



AOMSUC-15 2025 FYSUC

THE 15TH ASIA-OCEANIA METEOROLOGICAL SATELLITE USERS' CONFERENCE (AOMSUC-15)
2025 FENGYUN SATELLITE USER CONFERENCE (2025 FYSUC)

Reconstruction of Fine-spatial-resolution FY-3D- Based Vegetation Indices to Achieve Farmland- scale Winter Wheat Yield Estimation via Fusion with Sentinel-2 Data

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CONTENTS

01

Background
and Objectives

02

Data and Methods

03

Results and Analysis

01

Background and Objectives

Research Background



Winter wheat monitoring requirements

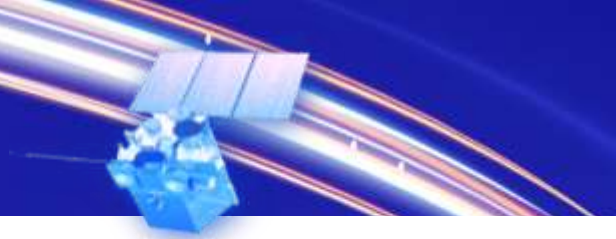
Winter wheat, as a staple food crop in northern China, requires high spatiotemporal resolution data support for yield estimation. Traditional FY-3D data has insufficient spatial resolution (250-1000m), making it difficult to meet the monitoring requirements at farmland scale (20-30m).

Integrating the advantages of different sensors

Sentinel-2 data (10-30 m) has high spatial resolution but low temporal resolution (5 days). Through spatiotemporal data fusion technology, the advantages of both types of data can be combined to achieve high-precision dynamic monitoring.

BIG DATA
VISUALIZATION





Research Objectives and Technical Approach

Research Objectives

A spatiotemporal fusion framework based on the vegetation indices of FY-3D and Sentinel-2 with a 20 m spatial resolution was constructed to estimate the yield of winter wheat at the field scale.

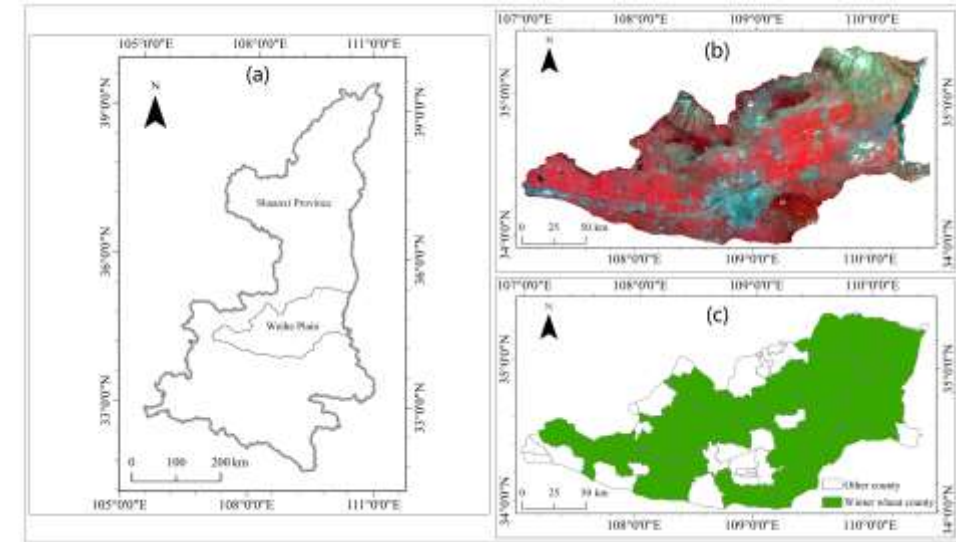
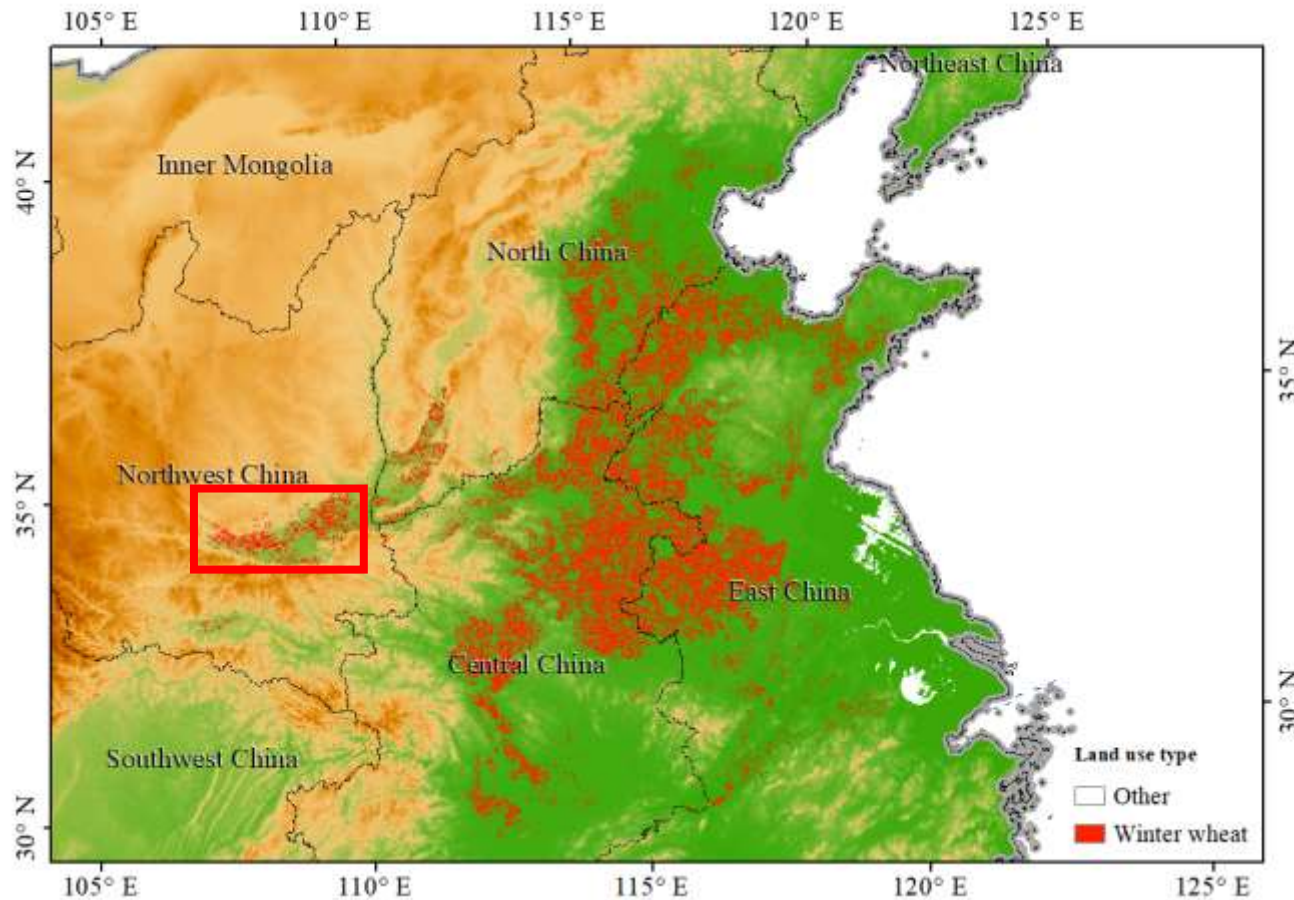
Technical Approach

Two-step method of "data fusion-yield modeling" was adopted:
1) reconstruct the 10-day interval vegetation indices data with 20 m spatial resolution by using spatiotemporal fusion models;
2) construct the yield estimation model by using BP neural network and MODIS GPP data.

