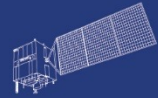


HY



HJ-1AB



CBERS



Gaofen



Beijing-2



Sentinel-1



Sentinel-2



Sentinel-3



Sentinel-5p



Aeolus

2023 DRAGON 5 SYMPOSIUM

3rd YEAR RESULTS REPORTING

11-15 SEPTEMBER 2023

[PROJECT ID. 58944]

[RETRIEVING CROP GROWTH INFORMATION
FROM MULTIPLE SOURCE SATELLITE DATA TO
SUPPORT SUSTAINABLE AGRICULTURE]

<WEDNESDAY & SEP 13,2023>

ID. 58944

PROJECT TITLE: RETRIEVING CROP GROWTH INFORMATION FROM MULTIPLE SOURCE SATELLITE DATA TO SUPPORT SUSTAINABLE AGRICULTURE

PRINCIPAL INVESTIGATORS:

CHINESE LI: PROF. JINLONG FAN, NATIONAL SATELLITE METEOROLOGICAL CENTER, CHINA

EUROPEAN LI: PROF. DEFOURNY PIERRE, UNIVERSITE CATHOLIQUE DE LOUVAIN, BELGIUM

CO-AUTHORS: [JINLONG FAN, DEFOURNY PIERRE]

PRESENTED BY: [JINLONG FAN]

- Inform on the project's objectives
 - Explore the crop monitoring with high resolution satellite for the diverse agricultural cultivation areas in China.
 - Extension of the crop mapping approach of Sen2Agri in China
 - Develop the fusion algorithm of optical and SAR to support the crop monitoring
 - Develop the algorithm of retrieving the biophysics parameters from optical and SAR high resolution satellite images
 - Summarize the advantage and advantage of monitoring agriculture in China with the open access high resolution satellite data

2021 Field Campaign

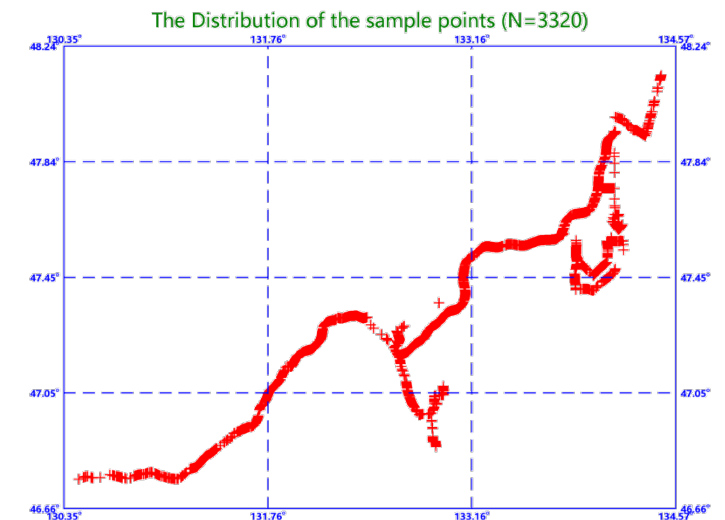
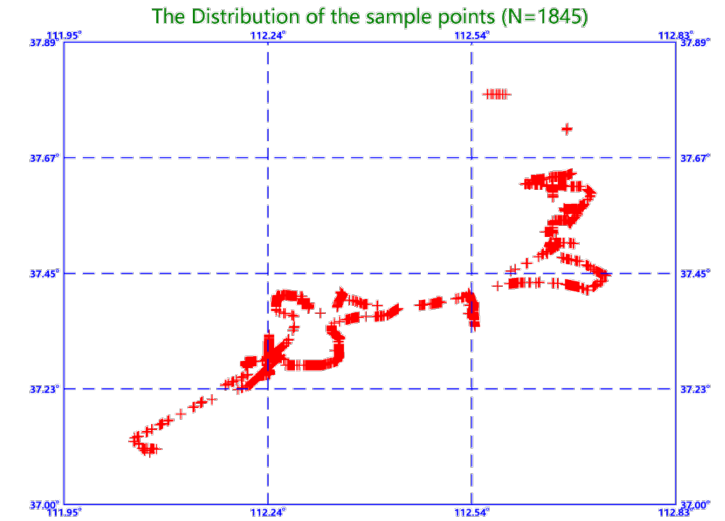
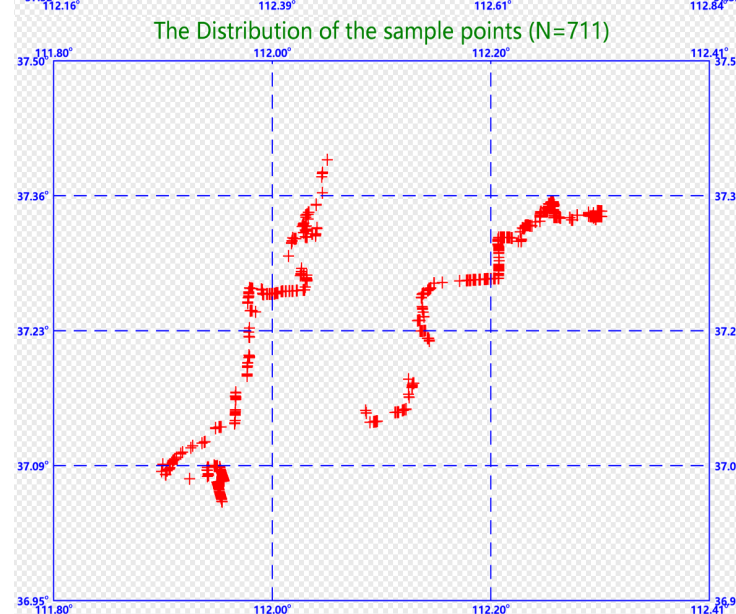
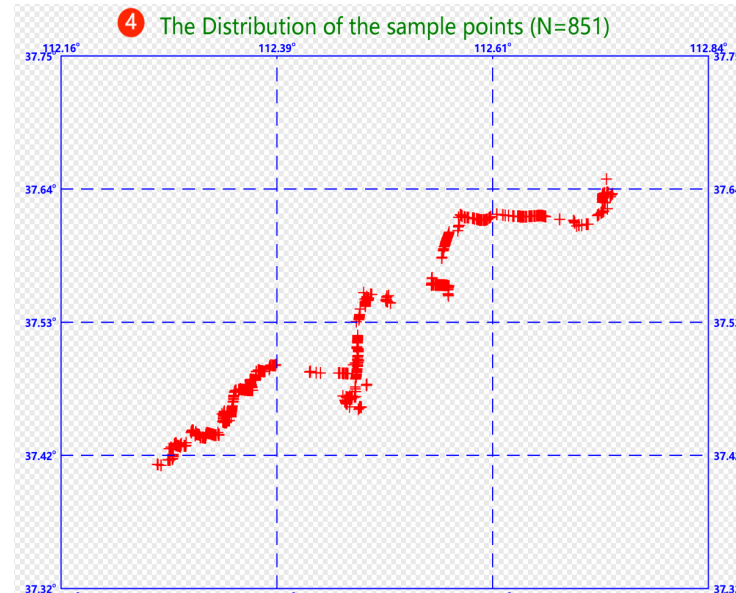
- Shannxi Site May 1-3, 2021
- Jiansanjiang Site August 23-27, 2021
- Shanxi Site Oct 14-15, 2021
- Hunan Site Nov 1-5, 2021

2022 Field Campaign

- Shanxi Site April 29-30, 2022
- Jiansanjiang Site July 26-28, 2022

2023 Field Campaign

- Shanxi Site Feb 24-26, 2023; May 28-29, 2023; July 17-19, 2023; Aug 16-17, 2023; Aug 23-24, 2023; Aug 31-Sep 1, 2023; Sep 6-7, 2023



Data access (list all missions and issues if any). NB. in the tables please insert cumulative figures (since July 2020) for no. of scenes of high bit rate data (e.g. S1 100 scenes). If data delivery is low bit rate by ftp, insert “ftp”

ESA Missions	No. Scenes	ESA Third Party Missions	No. Scenes	Chinese EO data	No. Scenes
1. Sentinel-1 A/B	50	1. Landsat 8/9	60	1. GF-1	40
2. Sentinel-2 A/B	200	2.		2. CBERS04	20
3.		3.		3. FY-3D MERISI	200
4.		4.		4. FY-3C VIRR	200
5.		5.		5. GF-3 SAR	50
6.		6.		6.	
Total:		Total:		Total:	
Issues:		Issues:		Issues:	

Name	Institution	Poster title	Contribution including period of research
Jean Bouchat	Universite Catholique de Louvain	Leaf Area Index Retrieval in Shanxi Province of China Using Sentinel-1 Data	Development of a reliable SAR-to-Optical LAI estimation method for Maize based on recurrent neural network and dual-pol SAR data; Assessment of its temporal and spatial transferability
Sebastien Saelens	Universite Catholique de Louvain	Leaf Area Index Retrieval in Shanxi Province of China Using Sentinel-1 Data	Development of a reliable SAR-to-Optical LAI estimation method for Maize based on recurrent neural network and dual-pol SAR data; Assessment of its temporal and spatial transferability

Name	Institution	Poster title	Contribution including period of research
Xiangsuo Fan (Ph. D, Ass. Prof.)	1. Guangxi University of Science and Technology	Multi spectral remote sensing agricultural classification based on fusion of channel attention mechanism and multi feature perception parallel network structure	Proposed a parallel network architecture integrating channel attention mechanism and multi-layer perceptron to provide richer expression of word meaning features.
Zeng Weili (Master)	1. Taiyuan University of Technology 2. National Satellite Meteorological Center	Study on Crop Classification Using Sentinel-2 Satellite Data	explores the effects of different feature combinations on the extraction accuracy of corn, using the random forest in the mountainous areas of Shanxi Province, China
Liao Yuejiao (Master)	1. Taiyuan University of Technology 2. National Satellite Meteorological Center	Study on Crop Classification Using Sentinel-2 Satellite Data	explores the effects of different feature combinations on the extraction accuracy of corn, using the random forest in the mountainous areas of Shanxi Province, China

Study on Crop Classification Using Sentinel-2 Satellite Data

Weili Zeng¹, Qiaomei Su¹, Rong Pan¹, Jinlong Fan², Jean Bouchat³
1: Taiyuan University of Technology, China, People's Republic of;
2: NSMC, China, People's Republic of;
3: Universite Catholique de Louvain, Belgium

ABSTRACT

Precise classification of crops is an important way to realise precision agriculture. In order to improve the extraction accuracy of crop information from medium and high resolution remote sensing images in farming areas, this paper uses Sentinel-2 satellite data and DEM data, constructs spectral features, remote sensing index features, texture features and terrain features, and uses the random forest model based on feature preference to finely extract corn in some mountainous areas of Shanxi Province, China, and explores the effects of different feature combinations on the extraction accuracy of corn. The results show that the multi-feature combination effectively improves the classification accuracy of crops, in which the classification result of fusing four types of feature variables is the best, and its overall accuracy reaches 94%. The preferred texture features and terrain features help to present the information of mountainous areas, and can significantly improve the extraction accuracy of the mountainous crop information. Random Forest algorithm can effectively perform data mining of feature variables while still ensuring high extraction accuracy, and can be used as a powerful tool for bulk crop extraction.

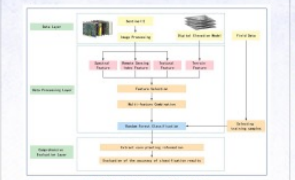
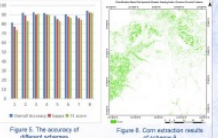


Figure 2: The technical route of the study

Construct feature variables

Table with 2 columns: Spectral feature, NDVI, NDWI, NDMI, LSWI, SAVI, SAVI2, SAVI3, SAVI4, SAVI5, SAVI6, SAVI7, SAVI8, SAVI9, SAVI10, SAVI11, SAVI12, SAVI13, SAVI14, SAVI15, SAVI16, SAVI17, SAVI18, SAVI19, SAVI20, SAVI21, SAVI22, SAVI23, SAVI24, SAVI25, SAVI26, SAVI27, SAVI28, SAVI29, SAVI30, SAVI31, SAVI32, SAVI33, SAVI34, SAVI35, SAVI36, SAVI37, SAVI38, SAVI39, SAVI40, SAVI41, SAVI42, SAVI43, SAVI44, SAVI45, SAVI46, SAVI47, SAVI48, SAVI49, SAVI50, SAVI51, SAVI52, SAVI53, SAVI54, SAVI55, SAVI56, SAVI57, SAVI58, SAVI59, SAVI60, SAVI61, SAVI62, SAVI63, SAVI64, SAVI65, SAVI66, SAVI67, SAVI68, SAVI69, SAVI70, SAVI71, SAVI72, SAVI73, SAVI74, SAVI75, SAVI76, SAVI77, SAVI78, SAVI79, SAVI80, SAVI81, SAVI82, SAVI83, SAVI84, SAVI85, SAVI86, SAVI87, SAVI88, SAVI89, SAVI90, SAVI91, SAVI92, SAVI93, SAVI94, SAVI95, SAVI96, SAVI97, SAVI98, SAVI99, SAVI100. Rows include formulas for each index.

Compared with single feature variables, the overall accuracy and Kappa coefficient of classification based on multi-feature optimization combination for crop extraction are significantly improved. The best classification result is scheme 8, based on spectral features + remote sensing index features + texture features + terrain features, which has an overall accuracy of 94%, a Kappa coefficient of 0.92, and an F1 Score of 91.7%, which is better than the other schemes, and improves 12.8%, 0.15, and 18.31% over the results of the classification using only spectral features, respectively.



DISCUSSION

Based on Sentinel satellite data, this study adopts a feature optimization algorithm combined with a random forest classifier to realize the extraction of information on the planting structure of typical crops in the study area. The region of this study is relatively small and only focuses on one growing season, and the applicability and robustness of the conclusions of this study will be examined by conducting corn planting area extraction studies on a larger scale for multiple growing seasons. For the next study, whether the feature selection algorithm based on multi-temporal phase and multi-feature can be combined with high-resolution remote sensing imagery and generalized to other regions needs to be further explored.

CONCLUSIONS

- 1. Spectral features are the basis of feature classification, and most of the crop information can be captured by spectral features, but the effect of corn extraction is ordinary.
- 2. Adding remote sensing index features, texture features, and terrain features can effectively improve the classification accuracy.
- 3. The integration of texture features and topographic features contributes to the presentation of information, enriches the information content of multi-spectral images, and is beneficial to the extraction of crop information.
- 4. The random forest model can achieve fast and accurate crop information extraction. It can be used as a powerful tool for bulk crop extraction.

MAJOR REFERENCES

[1] Fan, H. Land-use mapping in the Nujang Grand Canyon: integrating spectral, textural, and topographic data in a random forest classifier. *Int. J. Remote Sens.* 2013, 34, 7567-7587.
[2] Fan, J., Zhang, X., Zhao, C., Qin, Z., De Vroey, M., Defourny, P. Evaluation of Crop Type Classification with Different High Resolution Satellite Data Sources. *Remote Sens.* 2021, 13, 911

LEAF AREA INDEX RETRIEVAL IN SHANXI PROVINCE OF CHINA USING SENTINEL-1 DATA

Jean Bouchat¹, Quentin Defense¹, Yuejiao Liao², Rong Pan², Ying Song², Sébastien Saelens¹, Qiaomei Su², Jinlong Fan² and Pierre Defourny¹

¹ Earth and Life Institute, Université catholique de Louvain, 1348 Louvain-la-Neuve, Belgium
² Department of Surveying and Mapping, College of Mining Engineering, Taiyuan University of Technology, 030024 Taiyuan, China
³ National Satellite Meteorological Center, China Meteorological Administration, 100081 Beijing, China

Context

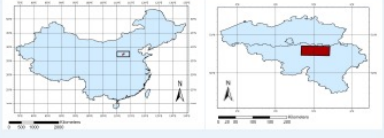
- Leaf area index (LAI) is a key variable for agricultural monitoring
- The most accurate LAI estimation methods exploit optical data (e.g., [1]) and are rendered ineffective in the case of frequent cloud cover
- Synthetic aperture radar (SAR) can allow the remote estimation of LAI at the parcel-level, on a large scale, regardless of cloud cover [2]
- SAR-to-optical regression methods have shown promising results for NDVI monitoring [3]

Objectives

1. Development of a reliable SAR-to-optical LAI estimation method for maize based on recurrent neural network and dual-pol SAR data
2. Assessment of its temporal and spatial (Belgium and China) transferability

Data

- Two geographically distinct regions: Shanxi province of China and Hesbaye region of Belgium



- Field-average values

Training & testing

- SAR backscatter data (σ_{HH}^0 , σ_{HV}^0 , σ_{VH}^0) from Sentinel-1, from 2019 to 2023
- LAI derived from Sentinel-2 optical imagery [1], from 2019 to 2023

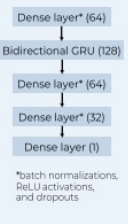
External validation

- LAI measured in situ in 5 sites in the Shanxi province of China in 2023 (ongoing)



Methods

- Model
- Recurrent neural network
- Time series (May to mid-October) of field-average values



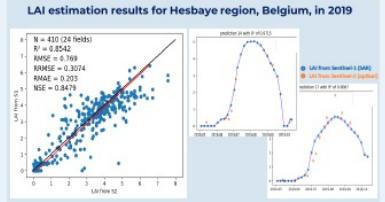
- Features (Sentinel-1)
 - Mean, std, min, and max for VV and VH
 - VV/VH ratio
 - Incidence angle
 - Dual Pol Radar Vegetation Index (dprVI)

- Labels (Sentinel-2)
 - LAI derived from Sentinel-2
 - Interpolated with a nearest neighbor algorithm on Sentinel-1 DSC acquisition grid
 - Label masked if > 5 days apart from nearest Sentinel-1 acquisition

- Training and validation
 - 10-to-1 train/test split
 - External validation against LAI measured in situ with Licor LAI-2000

Results

- Field campaign in Shanxi still ongoing
- Preliminary study conducted on 231 maize fields in Belgium with Sentinel-1 and -2 images from 2019



References

[1] Delloye, C., Weiss, M., & Defourny, P. (2018). Retrieval of the canopy chlorophyll content from Sentinel-2 spectral bands to estimate nitrogen uptake in intensive winter cropping systems. *Remote Sensing of Environment*, 216, 245-261.
[2] Bouchat, J., Tronquo, E., Orban, A., Neyt, X., Verhoest, N. E., & Defourny, P. (2022). Green area index and soil moisture retrieval in maize fields using multi-polarized C-band L-Band SAR data and the water cloud model. *Remote Sensing*, 14(10), 2406.
[3] Cariouat, A., Valero, S., Giordano, S., & Mallet, C. (2021). Recurrent-based regression of Sentinel time series for continuous vegetation monitoring. *Remote Sensing of Environment*, 262, 112419.

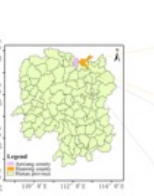
Multi spectral remote sensing agricultural classification based on fusion of channel attention mechanism and multi feature perception parallel network structure

Xiangsuo Fan¹, Xuyang Li¹, Jinlong Fan², Chuan Yan³
1. Guangxi University of Science and Technology
2. National Satellite Meteorological Center

Introduction

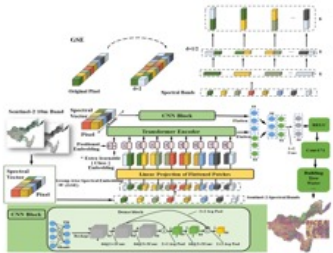
We proposed a parallel network architecture that integrates channel attention mechanism and multi-layer perception based on feature channel attribution, effectively mining the global association information of images and the feature information between different channels, fully integrating spatial and channel position associations while providing richer expression of word meaning features. Finally, we fused using neural networks to better achieve pixel-level image classification.

Study Area and Data



Huarong County is located in Jiangxi City, Hunan Province, China, between 25° 10' 18" - 25° 48' 27" N and 112° 54' 31" - 113° 5' 32" E. It is situated on the northern border of Hunan Province, in the western part of Jiangxi City. The geographic zoning features are relatively clear: the northwest is low mountains and hills area, with valleys and plateaus between them; the central and southern parts are hilly areas, and the west and east of Huarong County are also surrounded by lakes, with extremely developed water systems and abundant water resources. It has created good environment for local farmers to develop aquaculture, with main characteristic aquaculture including crayfish, chub, head fish, bullfrog, etc. The research area is shown in Figure 1 has a large number of crayfish farming areas (ponds), and accurate and effective acquisition of pond area is of great significance for the development of local aquaculture industry and yield extraction.

Methods



Results

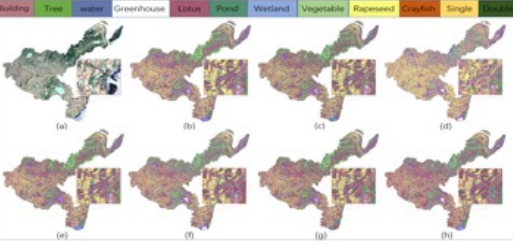


Fig. the classification results obtained by different models in the data of Huarong County.

Conclusions

The network architecture adopts a fusion channel attention mechanism and a multi-layer perception parallel based on feature channel attribution. In order to enhance local information exchange between bands, after adding spatial and channel information, grouped spectral sensing is used to generate features. Next, by the VIT branch, by incorporating channel attention mechanism, the information between spectral features is deeply mined; in another branch, a multi-layer perception network based on feature channel attribution was designed to improve the network's ability to extract features from different feature channels. Finally, the feature information obtained from both is fused, and the dimensionality of the features is reduced through a fully connected layer. Finally, the activation function and RGB are used. Head obtains the classification results. This algorithm can classify multi-spectral images at the pixel level. The experimental results show that in the algorithm proposed in this article, the accuracy of Building reaches 90.92%, the accuracy of Water reaches 93.85%, the overall accuracy is 93.02%, and the Transformer (ViT) is 95.81%. The performance of the Sentinel-2 dataset has a significant improvement for the Transformer.

