GSID24

# Minimizing Vegetation Influence on Soil Salinity Mapping with Novel Bare Soil Pixels from Multi-Temporal Images

Presenter:Danyang Wang
Supervisor:Prof.Zhaofu Li
E-mail:2021203039@stu.njau.edu.cn

南京农业大学
NANJING AGRICULTURAL UNIVERSITY
资源与环境科学学院
College of Resource & Environmental Sciences

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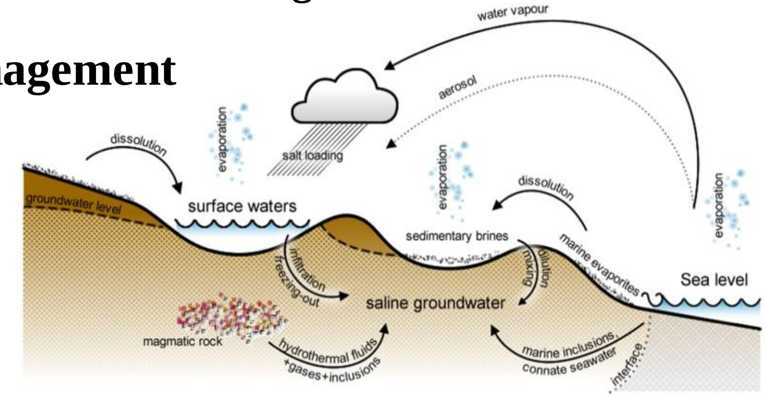
- Discussion, Conclusions and Prospects

# 1.Problem Statement



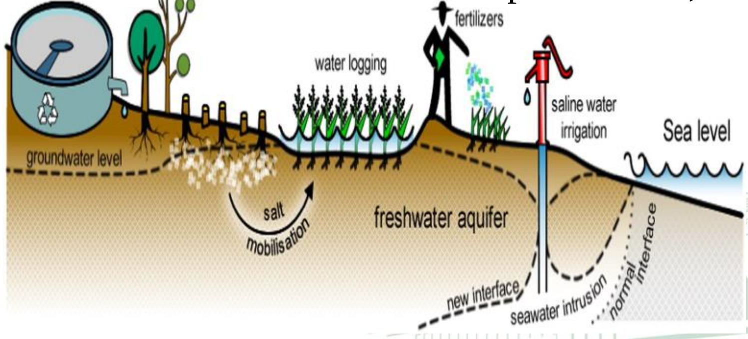
- Soil salinization is a prominent global issue associated with soil degradation
- Mapping salinization is crucial for land management

Global soil salinization




Primary soil salinity mechanisms

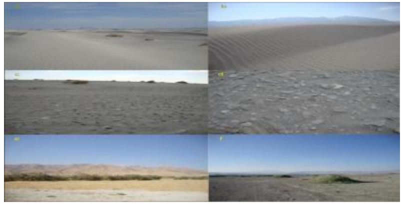
（Daliakopoulos et al., 2016）



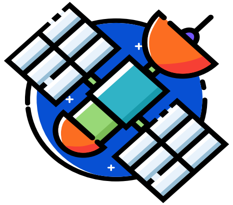

Secondary soil salinity mechanisms

# 1.Problem Statement

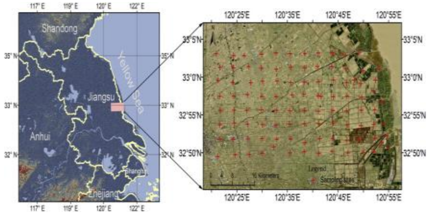
***Field investigation***

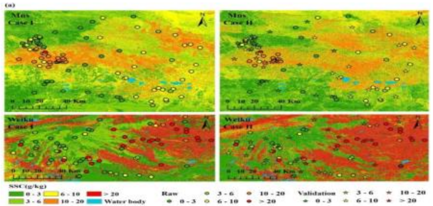


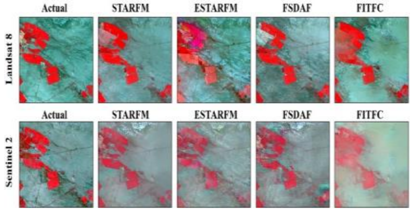
- ✓ provided precise information
- ➢ Limited in scope and slow for large areas.



***Remote sensing***






- ✓ broad coverage
- ✓ abundant spectral information

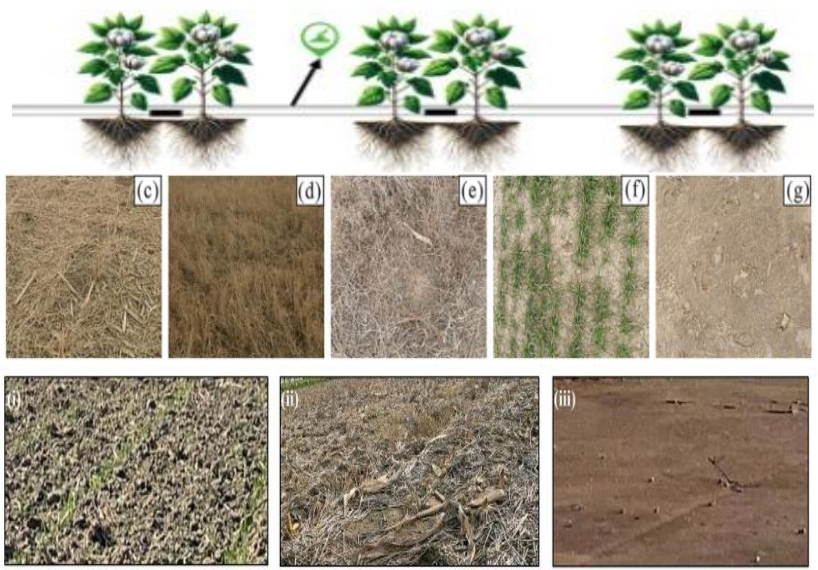
- **Optical remote sensing satellites are now mainstream for predicting and mapping soil salinization**

(Liu *et al.*, Geoderma,2019;Wang *et al.*, STOEN, 2021;Hesam *et al.*, Catena,2023; Wang *et al.*, Geoderma,2023;Neena *et al.*, 2024)