02

Data and Methods

Study Area and Data

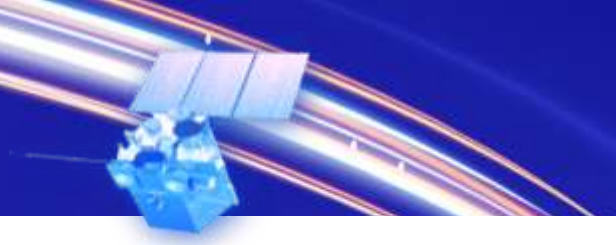


Overview of the Study Area

The study area is located in the Guanzhong Plain, Shaanxi Province (106°22'-110°24'E, 33°57'-35°39'N), a typical winter wheat planting area, an average annual temperature of 6-13 °C, and precipitation of 500-700 mm.

Data Sources and Preprocessing

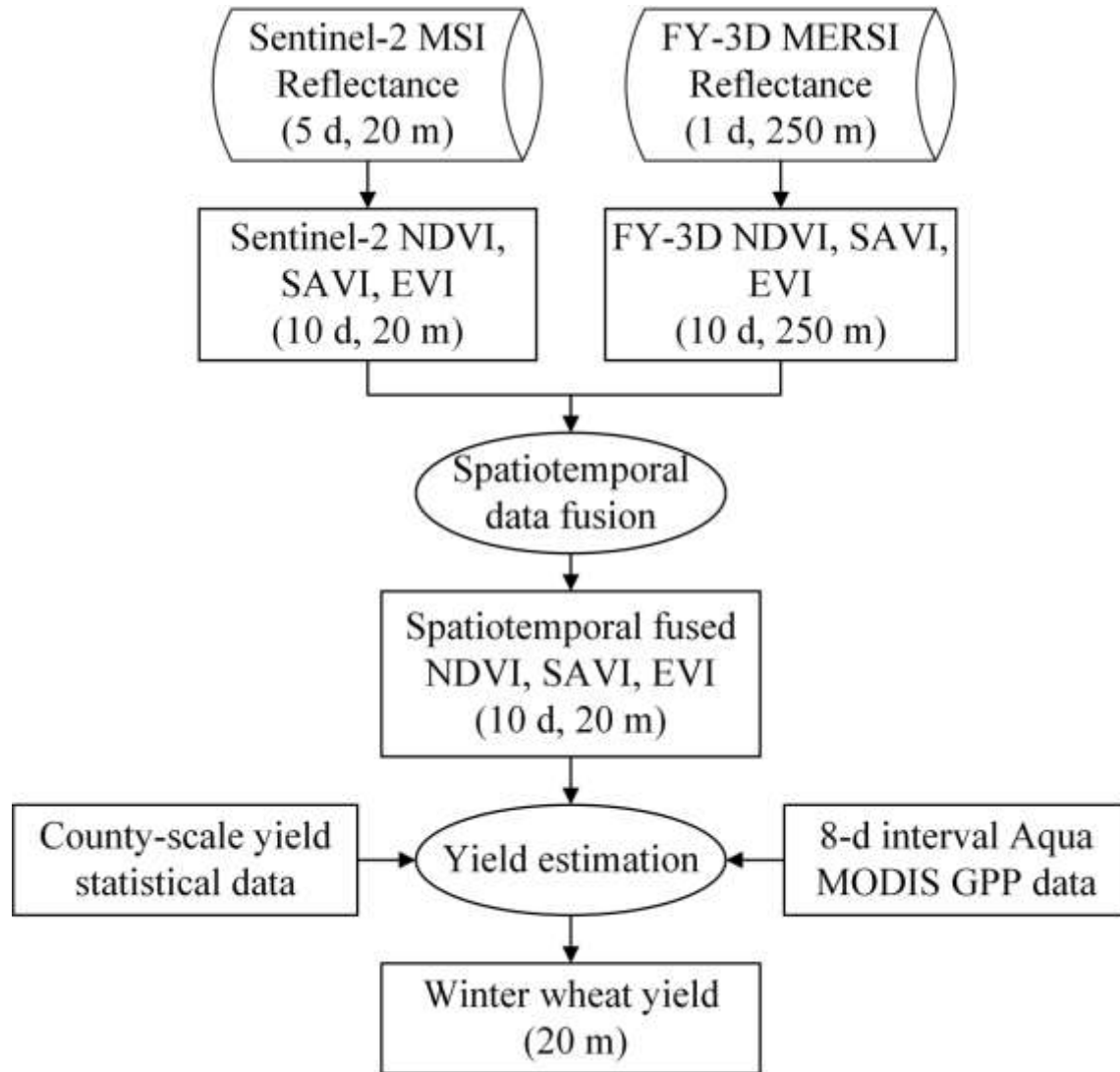
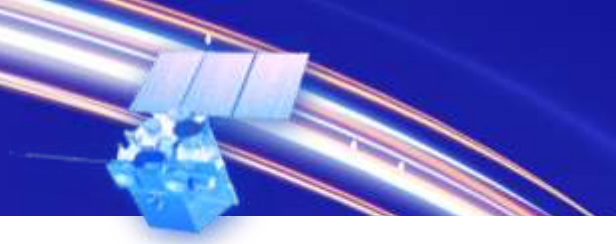
Data sources: FY-3D MERSI (250m), Sentinel-2 MSI (20m) vegetation index data and MODIS GPP products (500m) from 2020 to 2022, NDVI, SAVI and EVI indices were calculated.



Study Area and Data

Table 1.Dates of the Sentinel-2 and FY-3D data under cloudless conditions.