References

[1] Huang, C., Davis, L. S., & Townshend, J. R. (2002). An assessment of support vector machines for land cover classification. *International Journal of Remote Sensing*, 23(4), 725-749.
[2] Zhang, X., Wang, Y., Zhao, X., & Dai, Q. (2016). Comparison of decision tree, random forest and support vector machine for classification accuracy for major vegetation types in China using SPOT-2 MERIS imagery. *Remote Sensing*, 8(7), 751.
[3] Chen, Y., Wang, X., Zhang, Q., Tang, X., Liu, Z., & Li, J. (2018). Rapid extraction of transverse extent during the Yangtze River flood using Sentinel-1A dual-polarization SAR imagery. *Remote Sensing*, 10(5), 793.
[4] Guo, J., Huang, A., Ni, W., & Padoa, D. (2016). Cloud-based infrastructure for Earth observation data management and analysis: Case study of the Geospatial Cyberinfrastructure at the University of Arizona. *ISPRS International Journal of Geo-Information*, 5(5), 86.
[5] Huang, J., Bradford, K. J., & Jordan, R. L. (2015). Infrared thermometry: a remote sensing approach to crop water stress detection. *Agricultural and Forest Meteorology*, 241(4-5), 149-195.

Acknowledgement: Dragon(58944)

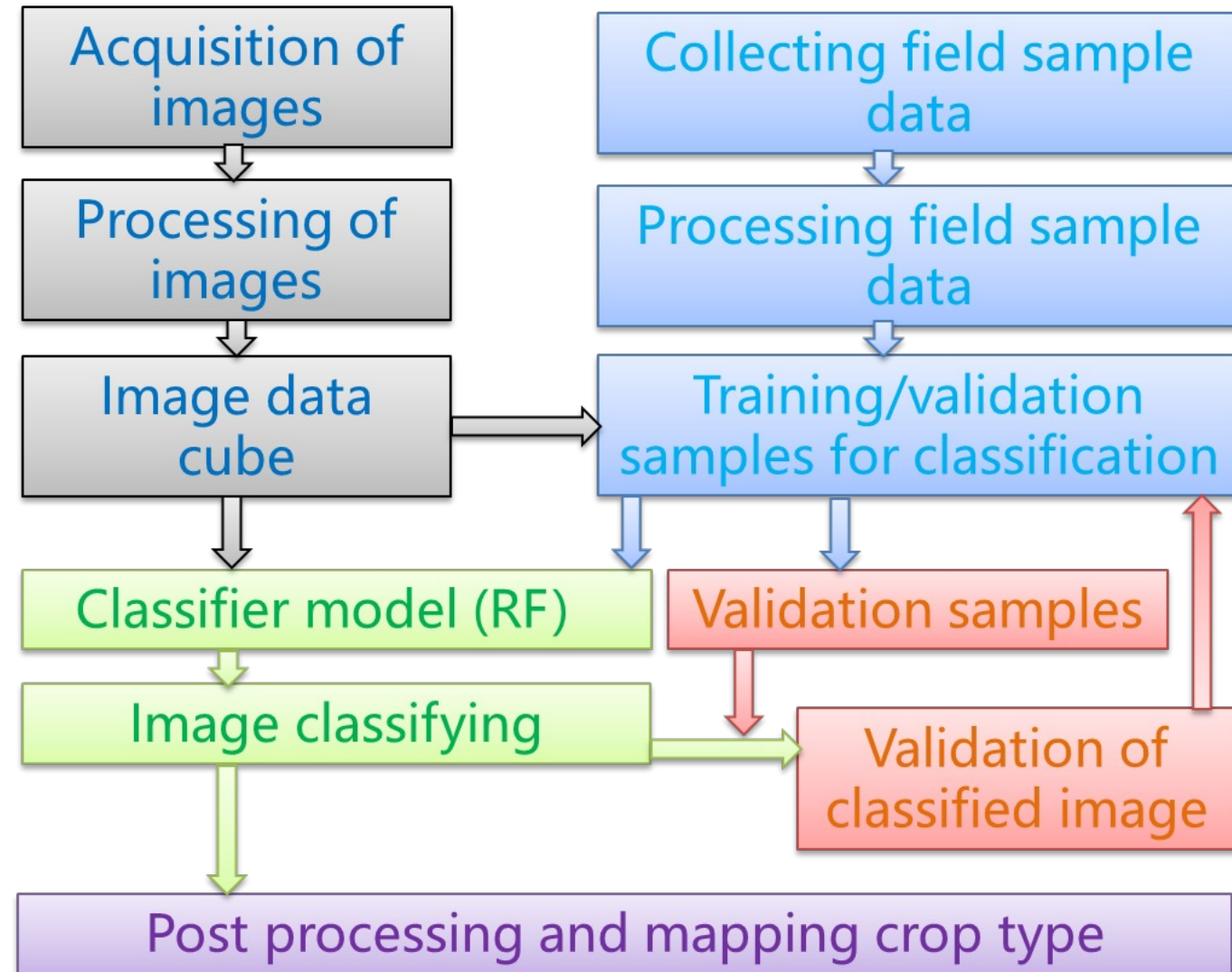
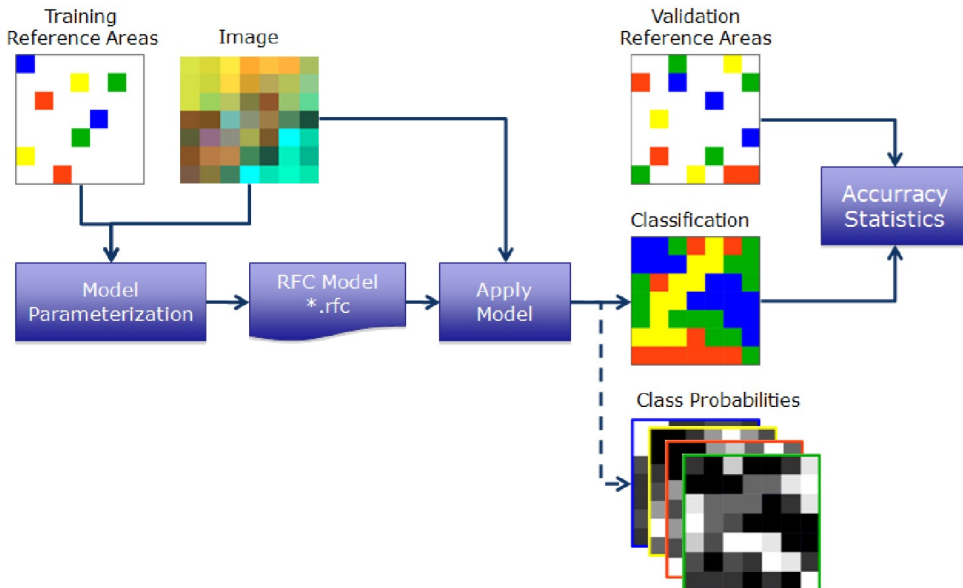
DRAGON 5 3rd YEAR RESULTS REPORTING

Navigation and control elements for the presentation, including a search bar, zoom controls, and a list of items.

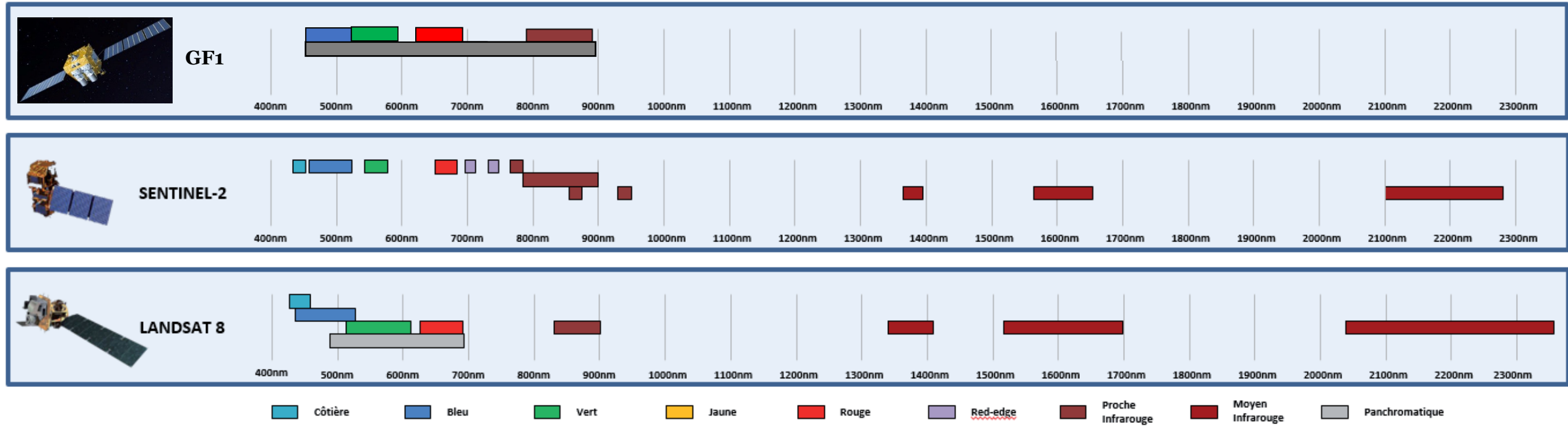
- Inform on the results after 3 years of activity
 - Crop Mapping with Chinese high resolution satellite data at provincial level
 - Mapping the flood affected crop area
 - Identifying the crop practices of conservation agriculture with Sen2Agri
 - Promoting the remote sensing application in large and modern farm

Crop Mapping Key steps

- Remote sensing data processing
- Training sample collection and evaluation
- Classification algorithm and application
- Validation and feedback
- Post classification and noise filtering



Spectra of high-resolution satellite data



- L8 <https://earthexplorer.usgs.gov>
- Sentinel <https://scihub.copernicus.eu/>
- GF <http://218.247.138.119:7777/DSSPlatform/index.html>

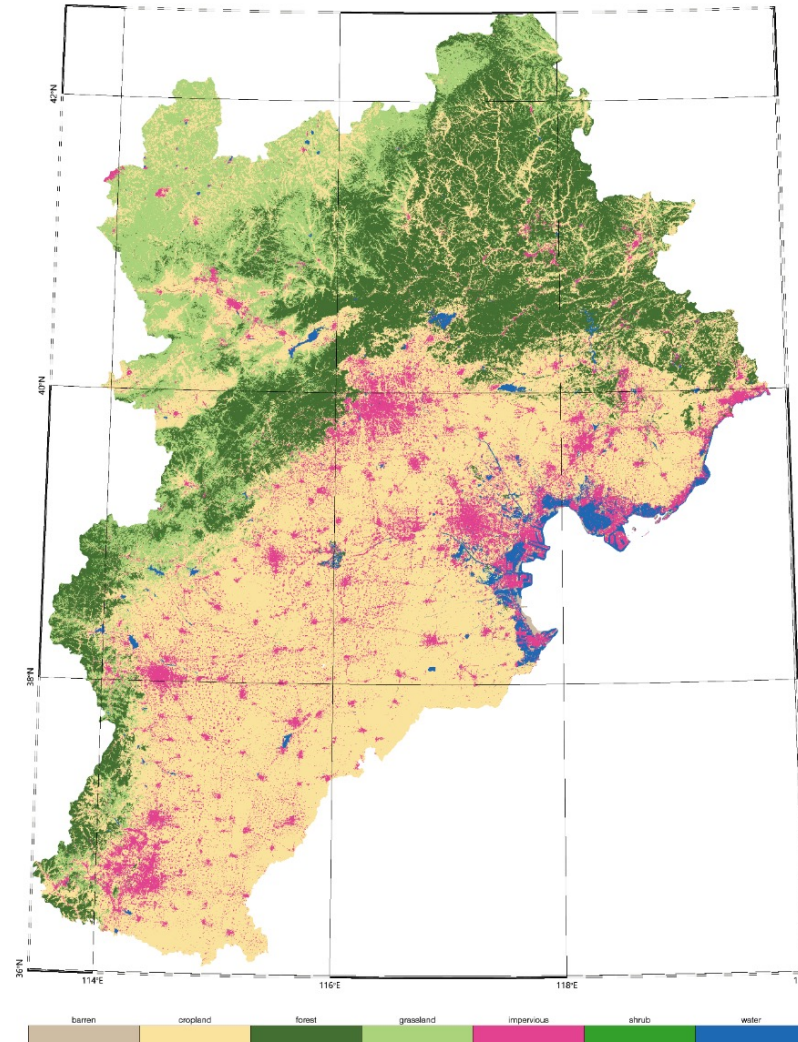
1 Crop Mapping with Chinese high resolution satellite data at provincial level

Mapping Land Cover

Beijing, Tianjin and Hebei

- Landsat 8 data
- Cloud free image by spatial Mosaic and temporal composite
- Training samples collected from published products

L8 2020-04 LandcoverMap



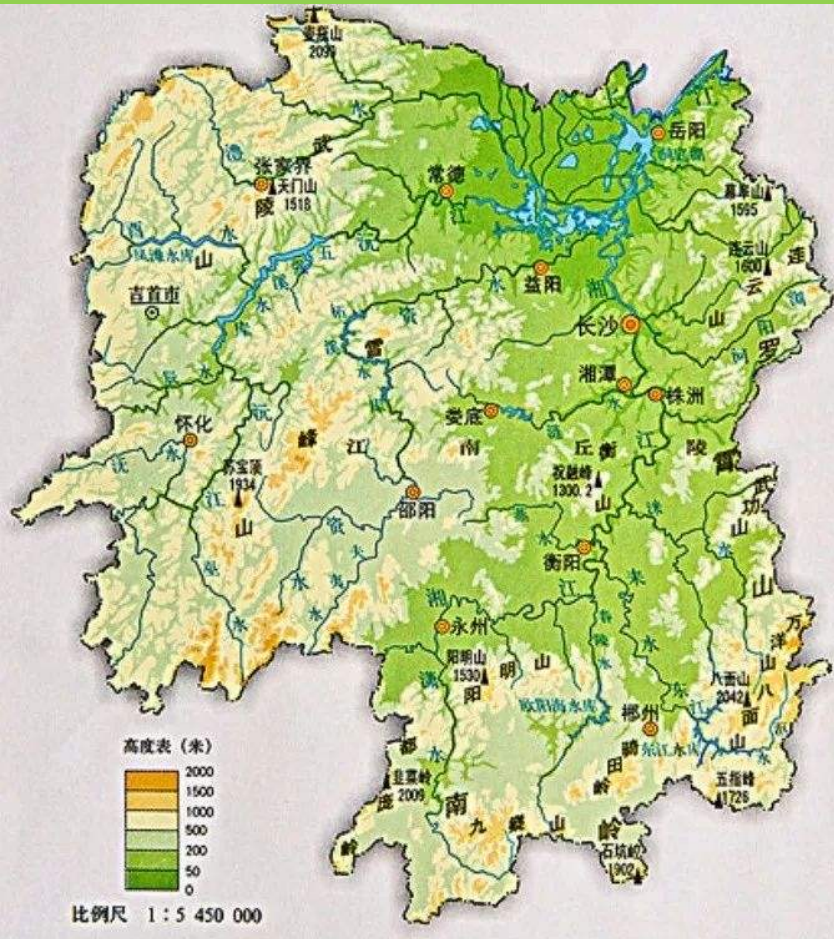
京津冀都市圈区域图



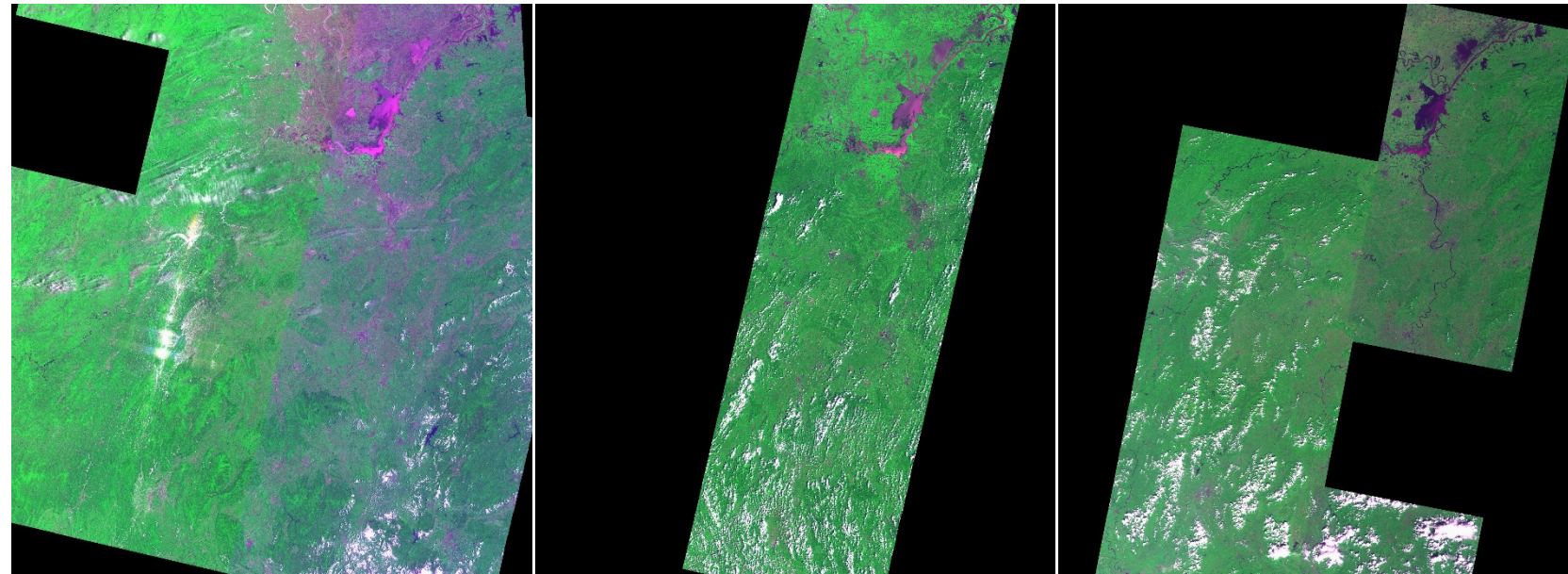
1 Crop Mapping with Chinese high resolution satellite data at provincial level

- From Jan 3 to Oct 23, 2021, 341 scenes images of GF-1 in 91 of 284 days
- The best coverage was made on June 5, 2021

Single day mosaic of GF-1 WFV



Hunan Province



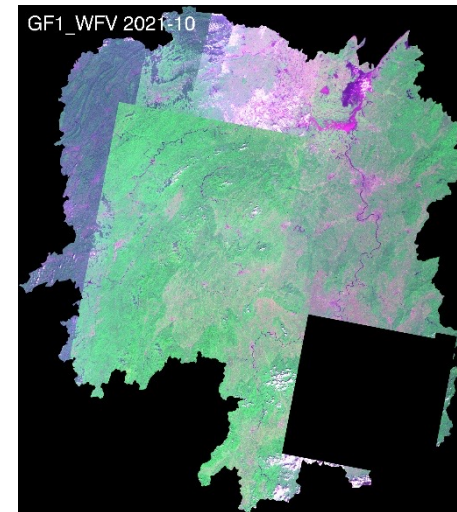
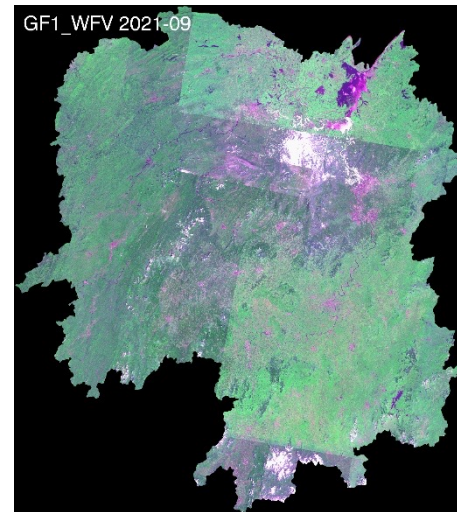
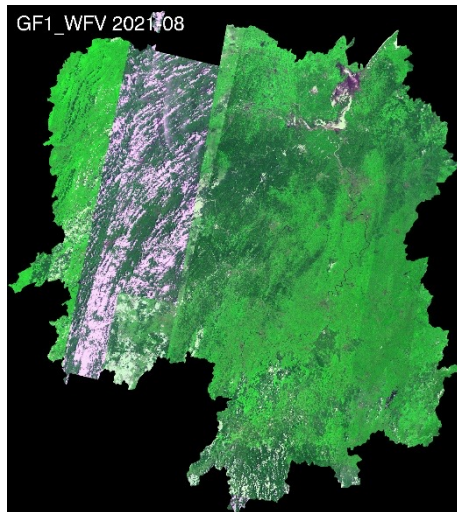
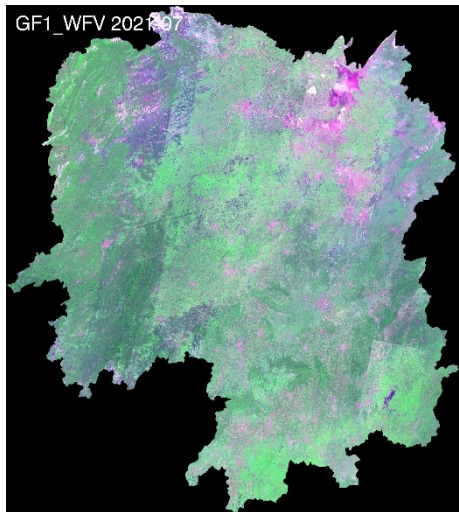
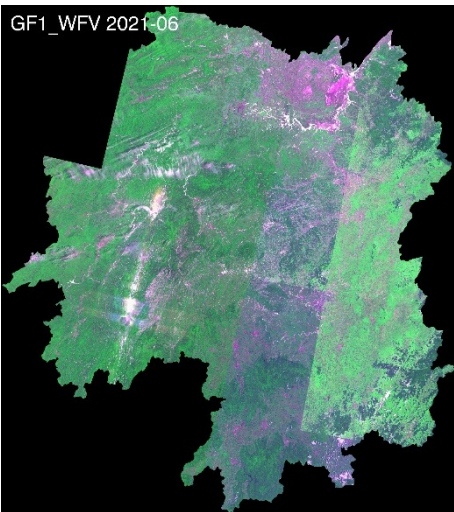
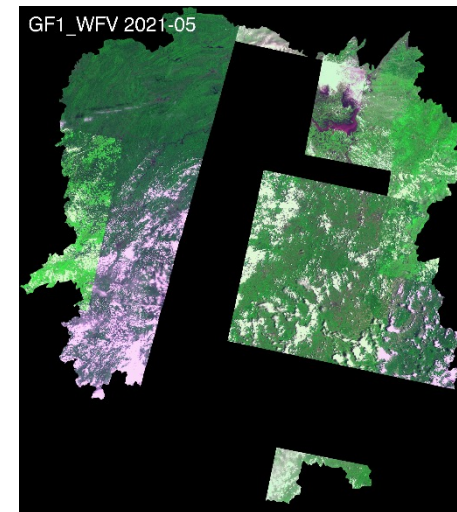
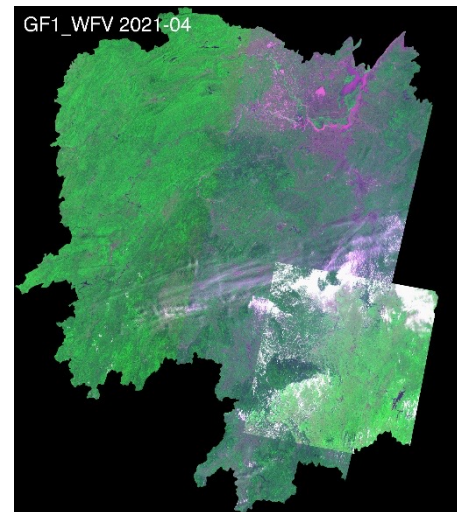
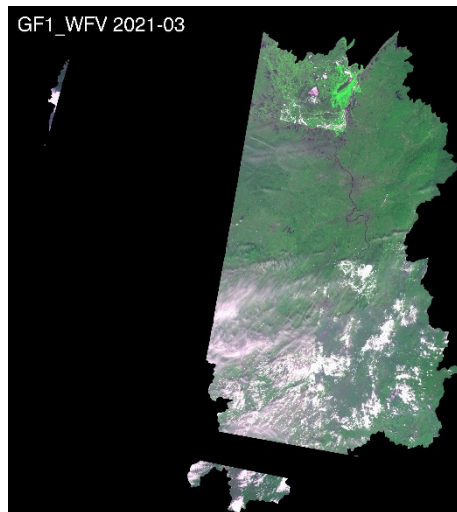
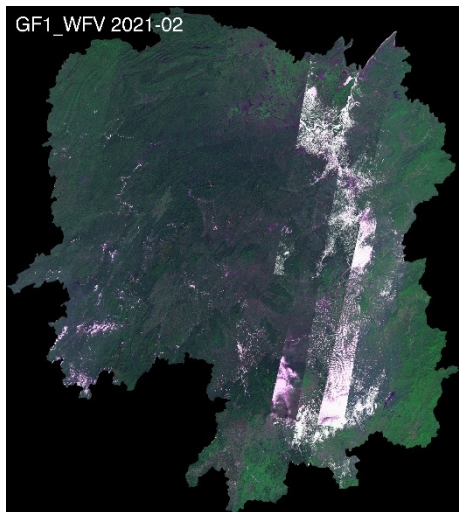
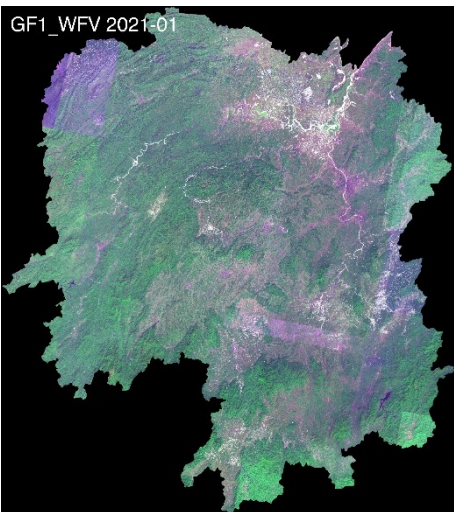
June 5 2021