# 1.Problem Statement

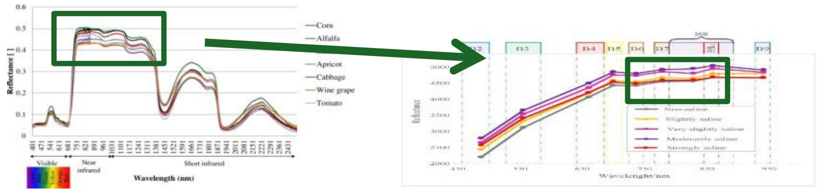


## The salt return period is considered optimal for observing topsoil salinity

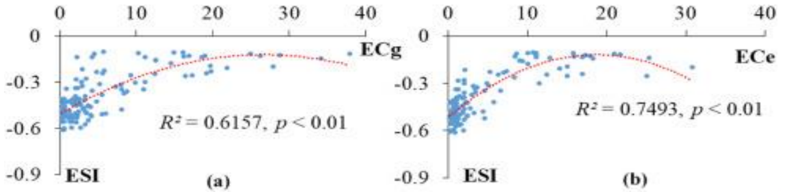



- The salt return period often overlaps with key crop growth stages

- **Vegetation cover** alters the spectral characteristics of saline soils




- Finding a single spectral index for topsoil salinity mapping is challenging




（Thuong V. *et al.*, STOEN, 2021; Gordana Kaplan *et al.*, 2023）

**Key focus: mitigating vegetation impact on spectra and extract soil reflectance**

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# 2.Research Progress



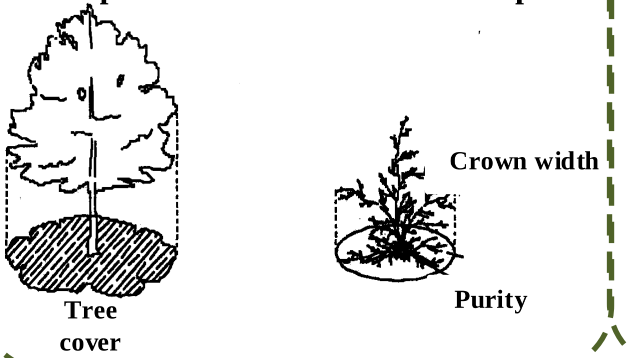
## Three methods for "mitigating" vegetation spectral interference

### Optical vegetation cover

*Ratio of actual vegetation's optical information to total vegetation in the observation range*

- The bare soil biomass baseline
- The near-infrared spectral brightness of full vegetation

➢ **Complex to invert and difficult to operate**

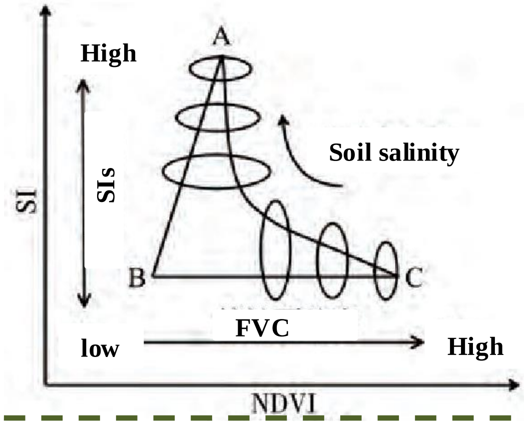



### Eigenspace method

*•Indirect estimation of soil salinity through spectral-vegetation relationships*

➢ Soil salinization alone doesn't determine vegetation growth

➢ **limiting model generalization**




### Mixed element decomposition

***•Non-negative Matrix Factorization (NMF)method**:*

*•Extracts positive spectra, simple operation;*
*•Based on spectral angle of* ***central*** *and* ***nearby bare soil pixels***

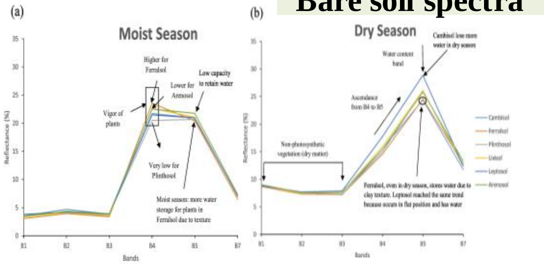
➢ **Difficult to represent the central pixel's true spectral information**

(Liu et al., 1997; Sandhold *et al.*, 2002; Liu *et al.*, *Geoderma*,2019)

# 2.Research Progress



## Bare soil spectra

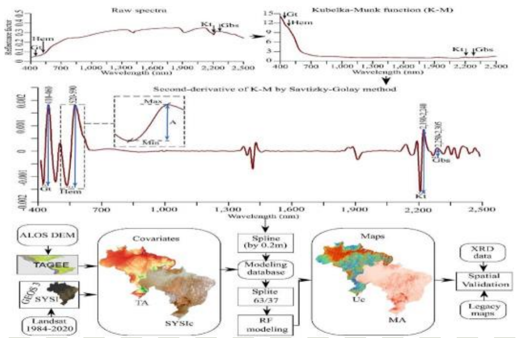




Spectral features of soil types contain different vegetation information

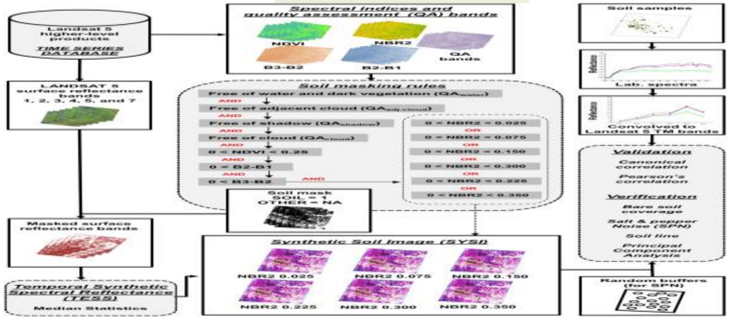
**Bare soil spectra** accurately reflect core pixel soil characteristics

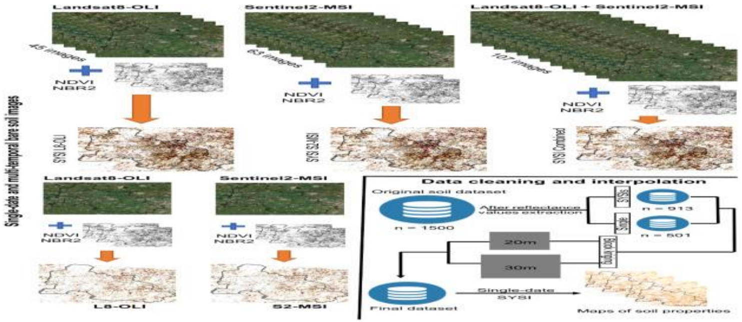
## Soil salinity fluctuations




- Soil salinity fluctuations highly
- Using **only bare soil data images** is difficult

## GeoS3 method




GeoS3 acquires **bare soil pixels(SYSI)**

***Thinking*: Fusing spectral data from the salt return period with SYSI and accounting for soil types effectively could capture pixel-level salinity characteristics ? ? ?**

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**A new strategy: minimize vegetation influence on soil salinity mapping by fusing spectral information of salt recurrence period and SYSI**

