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2025 DRAGON 6 SYMPOSIUM

14-18 JULY 2025

[PROJECT ID. 95250]

OPTICAL AND THERMAL COPERNICUS-CHINESE EO DATA FOR ANALYZING THE DRIVING FACTORS, IMPACTING ON FOOD SECURITY AND QUALITY





2025 Dragon 6 Symposium

<15/JULY/2025: 14:00-15:30>

ID. 95250

PROJECT TITLE: OPTICAL AND THERMAL COPERNICUS-CHINESE EO DATA FOR ANALYZING THE DRIVING FACTORS, IMPACTING ON FOOD SECURITY AND QUALITY

PRINCIPAL INVESTIGATORS: S. PIGNATTI, W. HUANG

CO-AUTHORS: RAFFAELE CASA, YINGYING DONG, WENJIANG HUANG, GIOVANNI LANEVE, ZHENHAI LI, LINYI LIU, SAHAM MIRZAEI, SIMONE PASCUCCI, STEFANO PIGNATTI, FRANCESCO ROSSI, BIYAO ZHANG, GUIJUN YANG, HAO YANG

PRESENTED BY: S. PIGNATTI, W. HUANG

Dragon 6 EO Data Delivery

Data access (list all missions and issues if any). NB. in the tables please insert cumulative figures (since June 2024) for no. of scenes of high bit rate data (e.g. S1 100 scenes). If data delivery is low bit rate by ftp, insert “ftp”

ESA /Copernicus Missions	No. Scenes
1. Sentinel- 1	85+30
2. Sentinel - 2	60+80
3.	
4.	
5.	
6.	
Total:	255
Issues:	

ESA Third Party Missions	No. Scenes
1. SAOCOM	65
2. Landsat-8	25
3. MODIS	30
4. PRISMA	50
5.	
6.	
Total:	170
Issues:	

Chinese EO data	No. Scenes
1. GF-1	50
2. GF-2	55
3. GF-6	60
4.	
5.	
6.	
Total:	165
Issues:	

European Young Scientists contributions in Dragon 6

Name	Institution	Poster title	Contribution including period of research
Francesco Rossi 	University of Rome ‘La Sapienza’ / CNR IMAA	ISAC and TES Algorithms optimization for topsoil characterization in view of the LSTM mission ID#260	2020-2024 : analysis of complex datasets, optimizes predictive models, and contributes to research, as shown by his publications and conference contributions. He aims to apply his expertise in remote sensing, data analysis, and machine learning to solutions in precision agriculture or environmental monitoring.
Saham Mirzaei	CNR IMAA	N/A	Time series PRISMA/ENMAP to support CHIME simulation
Alberto Ossola	University of Rome ‘La Sapienza’	N/A	2024 – 2025: as an agronomist he aims to apply remote sensing data to study one of the diseases which are affecting kiwi plantations.
Jepther Ondieki	University of Rome ‘La Sapienza’	N/A	2022 – 2025: he is working on the implementation of SAR based data procedure to obtain high resolution soil moisture maps in agricultural areas

Chinese Young Scientists contributions in Dragon 6

Name	Institution	Poster title	Contribution including period of research
Xiaokang Zhang	Shandong University of Science and Technology	Adjusted CBA-Wheat model for predicting aboveground biomass in winter wheat from hyperspectral data	Developing the relative day of the year (RDOY) to improve the accuracy of winter wheat biomass estimation within the CBA-Wheat model, and RDOY is a superior alternative to traditional phenological observations and can potentially enhance the performance of conventional machine learning models.
Xiaobin Xu	Shandong University of Science and Technology	Phenology-guided Remote Sensing Prediction Model for Wheat Quality and Its Uncertainty Assessment	A phenology-guided prediction model for protein content in winter wheat grains was constructed, and accidental and random uncertainty analyses were conducted on the model and the dataset
Zhengdong Wang	Shandong University of Science and Technology	A Unified Framework for Automatic Joint Recognition of Wheat and Field Boundaries	Accurate extraction of wheat fields is essential for understanding crop distribution, supporting agricultural management and policymaking, and enhancing the efficiency of yield monitoring, pest forecasting, and farmland resource utilization.
Biyao Zhang	Aerospace Information Research Institute, Chinese Academy of Sciences (AIRCAS)	N/A	Developing satellite remote sensing monitoring method for the discolored trees caused by pine wilt disease (PWD) and the suitable area of PWD.
Jing Guo	AIRCAS	N/A	Developing large-scale remote sensing monitoring method for grasshopper habitat

Overview of European YSs research

2024-2025:

Francesco Rossi: PhD Graduate in Remote Sensing and Agricultural Monitoring from Sapienza University of Rome, with a focus on hyperspectral satellite data and Machine Learning for agricultural management. His doctoral research explored the retrieval of crop biophysical variables and topsoil properties, addressing challenges like soil moisture influence and parameter distribution uncertainties through domain adaptation techniques.

Saham Mirzaei: Postdoc @ CNR IMAA working on PRIMA EnMAP temporal timeseries for retrieving topsoil constituents

Alberto Ossola: PhD student of the Italian National PhD on Earth Observation of Sapienza University of Rome, is focusing his work on the use of satellite images to detect diseases in kiwi plantation.

Jepther Ondieki: PhD student of the PhD course on Aeronautics and Space Engineering of Sapienza University of Rome, is focusing his work on the use of SAR imagery to obtain high resolution maps of soil moisture in agricultural areas.

