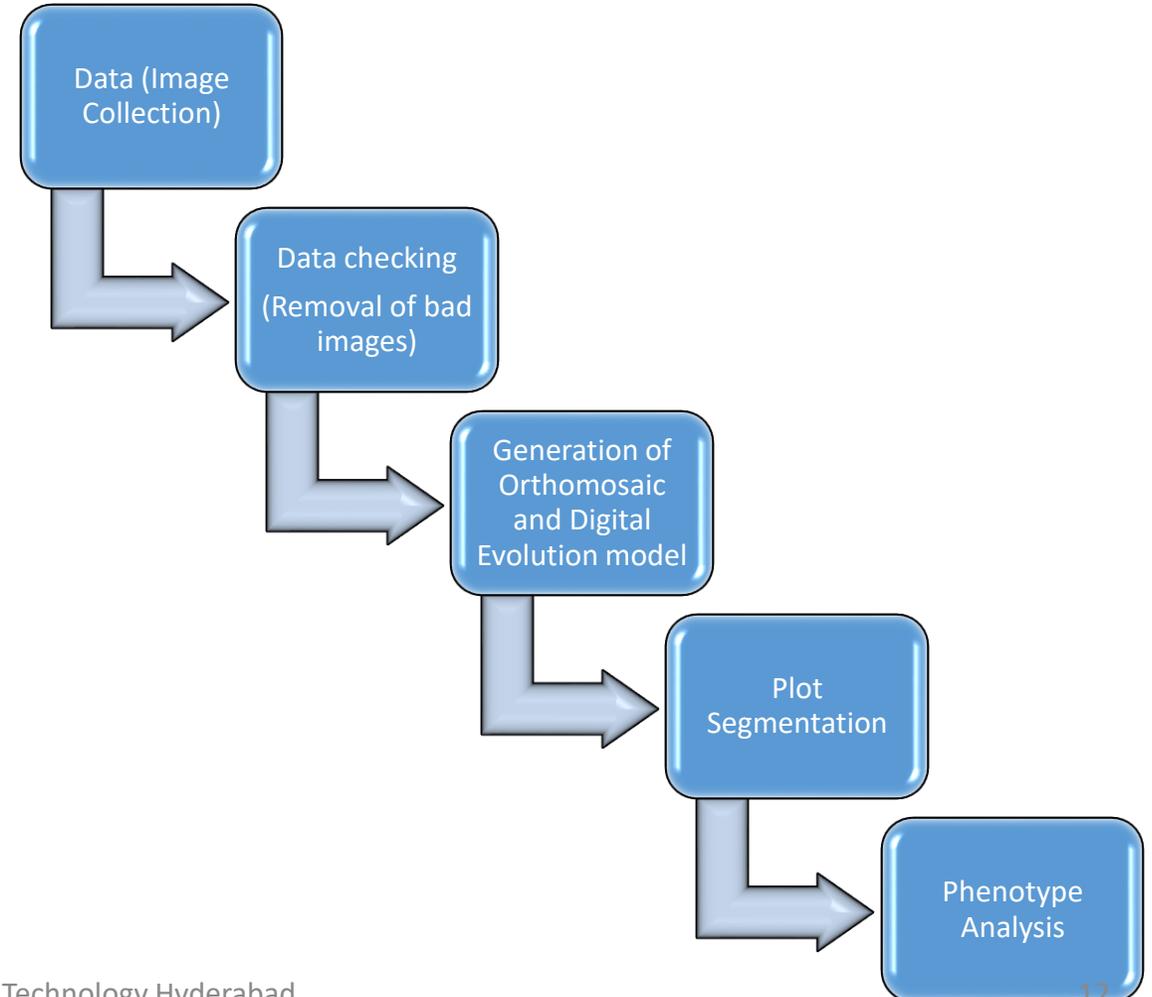


Orthomosaic of the Rice field

Field lay-out of Aerobic RIL mapping population
Kharif 2017

		Rep-I								REP-II							
BUND	27	85	40	96	94	207	87	108	203	130	178	135	53	122	96	84	1
	26	95	13	70	42	214	37	137	118	160	83	133	89	187	200	138	203
	25	52	212	122	65	152	4	116	196	73	14	77	18	69	123	113	213
	24	166	210	109	188	197	2	213	23	39	48	158	191	140	13	82	199
	23	125	93	107	160	44	149	182	105	47	114	28	22	57	185	80	8
	22	7	41	158	90	86	190	26	200	132	42	55	150	101	196	148	110
	21	163	21	172	24	171	30	157	183	153	124	58	212	17	126	19	136
	20	177	178	60	1	58	29	154	22	65	4	11	52	98	33	128	10
	19	181	165	19	129	84	151	127	14	44	20	164	29	172	86	61	118
	18	15	216	156	53	179	144	82	51	143	131	2	214	206	78	216	75
	17	124	148	101	138	31	47	209	208	7	62	109	192	6	27	35	174
	16	142	153	39	168	73	170	11	175	188	194	145	215	112	45	9	161
	15	113	194	69	198	67	112	133	83	202	189	163	76	151	100	56	167
	14	34	49	20	106	150	43	74	117	103	171	141	168	104	207	30	190
	13	32	162	167	33	134	91	146	136	177	37	173	119	165	208	211	16
	12	9	16	81	131	173	79	50	66	102	152	74	5	180	166	210	154
	11	191	104	68	35	38	123	110	64	127	23	107	99	66	49	125	183
10	54	28	97	8	199	72	143	132	46	34	195	60	181	209	156	68	
9	10	46	169	114	215	56	120	100	85	182	41	79	25	108	3	71	
8	48	18	159	17	3	211	45	80	50	120	64	21	176	24	193	134	
7	139	76	201	161	78	189	176	186	106	81	116	170	92	88	142	67	
6	36	145	184	180	140	202	121	195	54	157	93	198	149	15	115	111	
5	111	130	206	174	62	128	119	147	121	144	137	169	197	72	63	70	