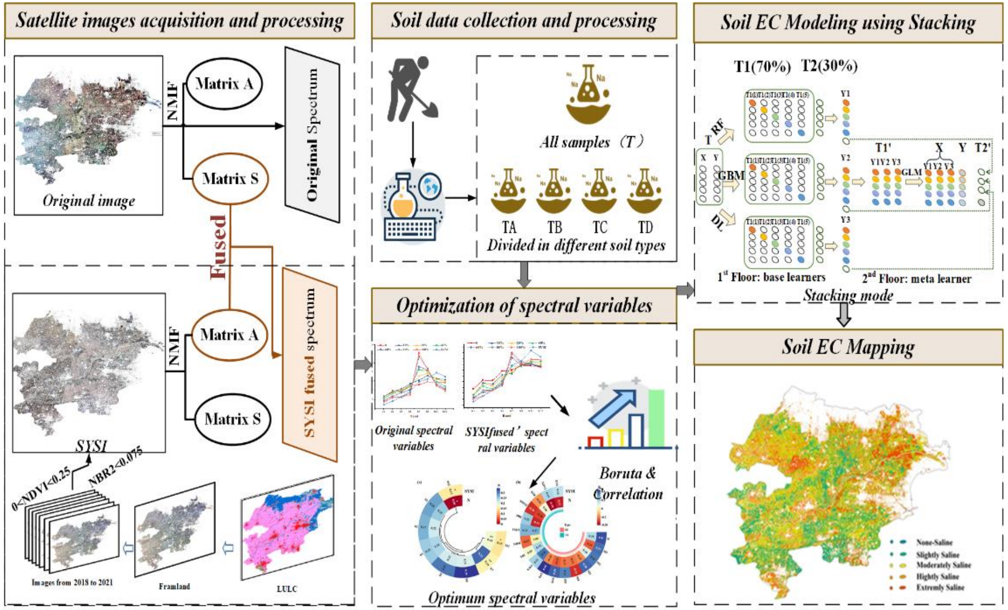
# Objectives:

- To explore the influence of **fusing SYSI with the original image** on the accuracy of soil salinity prediction
- To investigate the impact of **different soil subtypes** on the accuracy of soil salinity prediction
- To evaluate the effectiveness of the **stacking algorithm** for soil salinity prediction

# 3.Scientific issues and Methodology



## Hypothesis: The NMF method improves central pixel soil representation by fusing spectral data from vegetation and bare soil periods




- **Method**

  Applied NMF to Sentinel-2 MSI images to obtain endmember matrix A and abundance matrix S for SYSI and original image

- **Correction**

  Original matrix S used as a correction coefficient, fused with SYSI matrix A to reconstruct fused spectra

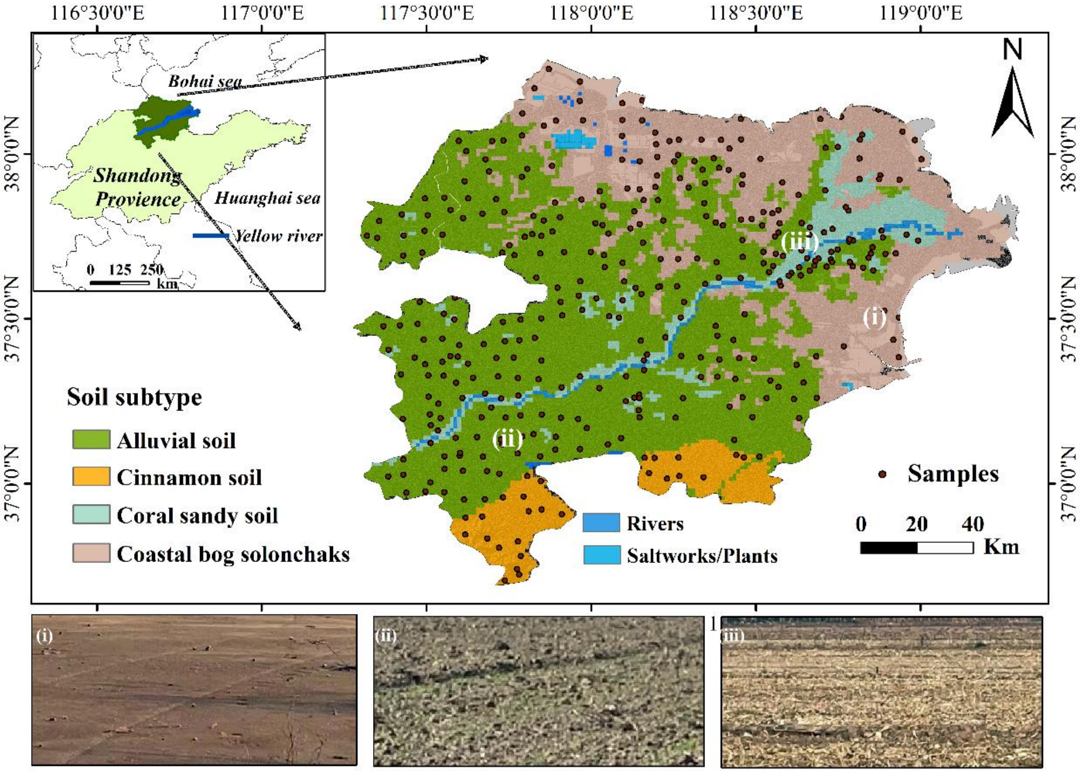
- **Outcome**

  Created salt content prediction maps for different soil types using fused spectra and stacking ensemble learning algorithm

# 3.Scientific issues and Methodology



## Study area




The location of the study area and the distribution of sample points (i:no vegetation cover area；ii:winter wheat seeding area; iii:straw mulching area)