<u>2025-2027</u>

TBD: public examination for a position for PhD candidate @ University of Viterbo in 2025 (Italy), call ongoing

Overview of Chinese YSs research

2024-2025:
Xiaokang Zhang: A lecturer at Shandong University of Science and Technology, with research focused on chlorophyll fluorescence remote sensing, climate change and terrestrial carbon cycle.

Xiaobin Xu: Postdoctoral fellow at Shandong University of Science and Technology. Mainly engaged in research on remote sensing monitoring of agricultural conditions and prediction of yield and quality.

Zhengdong Wang: A lecturer at Shandong University of Science and Technology, with research focused on the intelligent monitoring of crop growth, farming operations, agricultural conditions, and agro-meteorological information throughout the entire crop lifecycle.

Biyao Zhang: research assistant of AIRCAS, his research interest is forest biological disaster monitoring and forecasting, especially for the pine wilt disease monitoring using high spatial resolution satellite image.

Jing Guo: PhD student of AIRCAS, is focusing on the grasshopper monitoring and forecasting.

Project objectives

Identify the optimal RTM models and MLR algorithms to improve the accuracy in the estimation of crop biophysical variables such as pigments (i.e. including carotenoids and anthocyanins), nitrogen related variables and water stress providing an accuracy evaluation;

- **1st objective**

Explore innovative and advanced methods (e.g., GPR in comparison with Kernel Ridge Regression: KRR and Artificial Neural networks: ANNs) including the Active Learning (AT) processes for crop plant key parameters retrieval at the different growth stages providing an uncertainty estimate;

- **2nd objective**

Explore the suitability of GF-6 data as well S-2, FLEX, PRISMA and ENMAP data to retrieve SOC. This to explore how the CHIME simulated products; soil moisture retrieval by multi-frequency data

- **3° objective**

Assimilate multivariate and multi-scale remotely sensed variables into agricultural models (i.e. crop growing, pest and disease). A hierarchical prediction model using remote sensing and meteorological data will be proposed to predict crop grain yield & quality;

- **4th objective**

Explore the added value of thermal infrared data for the integration of LST, emissivity (i.e. considering the upcoming LSTM, SBG-TIR and TRISHNA missions) and evapotranspiration in the monitoring of crop stress. These with the aim to better distinguish water from other abiotic and biotic stresses conditions;

- **5th objective**

Access to large amounts of open and free Earth observation data, products and cloud computing resources. Exploit GEE (Google Earth Engine) catalog and resources to perform multi temporal and multi sensors analysis sharing algorithms.

- **6th objective**

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1st objective:

HYPERSPECTRAL REMOTE SENSING DATA FOR RETRIEVING CROP BIOPHYSICAL VARIABLES







PROSAIL Parameter Distribution and Transfer Learning

Research Questions:

1. To what extent does the **parameter distribution** influence the performance of ML-based LUT inversion for vegetation parameter retrieval?
2. How can **transfer learning** techniques be effectively used to reduce or eliminate the need to pre-define the distribution of PROSAIL model parameters?.
3. What are the optimal **pre-processing** for inverting LUTs derived from PROSAIL using PRISMA HS data?

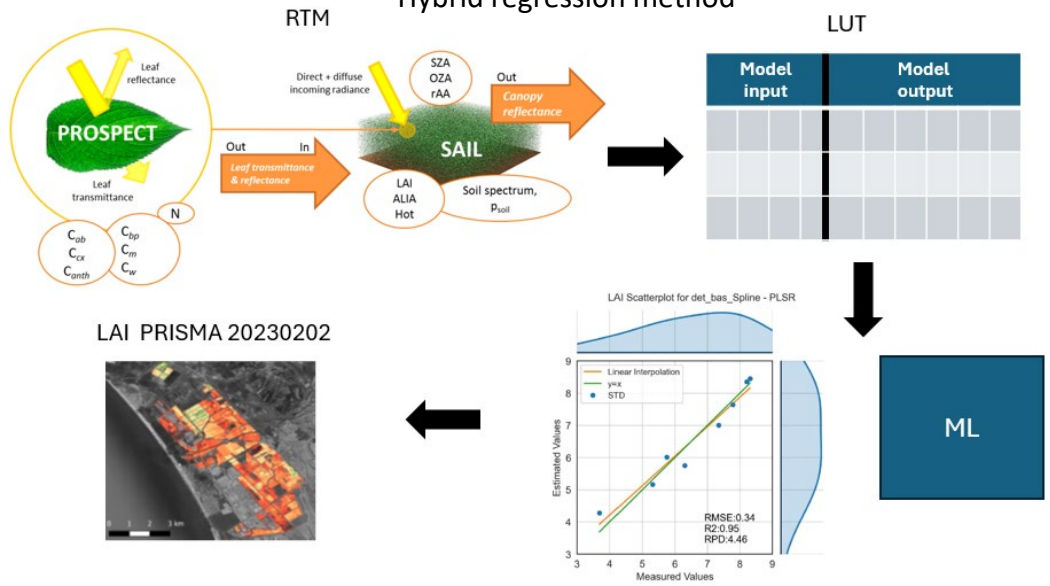
In situ LAI measurement methods**:**

- **Direct methods:** partial defoliation of the canopy
- **Indirect methods:**
  - Hemispherical Photography
  - Transmittance (Beer's Law)
  - Reflectance

