Combined Use of Optical and SAR Data for Soil Moisture Retrieval over Vegetated Areas

Linlin Zhang

Aerospace Information Research Institute

Chinese Academy of Sciences

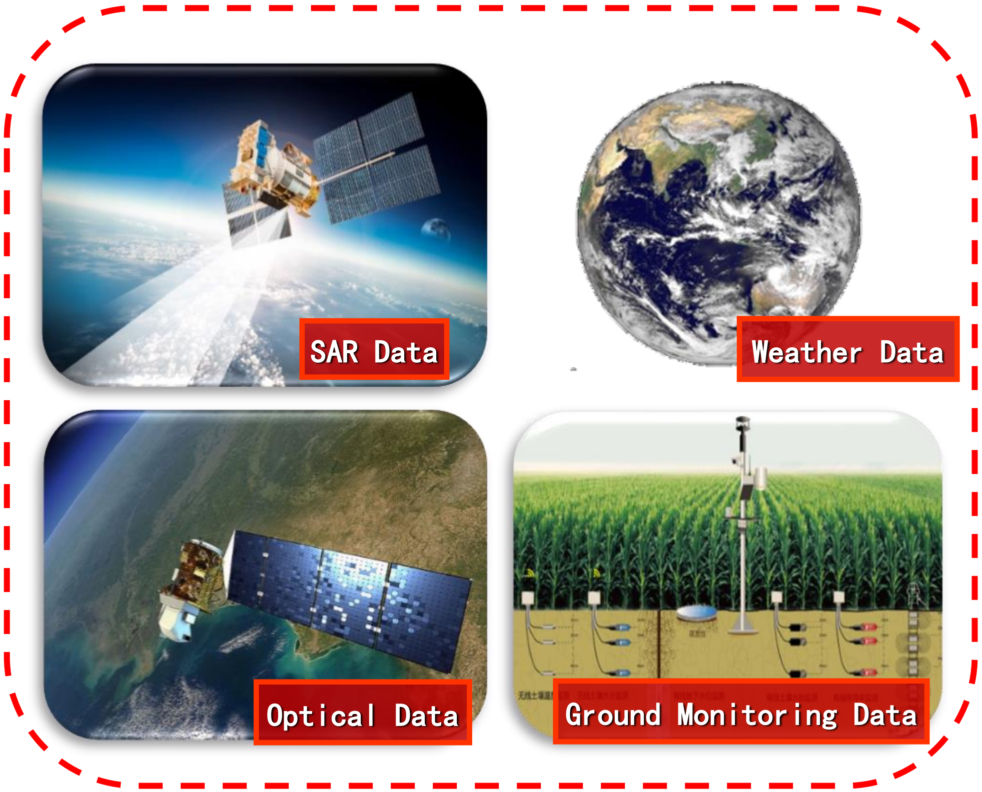
Email：zhangll@aircas.ac.cn

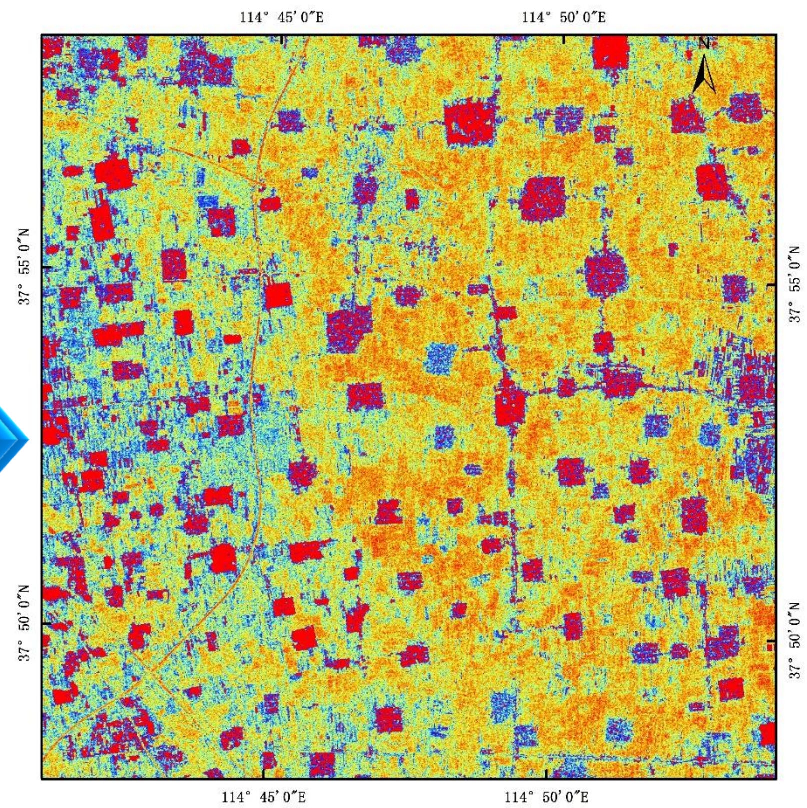
1. Research Background

Surface soil moisture plays a key role in hydrologic, agronomic, and meteorological process, and controls evaporation and transpiration fluxes from bare soil and vegetated areas, respectively. In farmland ecosystems, soil moisture is the basic condition for crop growth and development.




1. Research Background





Microwave and optical remote sensing have obvious advantages in soil moisture monitoring.

The use of multi-source data to invert soil moisture has become an international trend!

1. Research Background

Multi-source Remote Sensing

“Radar and optical remote sensing can effectively improve soil moisture inversion accuracy”

Researcher	List of research contents
Baghdadi, N.N.（2016）	develop an inversion technique based on neural networks to estimate soil surface moisture and leaf area index (LAI) in irrigated grasslands by combining fully polarimetric RADARSAT-2 C-band SAR and optical data (LANDSAT).
Notarnicola（2006）	An inversion procedure based on a Bayesian algorithm has been applied to soil moisture retrieval from remotely sensed data. The data derived from the SMEX’02 experiments are the ground truth measurements, AirSAR and Landsat images.
Saradjian（2011） Cristian（2012）	The results indicate that information on vegetation (through a vegetation index such as NDVI) is useful for the estimation of soil moisture through the semi-empirical regressions.
Wang（2004）	Calculate NDVI using Landsat 5 data and combine ERS 2 data to invert soil moisture in semi-arid areas, but this method can only be used for sparse vegetation coverage (NDVI ≤ 0.45).
Rowlandson（2015）	The error of soil moisture inversion was compared by using LAI inversion of PALS and VWC of vegetation into the passive microwave radiation transmission model.

1. Research Background

Existing problems in soil moisture monitoring technology

Problem 1	Problem 2	Problem 3
Surface parameter influence	**Chinese SAR data application is not perfect**	**Insufficient operational monitoring**
Influenced by surface parameters such as surface roughness and vegetation cover	The first C-band SAR satellite (Gaofen-3) in China is less used in soil moisture monitoring	The scale of soil moisture monitoring is small, and the multi-source remote sensing massive data processing efficiency is low

It is urgent to establish a multi-source remote sensing collaborative soil moisture inversion algorithm for GF-3 SAR satellite

