A Novel Crop Classification Method Based on ppfSVM Classifier with Time-series Alignment Kernel from Dual-polarization SAR Datasets

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CONTENTS

01

Introduction

Crop type mapping with remote sensing technology

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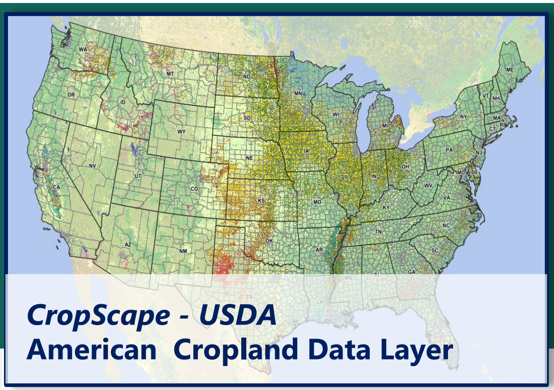
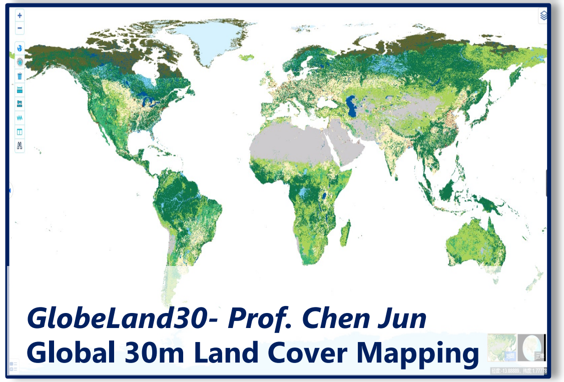
- *Mapping of cultivated land type, crop type and its change is the **engine** for protecting food safety,*
- *the corresponding **products** and applications are developing rapidly.*

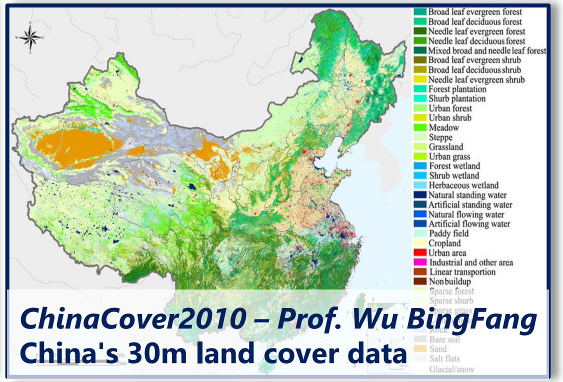
ESA WorldCover – ESA
Global 10m Land Cover Product



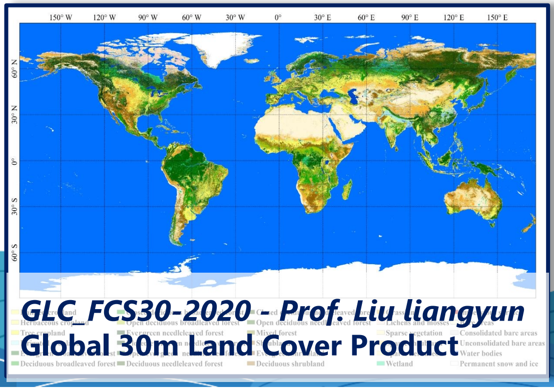
CropScape - USDA
American Cropland Data Layer



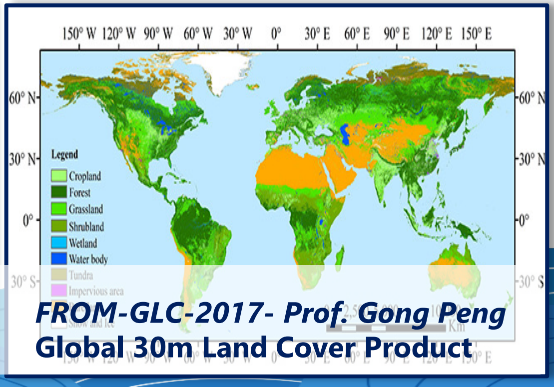
GlobeLand30- Prof. Chen Jun
Global 30m Land Cover Mapping



ChinaCover2010 – Prof. Wu BingFang
China's 30m land cover data



GLC_FCS30-2020 - Prof. Liu liangyun
Global 30m Land Cover Product



FROM-GLC-2017- Prof. Gong Peng
Global 30m Land Cover Product

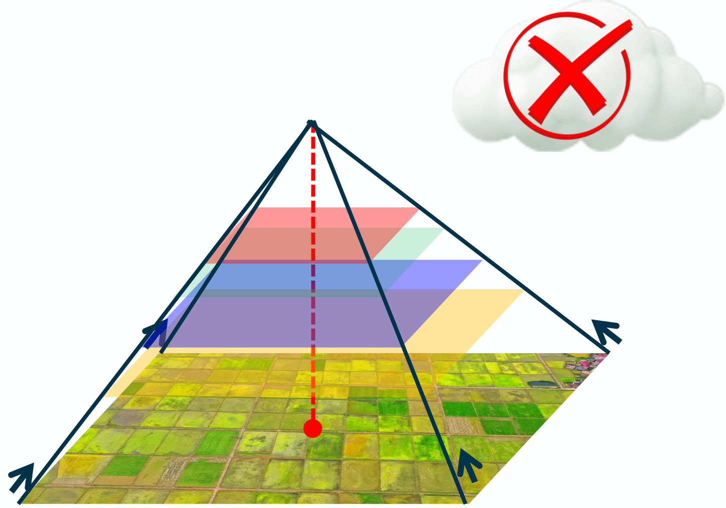
Advantage of Radar Sensing Technology

Manual investigation

High measurement accuracy in small-scale parcels.

Low efficiency

Strong subjectivity and low confidence

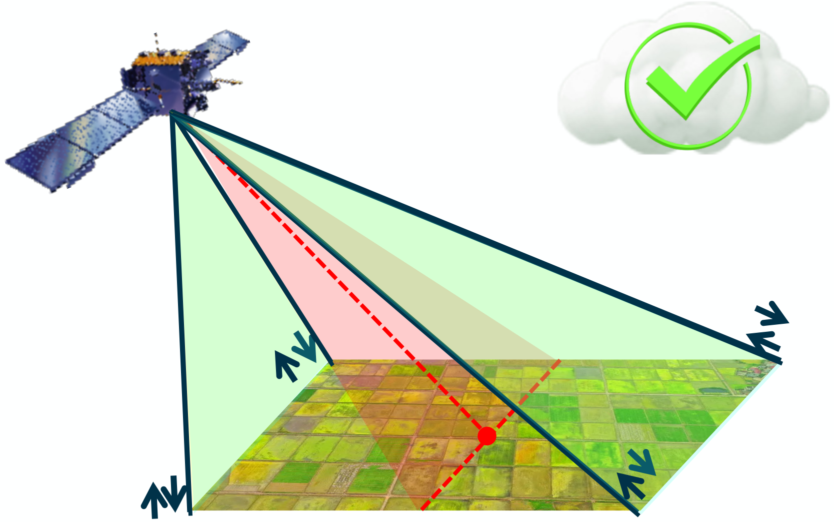


Optical Remote Sensing

Fast monitoring in large scale parcels

Multi-spectral data, sensitive for the Physicochemical parameters

Susceptible to cloudy weather, hard to continuously monitor crop growth



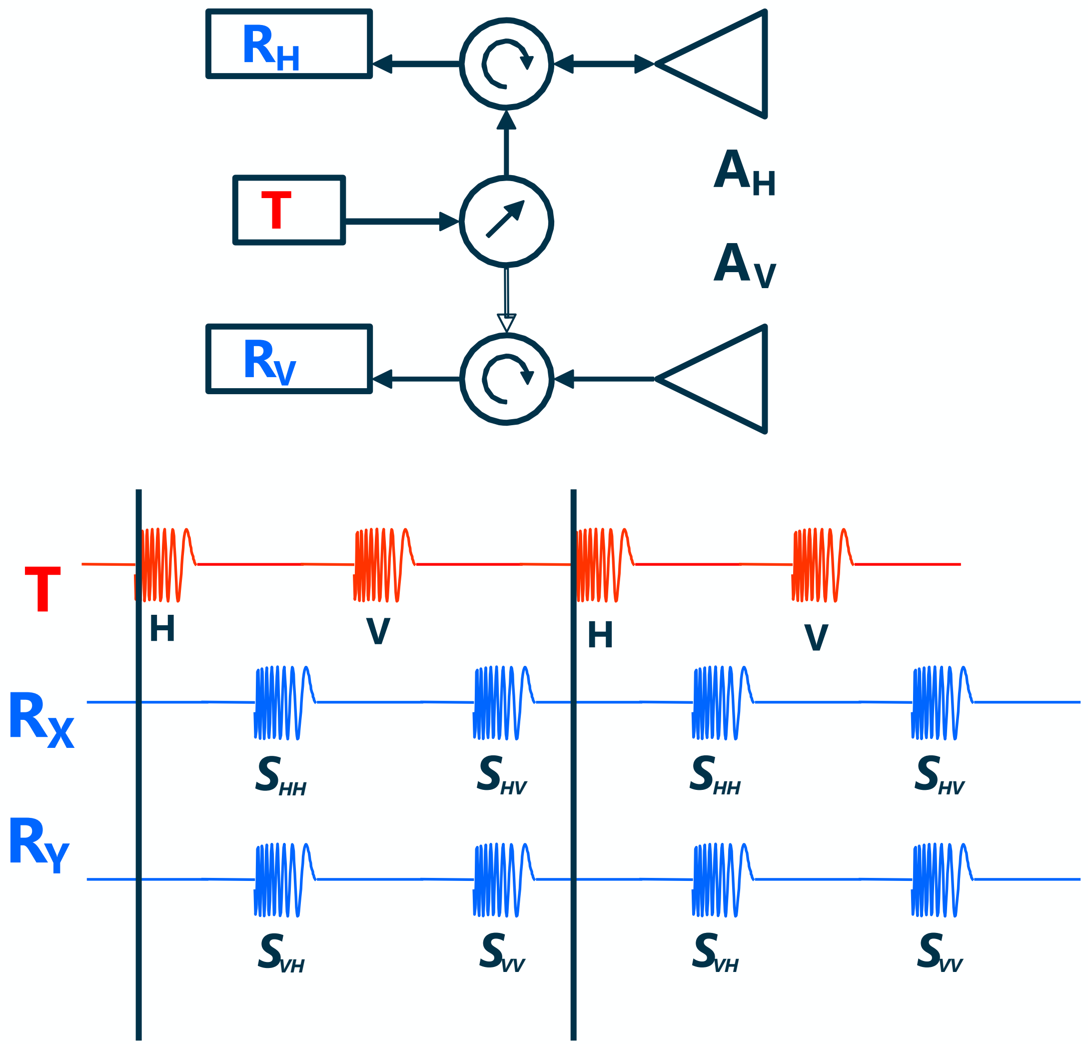
Radar Remote Sensing

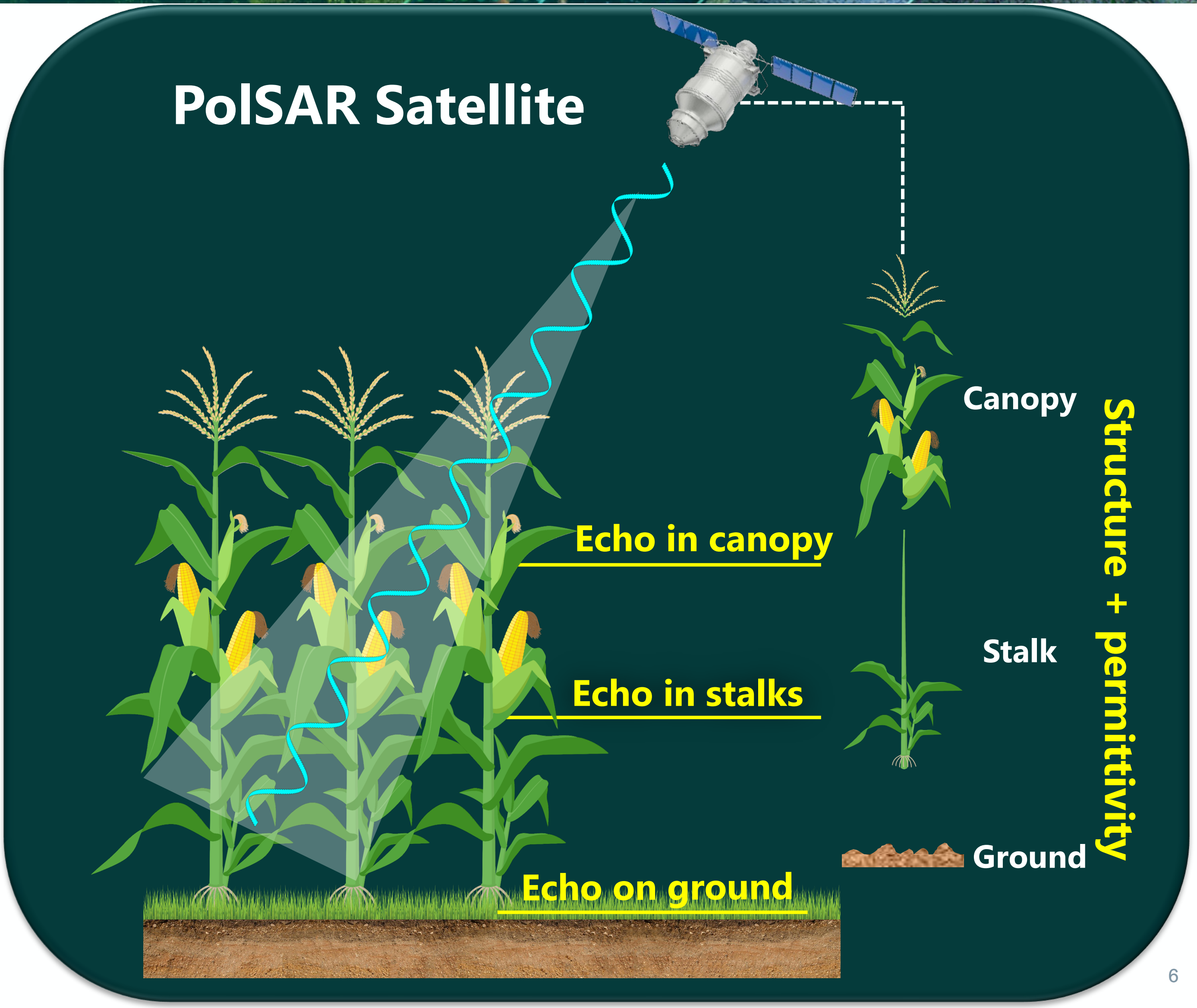
Fast monitoring in large scale parcels

Microwave data, sensitive for the structure and permittivity properties.