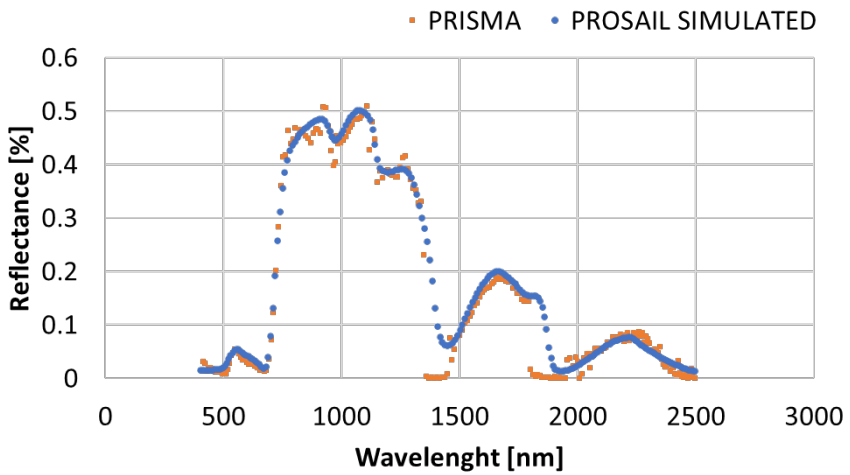
Remote Sensing LAI measurement methods based on the use of **Look Up Table (LUT)** generated by **Radiative Transfer Models (RTM):**

- Inversion based on cost functions
- **Hybrid regression method**

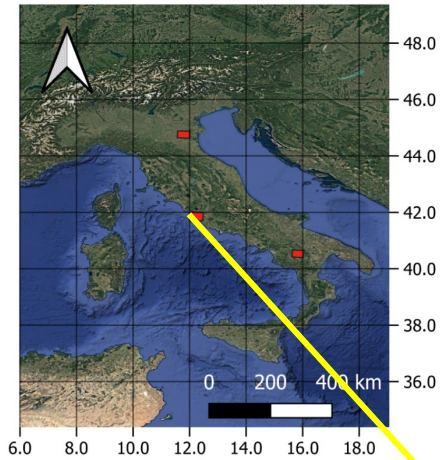
Hybrid regression method



PROSAIL signal can be very similar to HS satellite data



Study Area and Data Collection

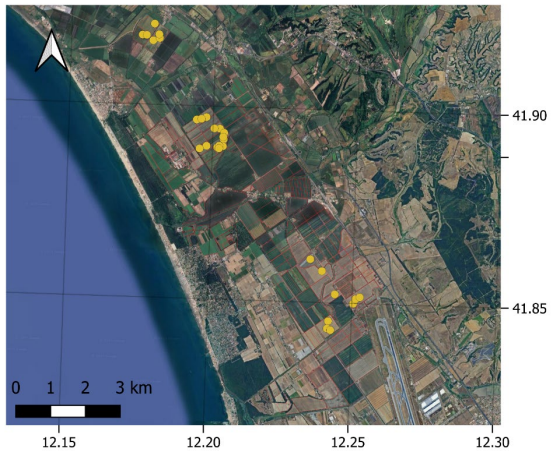


LAI-2200

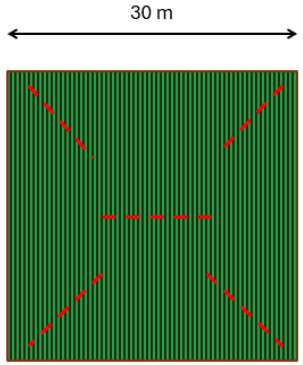


Fraction of blue light (320–490 nm)

Transect-based sampling method



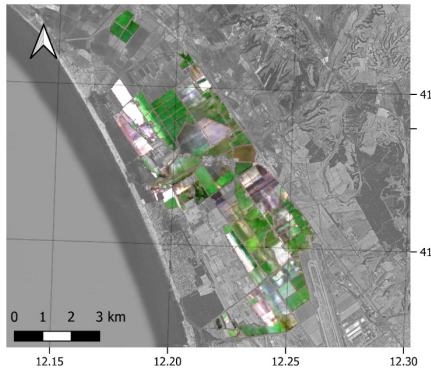
- 15 measurements were taken for each transept.
- Average for each square, for a total of 42 measured squares.



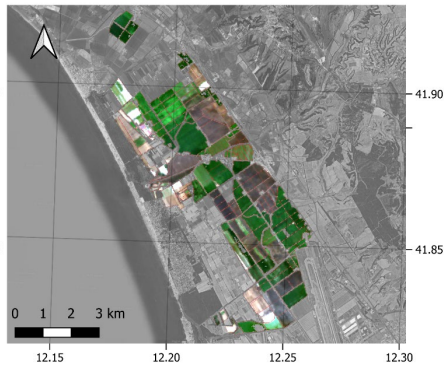
Measured exclusively at Maccarese

EO Data Acquisition

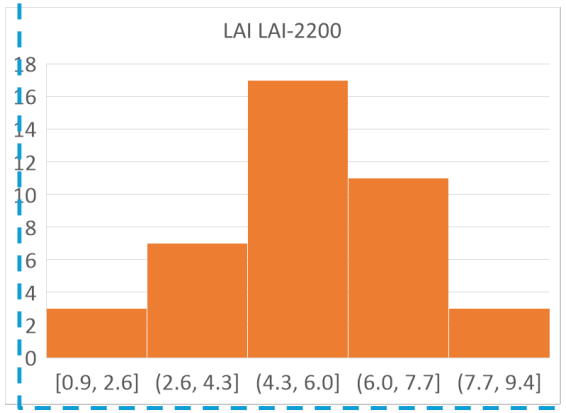
PRISMA RGB 02/02/2023



PRISMA RGB 21/03/2023



In situ data distribution



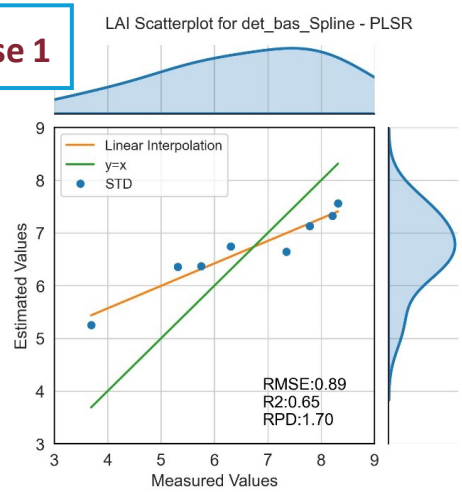
	LAI [m²/m²]
MIN	*0.86*
MAX	*8.32*
Average	*5.19*
STD	*1.71*