4	89	187	135	75	164	88	63	141	201	95	155	159	87	117	90	59	
3	55	98	102	192	57	5	126	92	162	139	205	40	36	26	91	146	
2	27	71	99	103	204	115	193	185	43	175	105	186	129	179	147	184	
1	25	59	155	12	6	77	61	205	97	32	38	31	94	204	12	51	
	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8	
	9.4 mt								1mt	9.4 mt							
	ROAD																

Flow of Drone Image analysis



Drones in the Field:



How to prepare the field and drone for flight

- These are following things we should take care before flying the drone and during the flight of drone:
 - ✓ GCPs are very important for stitching the drone images with high accuracy and to get very good orthomosaic. **We can tolerate the error of 10cm in the projection of GCPs while generating orthomosaic.** Therefore the GCPs should be made very precisely.
 - ✓ We need proper overlapping between images taken by drone therefore the drone speed and interval of capturing the images should be checked properly.
 - ✓ The drone-camera should be checked for the focus. It should be properly focused at the crop.
 - ✓ **We must take the picture of calibrated reflectance panel (CRP) before and after capturing the field images with RedEdge-multispectral camera. Those images of CRP are for calibration and estimation of incoming solar radiation while calculating different indices for crop.**
 - ✓ **We must check that the GPS location of images (taken by both the cameras) should be embedded in the images.**

Field	No of Images	No. of Images
Paddy	120~130 (10m)	80~90 (15m)
Maize	240~260 (15m)	160~190 (30m)