All daylight and all weather conditions, able to continuously monitor crop growth.

PolSAR Technology

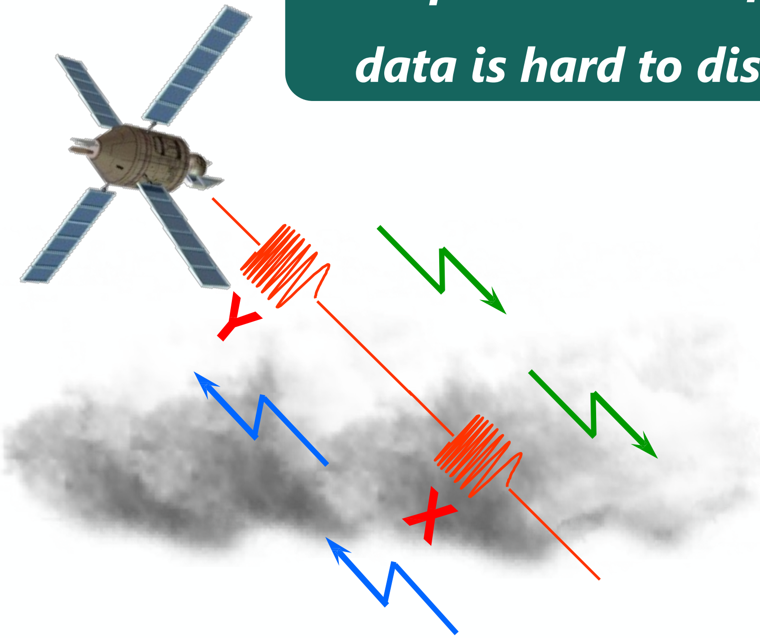


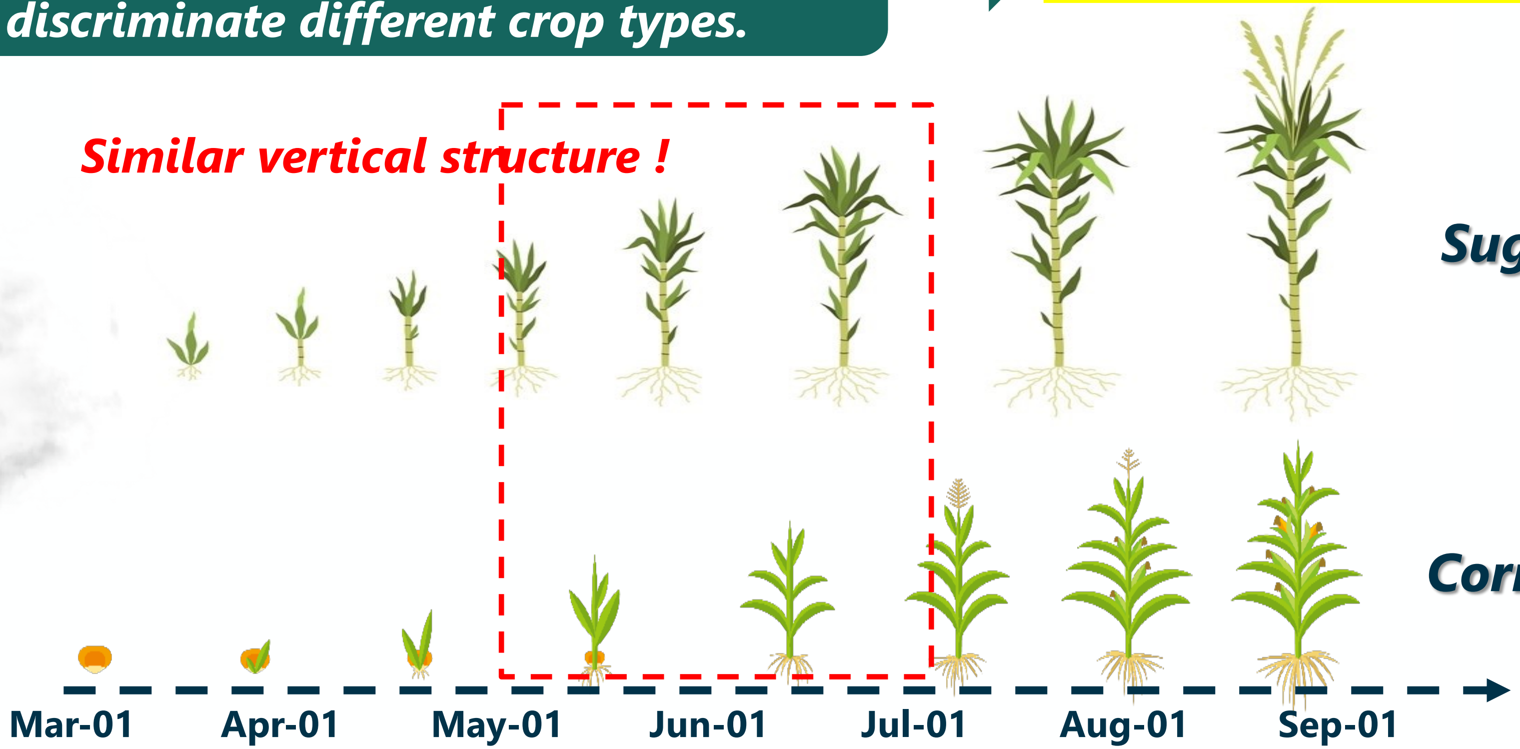


Time Series PolSAR observation for crops

Crop is the kind of time-varying object, single-date data is hard to discriminate different crop types.

→ *Time series PolSAR data ~!*





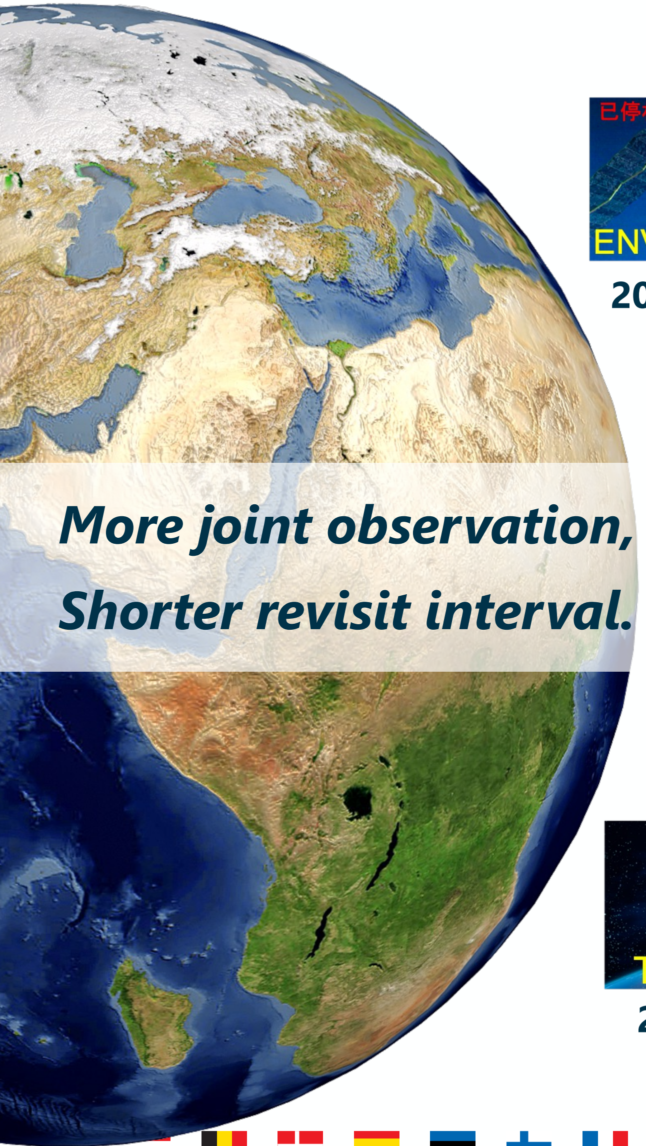
Available

Unavailable

PolSAR data

Optical data

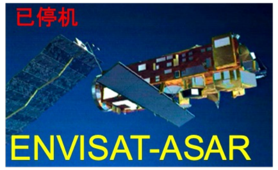
Main PolSAR Satellites in 2000 - 2023



More joint observation,
Shorter revisit interval.

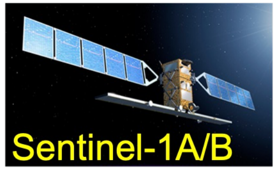
Global revisit in 1-2 days

35 days



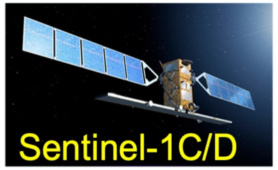
2002 C band

12 / 6 days



2014/2016 C band

12 / 6 days

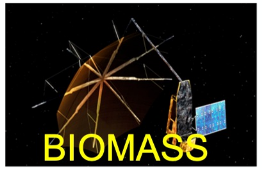


2022/2023 C band

10-12.5 days

2027 L band

25-45天

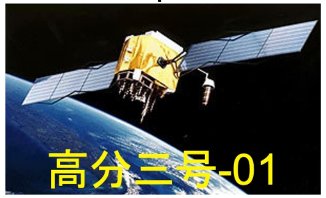


2023 P band

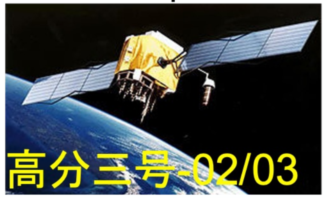
12 days

2023 L/S band

1 days

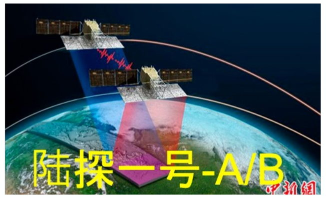


2016 C band



2021/2022 C band

4 days



2022 L band

24 days

2007 C band

4 days

2019 C band

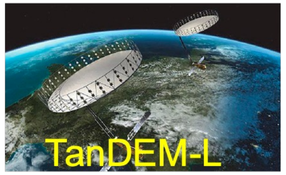
11 days

2007 X band

11 days

2010 X band

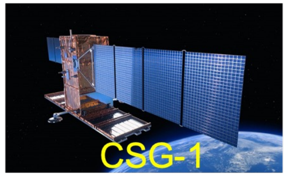
16 days



2023 L band

<2.5 days

~5 days



2019 X band

~5 days

2022 X band

11 days

2018 X band

Crop Classification methods with Time series PolSAR data

esa

The stack of features ← **Time series features** → **Phenological knowledge or time-varying characteristic**

Machine learning algorithms

Maximum Likelihood

Wishart-pdf → C3

Gaussian-pdf → F

(Skriver, 2012; Hoekman, 2003)

Decision Tree & Random Forest

(Huang et al., 2017; Waske et al, 2009)

Support Vector Machine

(Sonobe et al., 2015; Shuai et al., 2019)

Neural Network *(Ndikumana et al., 2018)*

Ensemble Learning *(Peijun Du，Nanjing University)*

Drawbacks:

these methods have not revealed the dynamical characteristics of SAR datasets in the temporal dimension

Introduction of Phenology Information

1) **Feature selection** *Hariharan et al. (2018)*
2) **phenology pattern** *Bargiel (2017)*
3) **Hidden Markov Model** *Leite et al., 2011)*
4) **Conditional Random Field** *Kenduiywo et al., 2017*

Drawbacks:

1）High cost of time series phenological measures collections;

2）Ignore the phenological unalignment situation. (Kenduiywo et al., 2017).

