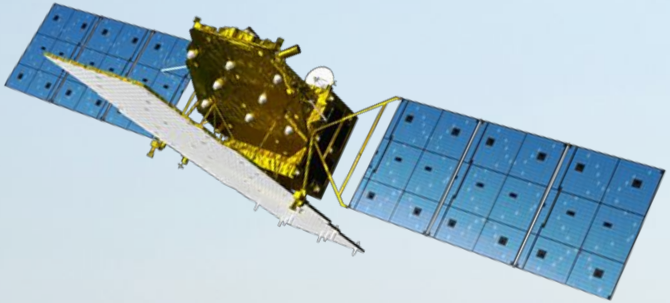
2024/02/01

International Meeting on Land Cover/Land Use Change (LCLUC) in South/Southeast Asia Synthesis in Hanoi, Vietnam



Dynamic LULC mapping for agriculture in Suphanburi, Thailand using ALOS-2/PALSAR-2

University of Tsukuba (Japan)
College of Agro-Biological Resource Sciences, B4

金居 新大 **Shindai Kanai**

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*1: HII, *2: JAXA, *3:RESTEC, *4: University of Tsukuba

Joint research of

Japan Aerospace Exploration Agency

Operates Earth observation satellites

&

Hydro - Informatics Institute

Pursues efficient water utilization and management with information technology

▶ **Synthesize strengths and knowledge of both to make a good product for Thai water resource management.**

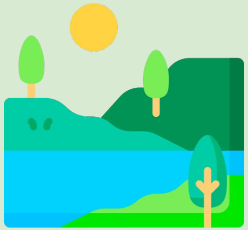
Land-use Land-cover (LULC) map is
A color-coded image of the land appearance using satellite data.

Land use･Land cover

How human use the land

field
paddy
orchard
etc.

Physical surface covering the land



bareland
grassland
water
etc.

If we focus on **Land cover (LC)** category on cropland…

Cropland

Dry + No Crop

▶ **Bare land**

Dry + Crop

▶ **Grassland**

Flooded + No Crop

▶ **Water body**

Dynamic changes happen on croplands.

Water demand and methane emissions change accordingly.

Purpose of this reserach

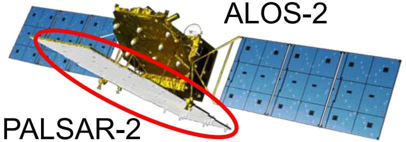
Dynamic LULC mapping

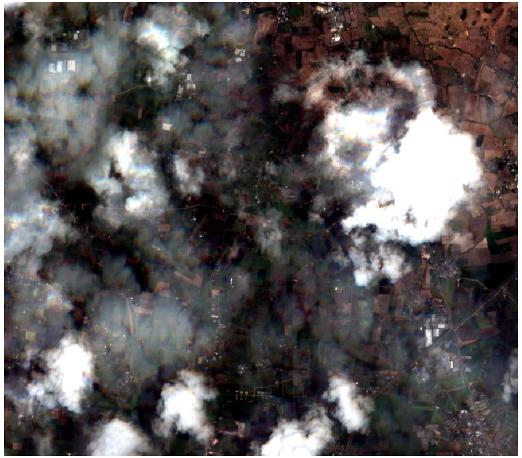
Capture a moment on agricultural lands in LULC map

But, it is hard to get a cloud-free image during rainy season in the tropic….

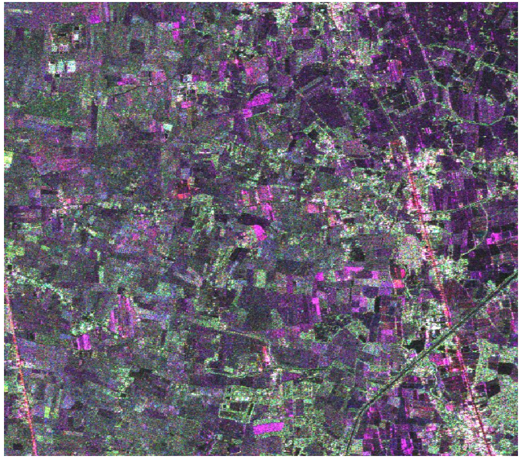
Satellite data for dynamic classification

ALOS-2/PALSAR-2 full polarimetric





Sentinel-2 (2023/09/02)



PALSAR-2 (2023/08/05)
HH: Red, HV: Green, VV: Blue

Feature values

1. HH (amplitude)
2. HV (amplitude)
3. VH (amplitude)
4. VV (amplitude)
5. Double bounce component (Yamaguchi decomposition)
6. Volume scattering component (Yamaguchi decomposition)
7. Surface scattering component (Yamaguchi decomposition)
8. Helix scattering component (Yamaguchi decomposition)
9. Even (Pauli decomposition)
10. Cross (Pauli decomposition)
11. Odd (Pauli decomposition)
12. Entropy (Entropy-Alpha decomposition)
13. Alpha (Entropy-Alpha decomposition)
14. Anisotropy (Entropy-Alpha decomposition)
15. Texture image

Observed **every 2 weeks** since 2022/05/28 (several days not observed)

High Resolution Mode (HBQ). Spatial resolution is **6 m.**

HBQ: High Beam Quad pol.

Method①

Field survey

Conducted field survey during my study abroad in Thailand
Took photos of Land-cover and collected locational information

Dates
- 2022/08/16-18
- 2022/10/27-28
- 2023/01/26
- 2023/03/24
- 2023/05/16
- 2023/08/03

total: 6 times

2022/10/27

2023/01/26

2023/03/24

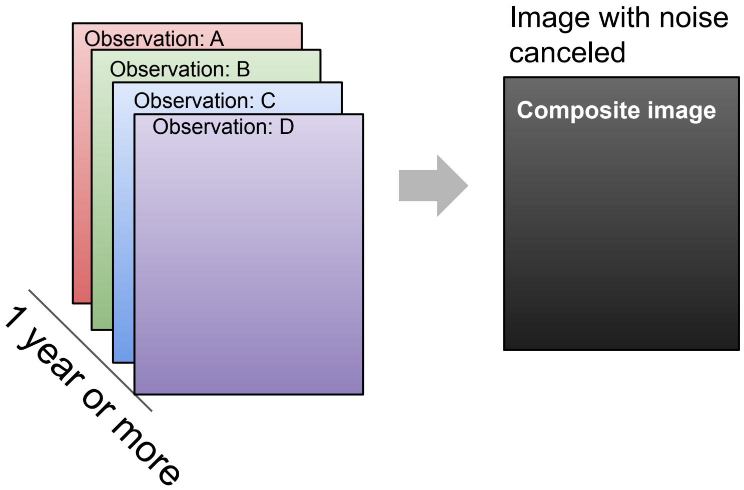
Land-cover change on sugarcane field (harvest)

Method②

Spatial averaging for satellites data $\overline{\sigma}_0 = 10^{-8.3}\overline{DN^2}$

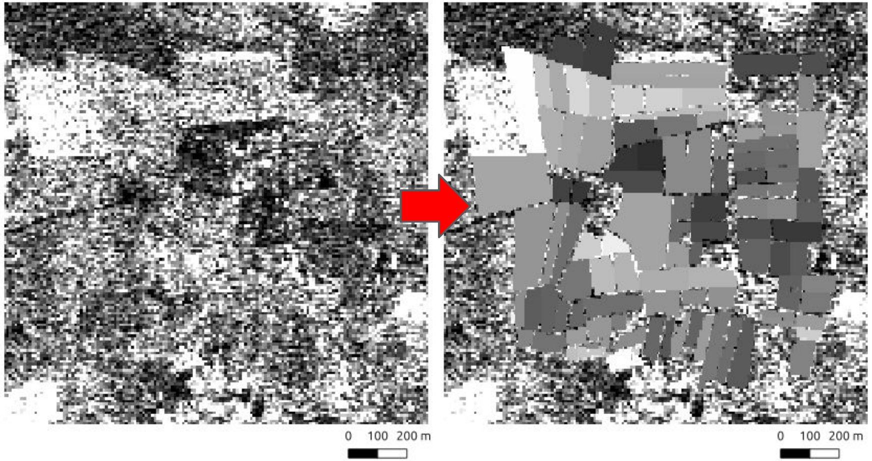
But I took the average of DN for entropy-alpha decomposition and texture image

Normal method (for static LULC)



My method:

Average values for each polygon (cropland) on 1 image



In dynamic LULC mapping, it is impossible to combine many satellite images because time period of observation is limited.

So, **I tried to reduce noise by spatial average for each field**.

Method②

Spatial averaging for satellites data

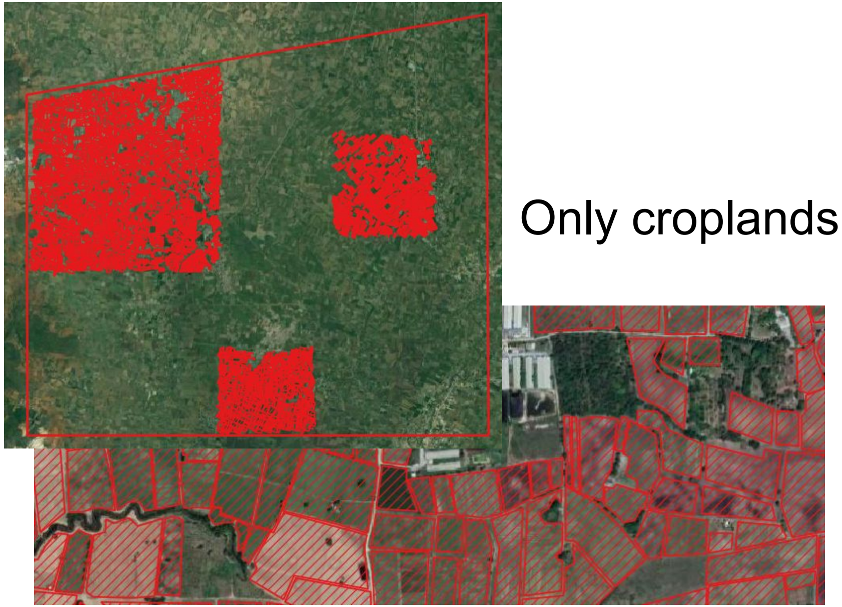
Auto-made polygons

Segmentation algorithm (eCognition) over PlanetScope image

Not only croplands

Handmade polygons (for comparison)

