Outline

6 Crop Change Automatic Detection Technology

- Research Background and Significance
- Research Objectives and Content
- Data Preprocessing
- Data Source Comparison
- Red Edge Feature Mining
- Feature Evaluation Method
- Research Area and Samples
- Research Area Classification Results

1. Research Background and Significance

- **Crop remote sensing identification and classification is an important part of remote sensing monitoring of agricultural conditions, and it is the basis and key link for the application of remote sensing technology in the agricultural field. The timely and accurate remote sensing classification of crops can achieve accurate judgments of the planted area, spatial distribution and planting structure of crops, guide the daily management of crops, and is the basis for detecting changes in different types of crops.**
- **Crop changes are mainly divided into two categories: one is the change with the season and the growth of the crop itself (seasonal rhythm or phenological characteristics); the other is the change of crop types due to external forces or the change from vegetation to non-vegetation (planting structure, cultivated land abandonment). Remote sensing technology has been widely used in crop classification and agricultural condition monitoring because of its fast, accurate, time-saving, labor-saving, and good continuity.**

1. Research Background and Significance

- **The red edge band is a sensitive characteristic spectral band of crops and other vegetation, which helps to improve the accuracy of remote sensing identification and classification of crops. More and more multi-spectral satellite loads have begun to increase the application ability by adding red band and other spectral bands. RapidEye, WorldView-2 / 3 added a red edge band, while GF-6 and Sentinel-2 added multiple red edge bands.**

- **China's Gaofen-6 satellite was successfully launched at Jiuquan Satellite Launch Center on June 2, 2018, and was officially put into use after March 20, 2019.**

- **ESA ’s Sentinel II satellite includes two satellite constellations, Sentinel-2A and Sentinel-2B, which were successfully launched in 2015 and 2017, respectively, and are now operating normally.**

1. Research Background and Significance

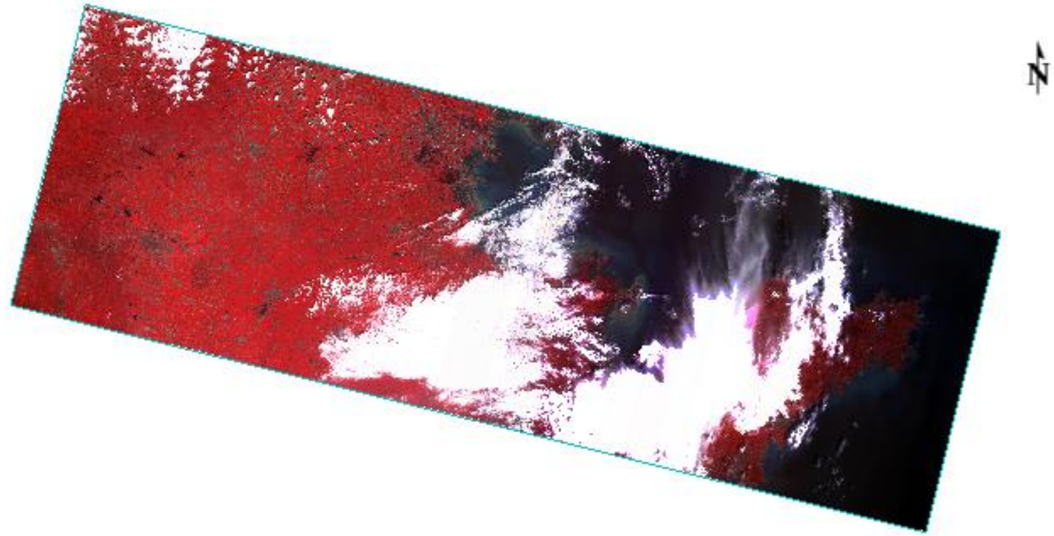
GF-6 Satellite Orbit and Payload Parameter Table

Orbit type	Sun-synchronous orbit	Orbit height / km	645km（GF-1）
Orbit inclination	98.0506 º	Down intersection local time	10:30AM
Regression period	41 days	Quantified radiation	12 bit
Satellite payload	Panchromatic Multispectral Camera（PMS）		Multispectral Wide-Frame Camera（WFV）
Spectral range / μm	Multispectral	0.45-0.52 blue 0.52-0.59 green 0.63-0.69 red 0.77-0.89 near-infrared	0.40-0.45 violet 0.45-0.52 blue 0.52-0.59 green 0.59-0.63 yellow 0.63-0.69 red 0.69-0.73 red edge1 0.73-0.77 red edge2 0.77-0.89 near-infrared
	Panchromatic	0.45-0.90	
Spatial resolution / m	Multispectral	8	16
	Panchromatic	2	
Revisit period / day	4（Side swing ability: ±35º）		2（Side swing ability: ±34º）
Width / km	≥60（A camera）		≥800（A camera）

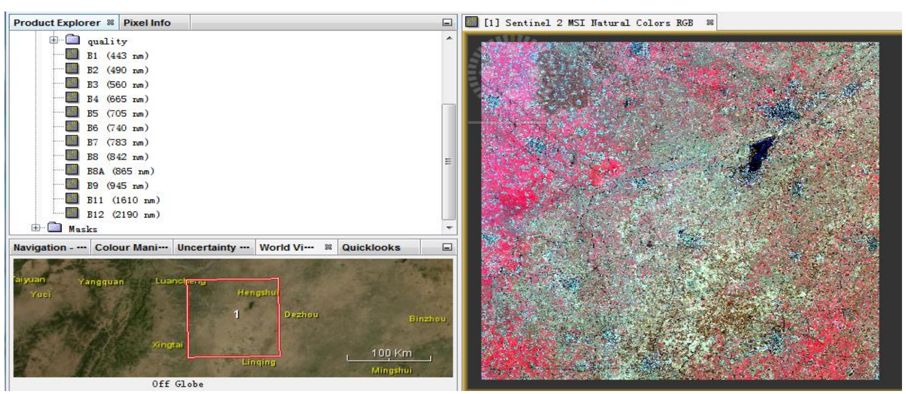
1. Research Background and Significance

Sentinel-2 Bands	Central Wavelength (µm)	Resolution (m)
Band 1 - Coastal aerosol	0.443	60
Band 2 - Blue	0.490	10
Band 3 - Green	0.560	10
Band 4 - Red	0.665	10
Band 5 - Vegetation Red Edge	0.705	20
Band 6 - Vegetation Red Edge	0.740	20
Band 7 - Vegetation Red Edge	0.783	20
Band 8 - NIR	0.842	10
Band 8A - Vegetation Red Edge	0.865	20
Band 9 - Water vapour	0.945	60
Band 10 - SWIR - Cirrus	1.375	60
Band 11 - SWIR	1.610	20
Band 12 - SWIR	2.190	20

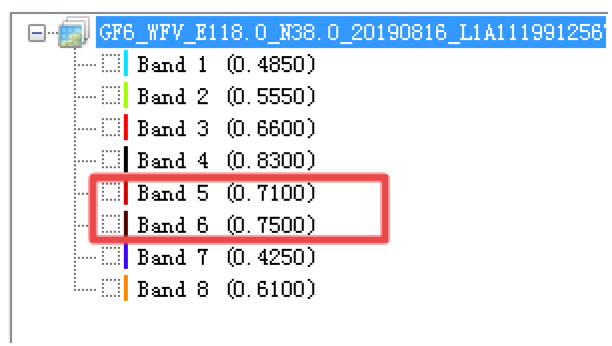
Sentinel-2 satellite payload information



GF-6 WFV remote sensing image data



Sentinel-2 remote sensing image data



GF-6 WFV数据
B1-蓝色
B2-绿色
B3-红色
B4-近红外
B5-近边705
B6-红边750
B7-蓝边
B8-黄色

GF-6 WFV remote sensing data band information

1. Research Background and Significance

- **Gaofen-6 is a low-orbit optical remote sensing satellite, and it is also the first high-resolution satellite for precision agricultural observation in China. It has a combination of high resolution and wide coverage. With a life span of 8 years, it will operate in conjunction with the on-orbit high satellite GaoFen-1 satellite, greatly improving the ability to monitor resources in agriculture, forestry, and grasslands.**

1. Research Background and Significance

Achievements and Shortcomings

Achievements:

- ✓ **The vegetation index time series classification method and object-oriented classification technology improve the accuracy of vegetation classification such as crops.**
- ✓ **The red edge feature participates in classification to improve the classification accuracy of different crops.**
- ✓ **Feature analysis and selection methods such as random forest reduce redundancy of classification features and improve classification accuracy and efficiency.**

Shortcomings

- **Mining red-edge features of multispectral satellites with multiple red-edge bands is not sufficient.**
- **There are few studies on the application and importance evaluation of various red edge features and feature combinations in crop classification.**
- **Comparison and evaluation of crop classification based on multi-source data and multi-feature combination or fusion, such as red edges, short time series, and other features, compared and evaluated between Sentinel-2 and GF-6**

Outline

6 Crop Change Automatic Detection Technology

- Research Background and Significance
- Research Objectives and Content
- Data Preprocessing
- Data Source Comparison
- Red Edge Feature Mining
- Feature Evaluation Method
- Research Area and Samples
- Research Area Classification Results

2. Research Objectives and Content

Based on the fine classification of vegetation types and high-precision automatic detection technology of vegetation changes based on GF-6 satellite imagery, the automatic extraction and analysis of vegetation type change information is realized to improve the accuracy and automation of vegetation classification and change detection.

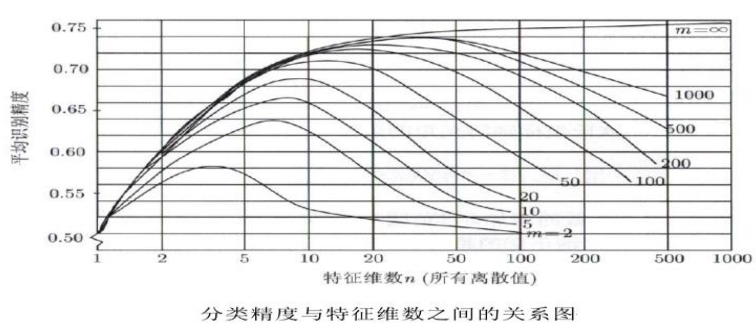
With crops as the main research object, fine classification of different crop types and detection of changes in crop planting structure were carried out.

2.2 Research Content

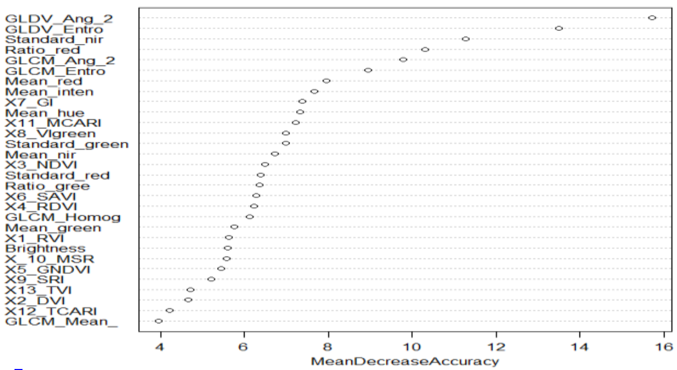
(1) Analysis and selection of crop classification features

As more and more relevant features are involved in crop classification, the feature dimension tends to be very high. High-dimensional features can have certain effects on the performance of the classifier, and a "Hughes" phenomenon similar to hyperspectral remote sensing appears. Too many features can easily lead to feature redundancy, leading to a reduction in classification accuracy. Therefore, it is necessary to analyze or select the importance of classification features by trying or improving some algorithms (random forest RF, ReliefF, etc.).

The research will focus on the spectral characteristics of different red edge bands and their derived red edge index (REVI), red edge texture (GLCM, GLDV) and other characteristics, and evaluate the impact of different red edge features or combinations on crop classification.



"Hughes" phenomenon



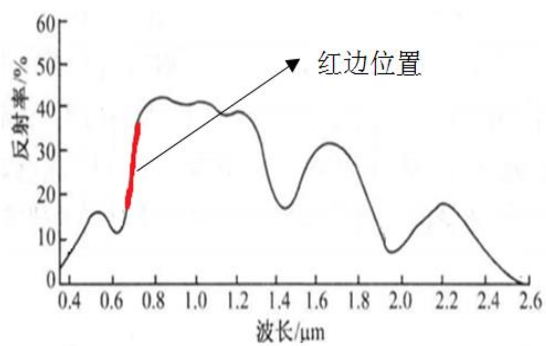
Random Forest RF Feature Importance Analysis (Average accuracy reduction: MDA)

2.2 Research Content

(2) Recognition and classification of crops based on single phase and multiple feature optimization

Multi-features include features such as spectrum, texture, shape, vegetation index, red edge, and SAR backscatter. Using the differences in the features of different crops in remote sensing images, according to the importance of different features of crop classification, combining different feature combination schemes, Some algorithms (CART decision tree, ReliefF) evaluate and select classification features, use a variety of different intelligent classifiers (SVM, RF), and object-oriented methods to classify crops and perform comparative analysis of different feature combinations.

In the study, a variety of crop classification schemes will be designed for different red edge features and combinations to evaluate the impact of different red edge features on crop classification.



绿色植被的光谱响应特征

$$NDVI_{705} = \frac{\rho_{750}-\rho_{705}}{\rho_{750}+\rho_{705}}$$

红边归一化植被指数

$$mSR_{705} = \frac{\rho_{750}-\rho_{445}}{\rho_{750}+\rho_{445}}$$

改进红边比值植被指数

$$mNDVI_{705} = \frac{\rho_{750}-\rho_{705}}{\rho_{750}+\rho_{705}-2\rho_{445}}$$

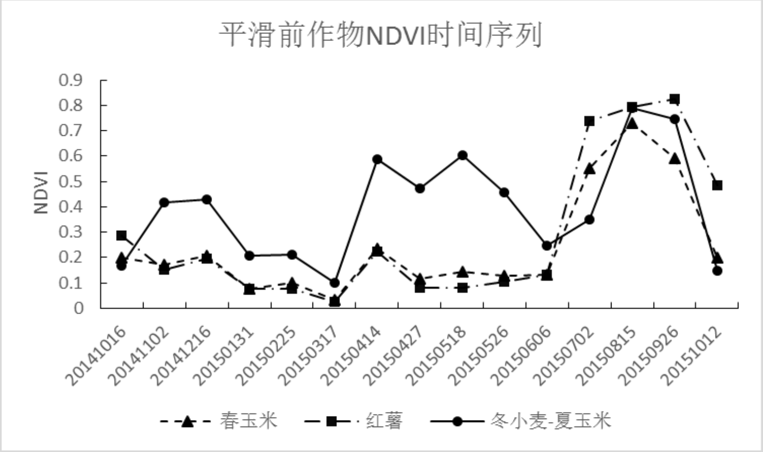
改进红边归一化植被指数

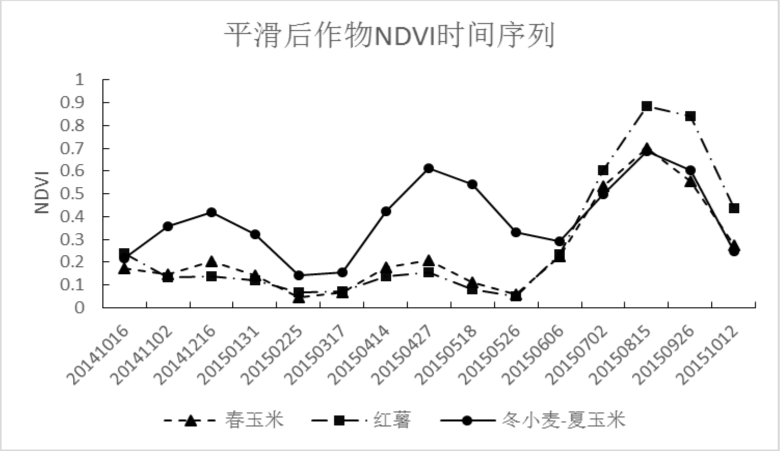
Several red-edge vegetation indices

2.2 Research Content

(3) Crop classification based on red edge characteristics of multi-temporal time-series remote sensing data

Construct NDVI, EVI and other crop vegetation index time series based on GF-6 and Sentinel-2 satellite data, perform smooth denoising processing (HANTS or SG) on time series data, and mine classification features such as different crop phenology in time series data. Determine the best time for the classification of different crops, and carry out identification and classification studies on different crops. In the study, the red edge feature (REVI) will be integrated into the time series data, and for some key phases in the crop growth period, a short time series will be used to obtain the results of crop classification in advance to improve the accuracy and timeliness of crop classification.





2. Research Objectives and Content

Key Technology

1. Object-oriented crop classification technology based on multiple features

Multi-features include vegetation index features, spectral features, texture features, shape features, red edge features, time-series features, SAR image backscattering features, phenological features, etc. In the study, different feature combination schemes will be used, using object-oriented and intelligent The classifier method is used to classify crops. The classification results of different schemes are compared and the reasons are discussed.

2. Classification feature analysis and selection technology

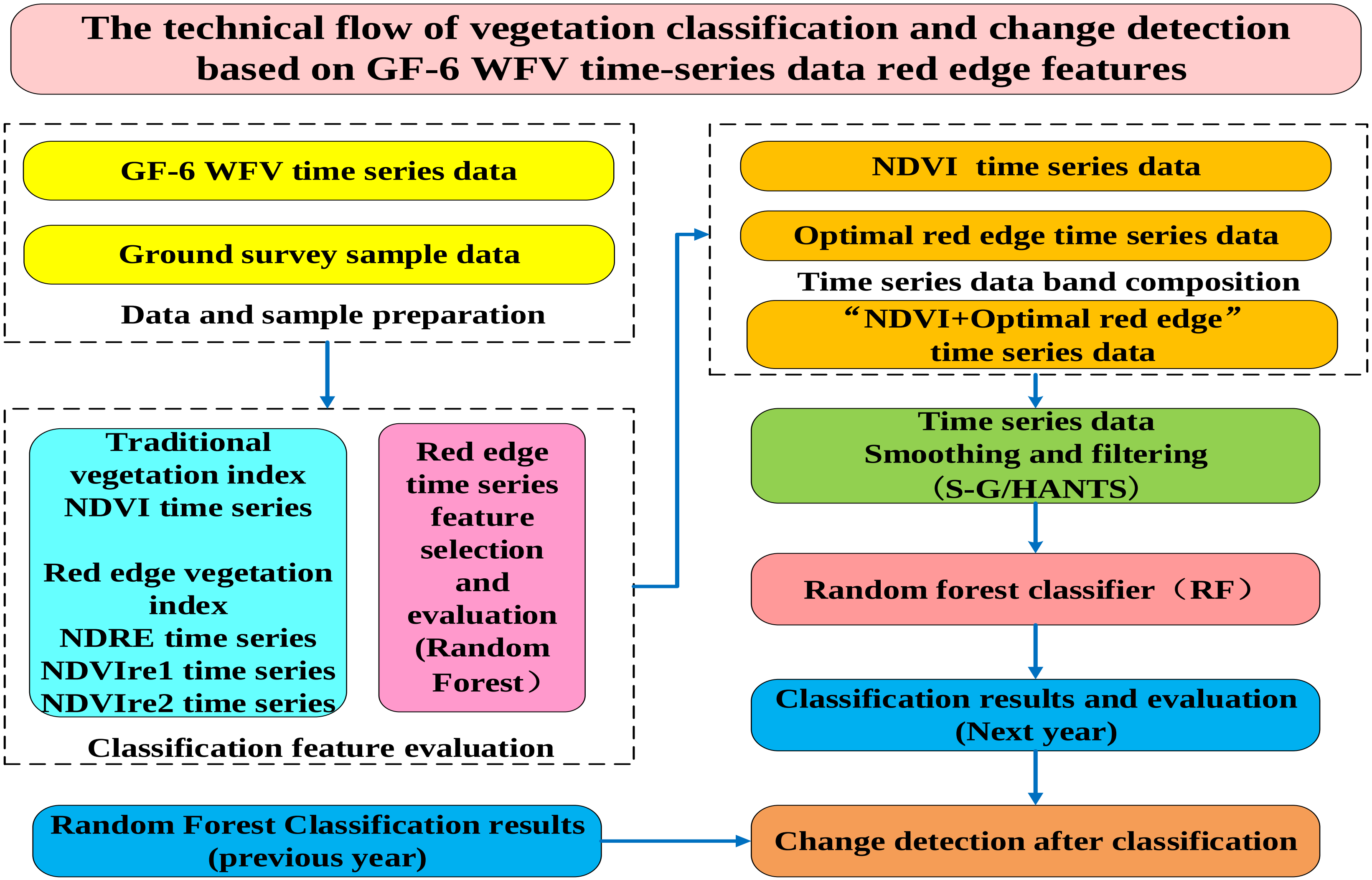
The dimensionality of image features such as spectrum, texture, and shape extracted in object-oriented classification is often relatively high, and high-dimensional features can have a certain impact on the performance of the classifier. Too many features can easily lead to feature redundancy, leading to a reduction in classification accuracy. Therefore, it is necessary to analyze or select classification features by trying or improving some algorithms (random forest, ReliefF, etc.).

3. Crop monitoring technology based on post-classification change detection

The change detection method of the crop planting structure and planting area is detected by the change detection method after classification, so as to reflect the change of the crop region, type and area in the study area.