Classification with time series alignment algorithm

Euclidean distance (*Xu et al., 2019*)

DTW distance (*Petitjean, 2012*)

TWDTW distance (*Maus et al., 2016*)

Frechet distance *(Gao, 2020)*

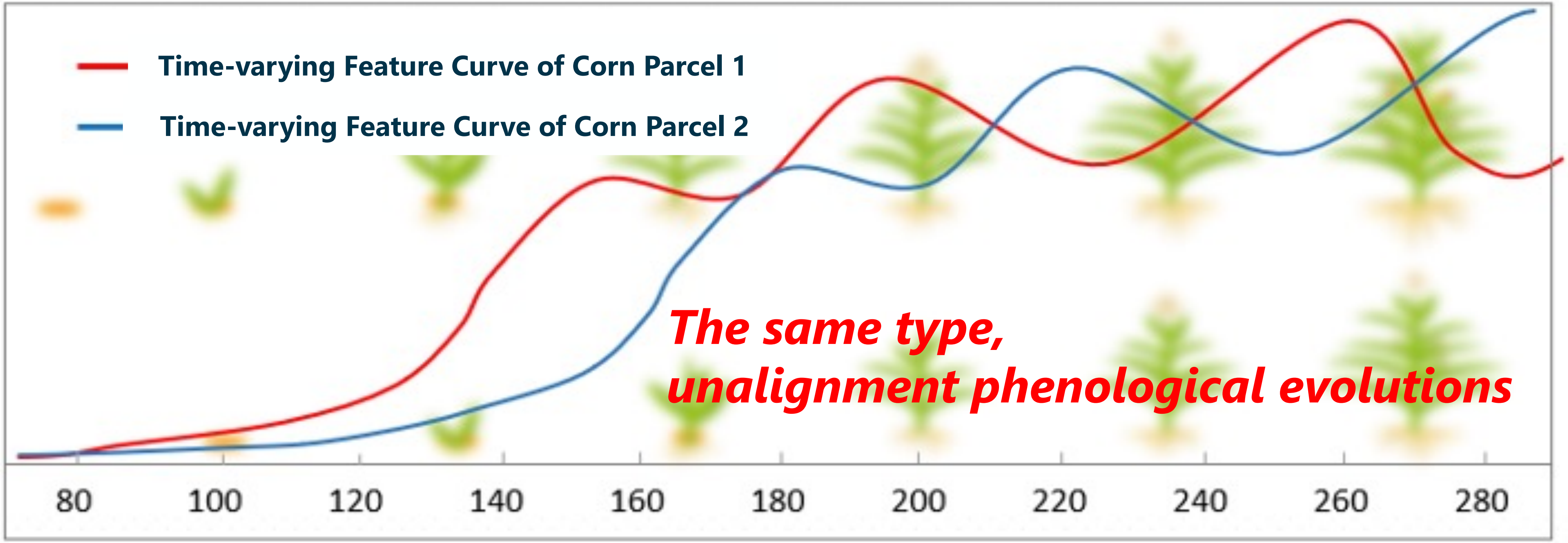
LCSS distance (*Han Su, 2019*)

ERP distance (*Han Su, 2019*)

Phenology Unalignment Phenomenon

Definition:

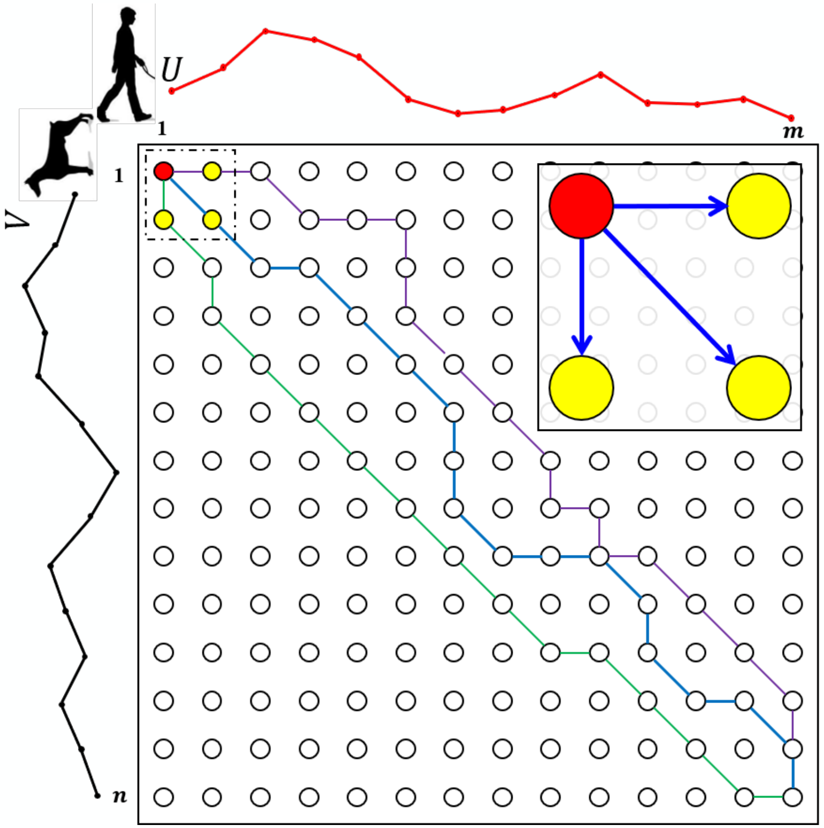
- *caused by the random variations of agroclimatic conditions and agricultural practices, which is presented as* ***the time-series unalignment*** *of different parcels from a give crop type.*
- *two neighboring parcels of the same type may have different phenological evolutions.*

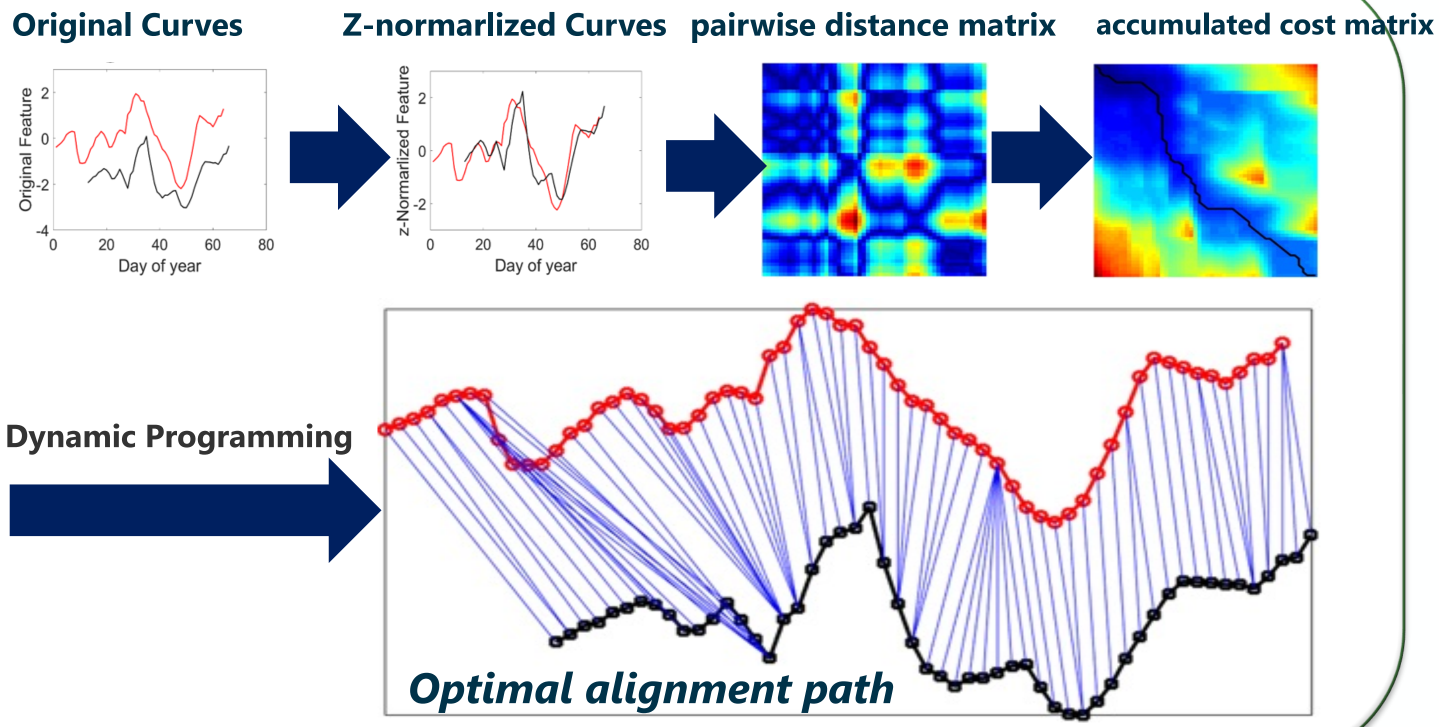


DTW Alignment Algorithm

Dynamic Time Warping Alignment:

It searches for a global optimal matching path under the boundary and monotonicity constraints, and allows time-varying curves to be locally shifted, contracted and stretched (Zhao and Itti, 2018).





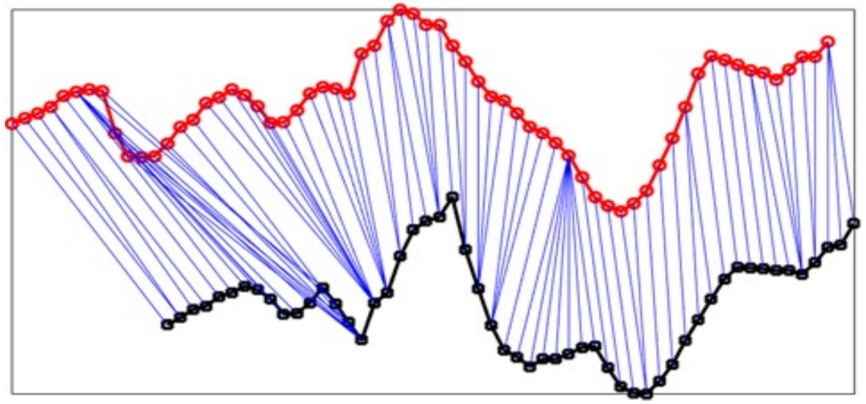
Traditional Classification Scheme

Nearest Neighbor (NN) Classification with time series alignment similarity

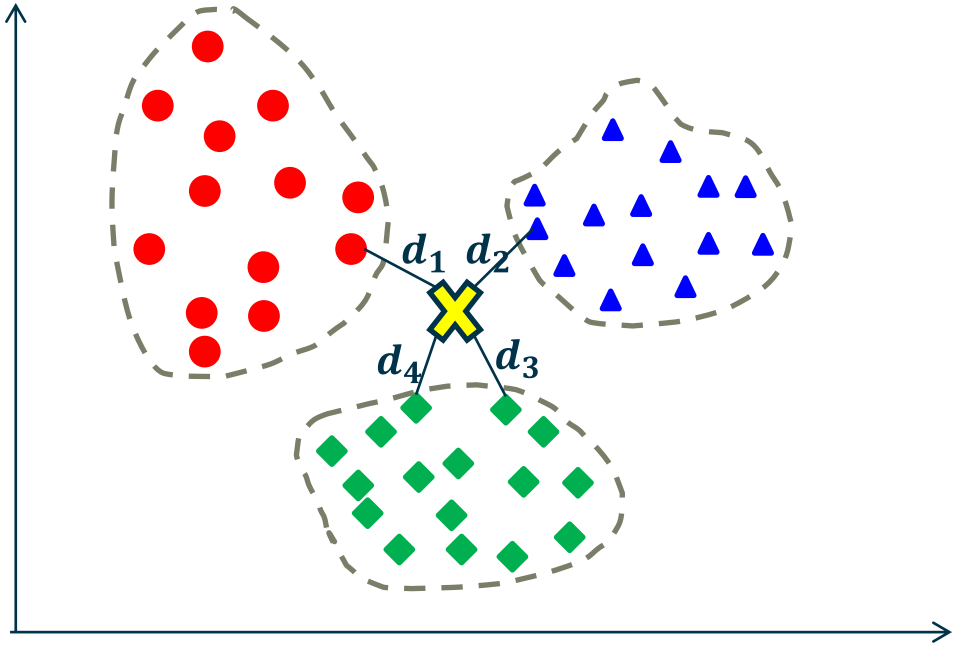
Similarity

$$\delta_{SS} = \frac{\gamma_{m,n}}{K} = \frac{1}{K} \sum_{(i,j)\in P} \left(\left|\bar{u}_i - \bar{v}_j\right|\right)$$

$$\delta_{FS} = \frac{1}{K} \sum_{(i,j)\in P} \left(\left|u_i - v_j\right|\right)$$



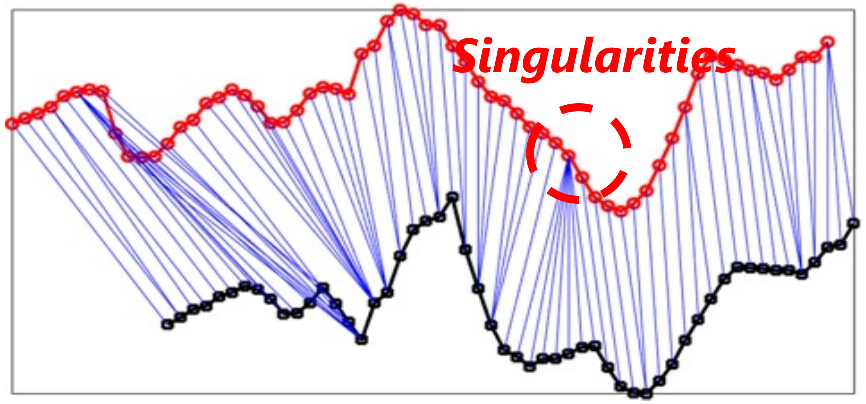
NN Classifier



Existing Problems of Crop Classification

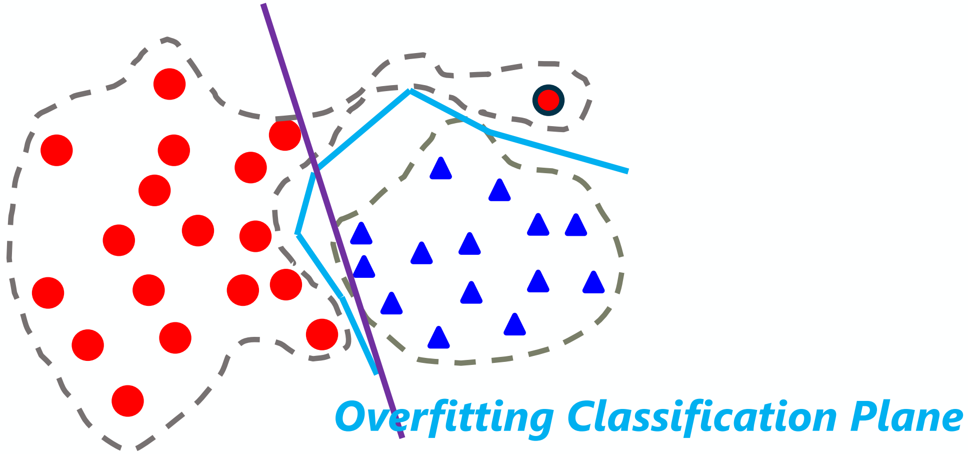
①

DTW alignment is a point-to-point matching, which is unreliable, leading to perceptually nonsensible alignments. (Singularities behaviors, one point to multiple points).