**Yellow River Delta**

Soil types:
saline-alkali soil、tidal soil

Land surface：
covered by vegetation for extended periods

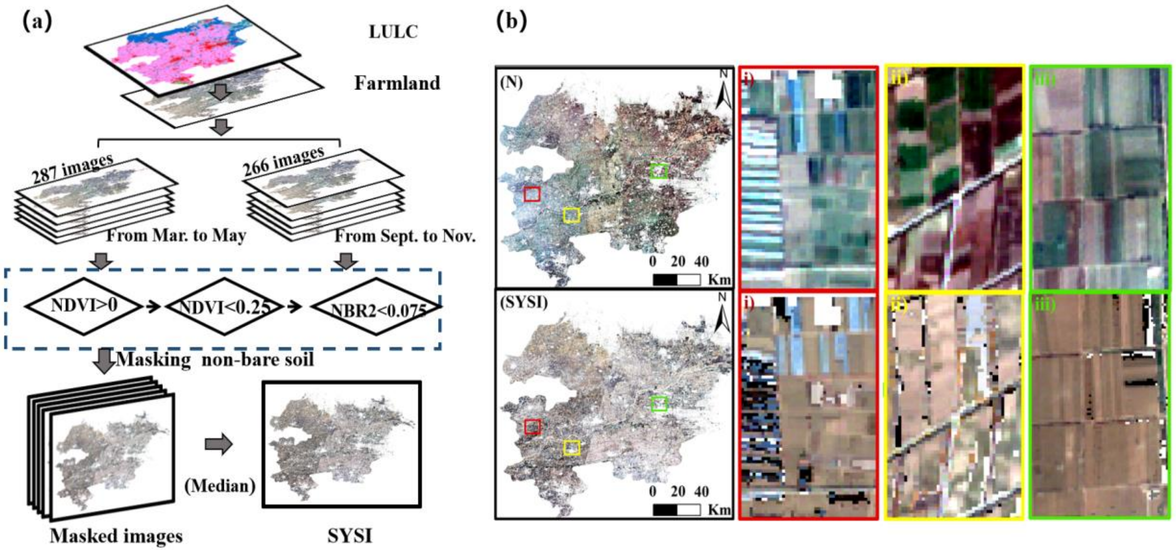
Seasonal salt return

## Soil dataset

255 soil observations obtained at 0-10 cm from soil surveys performed October, 2020, with the soil surfaces covered straw or wheat seedlings

## Imagery datasets and preprocessing

Remote sensing images: original image and the SYSI of bare soil pixels (S2,GEE,10m)



## Incorporation of SYSI based NMF

MATLAB 2018a

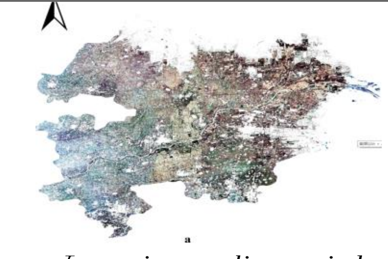


*Image in sampling period*

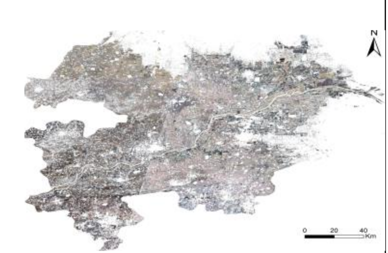
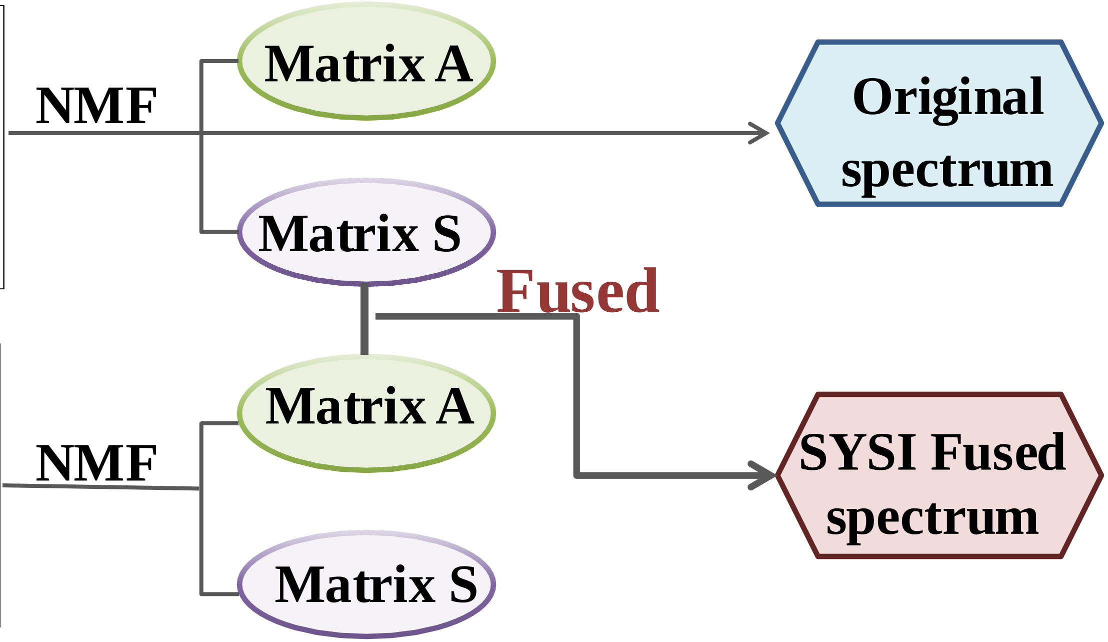


*Image in bared soil period*




The matrix A: Consists of columns representing individual endmember spectra

The matrix S: Comprised columns representing the abundance values of different endmembers for each pixel

**Matrix A of SYSI, unaffected by surface vegetation, contained pure spectra reflecting soil salinity more accurately**

# Selection of characteristic spectral indices

| | Spectral index | Description | Formula | Reference |
|---|---|---|---|---|
| Vegetable indices (VIs) | CRSI | Canopy salinity response vegetation index | $\left[\frac{(NIR\times R)-(G\times B)}{(NIR\times R)+(G\times B)}\right]^{0.5}$ | (Scudiero et al. 2014) |
| | DDI | Distance drought index | $\frac{\sqrt{R^2+NIR^2}}{1+NDVI}$ | (Yang et al. 2023) |
| | EVI | Enhanced vegetation index | $G\frac{NIR-R}{NIR+C_1\times R-C_2\times B+L}$ | |
| | NDSI | Normalized difference salinity index | $(R-NIR)/(R+NIR)$ | |
| | NDVI | Normalized difference vegetation index | $(NIR-R)/(NIR+R)$ | |
| | SAVI | Soil adjusted vegetation index | $(1+L)(NIR-R)/(NIR+R+L)$ | |
| | SIWSI | Shortwave infrared water stress index | $(SWIR-NIR)/(SWIR+NIR)$ | (Wang et al. 2019) |
| | STR | Shortwave infrared transformed reflectance | $(1-SWIR)^2/2SWIR$ | |
| | TBI | Three-band index | $(SWIR2-G)/(G-SWIR1)$ | |
| | VSDI | Visible and shortwave-infrared drought | $1-(SWIR+R-2B)$ | |