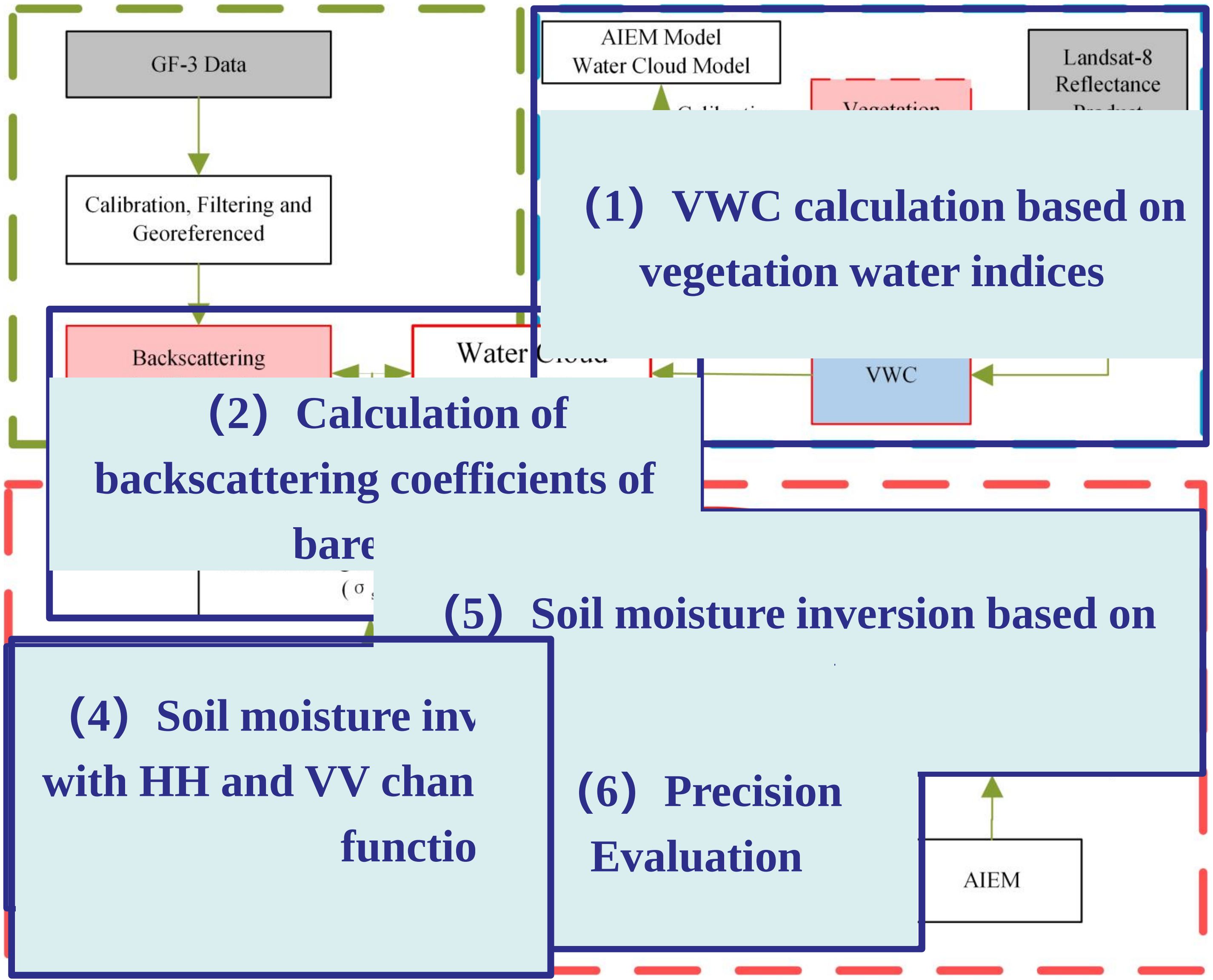
2. Research Content and Technical Route

Research objectives

1. **Soil moisture retrieval based on backscattering simulation database**
2. **Soil moisture retrieval based on artificial neural network**

2. Research Content and Technical Route

Research Content



(1) VWC calculation based on vegetation water indices

(2) Calculation of backscattering coefficients of bare

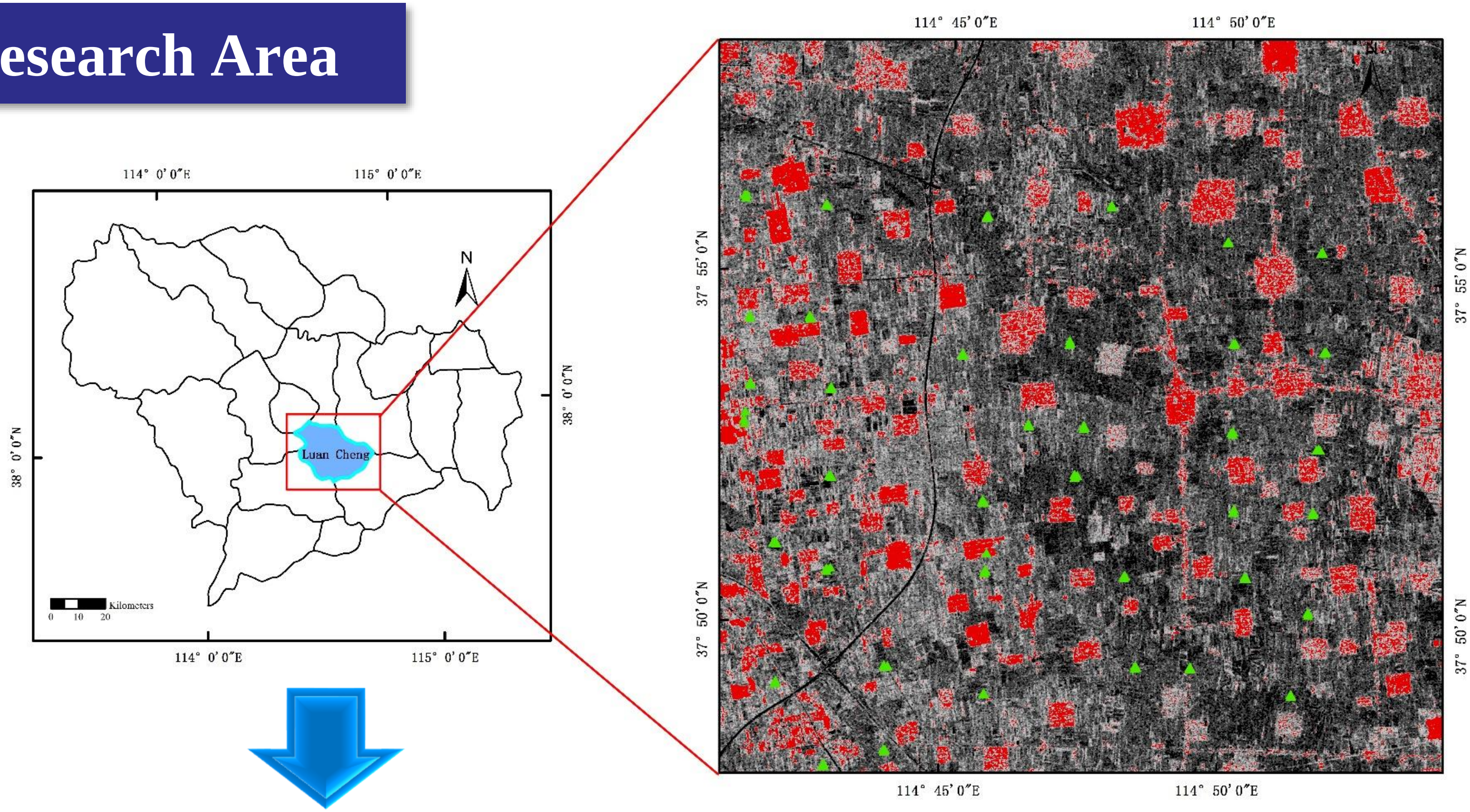
(5) Soil moisture inversion based on

(4) Soil moisture inv with HH and VV chan functio

(6) Precision Evaluation

2. Research Content and Technical Route

Research Area

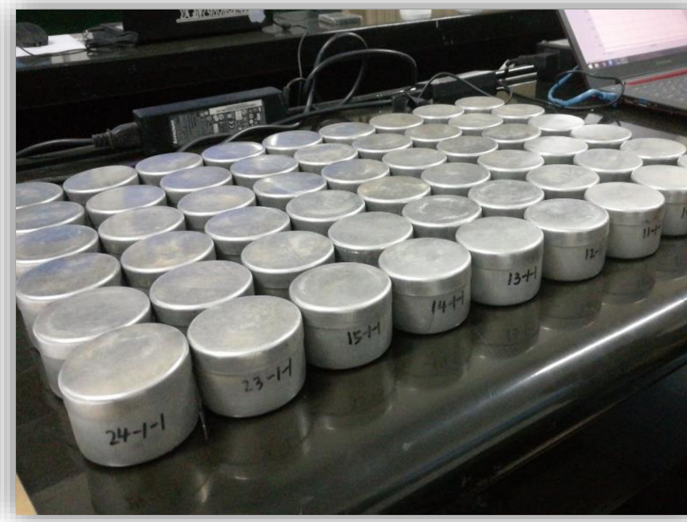


- North China Plain， Centered at 37°42′N， 114°39′E.
- a typical sub-humid north-temperate, continental monsoon climate
- mainly cinnamon soil with high nutrient content, which is suitable for crop growth.
- main grain crops are wheat and corn.