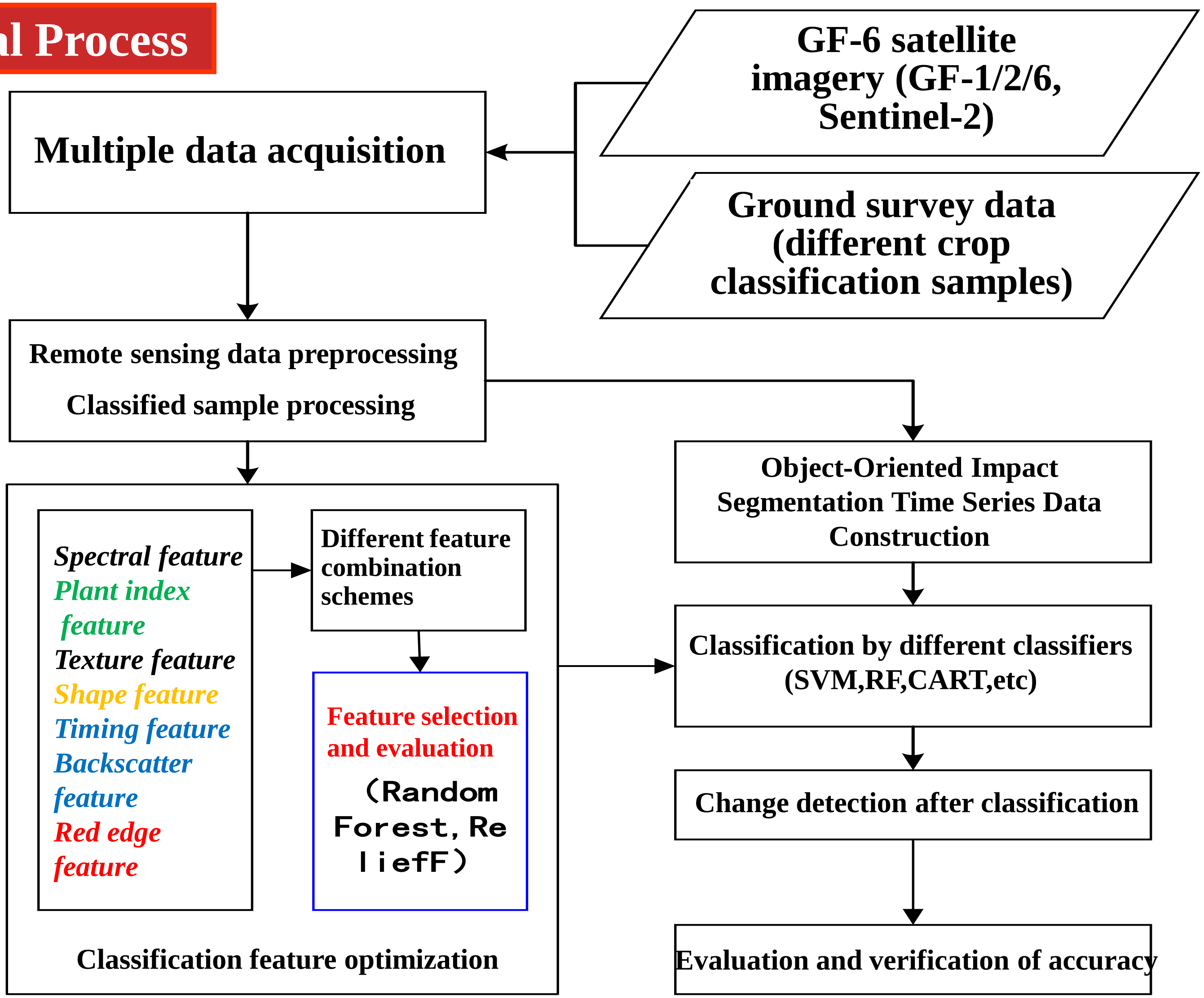
2. Research Objectives and Content

Technical Process



2. Research Objectives and Content

Technical Process



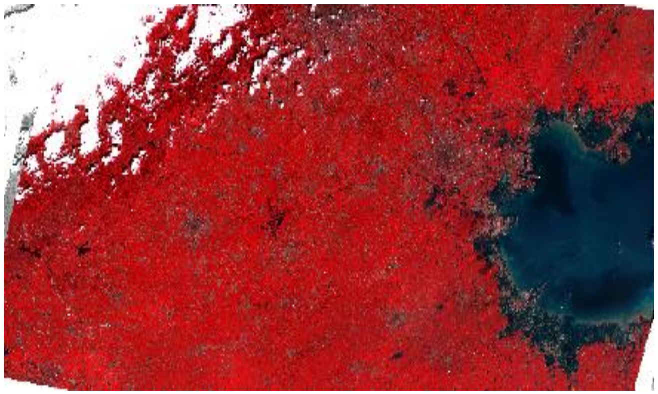
Outline

6 Crop Change Automatic Detection Technology

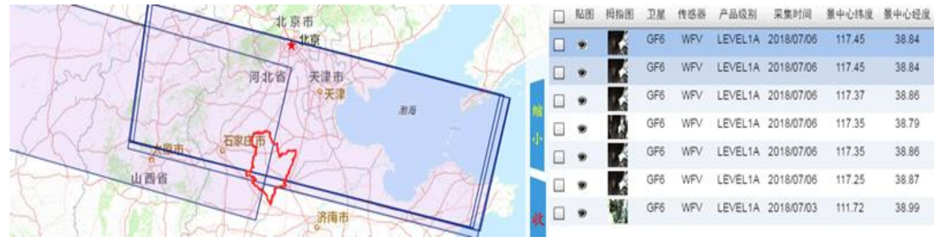
- Research Background and Significance
- Research Objectives and Content
- Data Preprocessing
- Data Source Comparison
- Red Edge Feature Mining
- Feature Evaluation Method
- Research Area and Samples
- Research Area Classification Results

3. Data Preprocessing

Data Source

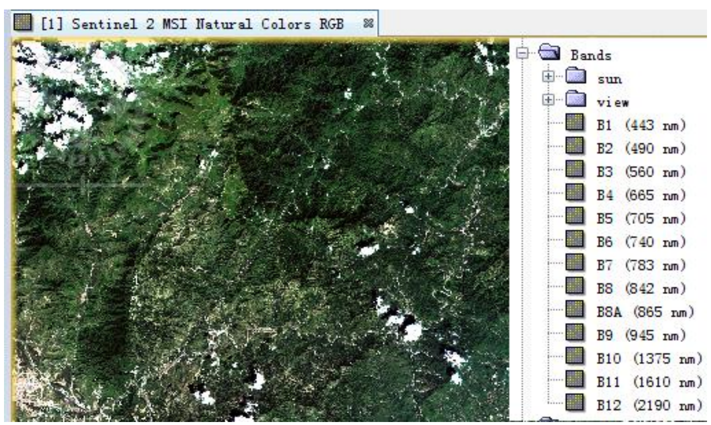


GF-6 WFV remote sensing image data

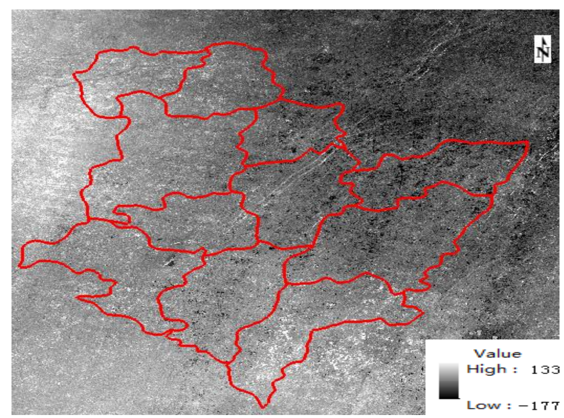


GF-6 PMS	0.0505	0	0.0825	0	0.0663	0	0.0513	0	0.0298	0
GF-6 WFV B1-B4	/	/	0.0667	0	0.0517	0	0.0485	0	0.0298	0
GF-6 WFV B5-B8	/	/	0.0530	0	0.0445	0	0.0814	0	0.0559	0

GF-6 Remote sensing image data query and calibration coefficient



Sentinel-2 remote sensing image data



DEM data（GDEMV2）

The research mainly focused on GF-6 WFV data and Sentine-2 data

3. Data Preprocessing

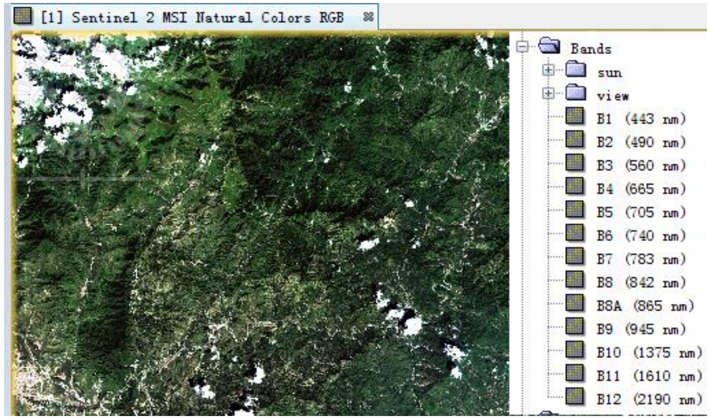
Data Source

Medium and high resolution optical remote sensing image

GF-1 remote sensing image data

GF-6 Remote Sensing Image Data Query and Calibration Coefficient

GF-6 PMS	0.0505	0	0.0825	0	0.0663	0	0.0513	0	0.0298	0
GF-6 WFV B1-B4	/	/	0.0667	0	0.0517	0	0.0485	0	0.0298	0
GF-6 WFV B5-B8	/	/	0.0530	0	0.0445	0	0.0814	0	0.0559	0



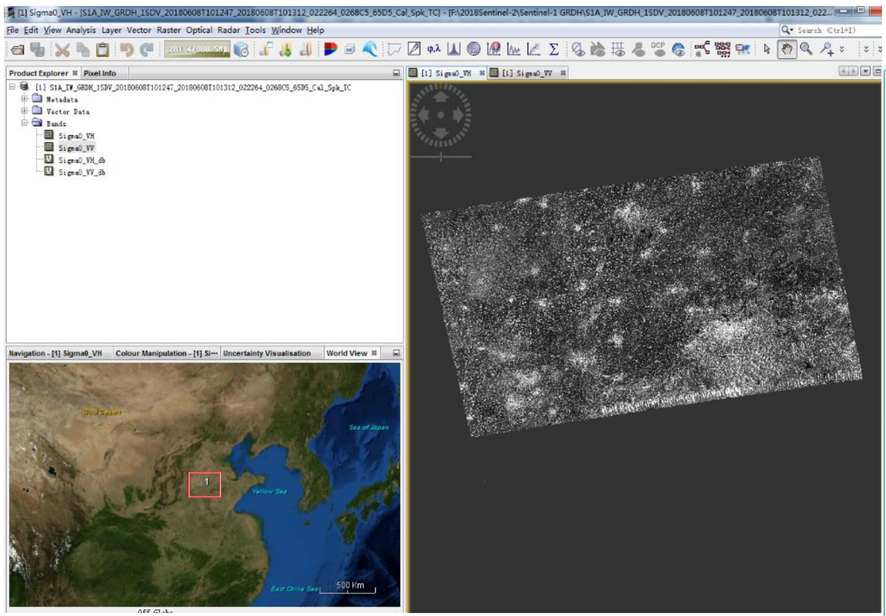
Sentinel-2 remote sensing image data

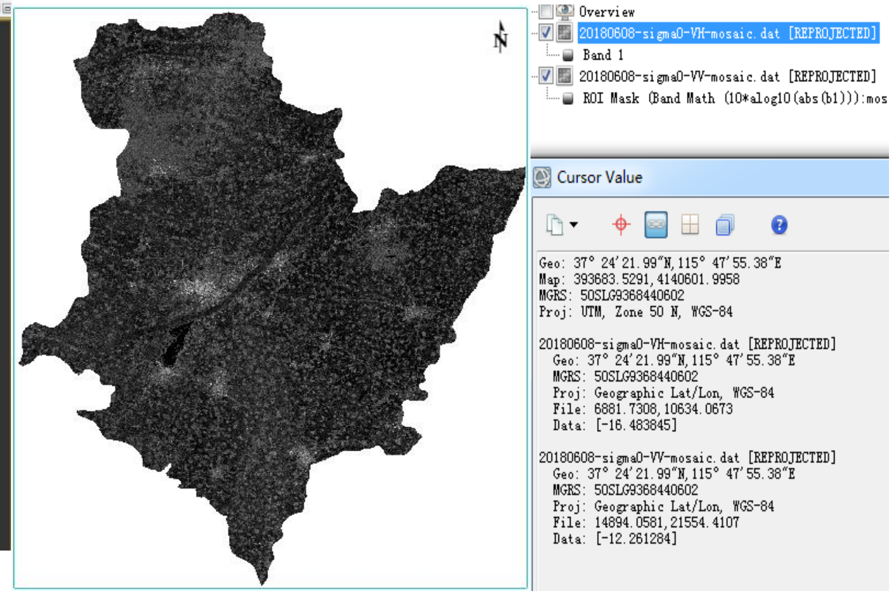
GF-6 remote sensing image data

This phase mainly focuses on GF series satellites and Sentinel-2 data.

3. Data Preprocessing

Data Source





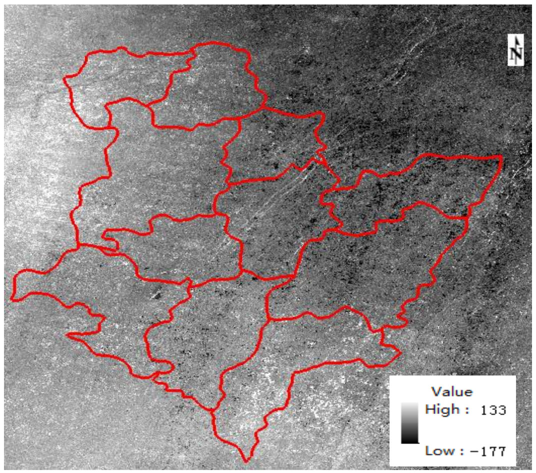
Sentinel-1 image

（GRD image VH+VV polarization）

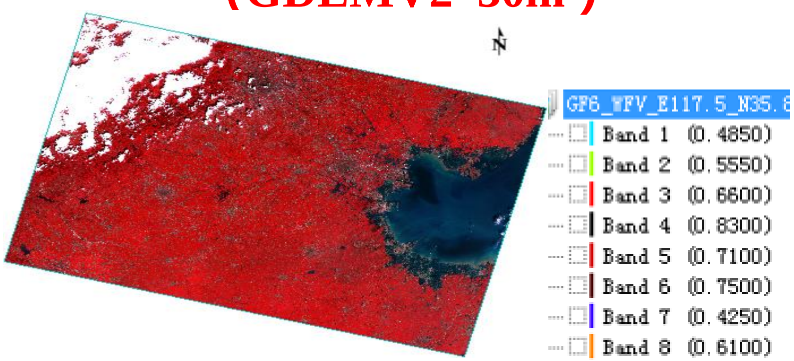
The Sentinel-1 satellite data was also used in the study. SNAP was used to perform preprocessing operations such as 1,radiation correction, 2, speckle noise suppression, and 3, geometric correction, etc., obtain the SAR image backscattering coefficient image.

3. Data Preprocessing

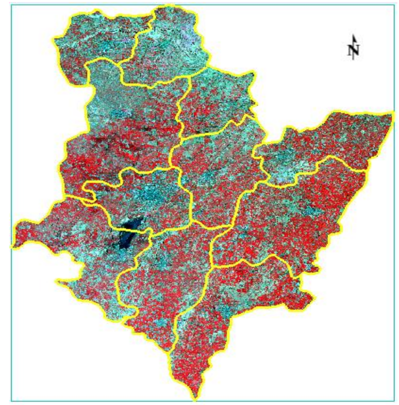
Supplementary Data



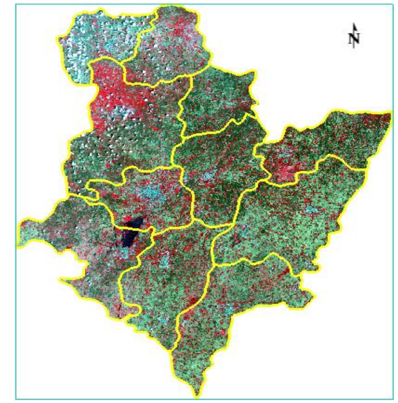
Hengshui DEM data
（GDEMV2 30m ）



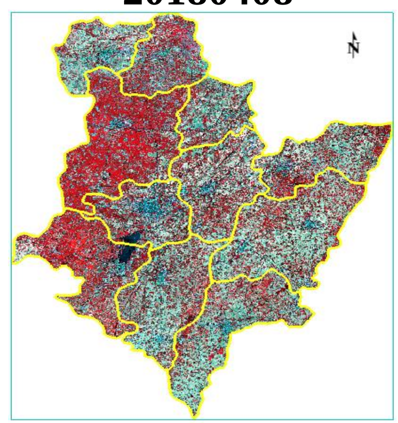
GF-6 WFV remote sensing image



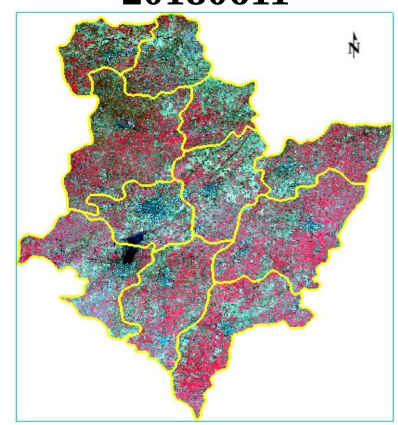
20180408



20180611



20181001



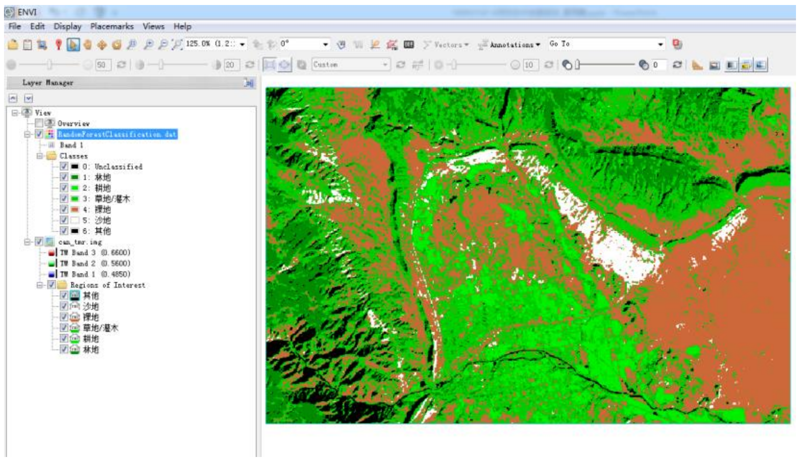
20181204

Landsat-8 OLI remote sensing data

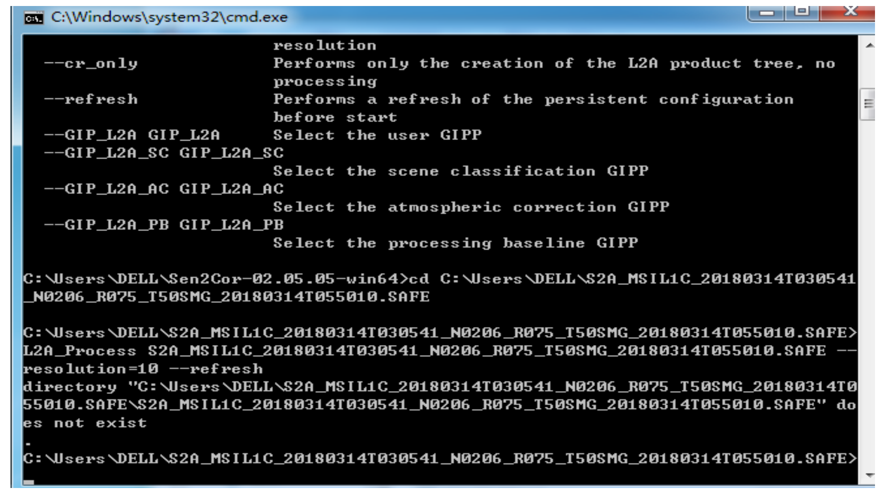
3. Data Preprocessing

Different Data Processing Methods

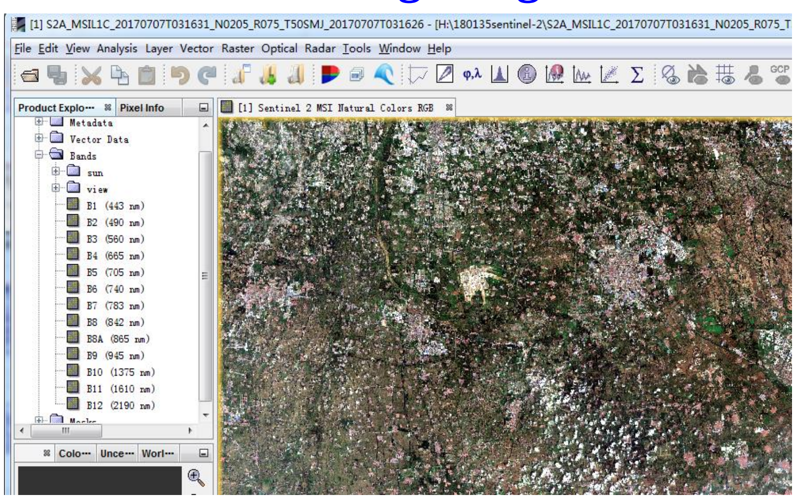
ENVI, SEN2COR, SNAP, GEE



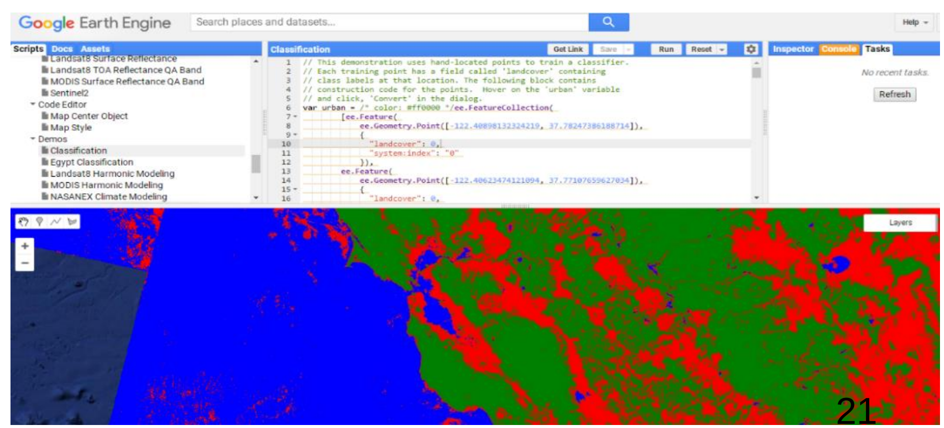
ENVI Remote Sensing Image Classification



SEN2COR plug-in atmospheric correction



SNAP sentinel data processing

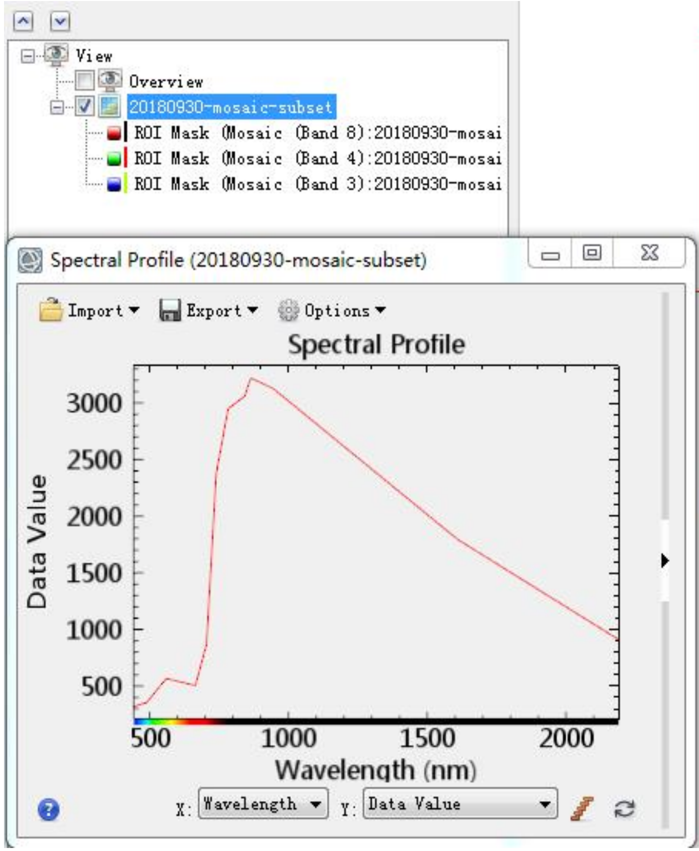


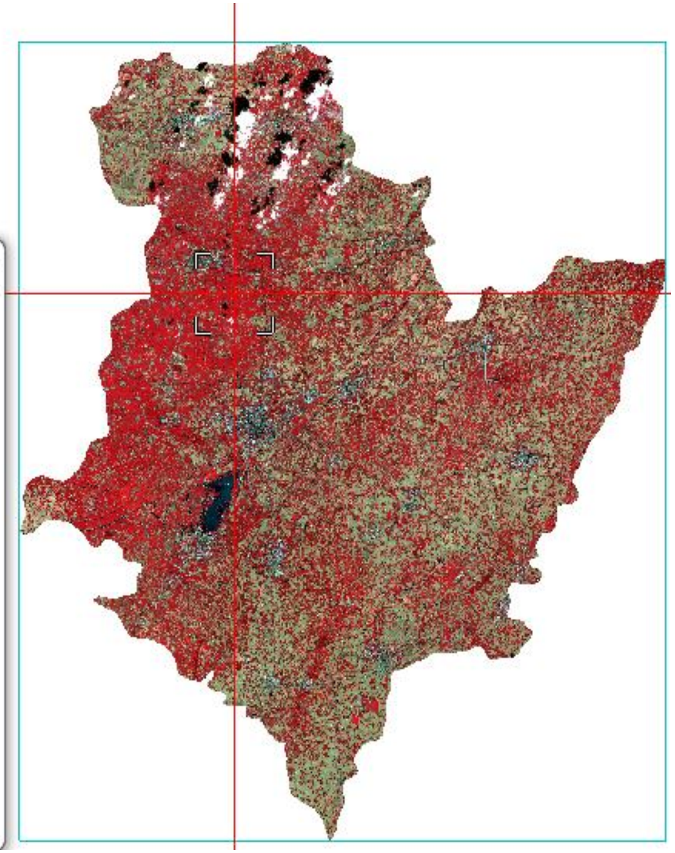
Google Earth Engine data processing

3. Data Preprocessing

Data Preprocessing Results

Sentinel-2 Satellite image





The pre-processed surface reflectance data uses software such as SNAP and ENVI to perform atmospheric correction on the original data to convert the S1C data into S2A Data, and then perform re-sampling, band synthesis, stitching, cropping and other operations to complete the pre-processing of the data.