August 30
2021

October 1 2021

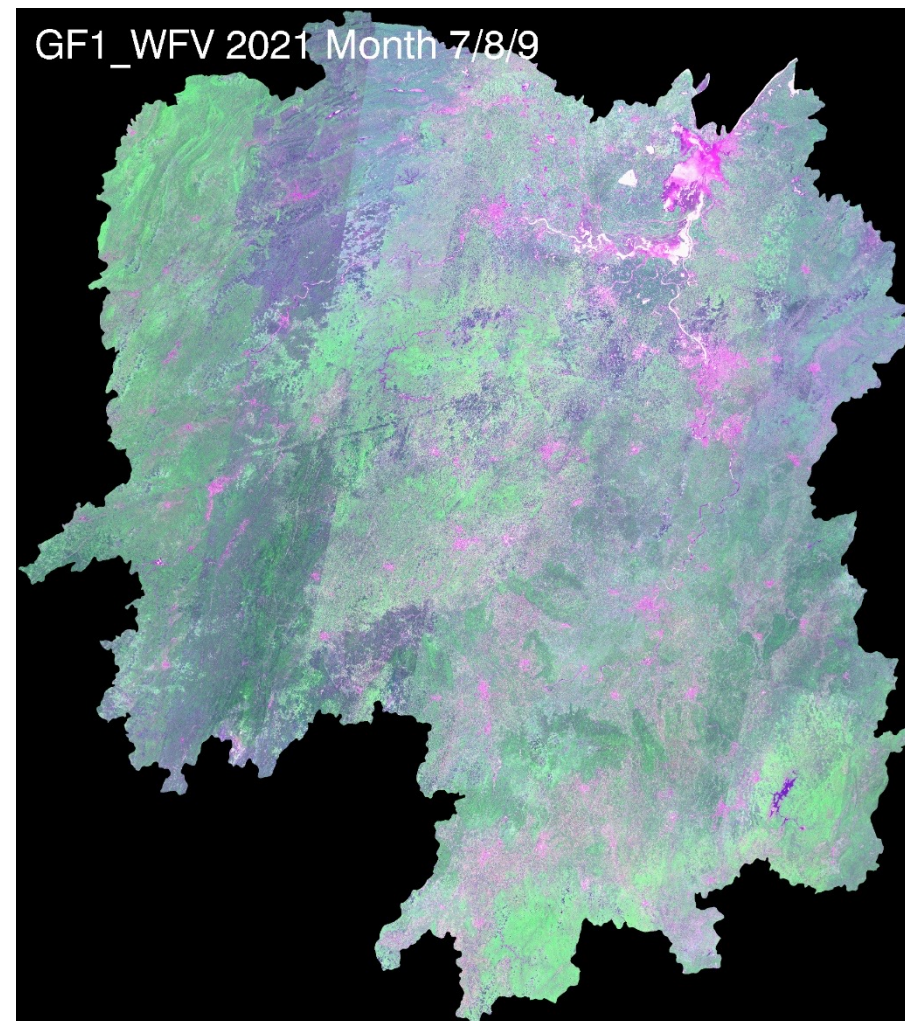
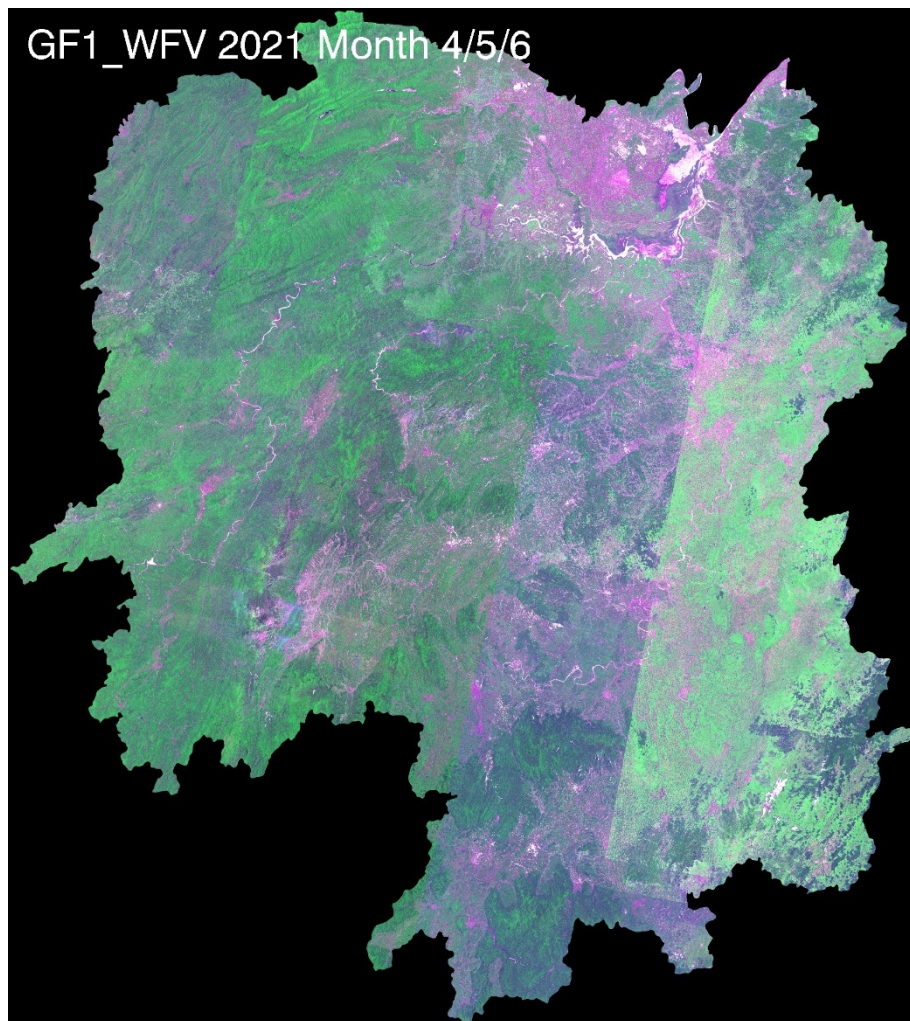
1 Crop Mapping with Chinese high resolution satellite data at provincial level

Monthly mosaic of GF-1 WFV



1 Crop Mapping with Chinese high resolution satellite data at provincial level

Seasonally mosaic of GF-1 WFV

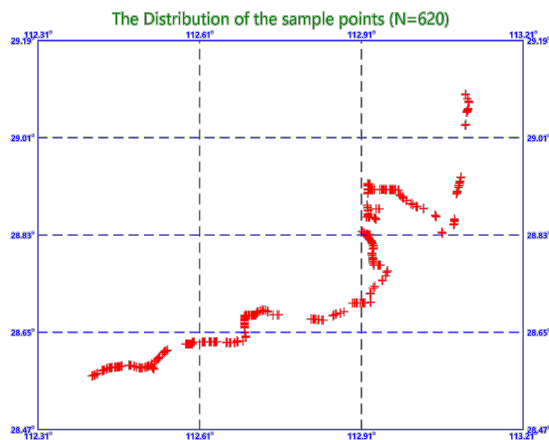
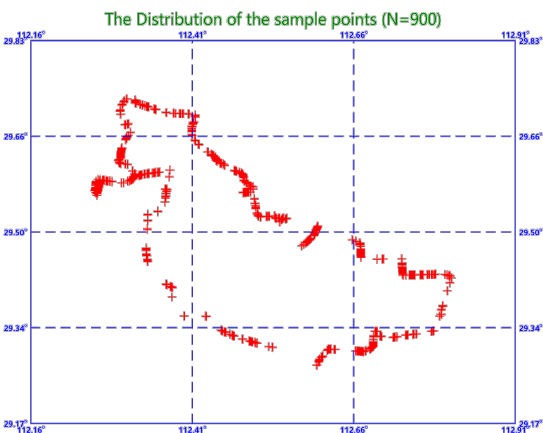
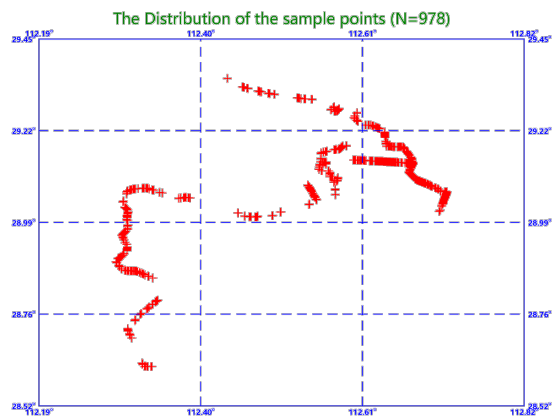


1 Crop Mapping with Chinese high resolution satellite data at provincial level

Field Survey

In early Nov. 2021, 3 students visited the Dongting lake area in Huanan province

- Collected +2500 photo samples with GPS location
- Understand the summer crop and autumn crop practices

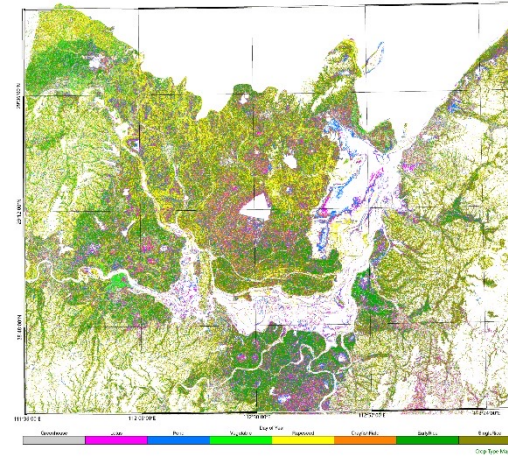


1 Crop Mapping with Chinese high resolution satellite data at provincial level

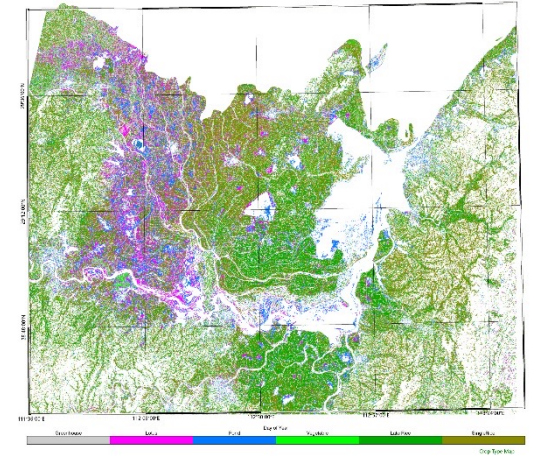
Training sample pixel counts

Classes	Summer Crop	Autumn Crop
Built-up	2363	2257
Shrub and Tree	7650	7767
Water Body	11942	12099
GreenHouse	1481	1729
Lotus	1081	1289
Fish Pond	3092	2955
Wetland	5492	5724
Vegetable	510	529
Rapeseeds	1110	
Shrimp Field	2331	
Early/Later Rice	1577	2032
Single Rice	2136	4492
Total	40765	40873