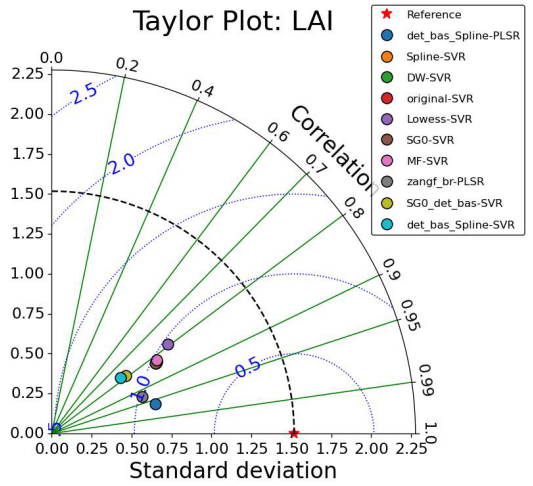
Key Results

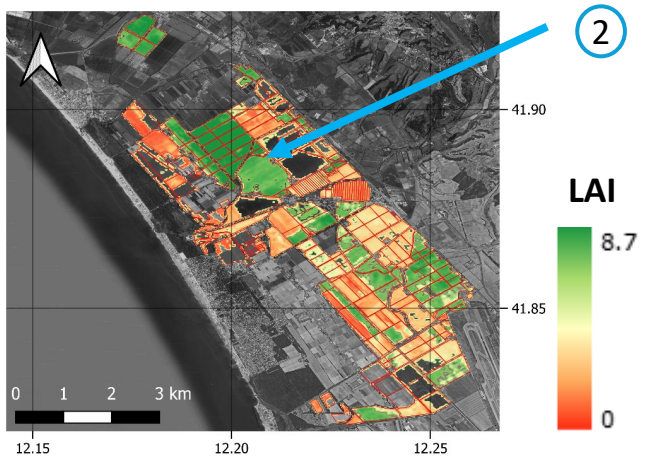
LAI estimation 21/03/2023

Crops_case 1

NO Domain Adaptation



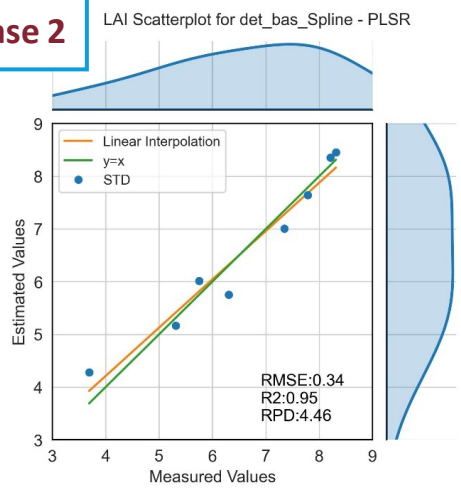


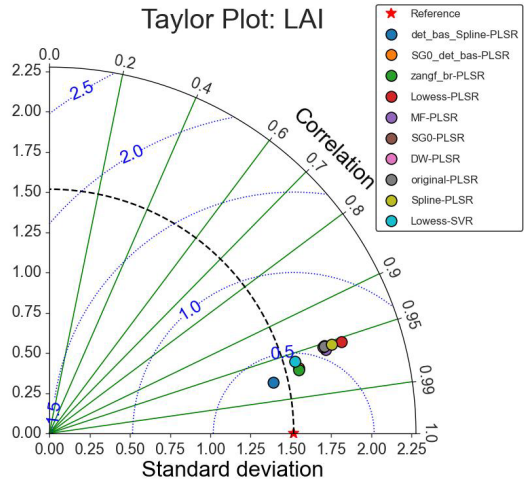


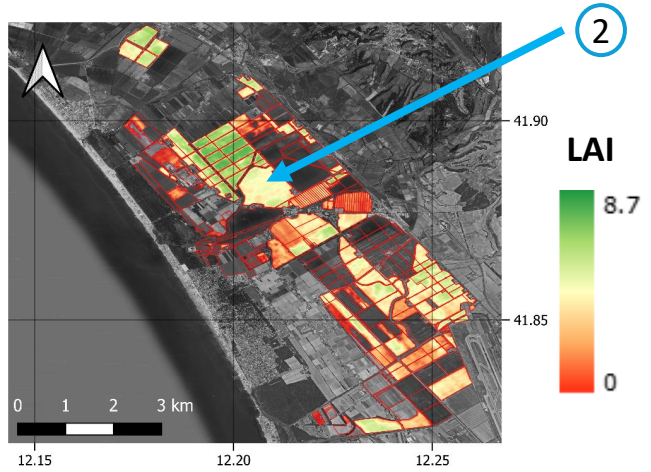
1 Some preprocessing yielded inferior results compared to the original data.