Period	2020		2021		2022	
	Sentinel-2	FY-3D	Sentinel-2	FY-3D	Sentinel-2	FY-3D
Early March	4	4		3	4	2, 7, 10
Mid-March		14, 17-19		12, 13		13
Late March		23, 24	29	27, 28		28
Early April	8	8		8	8	6, 8, 10
Mid-April		12	18	12, 17, 18		13, 20
Late April	28	24-26, 28	28	28, 29, 30	23	21, 23, 25
Early May	3	1, 3	8	4, 5, 8, 9	3	2, 3, 6, 7
Mid-May	18	15, 16				16, 17, 19
Late May				24, 30, 31	23	22, 24



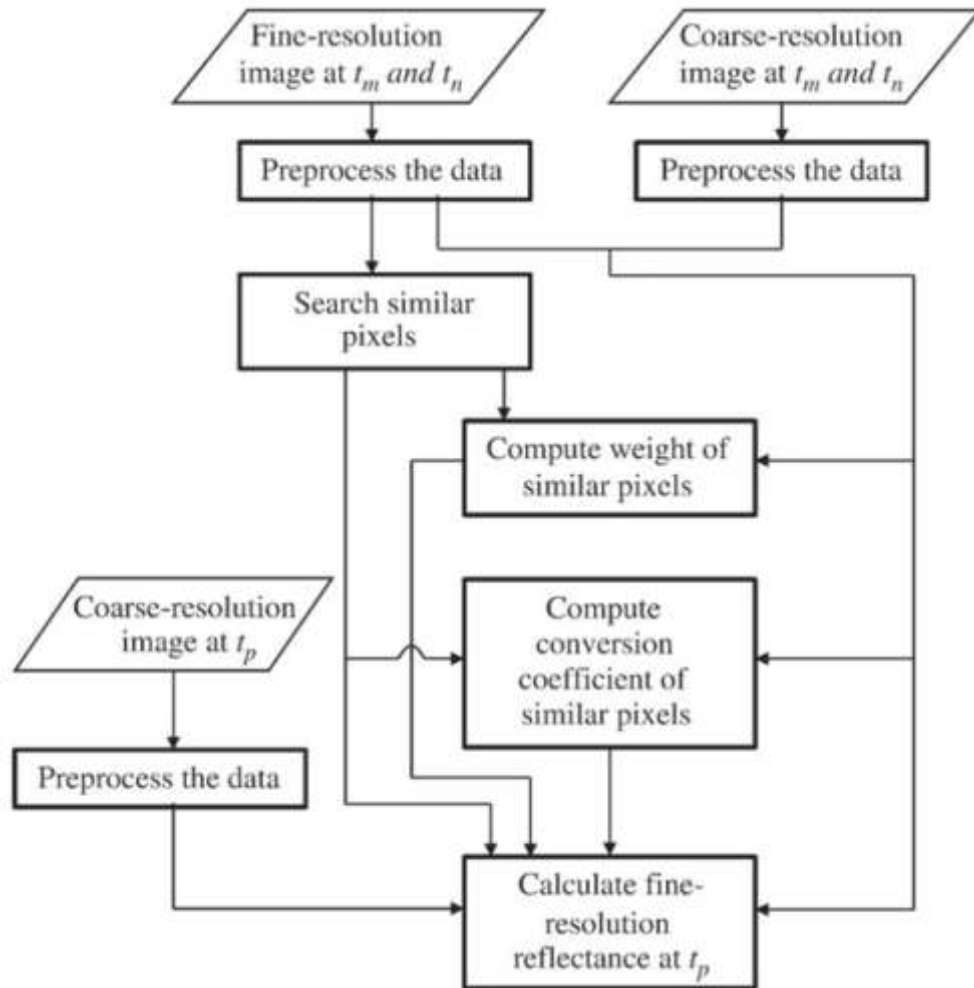
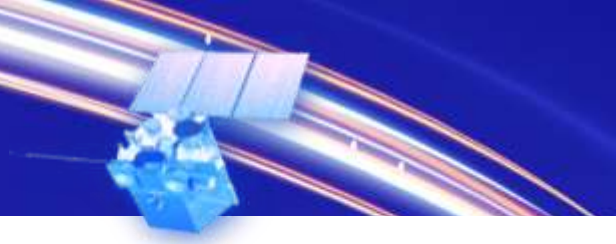
Technical Approach

Spatiotemporal data fusion models

the enhanced depth convolutional spatiotemporal fusion network (EDCSTFN), the enhanced spatial and temporal adaptive reflectance fusion model (ESTARFM) were used in this study

Winter wheat yield estimation model

Construct a two-level estimation framework: establish a linear regression model based on MODIS cumulative GPP and county-level yield data to generate a 500 m yield imagery, and then combine with the reconstructed VI data to train the BP neural network to achieve the yield retrieval at a 20 m scale.



(Zhu et al, 2010)

Key Technical Approach —ESTARFM Model

Input data

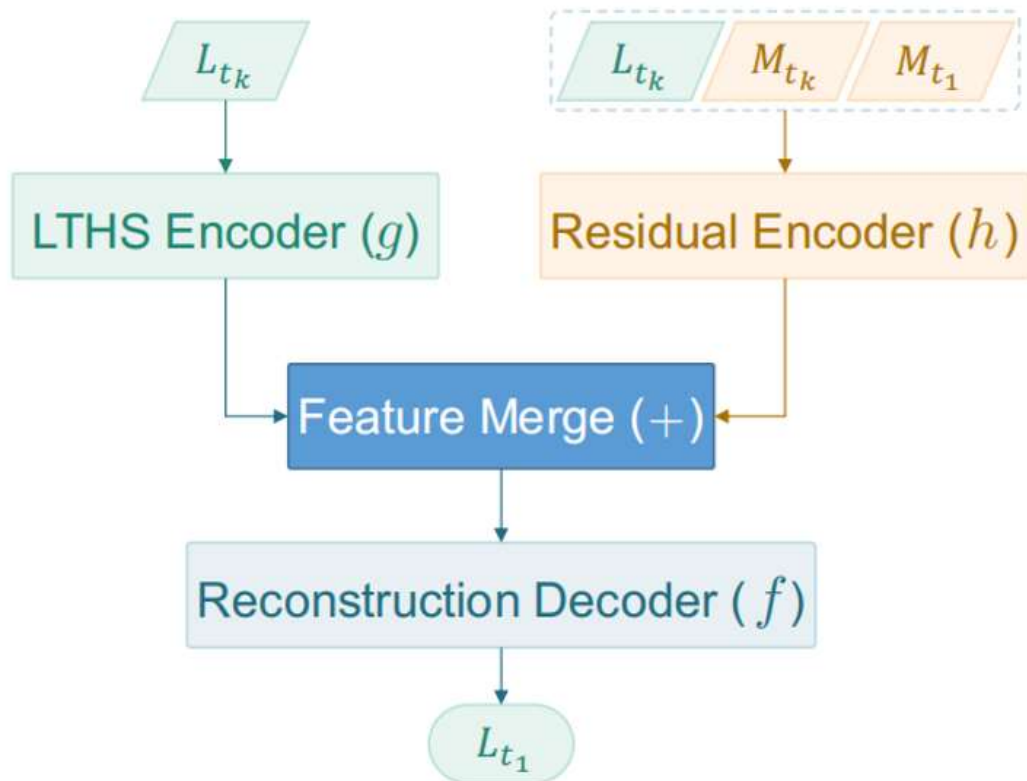
2 pairs of Sentinel-2 and FY-3D images as reference images; 1 FY-3D image of the predicted date

Date Setting Scheme

Select 2 pairs of reference images in mid-March and late April;

Predict the FY-3D vegetation index images with 20m spatial resolution from March to May.