Took more than 50 hours to make

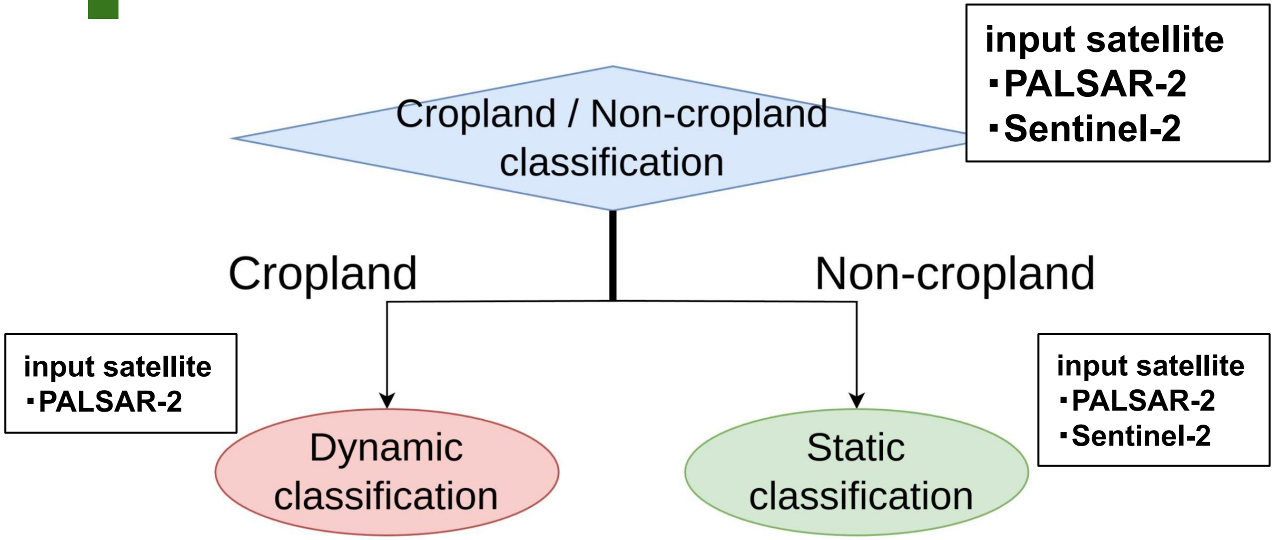


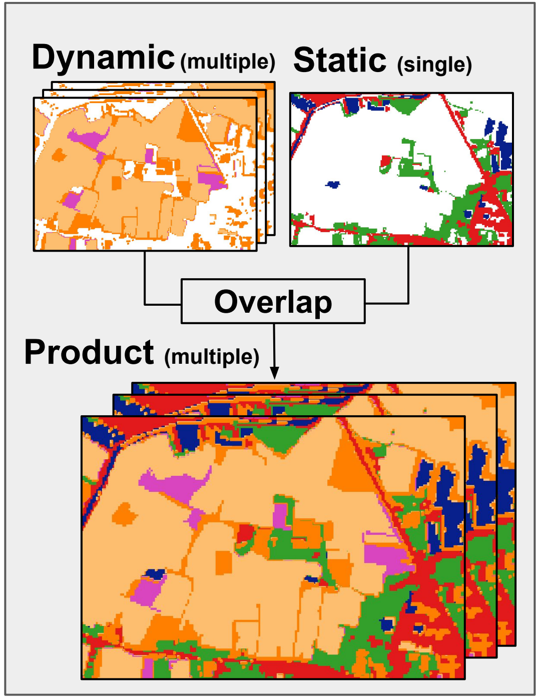
Only croplands

Method③

Classification

Supervised method, Random Forest was used





Dynamic categories

- Flooded with crop
- Dried with crop
- Dried without crop

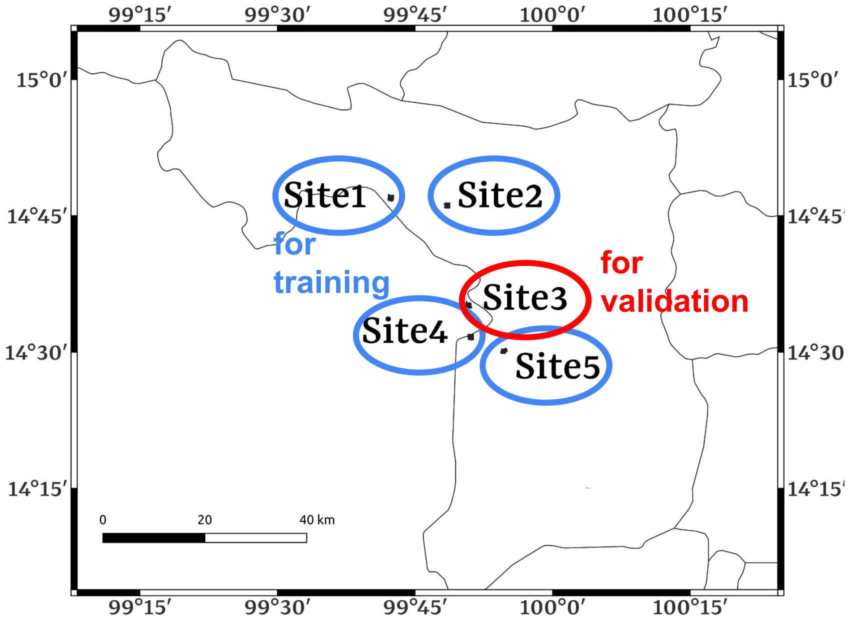
Static categories

- Permanent water
- Built-up
- Grassland
- Forest
- Bare land

Method③ Classification

“Dynamic classification”

Sites for field survey



Used Site 3 for validation of the Dynamic classifier trained in Site 1, 2, 4 and 5.

Only PALSAR-2 data is used for input to Dynamic classification.

Method③ Classification

“Dynamic classification”

Training data

6 field surveys

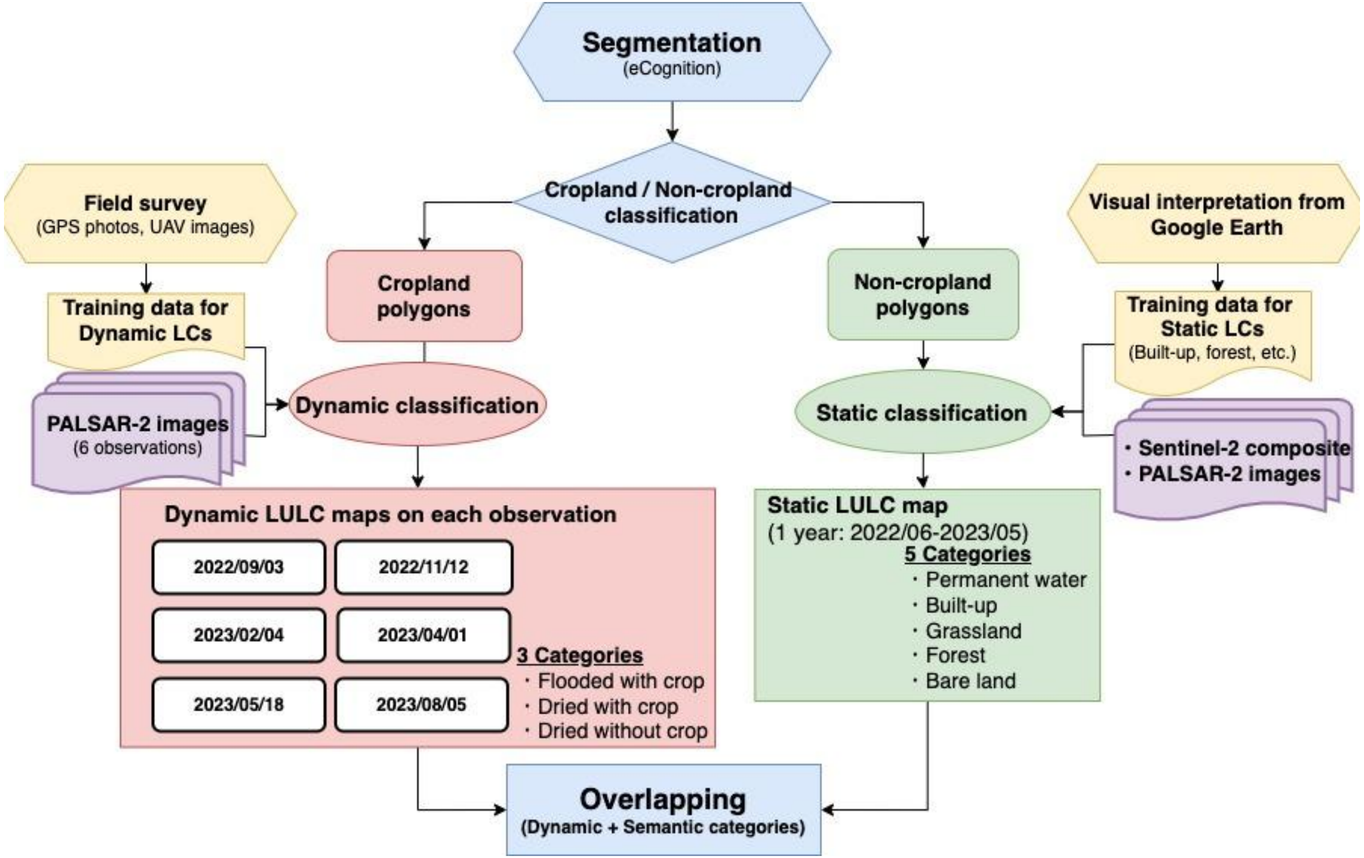
	2022/08/16-18			2022/10/27-28			2023/1/26			2023/3/24			2023/5/16			2023/8/3			Total
	D w/ C	D w/o C	F w/ C	D w/ C	D w/o C	F w/ C	D w/ C	D w/o C	F w/ C	D w/ C	D w/o C	F w/ C	D w/ C	D w/o C	F w/ C	D w/ C	D w/o C	F w/ C	
Site1	29	3	3	31	1	3	9	24	2	21	12	2	28	7	0	27	6	2	210
Site2	12	2	21	10	2	23	3	33	0	10	24	0	12	22	0	13	3	19	209
Site4	15	0	0	12	8	0	15	5	0	3	17	0	8	12	0	16	4	0	115
Site5	1	0	13	1	0	20	0	5	16	0	16	3	1	15	0	1	0	20	112
Total	57	5	37	54	11	46	27	67	18	34	69	5	49	56	0	57	13	41	646
	99			111			112			108			105			111			

Train the Dynamic classifier (RF)

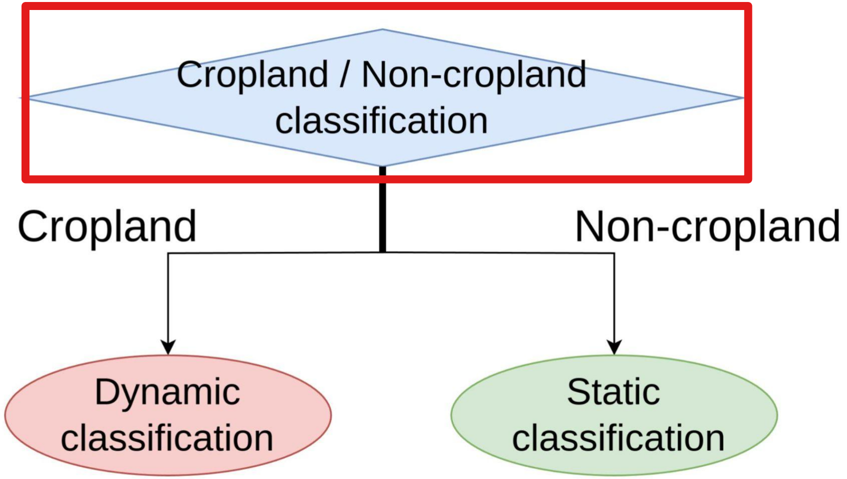
Dynamic categories

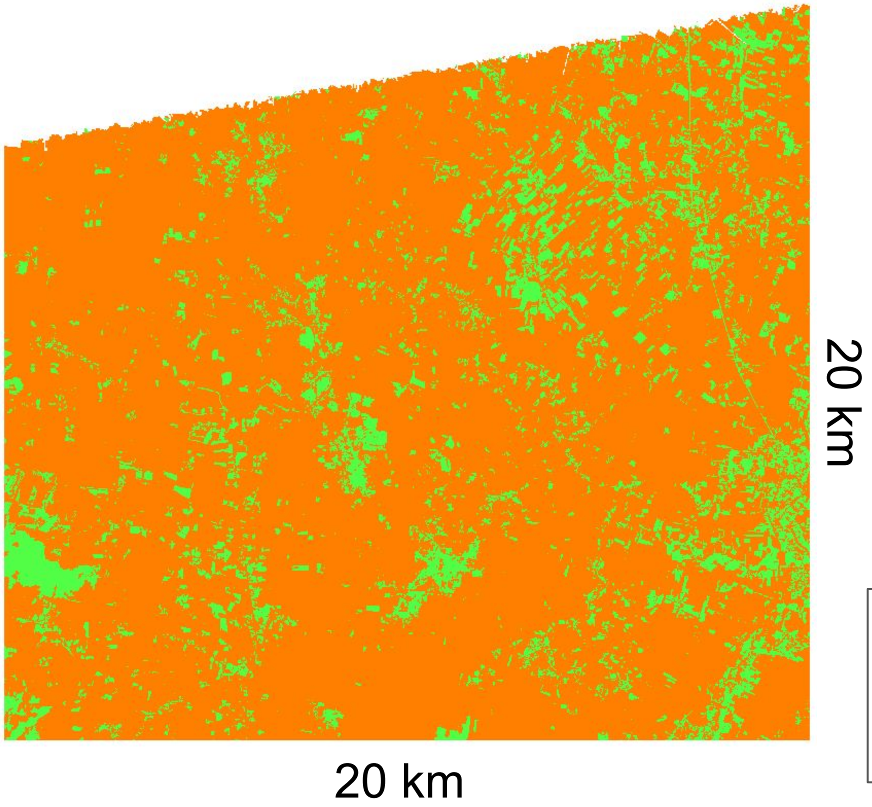
- Dried with crop (**D w/ C**)→278 points
- Dried without crop (**D w/o C**)→221 points
- Flooded with crop (**F w/ C**)→147 points