Crops_case 2

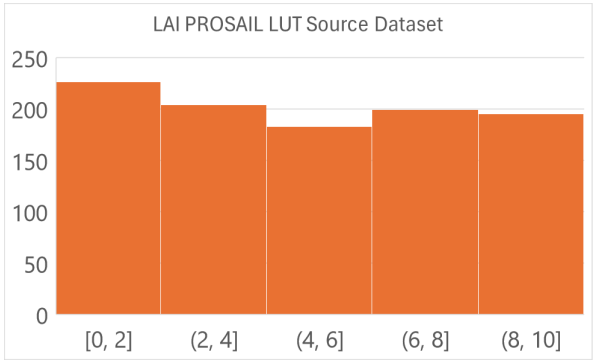
Domain Adaptation



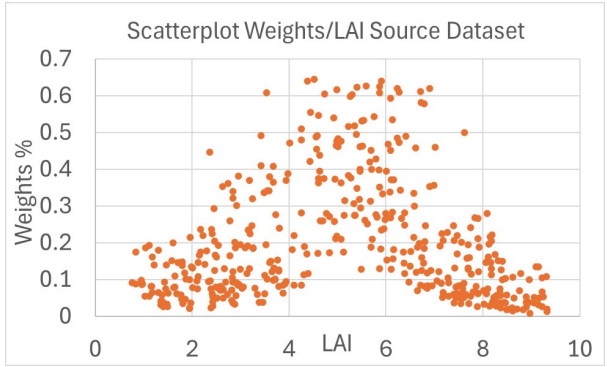




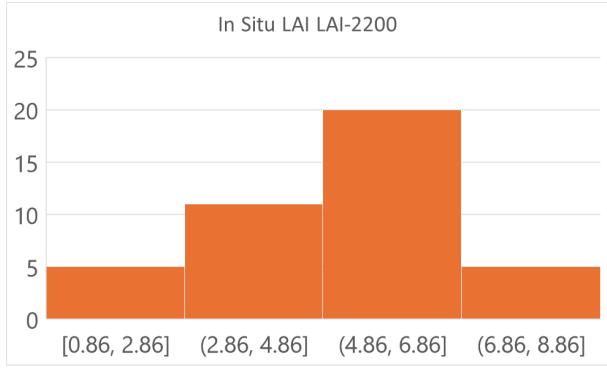
Simulated Dataset LAI Histogram



TrAdaBoostR2 assigned weights to the source dataset



In situ LAI Histogram



Research Questions:

1. To what extent does the **parameter distribution** influence the performance of ML-based LUT inversion for vegetation parameter retrieval.
2. How can **transfer learning** techniques be effectively used to reduce or eliminate the need to pre-define the distribution of PROSAIL model parameters.
3. What are the optimal **pre-processing** for inverting LUTs derived from PROSAIL using PRISMA HS data.

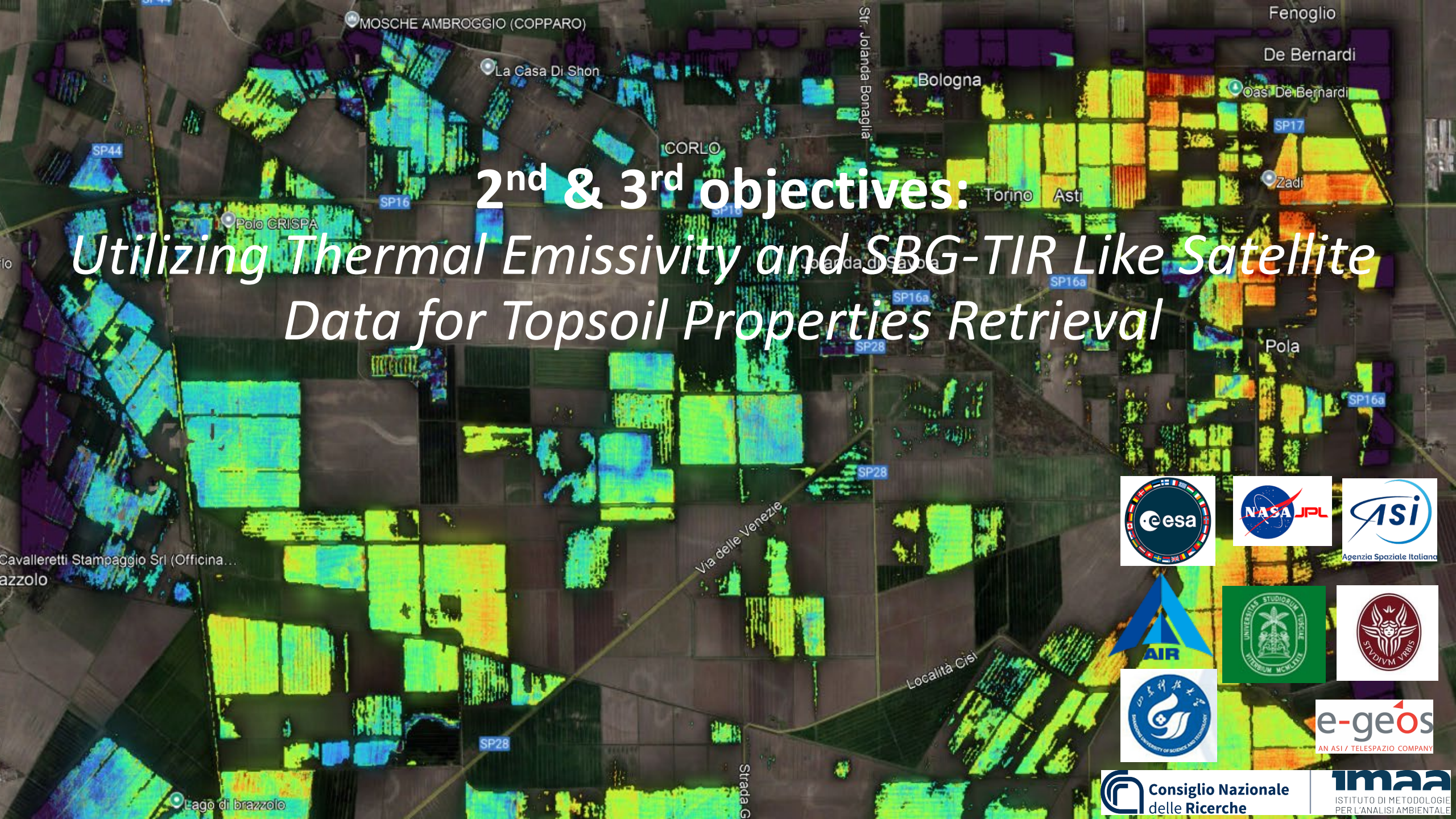
1. The correct parameter distribution improves the validation metrics.
2. The TradabostR2 assigning weight surpasses the necessity of pre-defining de PROSAIL distribution.
3. There is no optimal pre-processing algorithm. Also, some algorithms can decrease the score of the validation metrics.