2. Research Content and Technical Route

Field Measurements

- **3 district**
  - Shenzhou
  - Luanchen
  - Yucheng
- **Synchronize experimental data**
  - Soil dielectric constant
  - Soil roughness parameters
  - Soil moisture content measured by oven-drying method
  - Vegetation water content
  - Leaf area index
  - Soil bulk density
  - Spectral curves
  - Soil moisture content measured by TDR



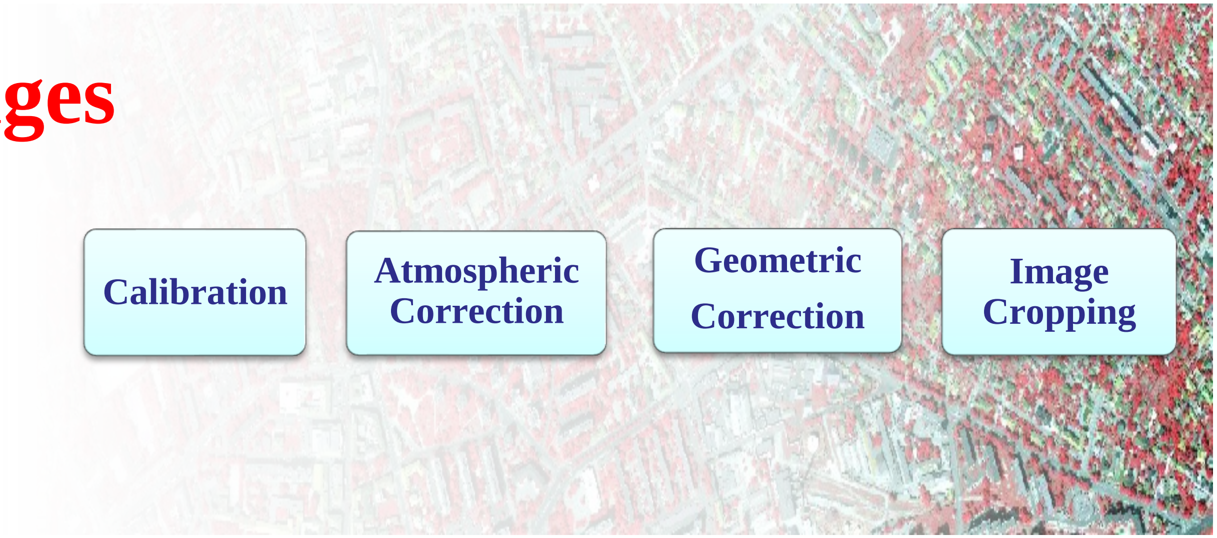
2. Research Content and Technical Route

● Landsat Images

USGS Website

30m spatial resolution

May 2017/July 2017



● GF-3 Images

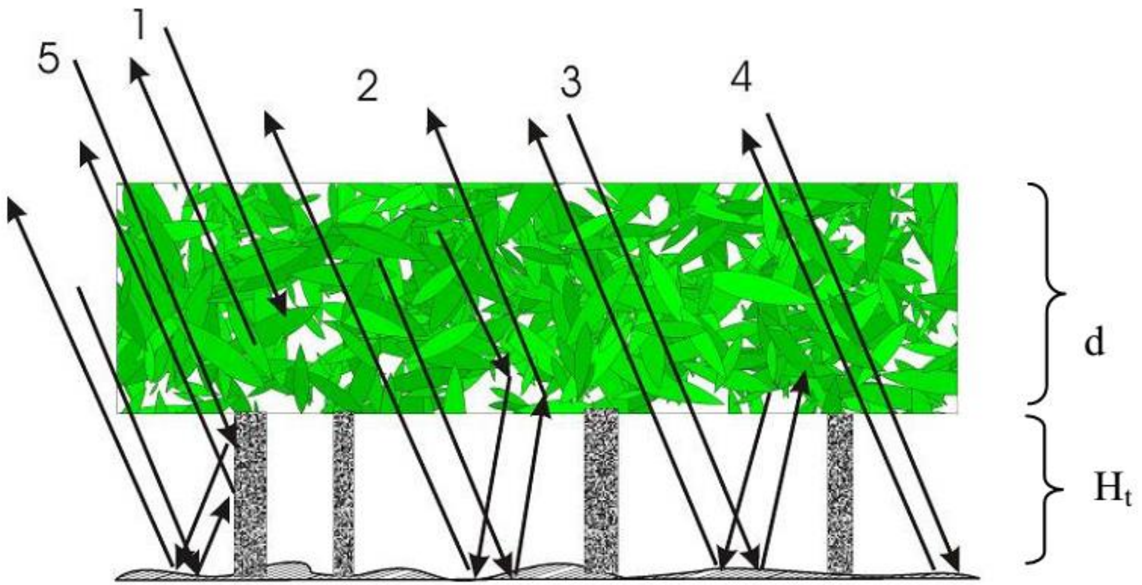
China Centre For Resources Satellite Data and Application Website

8m spatial resolution

May 2017/July 2017

2. Vegetation Water Content

Question： Why consider the impact of vegetation?



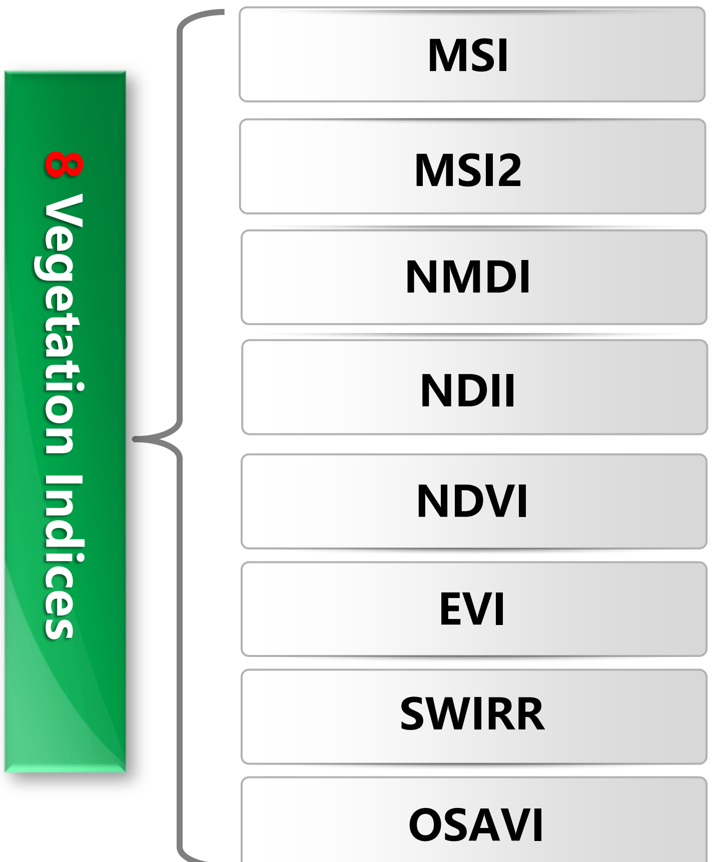
The impact of vegetation：

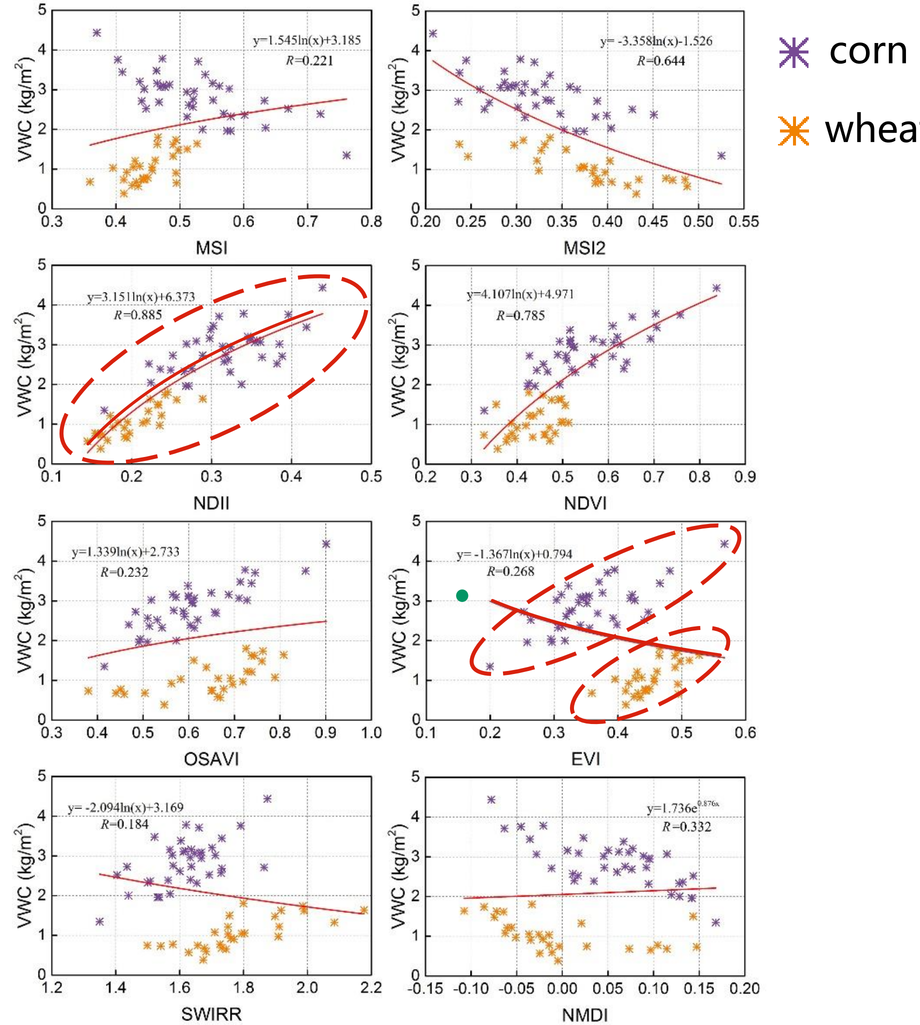
—Interfering with bare surface backscattering

—Theory： When the surface is covered by vegetation such as forests and crops, the various parts of the vegetation structure will contribute to the microwave backscattering, which will interfere with the judgment of backscatter from the bare surface.