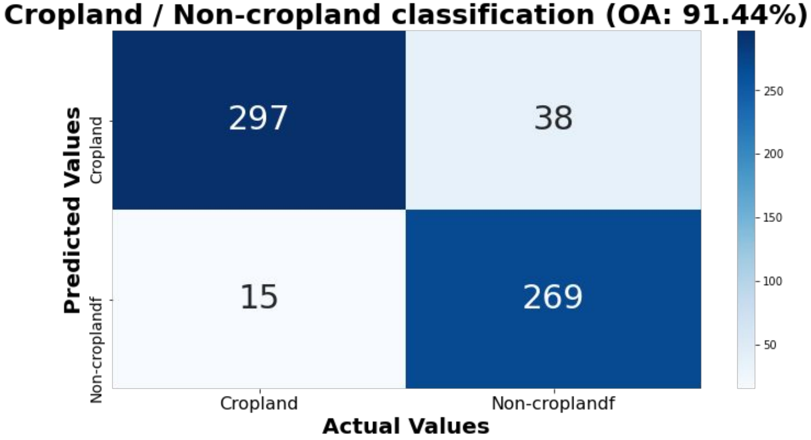
Workflow of classification (Dynamic + Static)



Result①
Cropland / Non-cropland classification

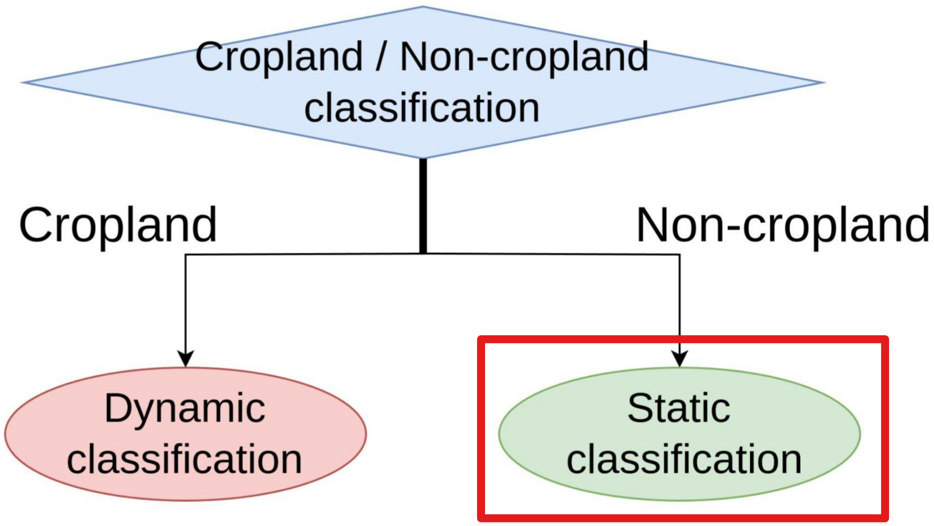


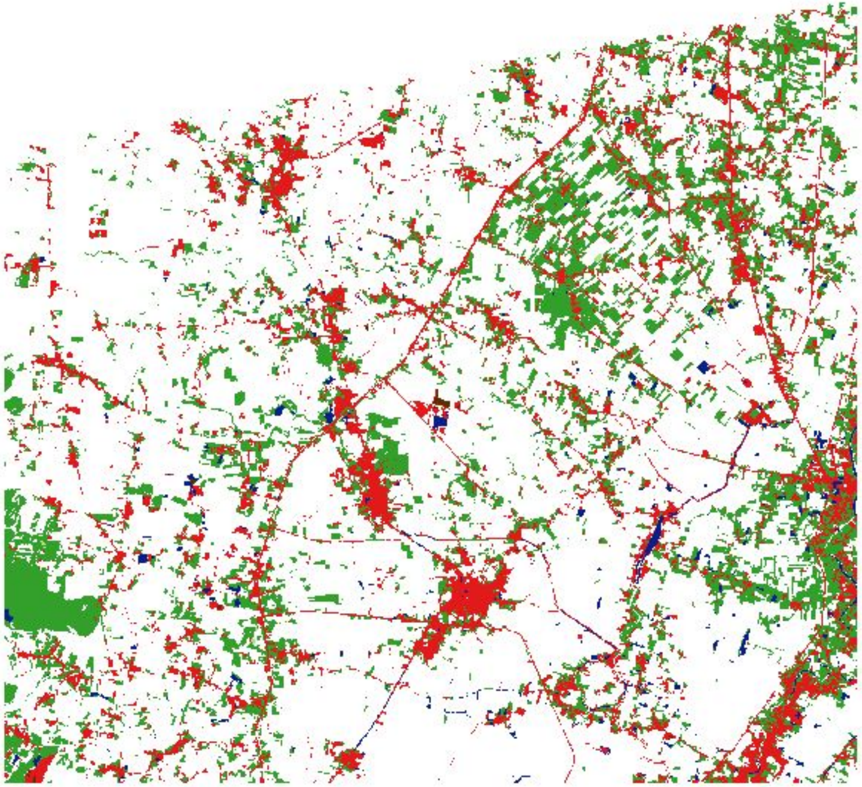




Cropland
Non-cropland

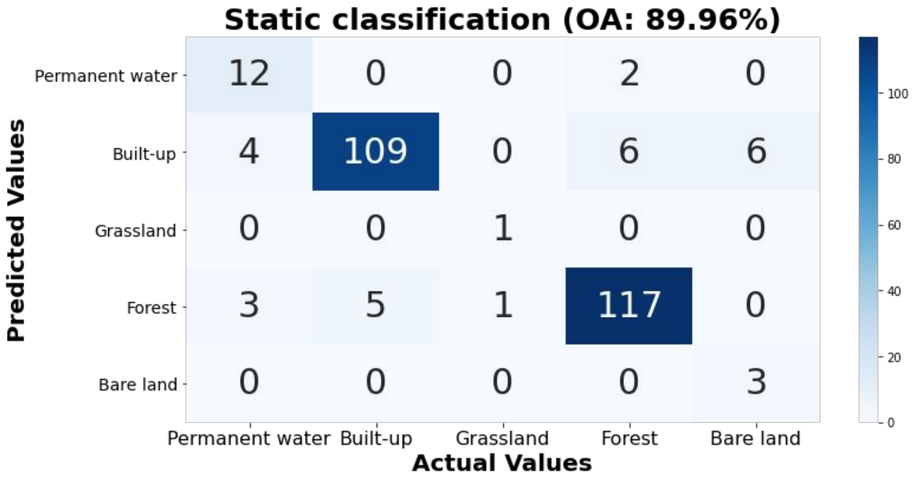
Result②
Static classification





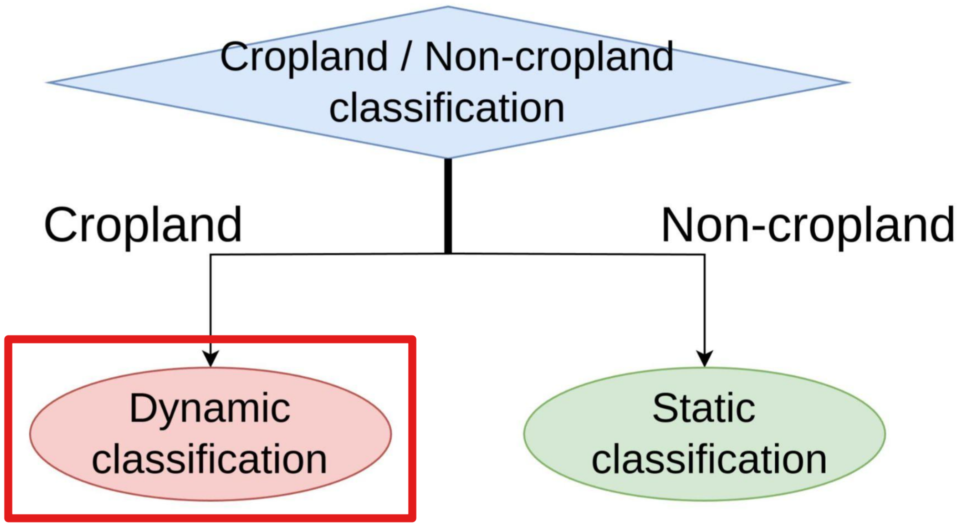
20 km

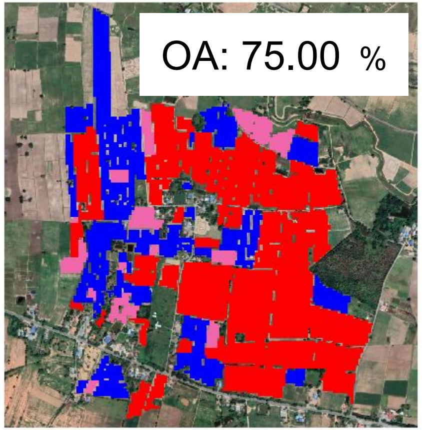
20 km



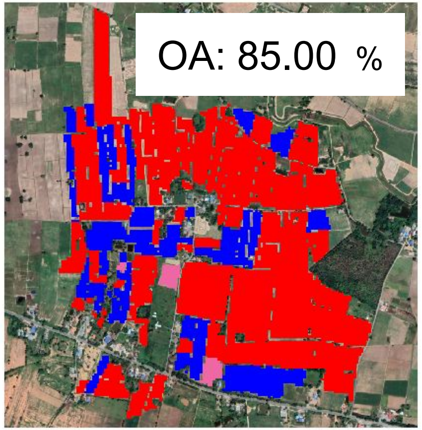
Forest
Built-up
Permanent water
Grassland
Bare land