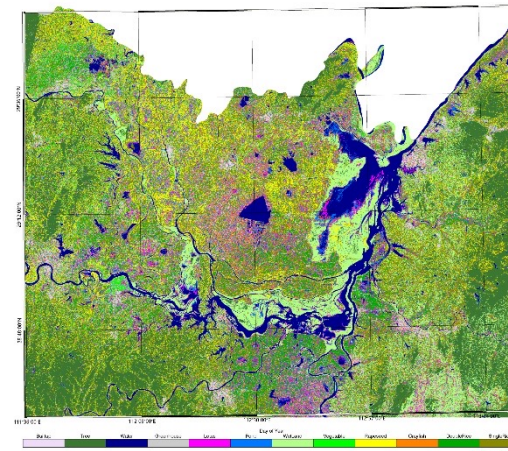
Crop Type Map in Spring for Dongting



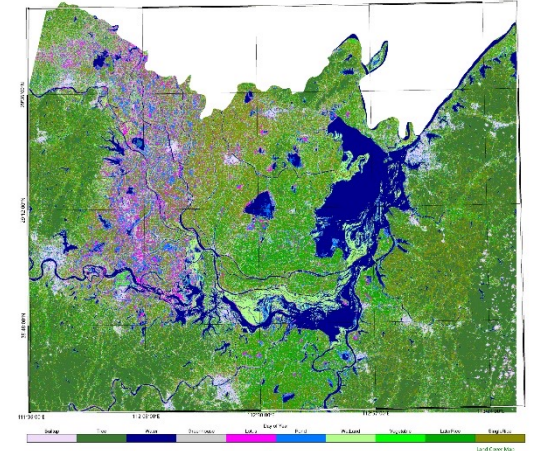
Crop Type Map in Autumn for Dongting



Landcover Map in Spring for Dongting



Landcover Map in Autumn for Dongting



1 Crop Mapping with Chinese high resolution satellite data at provincial level

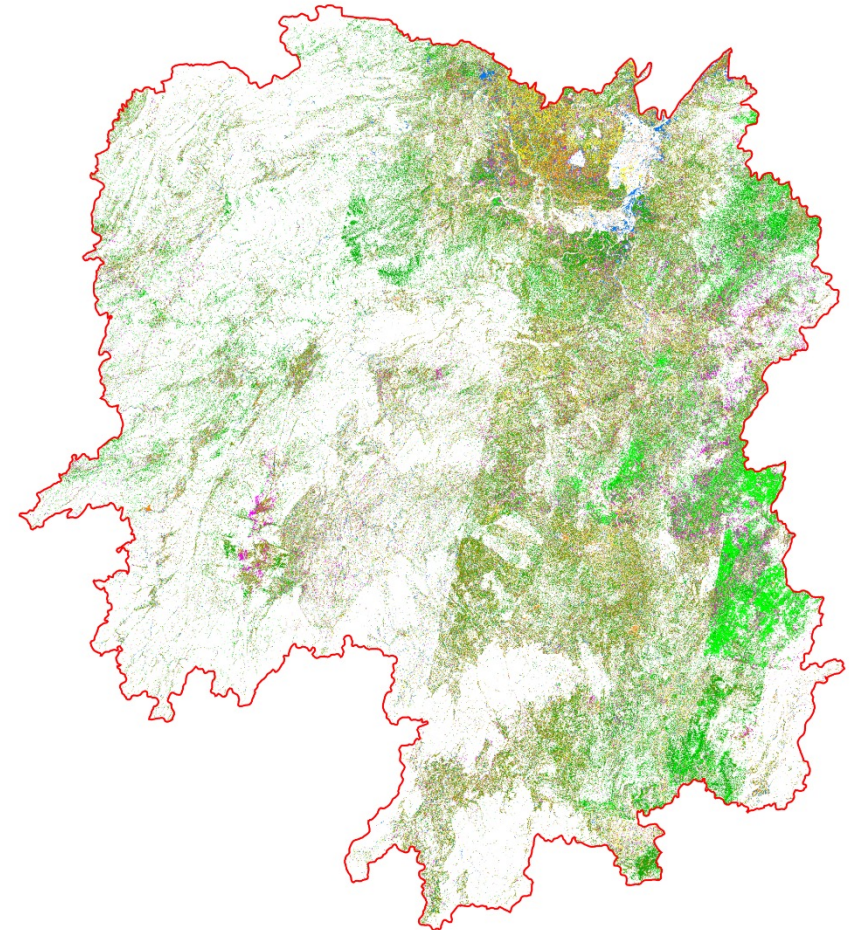
Landcover Map in Spring for Hunan

GF1-WFV 2021-04



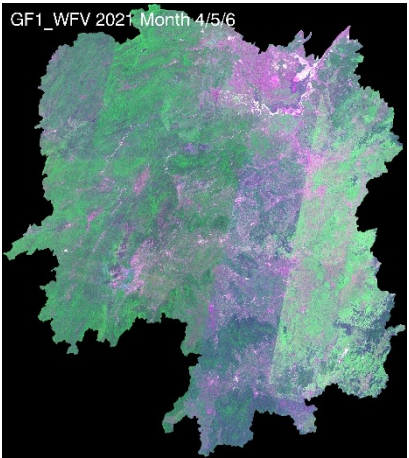
Crop Type Map in Spring for Hunan

GF1-WFV 2021-04



Input Image

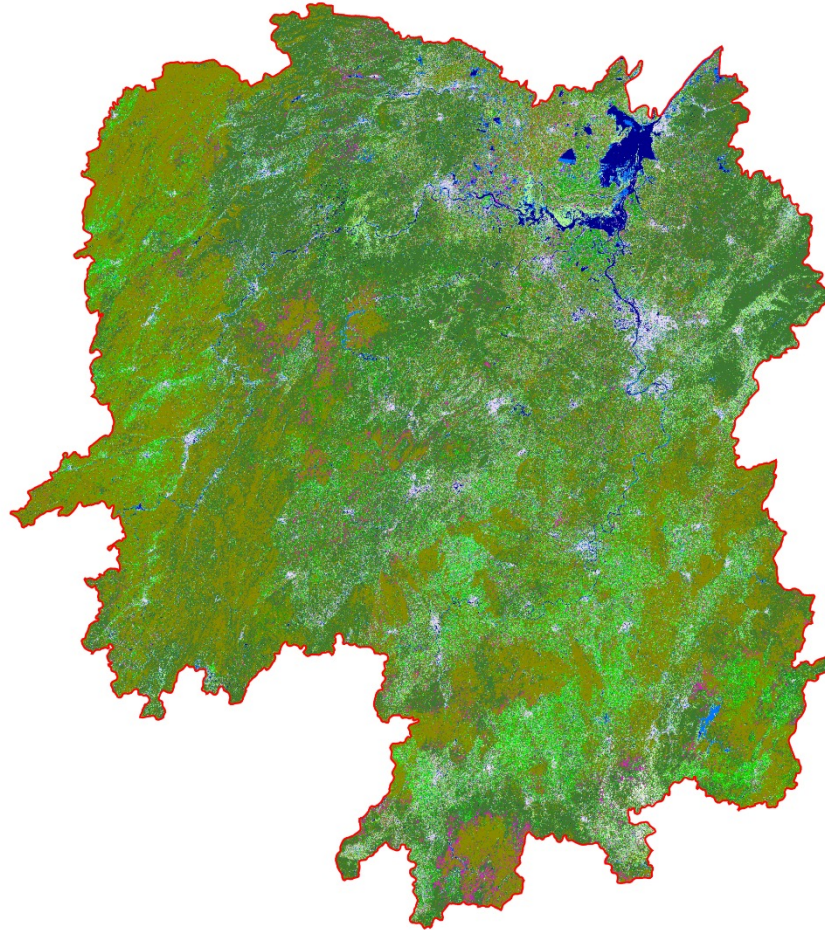
GF1_WFV 2021_Month 4/5/6



1 Crop Mapping with Chinese high resolution satellite data at provincial level

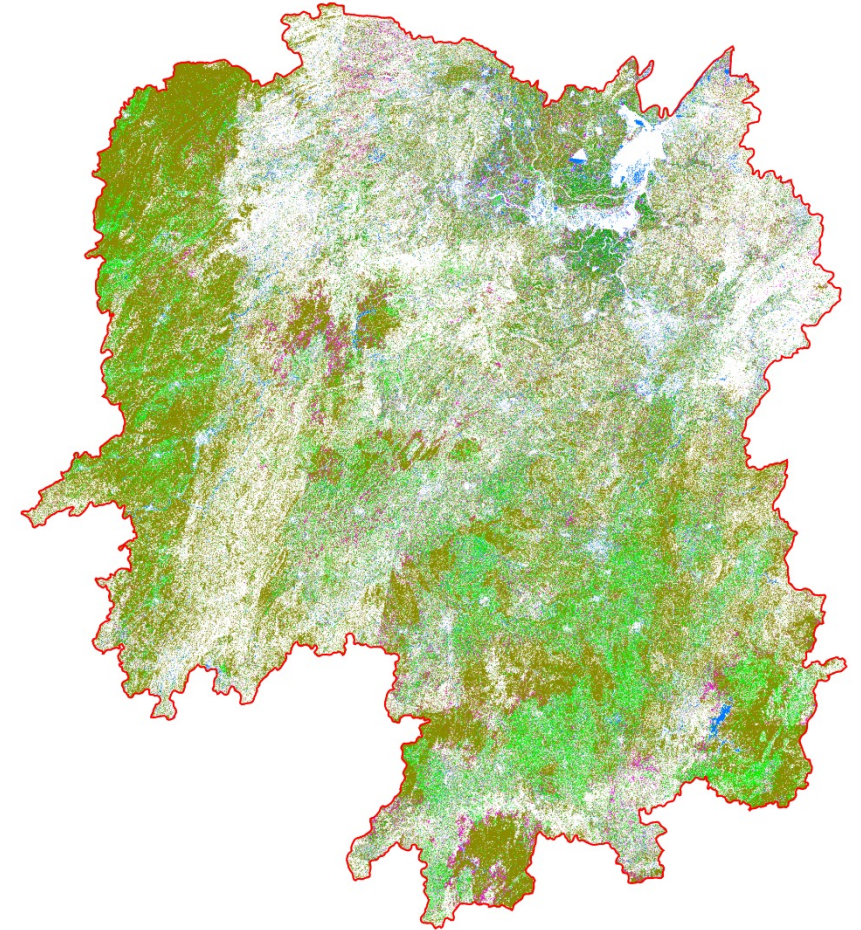
Landcover Map in Autumn for Hunan

GF1-WFV 2021-07

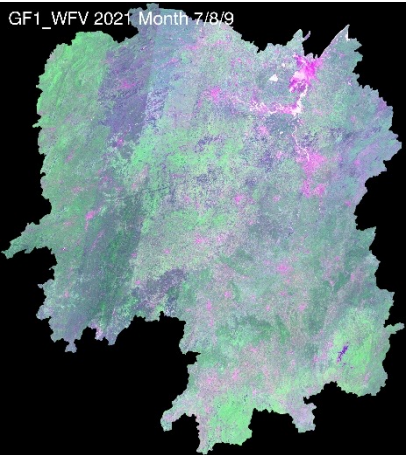


Crop Type Map in Autumn for Hunan

GF1-WFV 2021-07



Input Image

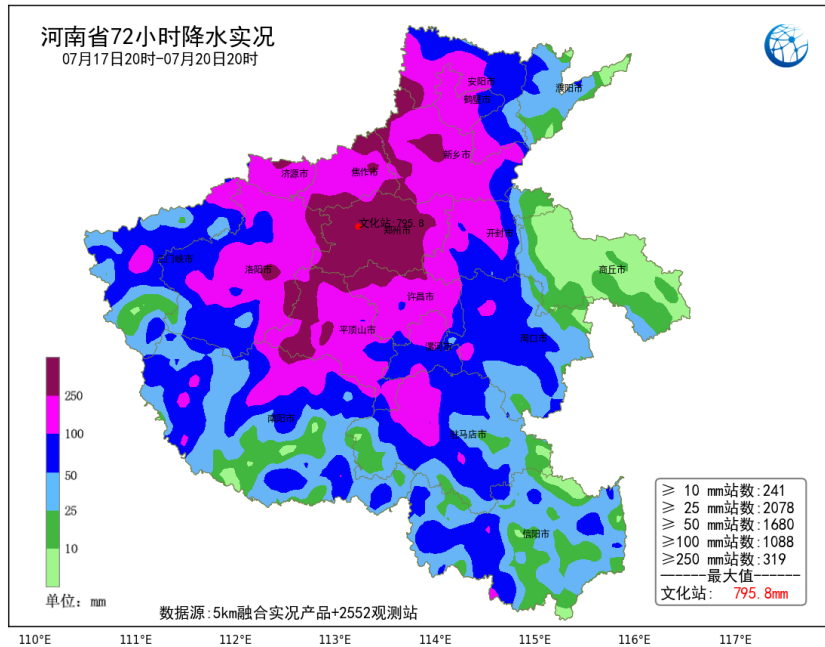


2 Mapping the flood affected crop area

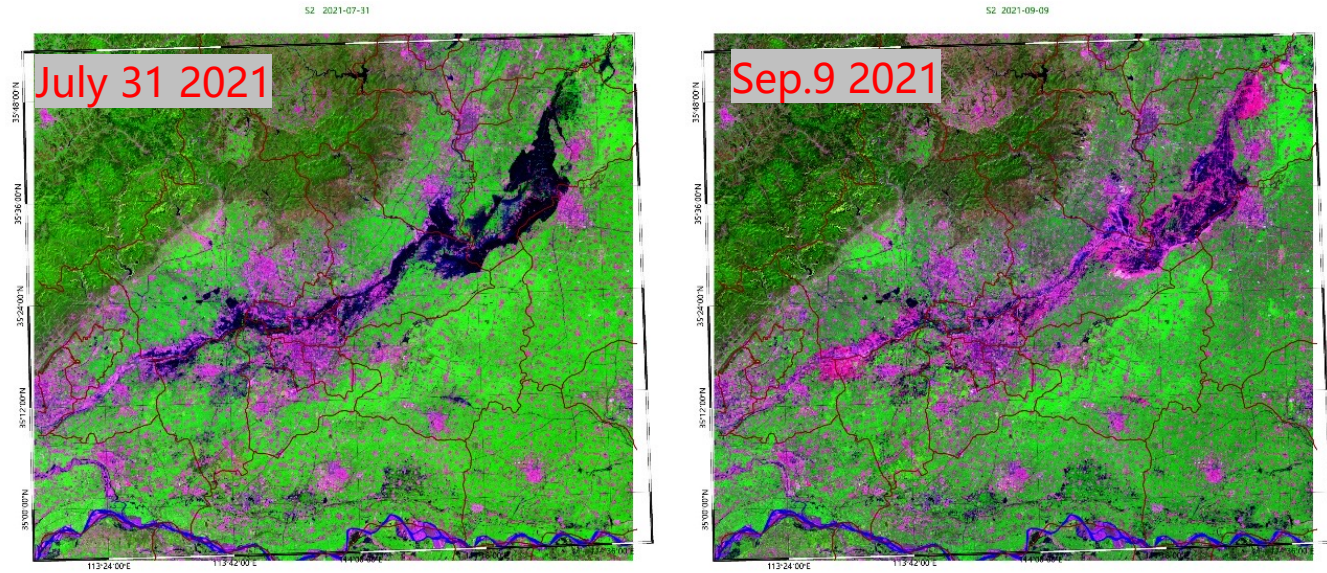
Henan 7.21 Flood 2021

July 17-22, 2021

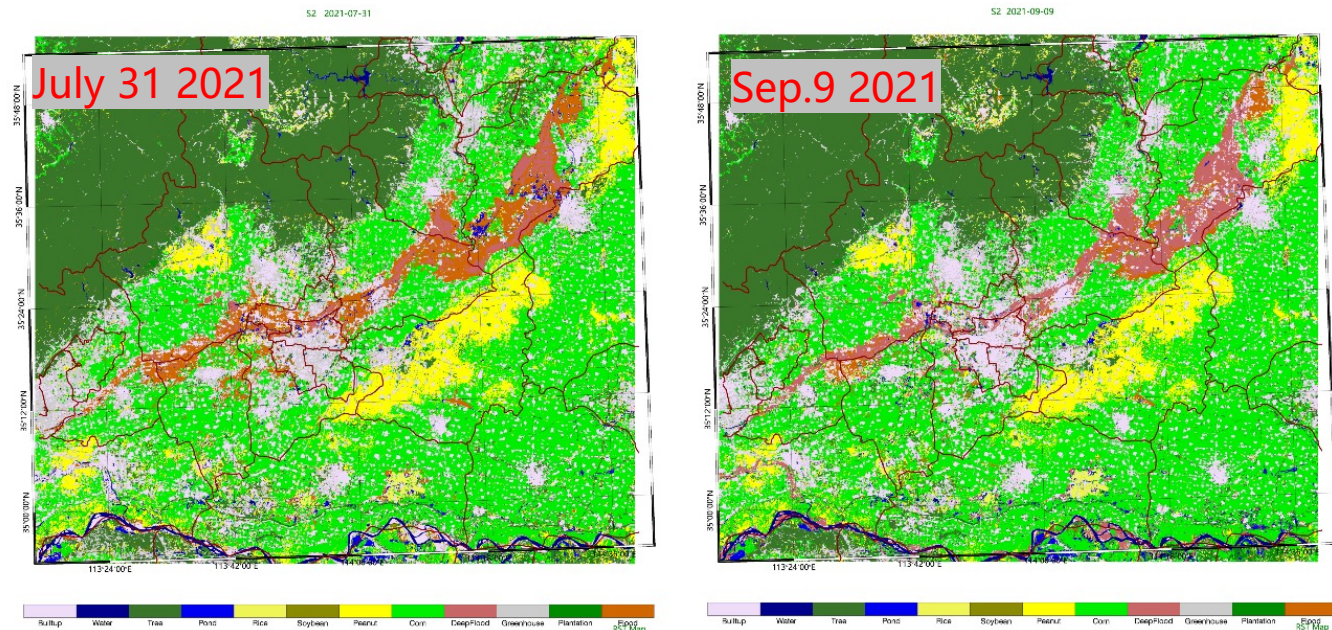
- 696.9 mm per day on July 20 in Zhengzhou & 640 mm annual



Satellite Images



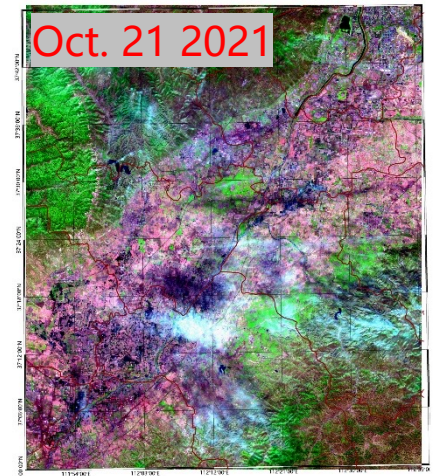
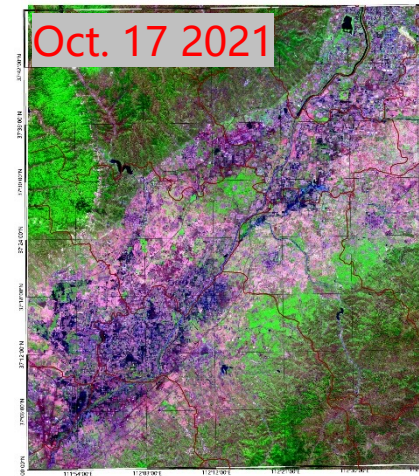
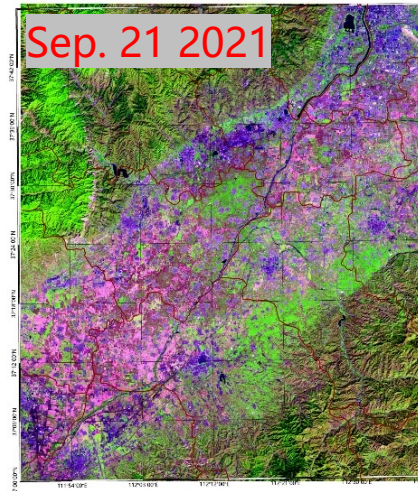
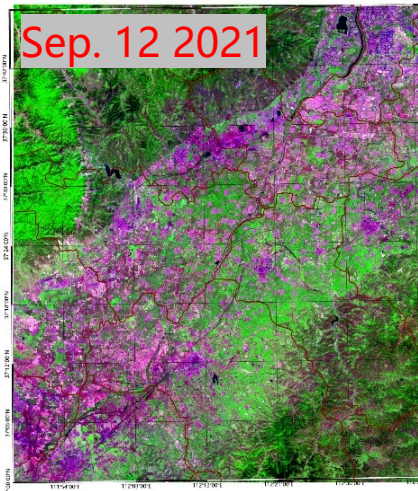
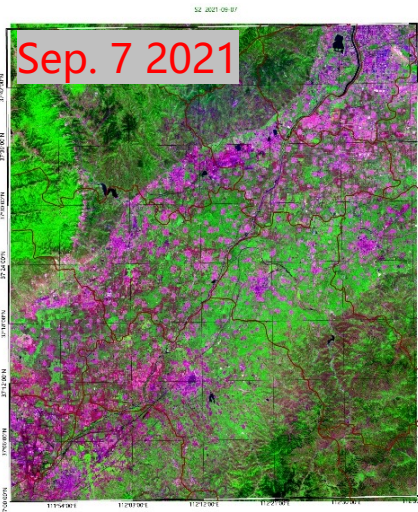
Flood situation Map



2 Mapping the flood affected crop area

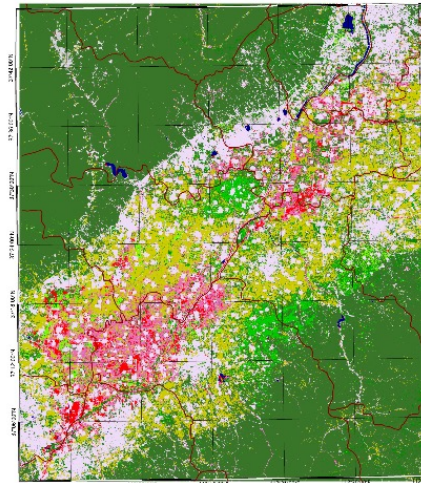
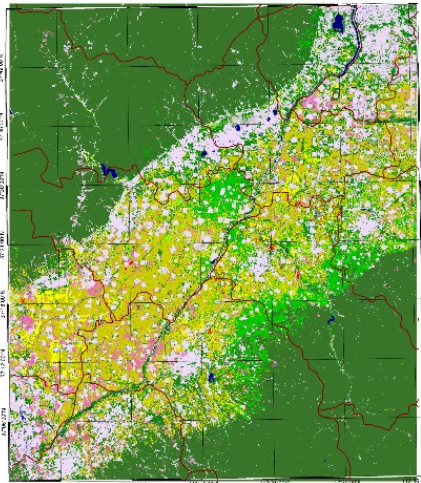
Satellite Images before flooded

Satellite Images after flooded



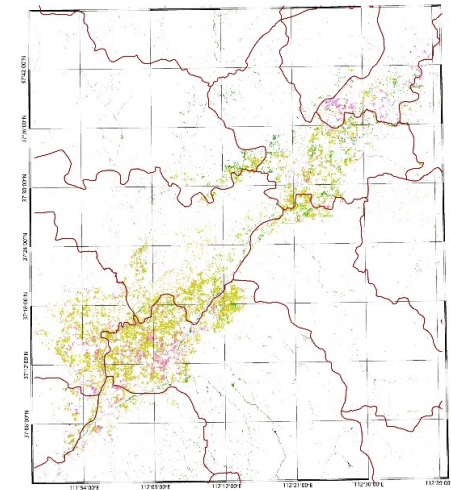
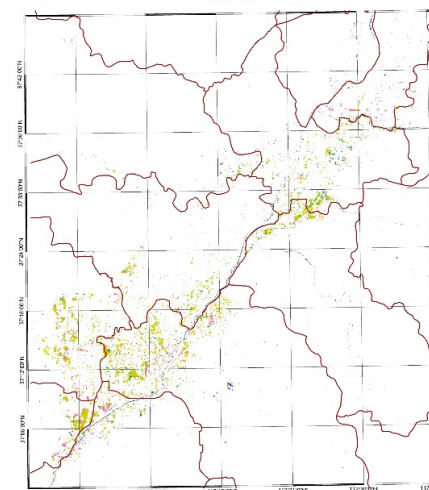
Land cover map before flooded

Flood situation map on Oct 17



Crops in deep water

Crops in shallow water

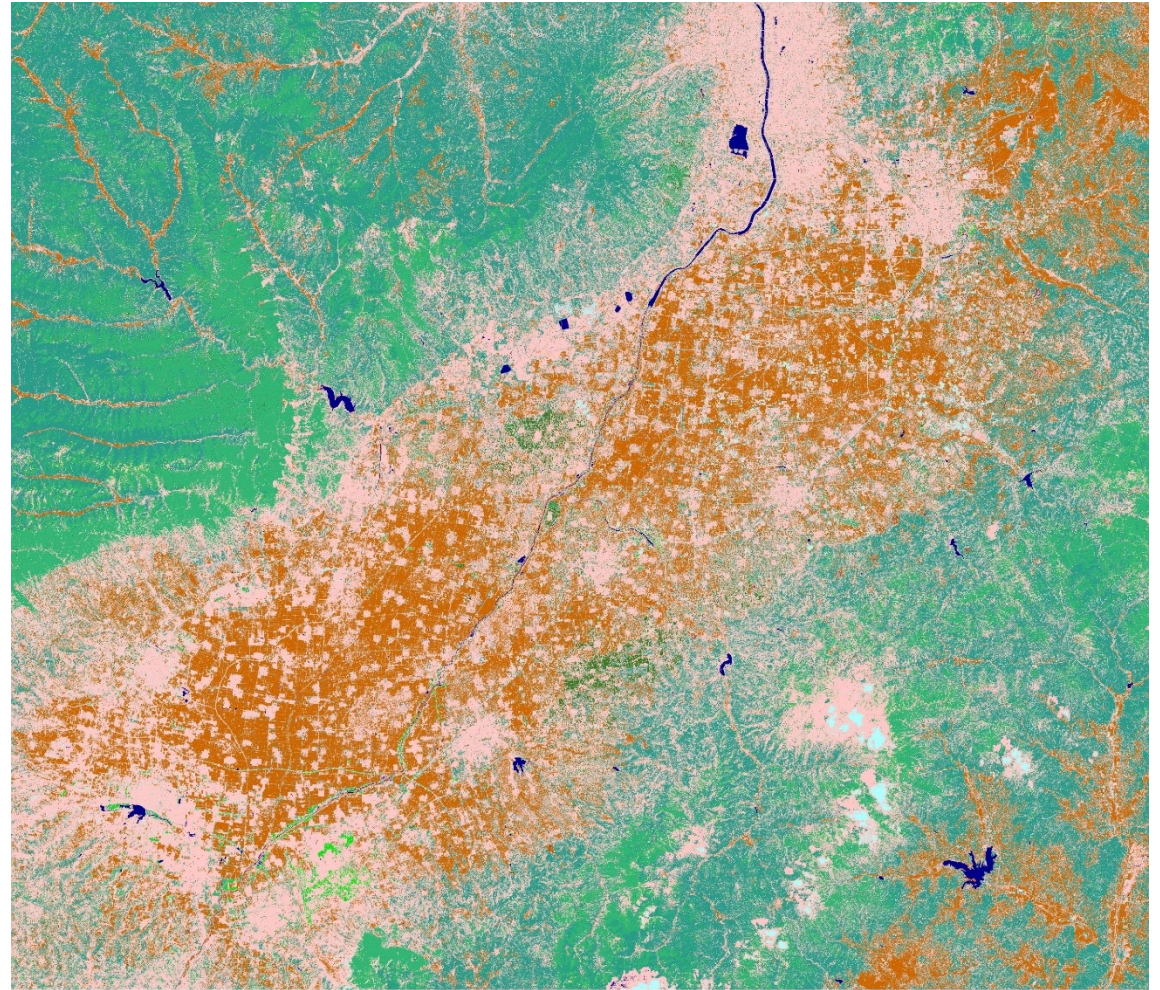
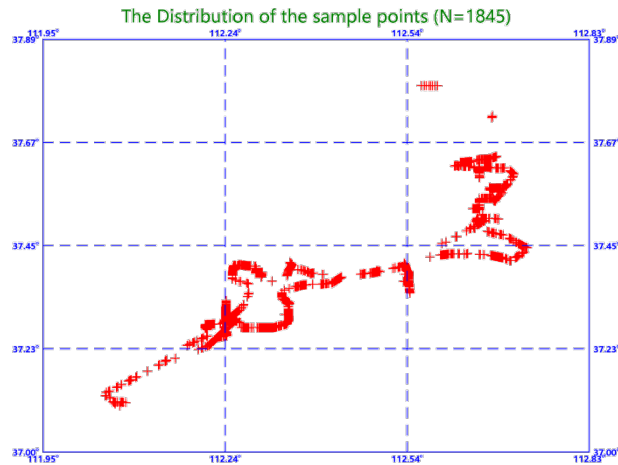
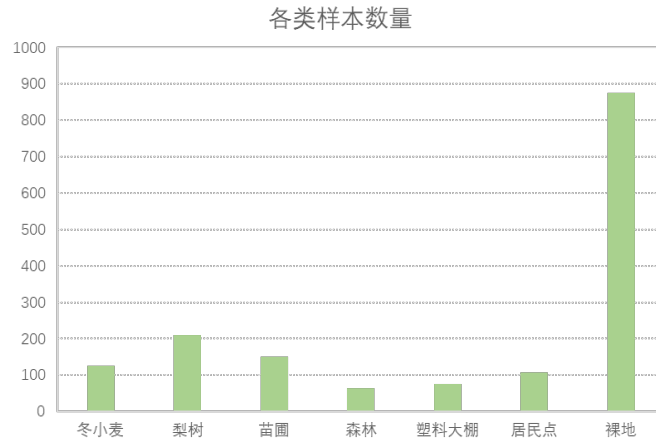