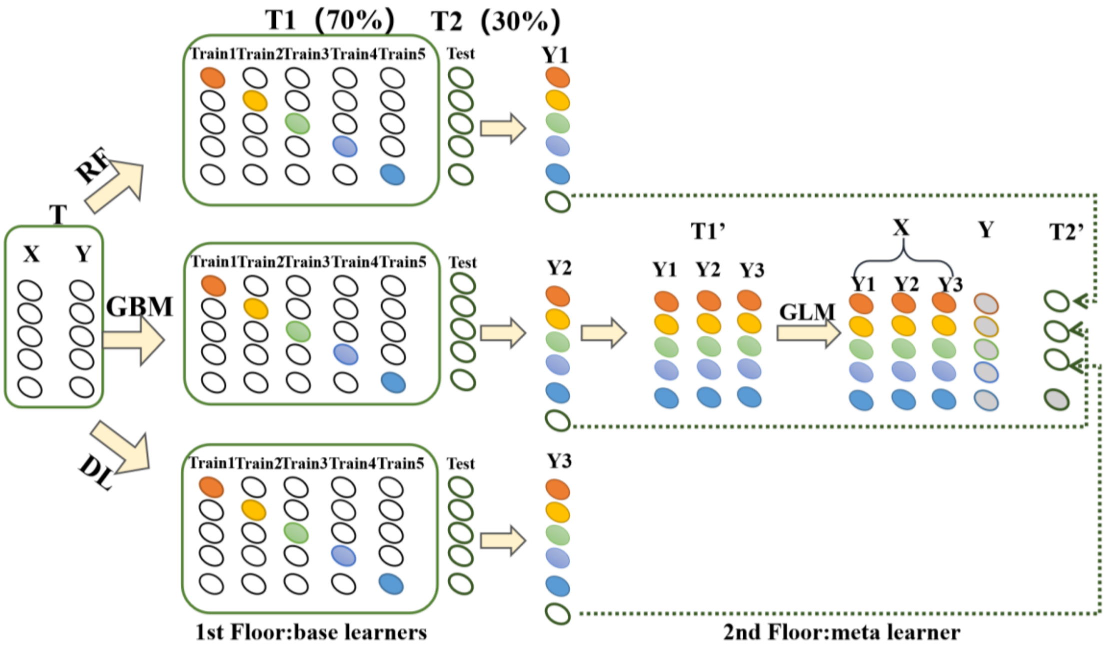
| | Spectral index | Description | Formula | Reference |
|---|---|---|---|---|
| Soil indices (SIs) | Int1 | Intensity index 1 | $(G+R)/2$ | (Yang et al. 2023) |
| | Int2 | Intensity index 2 | $(G+R+NIR)/2$ | |
| | SI | Salinity index | $R\times NIR/G$ | |
| | SI1 | Salinity index1 | $\sqrt{G\times R}$ | |
| | SI2 | Salinity index2 | $\sqrt{G^2+R^2+NIR^2}$ | |
| | SI3 | Salinity index3 | $\sqrt{G^2+R^2}$ | |
| | SI4 | Salinity index4 | $(G-RGE)/(G+RGE)$ | |
| | SI5 | Salinity index5 | $\sqrt{G\times RGE}$ | |

# 3.Scientific issues and Methodology



## Modelling and Mapping

H2O package in the R software




Model Evaluation Method:
Repeated 5-fold cross-validation

Performance Metrics:
$R^2$ (Coefficient of Determination)
RMSE (Root Mean Square Error)
MAE (Mean Absolute Error)

# *Impact of FVC on EC Prediction from Original Images*

**Objective**:

Analyze the effect of different FVC thresholds on salinity prediction accuracy

**Method:**

- Pixel dichotomy to obtain median FVC values during the sampling period
- Discussed EC distribution and prediction accuracy based on sampling points and original images

$$FVC = \frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}}$$ (Hu et al., 2019)

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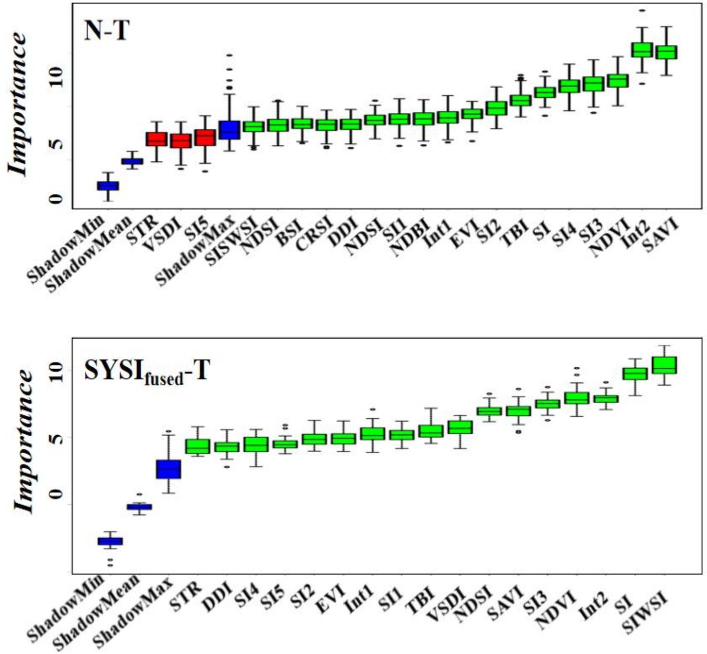
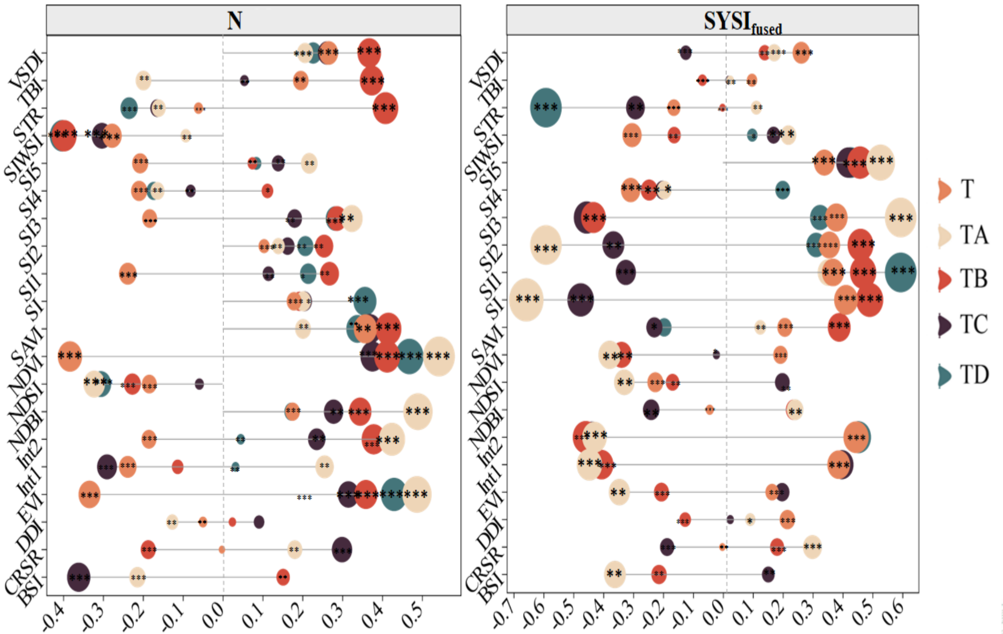
# 4.Research Results