Result③
Dynamic classification in Site3

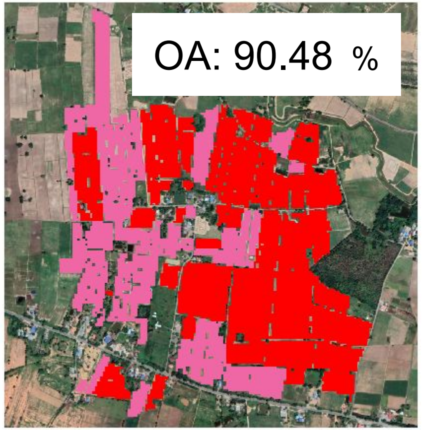




2022/09/03
Rainy season



2022/11/12
Rainy season



2023/02/04
Dry season

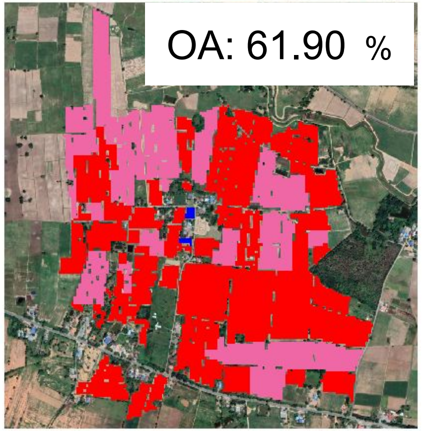
OA: Overall Accuracy

Dried **w/** crop

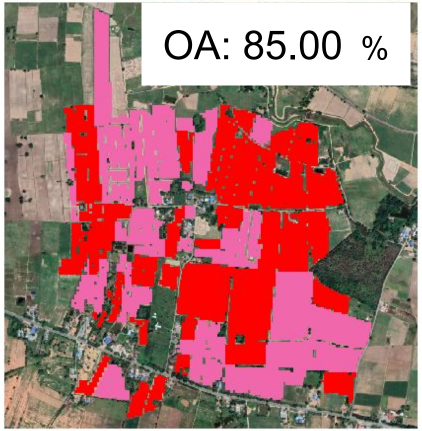
Dried **w/o** crop

Flooded **w/** crop

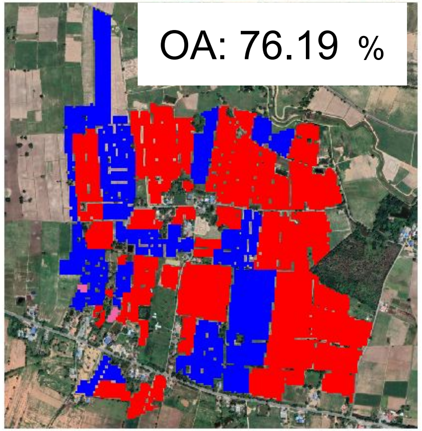
Thai rainy season:
June to November



2023/04/01
Dry season



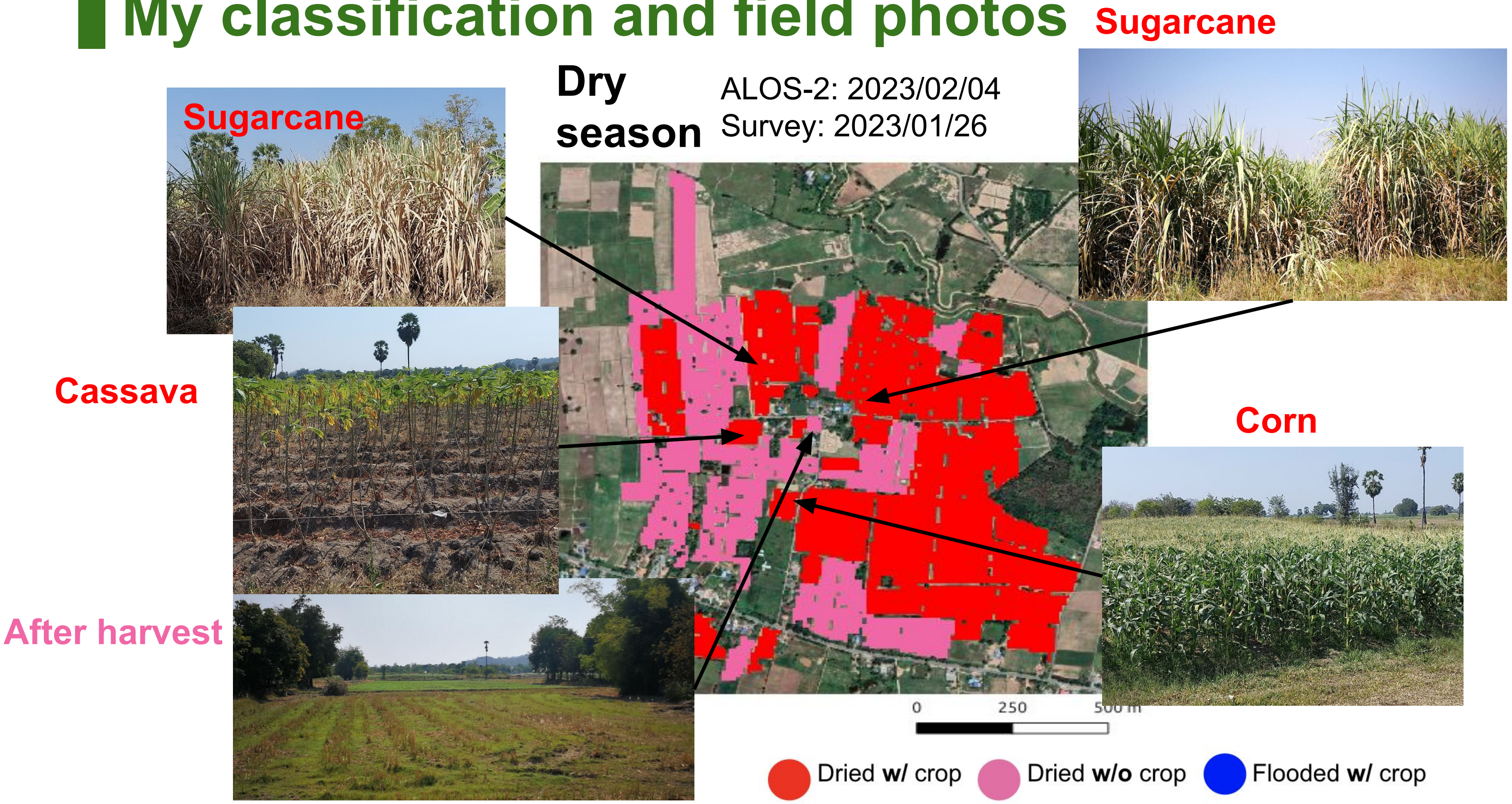
2023/05/13
Dry season



2023/08/05
Rainy season

Result

My classification and field photos



My classification and field photos

Rainy season

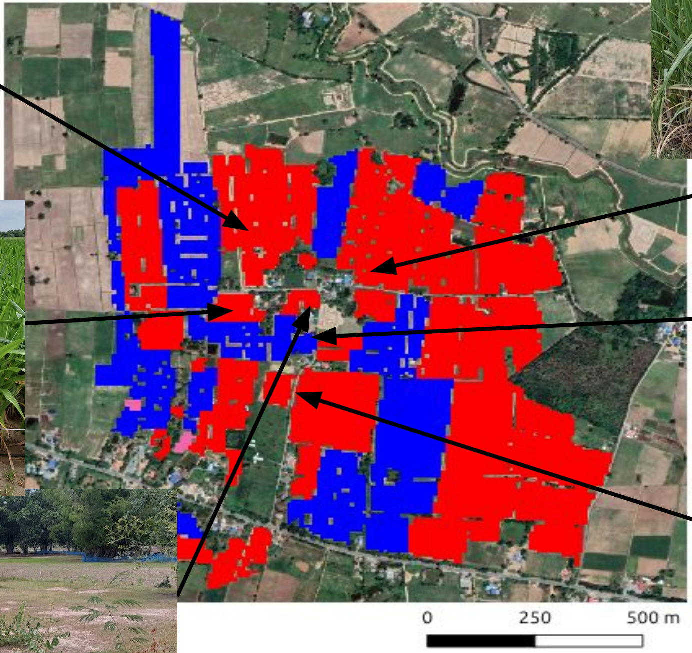
ALOS-2: 2023/08/05
Survey: 2023/08/03

Sugarcane

Sugarcane

After grazing

Misclassified to
Dried w/ crop



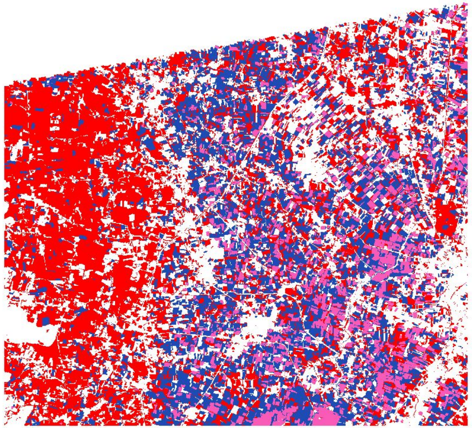
Dried **w/** crop   Dried **w/o** crop   Flooded **w/** crop

Sugarcane

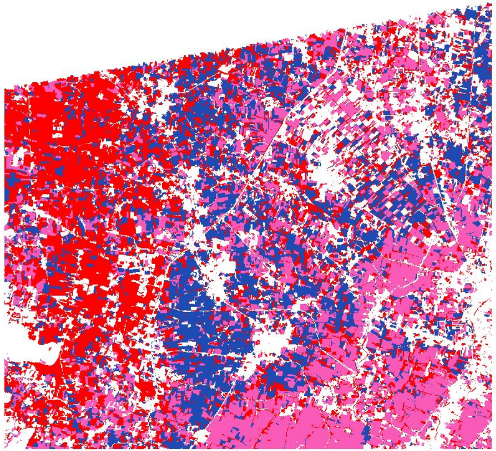
Rice

Result④
Dynamic classification on auto-made polygons

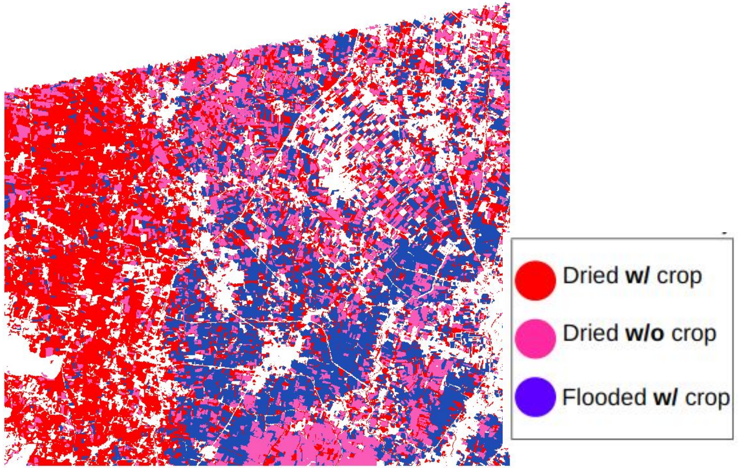
Expand the classification 20 km × 20 km,
with same the Dynamic classifier