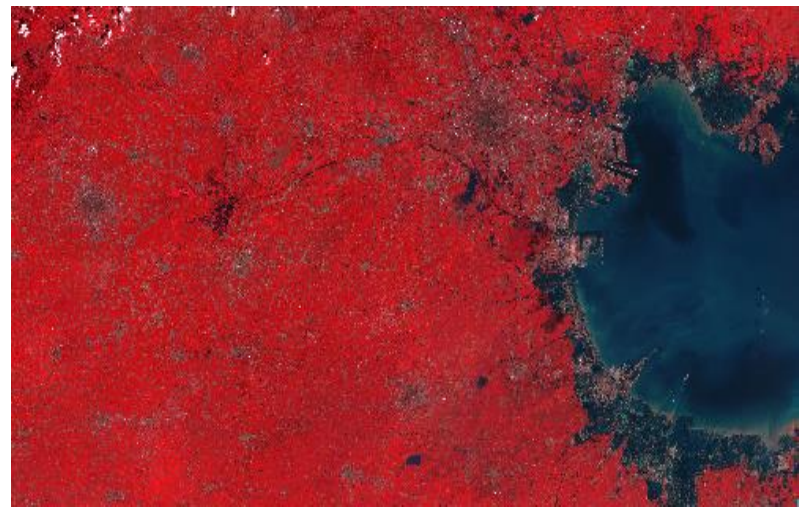
Sentinel-2 pre-processed surface reflectance data

3. Data Preprocessing

Data Preprocessing Results

GF6_WFV_E116.2_N38.0_20180906_L1A1119837353.dbf	2018/11/7 10:41	DBF 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353.jpg	2018/11/7 10:41	JPG 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353.nav	2018/11/7 10:17	NAV 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353.rpb	2018/11/7 10:17	RPB 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353.shp	2018/11/7 10:41	SHP 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353.shx	2018/11/7 10:41	SHX 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353.til	2018/11/7 10:17	TIL 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353.xml	2018/11/7 10:41	XML 文档
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353_thumb.jpg	2018/11/7 10:41	JPG 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-1.hdr	2018/11/16 9:11	HDR 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-1.jpg	2018/11/7 10:41	JPG 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-1.rpb	2018/11/7 10:17	RPB 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-1.rpb.aux.xml	2018/11/7 10:17	XML 文档
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-1.tiff	2018/11/7 10:41	TIFF 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-1.tiff.enp	2018/11/14 9:42	EndNote Prefe
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-1_thumb.jpg	2018/11/7 10:41	JPG 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-2.hdr	2018/12/14 22:17	HDR 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-2.jpg	2018/11/7 10:41	JPG 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-2.rpb	2018/11/7 10:17	RPB 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-2.tiff	2018/11/7 10:38	TIFF 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-2.tiff.enp	2018/11/16 13:57	EndNote Prefe
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-2_thumb.jpg	2018/11/7 10:41	JPG 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-3.hdr	2018/11/16 9:11	HDR 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-3.jpg	2018/11/7 10:41	JPG 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-3.rpb	2018/11/7 10:17	RPB 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-3.tiff	2018/11/7 10:33	TIFF 文件
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-3.tiff.enp	2018/11/16 9:06	EndNote Prefe
GF6_WFV_E116.2_N38.0_20180906_L1A1119837353-3_thumb.jpg	2018/11/7 10:41	JPG 文件
order.xml	2018/11/7 10:14	XML 文档

GF-6 WFV Satellite image



GF-6 WFV data

B1-blue B2-green B3-red B4-near-infrared B5-near edge 705 B6-red edge 750 B7-blue edge B8-yellow

GF-6 WFV Remote sensing data files and band settings

3. Data Preprocessing

Data Pre-processing Process

GF-6 WFV image processing

1.Open GF-6 image (.til file)

2. Crop study area (subset due to large width)

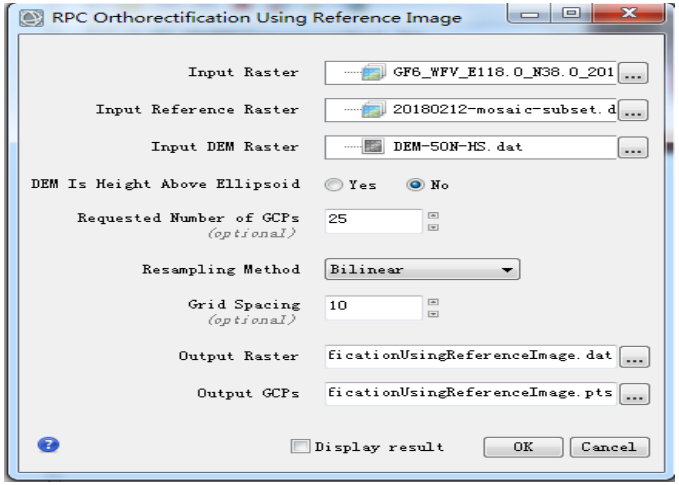
3. RPC ortho (orthorectification + geometric correction / registration)

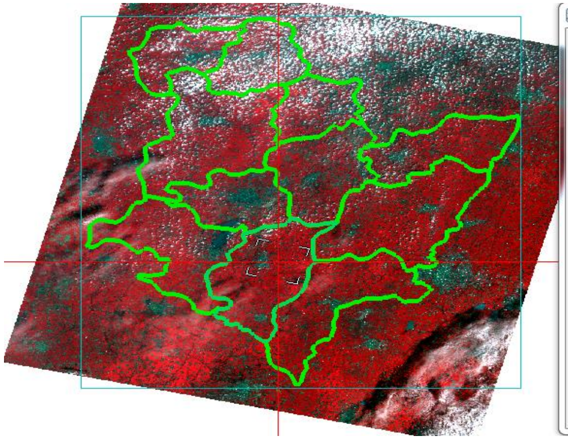
RPC Orthorectification Using Reference Workflow

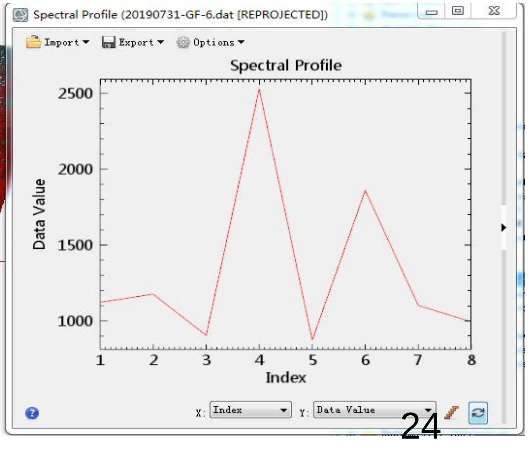
(Can use landsat-8, sentinel-2 for geometric correction / registration)

4. Radiation calibration (Gains, Offsets)

5. Atmospheric correction (FLAASH or QUAC)







Outline

6 Crop Change Automatic Detection Technology

- Research Background and Significance
- Research Objectives and Content
- Data Preprocessing
- Data Source Comparison
- Red Edge Feature Mining
- Feature Evaluation Method
- Research Area and Samples
- Research Area Classification Results

4. Data Source Comparison

GF-6 satellite orbit and payload parameter table

Orbit type	Sun-synchronous orbit	Orbit height / km	645km（GF-1）
Orbit inclination	98.0506 º	Down intersection local time	10:30AM
Regression period	41 days	Quantified radiation	12 bit
Satellite payload	Panchromatic Multispectral Camera（PMS）		Multispectral Wide-Frame Camera（WFV）
Spectral range / μm	Multispectral	0.45-0.52 blue 0.52-0.59 green 0.63-0.69 red 0.77-0.89 near-infrared	0.40-0.45 violet 0.45-0.52 blue 0.52-0.59 green 0.59-0.63 yellow 0.63-0.69 red 0.69-0.73 red edge1 0.73-0.77 red edge2 0.77-0.89 near-infrared
	Panchromatic	0.45-0.90	
Spatial resolution / m	Multispectral	8	16
	Panchromatic	2	
Revisit period / day	4（Side swing ability：±35º）		2（Side swing ability：±35º）
Width / km	≥60（A camera）		≥800（A camera）

4. Data Source Comparison

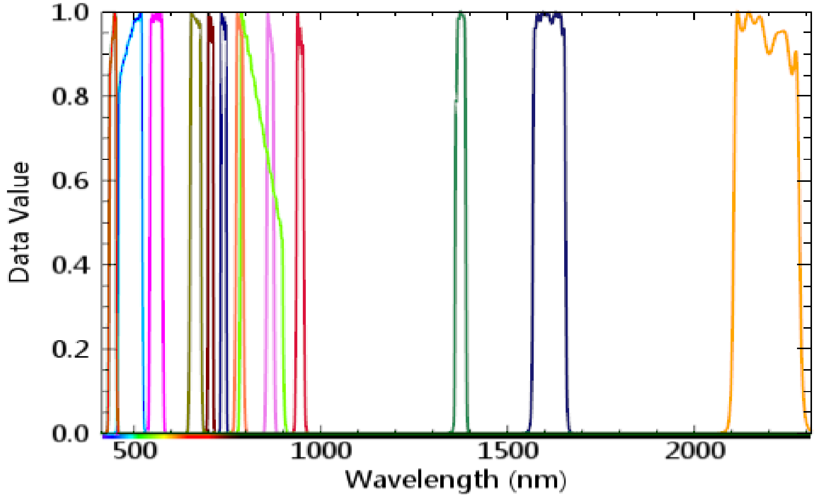
GF-6 WFV波段	中心波长 (um)	波段范围 (um)
B1-蓝	0.485	0.45-0.52
B2-绿	0.555	0.52-0.59
B3-红	0.660	0.63-0.69
B4-近红外	0.830	0.77-0.89
B5-红边1	**0.710**	**0.69-0.73**
B6-红边2	**0.750**	**0.73-0.77**
B7-紫	0.425	0.40-0.45
B8-黄	0.610	0.59-0.63

GF-6 WFV satellite band information

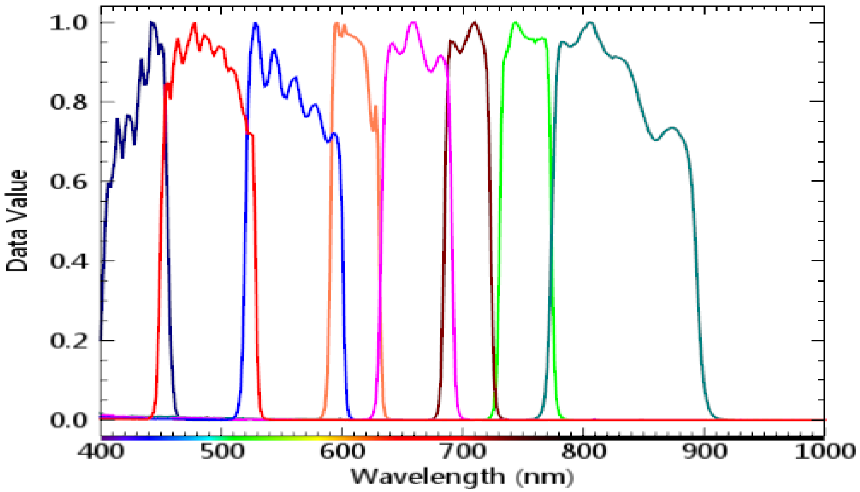
Sentinel-2 Bands	Central Wavelength (µm)	Resolution (m)
Band 1 - Coastal aerosol	0.443	60
Band 2 - Blue	0.490	10
Band 3 - Green	0.560	10
Band 4 - Red	0.665	10
Band 5 - Vegetation Red Edge	0.705	20
Band 6 - Vegetation Red Edge	0.740	20
Band 7 - Vegetation Red Edge	0.783	20
Band 8 - NIR	0.842	10
Band 8A - Vegetation Red Edge	0.865	20
Band 9 - Water vapour	0.945	60
Band 10 - SWIR - Cirrus	1.375	60
Band 11 - SWIR	1.610	20
Band 12 - SWIR	2.190	20

Sentinel-2 satellite band information

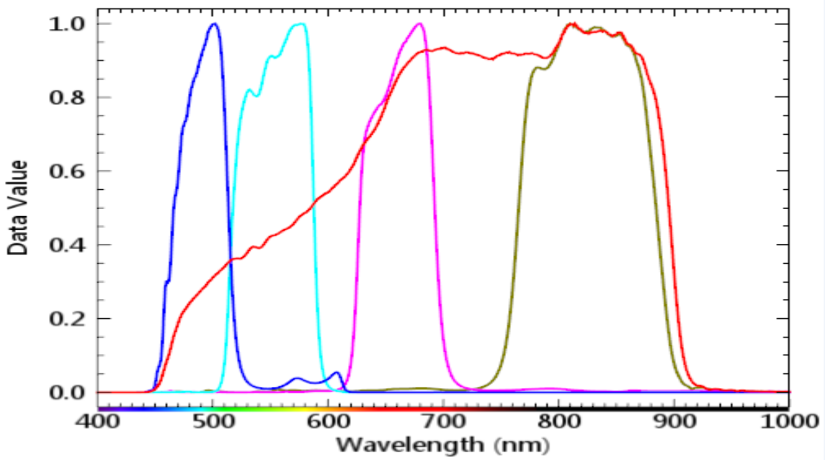
4. Data Source Comparison



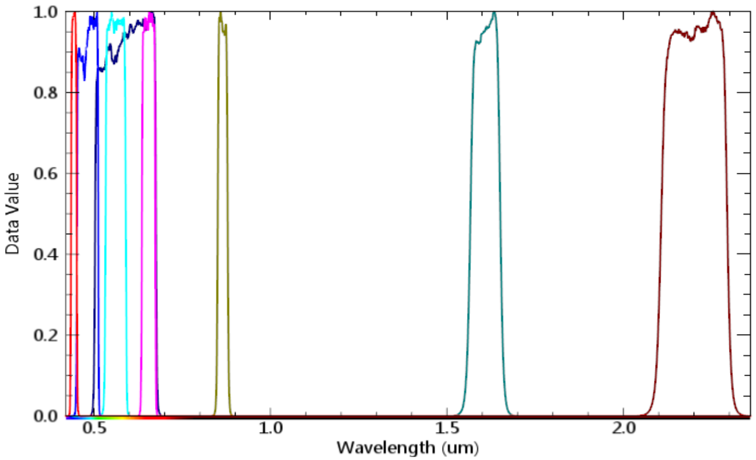
Sentinel-2 Image spectral response



GF-6 WFV Image spectral response



GF-1 WFV Image spectral response



landsat8 OLI Image spectral response

Image Spectral response of image data from different data sources

Outline

6 Crop Change Automatic Detection Technology

- Research Background and Significance
- Research Objectives and Content
- Data Preprocessing
- Data Source Comparison
- Red Edge Feature Mining
- Feature Evaluation Method
- Research Area and Samples
- Research Area Classification Results

5. Red Edge Feature Mining

Different Red Edge Features (red edge index)

Red Edge Index	Index of the Full Name	Computational Formula（GF-6 WFV）
NDRE	Normalized Difference Red-Edge	(float(b6)-b5)/(b6+b5)
NDVIre1	Normalized Difference Vegetation Index red-edge 1	(float(b4)-b5)/(b4+b5)
NDVIre2	Normalized Difference Vegetation Index red-edge 2	(float(b4)-b6)/(b4+b6)
CIre1	Chlorophyll Index red-edge 1	(float(b4))/(b5)-1
CIre2	Chlorophyll Index red-edge 2	(float(b4))/(b6)-1
MCARI1	Modified Chlorophyll Absorption Ratio Index 1	((float(b5)-b3)-0.2*(b5-b2))*(b5/b3)
MCARI2	Modified Chlorophyll Absorption Ratio Index 2	((float(b6)-b3)-0.2*(b6-b2))*(b6/b3)
TCARI1	Transformed Chlorophyll Absorption Reflectance Index 1	3*((float(b5)-b3)-0.2*(b5-b2)*(b5/b3))
TCARI2	Transformed Chlorophyll Absorption Reflectance Index 2	3*((float(b6)-b3)-0.2*(b6-b2)*(b6/b3))
MTCI	MERIS Terrestrial Chlorophyll Index	(float(b6)-b5)/(b5-b3)

Different Red Edge Index Features（GF-6 WFV data）

5. Red Edge Feature Mining

Other red edge features

1、Red edge position（REP）

The red edge position (REP) is generally obtained from the hyperspectral reflection data of vegetation. For multispectral remote sensing satellites, it can be calculated by linear interpolation. The calculation formula is as follows:

$$REP = 700 + 40\left[\left(R_{red\ edge} - R_{700}\right)/\left(R_{740} - R_{700}\right)\right]$$

$$R_{red\ edge} = \left(R_{670} + R_{780}\right)/2$$

2、 Red edge area（AREA）

$$AREA_{sentinel-2} = \left(\rho_{B6} + \rho_{B5}\right)\left(\lambda_{B6} - \lambda_{B5}\right)/2 + \left(\rho_{B7} + \rho_{B6}\right)\left(\lambda_{B7} - \lambda_{B6}\right)/2$$

$$AREA_{GF-6} = \left(\rho_{B6} + \rho_{B5}\right)\left(\lambda_{B6} - \lambda_{B5}\right)/2$$

3、 Red edge texture (GLCM，GLDV)

Outline

6 Crop Change Automatic Detection Technology

- Research Background and Significance
- Research Objectives and Content
- Data Preprocessing
- Data Source Comparison
- Red Edge Feature Mining
- Feature Evaluation Method
- Research Area and Samples
- Research Area Classification Results

6. Feature Evaluation Method

Random Forest Feature Evaluation Method

randomforest.R

```r
clear all
#install necessary packages
#install.packages(c("raster","sp","rgdal","randomForest","clusterGeneration","mnormt","party"),"D:\code\RF\R_library")
library(sp)
library(rgdal)
library(raster)
library(randomForest)
library(clusterGeneration)
library(mnormt)
library(party)
library(corrplot)
secretly<-read.csv("D:/software/random forest/170704 characteristics.csv", header=TRUE)
#train samples using random forest
rfdata <- randomForest(class~., data=secretly, importance=TRUE, proximity=TRUE)
#S=genPositiveDefMat("eigen",dim=30)
#S=genPositiveDefMat("unifcorrmat",dim=30)
#corrplot(cor(rfdata), order = "hclust")
importance(rfdata)
importance(rfdata,type=1)
varImpPlot(rfdata)
rfdata <- cforest(class~., data=secretly, control=cforest_unbiased(ntree=50))
varimp(rfdata)
#read the RS imagery
```

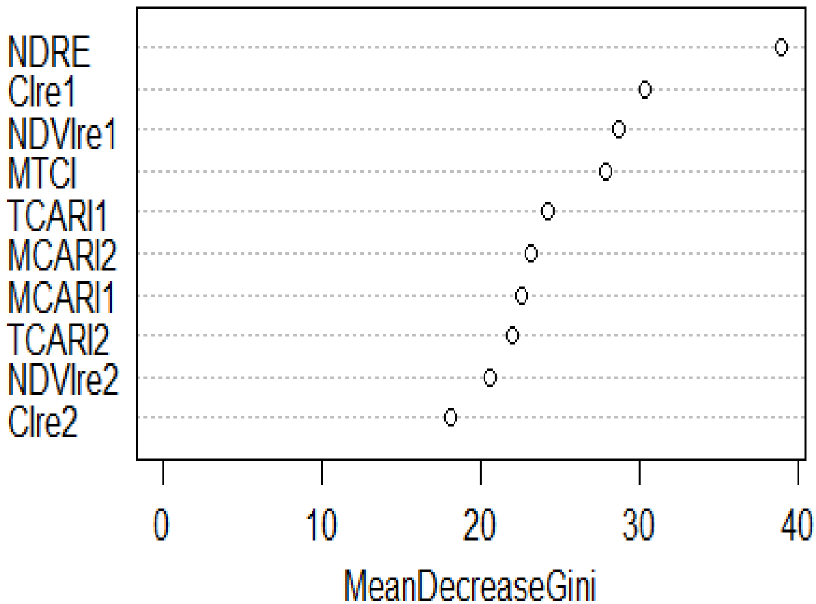
```python
import pandas as pd
import numpy as np
import scipy as sp
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
data = pd.read_csv('C:\\Users\DELL\Desktop\\190415 feature all1.csv')
X,y=data.iloc[:,1:].values,data.iloc[:,0].values
feat_labels=data.columns[1:]
print(feat_labels)
#print(X,y)
forest=RandomForestClassifier(n_estimators=10000,criterion='gini',n_jobs=-1,random_state=0)
forest.fit(X,y)
importances=forest.feature_importances_
#=100.0*(importances/max(importances))  #0-100 范围
#importances=(importances-min(importances))/(max(importances)-min(importances)) #0-1 范围
indices=np.argsort(importances)[::1]
print(indices)
```

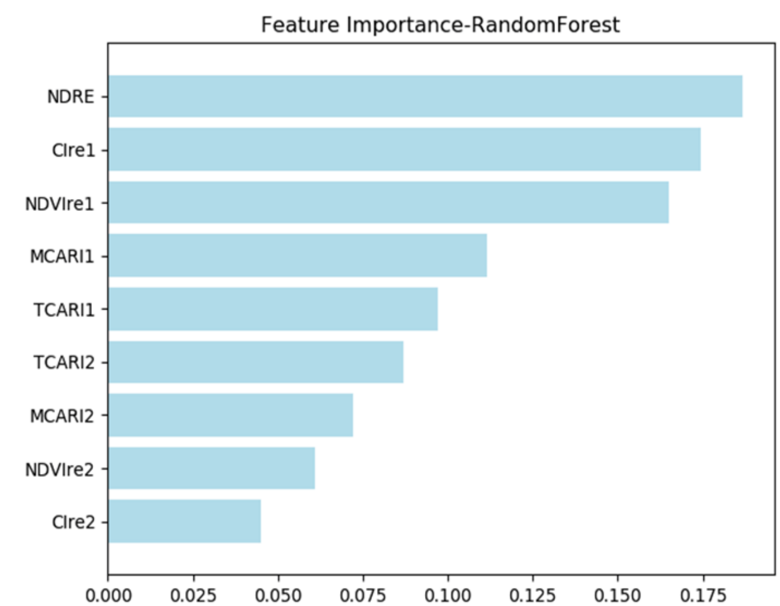
Random forest algorithm feature importance evaluation (R or Python)

Random forest is an integrated machine learning method. Generally, it randomly selects several feature subsets based on a random subspace, and uses a decision tree as a training algorithm to train and obtain the final classification result by voting. The random forest algorithm's measure of the importance of variables is a tool for feature selection in high-dimensional data, and it is an embedded feature selection algorithm.

6. Feature Evaluation Method

Random Forest Feature Evaluation Method





Feature Importance Score Map

The random forest algorithm is used to evaluate the importance of the features, and the importance score of each feature is obtained, which is expressed by the Mean Decrease Accuracy importance score or Mean Decrease Gini importance score . The impact of all features on the accuracy of the model is directly measured, and the importance of NDRE index is the highest.

6. Feature Evaluation Method

Stepwise discriminant analysis feature evaluation method

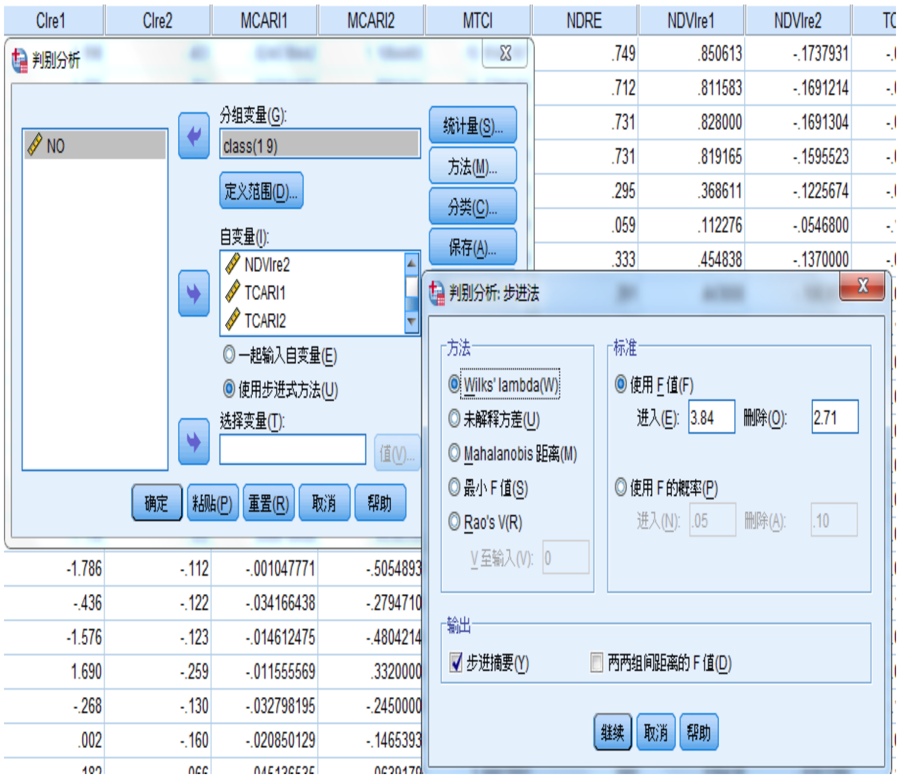


Table Stepwise discriminant analysis red edge index evaluation

Red edge index	F value	Wills' Lambda
CIre1	237.268	0.136
CIre2	46.414	0.445
MCARI1	64.475	0.366
MCARI2	54.886	0.404
MTCI	227.010	0.141
NDRE	387.008	0.088
NDVIre1	337.605	0.099
NDVIre2	52.812	0.414
TCARI1	115.514	0.244
TCARI2	9.566	0.796

Stepwise discriminant analysis of different red edge indices Evaluation results of feature importance

Stepwise discriminant analysis is a filtering feature selection method, in which the F value of NDRE index is the largest. Stepwise discriminant analysis method can be used for cross validation with the evaluation results of random forest feature importance.