## *Spectral variables selection*



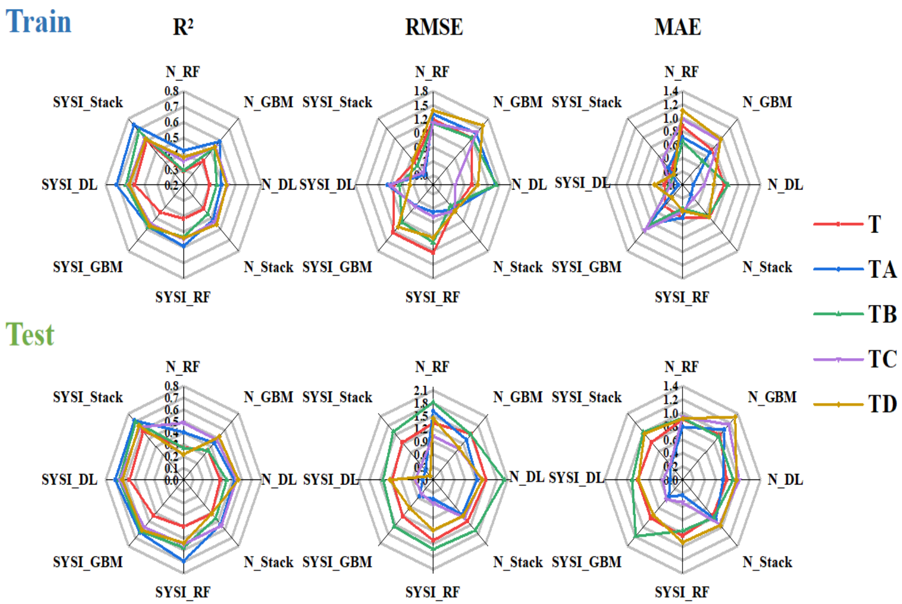



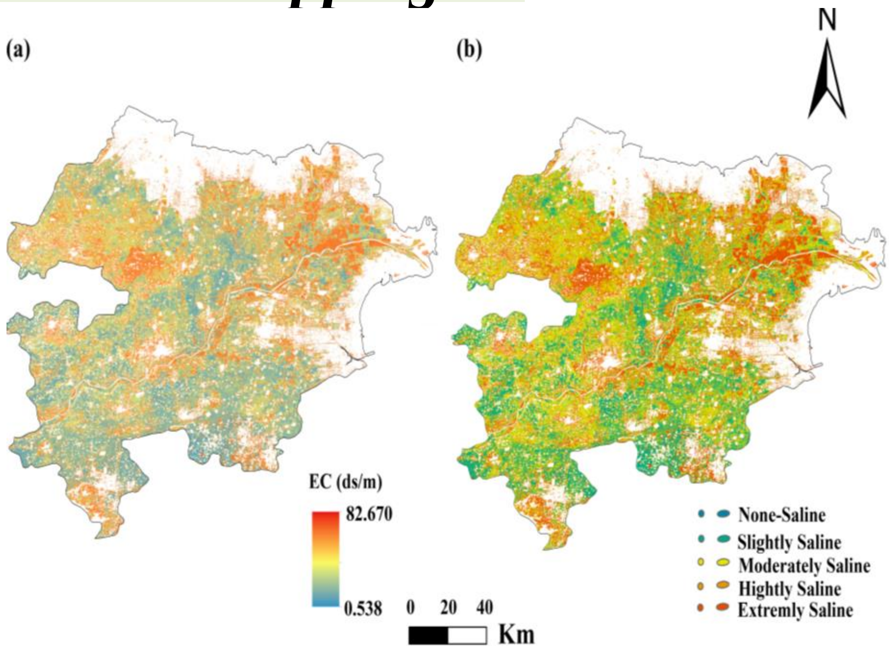

Important index: **Vegetable index** of original image;

**Soil index** of pured spectral

# 4.Research Results

## *Prediction performance comparison and EC mapping*

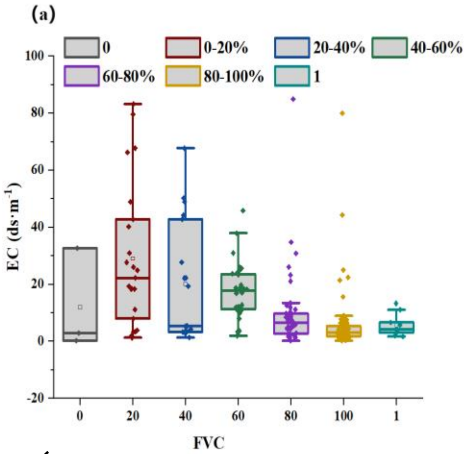


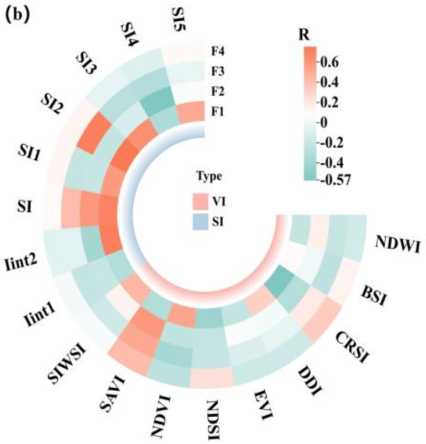




- ➢ **Stacking model** outperforms other models with significant reductions in RMSE and MAE.
- ➢ **Soil type classification** enhances prediction accuracy, with coral sand and brown soils achieving the highest accuracy.
- ➢ Incorporating **bare soil pixels** further improves model performance across all soil types.