GCP

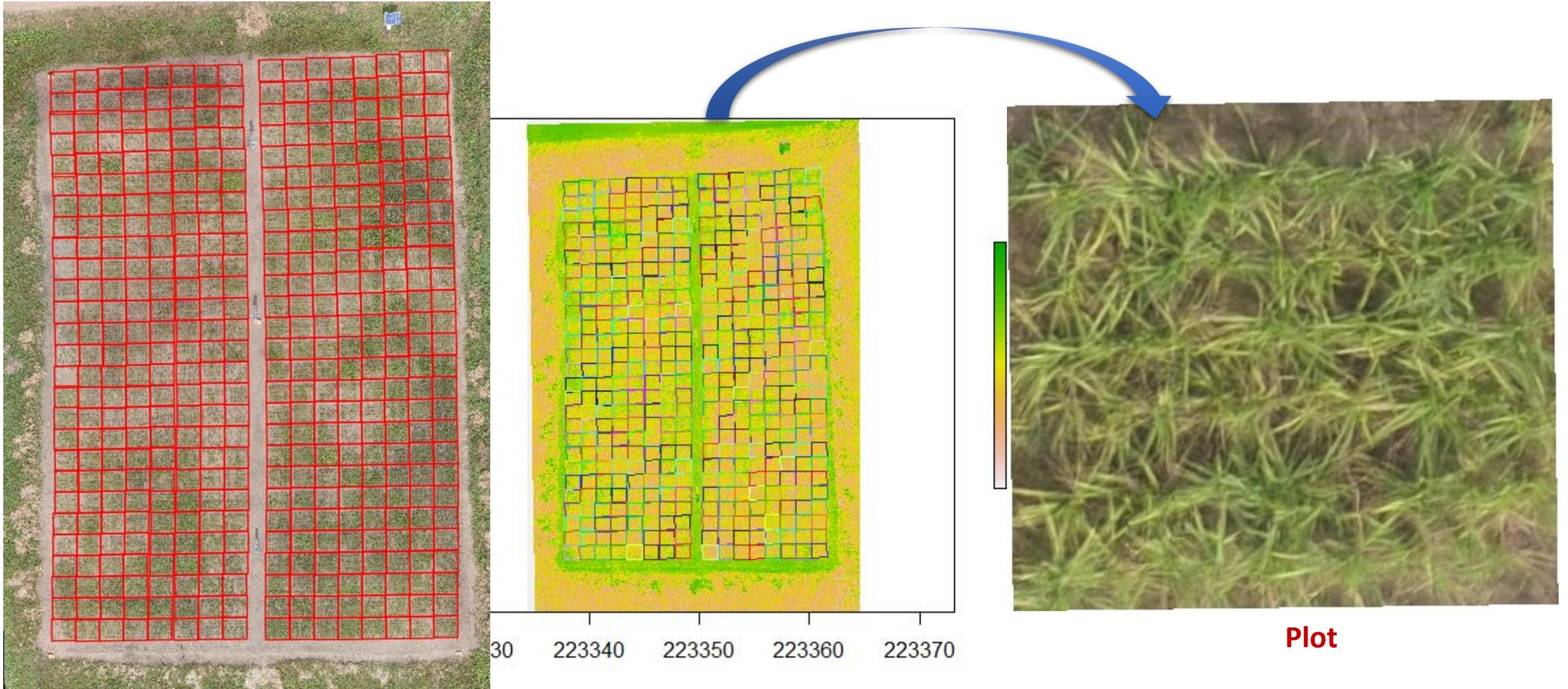


Area of Paddy Field = 603.8 m² (approx.)