6. Feature Evaluation Method

Random Forest Feature Evaluation Method

meanshiftseg.m | ReliefF.m | ReliefFall.m

```
clear all;
%将数据归一化
[A,text]=xlsread('0216.xlsx');
B = normalization(A);
B1=B;
%求解欧式距离与Relief权重
Rows=size(B,1);
Cols=size(B,2);
L(2:Rows+1,1)=B(:,1);
L1=L;
E=zeros(2,size(A,2));
for i=2:Cols
    a=find(isnan(B(:,i))==1);
    B(a,:)=[];
    L(a,:)=[];
    C = oushidistance1(B(:,i));%求解欧式距离
    C(:,1)=L';
    C(1,:)=L;
    D(i-1) = ReliefF( C );%求解Relief权重
    E(2,i)=D(i-1);
    B=B1;
    L=L1;
    C=[];
end
i=2;
for j=2:Cols
    if(D(j-1)>0.25)%将Relief权重小于0.5的去除
        G(2:Rows+1,i)=B(:,j);
        txt(i)=text(1,j);
        i=i+1;
    end
end
G(2:Rows+1,1)=A(:,1);
H=xlswrite('0216ReliefF',G);
H=xlswrite('0216ReliefF',txt);
```

meanshiftseg.m | ReliefF.m | ReliefFall.m | JMselection.m

```
clear all;
[A,text]=xlsread('ReliefF.xls');
Rows=size(A,1);
Cols=size(A,2);
a=unique(A(:,1));
B=zeros(Cols-1,size(a,1));
C=zeros(Cols-1,size(a,1));
D=zeros(Rows,2);
D(:,1)=A(:,1);
for l=1:size(a,1)
    E(l)=l;
end
j=1;
for i=2:Cols
    D(:,2)=A(:,i);
    B(j,:)=JMmean(D);%求解均值
    C(j,:)=JMvar(D);%求解方差
    J(:,:,j) = JMdistance( B(j,:),C(j,:) );%求解J-M距离
    J(2:size(a,1)+1,1,j)=E';
    J(1,2:size(a,1)+1,j)=E;
    j=j+1;
end
for k=2:size(a,1)
    for m=k+1:size(a,1)+1
        [F(k,m),s(k,m)]=max(J(k,m,:));
        [F(m,k),s(m,k)]=max(J(k,m,:));
        J(k,m,s(k,m))=min(J(k,m,:));
        [G(k,m),l(k,m)]=max(J(k,m,:));
        [G(m,k),l(m,k)]=max(J(k,m,:));
    end
end
F(1,2:size(a,1)+1)=E;
F(2:size(a,1)+1,1)=E';
s(1,2:size(a,1)+1)=E;
s(2:size(a,1)+1,1)=E';
G(1,2:size(a,1)+1)=E;
G(2:size(a,1)+1,1)=E';
l(1,2:size(a,1)+1)=E;
l(2:size(a,1)+1,1)=E';
xlswrite('JMfirstMax.xls',F);
xlswrite('JMfirstMaxlocation.xls',s);
xlswrite('JMsecondMax.xls',G);
```

ReliefF Algorithm and JM Distance Algorithm

ReliefF algorithm is used to remove features not related to classification, and then JM distance method is used to remove redundant features, so as to select crop classification features, reduce feature dimensions, and improve the accuracy and efficiency of classifier classification.

6. Feature Evaluation Method

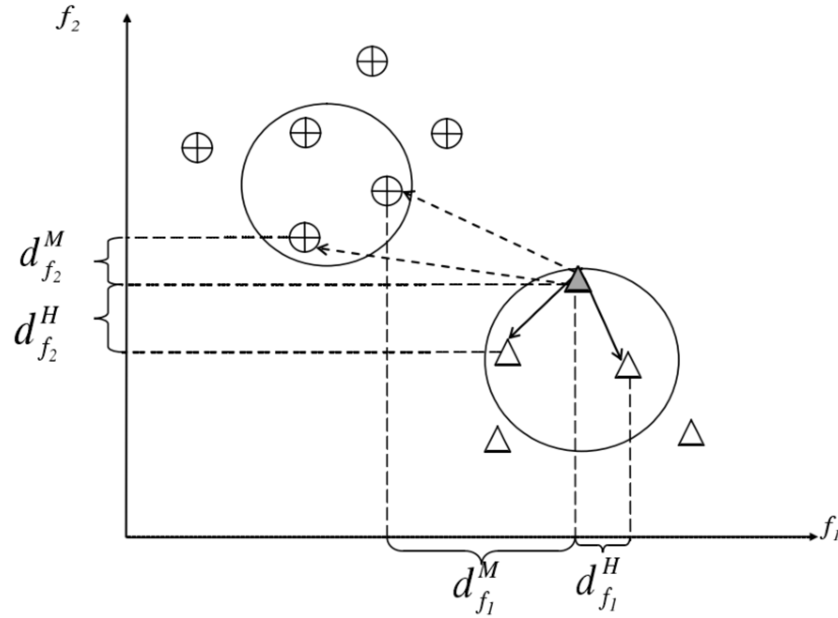
ReliefF Feature selection

Relief（two-class）：

Each one-dimensional feature in the feature set is given a weight value, and the weight updating formula is used for training, so that the feature with strong clustering correlation can obtain a larger weight value, and the feature with large weight value is used to form the optimal feature subset to express the category information. The eigenweight formula is:

$$W_f^i = W_f^{i-1} + \mathrm{diff}_f(x, M(x))/m - \mathrm{diff}_f(x, H)/m$$

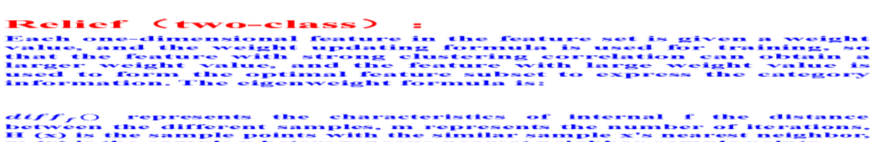
$diff_f()$ represents the characteristics of internal f the distance between the different samples, m represents the number of iterations, H (x) is the sample points with the similar sample x's nearest neighbor, m (x) is the sample x heterogeneous nearest neighbor sample points.



Relief method diagram

ReliefF（multi-class）：

ReliefF algorithm was improved on the basis of Relief. Classification was regarded as class-to-multi-class, and the "K-nearest neighbor" algorithm was adopted to solve the multi-category classification problem with noise. Its characteristic weight formula was as follows:



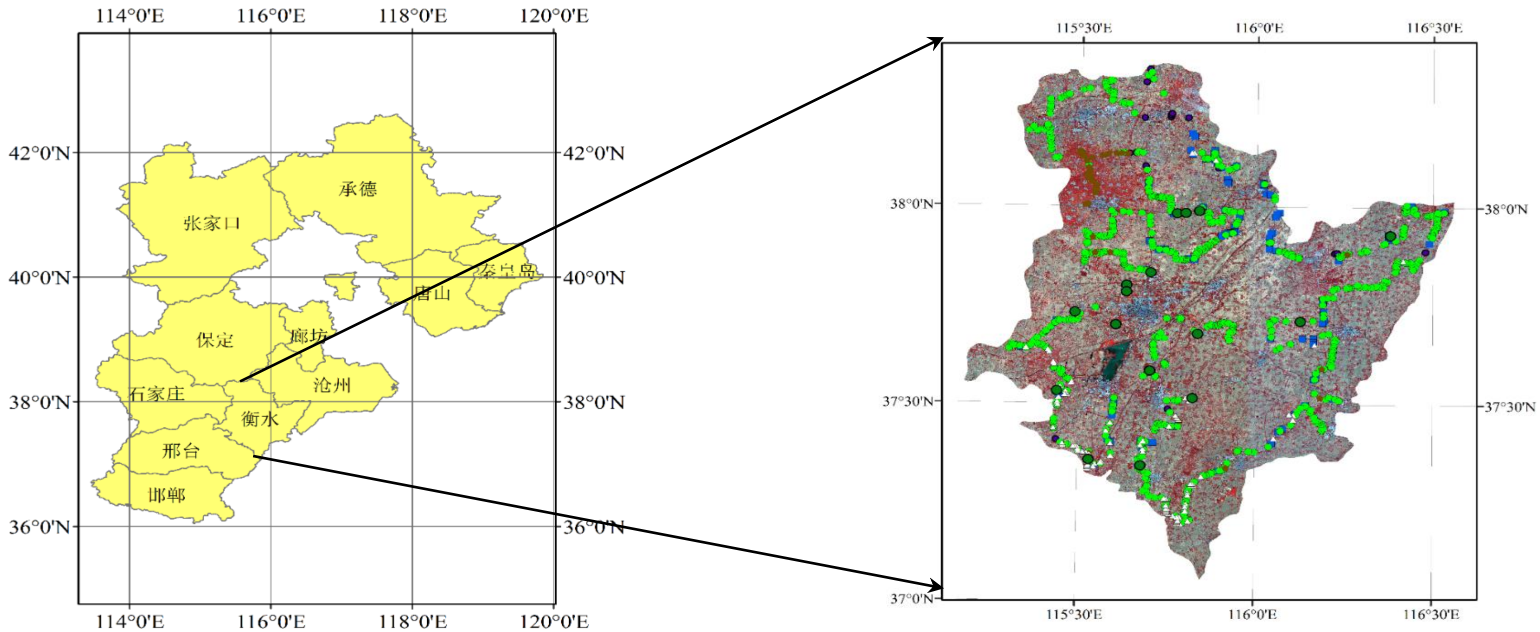
ReliefF algorithm first randomly selects a sample as the algorithm test sample, then finds k nearest neighbor samples from similar samples and different samples, and then calculates the update weight. The above process is repeated m times, and finally gets the weight of each feature.

Outline

6 Crop Change Automatic Detection Technology

- Research Background and Significance
- Research Objectives and Content
- Data Preprocessing
- Data Source Comparison
- Red Edge Feature Mining
- Feature Evaluation Method
- Research Area and Samples
- Research Area Classification Results

7. Research Area and Samples



The study selected Hengshui, Hebei Province in the Beijing-Tianjin-Hebei region as the Research area. This area is a typical area of winter wheat-summer corn rotation in North China. The main crops are winter wheat, spring corn, cotton, summer corn, fruit trees, peanuts, peppers, yam, soybeans, etc. In recent years, because of the effect of state's crop rotation fallow policy (groundwater funnel area fallow in Heilonggang Basin), there has been a certain change in the planting structure of crops (generally the winter wheat planting area has been reduced). Which is used for crops remote sensing classification and change detection area.

7. Research Area and Samples

Classification System

Combined with field sampling, determine a classification system based on 9 types: towns, water bodies, winter wheat-summer corn, cotton, spring corn, greenhouses, nurseries, fruit trees, and trees, and by calculating the separability of the samples (JM distance)， merge nursery, fruit tree and tree into "fruit tree-forest tree" to improve the classification effect.

Pair Separation (least to most);

guoshu-xunlian and shumu-xunlian - 1.37363921
guoshu-xunlian and miaopu-xunlian - 1.50398531
miaopu-xunlian and shumu-xunlian - 1.68030417
chunyumi-xunlian and miaopu-xunlian - 1.73161534
chunyumi-xunlian and mianhua-xunlian - 1.76235617
chunyumi-xunlian and dongxiaomai-xiayumi-xunlian - 1.780507
mianhua-xunlian and miaopu-xunlian - 1.79167729
guoshu-xunlian and mianhua-xunlian - 1.88036863
dapeng-xunlian and mianhua-xunlian - 1.90248949
chunyumi-xunlian and dapeng-xunlian - 1.94545988
dongxiaomai-xiayumi-xunlian and miaopu-xunlian - 1.94887980
dapeng-xunlian and miaopu-xunlian - 1.95236240
dongxiaomai-xiayumi-xunlian and shumu-xunlian - 1.96069913
mianhua-xunlian and shumu-xunlian - 1.96630442
chengzhen-xunlian and dapeng-xunlian - 1.97081040
chunyumi-xunlian and guoshu-xunlian - 1.97430458
dapeng-xunlian and shumu-xunlian - 1.97494932
dapeng-xunlian and guoshu-xunlian - 1.97656279

Before the merger

mianhua-xunlian and guoshu-linmu-xunlian - 1.72588927
chunyumi-xunlian and mianhua-xunlian - 1.76235617
chunyumi-xunlian and dongxiaomai-xiayumi-xunlian - 1.78050700
chunyumi-xunlian and guoshu-linmu-xunlian - 1.82594101
dapeng-xunlian and mianhua-xunlian - 1.90248949
dapeng-xunlian and guoshu-linmu-xunlian - 1.92389027
chunyumi-xunlian and dapeng-xunlian - 1.94545988
dongxiaomai-xiayumi-xunlian and guoshu-linmu-xunlian - 1.94805336
chengzhen-xunlian and dapeng-xunlian - 1.97081040
dongxiaomai-xiayumi-xunlian and mianhua-xunlian - 1.98813239
dapeng-xunlian and dongxiaomai-xiayumi-xunlian - 1.98840698
chengzhen-xunlian and guoshu-linmu-xunlian - 1.99154546
chengzhen-xunlian and dongxiaomai-xiayumi-xunlian - 1.99390011
chengzhen-xunlian and chunyumi-xunlian - 1.99467761
chengzhen-xunlian and mianhua-xunlian - 1.99581543
dapeng-xunlian and shuiti-xunlian - 1.99893192
chengzhen-xunlian and shuiti-xunlian - 1.99905156

After the merger

Separability of training samples-JM distance

7. Research Area and Samples

JM distance

J-M distance is a separability index based on conditional probability theory. It is a good algorithm to measure the separation in classification evaluation and can be used to evaluate the quality of training sample selection in supervised classification. On the basis of training samples, J-M distance obtains the separation degree of features between [0, k]. The calculation formula is as follows:

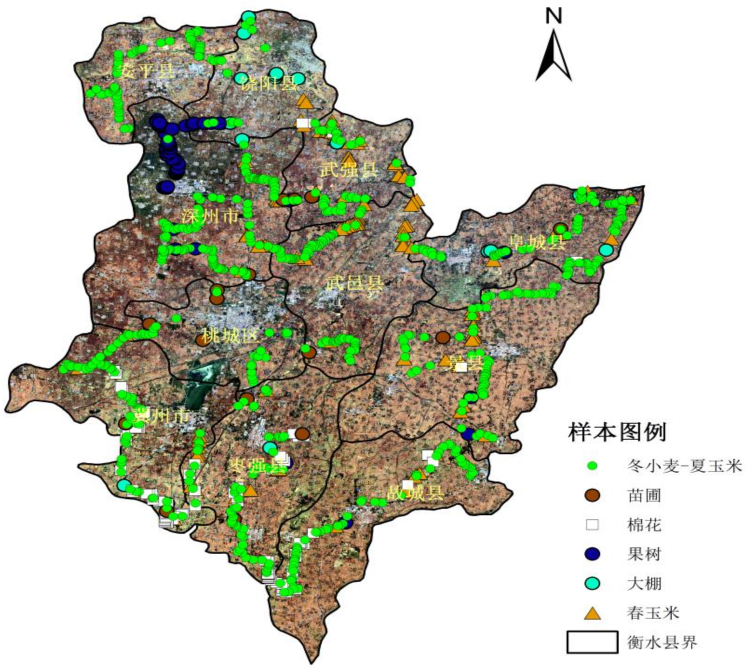
$$JM_{ij} = \mathrm{k}\sqrt{1 - e^{-\alpha}}$$

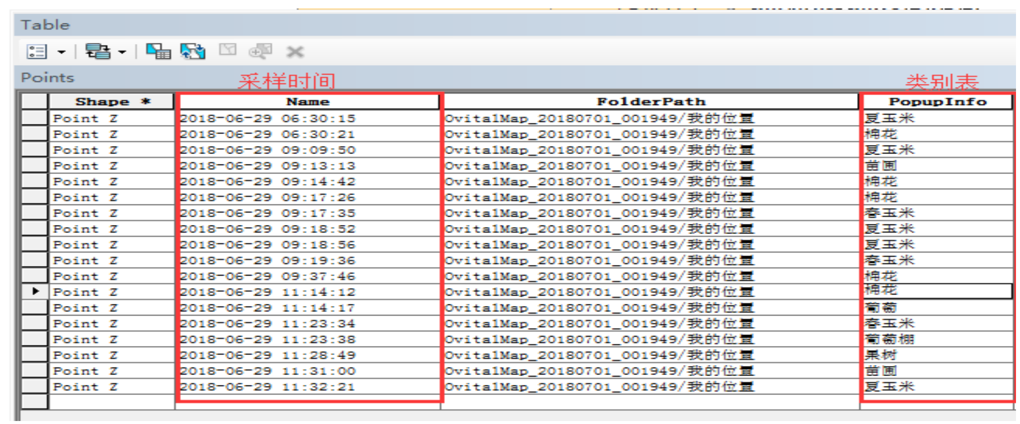
$$\alpha = \frac{1}{8}(\mu_i - \mu_j)^T \left(\frac{C_i + C_j}{2}\right)^{-1}(\mu_i - \mu_j) + \frac{1}{2}\ln\frac{\left|(C_i + C_j)/2\right|}{\sqrt{|C_i| \times |C_j|}}$$

Among them, the ***C*** i and ***C j*** class i and class j respectively sample covariance matrix, μ_i and μ_j is its corresponding sample mean vector and a is the distance between different classes. In theory, it is necessary to make a comprehensive analysis of the current situation if JM_{ij} =k (generally k = 2), the separation degree of the feature classification is the best. As JM_{ij} value is reduced, the characteristic is used for fault classification object increased.

It is generally believed that when the J-M distance is greater than 1.8 (1.9), there is good separability between samples.

7. Research Area and Samples





Table

Points

采样时间 类别表

Shape *	Name	FolderPath	PopupInfo
Point Z	2018-06-29 06:30:15	OvitalMap_20180701_001949/我的位置	夏玉米
Point Z	2018-06-29 06:30:21	OvitalMap_20180701_001949/我的位置	棉花
Point Z	2018-06-29 09:09:50	OvitalMap_20180701_001949/我的位置	夏玉米
Point Z	2018-06-29 09:13:13	OvitalMap_20180701_001949/我的位置	苗圃
Point Z	2018-06-29 09:14:42	OvitalMap_20180701_001949/我的位置	棉花
Point Z	2018-06-29 09:17:26	OvitalMap_20180701_001949/我的位置	棉花
Point Z	2018-06-29 09:17:35	OvitalMap_20180701_001949/我的位置	春玉米
Point Z	2018-06-29 09:18:52	OvitalMap_20180701_001949/我的位置	夏玉米
Point Z	2018-06-29 09:18:56	OvitalMap_20180701_001949/我的位置	夏玉米
Point Z	2018-06-29 09:19:36	OvitalMap_20180701_001949/我的位置	春玉米
Point Z	2018-06-29 09:37:46	OvitalMap_20180701_001949/我的位置	棉花
Point Z	2018-06-29 11:14:12	OvitalMap_20180701_001949/我的位置	棉花
Point Z	2018-06-29 11:14:17	OvitalMap_20180701_001949/我的位置	葡萄
Point Z	2018-06-29 11:23:34	OvitalMap_20180701_001949/我的位置	春玉米
Point Z	2018-06-29 11:23:38	OvitalMap_20180701_001949/我的位置	葡萄棚
Point Z	2018-06-29 11:28:49	OvitalMap_20180701_001949/我的位置	果树
Point Z	2018-06-29 11:31:00	OvitalMap_20180701_001949/我的位置	苗圃
Point Z	2018-06-29 11:32:21	OvitalMap_20180701_001949/我的位置	夏玉米

Sample point attribute category table

Hengshui Research Area
Sampling point distribution map
(Late June, early July 2018)

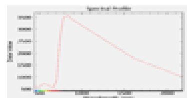
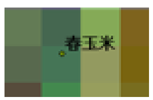
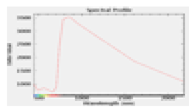
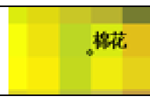
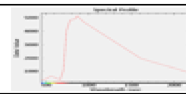
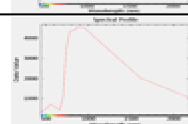
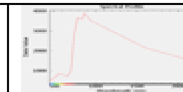
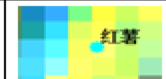
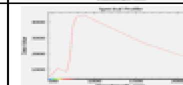
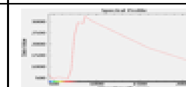
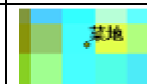
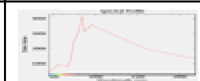
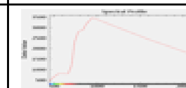
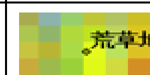
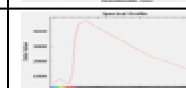
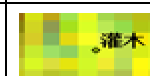
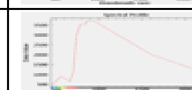




Fruit tree cotton Summer corn Peanut Spring corn

7. Research Area and Samples

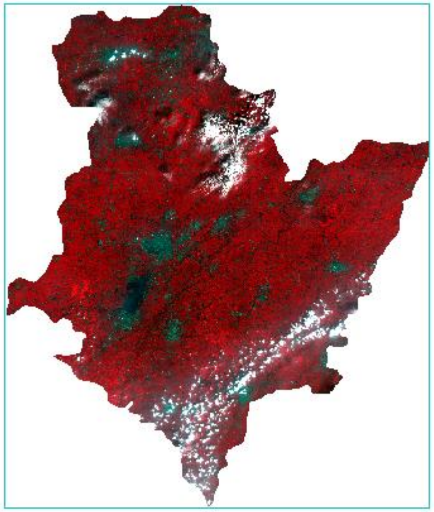
Sample Points and Reference Data Sets

1	冬小麦		
2	夏玉米		
3	春玉米		
4	棉花		
5	花生		
6	大豆		
7	辣椒		
8	山药		
9	桃树		
10	梨树		
11	谷子		
12	红薯		
13	苹果		
14	菜地		
15	苗圃		
16	树林		
17	荒草地		
18	灌木		
19	葡萄		
20	向日葵		

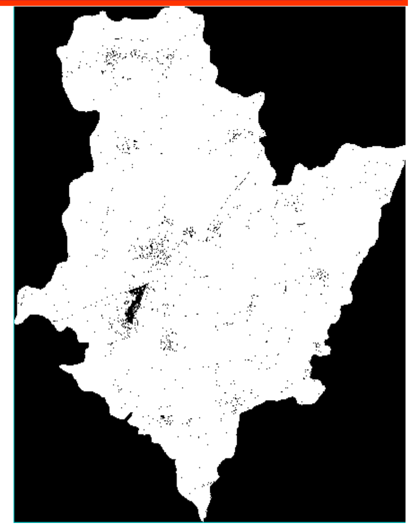
The above are sample points of crops and other vegetation collected in the field in the study area, and the spectral curves of 20 typical vegetation inspection reference data sets (in orbit) (August 2019).