Key Technical Approach—EDCSTFN Model



(b) EDCSTFN
Tan et al, 2019

Input data

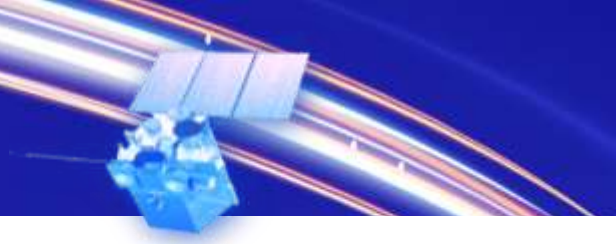
1-2 pairs of FY-3D and Sentinel-2 images as reference images;
1 FY-3D image on the prediction date

Model Training Scheme

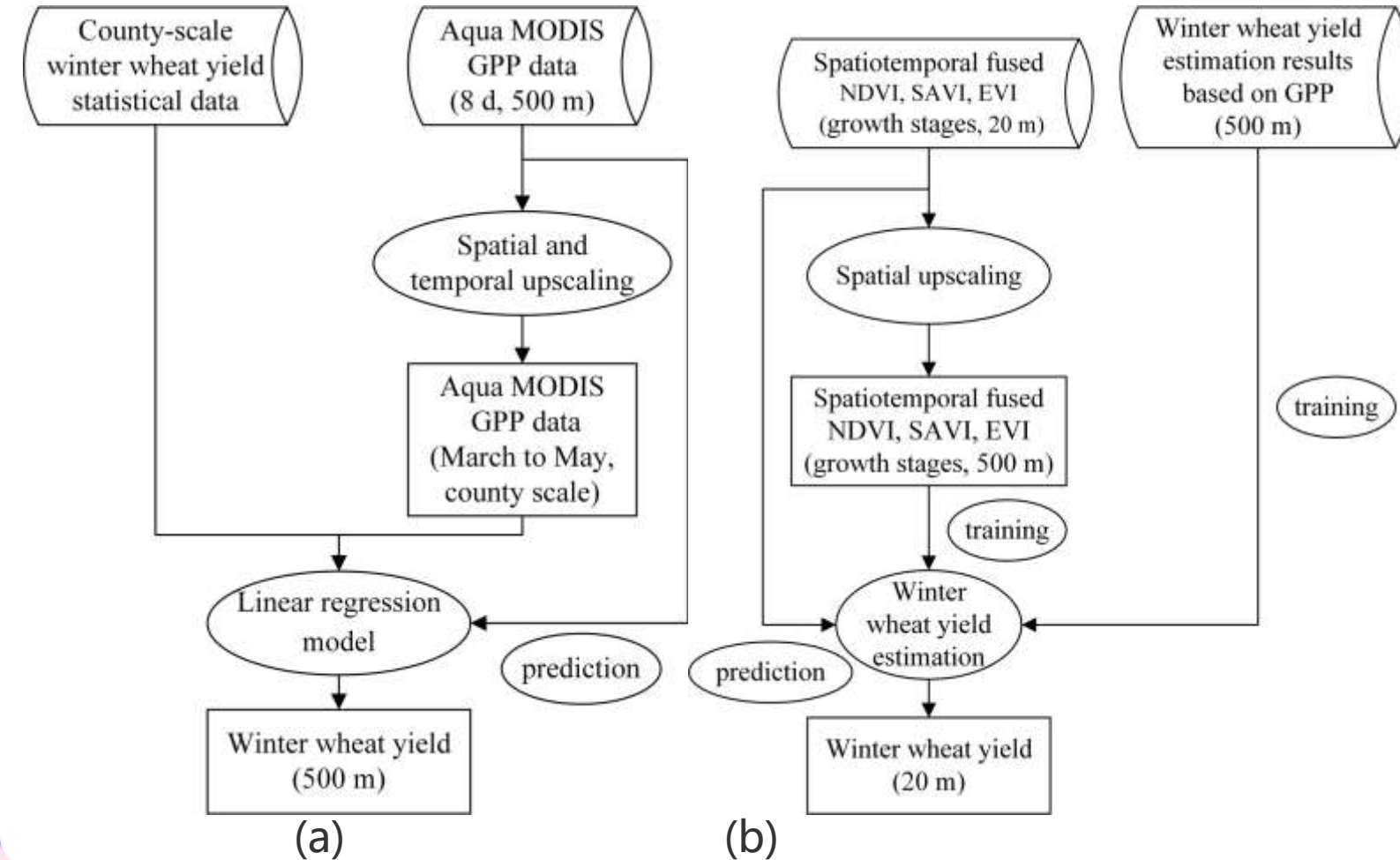
Two 1500*1500-pixel regions were selected in the western and central parts of the Guanzhong Plain. Two of them were randomly selected as training images and the other two as validation images.

Table 2.Data AQD for EDCSTFN training in 2020.

Data group	Reference imagery date	Predicted imagery date
1	Early March	Early April
2	Early April	Early March
3	Early April	Late April
4	Late April	Early April
5	Late April	Mid-May
6	Mid-May	Late April



Yield estimation model



Step 1: 500 m yield estimation

- 1) Develop a linear regression model between the cumulative Aqua MODIS GPP in March to May and county-level yield of Guanzhong Plain in 2014-2018
- 2) Use the developed model to estimate the 2020 winter wheat yield at 500 m

Step 2: 20 m yield estimation

- 1) Based on the 500 m yield data, a BP neural network yield estimation model based on the fused VIs was constructed.
- 2) The 20 m fused VIs were input into the winter wheat yield estimation model to estimate the 20 m winter wheat yield image

03

Results and Analysis

Data fusion Accuracy evaluation (2022)

Short-term prediction (2 scenes of reference image interval 1.5 months)

The R^2 of the two fusion models are all above 0.9, the overall accuracy is comparable, and the spatial detail retention capability is similar

Long-term prediction (2 scenes of reference image interval 2.5 months)

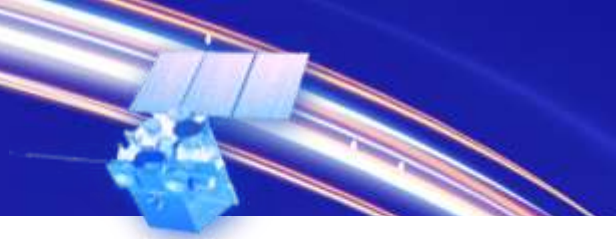
The fusion precision of EDCSTFN is significantly superior, with the R^2 of NDVI remaining above 0.75, an improvement of about 10% compared to ESTARFM (0.68).