Orthomosaic of Maize Field

Segmentation with Plot Number



Segmentation

Plot

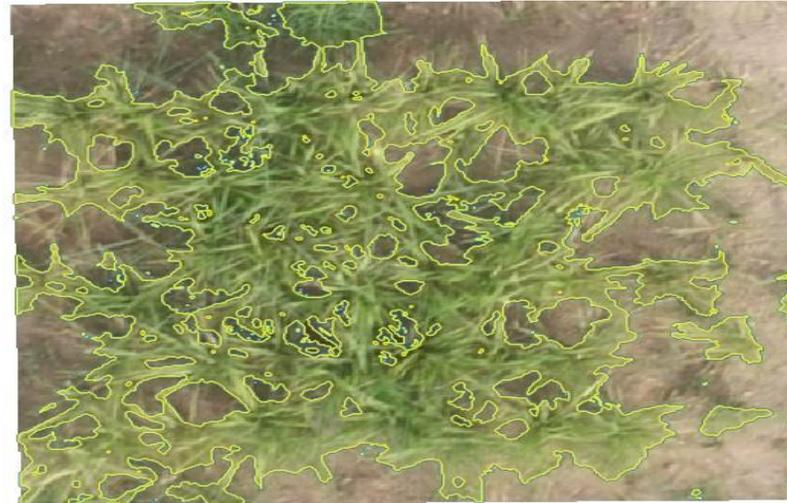
Canopy Coverage Estimation

Original Image

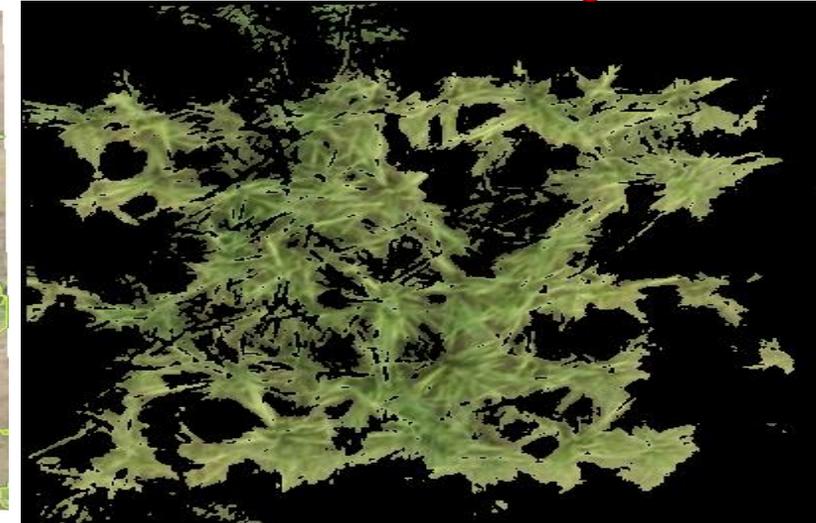
EasyPCC



K-Means Clustering



Automatic Thresholding-Otsu's



- Higher the canopy coverage, better is the health of crop. To estimate the canopy coverage, segmentation of crop from background is a key factor.
 - K- Means Clustering
 - EasyPCC (Decision Tree Based Tool)
 - Object Based Automatic Thresholding Method (Otsu)
- Canopy coverage : ratio of total number of green pixels in an image to the total number of pixel in the image.
- Otsu's method was performing well in comparison to K-means and EasyPCC. In this method, ExGI (excessive green index) was used as a classifying feature and its optimum threshold was calculated for crop and background segmentation.

Plots Classification

□ Rule of Classification

➤ Dense:

- $C_{plot} = \text{Max to } 70\% \text{ of } C_{max}$

➤ Medium:

- $C_{plot} = 40\% \text{ to } 70\% \text{ of } C_{max}$

➤ Sparse:

- $C_{plot} = \text{below } 40\% \text{ of } C_{max}$

✓ C_{max} = Maximum Canopy Coverage

✓ C_{plot} = Canopy Coverage of Plot



Dense



Medium



Sparse

Plots on 24 Nov 2017			
Rep	Dense	Medium	Sparse
I	51	142	23
II	17	174	25

Rate of Change of Canopy Coverage

$$\% \text{ Change in CC} = \frac{\text{Change in Canopy Coverage}}{\text{Initial Canopy Coverage}} \times 100$$

**Maximum growth found in Plot 88 of REPI:
Change in Canopy Coverage= 0.2970185
Growth = 196.129%**

Change in CC between 3 Nov 2017 to 17 Nov 2017		
Plot No	Change in Canopy Coverage	Change (in %)
7	0.049656654	36.37
10	0.079912061	47.7
23	0.063909244	24.6
99	0.059133435	28.1
106	0.005366008	1.6
115	0.090183903	30
143	0.197132929	99.54
161	0.138157305	69
170	0.154962131	80.73
206	0.108572103	37.24
211	0.161081037	64.4

Vegetation Indices

Acronym	Index	Formula
NDVI	Normalized Difference Vegetation Index	$(R_{NIR} - R_R) / (R_{NIR} + R_R)$
GNDVI	Green-NDVI	$(R_{NIR} - R_G) / (R_{NIR} + R_G)$
SAVI	Soil-Adjusted Vegetation Index	$(R_{NIR} - R_R) / (R_{NIR} + R_R + 0.5) \times 1.5$
OSAVI	Optimized Soil-Adjusted Vegetation Index	$(R_{NIR} - R_R) / (R_{NIR} + R_R + 1.6) \times 1.16$
PSRI	Plant Senescence Reflectance Index	$(R_R - R_B) / (R_{NIR})$
SIPI	Structure Insensitive Pigment Index	$(R_{NIR} - R_B) / (R_{NIR} + R_B)$
TVI	Transformational Vegetation Index	$\sqrt{NDVI + 0.5}$

R_x - represents reflectance in X band

- We have used canopy coverage and vegetative indices to estimate biomass.
- For plant height, we have used canopy coverage, vegetative indices and biomass to estimate plant height.
- We have used Artificial Neural Network (ANN) to train our model.
- We have biomass and plant height data for three dates 24 Nov, 1 Dec and 8Dec.