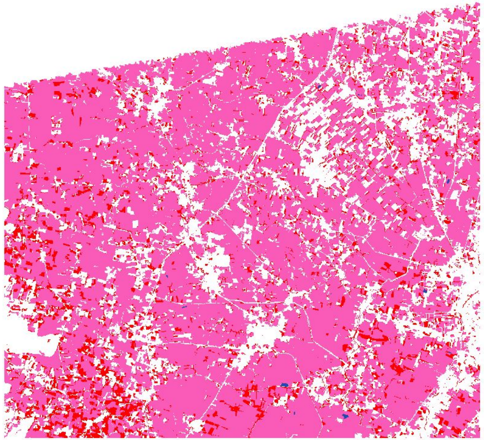
2022/09/03 Rainy season



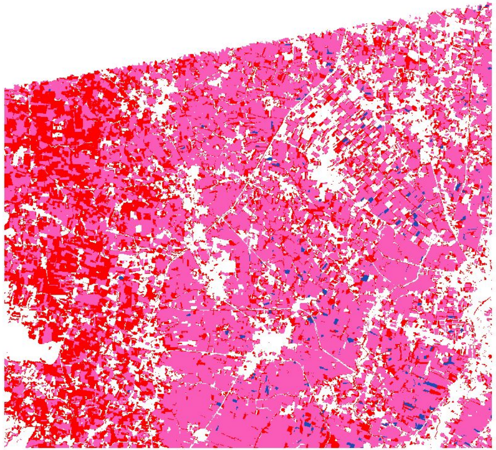
2022/11/12 Rainy season



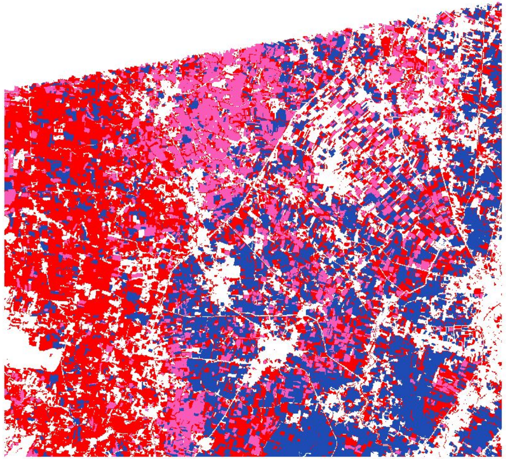
2023/02/04 Dry season



2023/04/01 Dry season



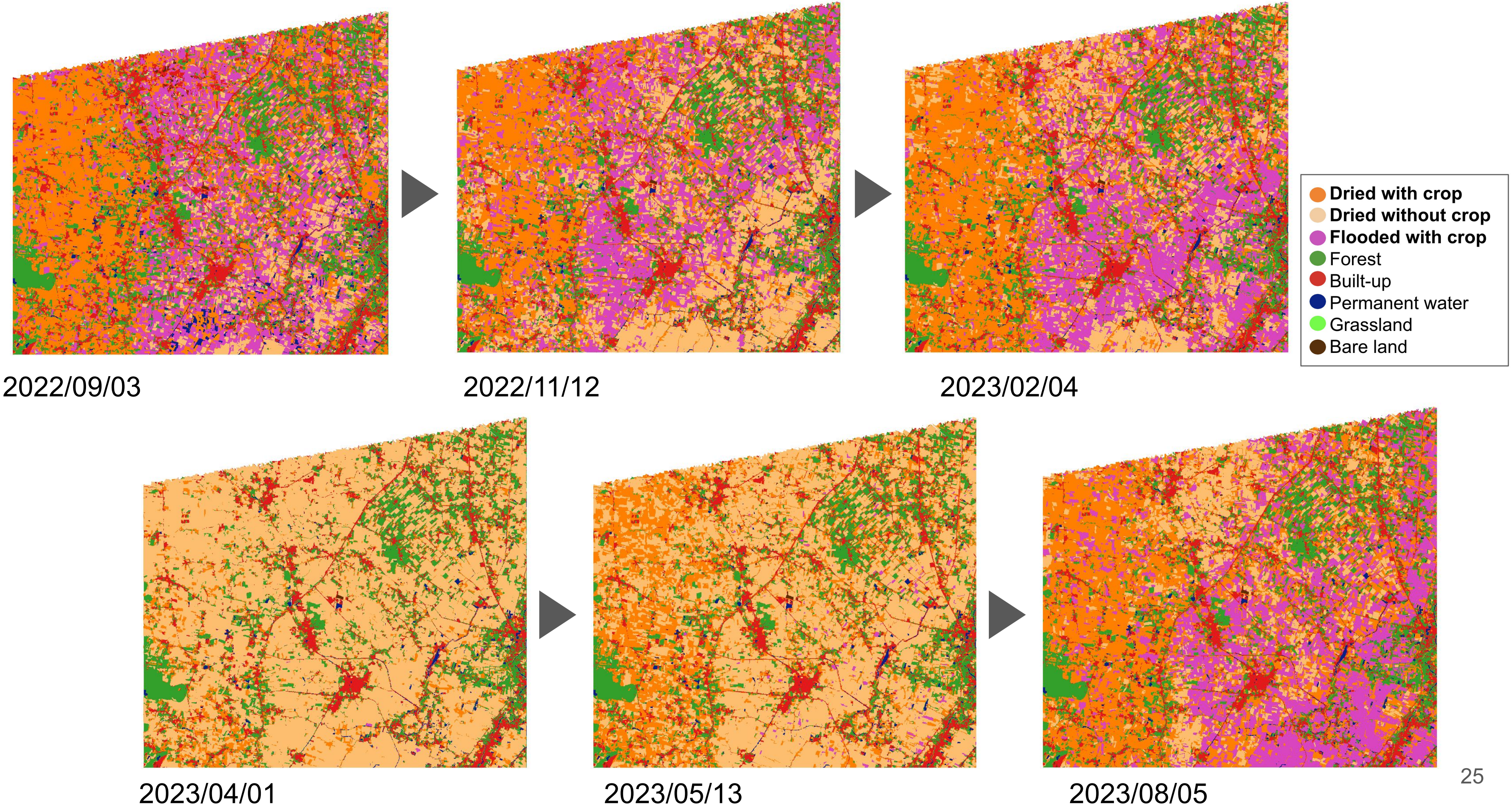
2023/05/13 Dry season



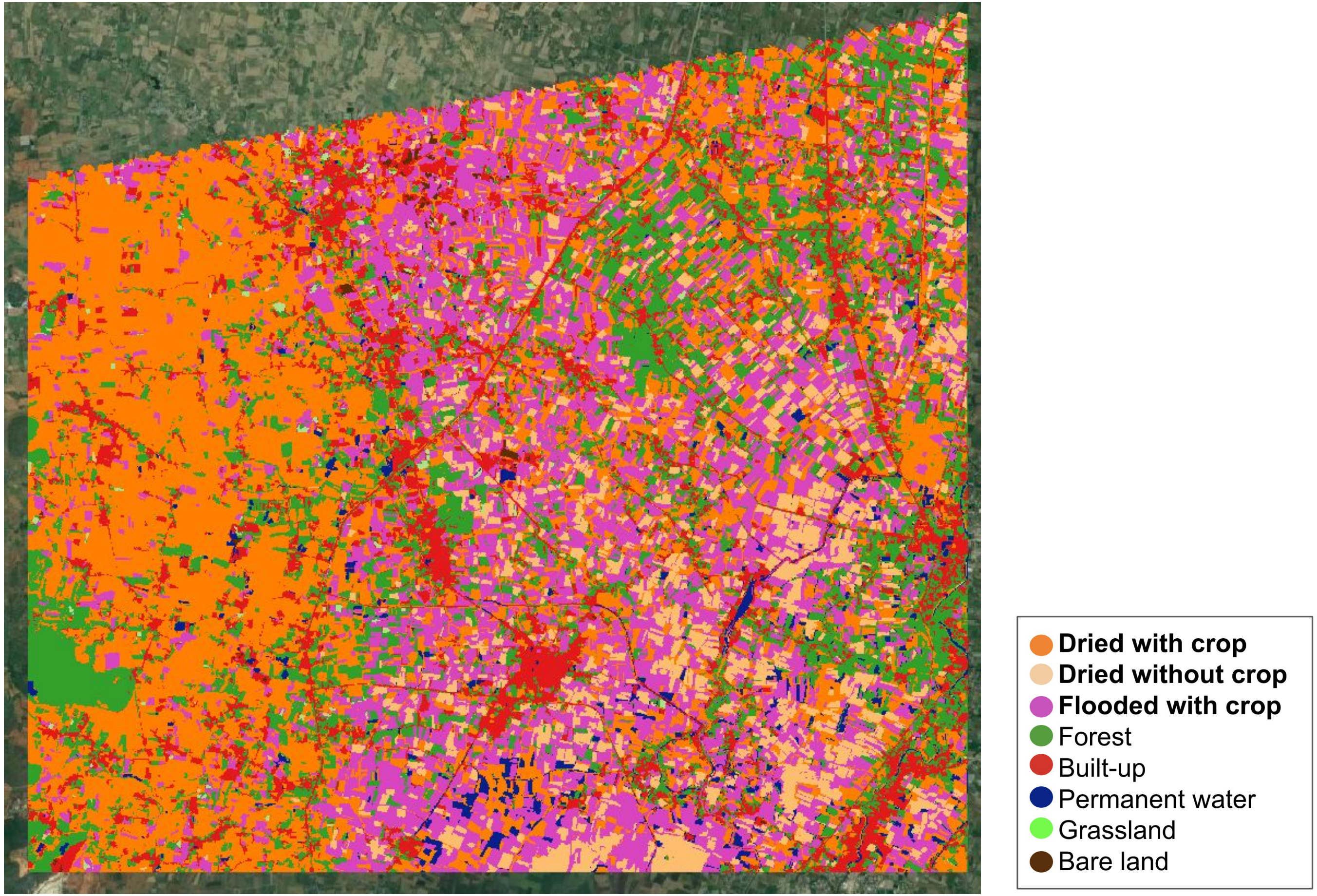
2023/08/05 Rainy season

Result⑤
Overlapping of Dynamic and Static

The final product

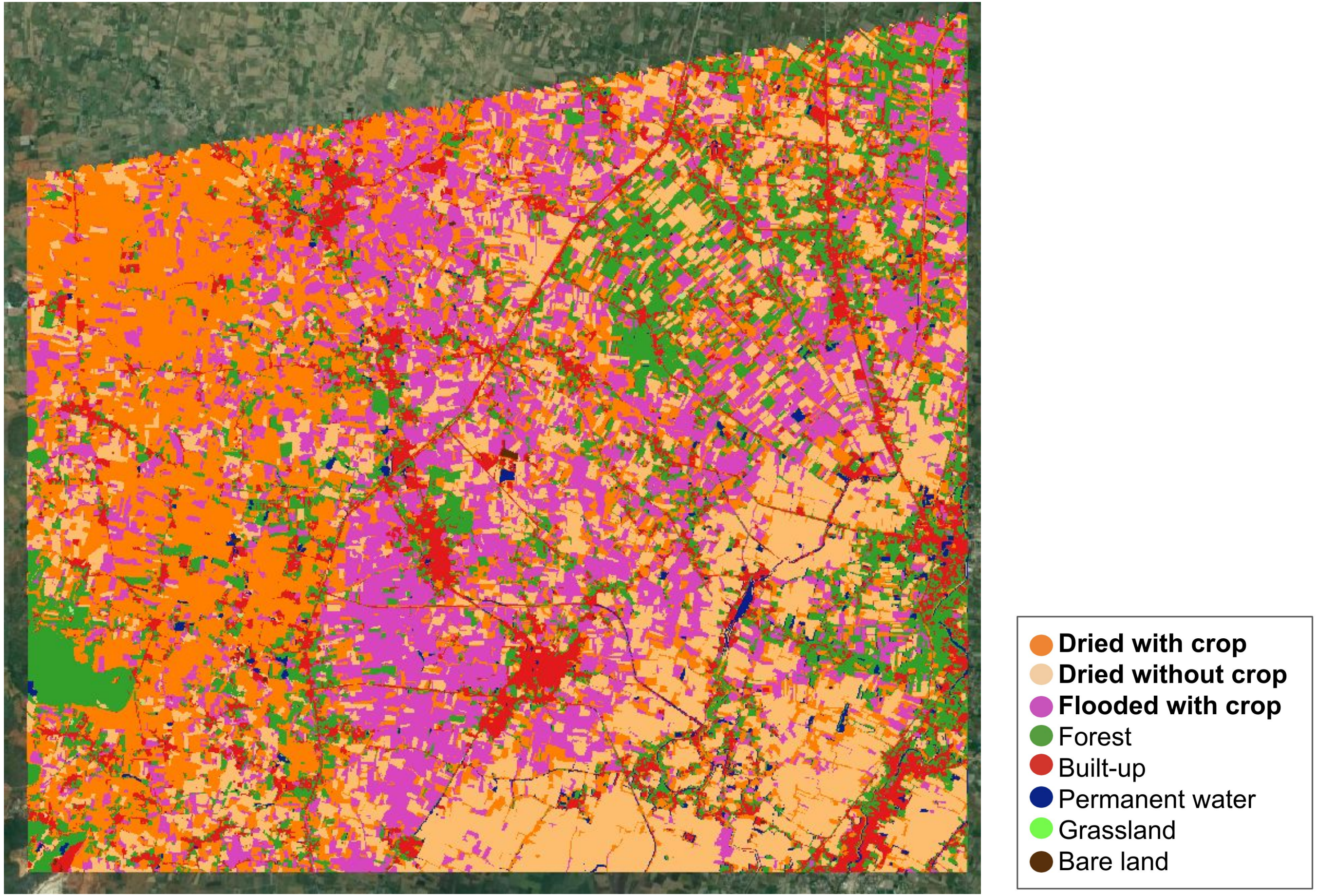

2022/09/03
2022/11/12
2023/02/04
Dried with crop
Dried without crop
Flooded with crop
Forest
Built-up
Permanent water
Grassland
Bare land
2023/04/01
2023/05/13
2023/08/05