②

The NN classifier occupies inadequate generalization performance



Our Innovations

The Classification Method Based on ppfSVM Classifier with Time-series Alignment Kernel from Dual-polarization SAR Datasets

Innovation 1: DTW Alignment → TWshapeDTW Alignment

Innovation 2: NN Classifier → ppfSVM Classifier

TWshapeDTW Alignment + ppfSVM Classifier → time series alignment kernel → **Novel Classification Method**

02

Methodology

Innovation 1: TWshapeDTW alignment

$$d_{i,j}^{TWshapeDTW} = \sqrt{\left\| sq_i^{\bar{U}} - sq_j^{\bar{V}} \right\| / l} + w_{i,j}$$

(1) point-to-point → shape descriptors (zhao, 2018)

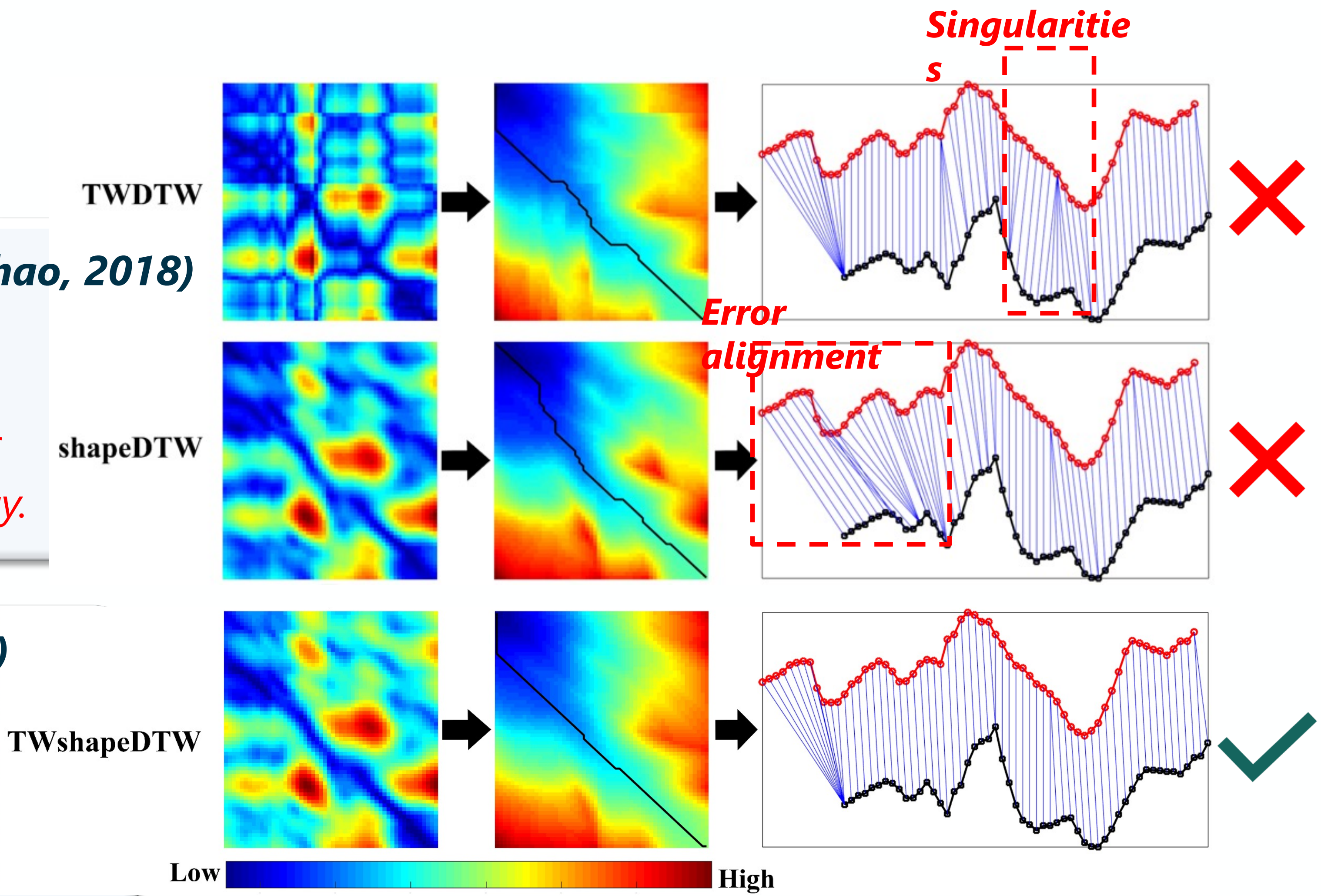
$$\left|\bar{u}_i - \bar{v}_j\right| \qquad \left\| sq_i^{\bar{U}} - sq_j^{\bar{V}} \right\|$$

Improvement: *Use the neighbor information of sub-sequence to improve the alignment accuracy.*

(2) Add the time weight (Maus et al., 2016)

$$w_{i,j} = \frac{1}{1 + e^{-\alpha_w(|t_i - t_j| - \beta_w)}}$$

Improvement: *Add the temporal constraint to avoid the unreasonable alignment.*



Innovation 1: TWshapeDTW alignment

Shape similarity (between two z-normalized curves)

$$\delta_{SS} = \frac{1}{K} \sum_{(i,j)\in P} \left(\sqrt{\left\| sq_i^{\bar{U}} - sq_j^{\bar{V}} \right\|_2 / l} + w_{i,j} \right)$$

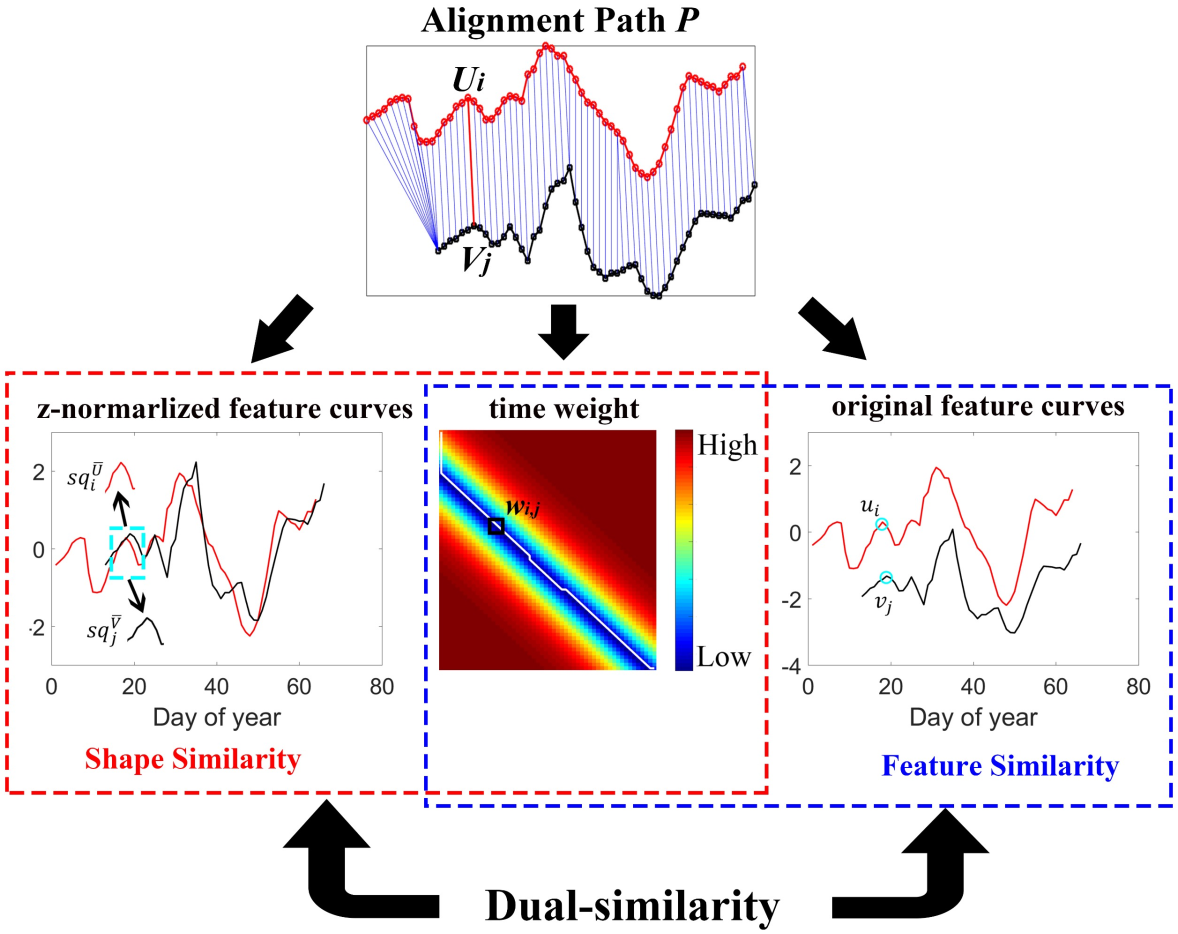
Describe the similarity of crop growth and change.

Share the same path.

Feature similarity (between two original curves)

$$\delta_{FS} = \frac{1}{K} \sum_{(i,j)\in P} \left(\sqrt{(u_i - v_j)^2} + w_{i,j} \right)$$

Describe the similarity of microwave signals.



Innovation 2: ppfSVM classifier with time series alignment kernel

How to combine them successfully ?

time series alignment similarity + **SVM classifier (machine learning)**

Thought: Use the similarity to replace the Euclidean distance in kernel function ?

Result: The kernel matrix **is not positive !**

ppfSVM (Pairwise Proximity Function SVM)

Dual-similarity of features

$$\chi_{SS} = (\phi_{SS}(f^1), \cdots, \phi_{SS}(f^I))$$

$$\chi_{FS} = (\phi_{FS}(f^1), \cdots, \phi_{FS}(f^I))$$

Proximity Vector

$$\chi = [\chi_{SS}, \chi_{FS}]$$

Proximity Matrix

$$Z = (\chi_1^T, \chi_2^T, \cdots, \chi_N^T)^T$$

Positive kernel matrix

$$\Lambda = ZZ^T$$

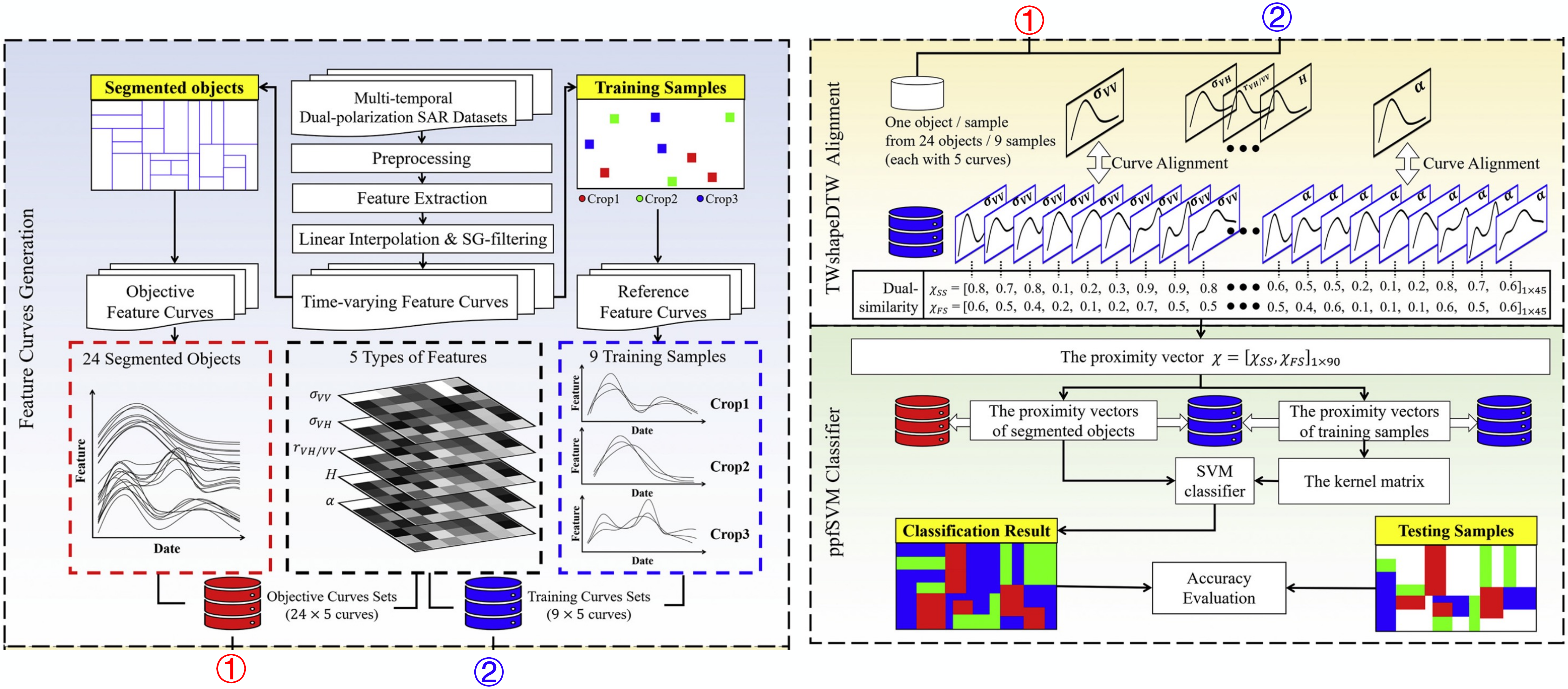
Solve the support vector with **SMO algorithm**