VI	Prediction date	EDCSTFN 10 min/imagery			ESTARFM 180 min/imagery		
		R^2	$RMSE_{fit}$	AD	R^2	$RMSE_{fit}$	AD
NDVI	Early April	0.89	0.05	-0.02	0.89	0.05	0.00
	Early May	0.86	0.05	0.03	0.88	0.05	0.03
SAVI	Early April	0.90	0.04	0.00	0.92	0.04	0.00
	Early May	0.92	0.04	0.01	0.92	0.04	0.00
EVI	Early April	0.92	0.05	-0.02	0.92	0.05	0.00
	Early May	0.91	0.05	-0.02	0.93	0.05	0.00

VI	Prediction date	EDCSTFN			ESTARFM		
		R^2	$RMSE_{fit}$	AD	R^2	$RMSE_{fit}$	AD
NDVI	Early April	0.77	0.07	-0.01	0.74	0.07	0.00
	Early May	0.84	0.05	-0.02	0.77	0.07	0.03
SAVI	Early April	0.75	0.06	0.01	0.69	0.07	0.01
	Early May	0.84	0.05	0.00	0.81	0.06	0.02
EVI	Early April	0.75	0.09	-0.01	0.68	0.10	0.01
	Early May	0.83	0.08	-0.04	0.79	0.09	0.00

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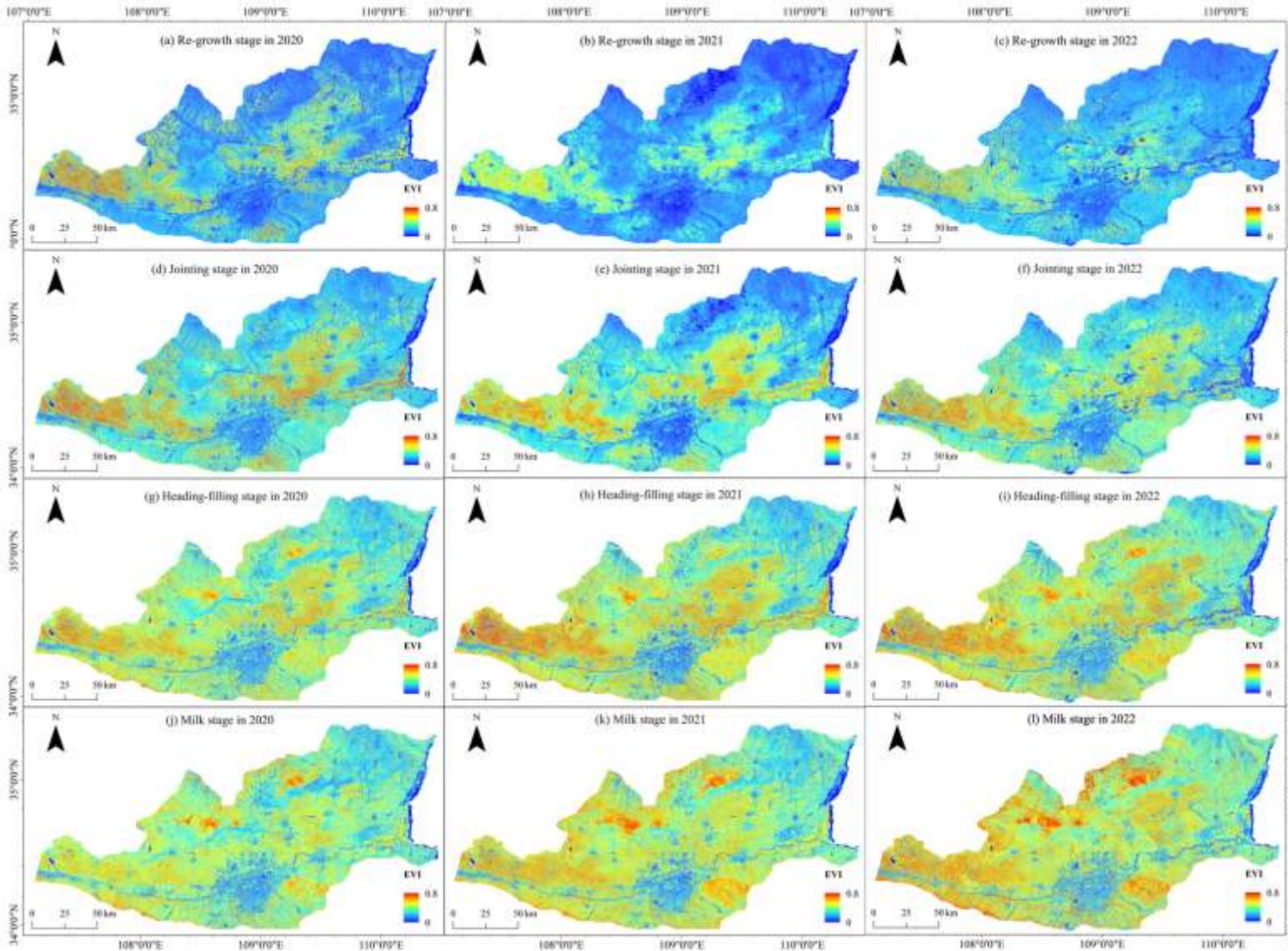
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Data fusion result (2020-2022)

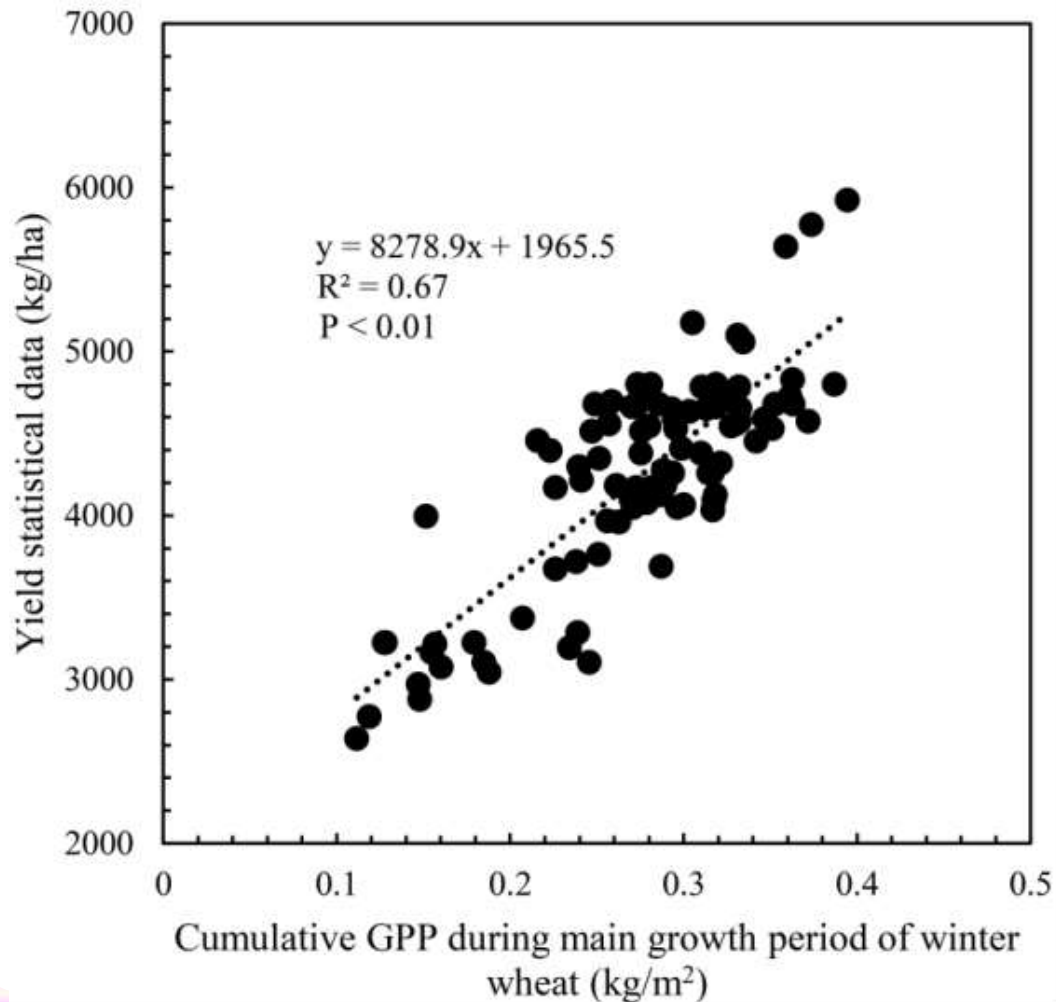
10-day fused VIs to 4 growing stages of winter wheat