Shanxi Fall Flood, 2021
 Oct 2-7, 2021
 ➤ 100-250 mm

3 Identifying the crop practices of conservation agriculture

Bare soil period duration

- conservation agriculture
- Soil wind erosion



图例

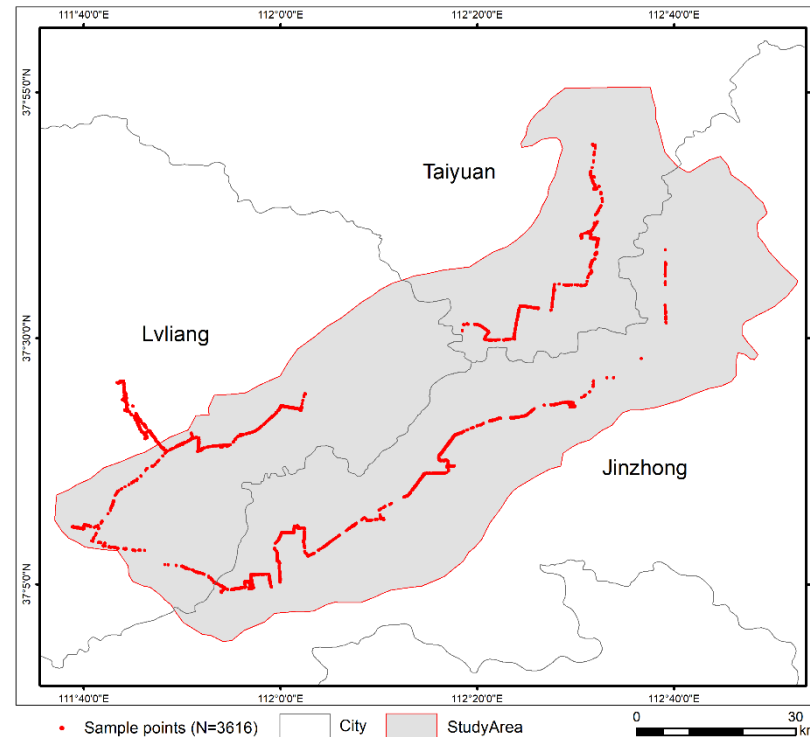
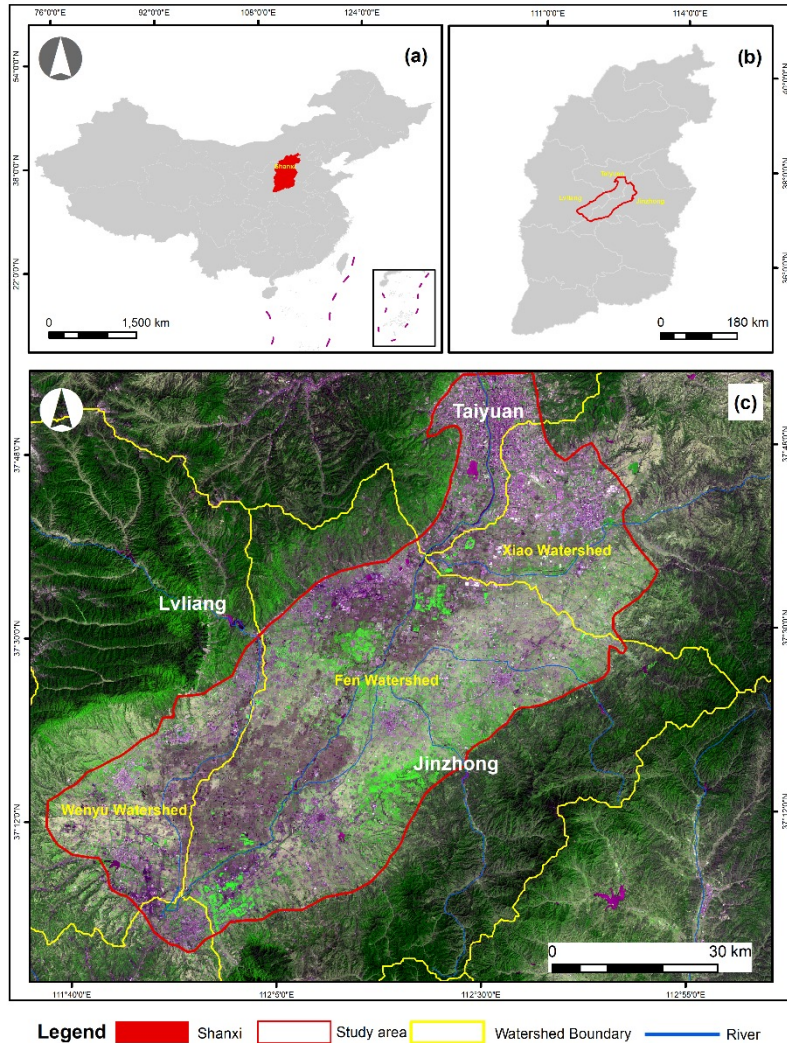
Bareland	Buildings	Forest	Greenhouse	Mountain	Pear	TreePlatation	Wasteland	Water	Winterwheat
----------	-----------	--------	------------	----------	------	---------------	-----------	-------	-------------

Source: Sentinel-2 April 25, 2022



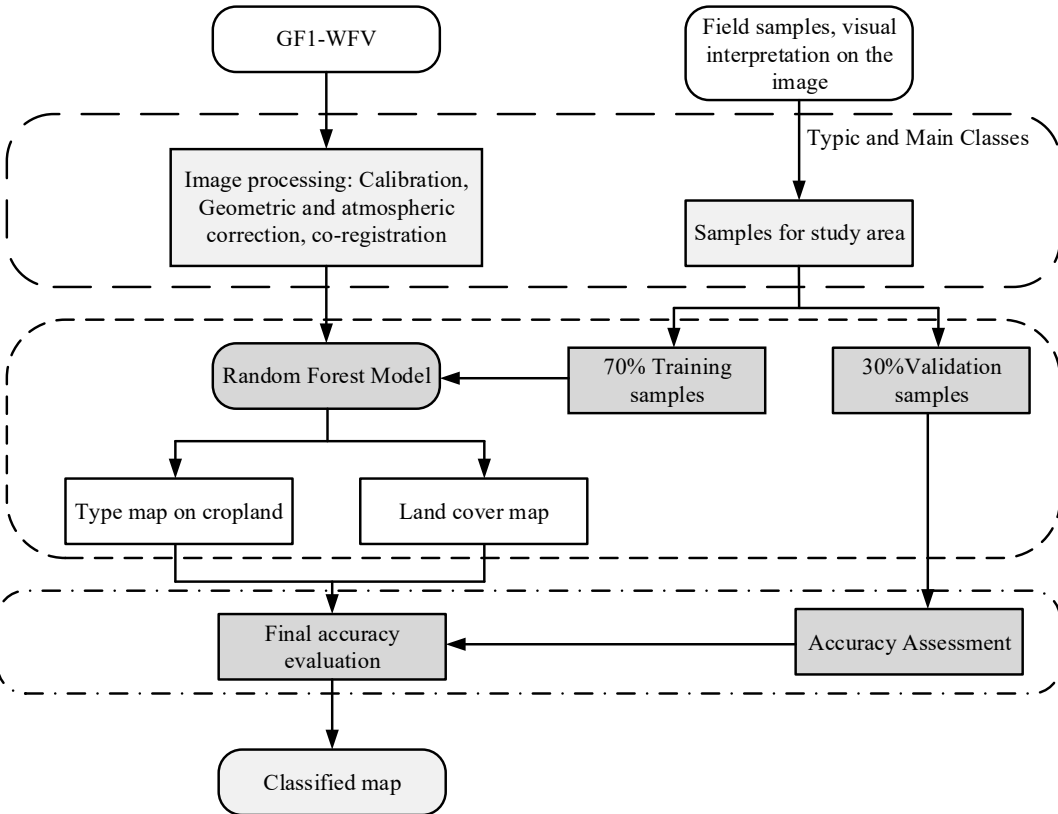
3 Identifying the crop practices of conservation agriculture

Identifying the Farm Fields Irrigated out of season with GF-1 Satellite Images

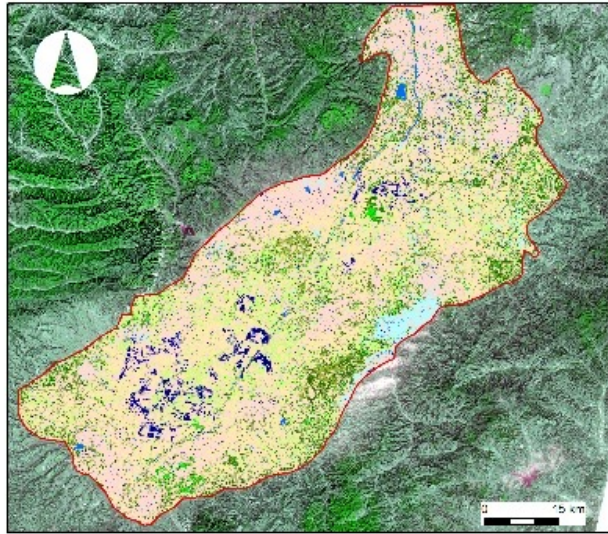


GF-1 Satellite Images

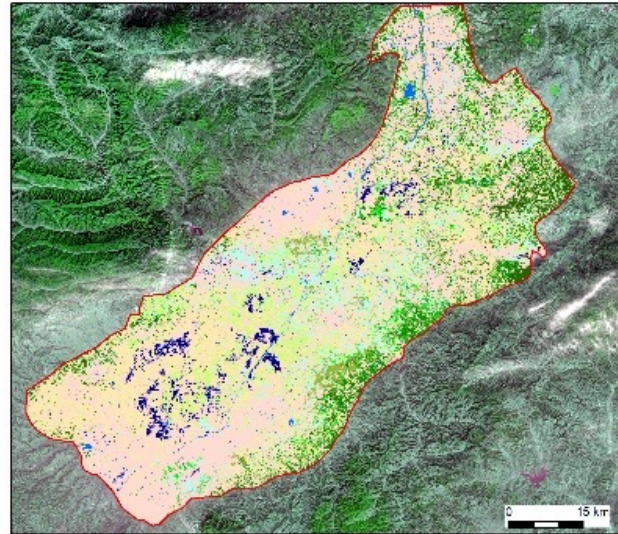
No.	Date
1	2022/12/27
2	2023/01/04
3	2023/01/25
4	2023/03/03
5	2023/03/27
6	2023/04/08
7	2023/04/29



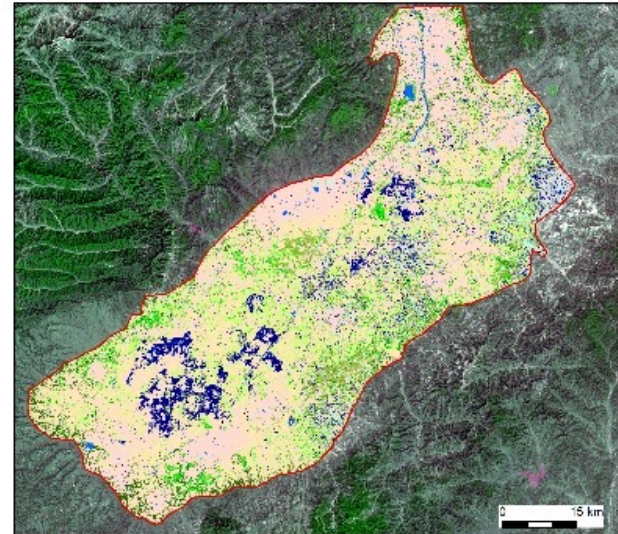
	Class	Acronym	Description
Cropland	Irrigation 1	I1	Waterlogged or Frozen field after irrigation
	Irrigation 2	I2	Field with high soil moisture after irrigation
	Winter Wheat	WW	Winter wheat field
	Straw Covered Cropland	SC	Cropland covered by the straw or other residues out of season
	Bare Cropland	BC	Bare and no covered cropland out of season
	Greenhouse	GH	Greenhouse for vegetable or other cash crops
	Orchards	OC	Fruit trees plantation
	Plantation	PL	Cropland planted with wood or shrub trees
Non Cropland	Built-up	BU	Artificial area including building, road, and factory
	Barren Land	BL	No vegetation covered area in rock mountain
	Deciduous Forest	DF	Deciduous tree and shrub
	Evergreen Forest	EF	Coniferous tree and shrub
	Water Body	WB	Lake, River, Dam, and other Water body



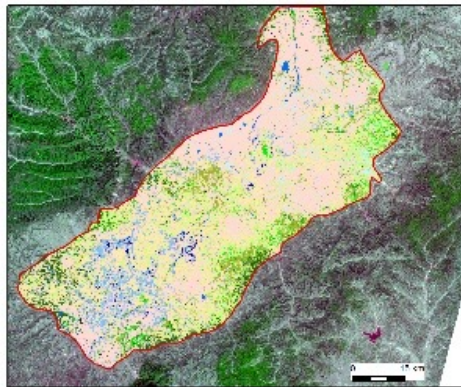
(a)



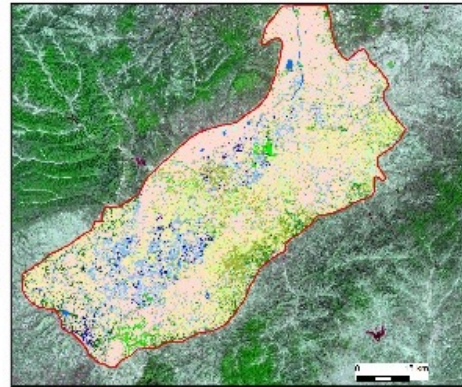
(b)



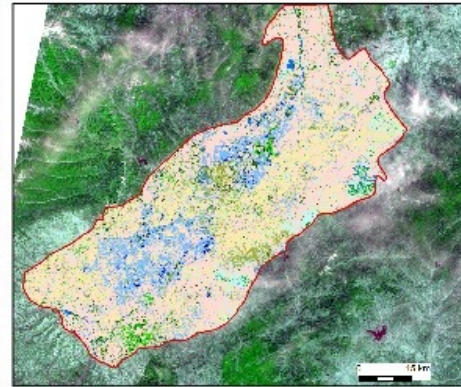
(c)



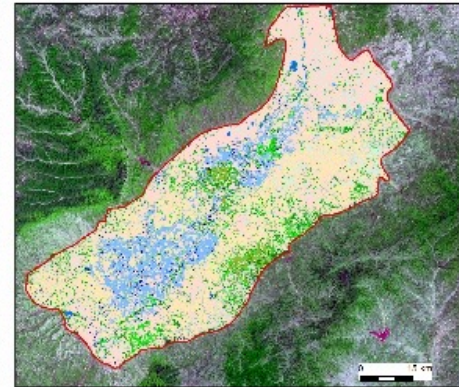
(d)



(e)



(f)

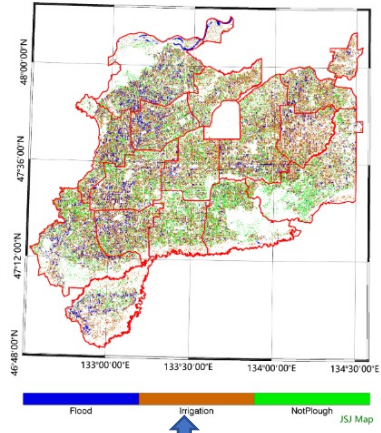


(g)

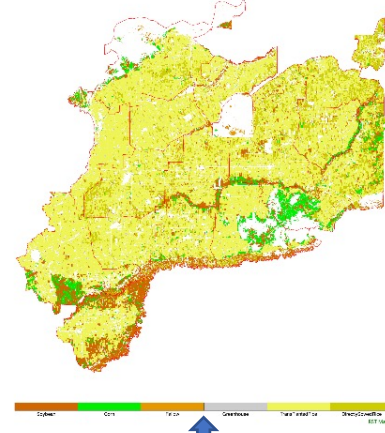


Date	sum	Fen River		Wenyu River		Xiao River	
		I1	I2	I1	I2	I1	I2
2022/12/27	98.6	65.8	-	22.9	-	9.9	-
2023/01/04	166.9	115.1	-	33.9	-	17.9	-
2023/01/25	208.0	143.1	-	37.6	-	27.3	-
2023/03/03	292.8	10.2	166.1	3.4	98.5	1.1	13.5
2023/03/27	538.0	6.2	306.4	1.3	166.0	0.3	57.8
2023/04/08	623.1	9.4	436.2	0.7	107.2	0.3	69.3
2023/04/29	653.8	5.8	453.1	1.1	120.5	0.9	72.4

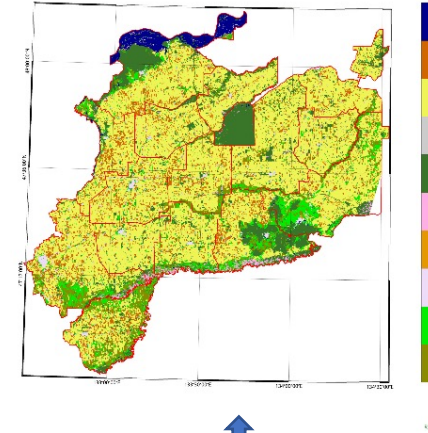
4 Promoting the remote sensing application in large and modern farm



Multiple images of field preparation



Crop type map



Harvest and plough maps

Middle April to Middle May
Field Preparation

Middle June to Middle July
Crop Type Mapping

Middle Sep. to end Oct.
Harvest and plough

农场	4/19 S2A 平地泡田	灌水未整地	未耕作
创业农场	22%	59%	19%
大兴农场	24%	60%	16%
红卫农场	11%	53%	36%
洪河农场	13%	59%	27%
浓江农场	23%	56%	20%
七星农场	19%	54%	26%
前锋农场	16%	62%	22%
前进农场	20%	56%	24%
前哨农场	16%	68%	16%
胜利农场	10%	48%	42%
八五九农场	12%	52%	36%
二道河农场	18%	70%	12%
勤得利农场	29%	49%	22%
青龙山农场	22%	58%	20%
鸭绿河农场	11%	65%	24%

Statistics for every farm

2021年建三江各农场农作物遥感面积

水稻种植方式遥感监测结果				
插秧稻 (万亩)	直播稻 (万亩)	水稻 (万亩)	大豆 (万亩)	玉米 (万亩)
53.9	3.0	56.9	6.6	13.3
48.7	8.6	57.2	4.7	3.3
89.5	24.8	114.3	8.1	3.1
58.6	9.6	68.2	7.5	1.3
57.7	3.4	61.2	2.1	1.9
81.5	14.2	95.7	5.1	6.0
59.1	4.7	63.9	0.1	0.0
44.5	6.8	51.3	2.7	0.2
72.5	17.5	90.0	1.7	0.4
55.3	5.2	60.5	0.3	0.2
105.7	3.2	108.9	14.9	13.1
51.6	2.8	54.4	24.7	13.2
74.0	29.3	103.2	15.9	26.9
47.5	11.4	58.8	2.5	2.9
46.2	30.0	76.2	3.0	1.0
946.4	174.5	1120.8	99.9	86.7

Cultivated acreages for paddy rice and dryland crops

农场	水稻收获占比(9.24)
胜利	20.4%
红卫	8.8%
前锋	4.6%
洪河	12.7%
青龙山	19.4%
勤得利	14.8%
浓江	12.3%
鸭绿河	5.5%
前进	16.9%
创业	10.8%
七星	19.4%
大兴	18.7%
八五九	8.5%
二道河	6.3%
前哨	9.5%
平均	12.6%

Statistics for Harvest and plough in fall

May 14

Re

June 8

Field Prepared for Rice

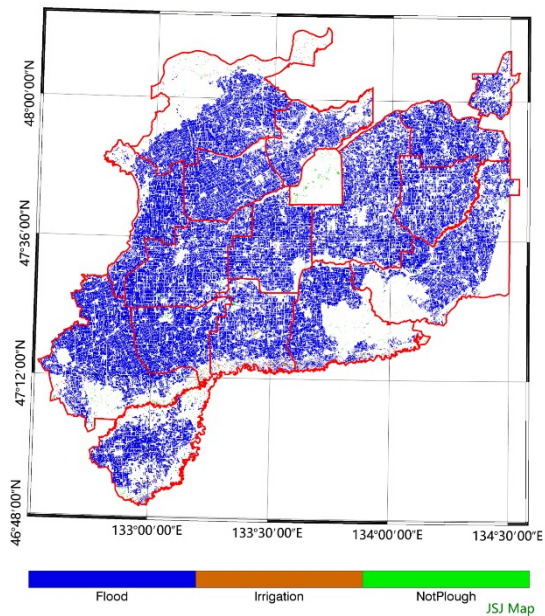
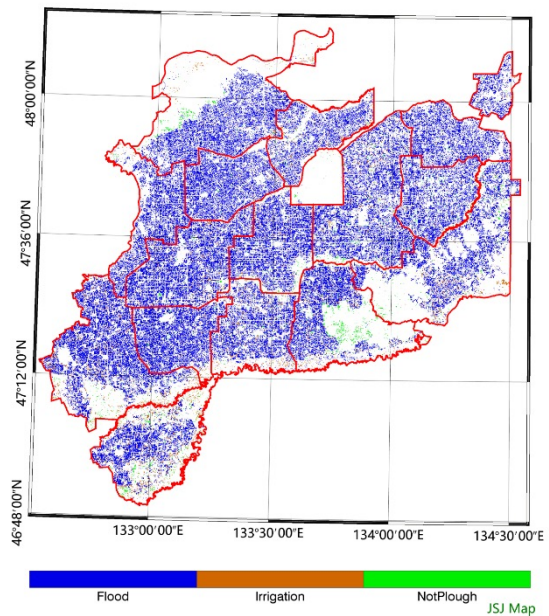
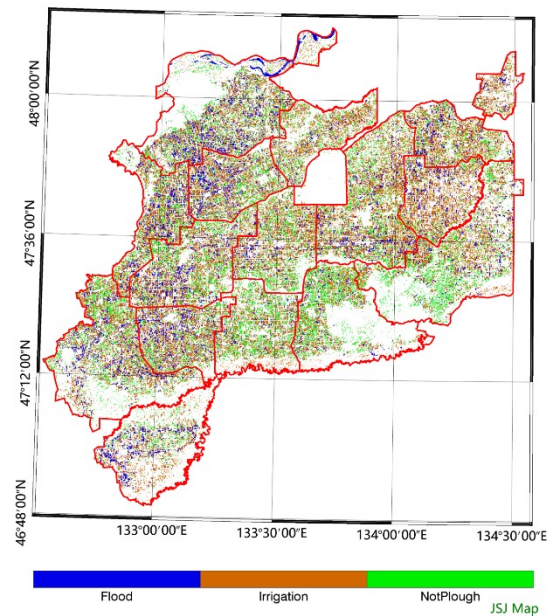
No Rice transplanted