$$min_\alpha \quad \frac{1}{2}\alpha^T Y \Lambda Y \alpha - \alpha^T 1$$

Determine the label with **decision function**

$$\Theta(f) = sgn(\alpha^T Y Z \chi + b)$$

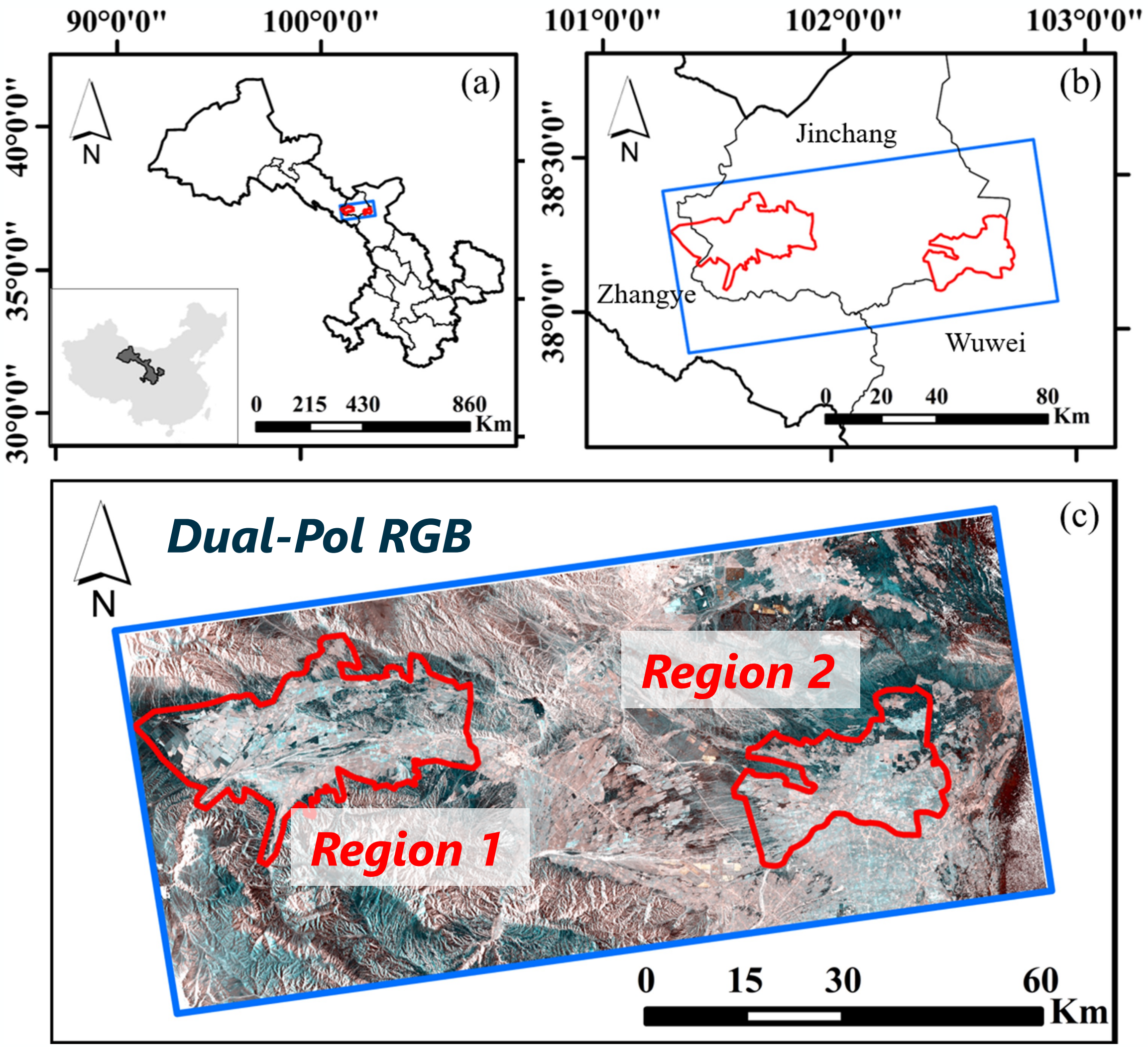
Total technology scheme



03

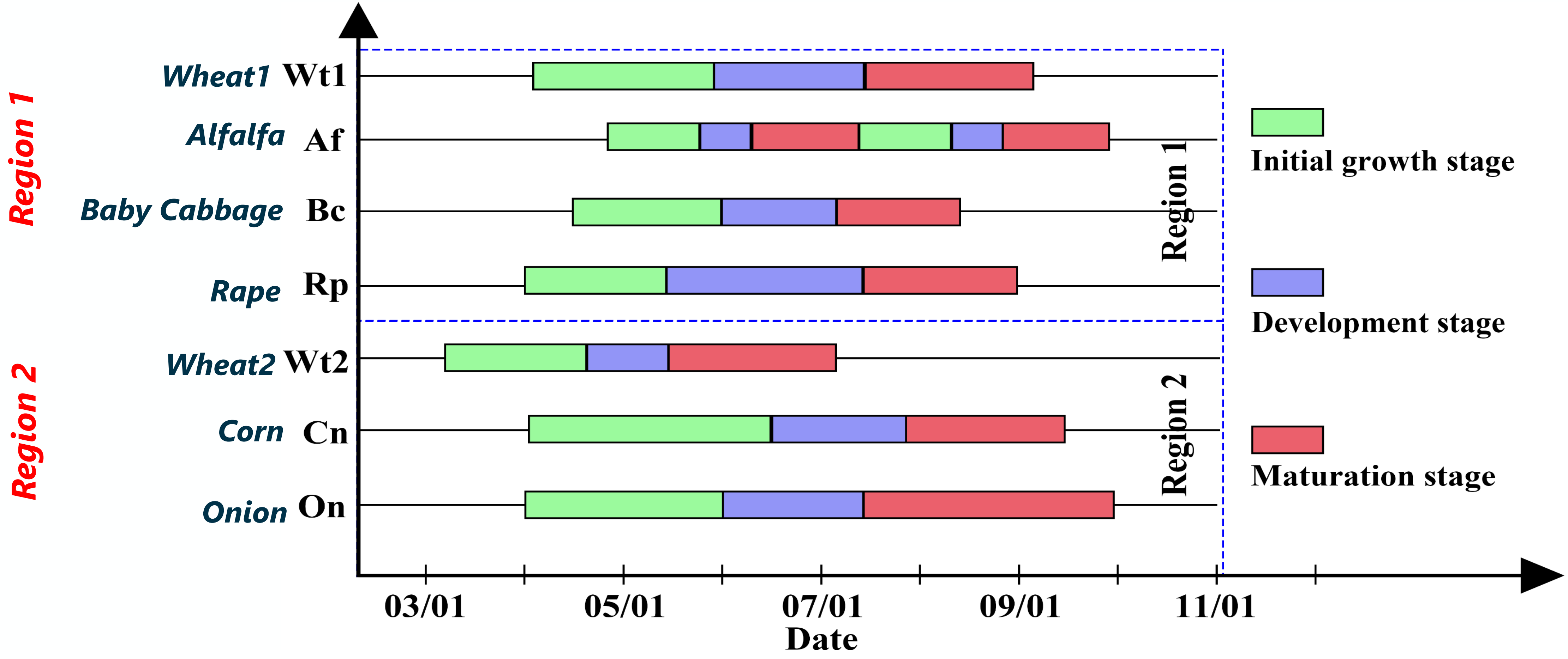
Study Area and Data

Study Area and Data

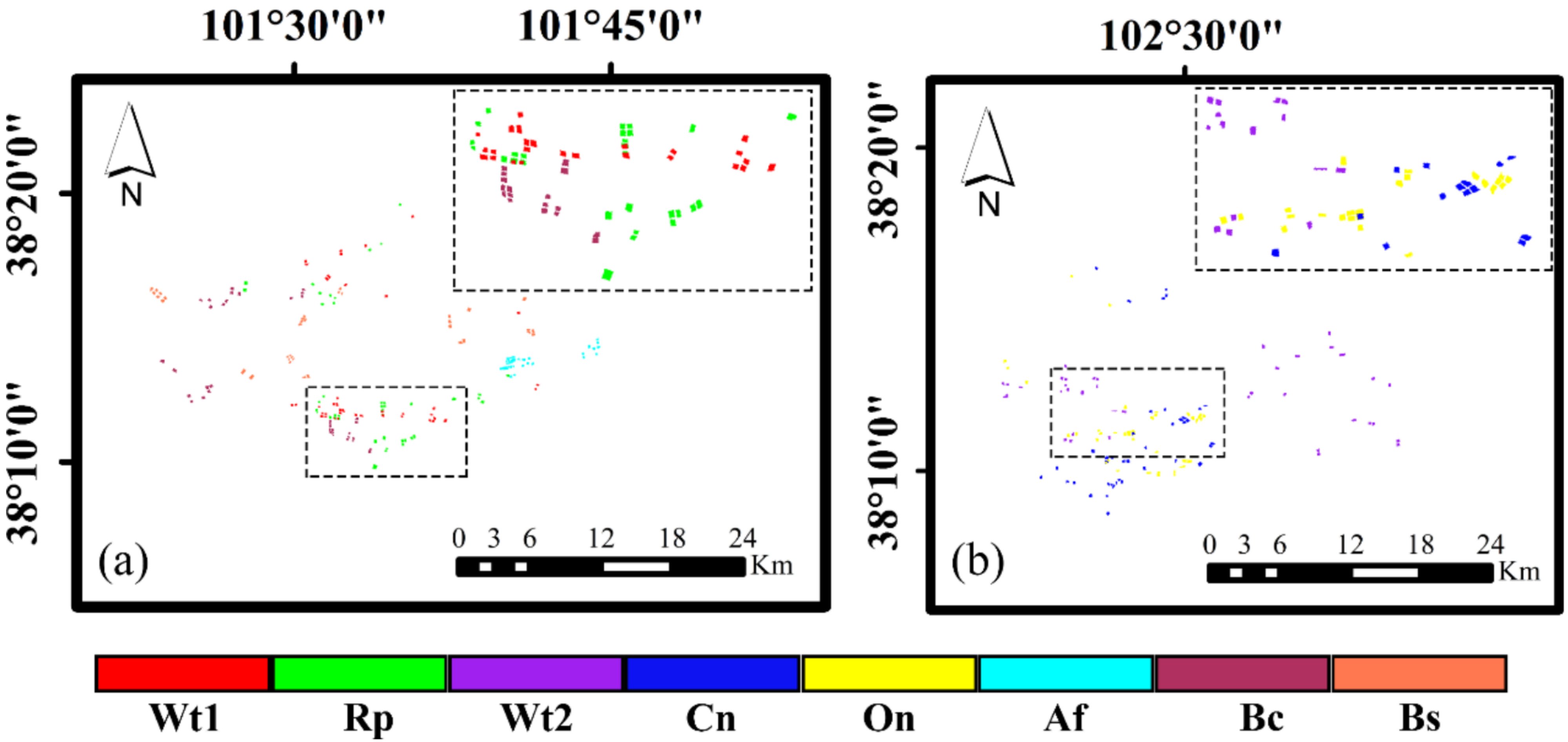


Parameters	Information
Satellite	Sentinel-1A
Path	128
Flight Direction	Ascending
Polarization Mode	VH + VV
Center incidence Angle	39.11 °
Azimuth Pixel Spacing	13.94 m
Range Pixel Spacing	2.33 m
Available Dates	20180303, 20180315, 20180327, 20180408, 20180420, 20180514, 20180526, 20180607, 20180619, 20180701, 20180713, 20180725, 20180818, 20180911, 20180923, 20181005, 20181017, 20181110, 20181204, 20181216, 20181228, 20190310, 20190322, 20190403, 20190415, 20190427, 20190521, 20190602, 20190614, 20190801, 20190813, 20190825, 20190906, 20190918, 20190930, 20191012, 20191024, 20191105, 20191117,20191129, 20191211, 20191223.