2022/09/03

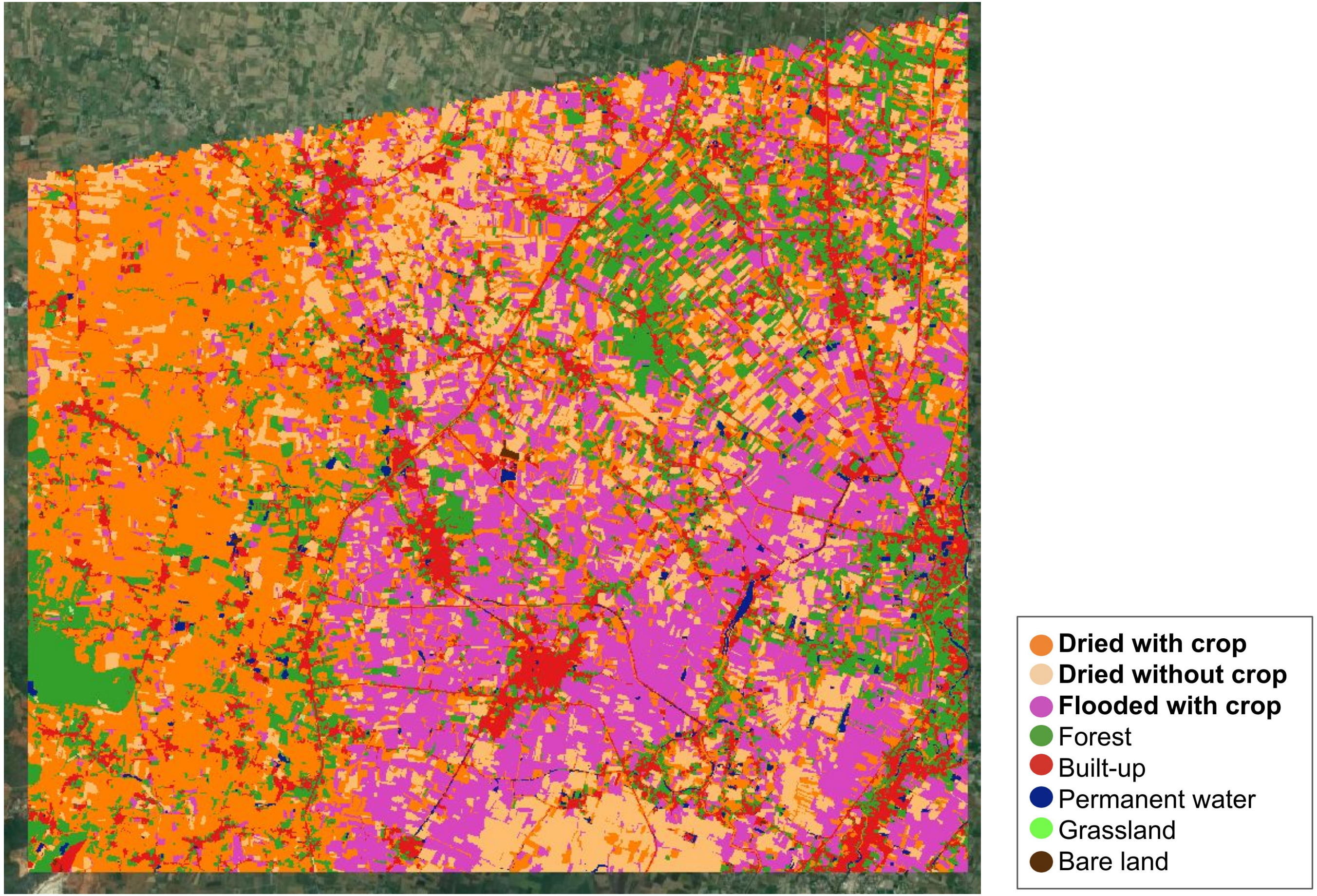


Dried with crop
Dried without crop
Flooded with crop
Forest
Built-up
Permanent water
Grassland
Bare land

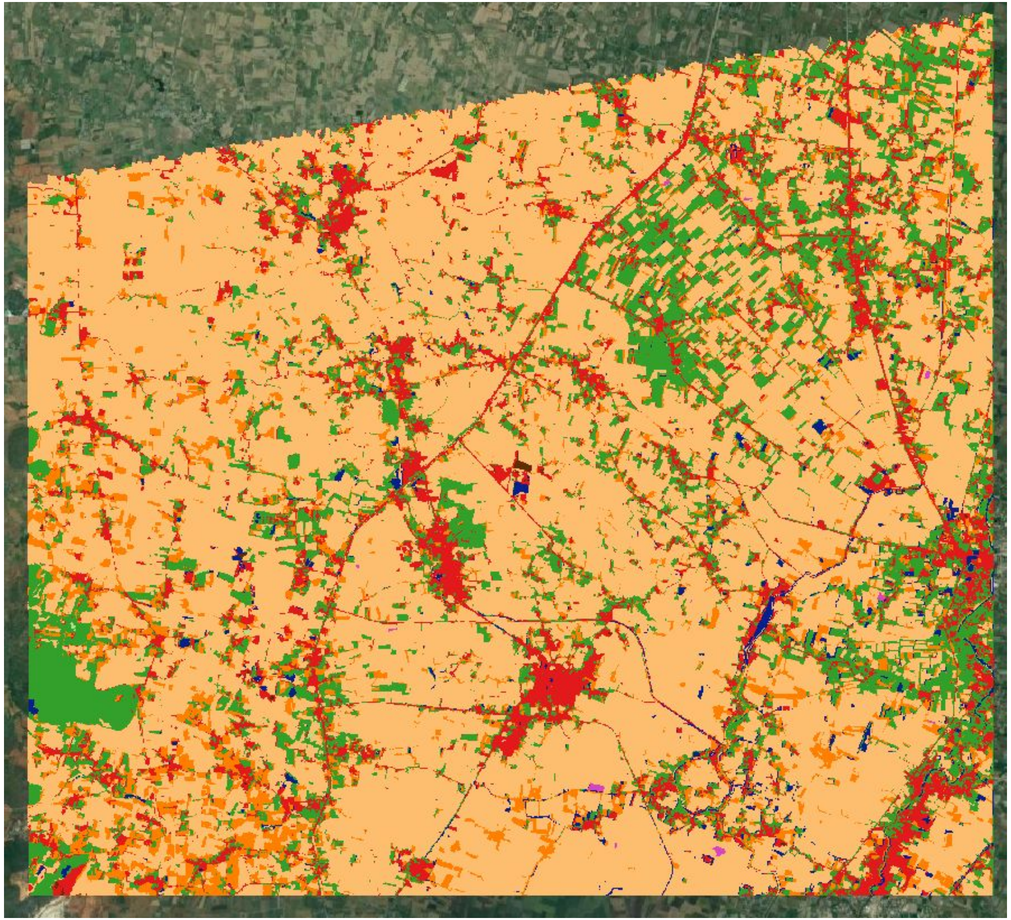
2022/11/12


Dried with crop
Dried without crop
Flooded with crop
Forest
Built-up
Permanent water
Grassland
Bare land

2023/02/04

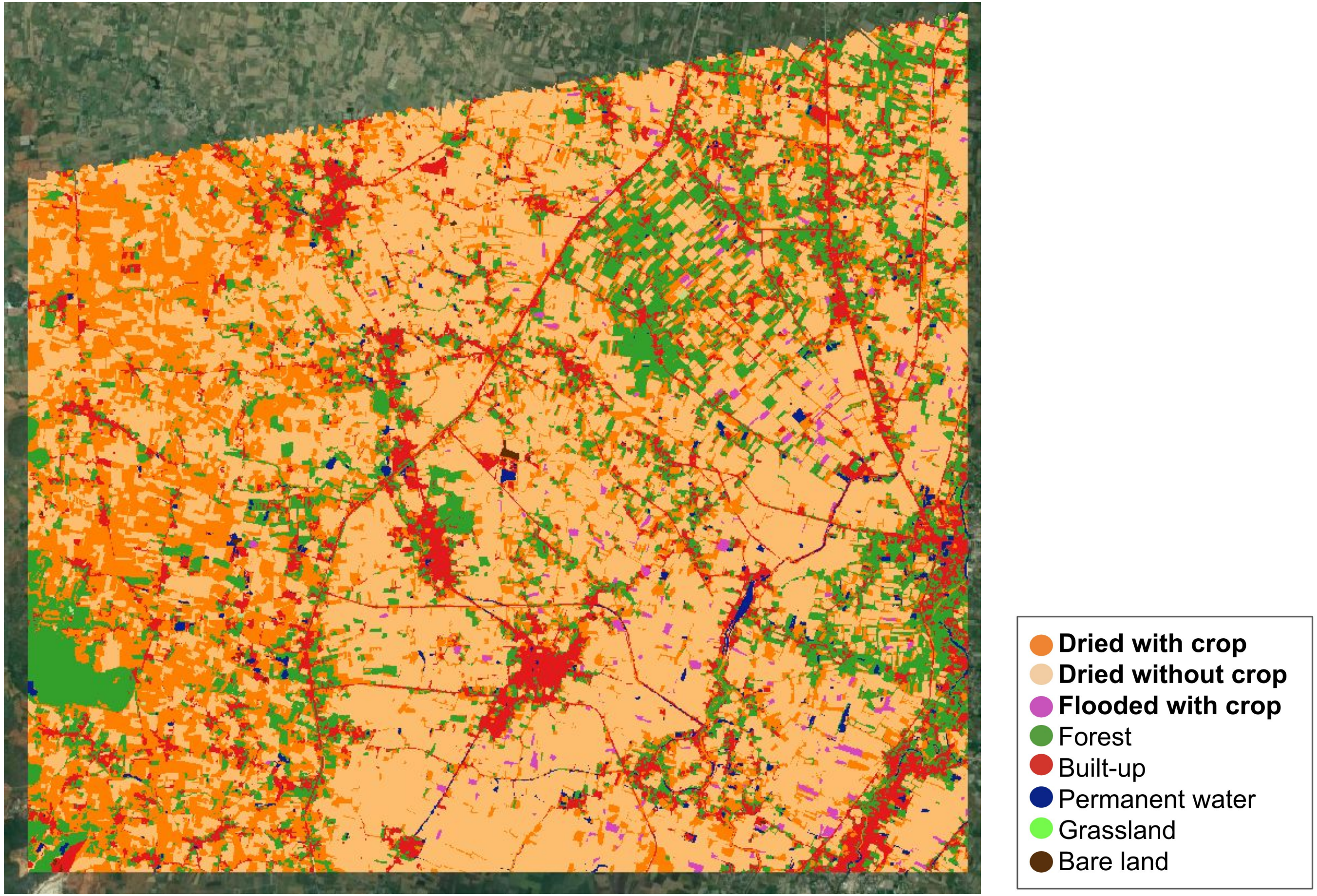

Dried with crop
Dried without crop
Flooded with crop
Forest
Built-up
Permanent water
Grassland
Bare land