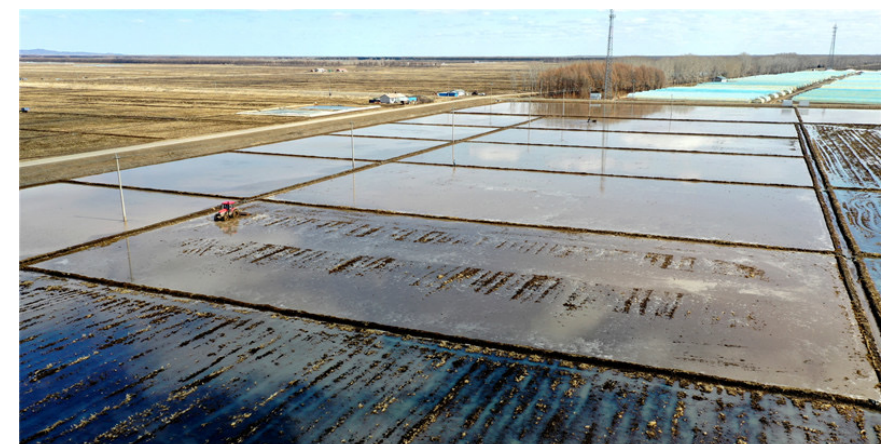
S2 2021-04-19

S2 2021-04-29

LC08 2021-05-03

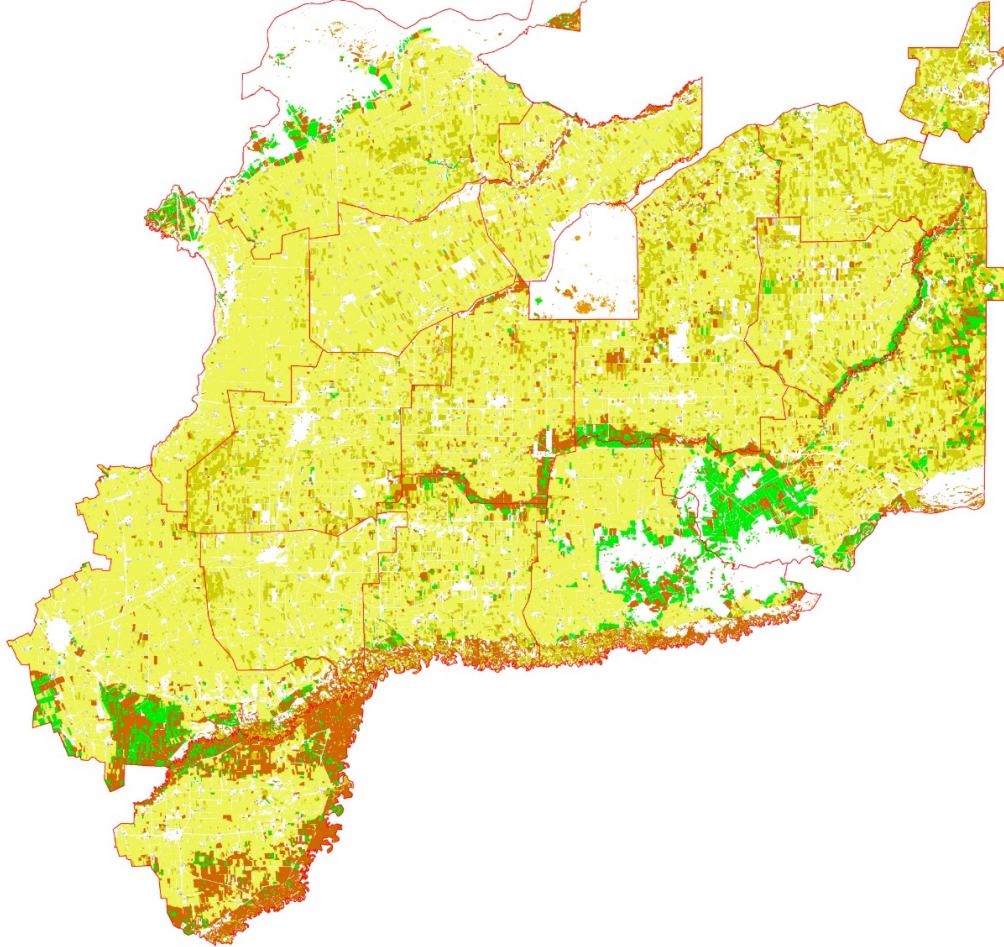
MI10 LITE ZOOM
AI QUAD CAMERA

	4/19 S2A			4/29 S21C			5/3 L8		
农场	平地泡田	灌水未整地	未耕作	平地泡田	灌水未整地	未耕作	平地泡田	灌水未整地	未耕作
创业农场	22%	59%	19%	96%	3%	1%	97%	2%	1%
大兴农场	24%	60%	16%	75%	18%	7%	90%	7%	3%
红卫农场	11%	53%	36%	88%	10%	2%	95%	4%	1%
洪河农场	13%	59%	27%	94%	4%	2%	99%	1%	0%
浓江农场	23%	56%	20%	96%	3%	1%	99%	1%	0%
七星农场	19%	54%	26%	89%	10%	2%	96%	3%	1%
前锋农场	16%	62%	22%	92%	5%	3%	98%	1%	1%
前进农场	20%	56%	24%	93%	5%	1%	97%	2%	1%
前哨农场	16%	68%	16%	97%	2%	1%	97%	2%	1%
胜利农场	10%	48%	42%	83%	8%	9%	95%	3%	1%
八五九农场	12%	52%	36%	87%	9%	5%	97%	2%	2%
二道河农场	18%	70%	12%	93%	3%	3%	97%	2%	1%
勤得利农场	29%	49%	22%	93%	3%	3%	97%	2%	1%
青龙山农场	22%	58%	20%	97%	2%	1%	99%	1%	0%
鸭绿河农场	11%	65%	24%	90%	8%	2%	95%	4%	1%

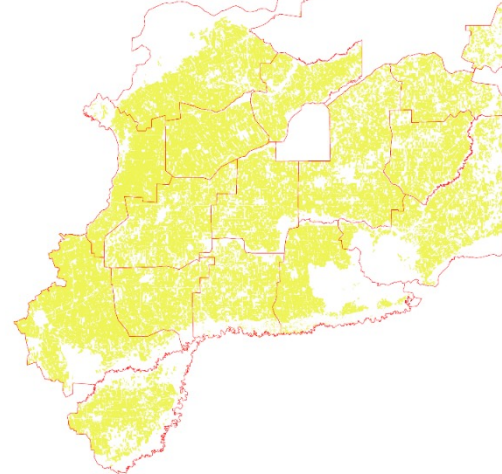


S2 2021

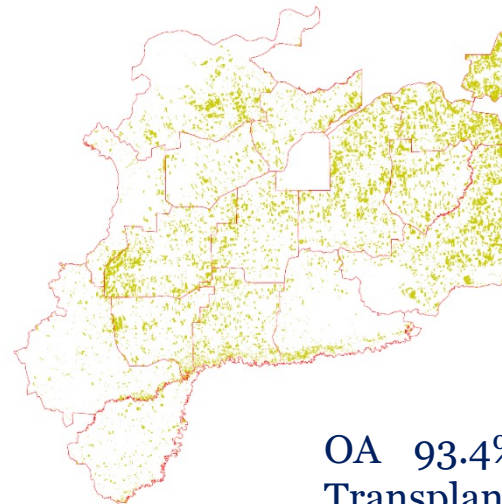
2021 Crop type map for Jiansanjiang Farms



Transplanted Rice



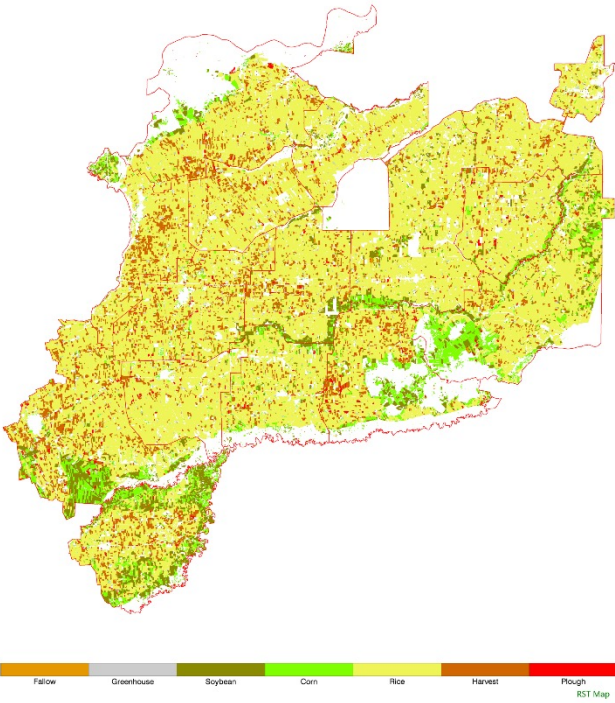
Directly sowed Rice



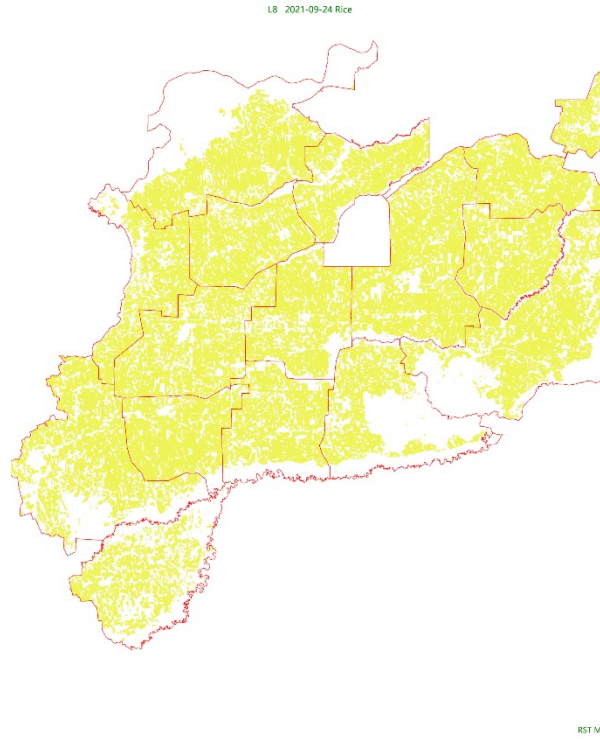
OA 93.4% , Soybean F1 97.8% , Maize F1 99.2% ,
 Transplanted Rice F1 93.8% , Directly Sowed Rice F1 87.7%

Source: Sentinel 2 images obtained on May 14, June 8, June 23, July 13, July 18, August 17, September 1 and September 6, 2021

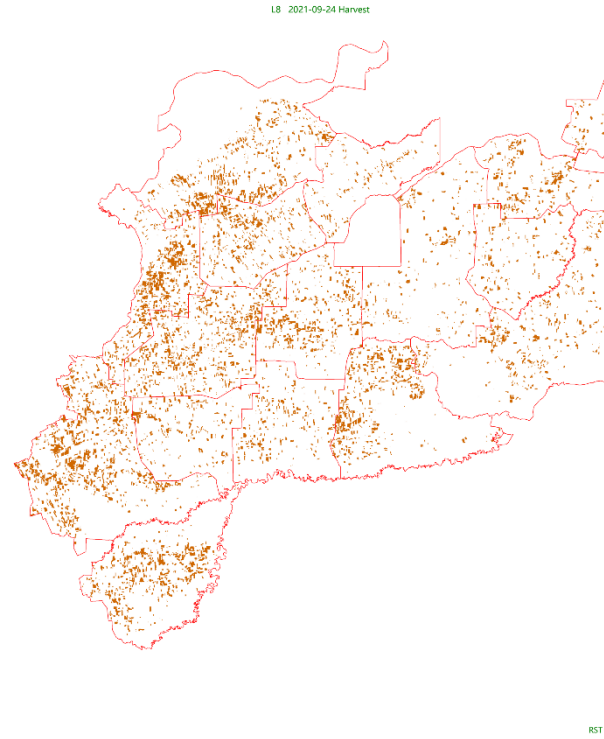
Field situation of farms in Jiansanjiang as of Sep.24, 2021



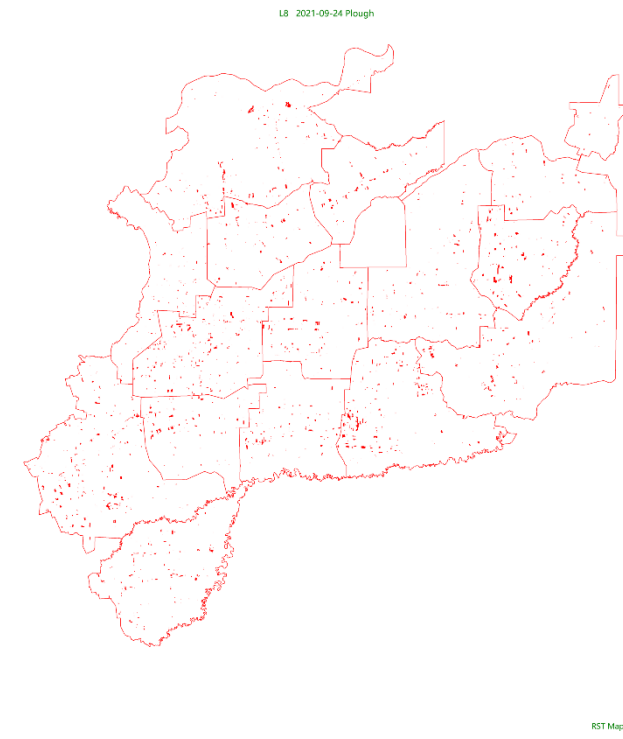
Not yet harvested rice



Harvested



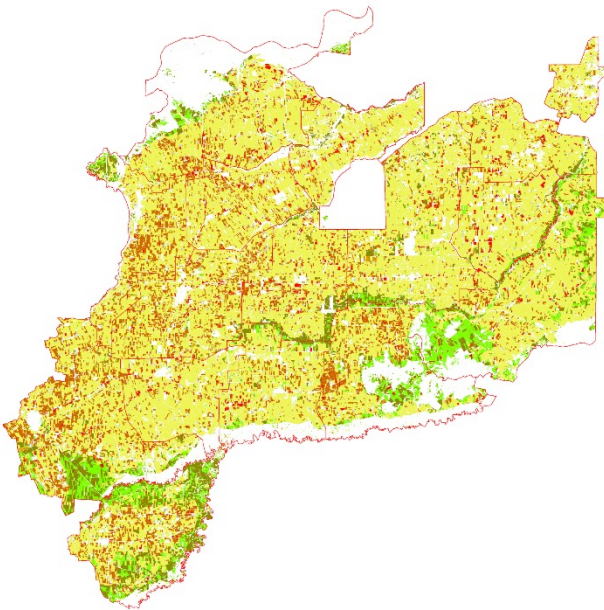
Ploughed



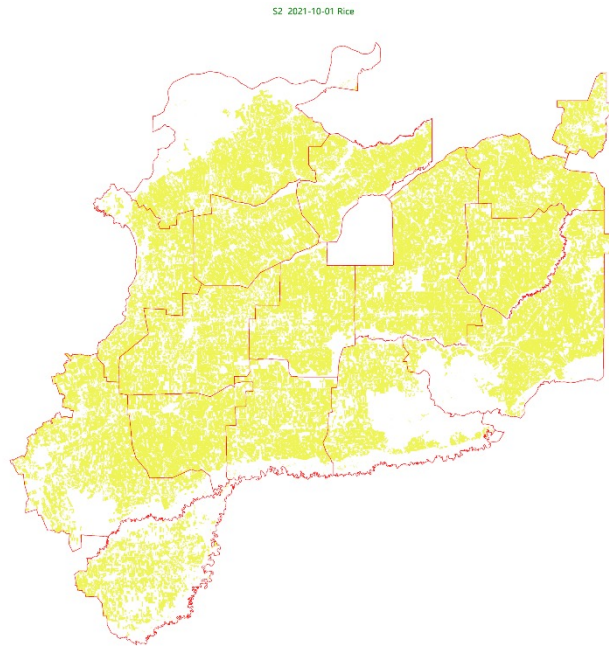
Source: L8 Sep. 24, 2021

OA 96.6%, Soybean F1 91.2%, Maize F1 87.6%, not yet harvested Rice F1 99.4%, Harvested Rice F1 93.3%, Ploughed F1 91.3%