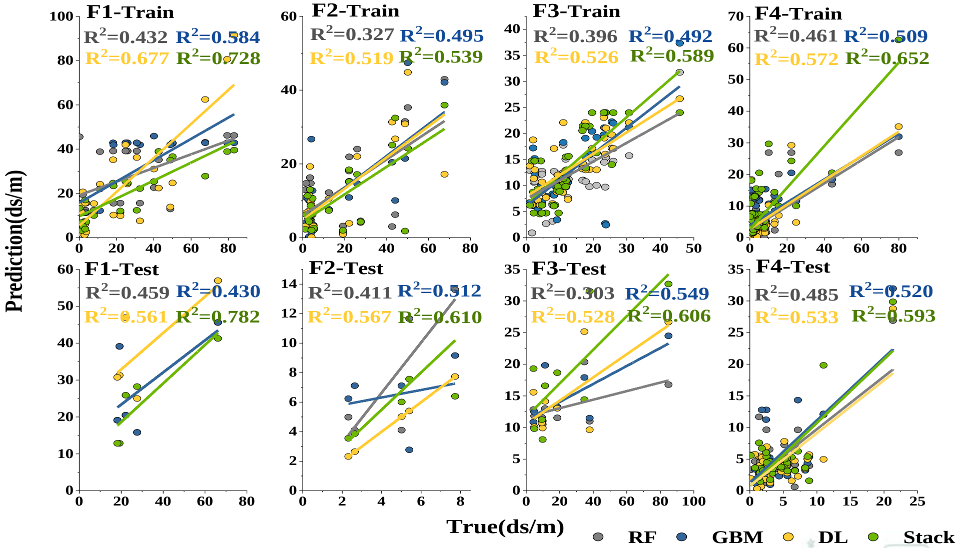
# 4.Research Results

## FVC’s Effects on soil EC prediction from original image




（F1=0-25%，F2=25-50%，F3=50-75%,F4=75-100%）




- ➢ FVC>40%: EC decreased with increasing FVC

| | Low Vegetation Cover | FVC>40% |
|---|---|---|
| Spectral Indices (SIs) | Positive | Decreases |
| Vegetation Indices | Positive | Strengthens |

F1 > F4 > F3 > F2

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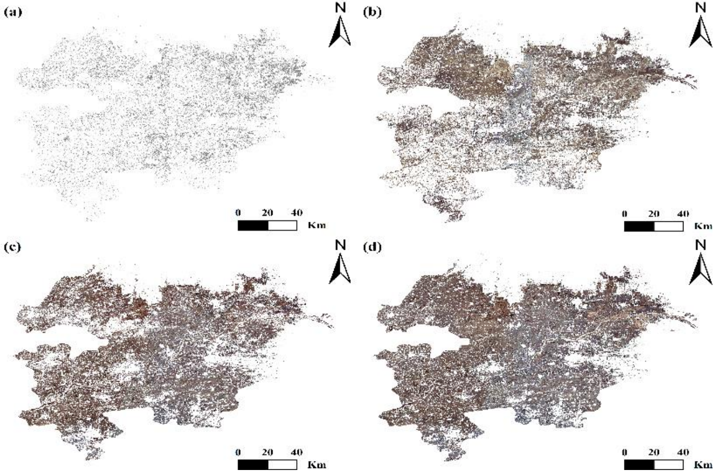
# 5.Discussion, Conclusions and Prospects

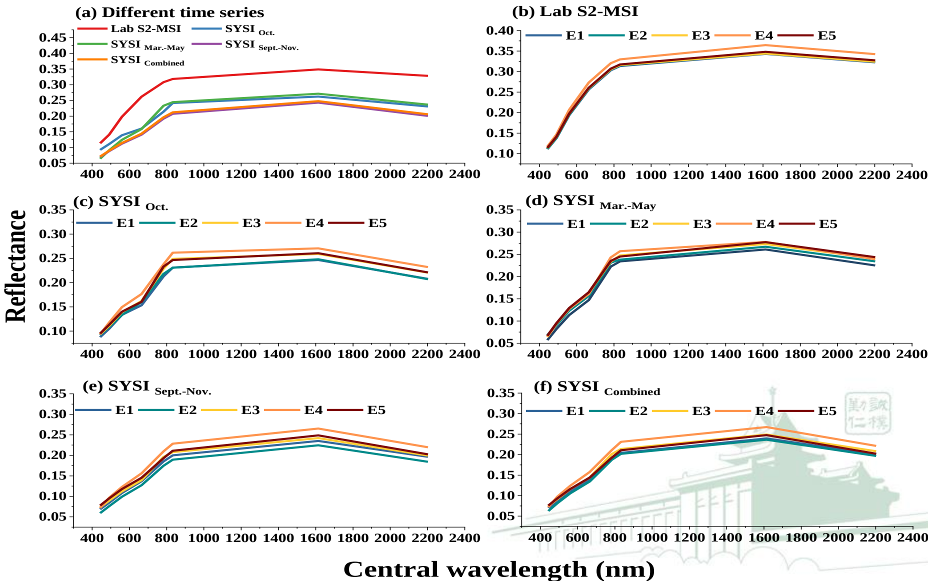


## *SYSI synthesized in different time windows*




SYSI Combined:

38% higher than SYSI Mar.-May
23% higher than SYSI Sept.-Nov.
5 times higher than SYSI Oct.

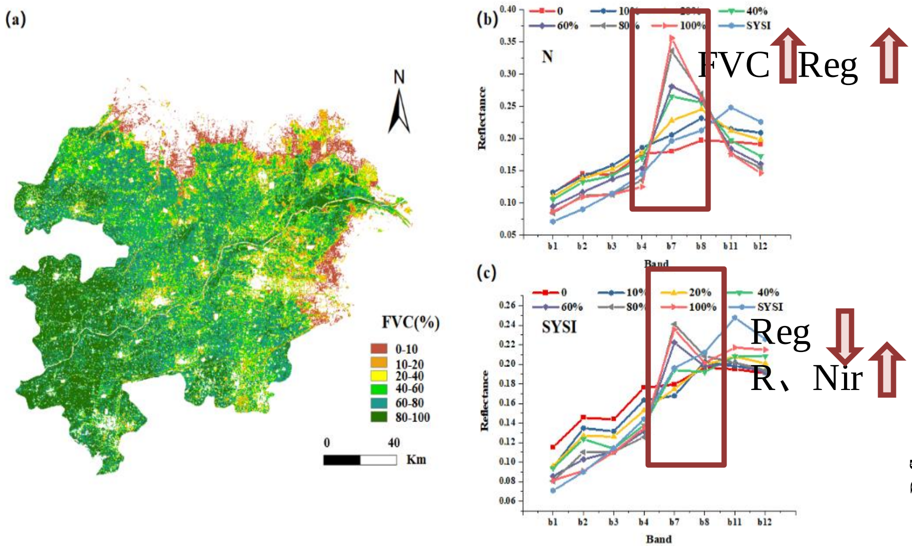



- ➢ $SYSI_{combined}$ curves mirror $SYSI_{Oct}$, a nonlinear rise in reflectance with increased salinity
- ➢ Median statistics and integrating images from March-May and September-November reduce external interference