Advancements

- **Enhanced LAI Estimation Accuracy**: The application of TrAdaBoostR2 domain adaptation significantly improved LAI estimation accuracy (RPD improving from 1.70 to 4.46) when inverting the PROSAIL model with PRISMA hyperspectral data.
- **Transfer Learning** can be a solution to the parameter instability due to equifinality

Limitations

- **Continued necessity of In-Situ Measurements**: Despite the advancements, in-situ measurements are still needed for TrAdaBoostR2 calibration.
- **Lack of Universal Pre-processing Method:** There is still no universally better-performing pre-processing method.



2nd & 3rd objectives:

Utilizing Thermal Emissivity and SBG-TIR Like Satellite Data for Topsoil Properties Retrieval

Agenzia Spaziale Italiana

Consiglio Nazionale delle Ricerche

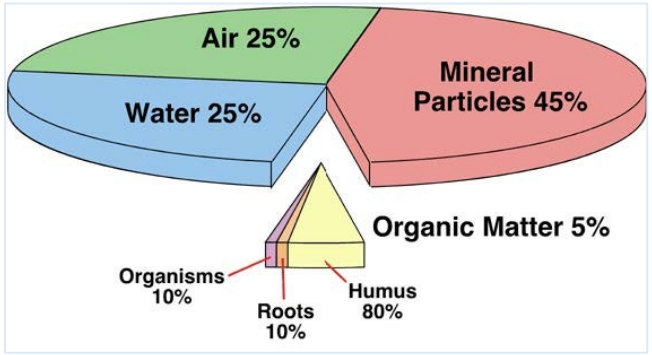
IMAA ISTITUTO DI METODOLOGIE PER L'ANALISI AMBIENTALE

Soil is a complex and heterogeneous material:

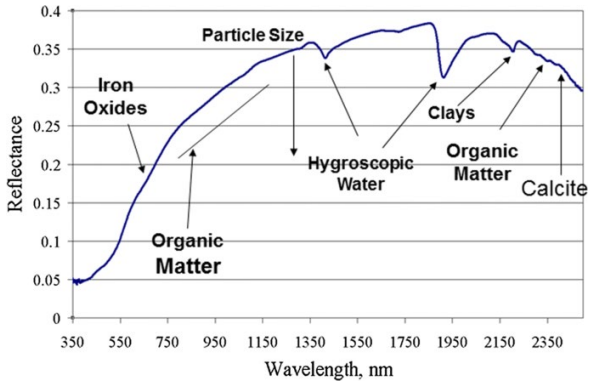
Soil tillage in agricultural areas roughly assure similar properties within the root zone (e.g. up to 20-30 cm)

- Physical properties - texture (sand, silt, and clay), bulk density
- Chemical properties (pH, SOC, EC)
- nutrients (Ca, Mg, K, Na, N, P)
- contaminants







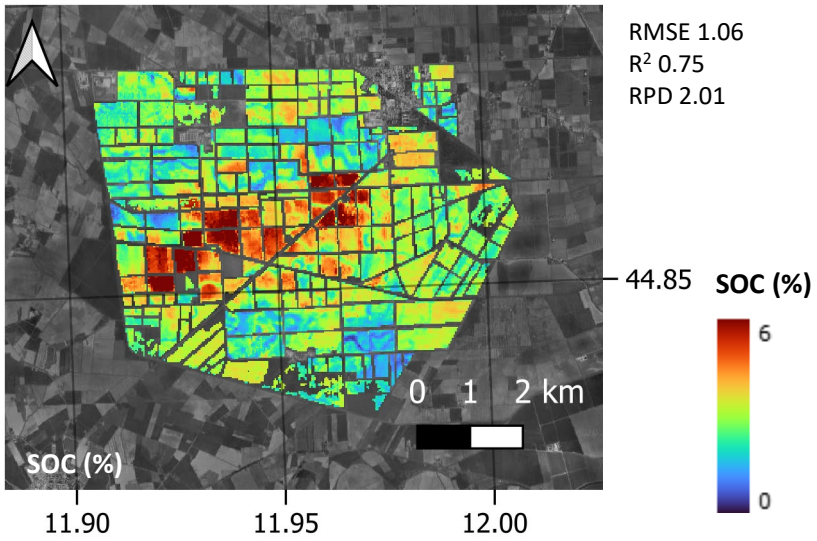


In the SWIR organic matter, water, iron oxides and chemical composition of transition metals in clay minerals are the major chromophores.