20-m SR NDVI, SAVI and EVI imagery for the 4 growing stages (regrowth stage, jointing stage, heading-filling stage, milk stage) were obtained by averaging the 10-day spatiotemporally fused NDVI, SAVI and EVI imagery from March to May from 2020 to 2022.





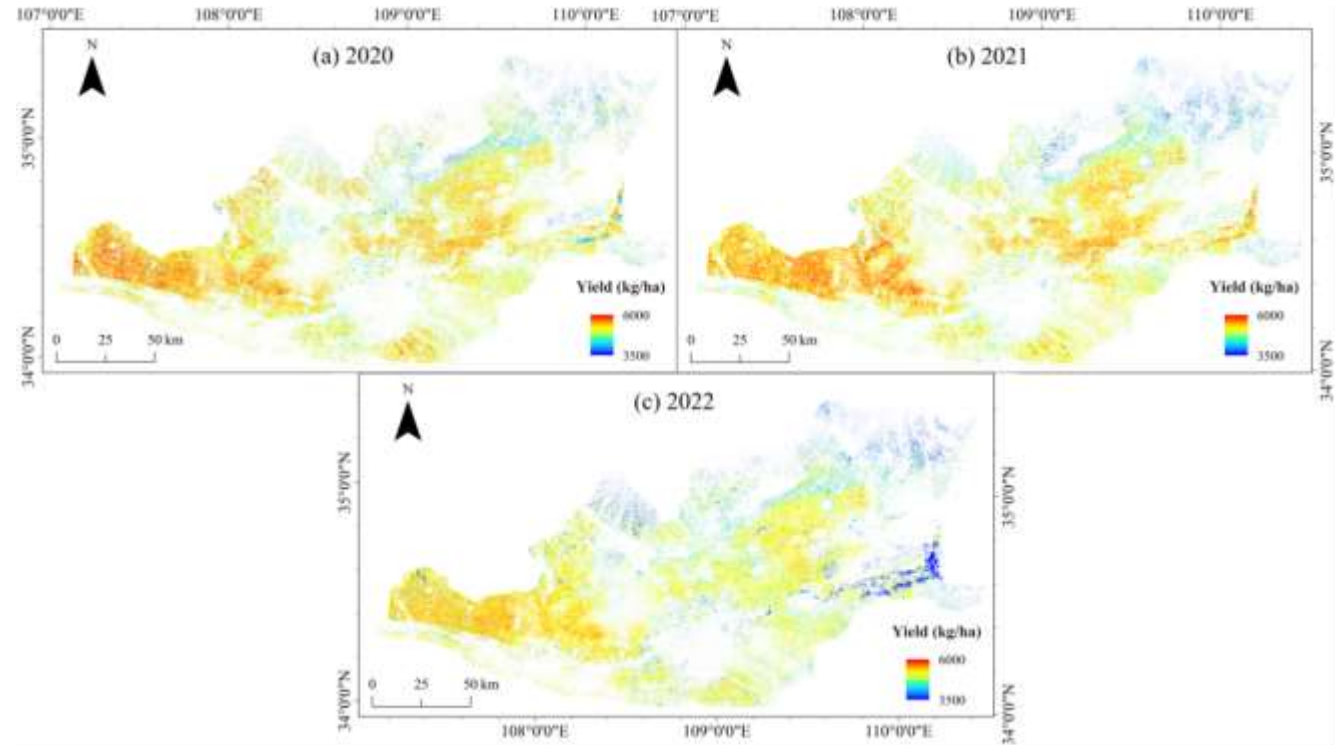
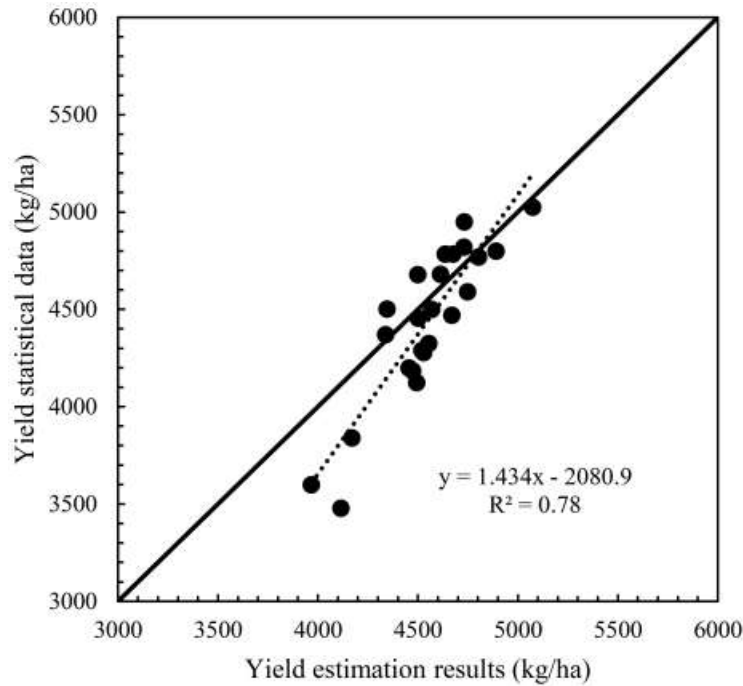
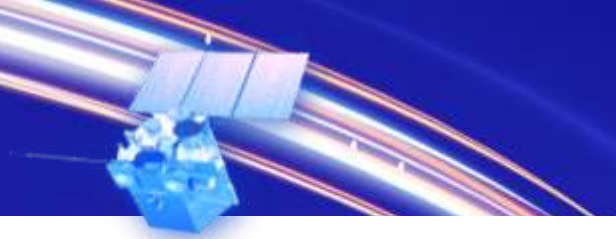
Winter wheat yield estimation result