Field situation of farms in Jiansanjiang as of Oct.1, 2021

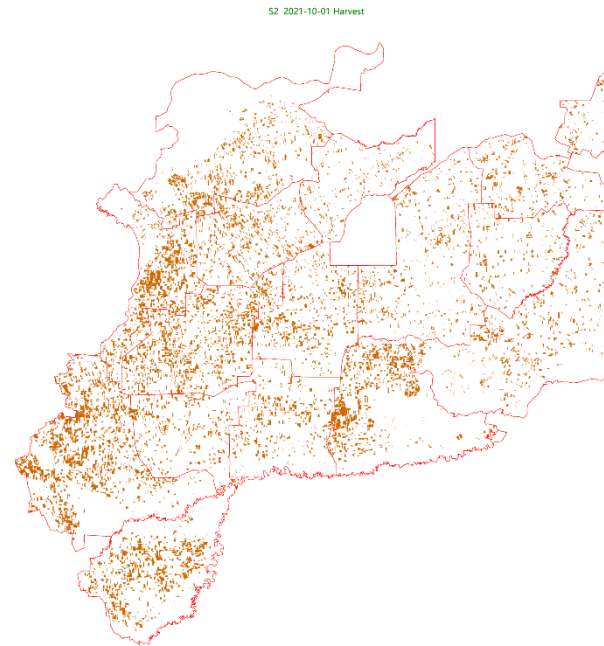


Not yet harvested rice



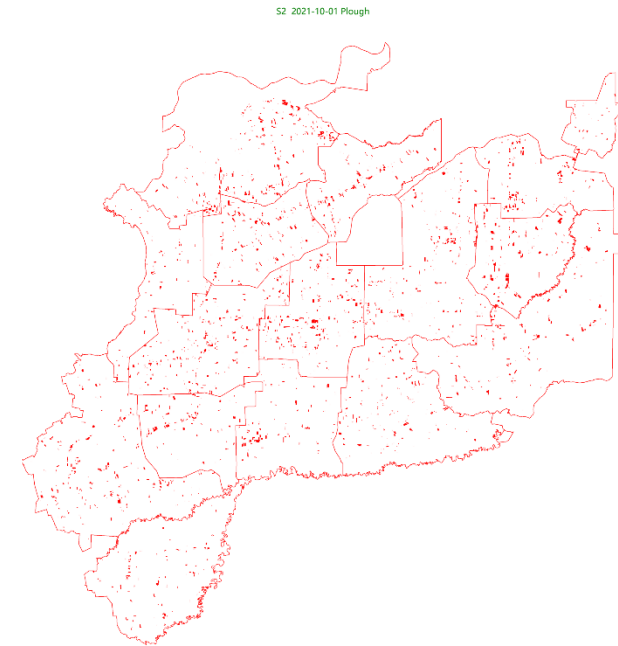
RST Map

Harvested



RST Map

Ploughed

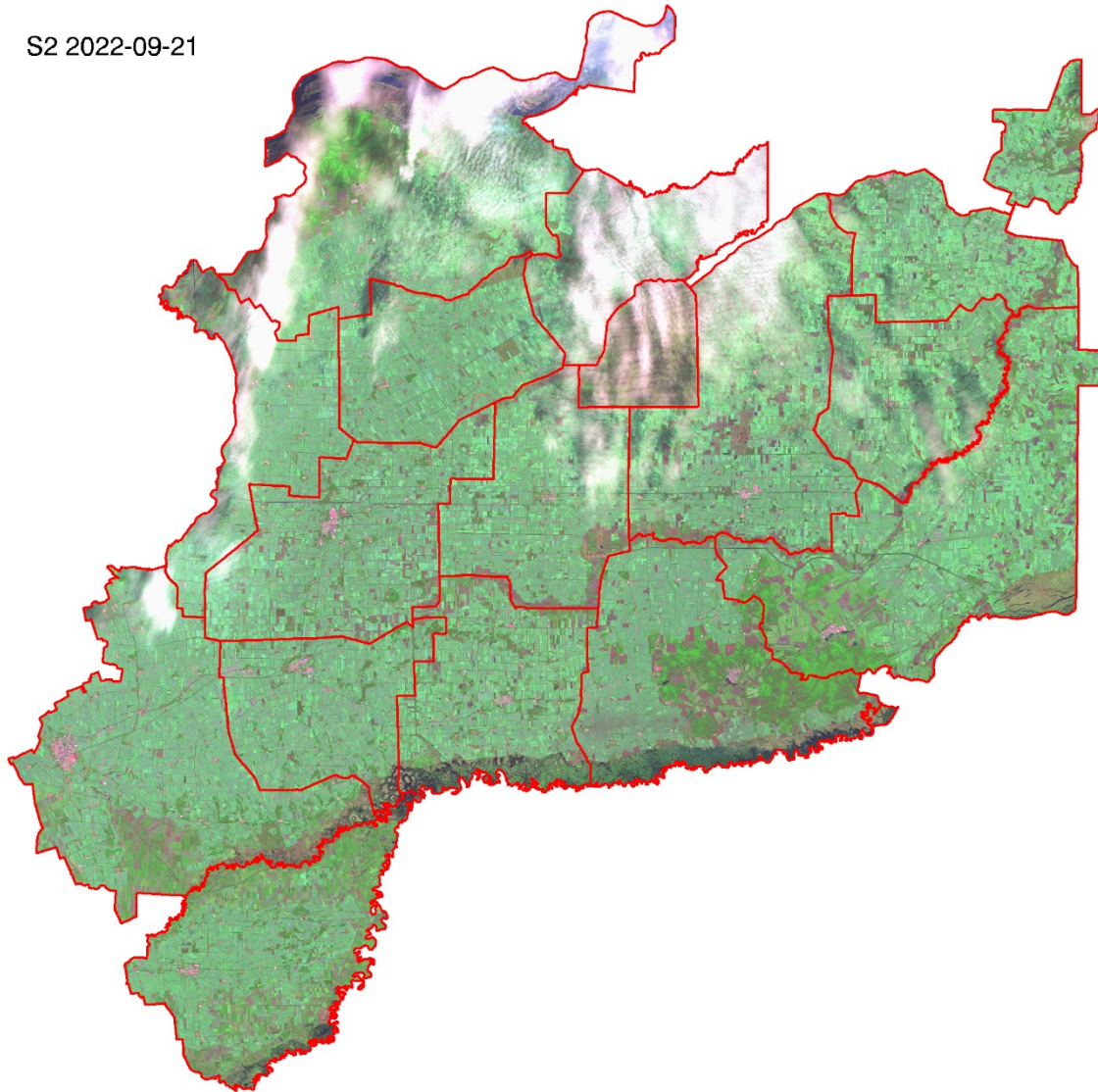


RST Map

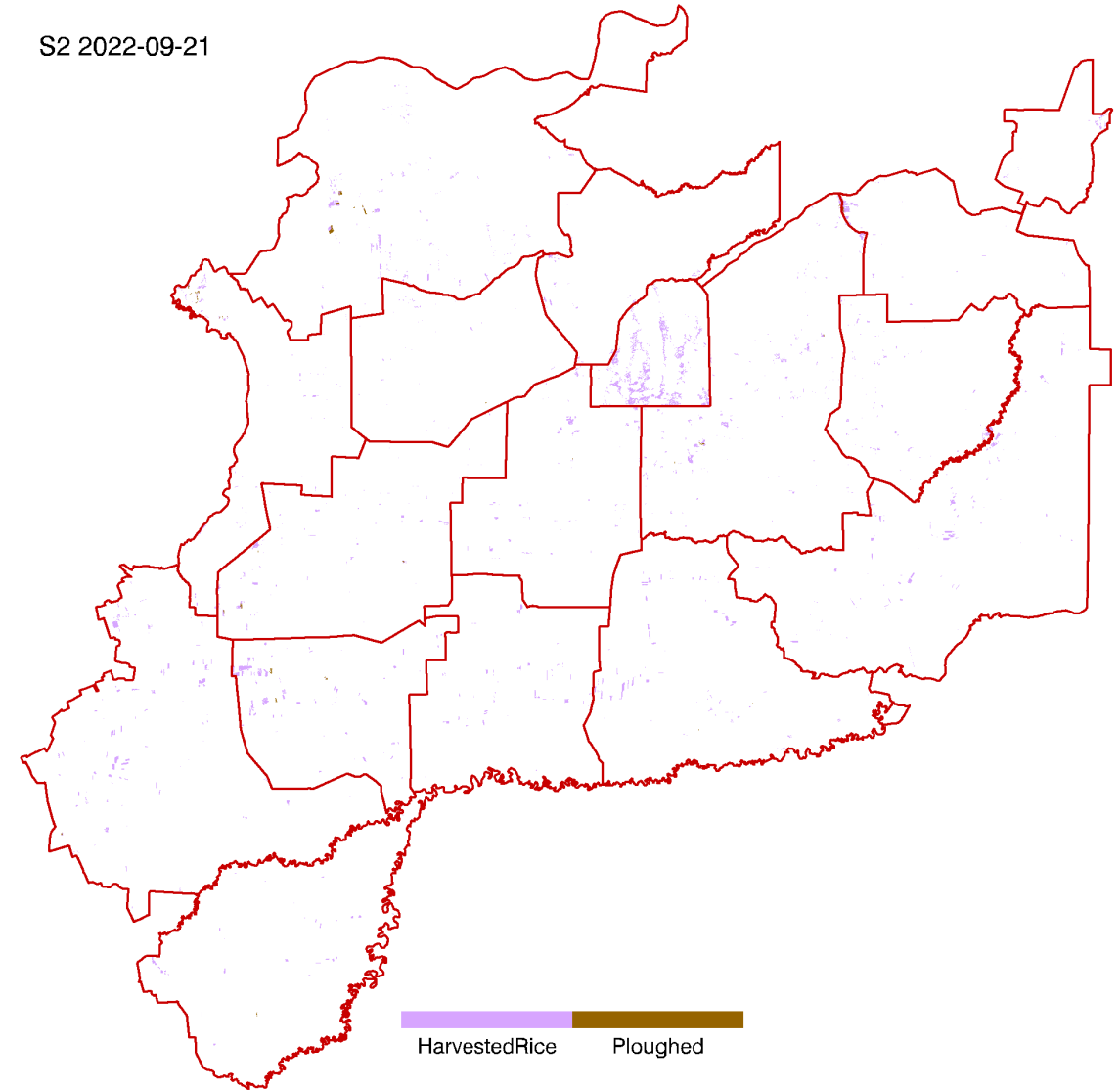
Source: S2 Oct. 1, 2021

OA 96.7%, Soybean F1 92.2%, Maize F1 91.3%, not yet harvested Rice F1 99.4%, Harvested Rice F1 85.4%, Ploughed F1 92.4%