7. Research Area and Samples

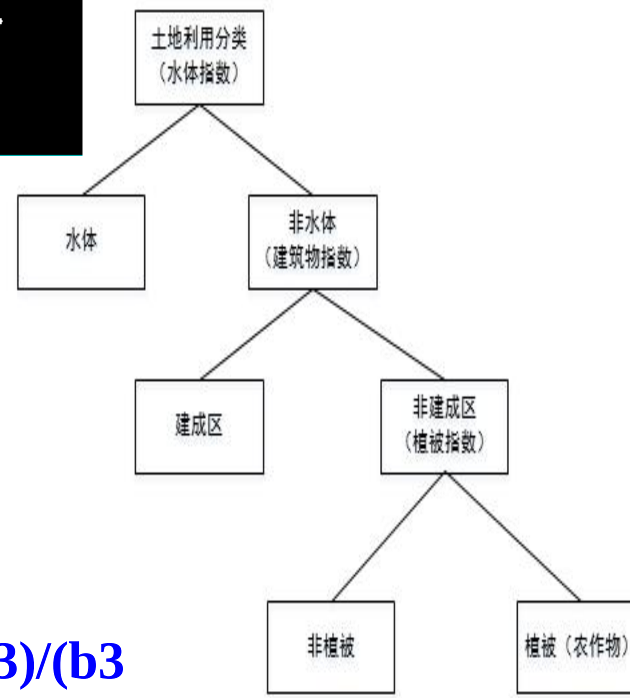
Extraction of Agricultural Land in the Research Area



Agricultural land extraction



Decision Tree Threshold Method for Extracting Agricultural Land Range

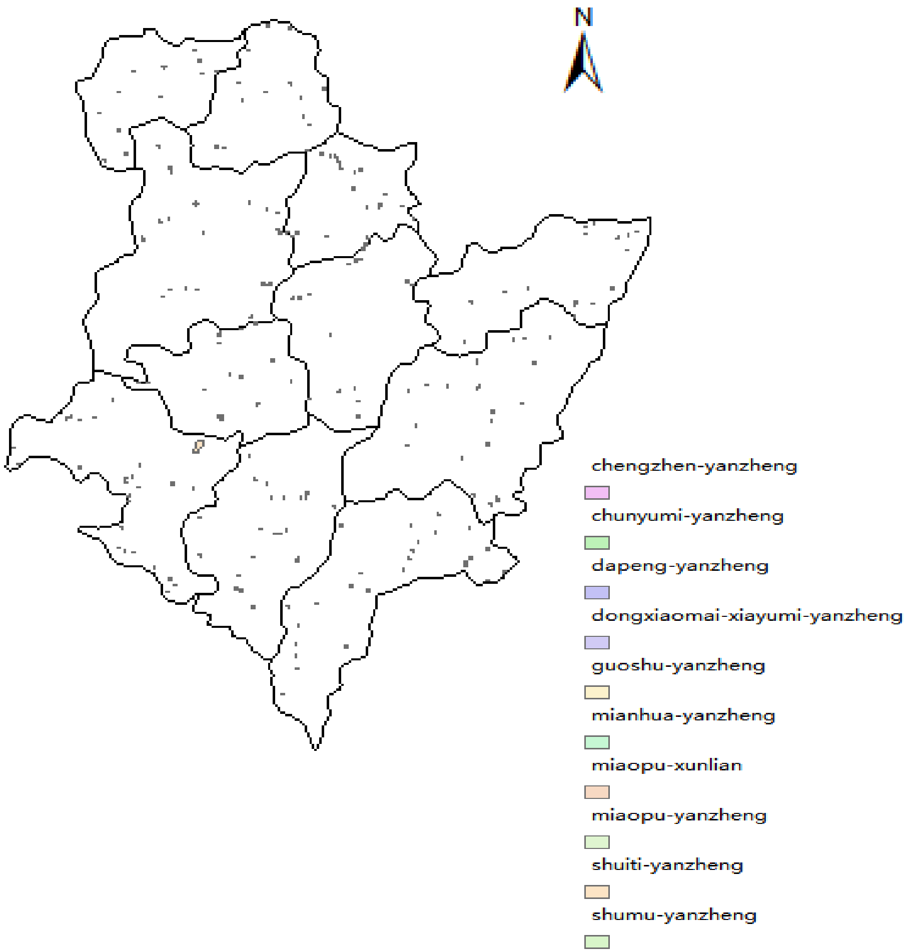


**Relevant indexes for decision tree classification extraction:NDVI=-1>(float(b8)-b4)/(b8+b4)<1；
NDWI=-1>(float(b3)-b8)/(b3+b8)<1；
MNDWI=-1>(float(b3)-b11)/(b3+b11)<1；
NDBI=-1>(float(b11)-b8)/(b11+b8)<1；
IBI=-1>(2*float(b11)/(b11+b8)-(float(b8)/(b8+b4)+float(b3)/(b3+b11)))/(2*float(b11)/(b11+b8)+(float(b8)/(b8+b4)+float(b3)/(b3+b11)))<1；**

7. Research Area and Samples

Point-Plane Samples

Training samples (plane samples)



Verification samples (plane samples)

7. Research Area and Samples

Mouth	Period of Ten Days	Winter Wheat	Summer Maize	Spring Maize	Cotton	Soybean
March	Early	Seedling				
	Mid					
	Late					
April	Early					
	Mid	Jointing			Sowing	
	Late				Seeding	Sowing
May	Early				Leaf	Seeding
	Mid	Heading		Sowing		
	Late					
June	Early	Mature				Leaf
	Mid		Sowing			
	Late			Jointing	Squaring	Boughs
July	Early					Early flowering
	Mid		Jointing			
	Late			Tasseling		Anthesis
August	Early				Anthesis	
	Mid		Tasseling			Podding
	Late					
September	Early			Mature	Cracked bell	Seed filling
	Mid		Mature			
	Late					
October	Early	Sowing				
	Mid					
	Late					

Crop Phenology (Agricultural calendar) of Hengshui Research Area

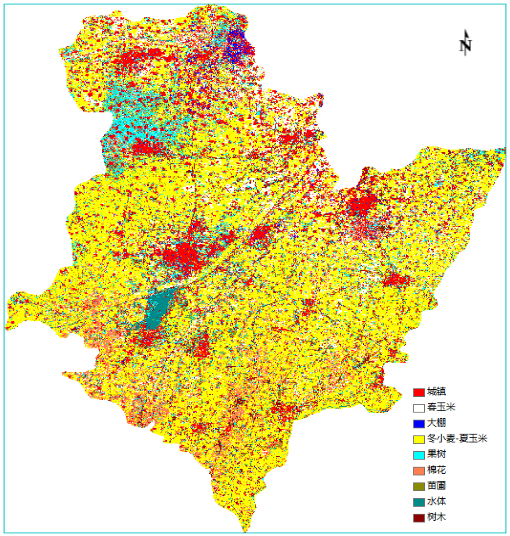
Outline

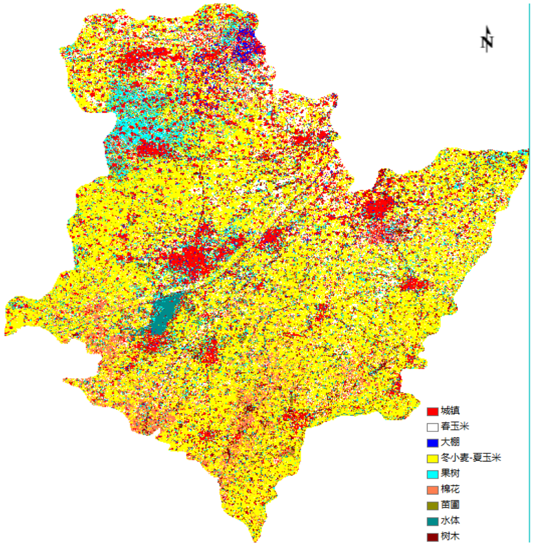
6 Crop Change Automatic Detection Technology

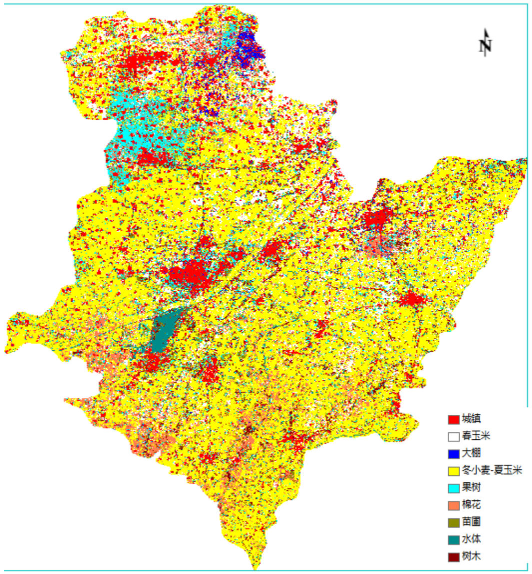
- Research Background and Significance
- Research Objectives and Content
- Data Preprocessing
- Data Source Comparison
- Red Edge Feature Mining
- Feature Evaluation Method
- Research Area and Samples
- Research Area Classification Results

8. Research Area Classification Results

Single Phase Classification Results (Sentinel-2)







4 Bands

Overall Accuracy = 85.7210%
Kappa = 0.8170

4 Bands +Red edge

Overall Accuracy = 87.5000%
Kappa = 0.8395

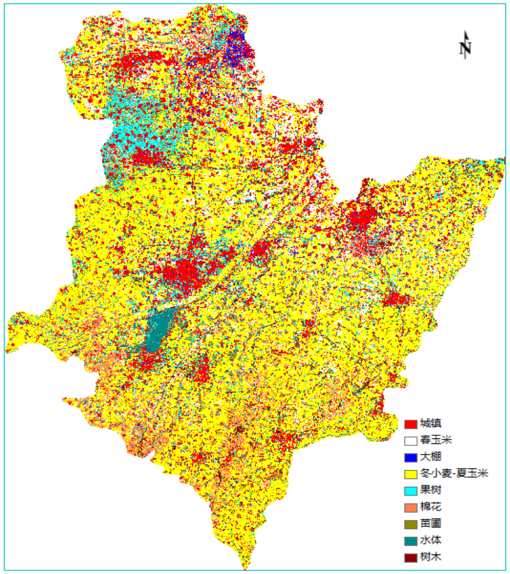
4 Bands +Red edge + Short-wave infrared4

Overall Accuracy = 89.8287%
Kappa = 0.8695

Random forest algorithm classification-9 categories (RF)

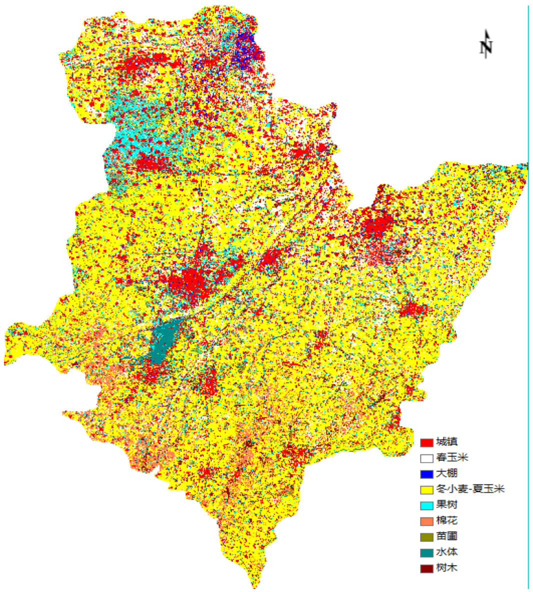
8. Research Area Classification Results

Single Phase Classification Results (Sentinel-2)



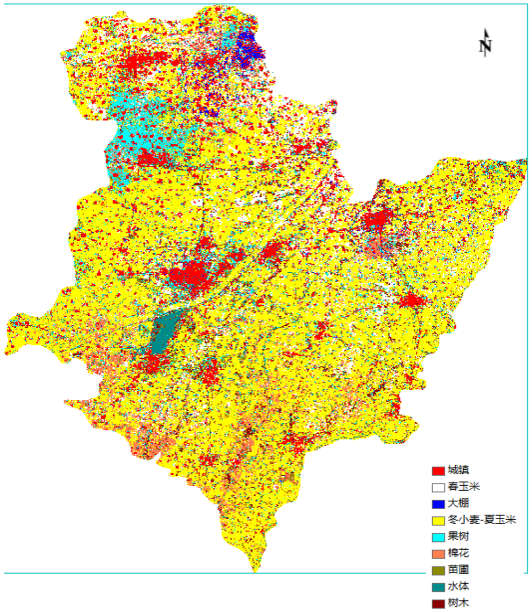
4 Bands

Overall Accuracy = 81.5983%
Kappa = 0.7698



4 Bands +Red edge

Overall Accuracy = 82.2226%
Kappa = 0.7777



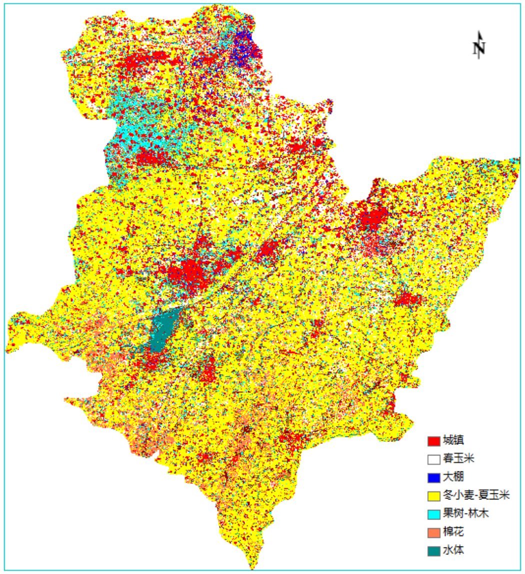
4 Bands +Red edges + Short-wave infrared

Overall Accuracy = 88.9850%
Kappa = 0.8605

Support Vector Machine Classification-9 categories (SVM)

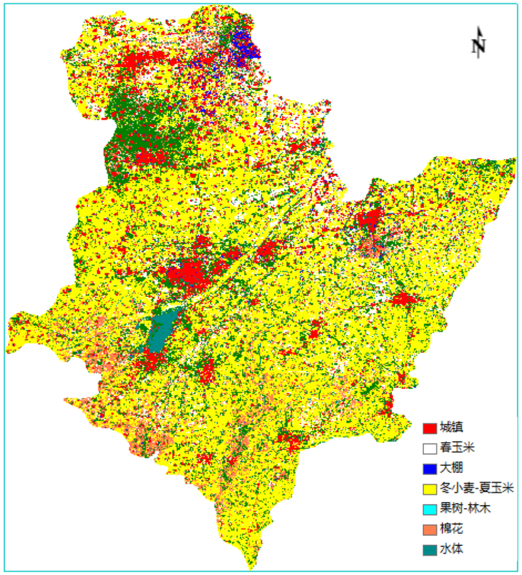
8. Research Area Classification Results

Single Phase Classification Results (Sentinel-2)



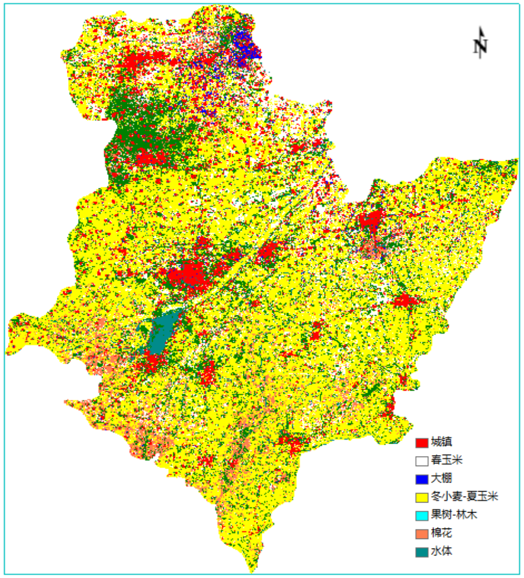
All bands(MLC)

Overall Accuracy = 91.36%
Kappa = 0.8898



All bands(RF)

Overall Accuracy = 92.27%
Kappa = 0.9004



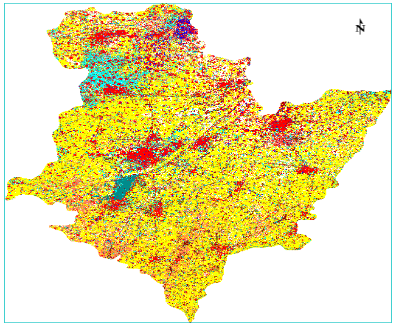
All bands(SVM)

Overall Accuracy = 93.0032%
Kappa = 0.9103

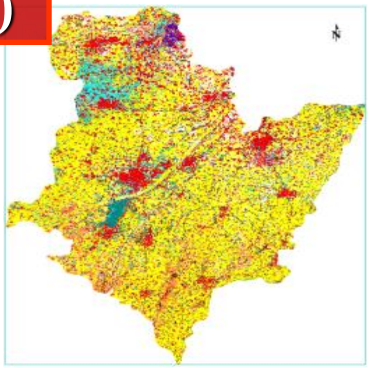
Classification results of different machine learning algorithms (7 categories, combined after classification)

8. Research Area Classification Results

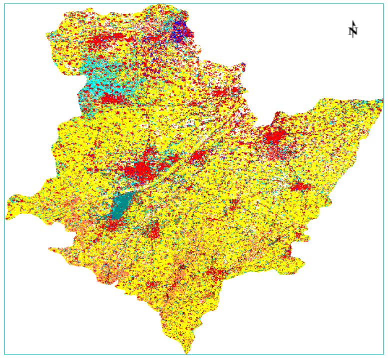
Single Phase Classification Results (GF-6 WFV)



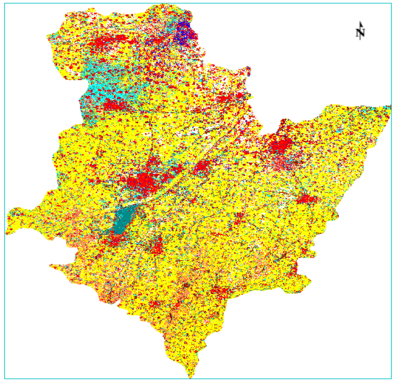
4 bands
(OA=73.99% Kappa=0.6817)



4 bands +red edge710
(OA=78.92% Kappa=0.7426)



4 bands +red edge750
(OA=76.89% Kappa=0.7176)

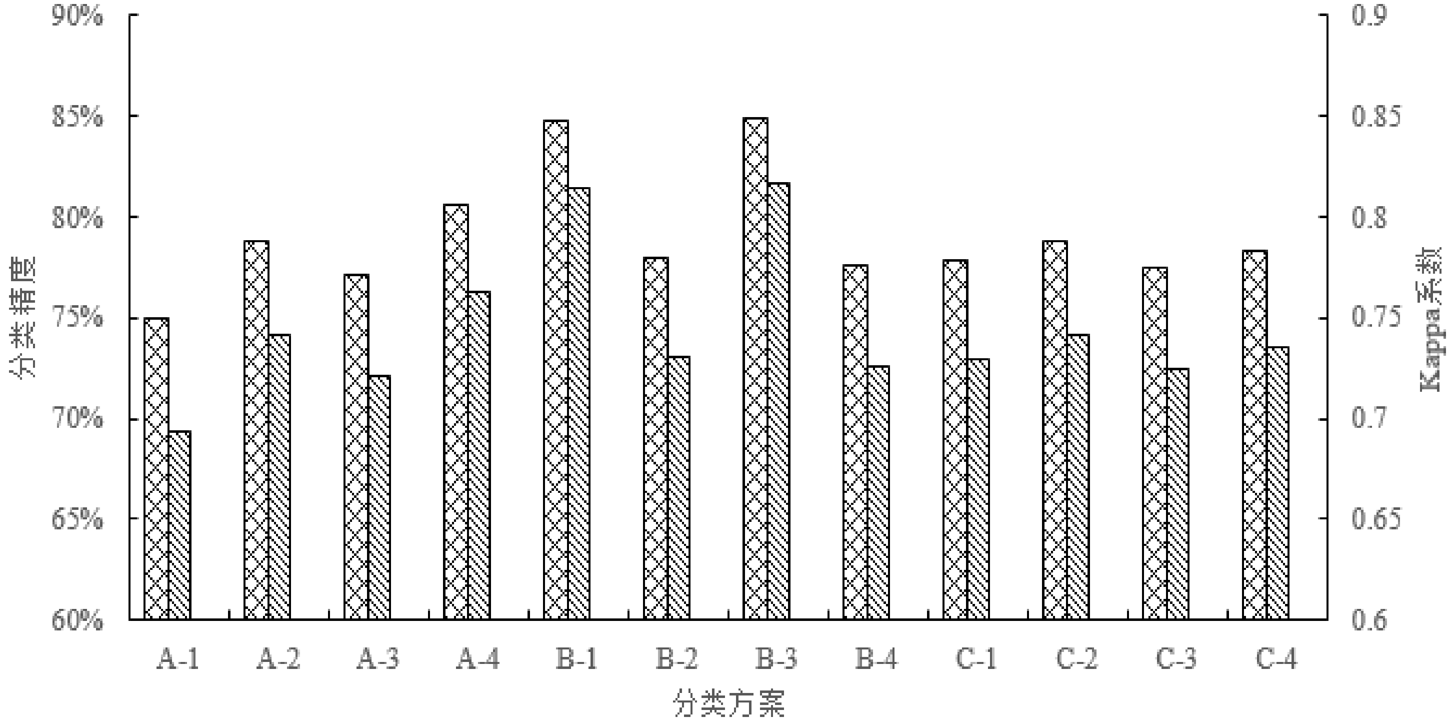


4 bands +NDVI
(OA=74.99% Kappa=0.6943)

Random Forest (RF) classification results of GF-6 WFV data in different classification schemes

8. Research Area Classification Results

Single Phase Classification Results (GF-6 WFV)



Total classification accuracy and Kappa coefficient of different classification schemes （RF classification）

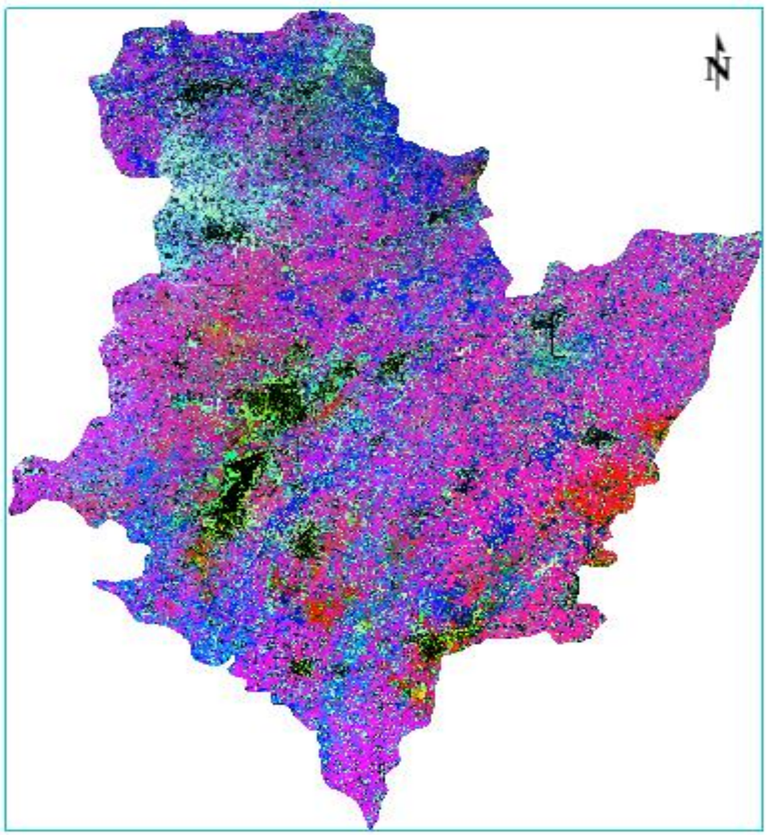
A-1： 4 bands
A-2： 4 bands+red-edge710
A-3： 4 bands +red edge-750
A-4： 4 bands+ red edge-750 +red edge-750

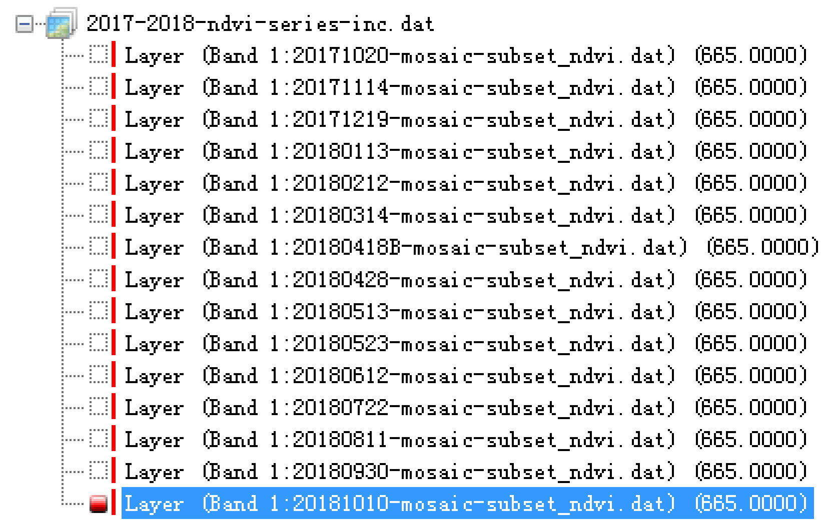
B-1： 4 bands +texture710
B-2： 4 bands +texture750
B-3： 4 bands +texture710+texture750
B-4： 4 bands +texture NIR