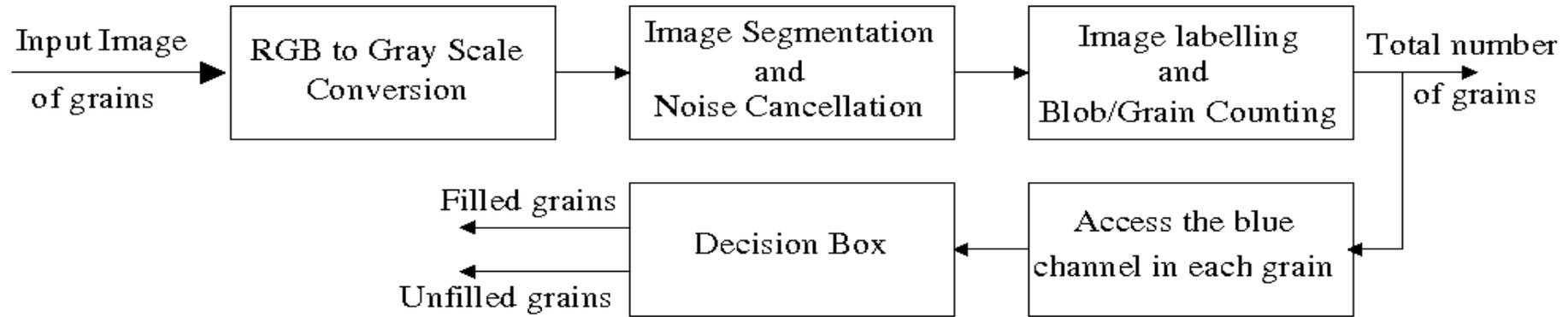
ongoing Work

- **Important Target:**
 - Improvement in generating orthomosaic
 - Quality improvement of image collected from drone
 - Quality improvement of image segmented from orthomosaic
- **Crop Weed Segmentation**
 - Pixel-wise labelling of data.
 - Semantic segmentation using different deep learning models
 - Estimation of weed density in the field
- **Target on Paddy field**
 - Head detection and counting
 - Estimation of Plant Height
 - Estimation of Biomass
 - Panicle Counting and Yield Estimation
- **Target on Maize field**
 - Plant counting
 - Leaf rolling detection or stress analysis

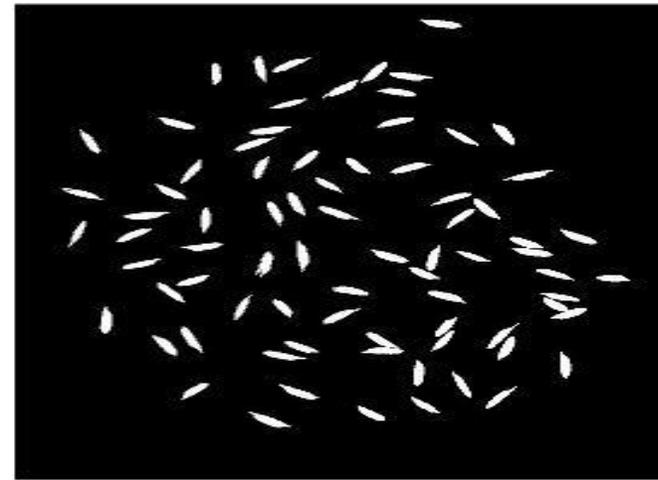
Automatic Counting of Filled and Unfilled Grains of Rice

- We propose a novel automated algorithm based on image analytics to count the number of filled and unfilled spikelet's/grains.
- In this algorithm, we use connected components algorithm to count the number of grains in the image.
- The filled and unfilled grains in the image is determined based on the discrimination observed in the blue component of the RGB image.
- The propose algorithm, when tested on 20 images, result with a root mean square error (RMSE) of 0.96 in detecting the number of grains, 2.9 and 3.2 in counting the filled and unfilled grains in the image.

The Proposed Algorithm



Threshed grains



Segmented Grains

Crop & Weed Segmentation

■ Why Weed Detection?

- Weed is directly related to crop health and yield. Weeds compete with crop plants for plant nutrients, soil moisture, space and sunlight.
- A recent estimate shows that weeds cause annual loss of Rs.19.8 billion to Indian Agricultural.