3. Vegetation Water Content

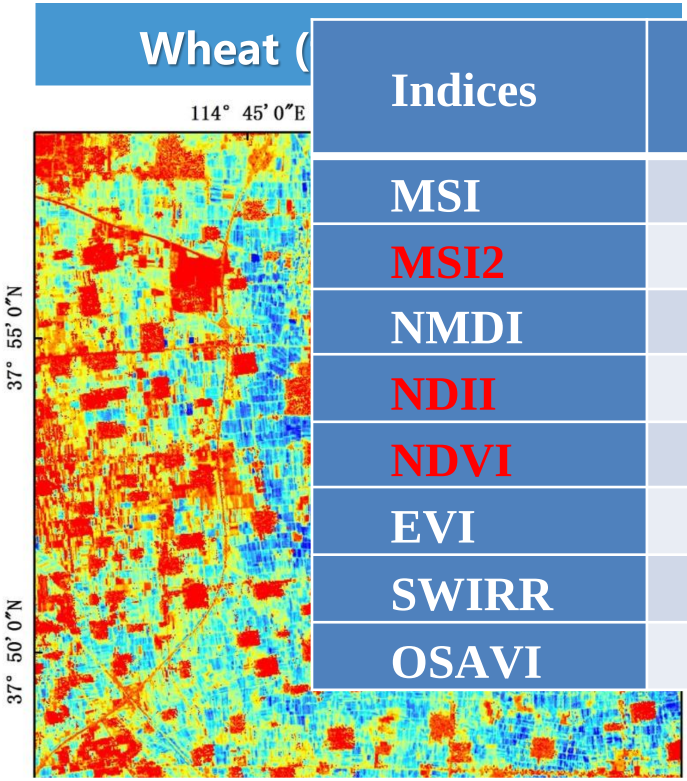
Based on moisture absorption peaks and valleys at 970, 1200, 1500, and 2200 nm, vegetation water indices can reflect changes in the water content of leaves, which provides a theoretical basis for estimating vegetation water content based on optical vegetation indices.

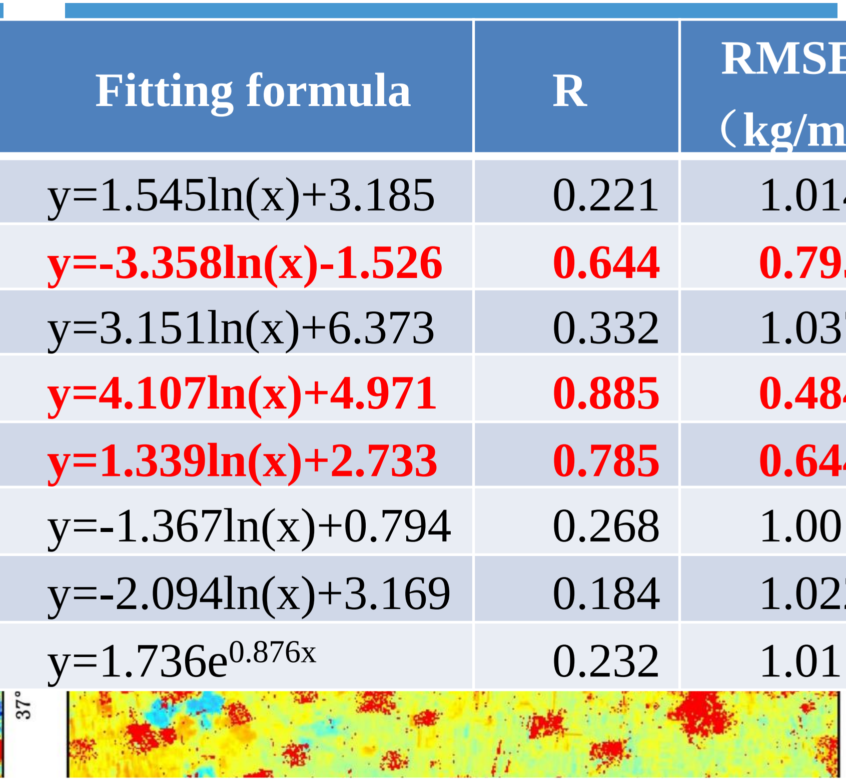




3. Vegetation Water Content

Based on moisture absorption peaks and valleys at 970, 1200, 1500, and 2200 nm, vegetation water indices can reflect changes in the water content of leaves, which provides a theoretical basis for estimating vegetation water content based on optical vegetation indices.





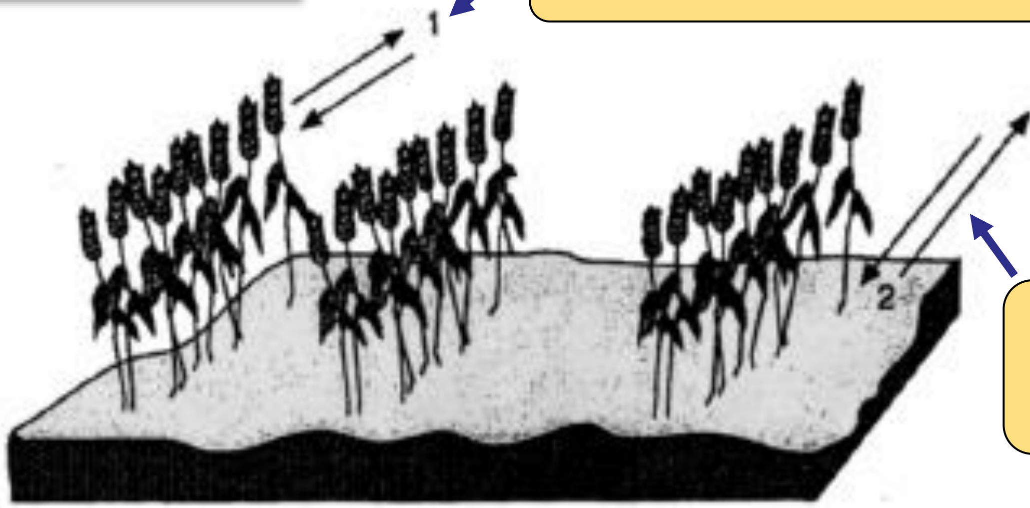
Indices	Fitting formula	R	RMSE（kg/m^2）
MSI	$y=1.545\ln(x)+3.185$	0.221	1.014
MSI2	$y=-3.358\ln(x)-1.526$	**0.644**	**0.795**
NMDI	$y=3.151\ln(x)+6.373$	0.332	1.037
NDII	$y=4.107\ln(x)+4.971$	**0.885**	**0.484**
NDVI	$y=1.339\ln(x)+2.733$	**0.785**	**0.644**
EVI	$y=-1.367\ln(x)+0.794$	0.268	1.001
SWIRR	$y=-2.094\ln(x)+3.169$	0.184	1.022
OSAVI	$y=1.736e^{0.876x}$	0.232	1.011

NDII exhibited the most precise fit and had the best applicability for both wheat and corn.

4. Bare Soil Backscattering

Water Cloud Model

Vegetation Scattering Contribution



Soil Surface Scattering

Figure 1 Backscattering mechanism of vegetation layer described by water cloud model

hypothesis：

- “Cloud” means that the vegetation layer consists of particles of the same size similar to water molecules and evenly distributed throughout the vegetation space;
- The vegetation layer is used as a uniform scatterer, and only single scattering is considered, and the effect of multiple scattering is not considered;
- The variable to be considered in the vegetation layer is the height and density of the “cloud”, and these two variables are proportional to the moisture content;

4. Bare Soil Backscattering

Water Cloud Model

$$\sigma^{\circ}_{total} = \sigma^{\circ}_{veg} + \tau^2 \sigma^{\circ}_{soil} \qquad \textbf{(1)}$$