Step 1: estimate 500 m winter wheat yield based on MODIS cumulative GPP data

8-day-scale Aqua MODIS GPP data for the main growing period (from March to May of each year) from 2014 to 2018 were collected, and a linear regression model relating the cumulative GPP data for the main growing period over the 5-year period and the county-scale yield statistical data was constructed

The regression results reveal that the cumulative GPP data for the main growing period on the Weihe Plain from 2014 to 2018 were strongly correlated with the yield statistical data at the county scale, with an R^2 value of 0.67 ($P < 0.01$)



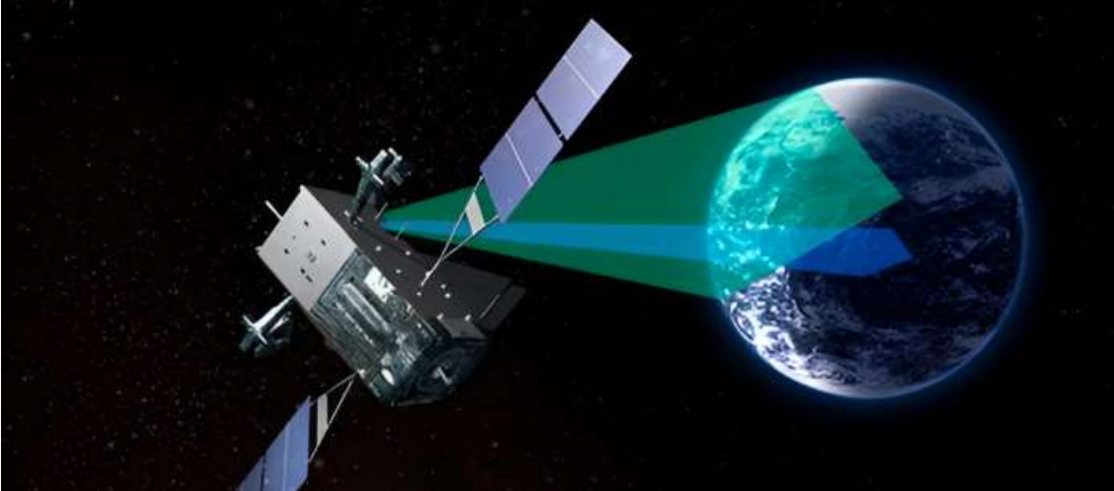
Step 2: estimating 20 m winter wheat yield based on spatiotemporal fusion vegetation index

The R^2 of the yield estimation results of BP neural network model reached to 0.78 ($p < 0.01$) in the verification at the county scale in 2020, which was 5-14% higher than that of the GPP linear model with a 500 m spatial resolution (0.65).

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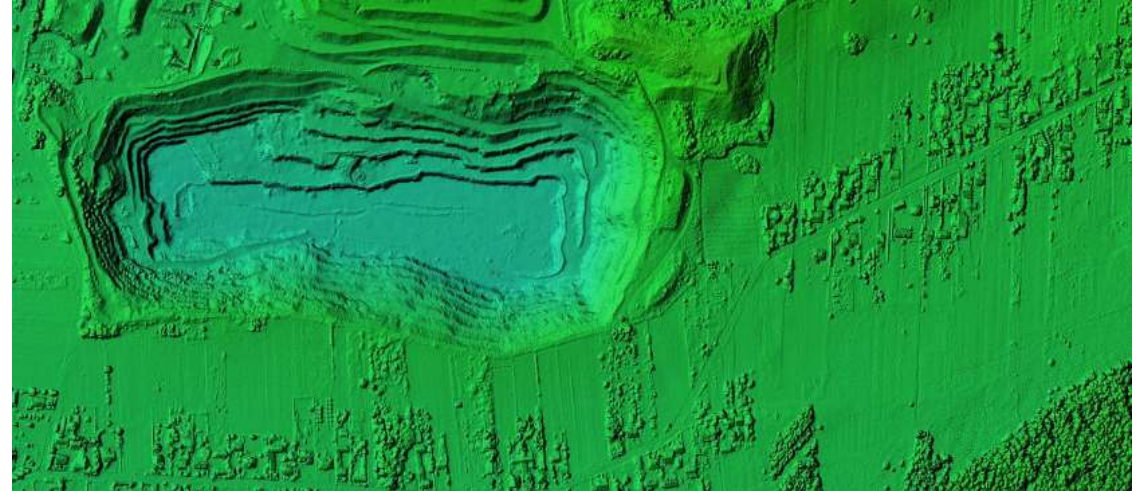
Discussion and Conclusion

Advantages and Limitations



Technological Innovations and Advantages

The deep learning spatiotemporal fusion of FY-3D and Sentinel-2 vegetation indices is realized, and provides a new way for the application of China's satellite data precision agriculture.