2023/04/01

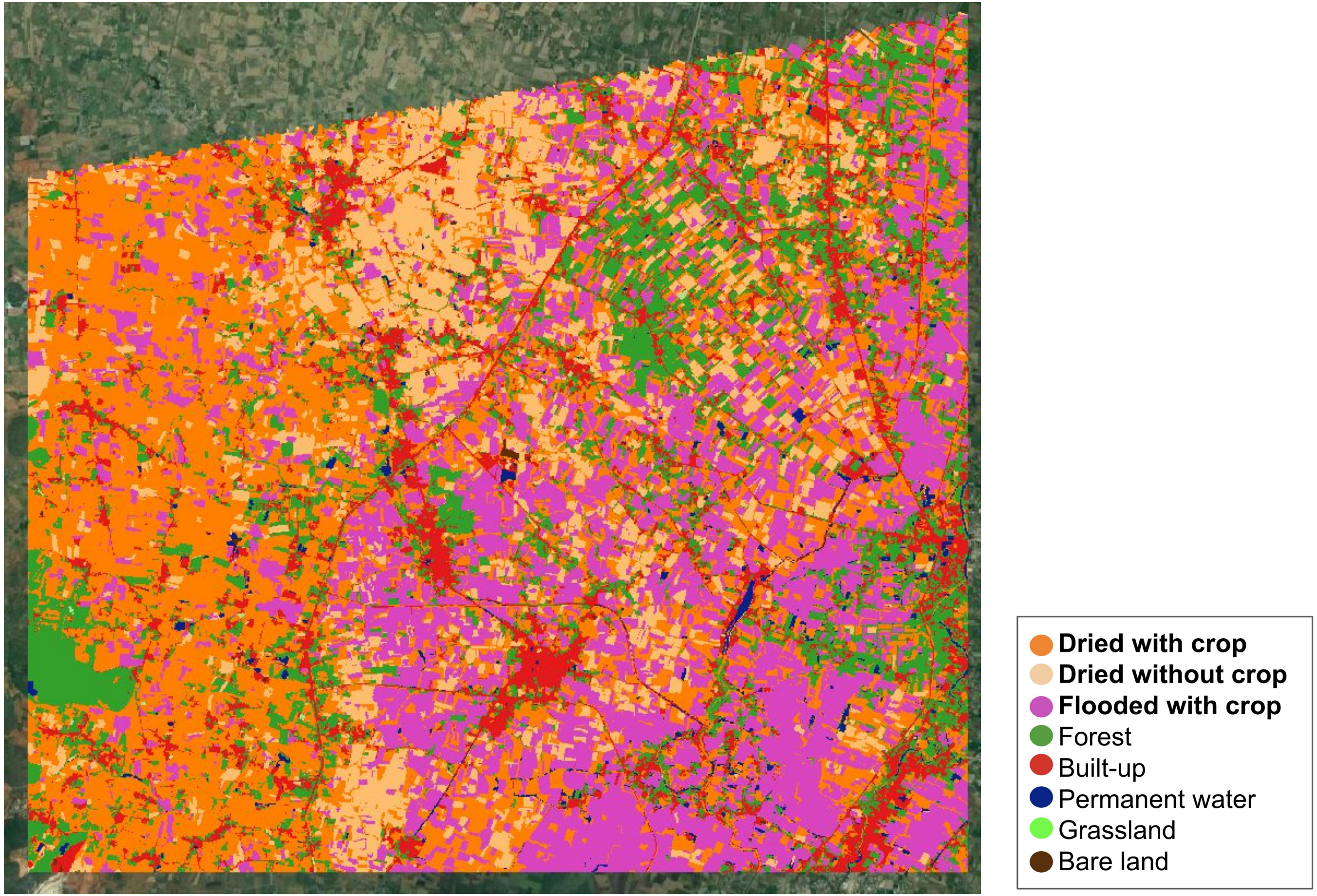


- **Dried with crop**
- **Dried without crop**
- **Flooded with crop**
- Forest
- Built-up
- Permanent water
- Grassland
- Bare land

2023/05/13


Dried with crop
Dried without crop
Flooded with crop
Forest
Built-up
Permanent water
Grassland
Bare land

2023/08/05


Dried with crop
Dried without crop
Flooded with crop
Forest
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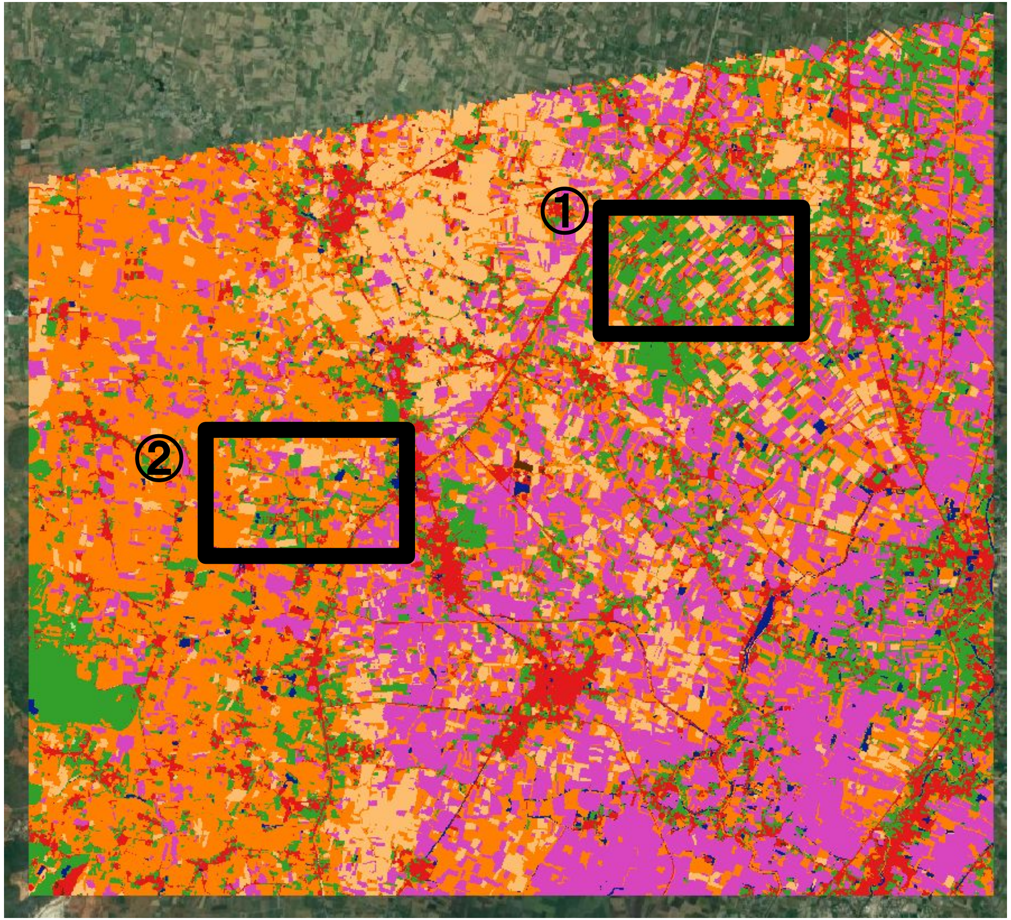
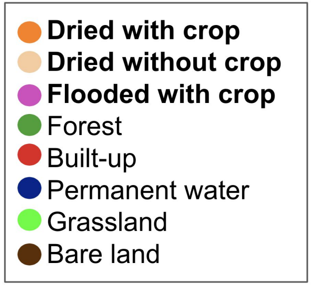
2023/08/05



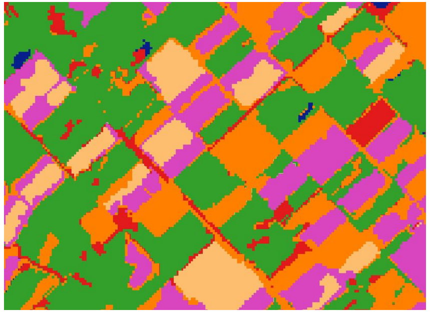
①
②



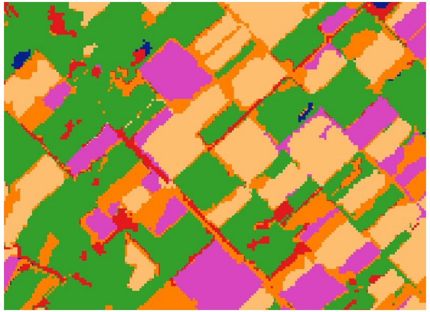
Dried with crop
Dried without crop
Flooded with crop
Forest
Built-up
Permanent water
Grassland
Bare land

Google Earth

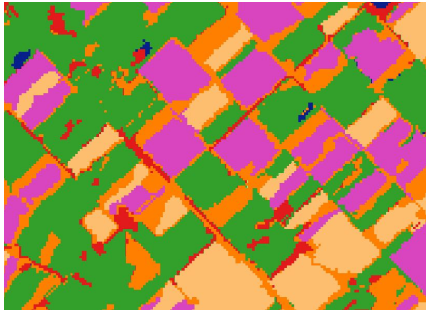
Center of this map
(99.965688,14.555412)



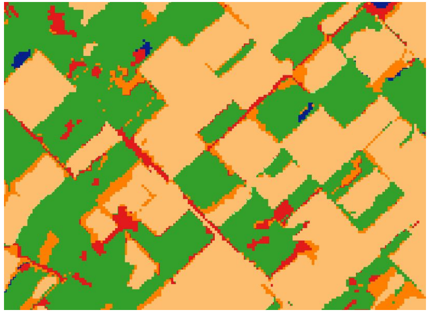
2022/09/03



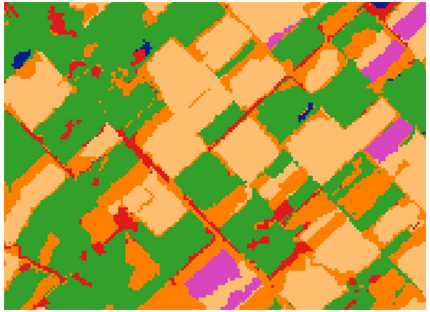
2022/02/04



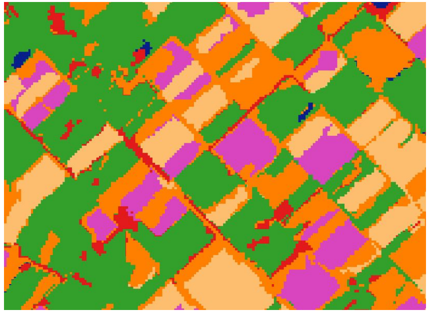
2022/11/12



2023/04/01



2023/05/13

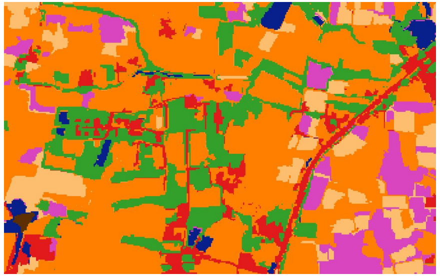


2023/08/05

Dried with crop
Dried without crop
Flooded with crop
Forest
Built-up
Permanent water

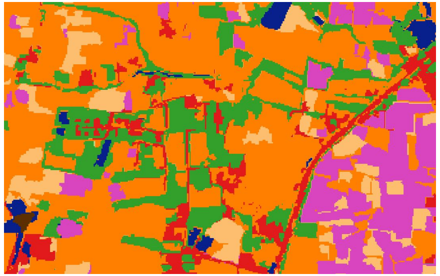
Google Earth

Center of this map
(99.894441,14.502216)