■ Dataset Collection

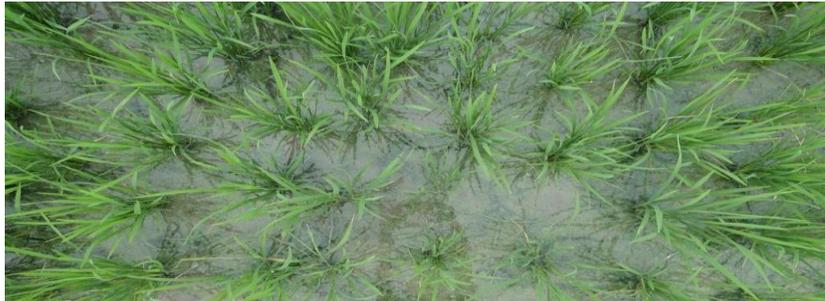
- Presence of 4-5 different types of weed in the field along with rice plant.
- We have used static camera to capture the images of plots containing both crop and weed.
- Images consisting of rice plant were taken after the removal of weed from the rice field.

■ Method Used

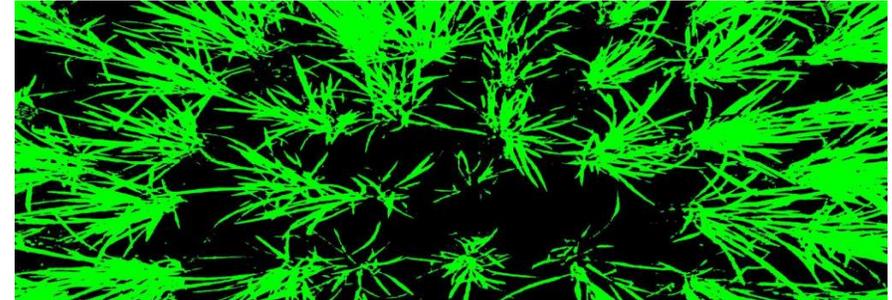
- We have used Fusion-Net architecture based on a convolution auto-encoder consisting of an encoding path and the symmetrical decoding path.
- Images which consists of only crop & only weed were given as different color mapping using clustering method.
- Those images were used to train the Fusion-Net model.
- The images which consists of both crop & weed were used to test the model.

Development of Training Data

Training Images	Images having only paddy	65
	Images having only weed	100
Testing Images	Images having both weed and paddy	100



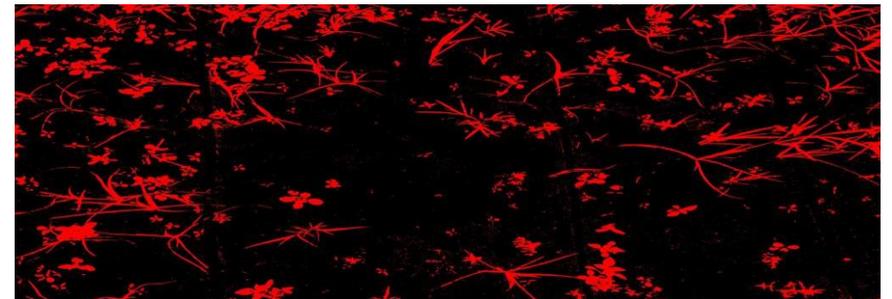
Paddy Crop



Labeled Image



Weed



Labeled Image

Weed in Rice Field

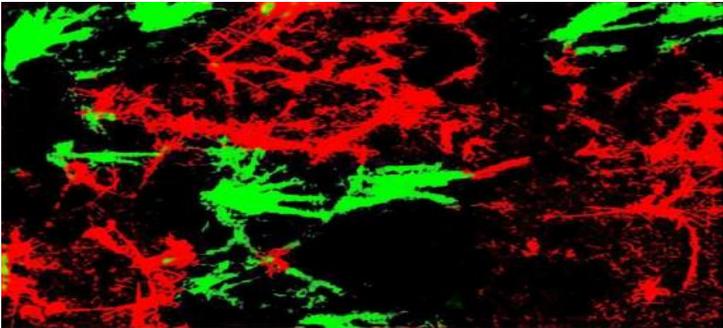
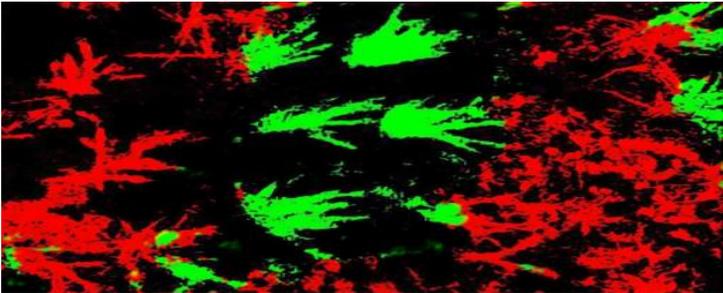
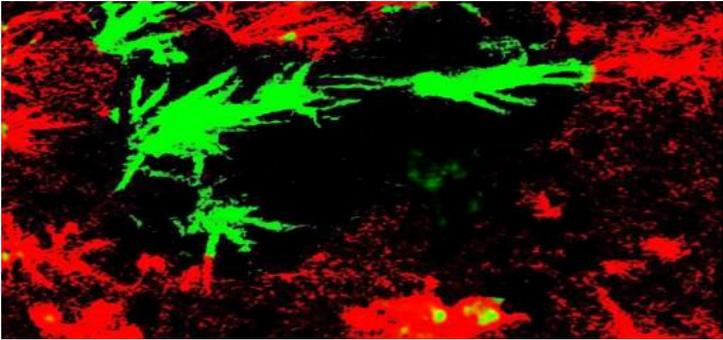