VSWIR time series – External Parameters Orthogonalization (EPO) retrieval

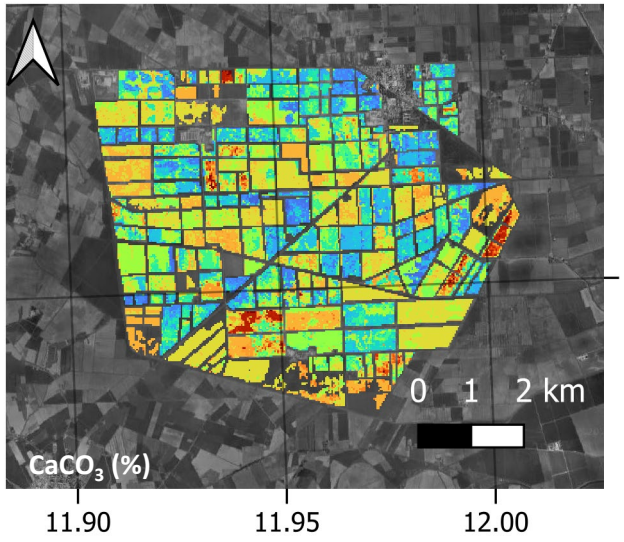
Reflectance image generated averaging the bare soil signal of the PRISMA/EnMAP time series (i.e. 2022-2025; 62/13 images)

GPR applied to SNV-Absorbance



RMSE 1.06
R^2 0.75
RPD 2.01

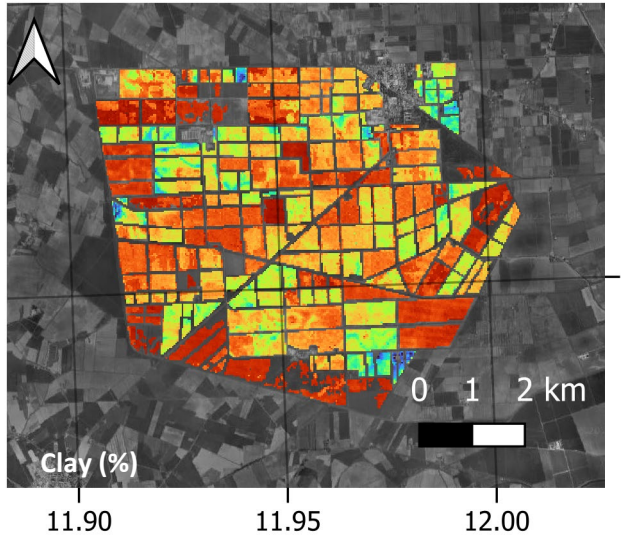
PLSR applied to SG0 – Baseline detrending