Study Area and data



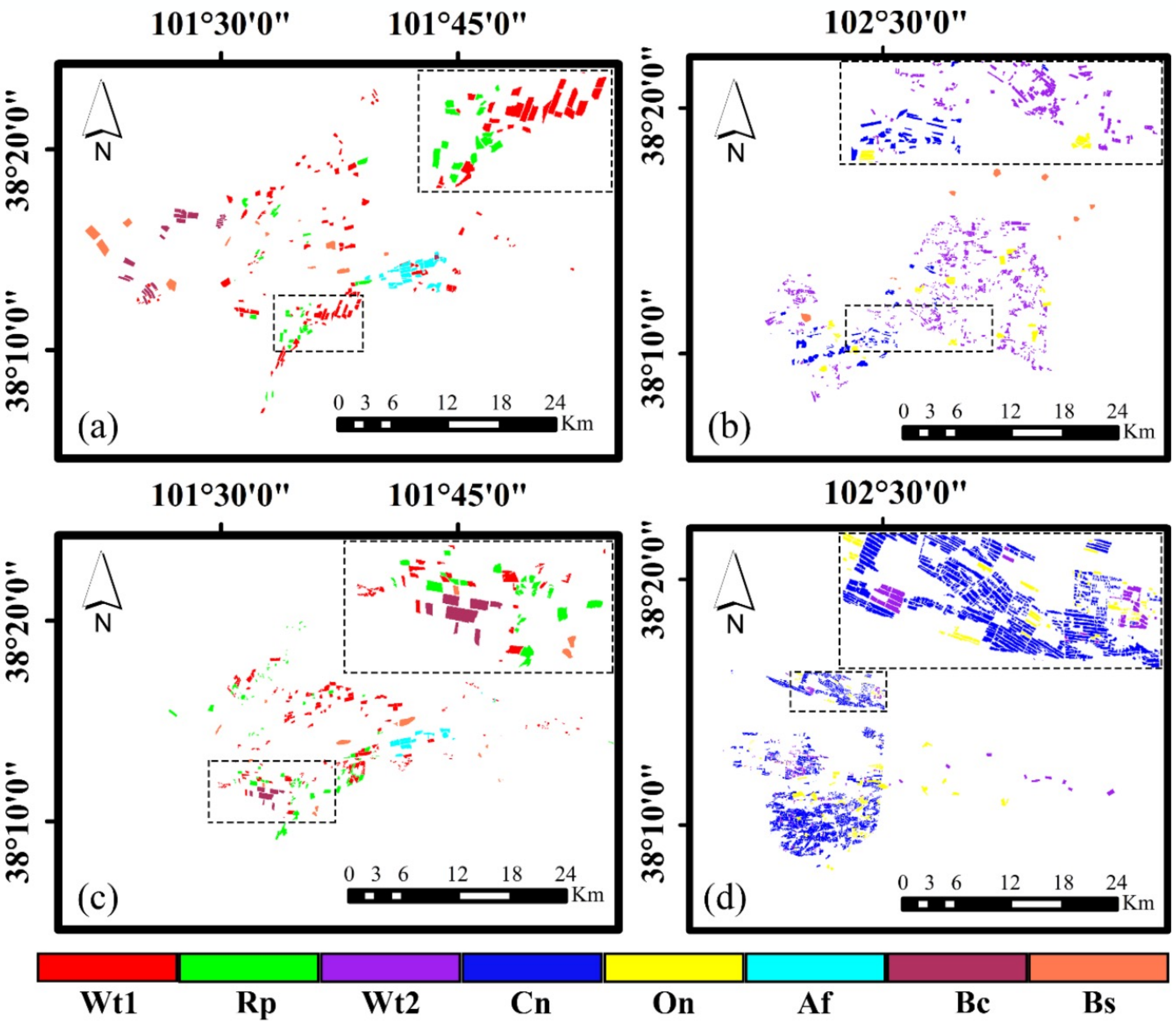
Training Samples



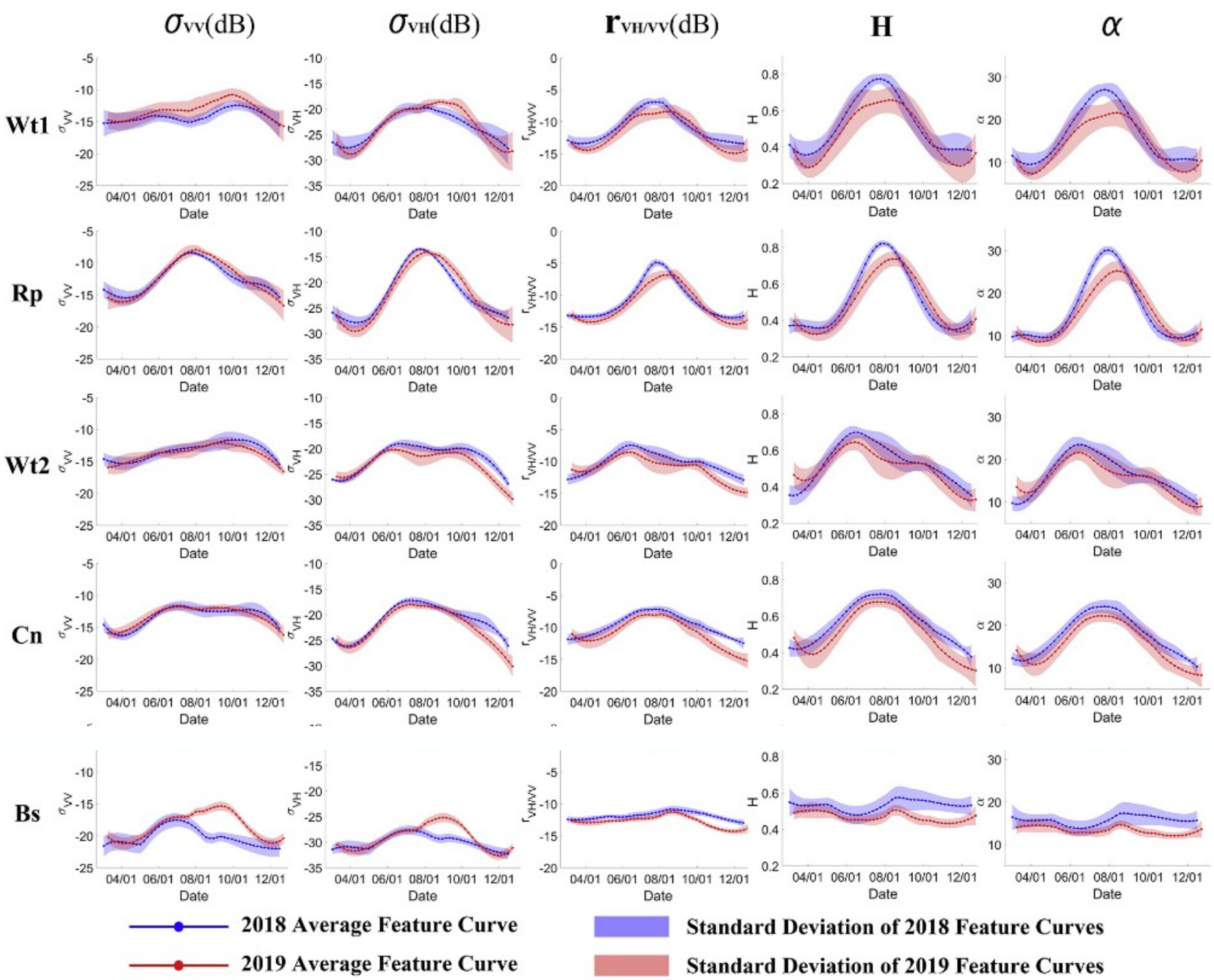
Testing Samples

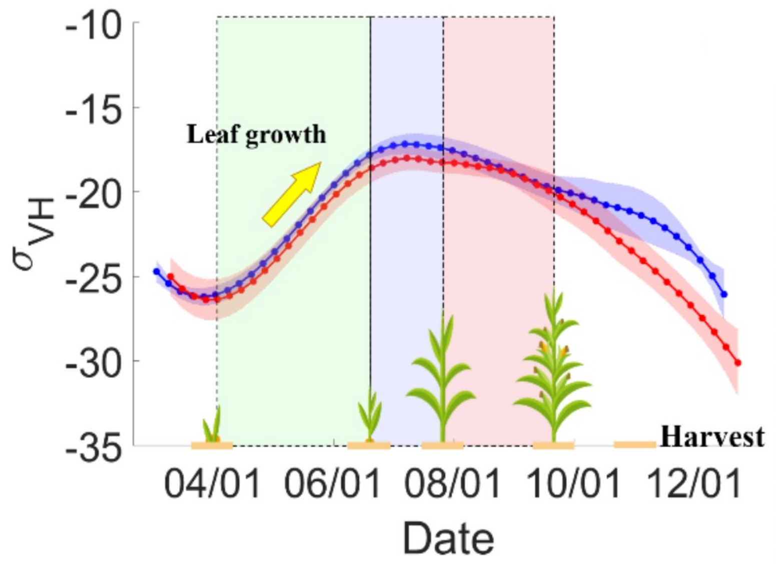
2018

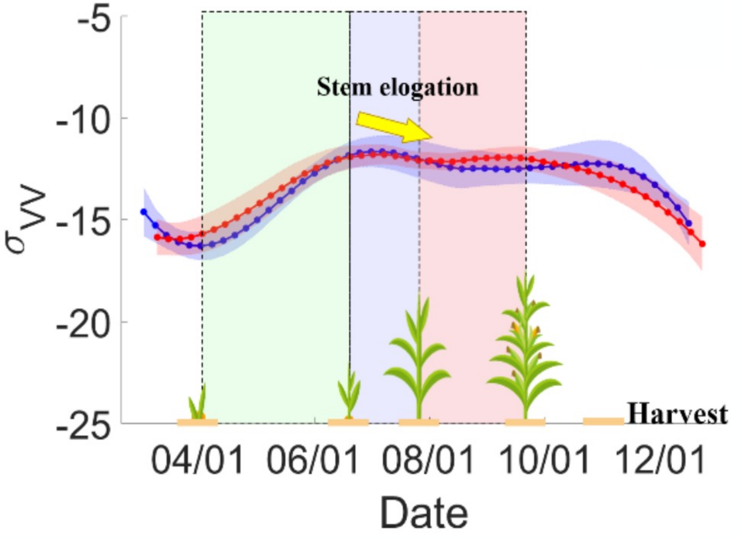
2019



Time-varying Feature Curves







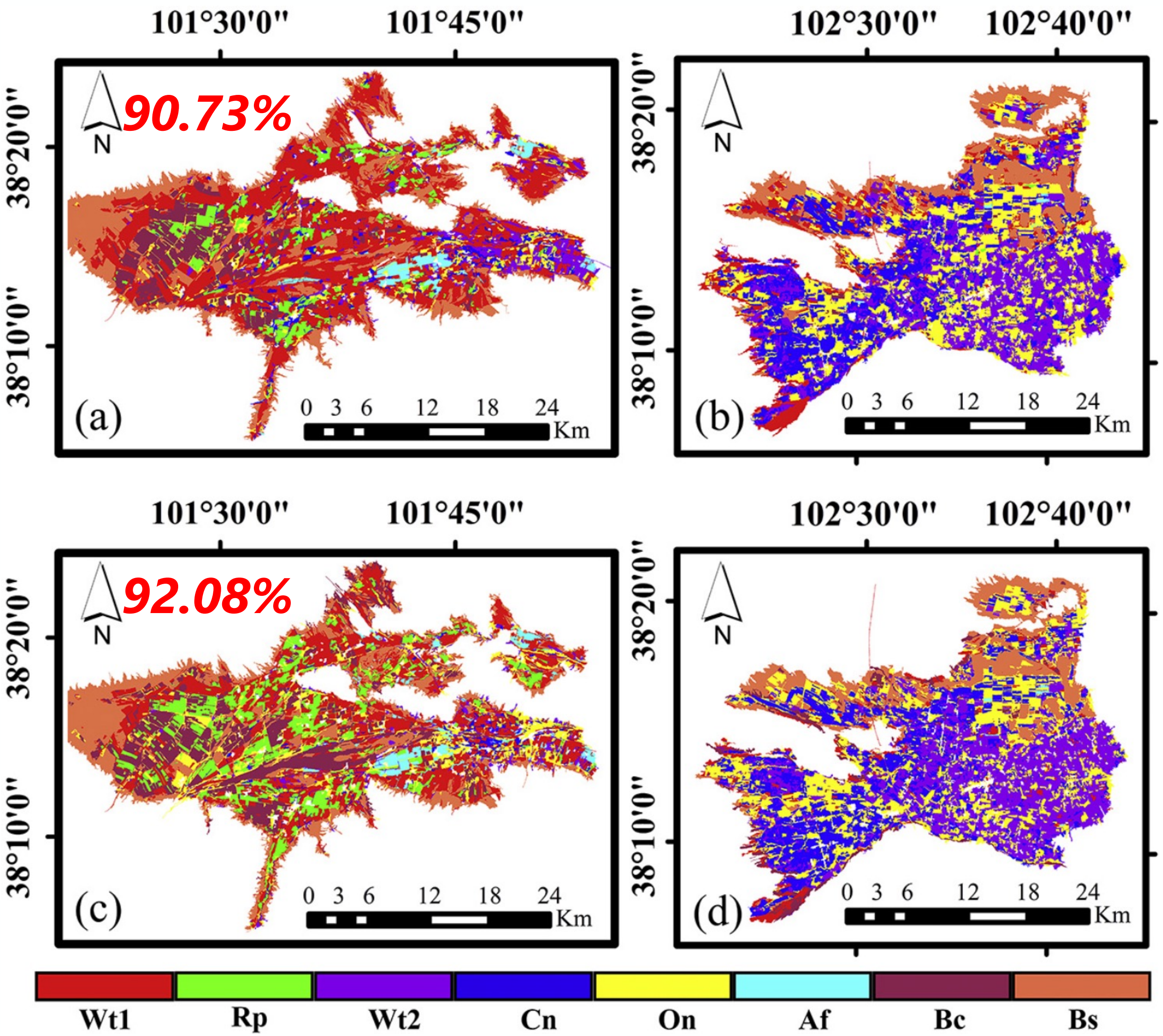
04

Results and Discussions

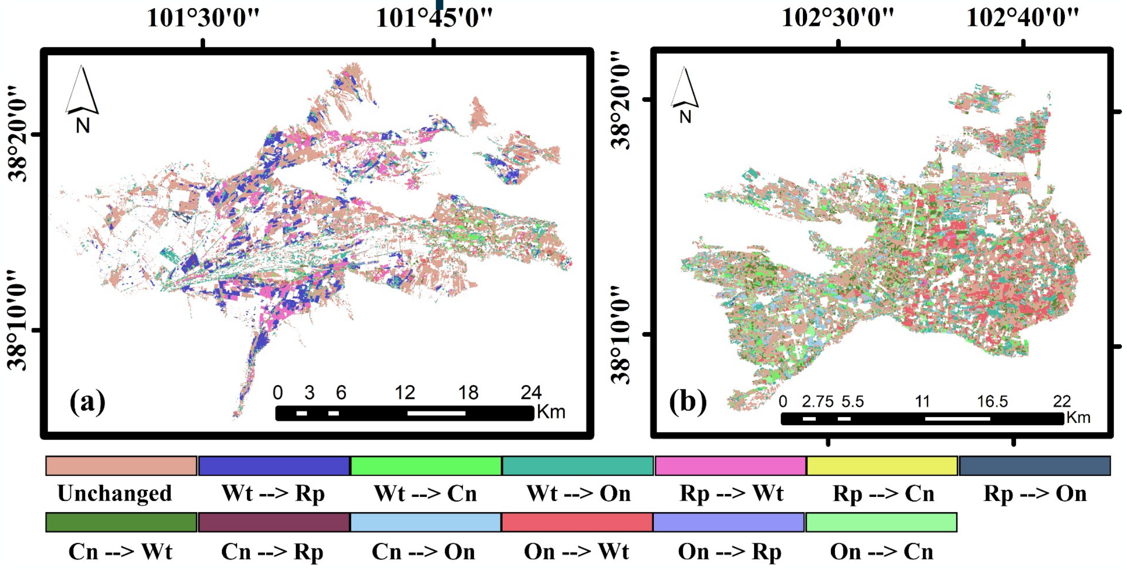
Our Classification Results

2018

2019



The crop rotation from 2018 to 2019



Region 1 : Wheat ←→ Rape

Region 2 : Onion ←→ Wheat / Corn

Consistent with local crop rotation.

The Comparison with Our Method and Other Classification Methods (Overall Accuracy)