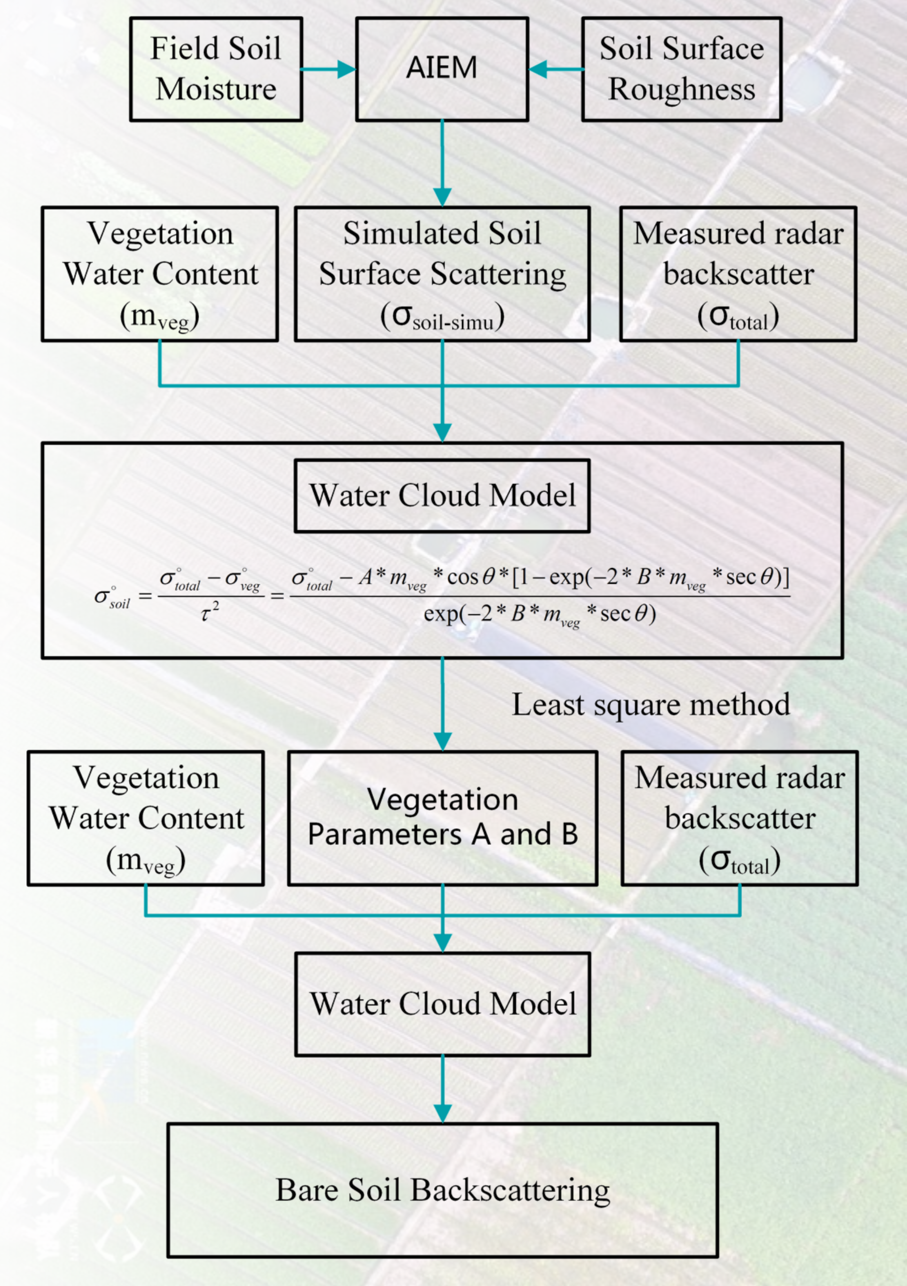
- σ°_{total} **is the radar backscattering from the canopy,**

  σ°_{veg} **is the vegetation scattering contribution,**
- σ°_{soil} **is the soil surface scattering,**
- τ^2 **is the two-way attenuation.**

$$\sigma^{\circ}_{veg} = (1-\tau^2) A \cdot m_{veg} \cos\theta \qquad \textbf{(2)}$$

$$\tau^2 = \exp\left[\frac{-2B \cdot m_{veg}}{\cos\theta}\right] \qquad \textbf{(3)}$$

- **A and B are both polarization dependent and crop dependent parameters,**
- **m_{veg} is the VWC (kg m-2),**
- **θ is the incidence angle.**



4. Bare Soil Backscattering

Water Cloud Model Accuracy Test

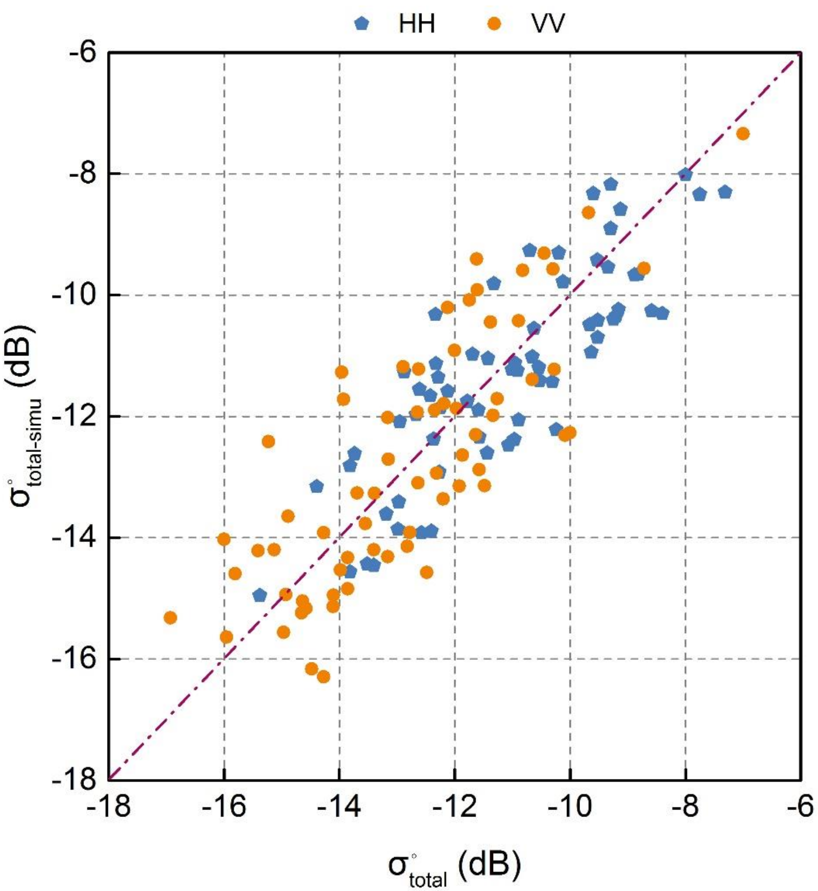
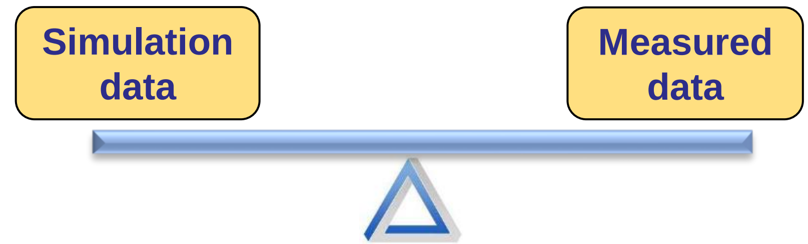
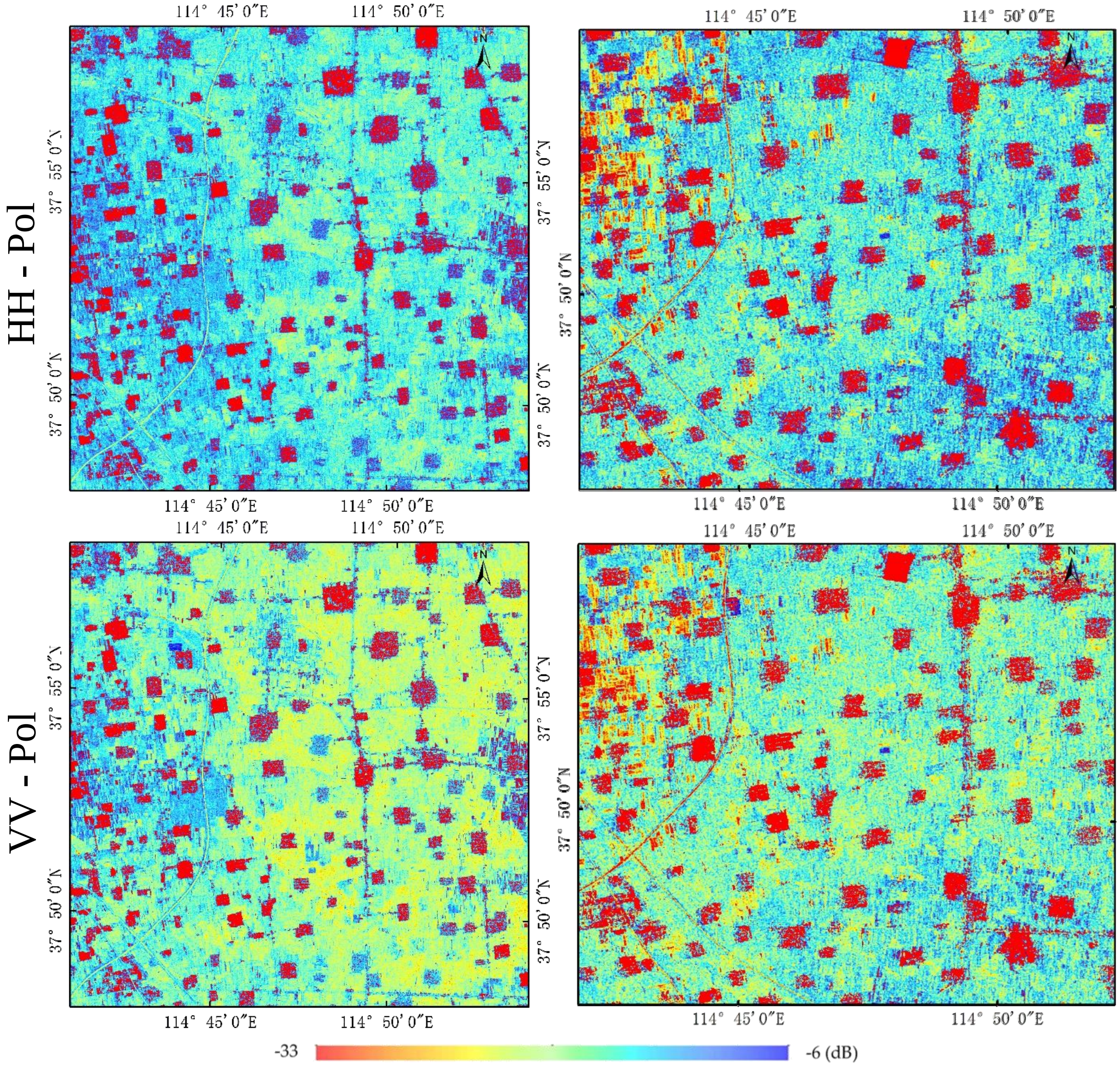