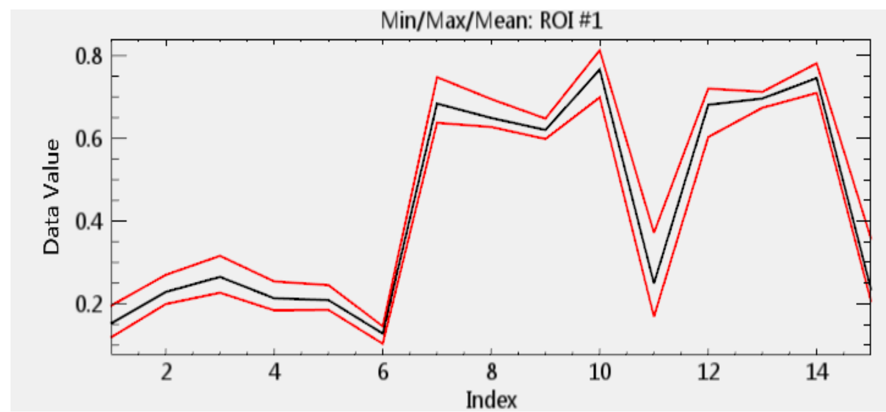
C-1： 4 bands +CIre1
C-2： 4 bands +MTCI
C-3： 4 bands +NDRE
C-4： 4 bands +NDVIre1

8. Research Area Classification Results

Multitemporal Classification



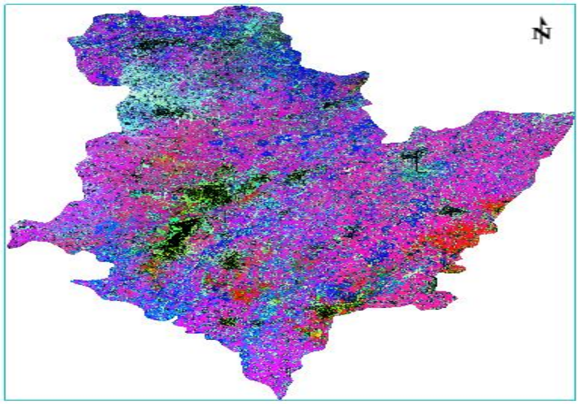




NDVI / EVI time series image data from March to October 2018

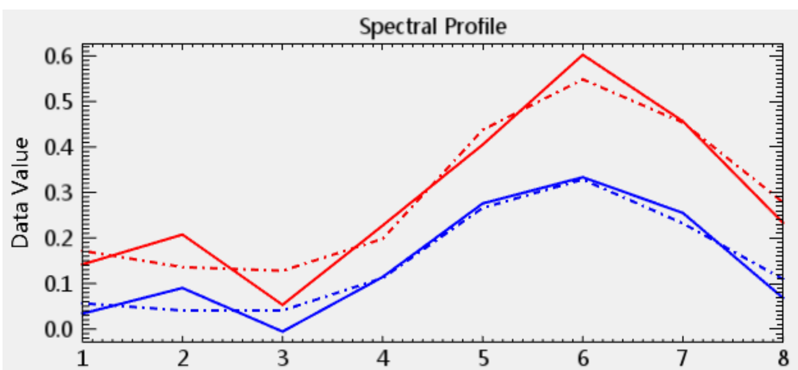
8. Research Area Classification Results

多时相分类



2019-NDVI-series0-SG1.dat
Layer (Band 1:190322-rad-ref-subset_NDVI_0.dat) (0.6600)
Layer (Band 1:190415-rad-ref-subset_NDVI_0.dat) (0.6600)
Layer (Band 1:190506-rad-ref-subset_NDVI_0.dat) (0.6600)
Layer (Band 1:190611-rad-ref-subset_NDVI_0.dat) (0.6600)
Layer (Band 1:190719-rad-ref-subset_NDVI_0.dat) (0.6600)
Layer (Band 1:190828-rad-ref-subset_NDVI_0.dat) (0.6600)
Layer (Band 1:190918-rad-ref-subset_NDVI_0.dat) (0.6600)
Layer (Band 1:191021-rad-ref-subset_NDVI_0.dat) (0.6600)

NDVI time series data



2019-NDRE-series0-SG2.dat
Layer (Band 1:190322-rad-ref-subset_NDRE_0.dat) (0.7100)
Layer (Band 1:190415-rad-ref-subset_NDRE_0.dat) (0.7100)
Layer (Band 1:190506-rad-ref-subset_NDRE_0.dat) (0.7100)
Layer (Band 1:190611-rad-ref-subset_NDRE_0.dat) (0.7100)
Layer (Band 1:190719-rad-ref-subset_NDRE_0.dat) (0.7100)
Layer (Band 1:190828-rad-ref-subset_NDRE_0.dat) (0.7100)
Layer (Band 1:190918-rad-ref-subset_NDRE_0.dat) (0.7100)
Layer (Band 1:191021-rad-ref-subset_NDRE_0.dat) (0.7100)

NDVI and NDRE time series data

NDRE red edge time series data

NDVI and NDRE time series image data from March to October 2019

8. Research Area Classification Results

Multitemporal Classification

1. **Traditional NDVI vegetation index**
2. **Optimal NDRE red edge vegetation index**
3. **“NDVI+ optimal NDRE” Band synthesis of vegetation index**

In the actual classification, the scheme of "NDVI + optimized red edge index" will be used for the classification and change detection of crops and other vegetation to ensure the accuracy of vegetation classification.

The random forest classifier was used to classify the data of different vegetation index time series combinations, and the classification confusion matrix (OA overall accuracy,Kappa coefficient), as well as the cartographic accuracy (PA), user accuracy (UA) and F1-score accuracy (the geometric average of PA and UA) of different crop classifications were obtained.

Y^{*}_{j+i}

8. Research Area Classification Results

Multitemporal Classification

S–G filtering method (Savitzky-Golay). It was proposed by Savitzky and Golay in 1964, by a least squares convolution algorithm for a given high-order polynomial within a sliding window.

$$Y_j^* = \frac{\sum_{i=-m}^{i=m} C_i \times Y_{j+i}}{N}$$

In the above equation, YJ+I and YJ are the data before and after reconstruction respectively; Ci is the coefficient fitted by s-g polynomial and represents the weight of the i th NDVI value processed by the filter.M is the range of I;N is the data point of the sliding window, the value of which is 2m+1. Two parameters need to be set.

S-G filtering can remove noise and smooth the time series such as NDVI, delete or recalculate null point and abnormal point, and can reflect the detailed changes of different crops and other vegetation, so as to obtain more effective (in line with phenological law) time series data research will be carried out using S-G smoothing algorithm.

8. Research Area Classification Results

Multitemporal Classification

1） S-G filter smoothing

S–G filtering method (Savitzky-Golay). It was proposed by Savitzky and Golay in 1964, by a least squares convolution algorithm for a given high-order polynomial within a sliding window.

2） HANTS algorithm

Harmonic Analysis of Time Series (HANTS) is an effective time series reconstruction algorithm based on Fourier transform and least squares improvement. Its formula is:

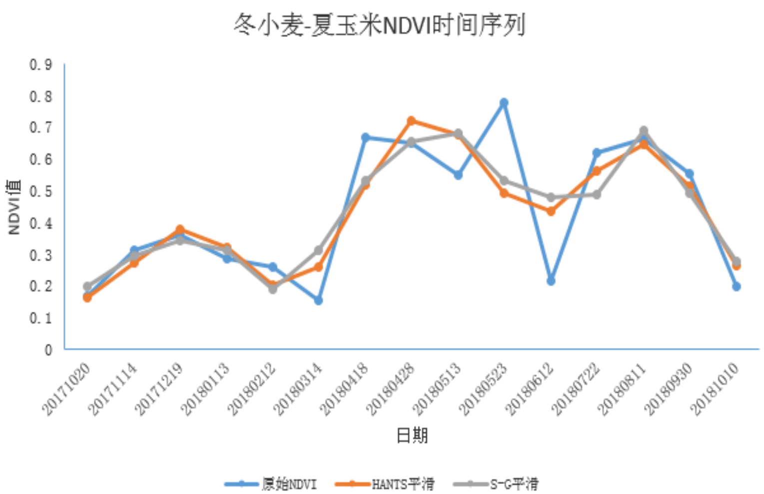
$$y_i = A_0 + \sum_{j=1}^{m} A_j \sin(X_i + X_j) \quad i{=}0,1,2\ldots\ldots, \quad N$$

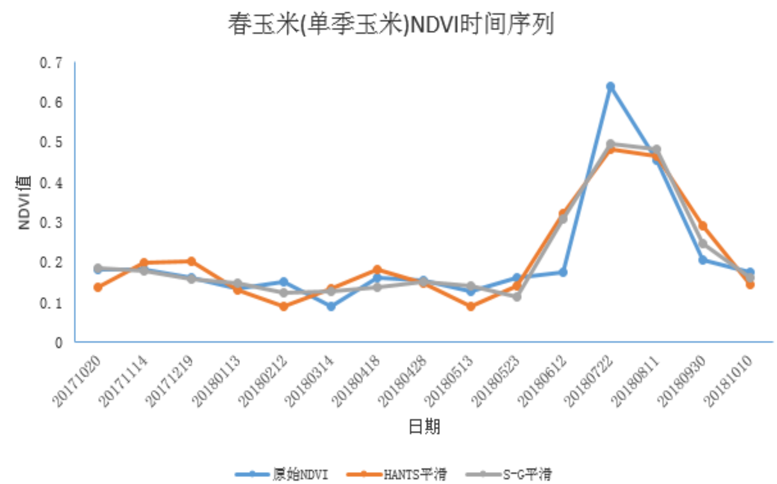
A_0 为各谐波的振幅，$X_j = 2j/N$ 为各谐波的频率，N 为序列的长度，Hj 为各谐波的初相位，m 为谐波的个数，等于 N-1。

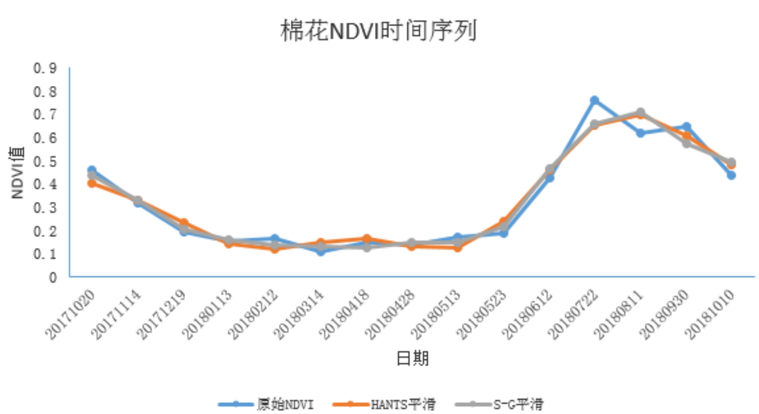
The HANTS algorithm and the S-G algorithm can perform noise removal and smoothing on time series such as NDVI, delete or recalculate null points and abnormal points, thereby obtaining more effective (in line with phenology) time series data.

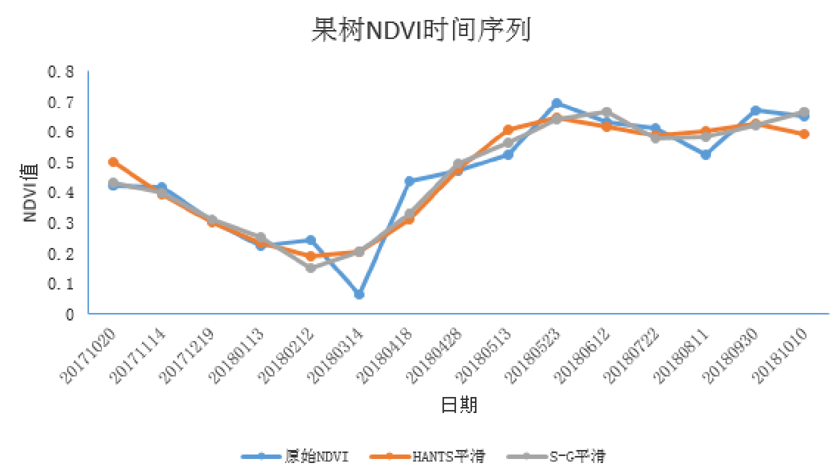
8. Research Area Classification Results

Multitemporal Classification





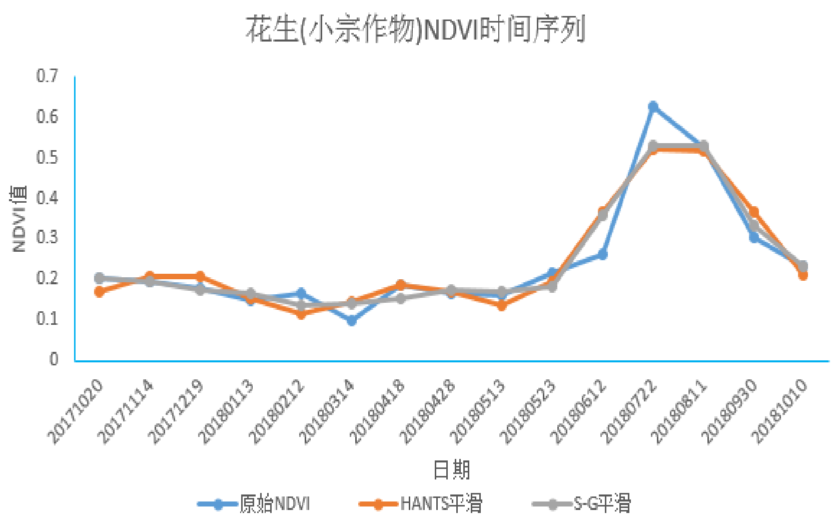


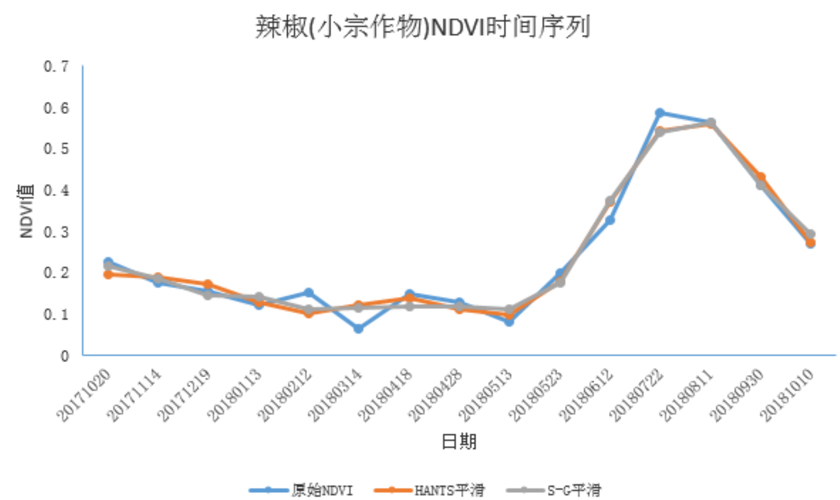


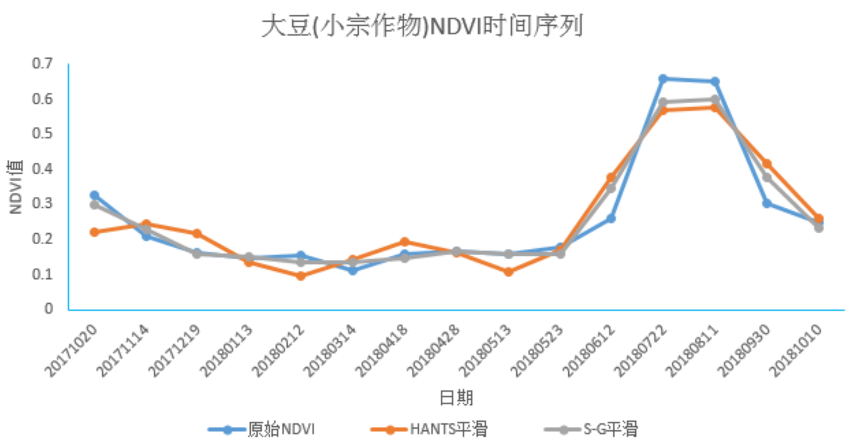
NDVI time series curve of main crops

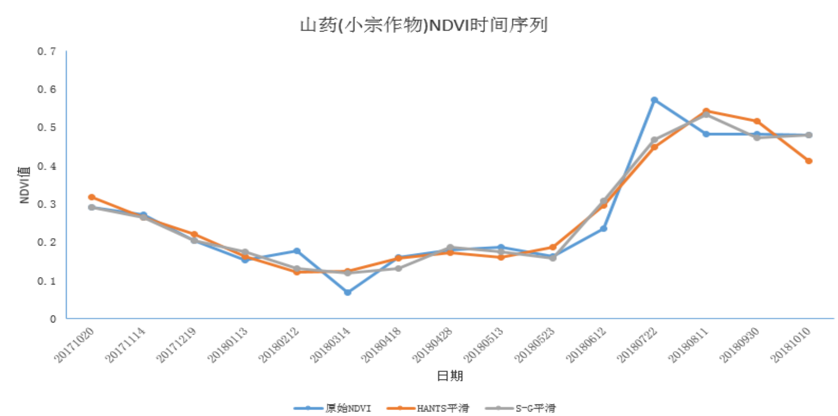
8. Research Area Classification Results

Multitemporal Classification





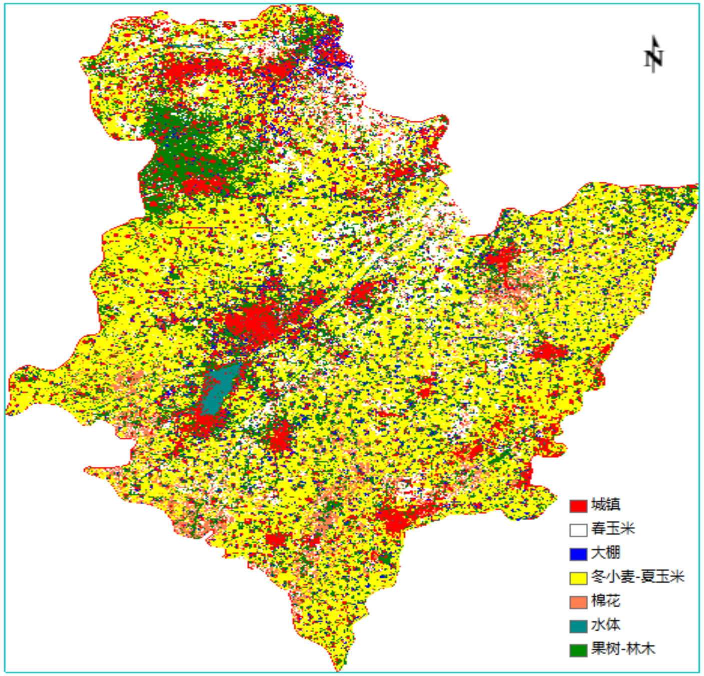


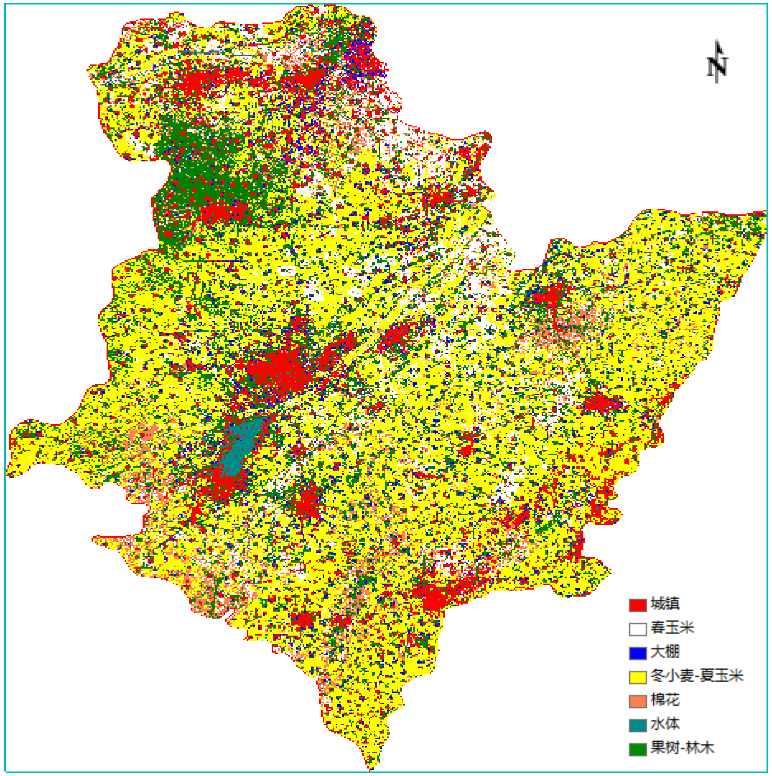


NDVI time series curve of minor crops

8. Research Area Classification Results

Multitemporal Classification





HANTS smooth RF classification results

Overall Accuracy = 94.6203%
Kappa = 0.9308

S-G smooth RF classification results

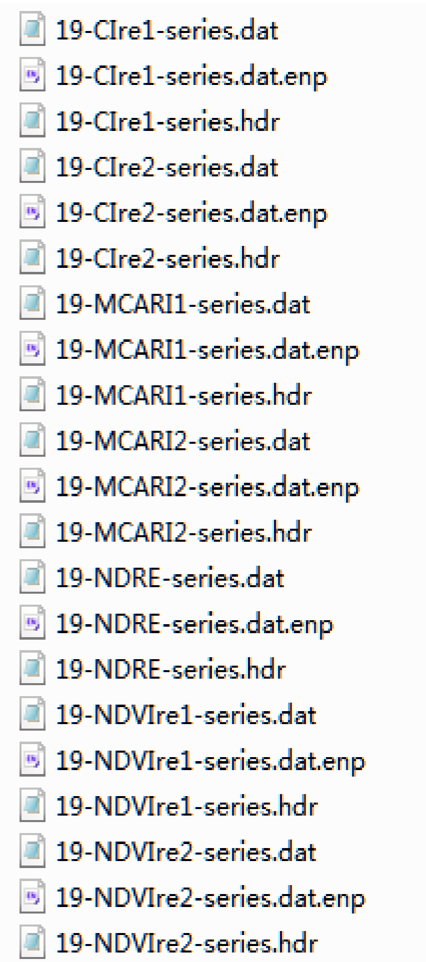
Overall Accuracy = 93.6104%
Kappa = 0.9177

8. Research Area Classification Results

Red Edge Time Series（GF-6 WFV）

Figure Different red edge indices characteristics（GF-6 WFV）

Red Edge Index	Index of the Full Name	Computational Formula（GF-6 WFV）
NDRE	Normalized Difference Red-Edge	(float(b6)-b5)/(b6+b5)
NDVIre1	Normalized Difference Vegetation Index red-edge 1	(float(b4)-b5)/(b4+b5)
NDVIre2	Normalized Difference Vegetation Index red-edge 2	(float(b4)-b6)/(b4+b6)
CIre1	Chlorophyll Index red-edge 1	(float(b4))/(b5)-1
CIre2	Chlorophyll Index red-edge 2	(float(b4))/(b6)-1
MCARI1	Modified Chlorophyll Absorption Ratio Index 1	((float(b5)-b3)-0.2*(b5-b2))*(b5/b3)
MCARI2	Modified Chlorophyll Absorption Ratio Index 2	((float(b6)-b3)-0.2*(b6-b2))*(b6/b3)
TCARI1	Transformed Chlorophyll Absorption Reflectance Index 1	3*((float(b5)-b3)-0.2*(b5-b2)*(b5/b3))
TCARI2	Transformed Chlorophyll Absorption Reflectance Index 2	3*((float(b6)-b3)-0.2*(b6-b2)*(b6/b3))
MTCI	MERIS Terrestrial Chlorophyll Index	(float(b6)-b5)/(b5-b3)