	Year	DS-TWshapeDTW-ppfSVM	SVM	DS-TWshapeDTW-NN	SS-TWDTW-NN
OA	2018	**90.73%**	87.60%	80.04%	77.15%
	2019	**92.08%**	91.01%	83.73%	79.98%
kappa	2018	**0.8878**	0.8512	0.7633	0.7305
	2019	**0.8962**	0.8814	0.7923	0.7471

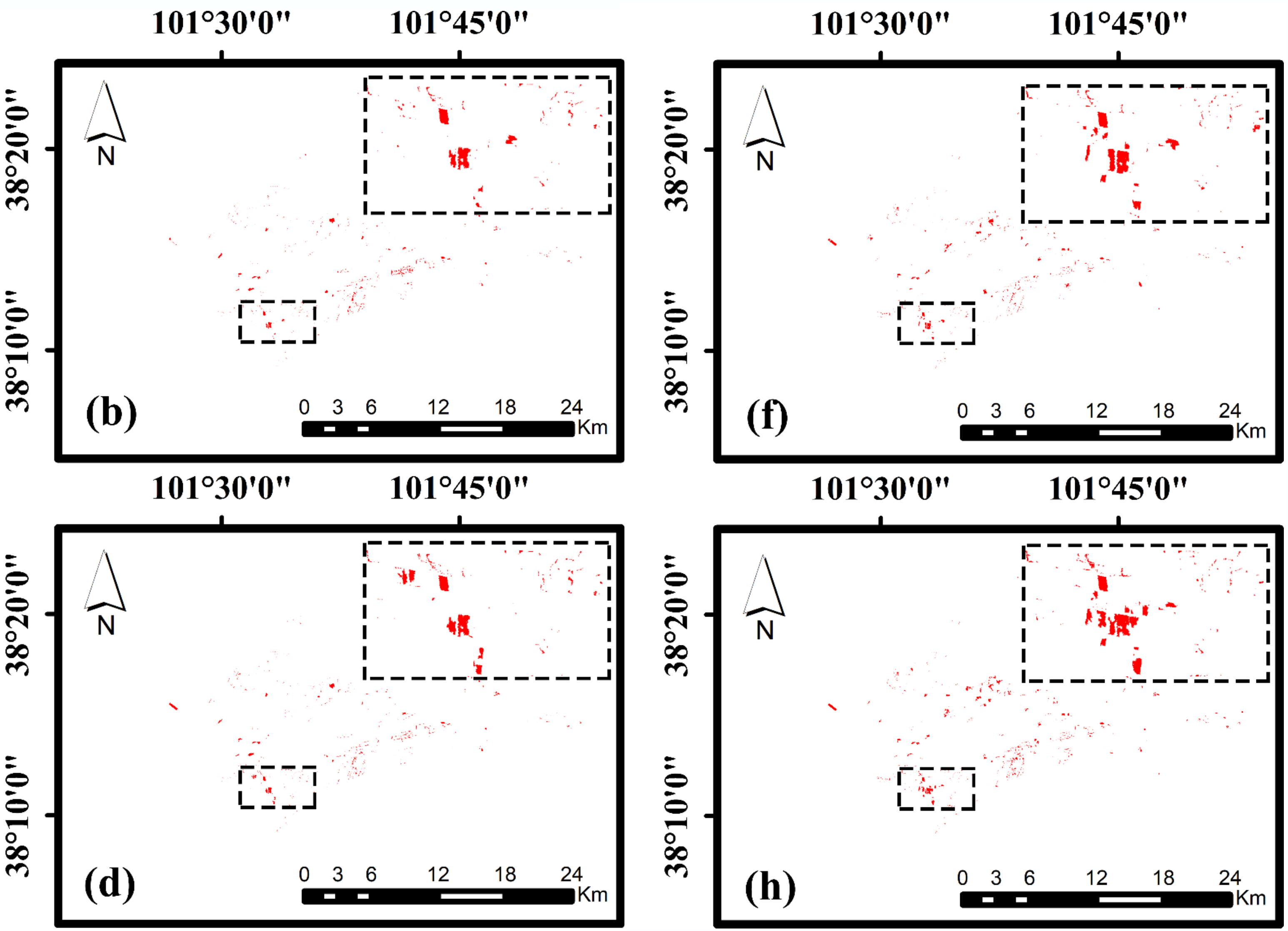
The Comparison with Our Method and Other Classification Methods (Classification Error Maps)

Our Method

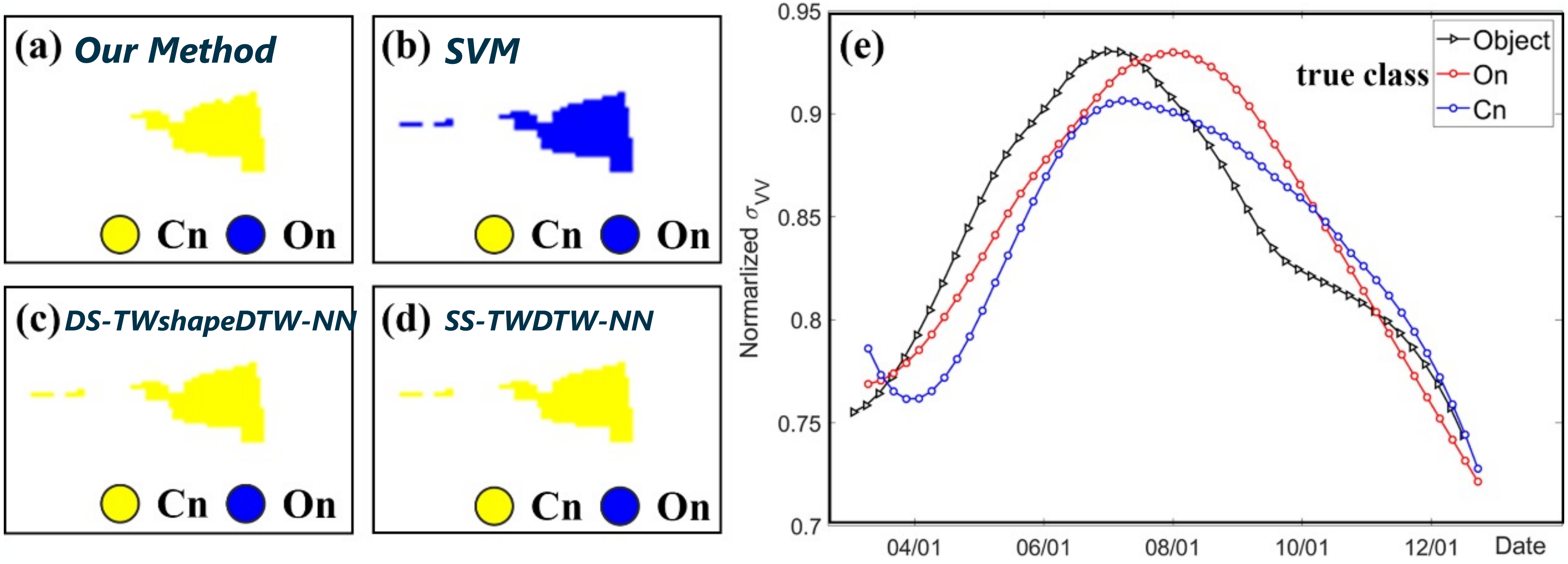
SVM

DS-TWshapeDTW-NN

SS-TWDTW-NN

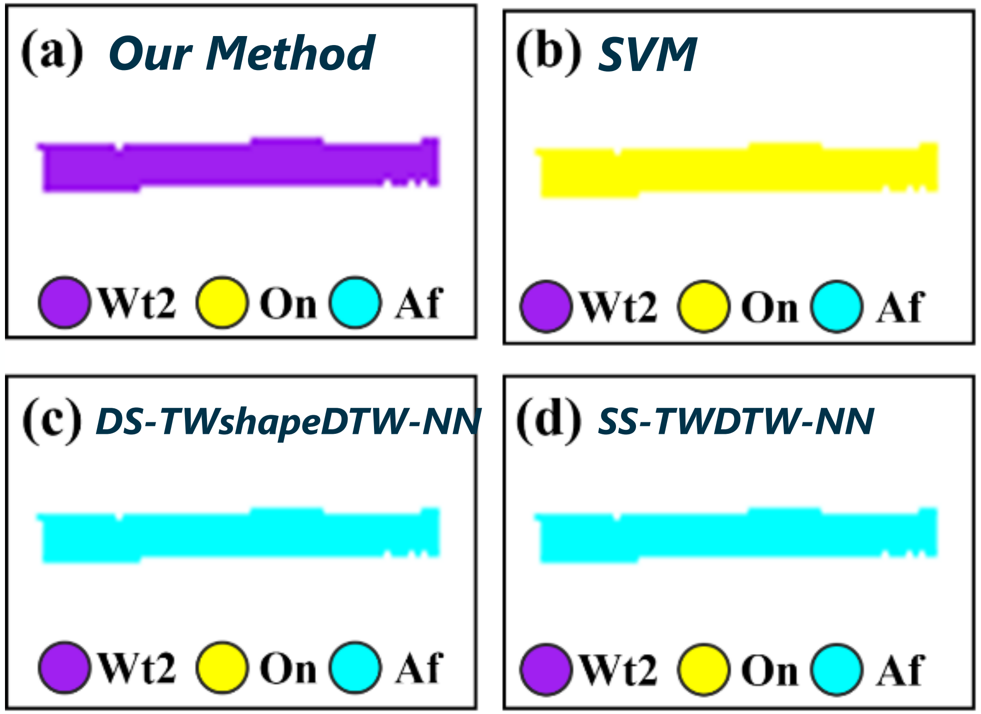


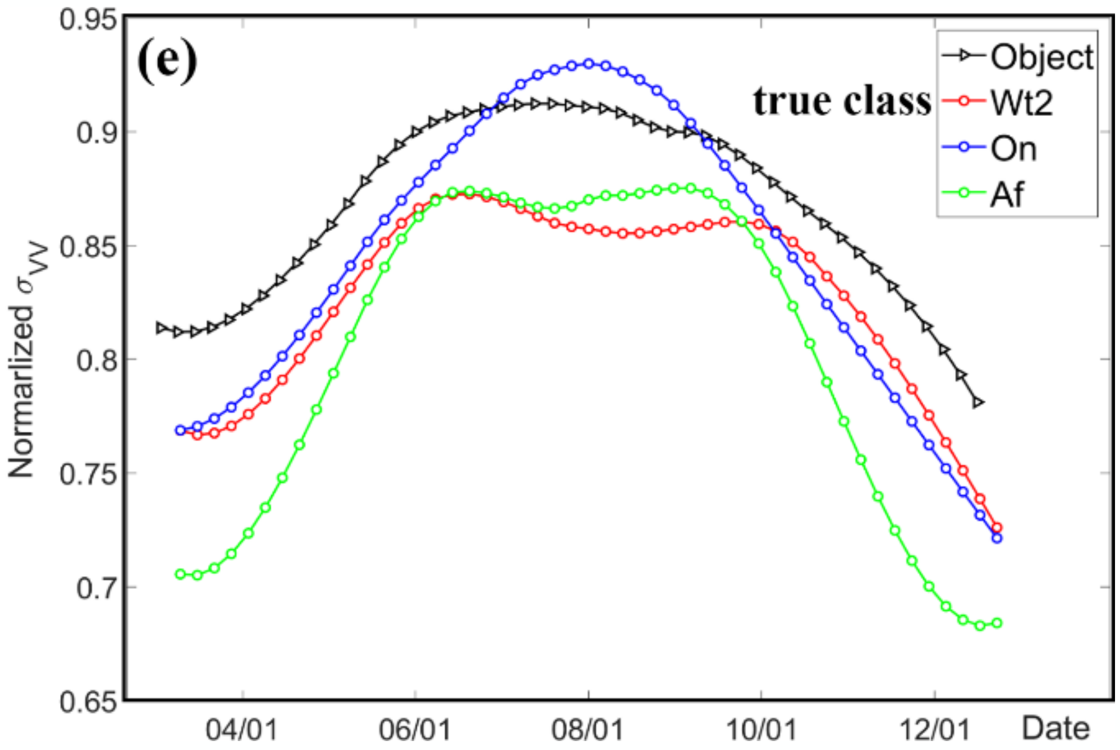
The Comparison with Our Method and Other Classification Methods (Typical Cases)



Considering the time series alignment, the parcel can be correctly discriminated as onion.