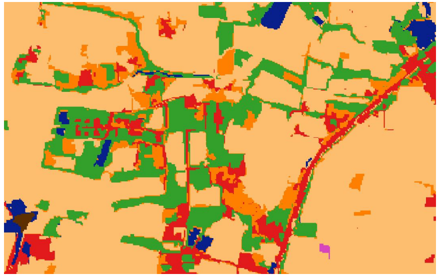


2022/09/03

2022/02/04



2022/11/12



2023/04/01

2023/05/13

2023/08/05

Dried with crop
Dried without crop
Flooded with crop
Forest
Built-up
Permanent water

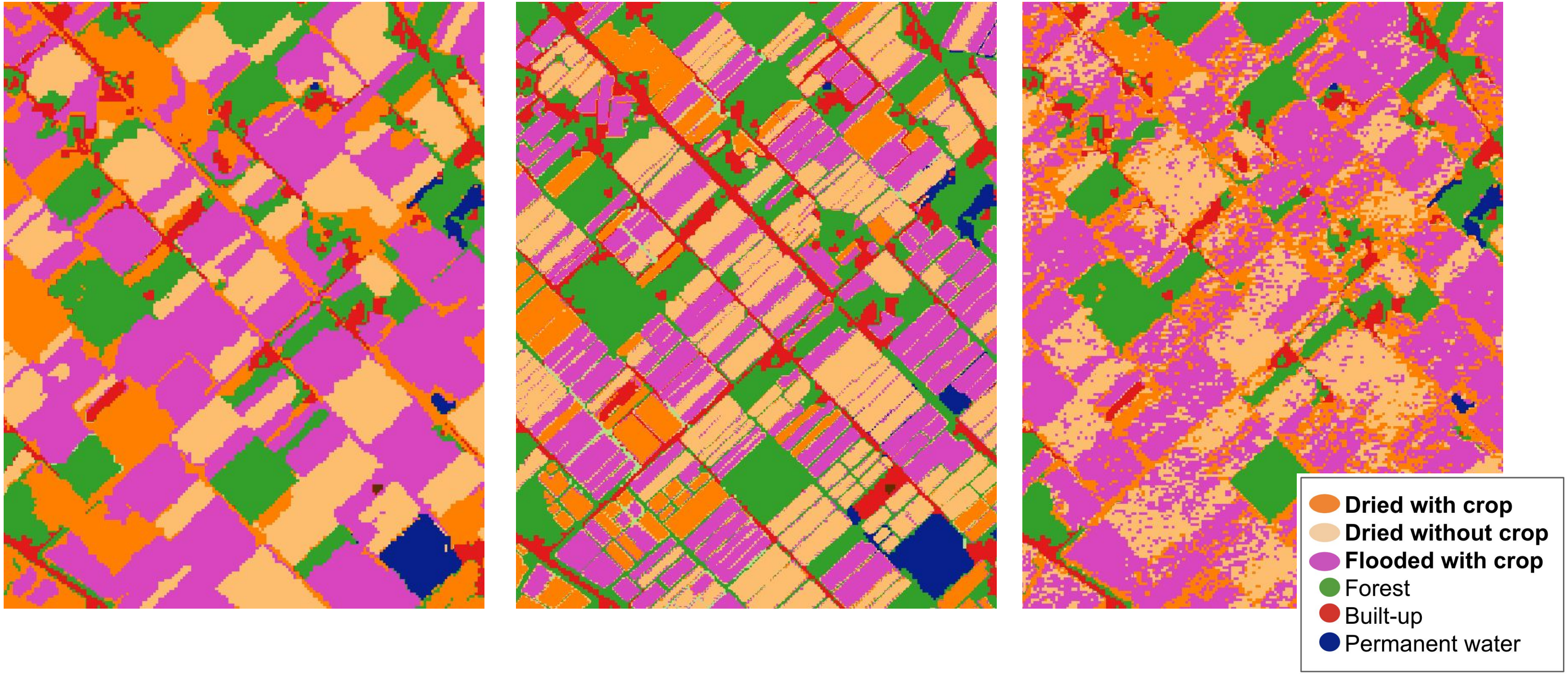
Result⑥
Auto-made vs Handmade polygons

2022/09/03

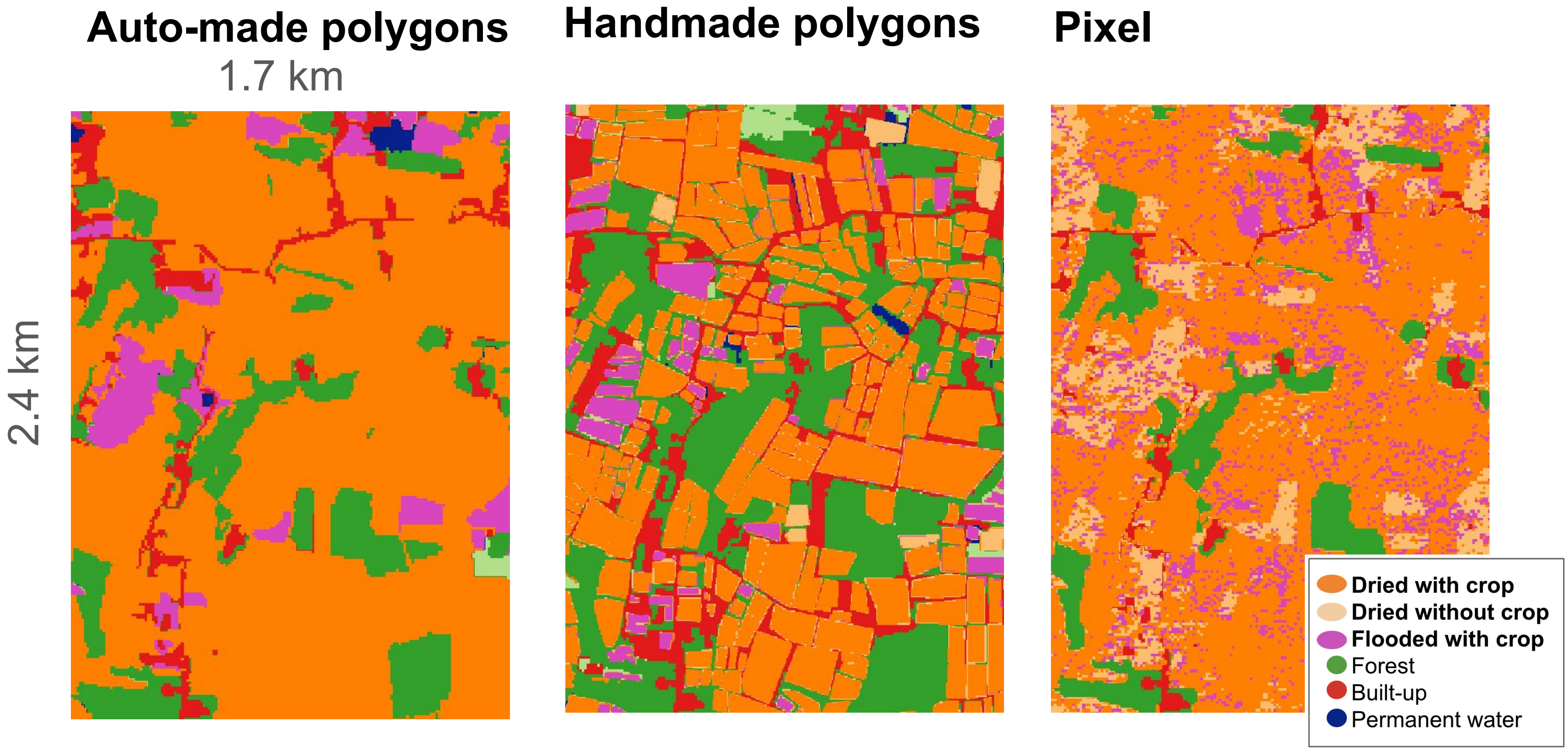
Auto-made polygons **Handmade polygons** **Pixel**

1.7 km

2.3 km



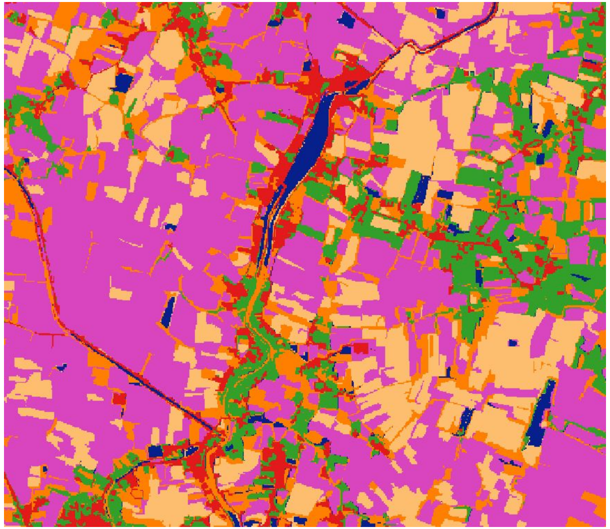
2022/09/03



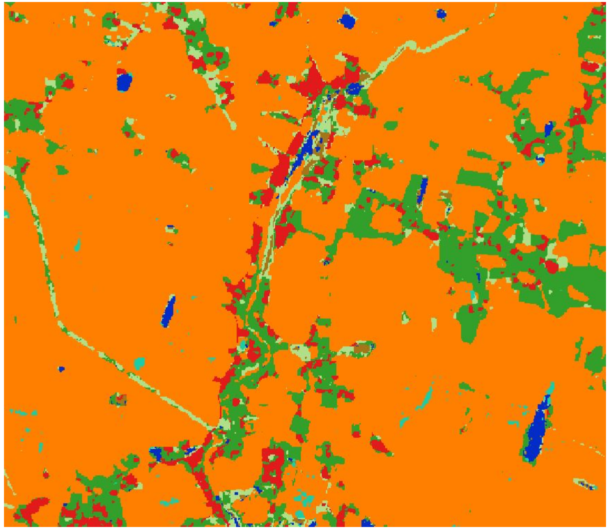
Auto-made polygons
1.7 km
2.4 km
Handmade polygons
Pixel
Dried with crop
Dried without crop
Flooded with crop
Forest
Built-up
Permanent water

Result⑦
Comparison with existing maps

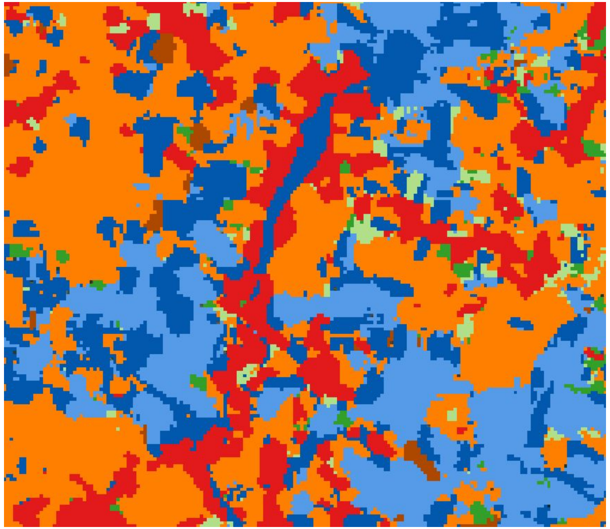
My product
(2022/09/03)



ESA WorldCover 10 m V200
(2021)



DynamicWorld v1
(2022/09 composite)



Disucussion

- **Succeeded in dynamically classifying agricultural lands by only PALSAR-2 data with high accuracy.**
  - By using full polarimetry, many feature values were available.
  - By visiting the site multiple times, high-quality training data were available.
- **Succeeded in creating more detailed maps.**
  - By averaging within each polygon, speckle noises was reduced without losing spatial features.
  - Although Handmade polygons was the best, Auto-made polygons are also sufficient to understand the land cover of agricultural land.