Figure 2. Scatterplot of simulated radar backscatter ($\sigma^{\circ}_{total-simu}$) from WCM and GF-3 measured radar backscatter (σ°_{total})



Both HH and VV simulated backscatter ($\sigma^{\circ}_{total-simu}$) agree well with GF-3 satellite measured backscatter ($\sigma^{\circ}_{total-simu}$) (R=0.839 for HH, and R=0.797 for VV).

4. Bare Soil Backscattering



Blue Patches

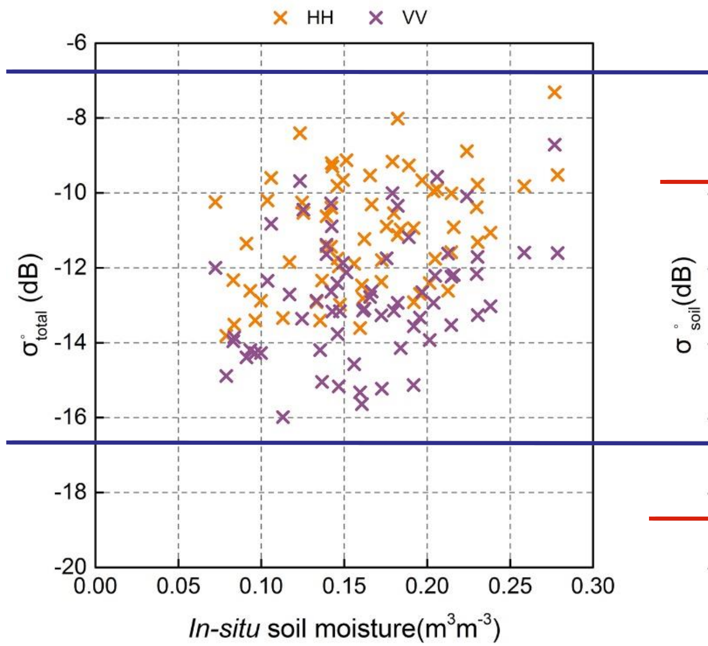
Yellow Patches

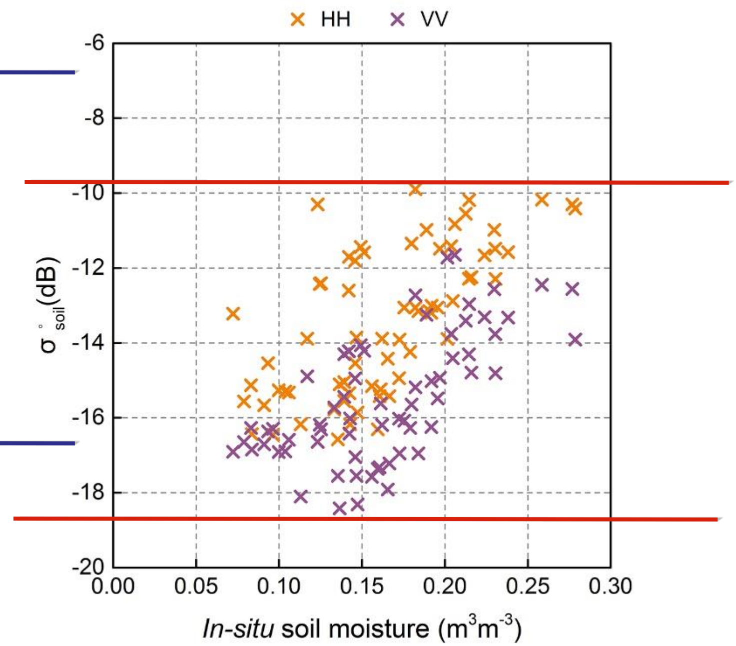
Filling Stage

Jointing Stage

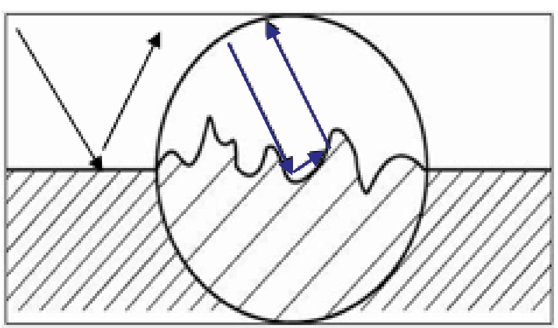
4. Bare Soil Backscattering

Question: Bare Soil Backscattering Linear **Soil Moisture?**





Soil surface roughness: — Interfere with bare surface backscattering



Polarization	R^2 (σ°_{total})	R^2 (σ°_{soil})
HH	0.147	0.442
VV	0.107	0.424

There is not simple linear or nonlinear fitting relationship between σ°_{soil} and soil moisture

4. AIEM Simulation Database

AIEM

Considering the influence of surface roughness

$$\sigma^{\circ}_{soil-simu} = AIEM(f, \theta, PP, SM, s, l, ACF)$$

Where:

$\boldsymbol{\sigma^{\circ}_{soil-simu}}$ **is the simulated bare soil backscattering**

$\boldsymbol{f}$ **is the satellite frequency**

$\boldsymbol{\theta}$ **is the incidence angle**

PP **is the polarization state**

SM **is the input soil moisture from the Dobson model**

s is the root mean square height

l **is the correlation length**

ACF **is the adopted exponential autocorrelation function**

theta	vv	hh	sig	cl	mv	fre
20.0	-35.1850331	-35.5516471	0.5000	10.0000	0.0100	5.4000
20.0	-33.1341690	-33.4971627	0.5000	10.0000	0.0200	5.4000
20.0	-31.3282084	-31.6841248	0.5000	10.0000	0.0300	5.4000
20.0	-29.7422218	-30.0893771	0.5000	10.0000	0.0400	5.4000
20.0	-28.3429060	-28.6811263	0.5000	10.0000	0.0500	5.4000
20.0	-27.1003325	-27.4306249	0.5000	10.0000	0.0600	5.4000
20.0	-25.9895692	-26.3138068	0.5000	10.0000	0.0700	5.4000
20.0	-24.9902702	-25.3109139	0.5000	10.0000	0.0800	5.4000
20.0	-24.0858858	-24.4057488	0.5000	10.0000	0.0900	5.4000
20.0	-23.2629131	-23.5849666	0.5000	10.0000	0.1000	5.4000
20.0	-22.5102892	-22.8375073	0.5000	10.0000	0.1100	5.4000
20.0	-21.8188789	-22.1541196	0.5000	10.0000	0.1200	5.4000
20.0	-21.1810964	-21.5270131	0.5000	10.0000	0.1300	5.4000
20.0	-20.5906000	-20.9495809	0.5000	10.0000	0.1400	5.4000
20.0	-20.0420494	-20.4161799	0.5000	10.0000	0.1500	5.4000
20.0	-19.5309159	-19.9219604	0.5000	10.0000	0.1600	5.4000
20.0	-19.0533408	-19.4627391	0.5000	10.0000	0.1700	5.4000
20.0	-18.6060017	-19.0348782	0.5000	10.0000	0.1800	5.4000
20.0	-18.1860392	-18.6352201	0.5000	10.0000	0.1900	5.4000
20.0	-17.7909523	-18.2609899	0.5000	10.0000	0.2000	5.4000
20.0	-17.4185593	-17.9097598	0.5000	10.0000	0.2100	5.4000
20.0	-17.0669414	-17.5793943	0.5000	10.0000	0.2200	5.4000
20.0	-16.7343976	-17.2680067	0.5000	10.0000	0.2300	5.4000
20.0	-16.4194108	-16.9739244	0.5000	10.0000	0.2400	5.4000
20.0	-16.1206313	-16.6956706	0.5000	10.0000	0.2500	5.4000
20.0	-15.8368412	-16.4319269	0.5000	10.0000	0.2600	5.4000
20.0	-15.5669468	-16.1815232	0.5000	10.0000	0.2700	5.4000
20.0	-15.3099559	-15.9434126	0.5000	10.0000	0.2800	5.4000
20.0	-15.0649657	-15.7166566	0.5000	10.0000	0.2900	5.4000
20.0	-14.8311575	-15.5004161	0.5000	10.0000	0.3000	5.4000
20.0	-14.6077833	-15.2939366	0.5000	10.0000	0.3100	5.4000
20.0	-14.3941560	-15.0965356	0.5000	10.0000	0.3200	5.4000
20.0	-14.1896480	-14.9075981	0.5000	10.0000	0.3300	5.4000
20.0	-13.9936826	-14.7265675	0.5000	10.0000	0.3400	5.4000
20.0	-13.8057264	-14.5529349	0.5000	10.0000	0.3500	5.4000
20.0	-13.6252933	-14.3862422	0.5000	10.0000	0.3600	5.4000
20.0	-13.4519296	-14.2260659	0.5000	10.0000	0.3700	5.4000