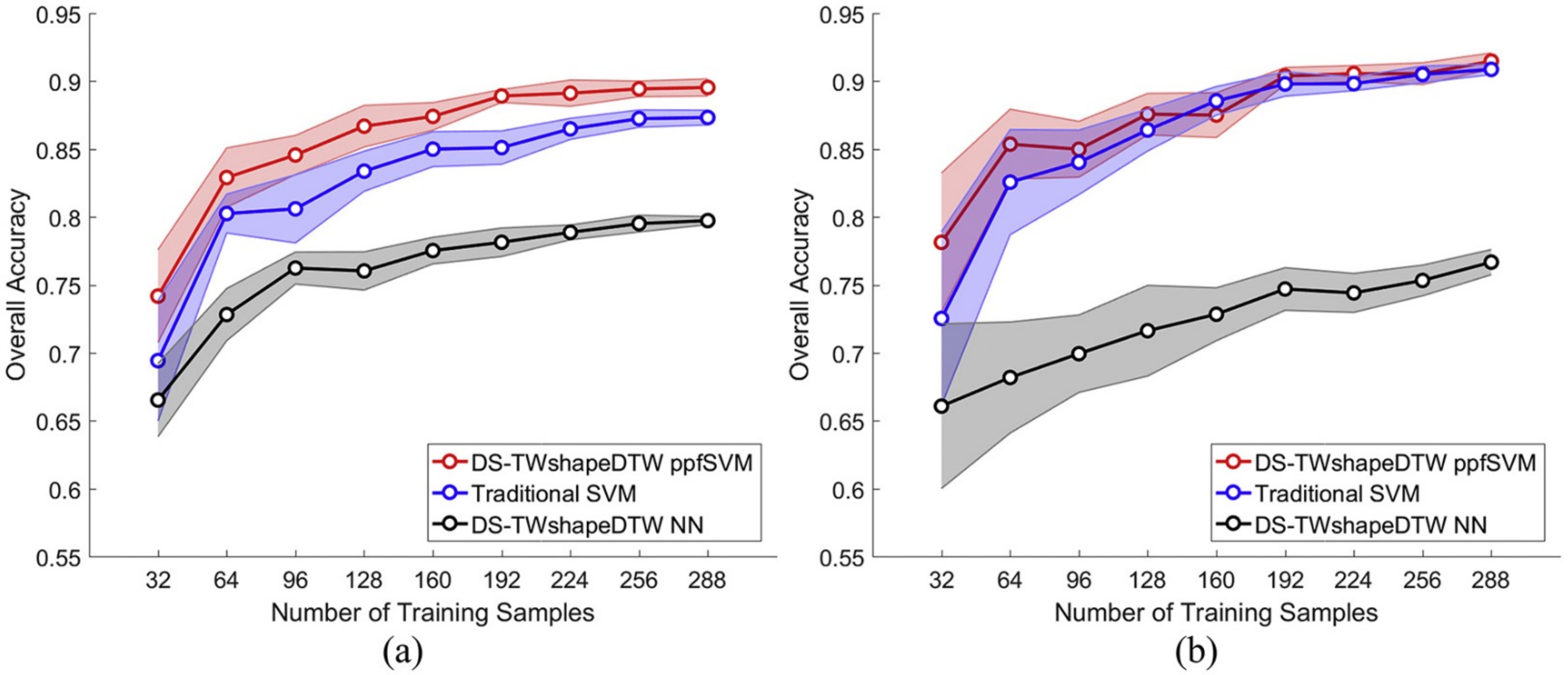
The Comparison with Our Method and Other Classification Methods (Typical Cases)





Considering the time series alignment + ppfSVM classifier the parcel can be correctly discriminated as wheat2.

The Comparison with Our Method and Other Classification Methods (Robustness)



The Comparison with Different Time Series Alignment

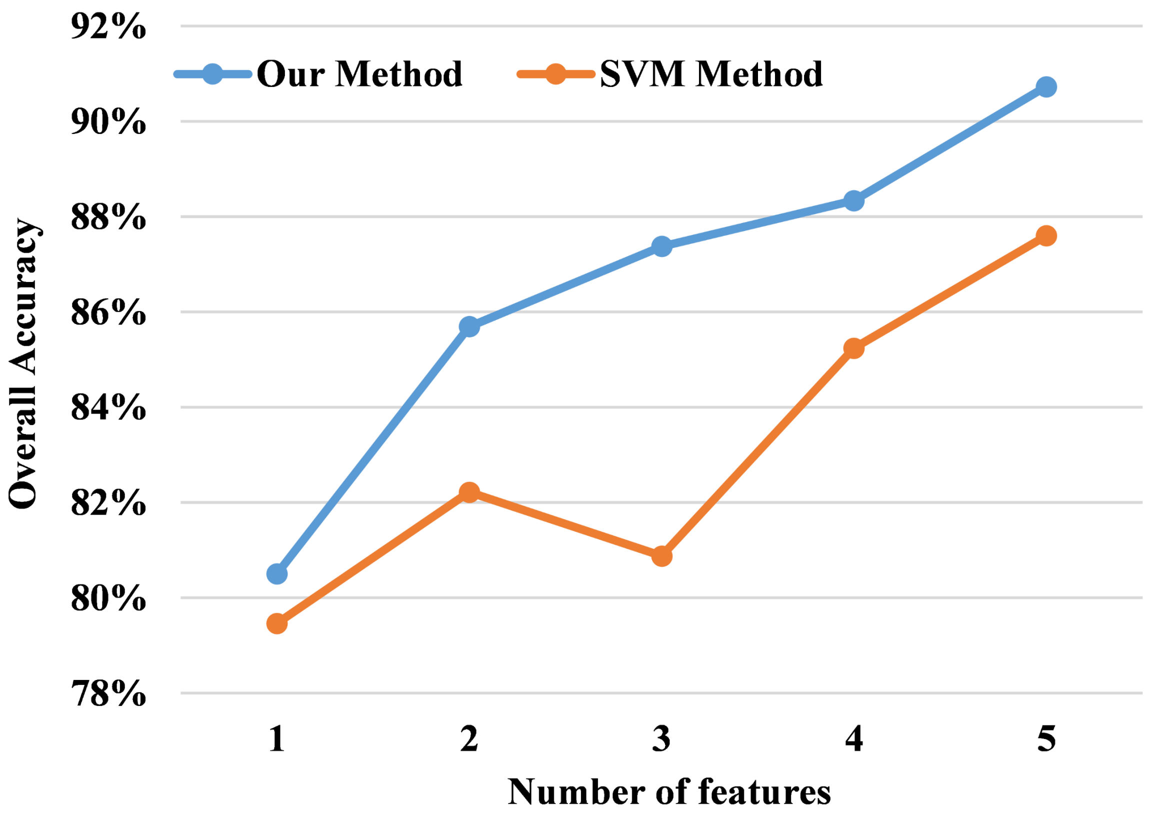
	Year	TWshapeDTW	TWDTW	shapeDTW	DTW
OA	2018	**90.73%**	89.00%	87.62%	85.33%
	2019	**92.08%**	90.19%	91.26%	88.22%
kappa	2018	**0.8878**	0.8672	0.8514	0.8235
	2019	**0.8962**	0.8726	0.8853	0.8465

The Influence of Various Features on Classification

	Year	All Features	σ_{VV}	σ_{VH}	H	α	r_{HVVV}
OA	2018	**90.73%**	80.51%	73.59%	79.90%	80.76%	79.57%
	2019	**92.08%**	88.25%	74.91%	82.54%	82.31%	81.52%
kappa	2018	**0.8878**	0.7657	0.6813	0.7587	0.7693	0.7548
	2019	**0.8962**	0.8466	0.6816	0.7754	0.7716	0.7623

The Sensitivity of Classification Methods to the Number of Features

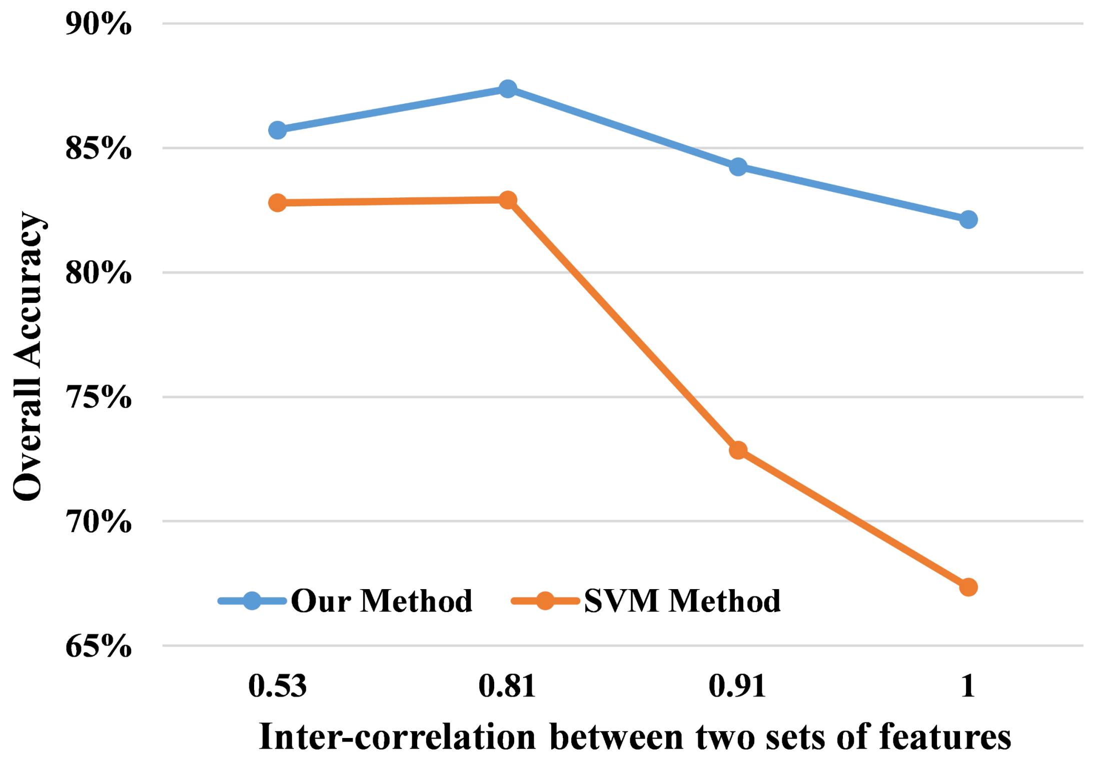
Feature sets	Number of Features
σ_{VV}	1
σ_{VV}, σ_{VH}	2
σ_{VV}, σ_{VH}, r_{HVVV}	3
σ_{VV}, σ_{VH}, r_{HVVV}, H	4
σ_{VV}, σ_{VH}, r_{HVVV}, H, α	5



The Sensitivity of Classification Methods to the Inter-correlation of Features

Table The inter-correlation of different features

	σ_{VV}	σ_{VH}	H	α	r_{HVVV}
σ_{VV}	1	0.86	0.81	0.81	0.91
σ_{VH}	0.86	1	0.53	0.53	0.64
H	0.81	0.53	1	1	0.91
α	0.81	0.53	1	1	0.90
r_{HVVV}	0.91	0.64	0.91	0.90	1



05

Conclusion

Conclusions

A novel crop classification method based on the ppfSVM classifier with the TWshapeDTW alignment kernel is proposed.

- *It establishes a* ***bridge*** *connecting multi-temporal PolSAR data and crop classification, and successfully* ***combines*** *the time series alignment and machine learning algorithms to improve classification ability.*

- *Compared with different classification methods, the proposed method can achieve the* ***highest OA*** *and the* ***best robustness*** *under different numbers of the training sample. It can be used in the* ***large-scale crop type mapping****.*

Thanks for the attention !

If you are interested in our work or the corresponding codes, welcome to contact me !

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Experimental details can be seen in following articles:

1. ***Gao H.***, *Wang C., Wang G., et al. A Novel Crop Classification Method Based on ppfSVM Classifier With Time-series Alignment Kernel From Dual-polarization SAR Datasets[J]. Remote Sensing of Environment, 264: 112628.*
2. ***Gao H.***, *Wang C., Wang G., et al. A New Crop Classification Method Based on the Time-Varying Feature Curves of Time Series Dual-Polarization Sentinel-1 Data Sets[J]. IEEE Geoscience and Remote Sensing Letters, 2019, 17(7): 1183-1187.*
3. *Wang, C., Ding L.,* ***Gao, H.****, *Lu L. Phenology Alignment-based PolSAR Crop Classification Considering Polarimetric Statistical and Time-Varying Curve Characteristics. IEEE Geoscience and Remote Sensing Letters, 2023, 20: 2501905*