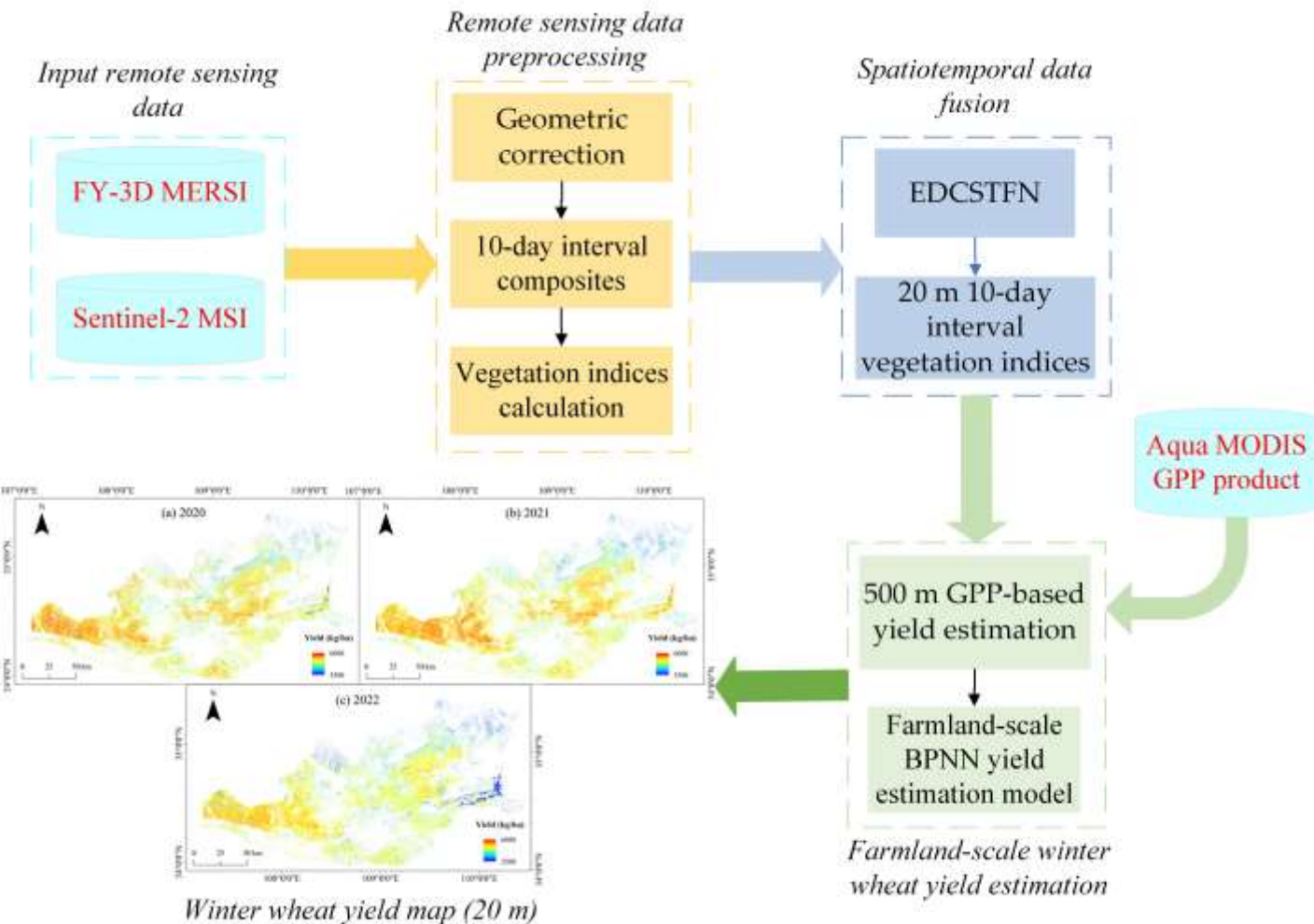


Limitations

Geometric correction bias of FY-3D data (1-2 pixels) leads to fusion uncertainty.

Sentinel-2's temporal resolution (5 d) is still low, and it is often impossible to obtain data in the wheat growth season with more clouds.

Conclusions and Prospects



Main conclusion

EDCSTFN can effectively reconstruct the vegetation index of FY-3D with a resolution of 20 m. Compared with the traditional ESTARFM model, it demonstrates significant advantages in accuracy and computational efficiency.

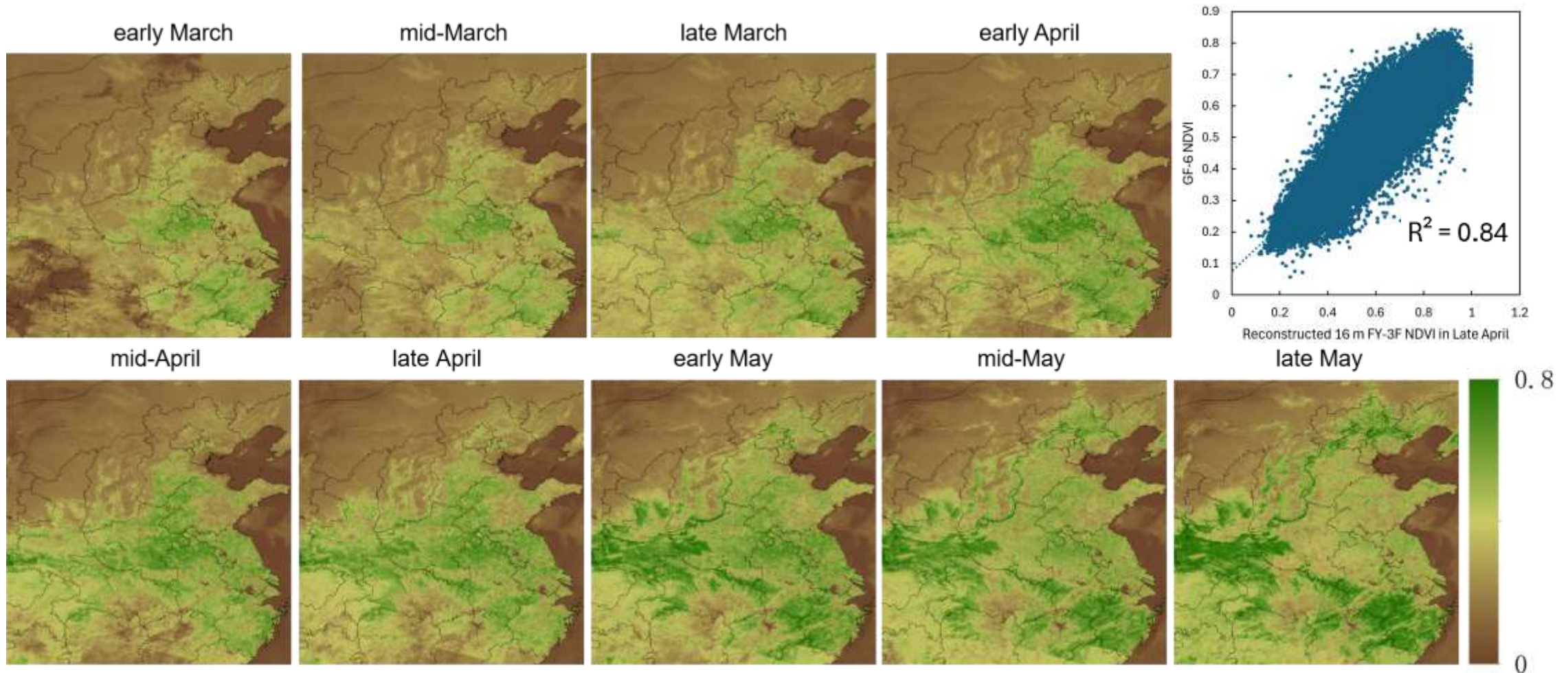
The reconstructed VI in multiple growth periods can achieve high-precision estimation of wheat yield at the field scale ($R^2 > 0.65$), and the spatial detail richness is better than the FY3D image estimation results.

Future Prospects

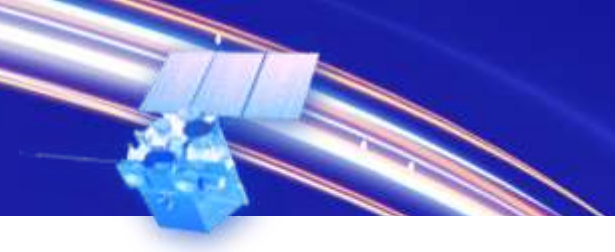
Integrates the GF and HJ series of domestic high-resolution data (with a temporal resolution of 2 days) and the FY-3D/F data (with a temporal resolution of 0.5 days), shortening the fusion temporal resolution to 5 days



The latest research findings based on GF-6 and FY-3F



Based on the EDCSTFN, the 16 m FY-3F NDVI images for every 10-day period from March to May 2024 in the winter wheat planting areas of eastern China were reconstructed. (Computational efficiency: 8h/imagery, Intel core i9-14900K)



THE END

Thanks