8. Research Area Classification Results

Red Edge Time Series

(1) NDRE1： Normalized Difference Red Edge Index

=-1>(float(b6)-b5)/(b6+b5)<1

(2) MCARI：Chlorophyll Absorption Index

= ((float(b5)-b4)-0.2*(b5-b3))*(b5/b4)/10000

(3) CI-red edge： Red Edge Chlorophyll Index

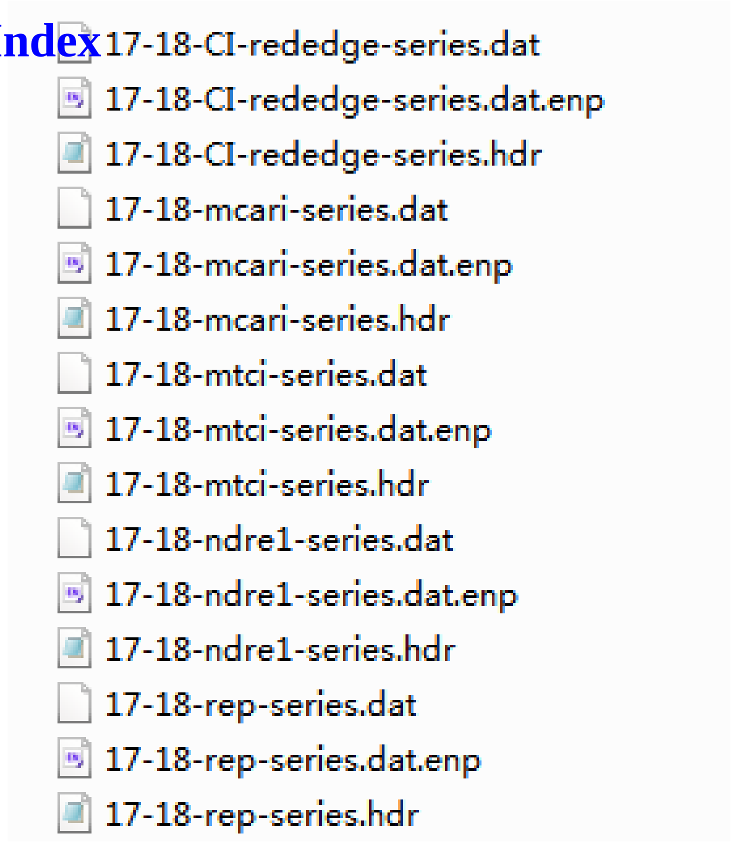
=(float(b8))/(b5)-1

(4) MTCI：Ground Chlorophyll Index

=(float(b6)-b5)/(b5-b4)

(5) REP： Red Edge Position Index

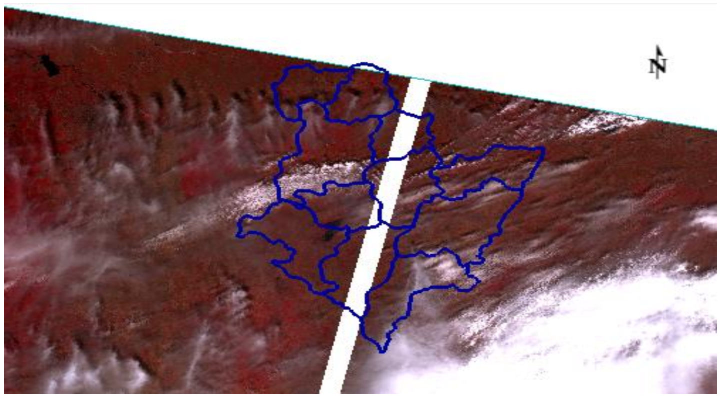
= 705+35*(0.5*(float(b4)+b7)-b5)/(b6-b5)



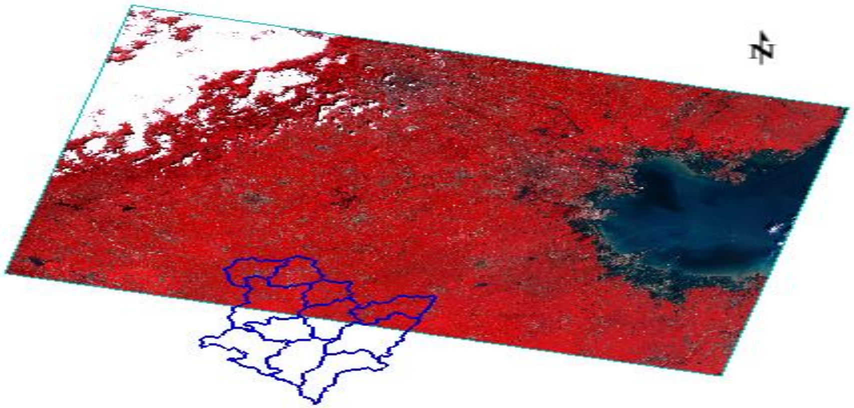
Sentinel-2 Red edge timing

8. Research Area Classification Results

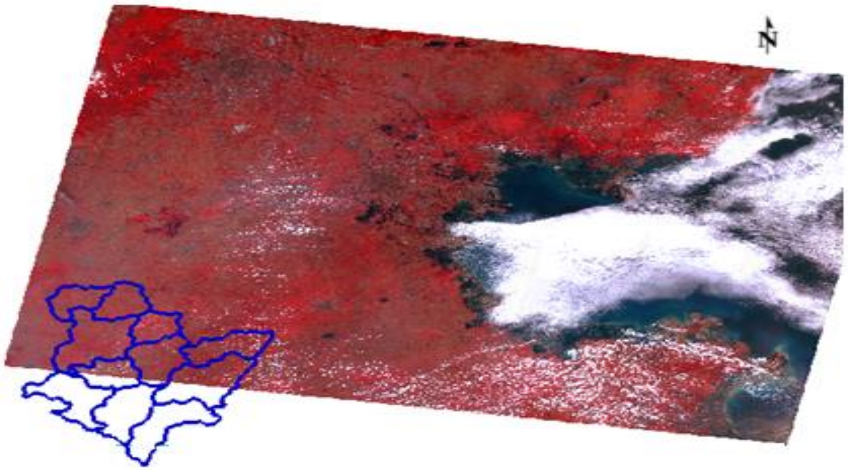
GF-6 Image Classification



GF-6 Satellite Image (June 7, 2018)



GF-6 Satellite Image (September 6, 2018)

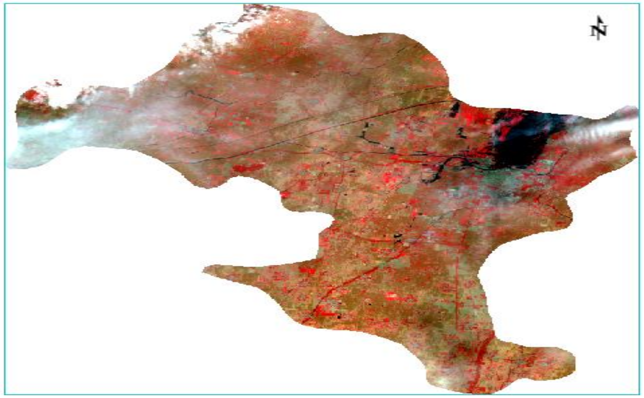


GF-6 Satellite Image (July 6, 2018)

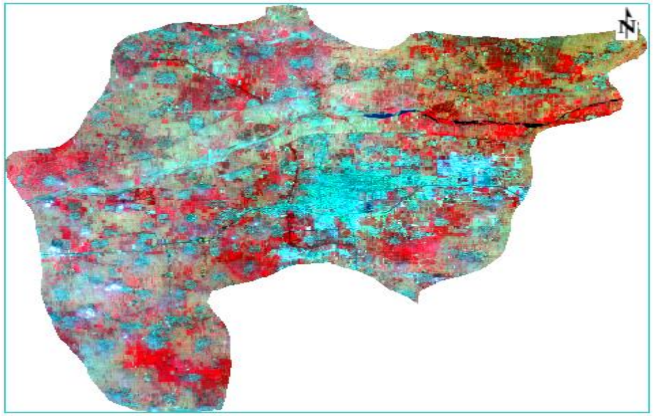
The current research has collected four scenery GF-6 satellite data from June to September 2018, of which the GF-6 remote sensing images in June, July and September can partially cover the study area (Jizhou, Anping, Raoyang, etc.) Next, crop classification studies will be carried out and compared with Sentinel-2 remote sensing data.

8. Research Area Classification Results

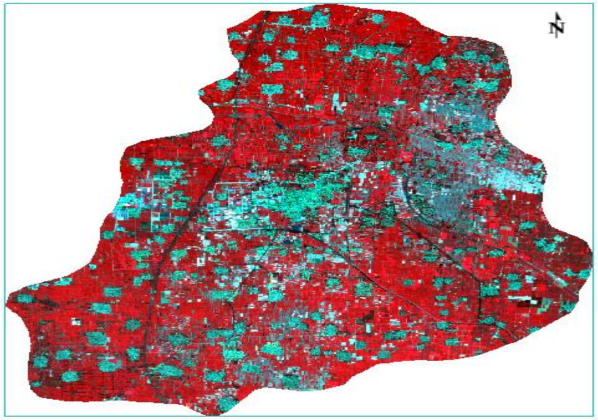
GF-6 Image Classification



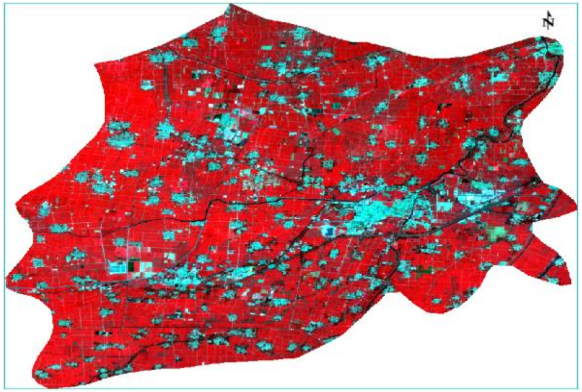
GF-6 Satellite Image of Jizhou City (June 7, 2018)



GF-6 Satellite Image of Anping County (July 6, 2018)

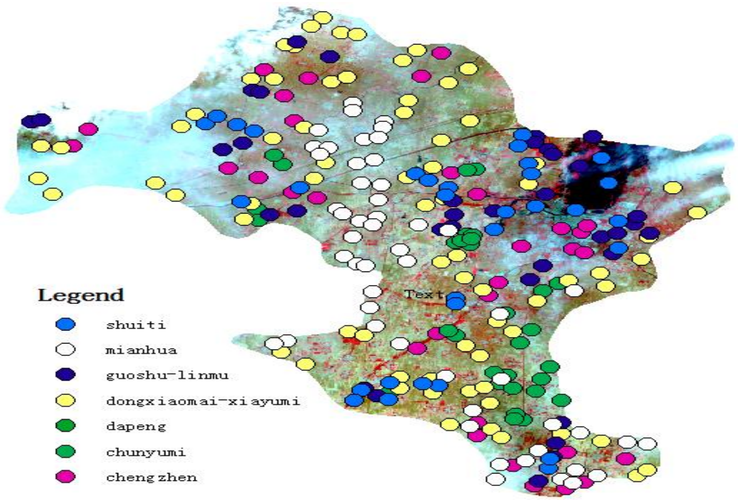


GF-6 Satellite Image of Raoyang County (September 6, 2018)

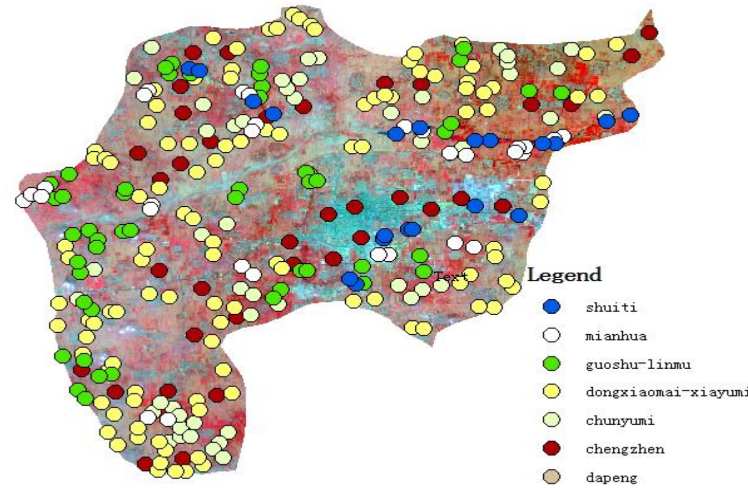


GF-6 Satellite Image of Wuqiang County (September 6, 2018)

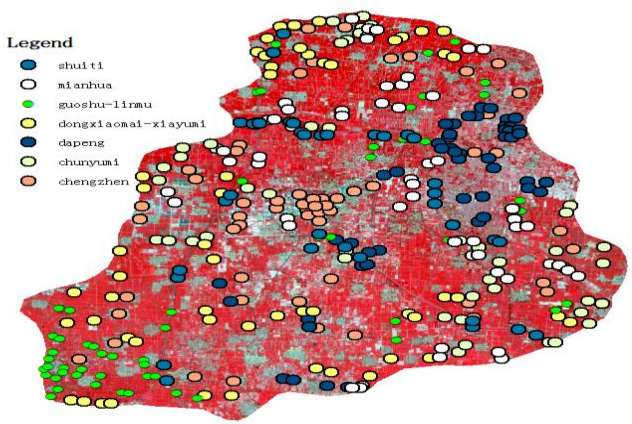
8. Research Area Classification Results



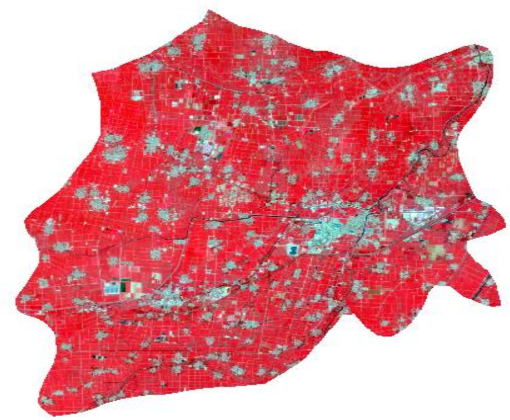
Jizhou GF-6 Satellite Image Sample



Anping County GF-6 Satellite Image Sample



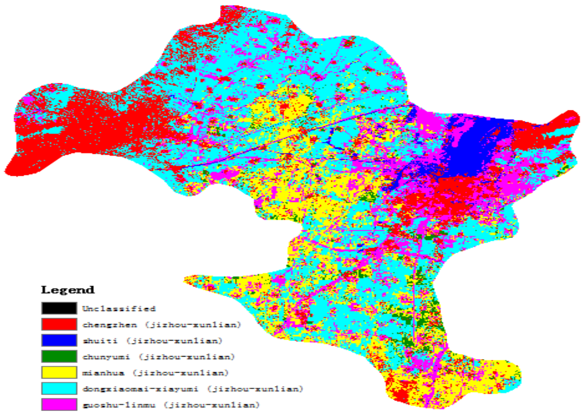
Raoyang County GF-6 Satellite Image Sample



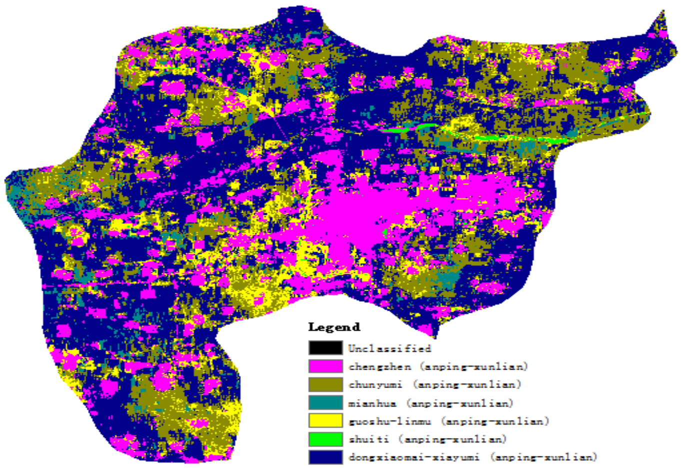
Wuqiang County GF-6 Satellite Image Sample

8. Research Area Classification Results

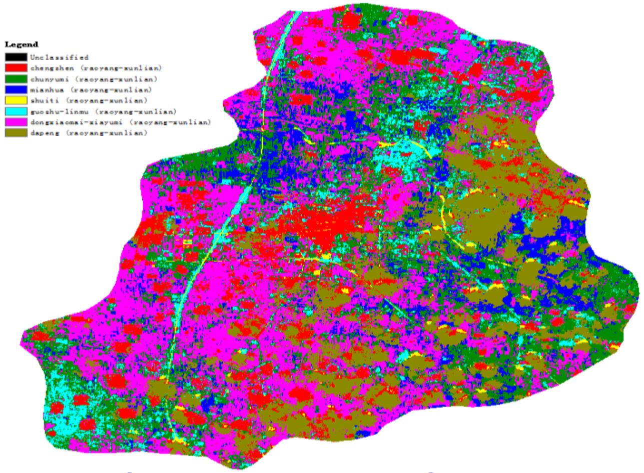
GF-6 Image Classification



Classification Results of Jizhou GF-6 Satellite Image



Classification results of GF-6 satellite imagery in Anping County

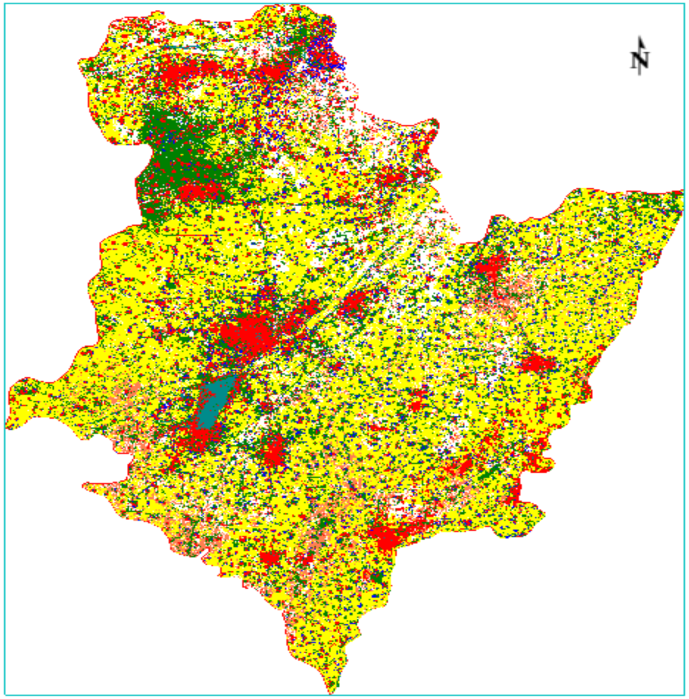


Classification results of GF-6 satellite imagery in Anping County

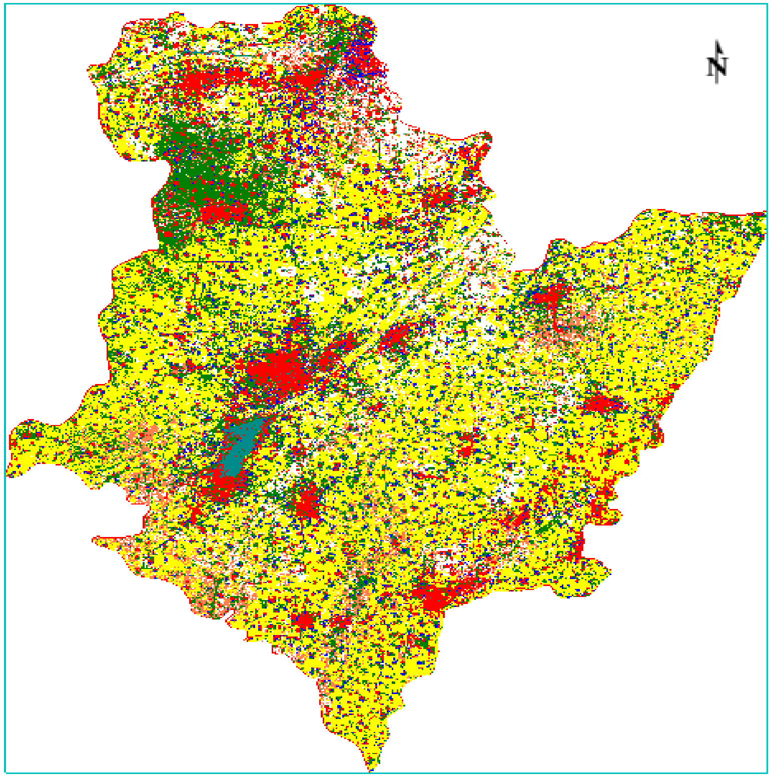
Machine learning methods such as MLC, RF, and SVM were used to classify crops and other vegetation in three counties and cities in Hengshui, with classification accuracy of about 90%.

8.Research Area Classification Results

Multitemporal classification



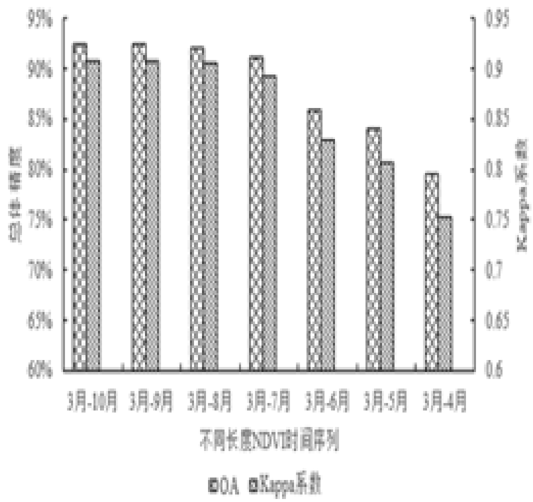
NDVI time series
Results of random forest classification in 2019
（OA=95.5622% Kappa=0.9458）



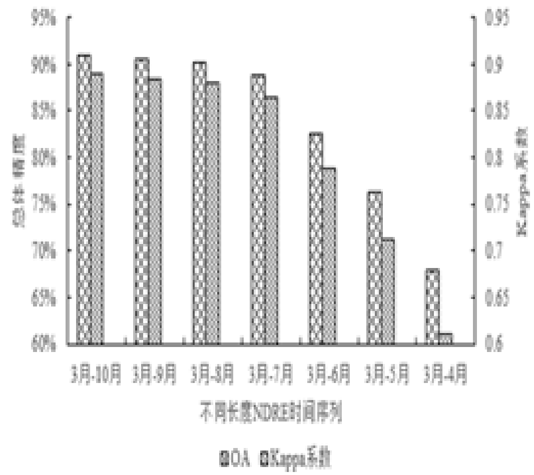
"NDVI+NDRE" time series
Results of random forest classification in 2019
（OA=95.9362% Kappa=0.95）