# 5.Discussion, Conclusions and Prospects



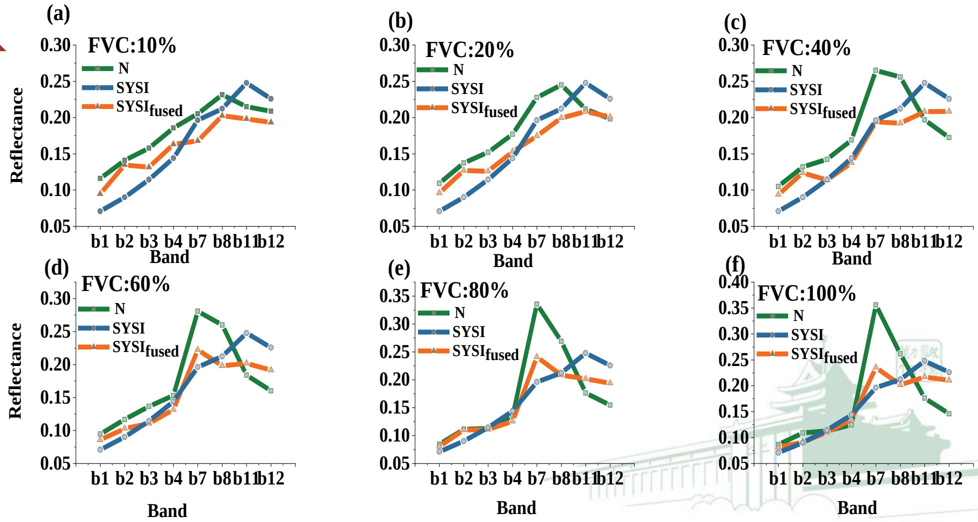
## The influence of the SYSI fusion on spectra




Spectral Differences Pre- and Post-Fusion

Significant spectral changes after fusion, closely tied to FVC

Fusion effectively reduces the impact of vegetation cover




Impact of FVC on Fusion Performance

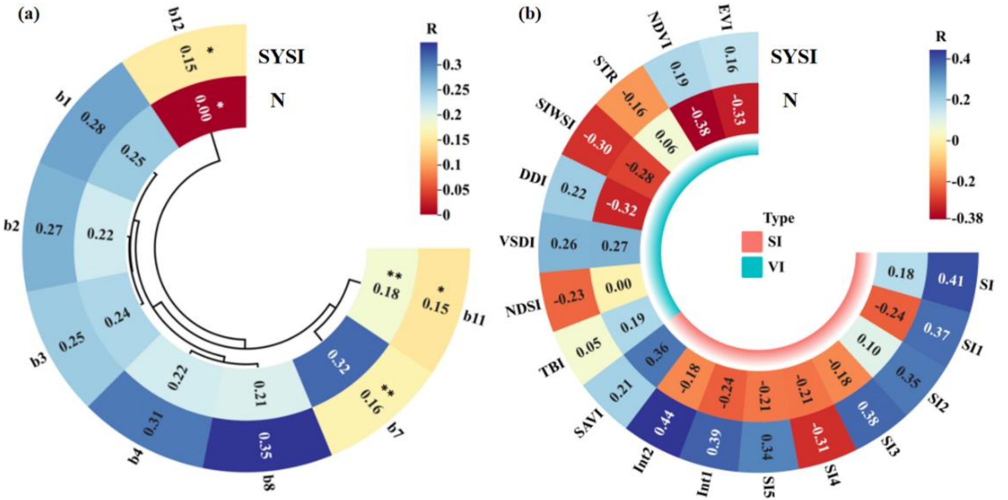
As FVC increases, post-fusion spectra begin to show vegetation traits, especially in band 7

Fusion performance declines, and soil spectral characteristics become less stable

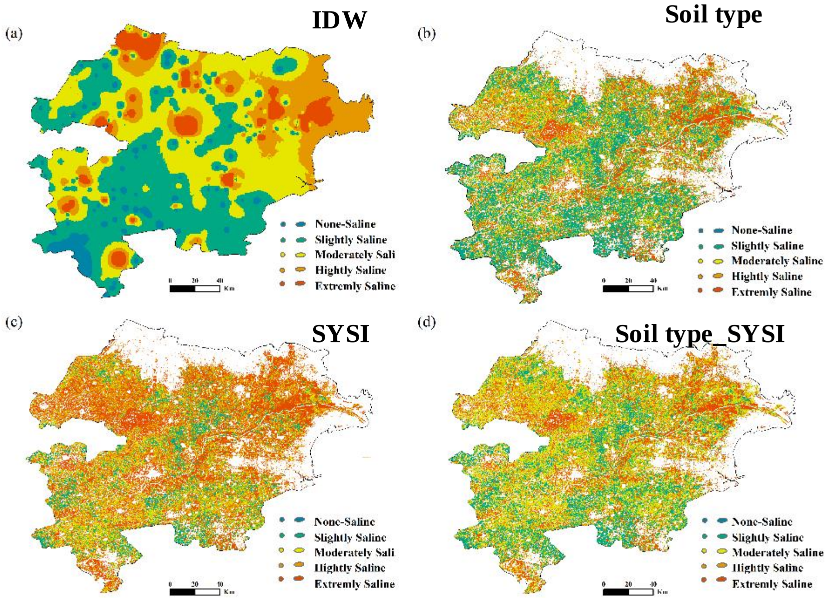
# 5.Discussion, Conclusions and Prospects



## *Performance of soil EC prediction after incorporating SYSI*




The correlation coefficients (R) between EC and the spectra,spectral index




- Pre-fusion: EC strongly correlated with spectral reflectance (B7 strongest), SIs weaker than VIs.
- Post-fusion: Opposite trend, SIs stronger than VIs.
- $R^2$ increased by 0.054–0.242; RMSE/MAE reduced by 0.049–0.780 / 0.012–0.546 ds/m.
- High salinity areas found in low vegetation regions, regardless of fusion;VIs underestimate soil salinity in areas with low vegetation cover

# Conclusions

- $SYSI_{fused}$ outperformed the original image (the $R^2$ increased by 0.054-0.242, RMSE and MAE decreased by 0.049-0.780 and 0.012-0.546)
- Based on the $SYSI_{fused}$, coastal bog solonchaks > alluvial soil > cinnamon soil > coral saline soil > overall samples, with improvements in $R^2$: 0.141, 0.085, 0.022, 0.012
- Best Prediction Model: Stacking models with the $SYSI_{fused}$ ($R^2$=0.742, RMSE=0.377, MAE=0.362).

## *Prospects*

**Study Limitations**:

- Soil salinity can vary over time, but remained stable in the study area from 2017 to 2021

**Mitigating Temporal Variability**:

- Used multi-year bare soil images from the salt return period and calculated the median reflectance to align spectra with the sampling period, reducing discrepancies

**Recommendations**:

- For areas with fluctuating salinity, narrow the temporal window for bare soil pixel capture
- Customize SYSI based on regional salinity dynamics for more accurate soil property mapping

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**Wish this international conference has a complete success!**

**Wish the soil data and information for deeper and more valuable exploration!**

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# THANK YOU !

Presenter:Danyang Wang
Supervisor:Prof.Zhaofu Li

南京農業大學
NANJING AGRICULTURAL UNIVERSITY
资源与环境科学学院
College of Resource & Environmental Sciences