Preliminary Result

Input Image



Predicted Output



ongoing Work

- Development of generalized algorithm for discrimination of panicle and yield estimation
- Improvement in detection of all type of weed in the crop field.
- Panicle counting – yield estimation

Awards and Publications:

□ Awards:

- ✓ Best oral presentation at **ICRISAT CORTEVA Plant Science Symposium 2018** at ICRISAT, Patancheru, Hyderabad India.

□ Publications:

➤ Conference

- ✓ Soumil Heble, Ajay Kumar, K.V.V. Durga Prasad, Soumya Samirana and P. Rajalakshmi, "A Low Power IoT Network for Smart Agriculture", **2018 IEEE World Forum on Internet of Things (WF-IoT), Singapore, 2018.**
- ✓ M. Prashant, Nagarjuna and P. Rajalakshmi, "Energy Efficient Mobile Data Gathering", **Twenty Fourth National Conference on Communications (NCC) 2018.**
- ✓ M. Taparia, A. Kumar, P. Rajalakshmi, B. Marathi. and U.B Desai, "A Threshold Based Segmentation Method For Estimating Canopy Coverage of Crop", **AFITA/WCCA, Bombay, Oct 24th -26th 2018.**
- ✓ A. Kumar, R. Bharath, M. Taparia, P. Rajalakshmi, B. Marathi, and U.B. Desai, "Automated Discrimination and Counting of Filled and Unfilled Spikelets of Aerobic Rice", **WF-IoT 2019 (Submitted).**

➤ Poster Presentation

- ✓ A. Kumar, R. Bharath, M. Taparia, P. Rajalakshmi, B. Marathi, and U.B. Desai, "Automated Counting of Filled and Unfilled Spikelets of Aerobic Rice Using Blue Channel Discrimination", **AFITA/WCCA, Bombay, Oct 24th -26th 2018.**

➤ Journal:

- ✓ Soumil Heble, K.V.V. Durga Prasad, , Ajay Kumar, P. Rajalakshmi, Balaji Naik B., Balram M., Uday B. Desaia, and Shabbir N. Merchant "A Novel design for Fringing Electric Field Soil Moisture Sensor based on IDT and Co-Planar Patterns ", **Computers and Electronics in Agriculture (Under review).**

References:

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- ✓ Duan, L., Huang, C., Chen, G., Xiong, L., Liu, Q. and Yang, W., “High-throughput estimation of yield for individual rice plant using multi-angle RGB imaging”, *In International Conference on Computer and Computing Technologies in Agriculture*, 16-19 September, 1-12, **2014**.
- ✓ Duan, L., Yang, W., Bi, K., Chen, S., Luo, Q. and Liu, Q., “Fast discrimination and counting of filled/unfilled rice spikelets based on bi-modal imaging”, *Computers and Electronics in Agriculture*, 75(1), 196-203, **2011**.
- ✓ Liu, T., Chen, W., Wang, Y., Wu, W., Sun, C., Ding, J. and Guo, W., “A shadow-based method to calculate the percentage of filled rice grains”, *Biosystems Engineering* 150, 79-88, **2016**.
- ✓ Quan, Tran Minh, David GC Hildebrand, and Won-Ki Jeong. "Fusionnet: A deep fully residual convolutional neural network for image segmentation in connectomics." *arXiv preprint arXiv:1612.05360*, 2016.
- ✓ Sa, Inkyu, et al. "weedNet: Dense Semantic Weed Classification Using Multispectral Images and MAV for Smart Farming." *IEEE Robotics and Automation Letters* 3.1 ,**2018**: 588-595

Thank You...!!