8.Research Area Classification Results

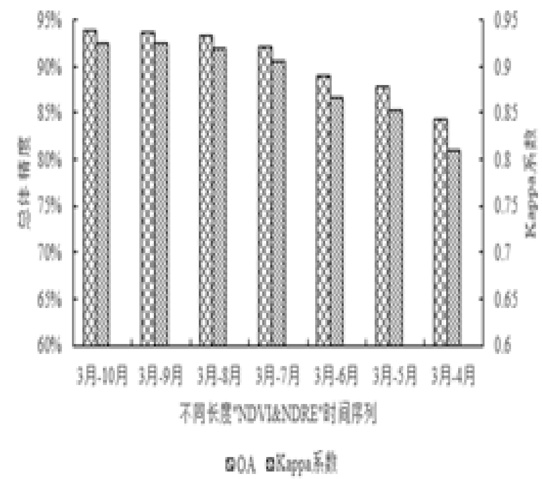
Multitemporal classification



（a）不同长度 NDVI 时间序列



（b）不同长度 NDRE 时间序列



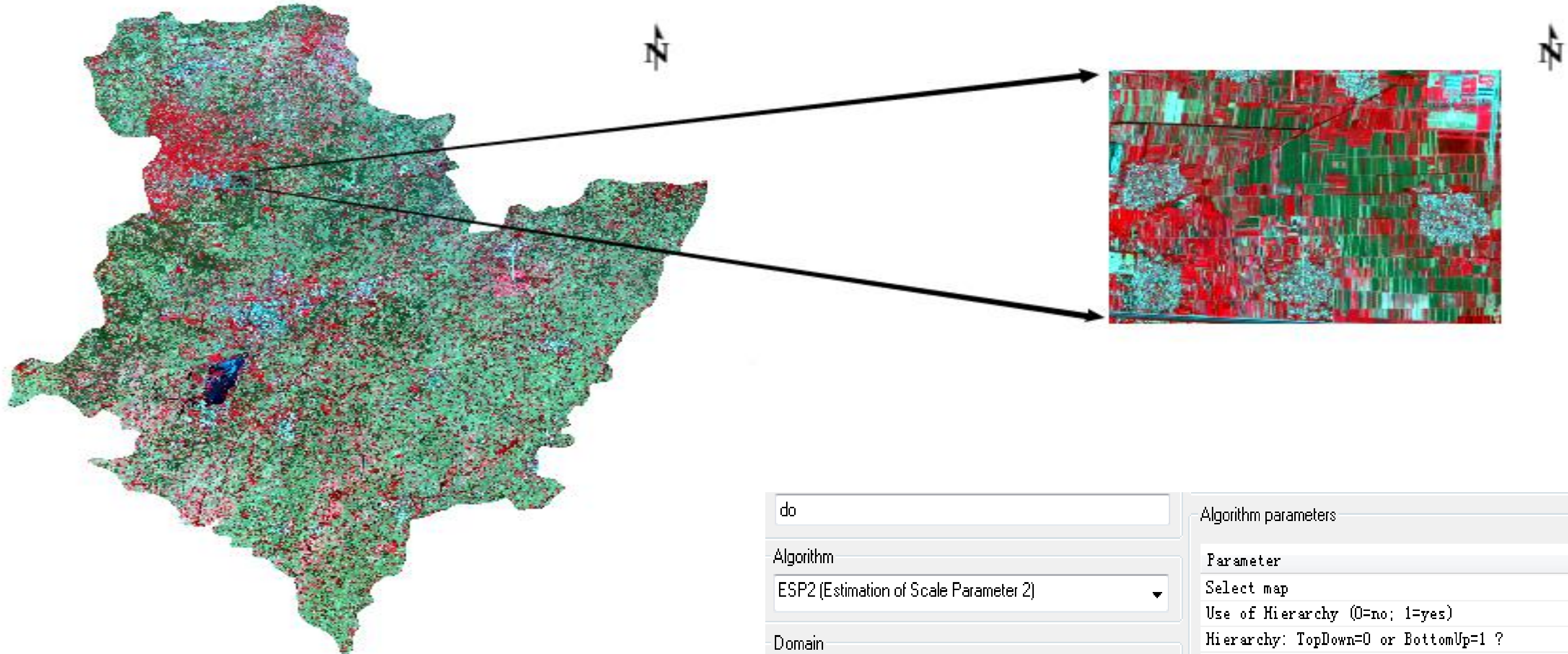
（c）不同长度 "NDVI&NDRE"时间序列

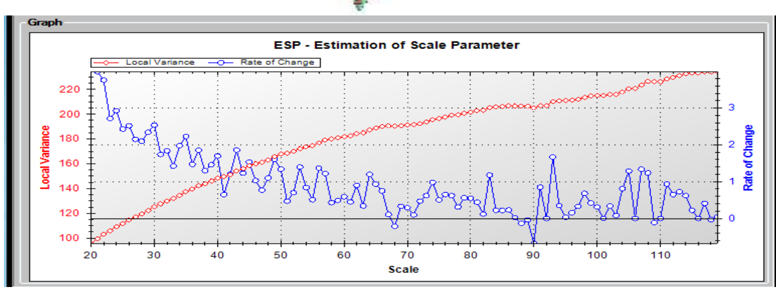
Classification accuracy charts of three different time series of different lengths

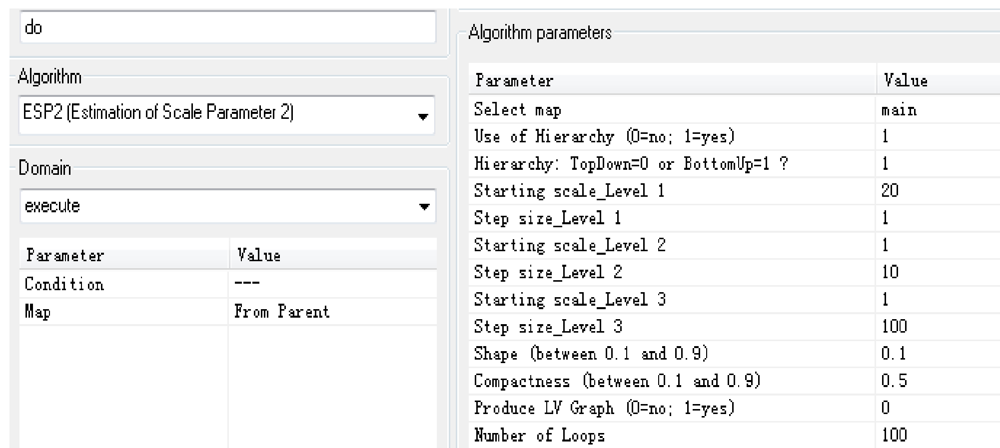
（a） Traditional NDVI time series； （b） Red edge NDRE time series； （c）"NDVI&NDRE"time series；

8. Research Area Classification Results

Object-oriented Classification (multi-scale segmentation)







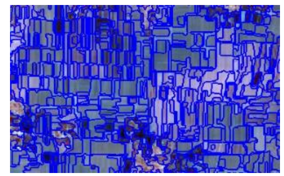
LV-ROC curve **ESP Plug-in interface**

eCognition multi-scale segmentation classification test results (ESP determines the segmentation scale)

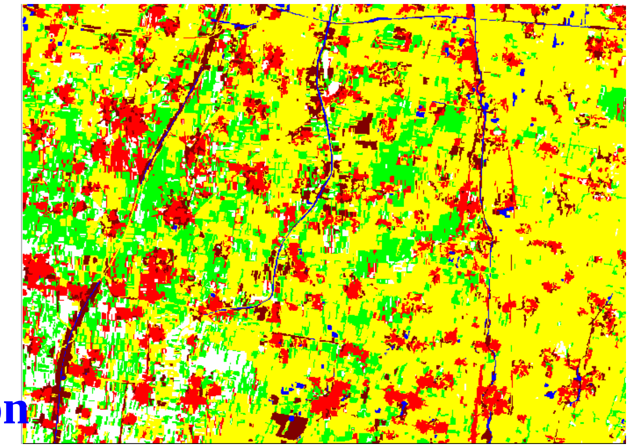
8. Research Area Classification Results

Object-oriented Classification (multi-scale segmentation)

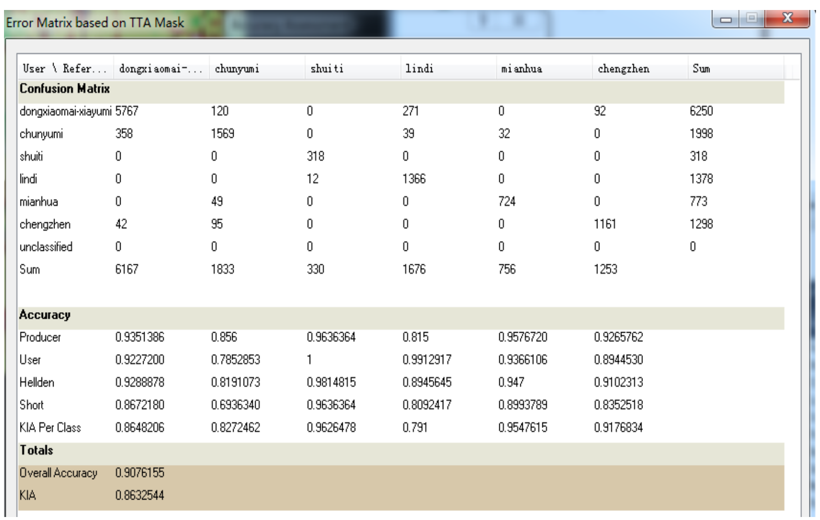
1. Original image



2. Image segmentation

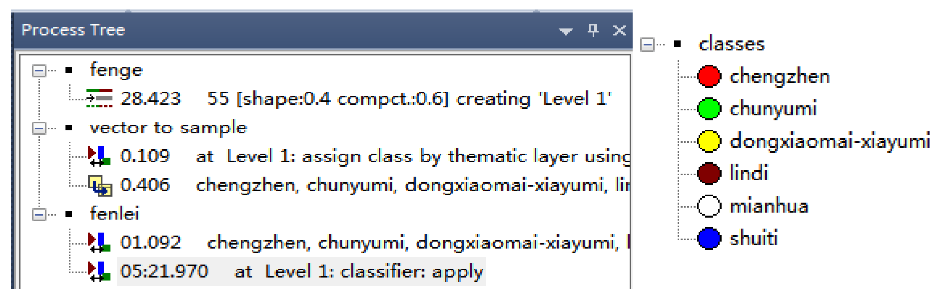


3. Image classification



User \ Refer...	dongxiaomai-...	chunyumi	shuiti	lindi	mianhua	chengzhen	Sum
Confusion Matrix							
dongxiaomai-xiayumi	5767	120	0	271	0	92	6250
chunyumi	358	1569	0	39	32	0	1998
shuiti	0	0	318	0	0	0	318
lindi	0	0	12	1366	0	0	1378
mianhua	0	49	0	0	724	0	773
chengzhen	42	95	0	0	0	1161	1298
unclassified	0	0	0	0	0	0	0
Sum	6167	1833	330	1676	756	1253	
Accuracy							
Producer	0.9351386	0.856	0.9636364	0.815	0.9576720	0.9265762	
User	0.9227200	0.7852853	1	0.9912917	0.9366106	0.8944530	
Hellden	0.9288878	0.8191073	0.9814815	0.8945645	0.947	0.9102313	
Short	0.8672180	0.6936340	0.9636364	0.8092417	0.8993789	0.8352518	
KIA Per Class	0.8648206	0.8272462	0.9626478	0.791	0.9547615	0.9176834	
Totals							
Overall Accuracy	0.9076155						
KIA	0.8632544						

4. Accuracy evaluation(OA=90%,Kappa=0.86 TTAMask)

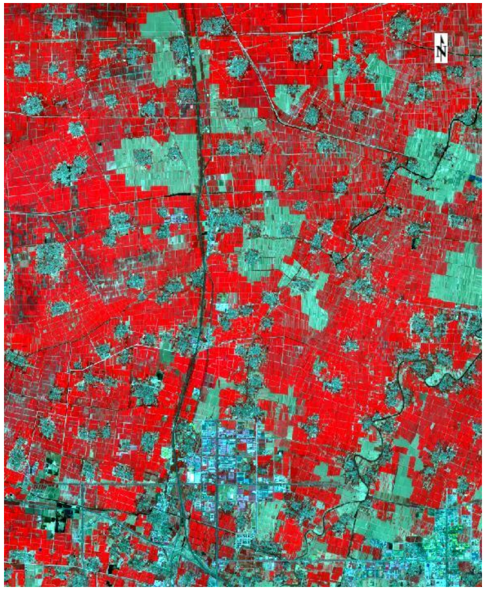


eCognition classification

eCognition multi-scale segmentation classification steps

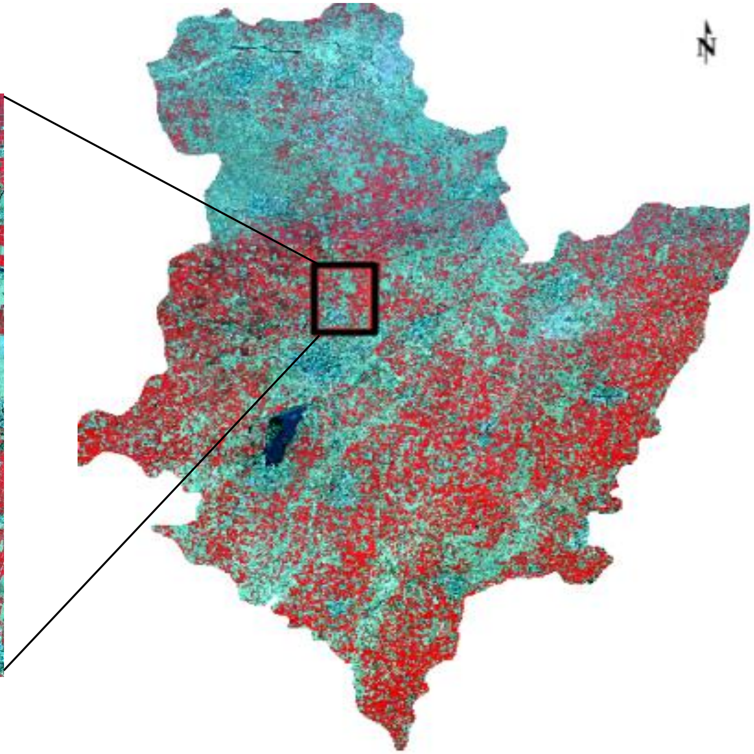
8. Research Area Classification Results

Change Detection



April 2018
Standard false color image

April 2019
Standard false color image

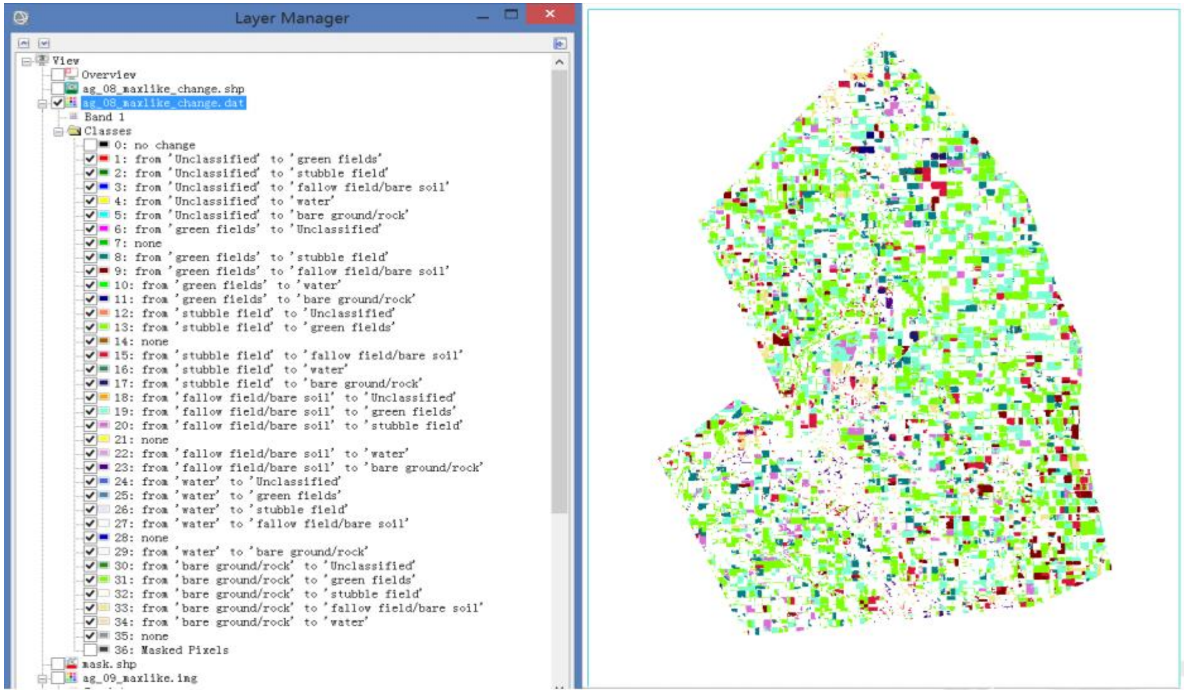


Combined with the standard false color images of Hengshui City in the study area of April 2018 and April 2019, red is displayed as "winter wheat-summer corn". From the intercepted images, it can be seen that the "winter wheat" planting area in some areas has decreased. The accuracy of change detection after classification is determined by the accuracy of crop classification, and is generally the product of classification accuracy (F1 accuracy).

$$F1=2\times UA\times PA/(UA+PA)\times 100\%$$ **(UA: User accuracy, PA: Mapping accuracy)**

8. Research Area Classification Results

Change Detection



Thematic Change Workflow module
Perform crop change detection

During the study, you can refer to the two modules of change detection related to "Thematic Change Workflow" and "Change Detection Statistics" in ENVI / IDL, to perform post-classification change detection of different types of crops and other vegetation, and statistics on related planting area and planting ratio analysis.

8. Research Area Classification Results

Change Detection

The accuracy of change detection depends on the accuracy of classification, which is usually the product of F1 score accuracy of different crops and other vegetation, and the detection accuracy of main crops is required to be better than 85%.

Figure 4-11 Recognition accuracy of different ground features in 2018

classes	F1-score	PA	UA
Winter wheat - Summer maize	0.992279593	0.9968	0.9878
Spring Maize	0.90901079	0.8979	0.9204
Cotton	0.828393536	0.8559	0.8026
Minor Crops	0.204865426	0.1649	0.2704
Orchard- Woods	0.974738487	0.9781	0.9714
Greenhouse	0.913660717	0.8884	0.9404
Town	0.984651475	0.9946	0.9749
Waterbody	0.990135367	0.9822	0.9982

Figure 4-12 Recognition accuracy of different ground features in 2019

classes	F1-score	PA	UA
Winter wheat - Summer maize	0.99849984	0.9981	0.9989
Spring Maize	0.929000581	0.9552	0.9042
Cotton	0.889427737	0.8716	0.908
Minor Crops	0.403441626	0.3634	0.4534
Orchard- Woods	0.968984303	0.9729	0.9651
Greenhouse	0.875971785	0.8491	0.9046
Town	0.987174676	0.9922	0.9822
Waterbody	0.991427131	0.983	1

8. Research Area Classification Results

Change Detection

Pixel Count | Percentage | Area (Square Meters) | Reference

Final State \ Initial State	dongxiaomai-xiayumi	chunyumi	mianhua	xiaozongzuowu	dapeng	shuiti	chengzhen	guoshu-linmu
Unclassified	0	0	0	0	0	0	0	0
dongxiaomai-xiayumi	0	0	0	0	0	202867	0	0
chunyumi	0	0	0	0	1335395	0	0	0
mianhua	0	0	0	0	0	0	2002485	0
xiaozongzuowu	0	0	1468626	0	0	0	0	0
dapeng	0	2024577	0	0	0	0	[illegible]	0
shuiti	9580511	0	0	0	0	0	[illegible]	0
chengzhen	0	0	0	261162	0	0	[illegible]	0
guoshu-linmu	0	0	0	0	0	0	0	5186388
Class Total	9580511	2024577	1468626	261162	1335395	202867	2002485	5186388
Class Changes	9580511	2024577	1468626	261162	1335395	202867	2002485	0
Image Difference	-9377644	-689182	533859	1207464	689182	9377644	-1741323	0

Figure. Transformation matrix of crop and other vegetation changes

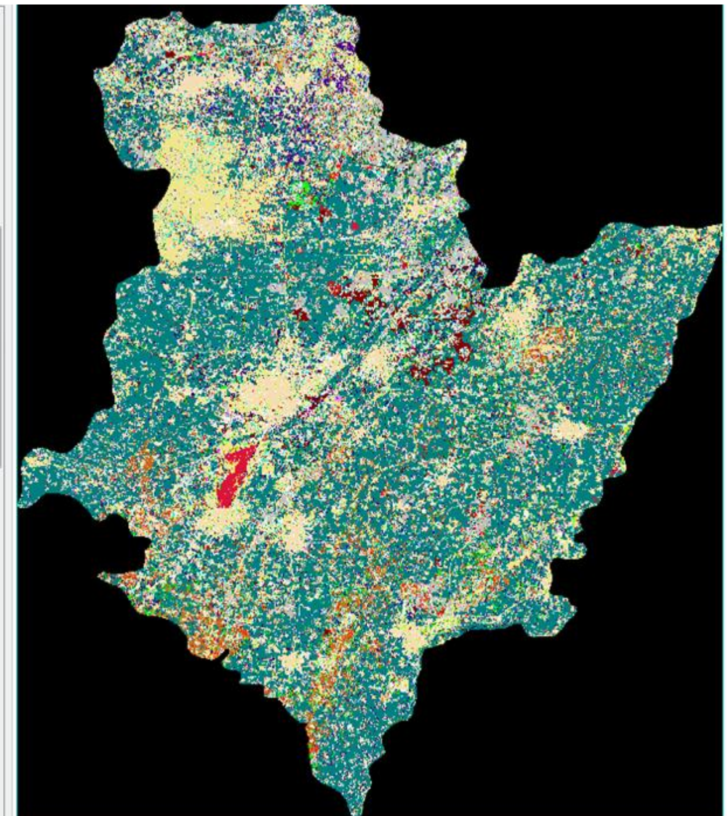
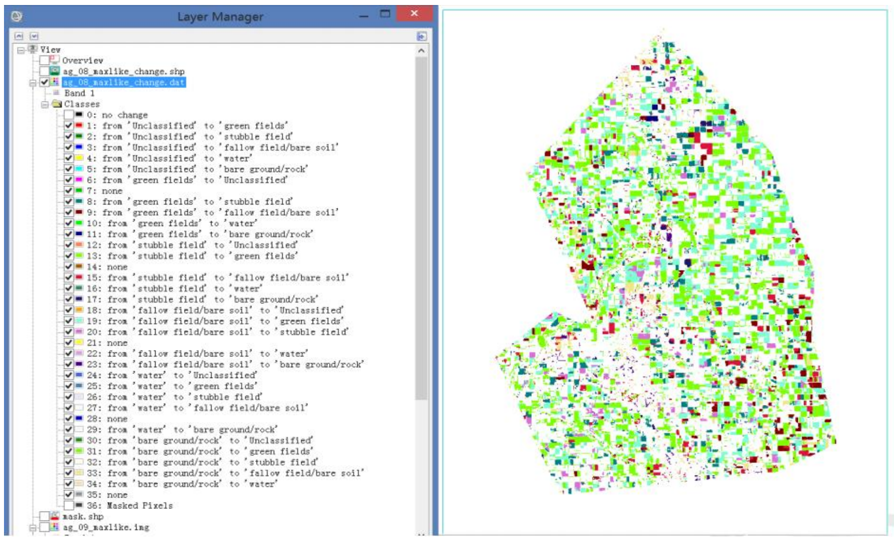


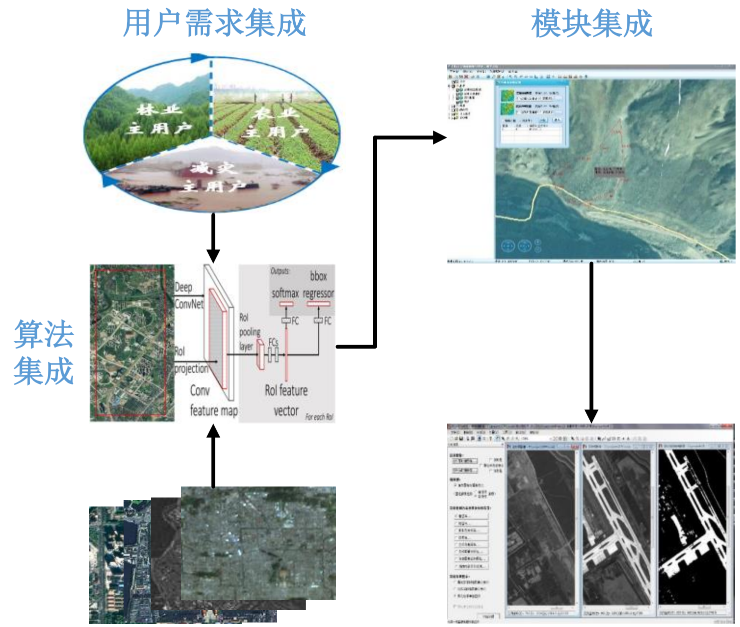
Figure. Change detection result diagram

8. Research Area Classification Results

Change Detection



Thematic Change Workflow module
Conduct crop change detection



Software plug-in development and integration process

In this study, we will call and refer to "Thematic Change Workflow" and "change detection statistics" in ENVI / IDL to detect the change of vegetation of different types of crops and other vegetation, and analyze the related planting area and planting proportion. At the same time, it provides reference for the development of high-precision automatic detection technology plug-in of vegetation change.

Scientific Significance

(1) Provide references for exploring new data such as GF-6 and Sentinel-2 and new features such as red edges in crop classification;

(2) To provide a reference for the adjustment and monitoring of agricultural planting structure in some areas of China, which has certain significance for the development of agricultural remote sensing in China;

(3) Promote the integration and intersection of remote sensing, agriculture, forestry and other disciplines, and promote the application of domestic high-scoring satellite data in the agricultural field.

Thanks!