5. Soil Moisture Retrieval

HH and VV channel

$$Z=\min\sqrt{\frac{1}{n}\sum\left(\left|\sigma^{\circ}_{soil}-\sigma^{\circ}_{soil-simu}\right|_{HH}+\left|\sigma^{\circ}_{soil}-\sigma^{\circ}_{soil-simu}\right|_{VV}\right)^2}$$

Where:

σ°_{soil} **is the bare soil backscattering,** $\sigma^{\circ}_{soil-simu}$ **is the simulated bare soil backscattering, n is the number of pixels in the image.**

Equation Analysis:

- **Suppose there are m simulated values for HH or VV;**
- **The row and column number of the SAR image are i,j, respectively**

$$Z=\min\sqrt{\frac{1}{n}\sum_{i,j}\left(\left|A_{H\,i,j}-A_{Hsim}\right|+\left|A_{V\,i,j}-A_{Vsim}\right|\right)^2}$$

$$A_{H\,i,j}=\begin{Bmatrix}\sigma^0_{soil\_HH\,i,j}\\ \sigma^0_{soil\_HH\,i,j}\\ \cdots\\ \sigma^0_{soil\_HH\,i,j}\end{Bmatrix}_{m\times 1}\qquad A_{Hsim}=\begin{Bmatrix}\sigma^0_{soil-simu\_HH_1}\\ \sigma^0_{soil-simu\_HH_2}\\ \cdots\\ \sigma^0_{soil-simu\_HH_m}\end{Bmatrix}_{m\times 1}$$

$$A_{V\,i,j}=\begin{Bmatrix}\sigma^0_{soil\_VV\,i,j}\\ \sigma^0_{soil\_VV\,i,j}\\ \cdots\\ \sigma^0_{soil\_VV\,i,j}\end{Bmatrix}_{m\times 1}\qquad A_{Vsim}=\begin{Bmatrix}\sigma^0_{soil-simu\_VV_1}\\ \sigma^0_{soil-simu\_VV_2}\\ \cdots\\ \sigma^0_{soil-simu\_VV_m}\end{Bmatrix}_{m\times 1}$$

Define the distance value matrix as *B*,

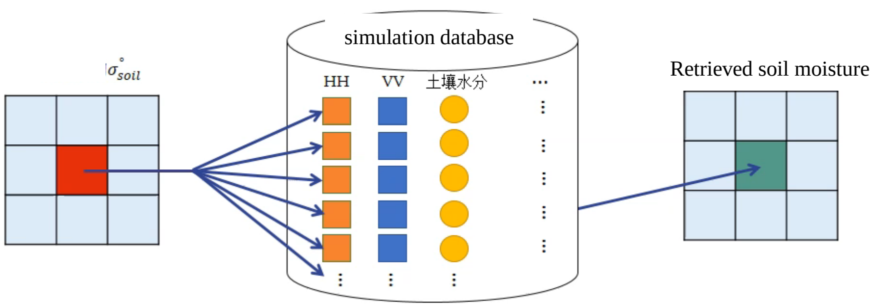
$$B_{H\,i,j}=\left|A_{H\,i,j}-A_{Hsim}\right|$$

Then the cost function is transformed into:

$$Z=\min\sqrt{\frac{1}{n}\sum_{i,j}\left(B_{H\,i,j}+B_{V\,i,j}\right)^2}$$

Define $C_{i,j}=B_{H\,i,j}+B_{V\,i,j}$ **Then:** $Z=\min\sqrt{\frac{1}{n}\sum_{i,j}C_{i,j}^2}$

$$\min C_{i,j}=\min\left(B_{H\,i,j}+B_{V\,i,j}\right)=\min\left(\left|A_{H\,i,j}-A_{Hsim}\right|+\left|A_{V\,i,j}-A_{Vsim}\right|\right)$$



5. Soil Moisture Retrieval

HH or VV channel

$$Z = \min \sqrt{\frac{1}{n}\sum(\sigma^{\circ}_{soil} - \sigma^{\circ}_{soil-simu})^2}$$

***Where*:**

σ°_{soil} **is the bare soil backscattering，** $\sigma^{\circ}_{soil-simu}$ **is the simulated bare soil backscattering， n is the number of pixels in the image.**

Equation Analysis：

- **Suppose there are m simulated values for HH or VV；**
- **The row and column number of the SAR image are i,j, respectively**

$$\underset{i,j}{A_{H}} = \begin{Bmatrix} \underset{i,j}{\sigma^{0}_{soil\_HH}} \\ \underset{i,j}{\sigma^{0}_{soil\_HH}} \\ \cdots \\ \underset{i,j}{\sigma^{0}_{soil\_HH}} \end{Bmatrix}_{m\times 1} \quad A_{Hsim} = \begin{Bmatrix} \sigma^{0}_{soil-simu\_HH_1} \\ \sigma^{0}_{soil-simu\_HH_2} \\ \cdots \\ \sigma^{0}_{soil-simu\_HH_m} \end{Bmatrix}_{m\times 1}$$

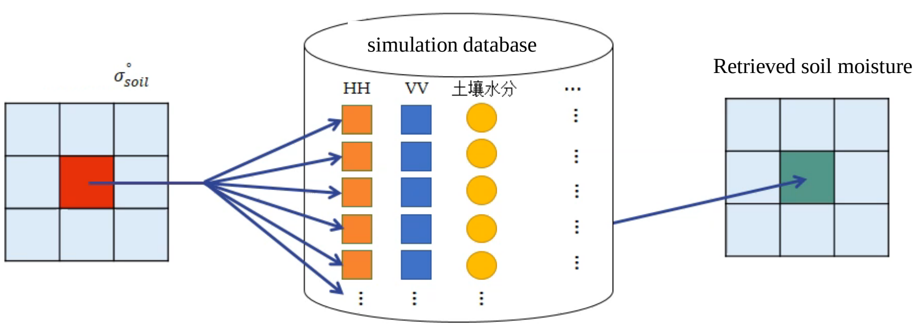
$$Z = \min \sqrt{\frac{1}{n}\sum_{i,j}\left(\left|\underset{i,j}{A_H} - A_{Hsim}\right| + \left|\underset{i,j}{A_V} - A_{Vsim}\right|\right)^2}$$

Define the distance value matrix as *B*,

$$\underset{i,j}{B_H} = \left|\underset{i,j}{A_H} - A_{Hsim}\right|$$

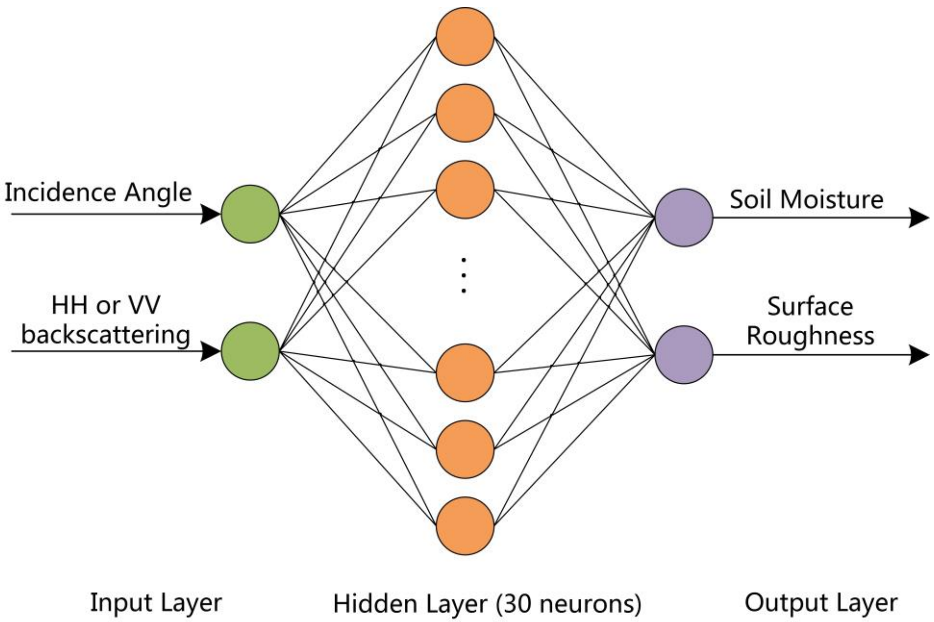
Then the cost function is transformed into:

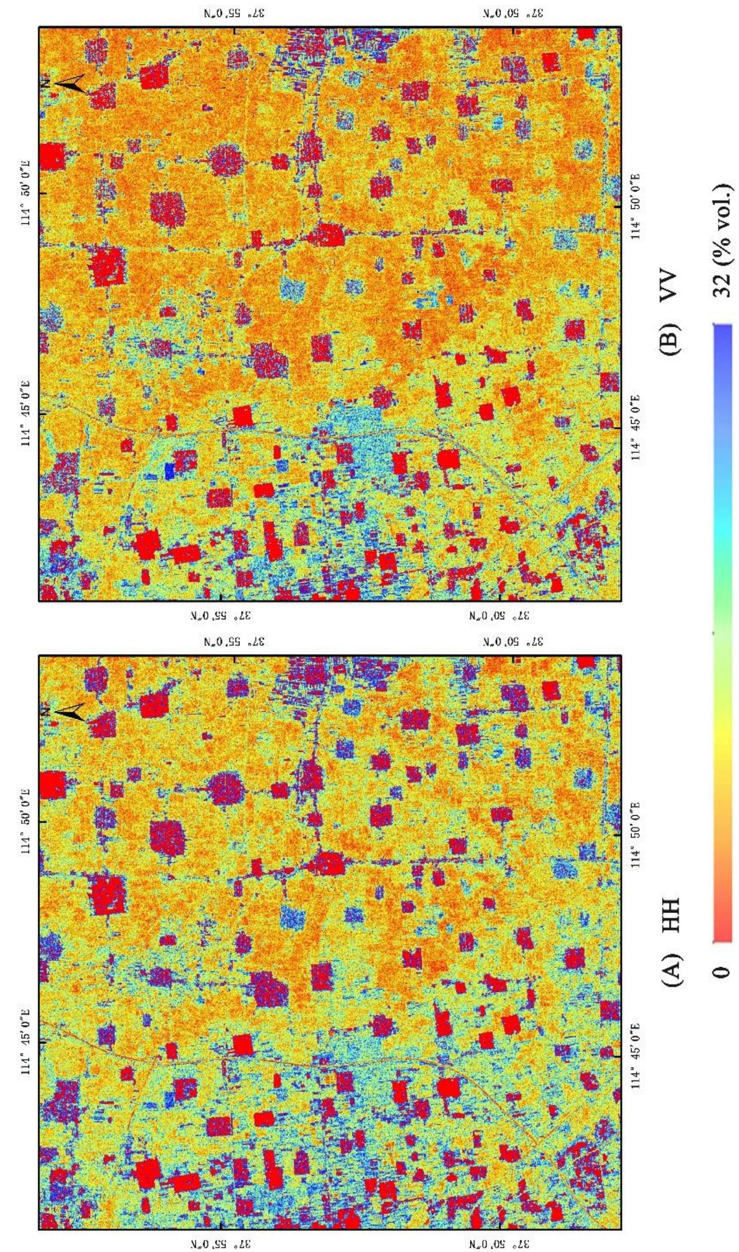
$$Z = \min \sqrt{\frac{1}{n}\sum_{i,j}(\underset{i,j}{\mathrm{B_H}})^2} \qquad \min(\underset{i,j}{\mathrm{B}_H}) = \min\left(\left|\underset{i,j}{A_H} - A_{Hsim}\right|\right)$$



6. Soil Moisture Retrieval

ANN architecture





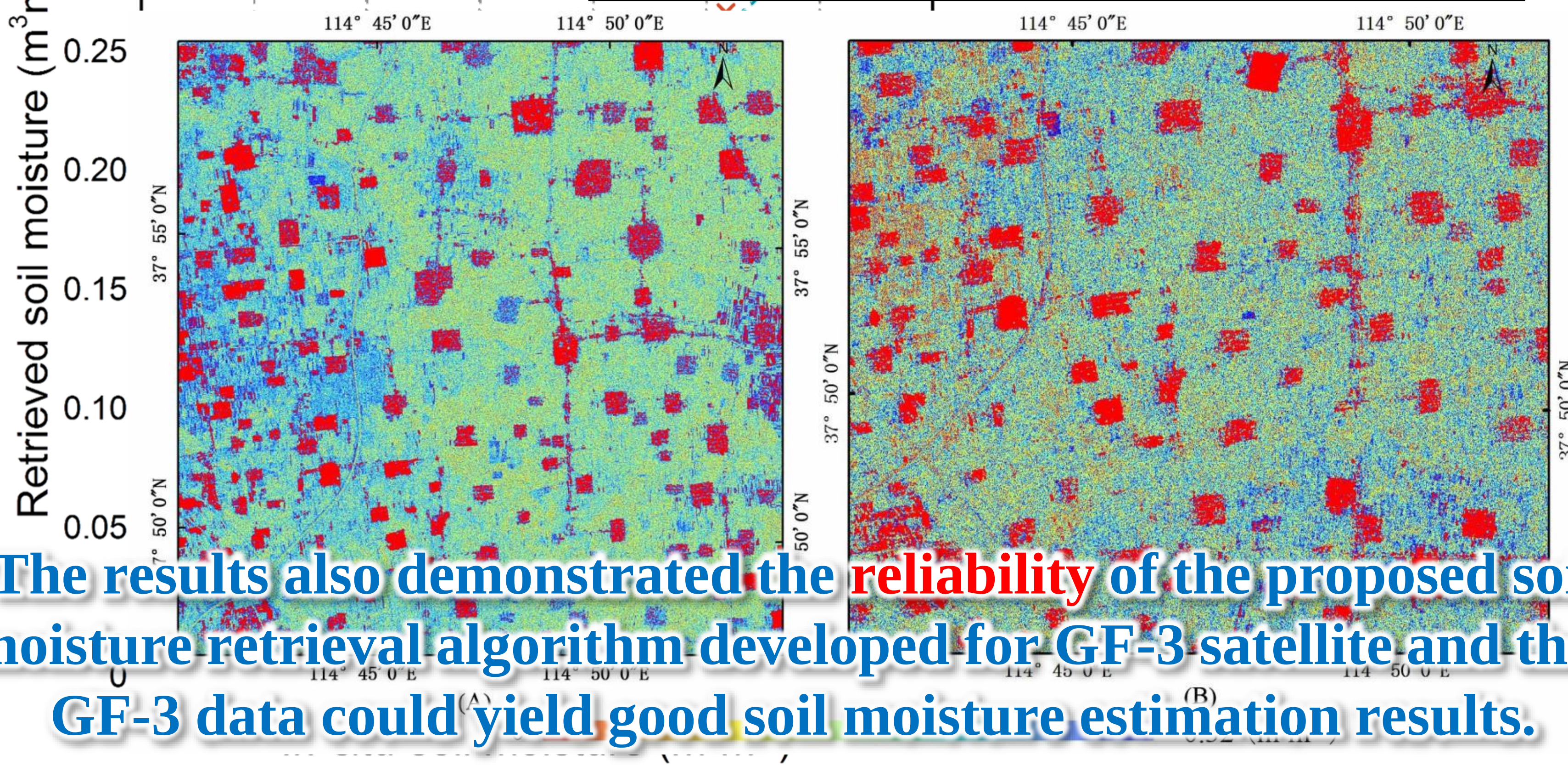
Structure Analysis：

- Input Layer（incidence angle 、HH or VV backscattering）；
- Hidden Layer (30 neurons) ;
- Output Layer (soil moisture and surface roughness);
- 90% of the cases were used for training the ANN; the remaining 10% of the cases were utilized during the testing process;
- Linear and tangent-sigmoid transfer functions were associated with the hidden layer and output nodes, respectively.

6. Soil Moisture Retrieval Precision Evaluation

Precision Evaluation

Polarization	R	RMSE (m^3m^{-3})
HH	0.652	0.049
VV	0.636	0.053
HH+VV	0.717	0.044



The results also demonstrated the reliability of the proposed soil moisture retrieval algorithm developed for GF-3 satellite and that GF-3 data could yield good soil moisture estimation results.


Thanks !