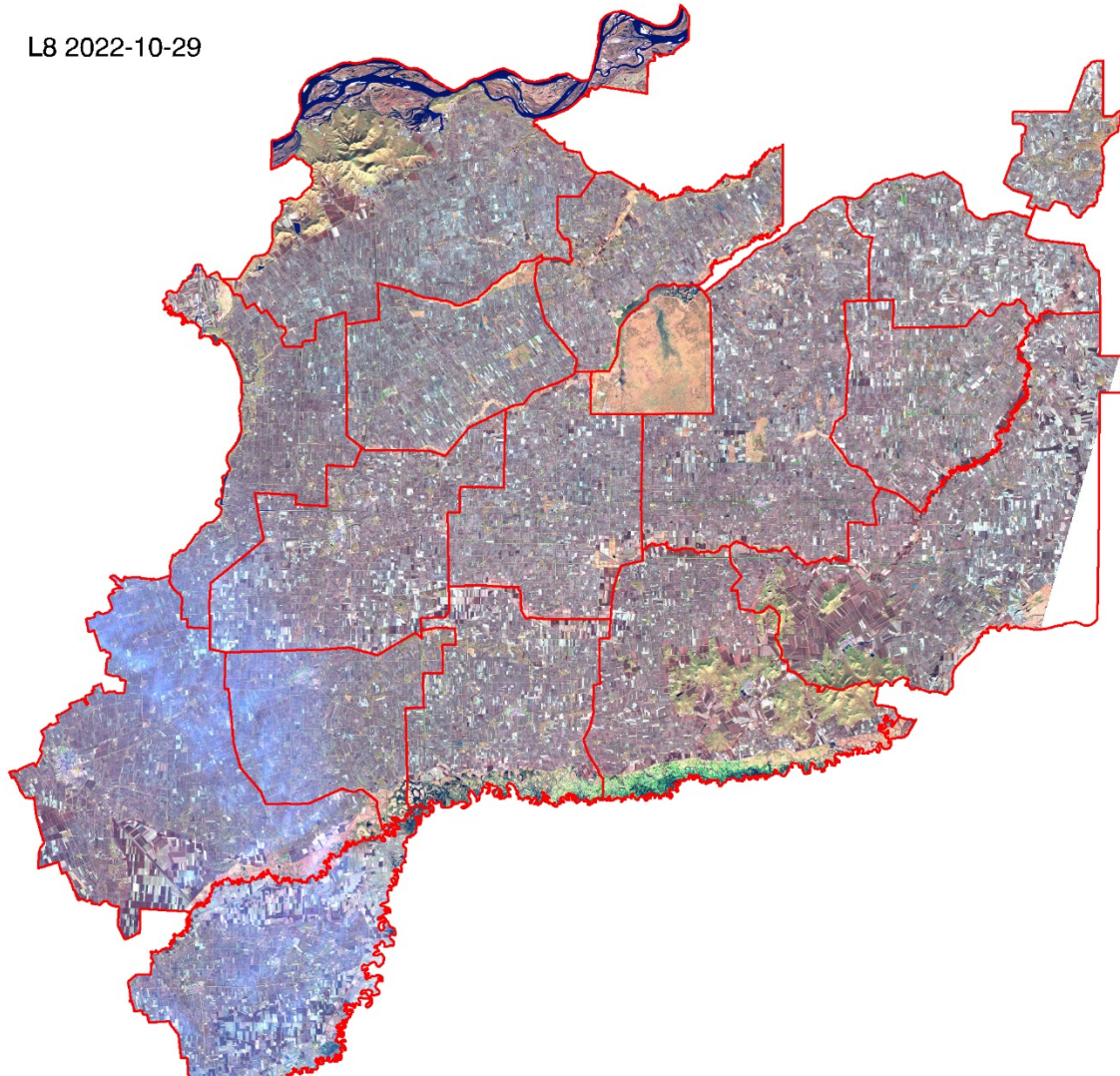
S2 2022-09-21



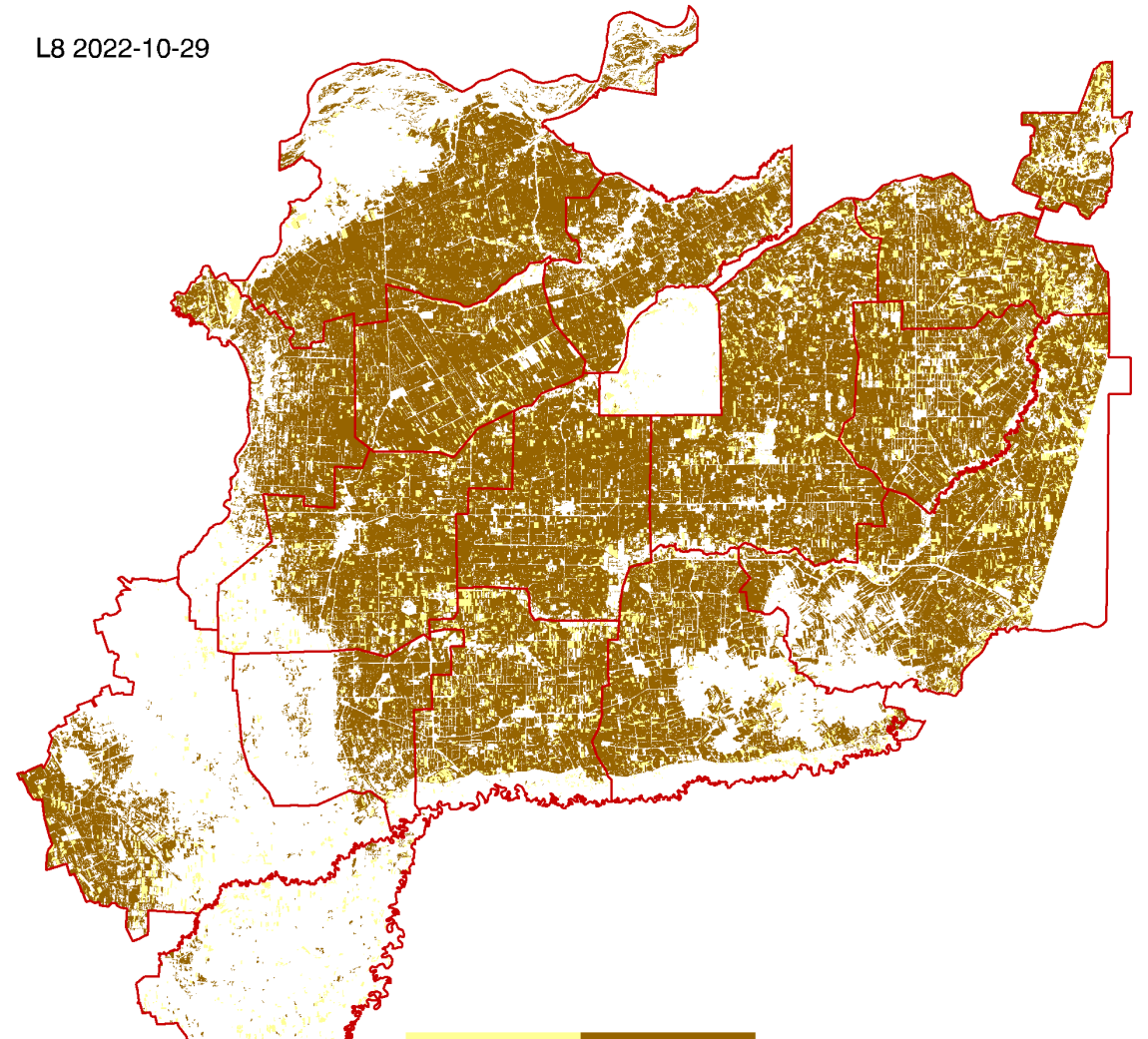
S2 2022-09-21



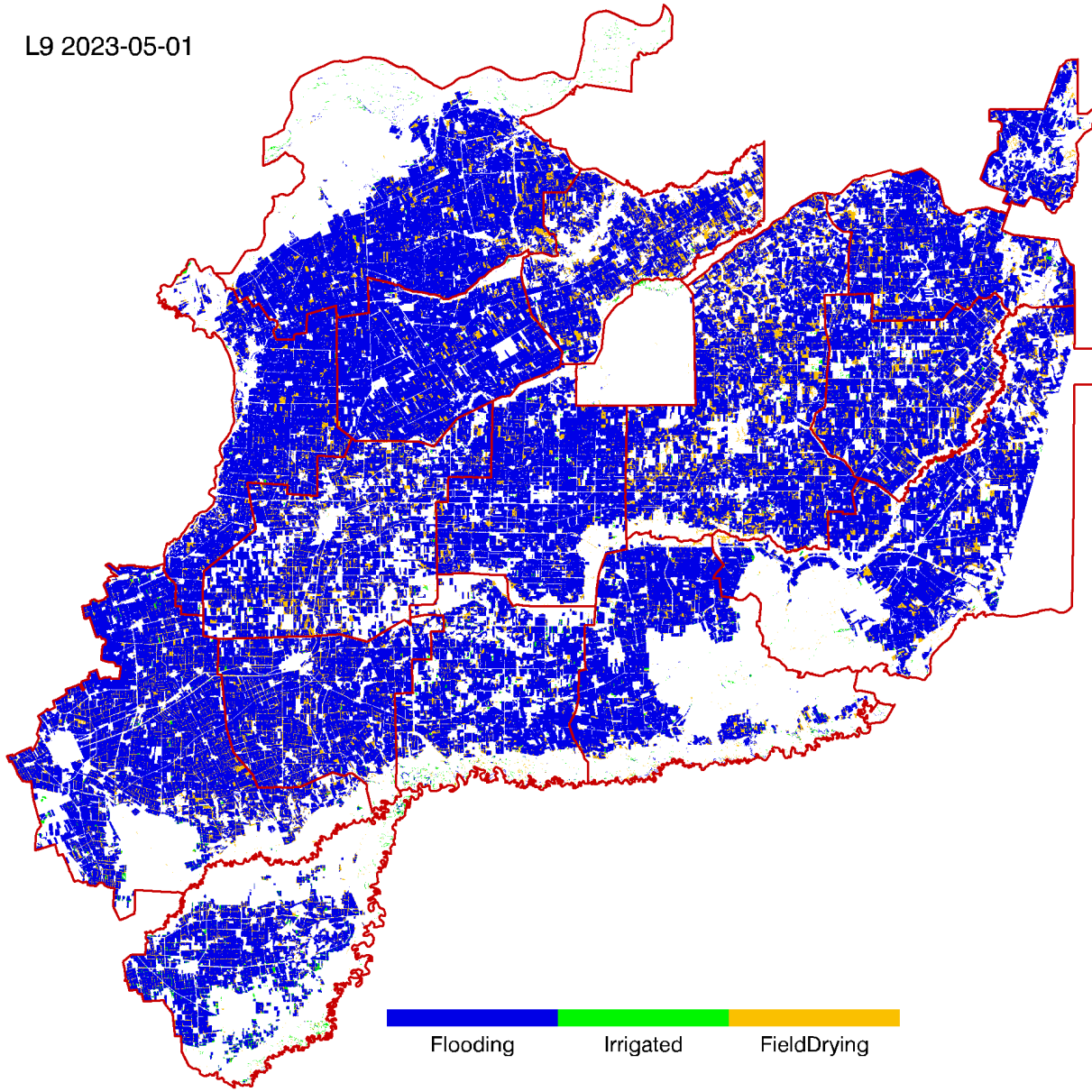
L8 2022-10-29



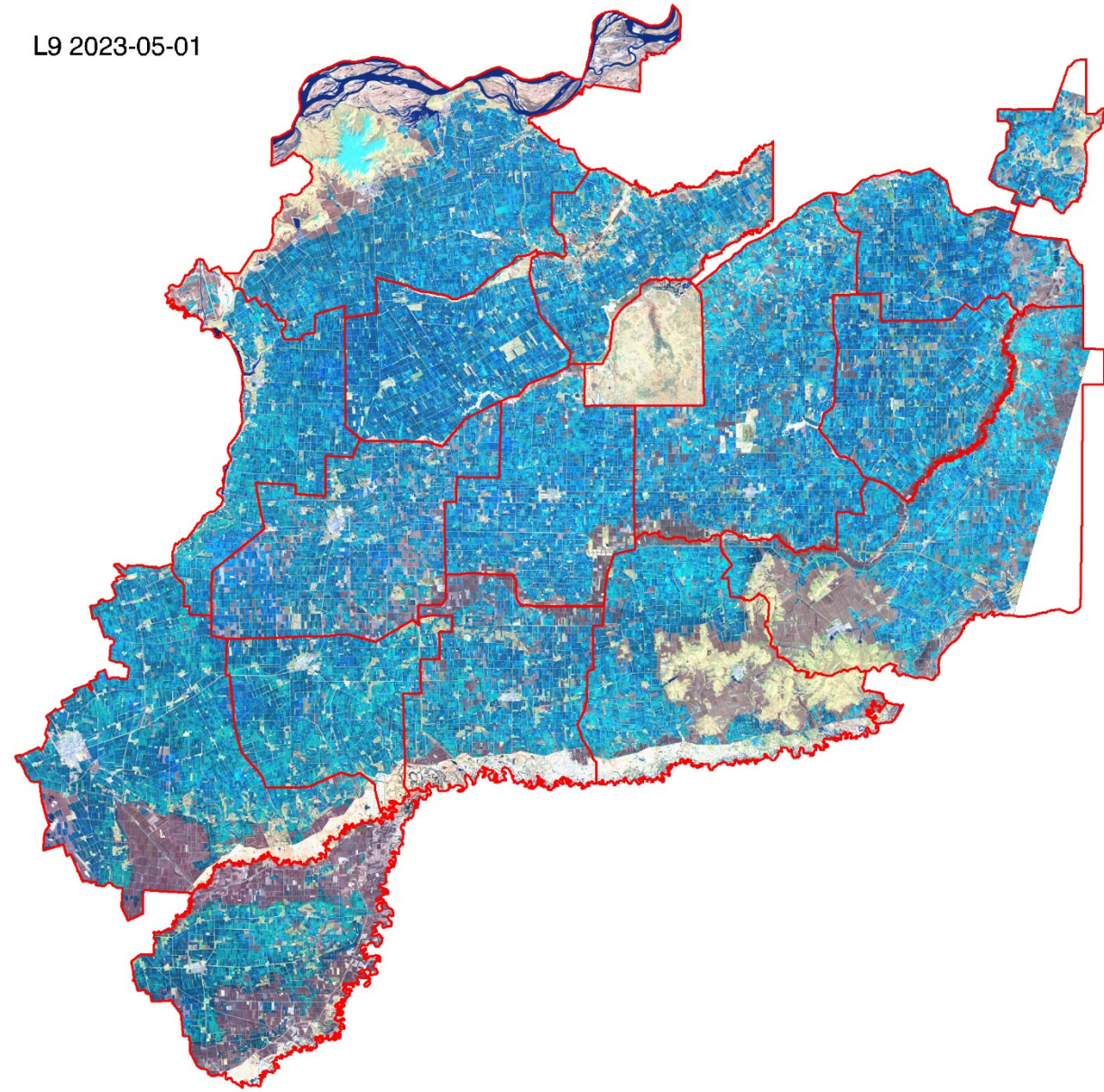
L8 2022-10-29



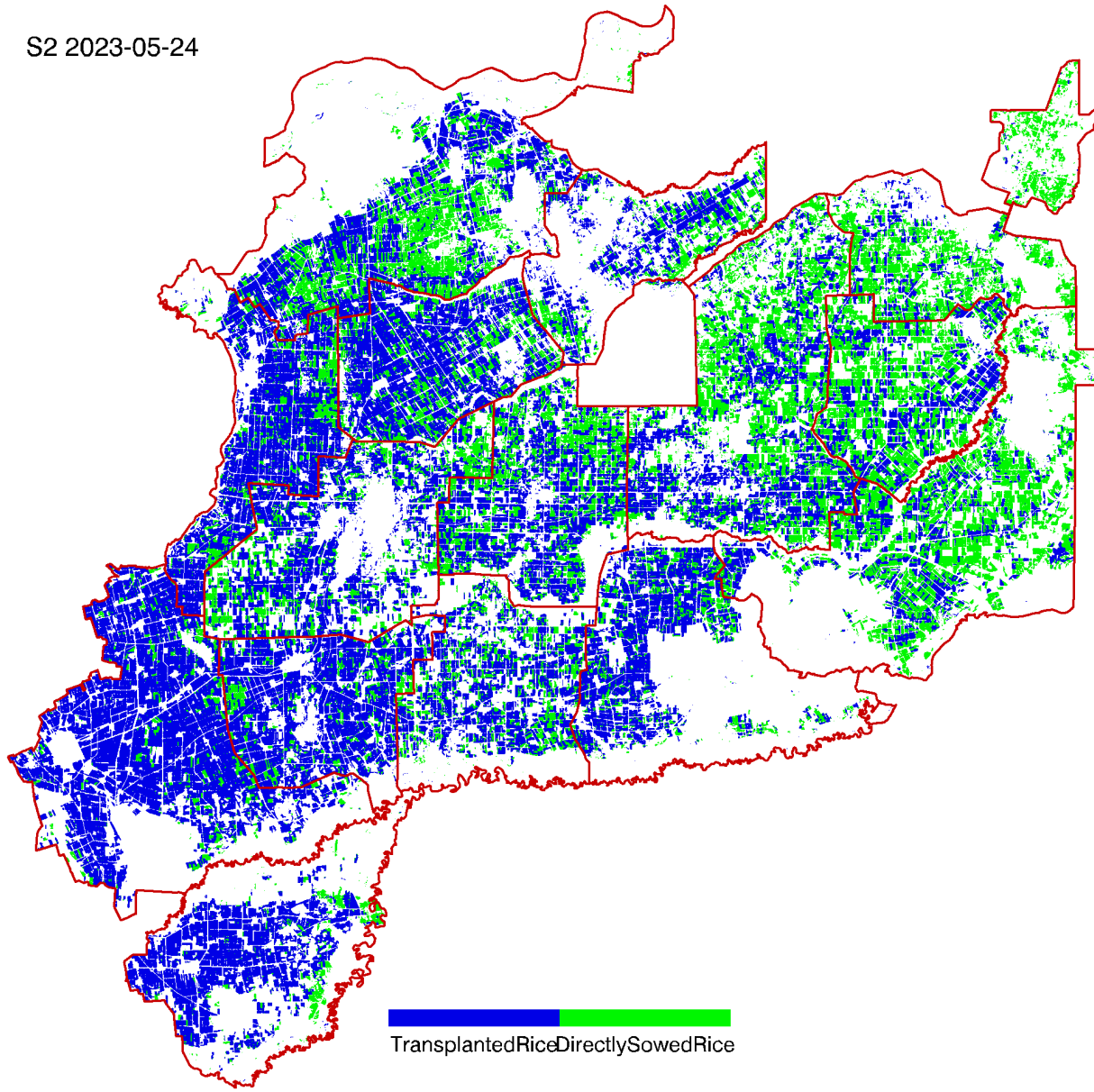
L9 2023-05-01



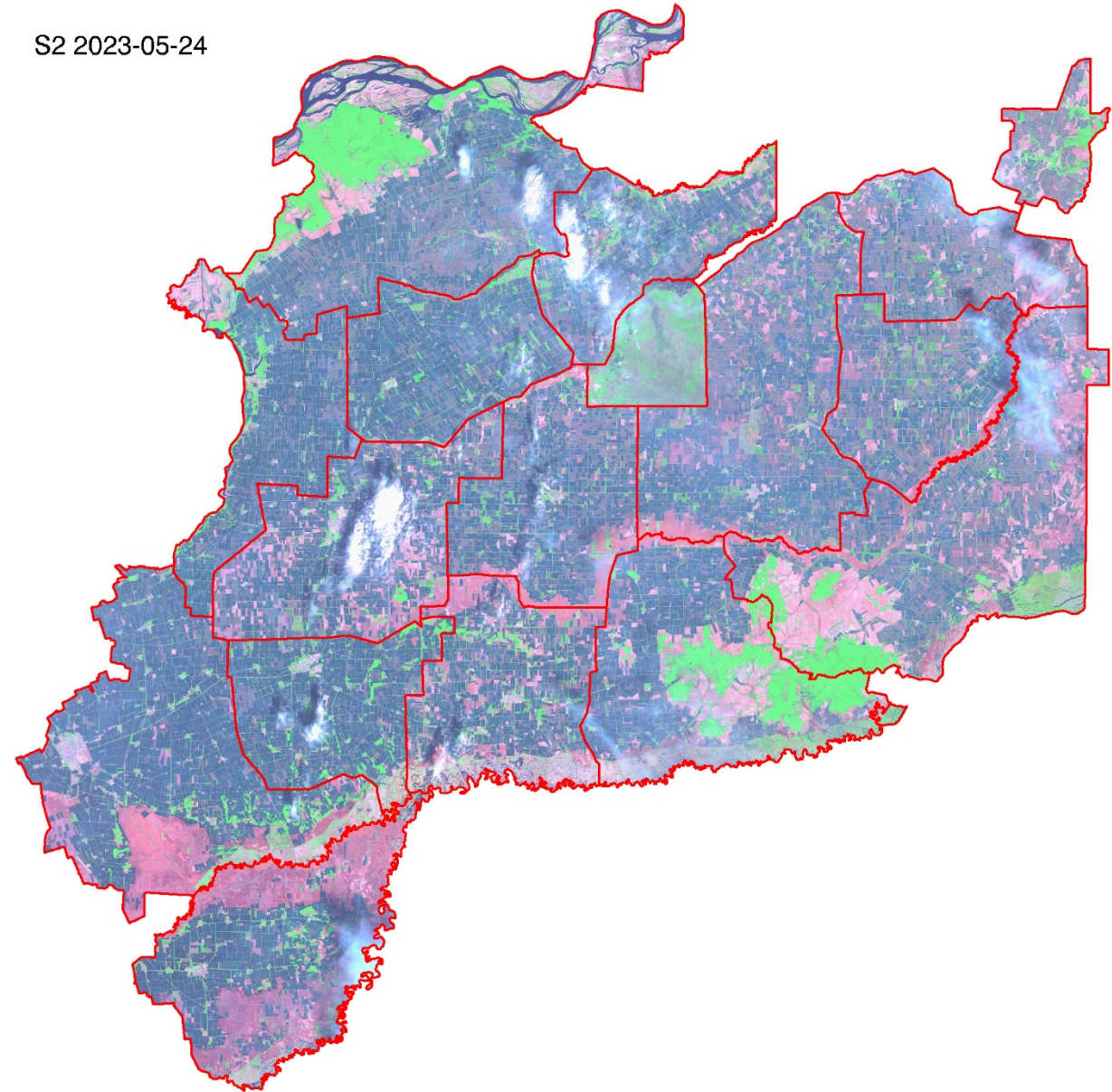
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S2 2023-05-24

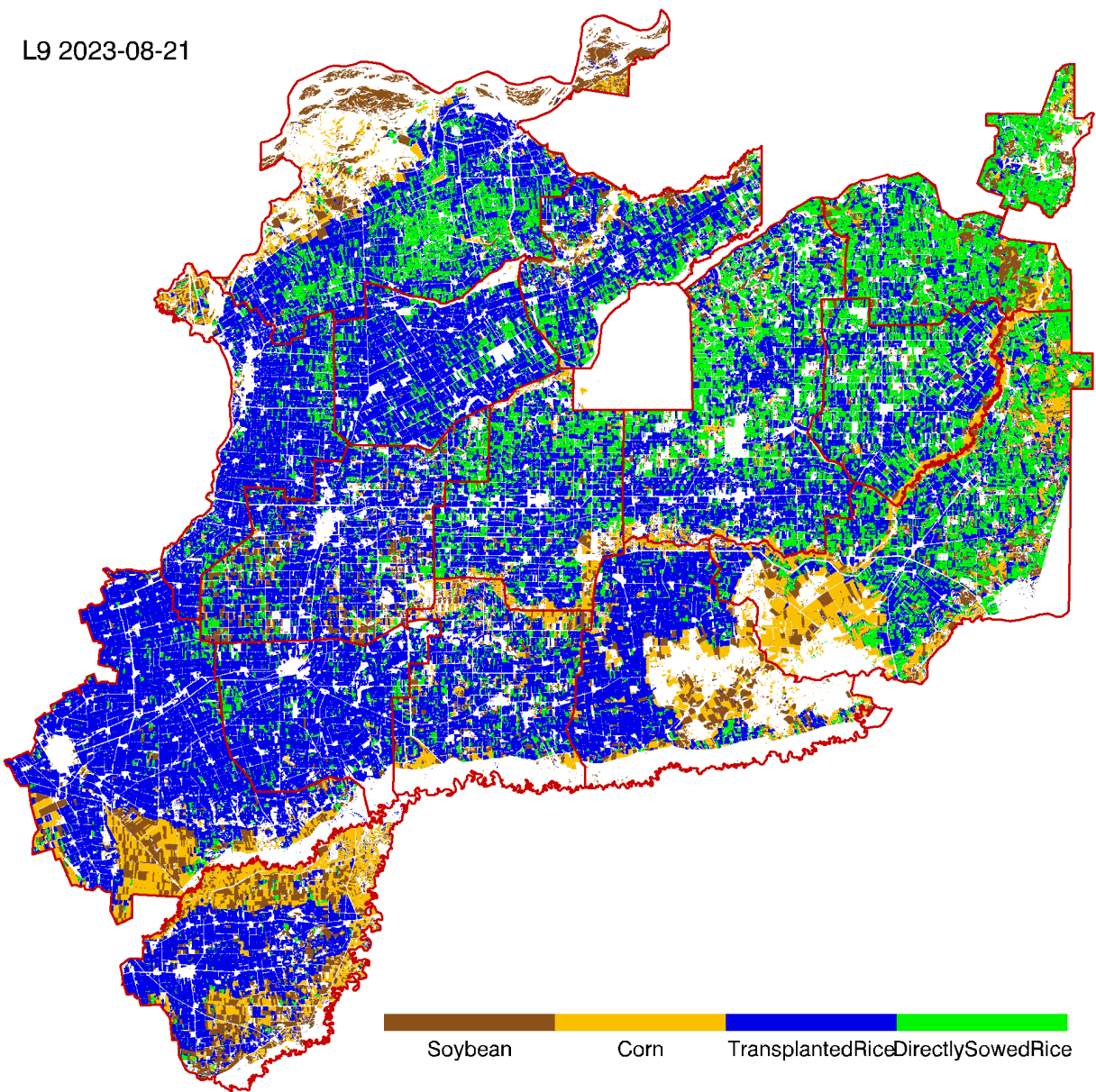


S2 2023-05-24

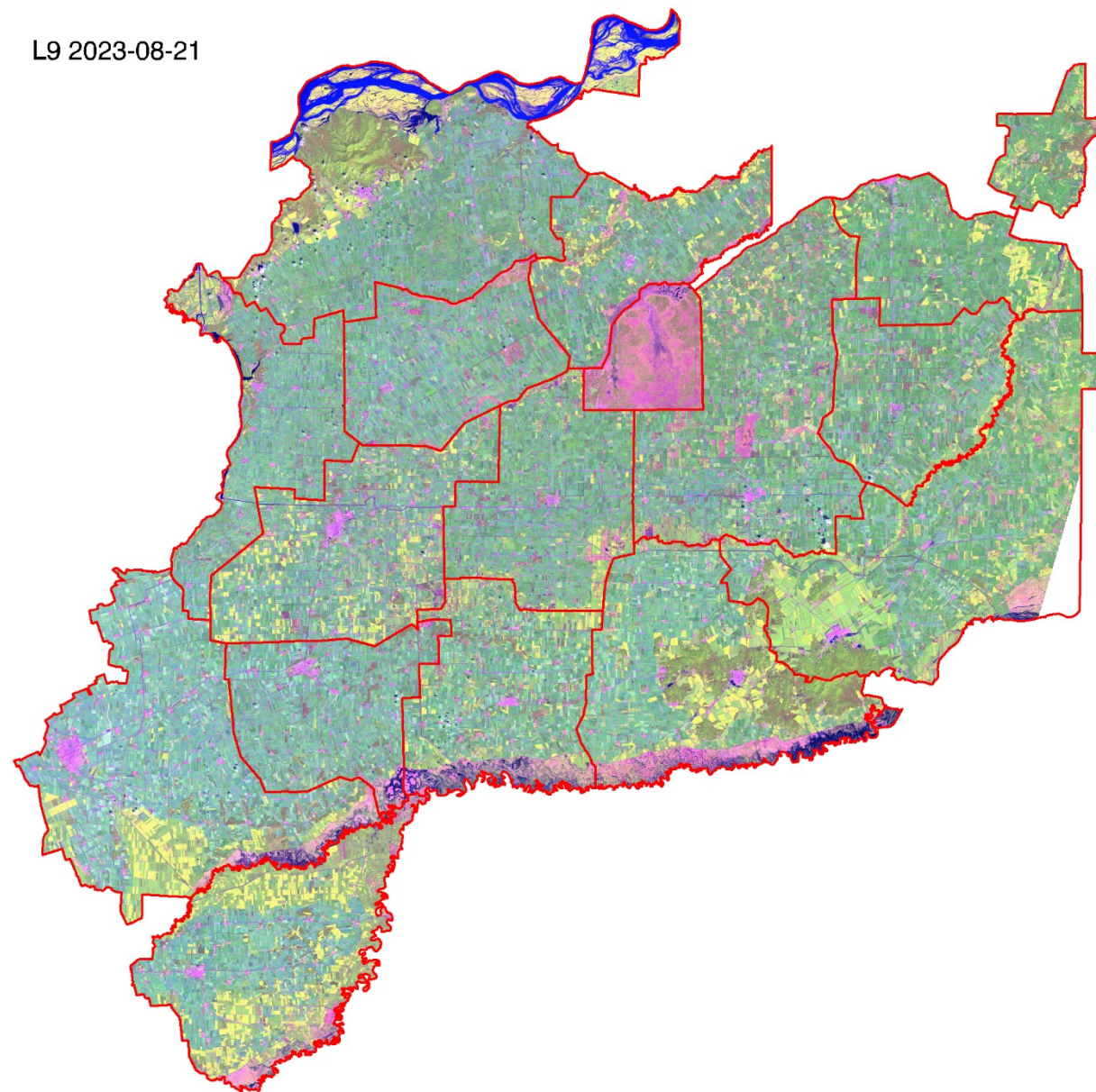


TransplantedRiceDirectlySowedRice

L9 2023-08-21



L9 2023-08-21



- Lists of the project's output

- Fan, X.; Li, X.; Yan, C.; Fan, J.; Chen, L.; Wang, N. Converging Channel Attention Mechanisms with Multilayer Perceptron Parallel Networks for Land Cover Classification. *Remote Sens.* 2023, 15(16), 3924; <https://doi.org/10.3390/rs15163924>.
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- Yan, C.; Fan, X.; Fan, J.; Yu, L.; Wang, N.; Chen, L.; Li, X. HyFormer: Hybrid Transformer and CNN for Pixel-Level Multispectral Image Land Cover Classification. *Int. J. Environ. Res. Public Health* 2023, 20(4), 3059; <https://doi.org/10.3390/ijerph20043059>.
- Yan, C.; Fan, X.; Fan, J.; Wang, N. Improved U-Net Remote Sensing Classification Algorithm Based on Multi-Feature Fusion Perception. *Remote Sens.* 2022, 14(5), 1118; <https://doi.org/10.3390/rs14051118>.
- Wang, N.; Fan, X.; Fan, J.; Yan, C. Random Forest Winter Wheat Extraction Algorithm Based on Spatial Features of Neighborhood Samples. *Mathematics* 2022, 10(13), 2206; <https://doi.org/10.3390/math10132206>.
- Fan, X.; Yan, C.; Fan, J.; Wang, N. Improved U-Net Remote Sensing Classification Algorithm Fusing Attention and Multiscale Features. *Remote Sens.* 2022, 14(15), 3591; <https://doi.org/10.3390/rs14153591>.
- Fan J, Defourny P, Zhang X, Dong Q, Wang L, Qin Z, De Vroey M, Zhao C. Crop Mapping with Combined Use of European and Chinese Satellite Data. *Remote Sensing.* 2021; 13(22):4641. <https://doi.org/10.3390/rs13224641>
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- Fan, J.; Defourny, P.; Dong, Q.; Zhang, X.; De Vroey, M.; Belleman, N.; Xu, Q.; Li, Q.; Zhang, L.; Gao, H. Sent2Agri System Based Crop Type Mapping in Yellow River Irrigation Area. *J. Geod. Geoinf. Sci.* 2020, 3, 110–117.

- Inform on the project's schedule, planning & contribution of the partners for the following year

□ European Team

- Crop type mapping with Sent2agri system
- Algorithm of crop biophysics parameter retrieved from high resolution SAR satellite
- Joint field survey

□ Chinese Team

- Project coordination and management
- Site manager, Field survey and data collection in study sites
- Crop type mapping with Chinese high resolution satellite data
- Algorithm of crop biophysics parameter retrieved from high resolution satellite
- Crop monitoring with high resolution satellite data

- Report on the level and training of young scientists on the project achievements, including plans for academic exchanges
 - 1. Young Scientists will be invited to join the field survey. This activity will help young scientists be familiar with and well understand the ground truth of research area.
 - 2. Young scientists will be guided in processing the Sentinel series and GF series satellite data. Thereafter, young scientists will be able to handle those data for the information retrieval.
 - 3. Young scientists will be guided for the crop mapping. Thereafter young scientists will be able to run the code to make a crop map.
 - 4. Young scientists will be guided for the crop biophysics parameter retrieval. Thereafter young scientists will be able to run the code to produce the product.
 - 5. Young scientists will also be engaged in manuscript writing that will enhance their academic experience.



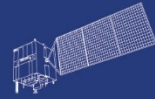
Dragon 5 3rd Year Results Reporting



HY



HJ-1AB



CBERS



Gaofen



Beijing-2



Sentinel-1



Sentinel-2



Sentinel-3



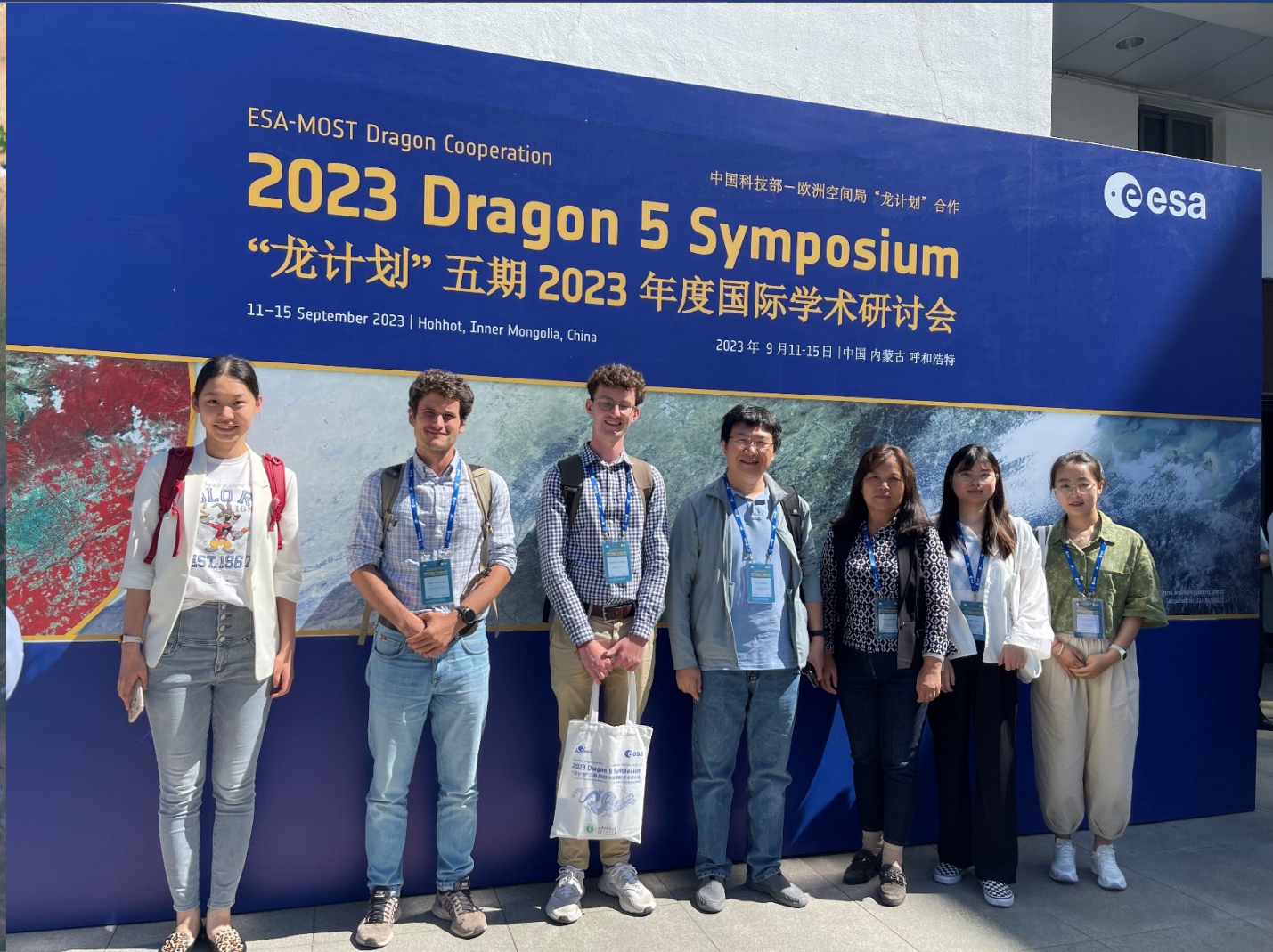
Sentinel-5p



Aeolus



Thank you very much
for your attentions!



ESA-MOST Dragon Cooperation

中国科技部-欧洲空间局“龙计划”合作

2023 Dragon 5 Symposium

“龙计划”五期 2023 年度国际学术研讨会

11-15 September 2023 | Hohhot, Inner Mongolia, China

2023年9月11-15日 | 中国内蒙古呼和浩特