RMSE 0.84
R^2 0.68
RPD 1.77

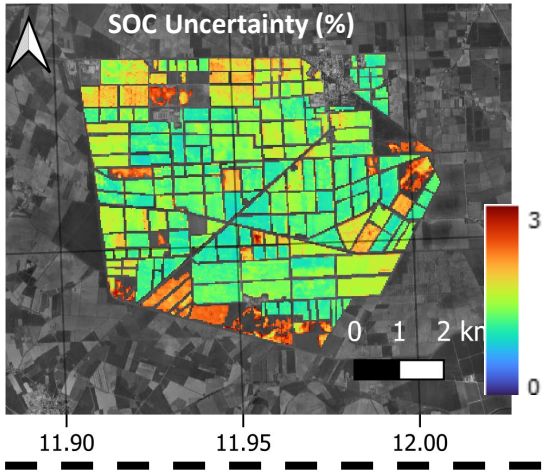


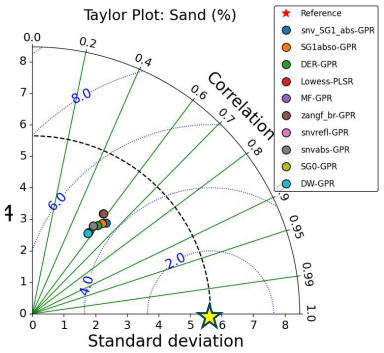
RF applied to SG1 – Absorbance

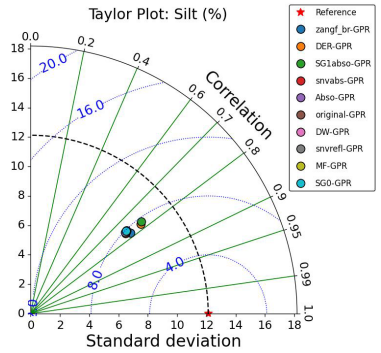


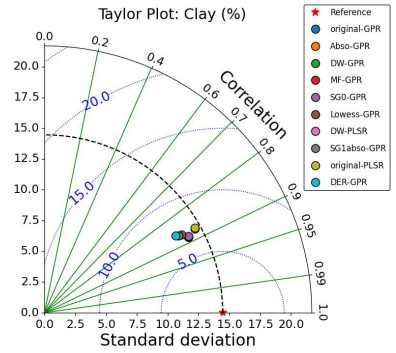
RMSE 9.50
R^2 0.62
RPD 1.61

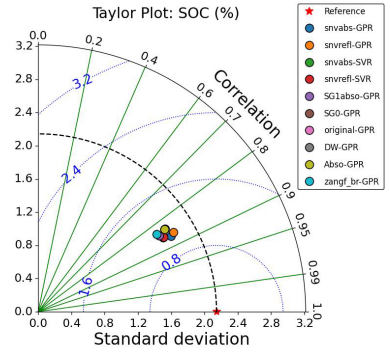


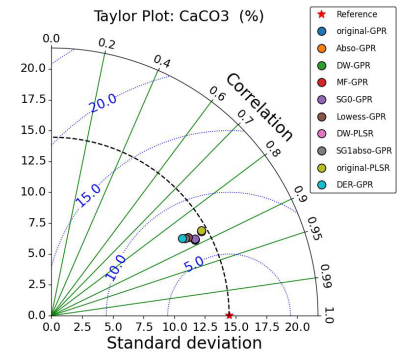




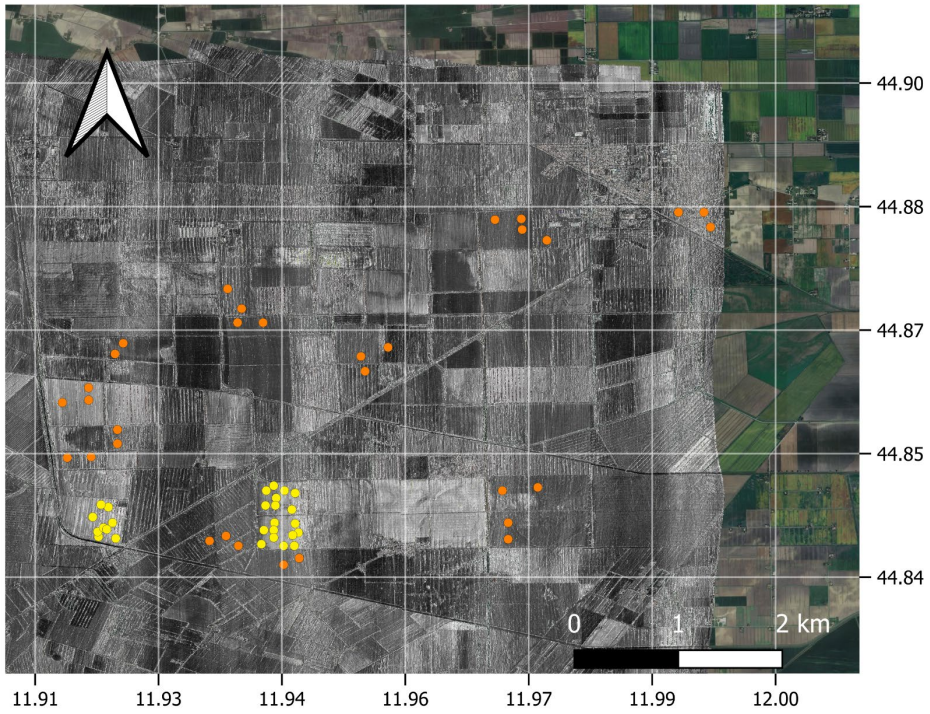








HyTES survey on June 22, 2023 @ 09:41/10:26; 11 flightlines N-S direction



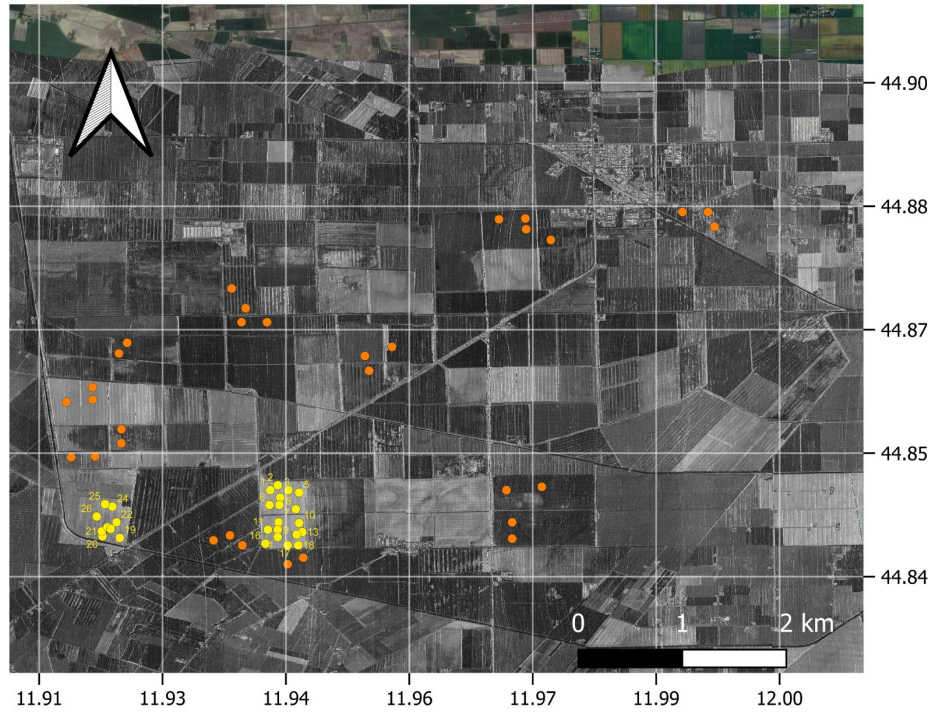
HyTES L2 v. B109 @ 9.81µm

32 sample collected during 2021/2022 field campaigns @ 30m ESU for PRISMA/EnMAP

27 samples collected in 2023 @ 3m ESU for HyTES survey.

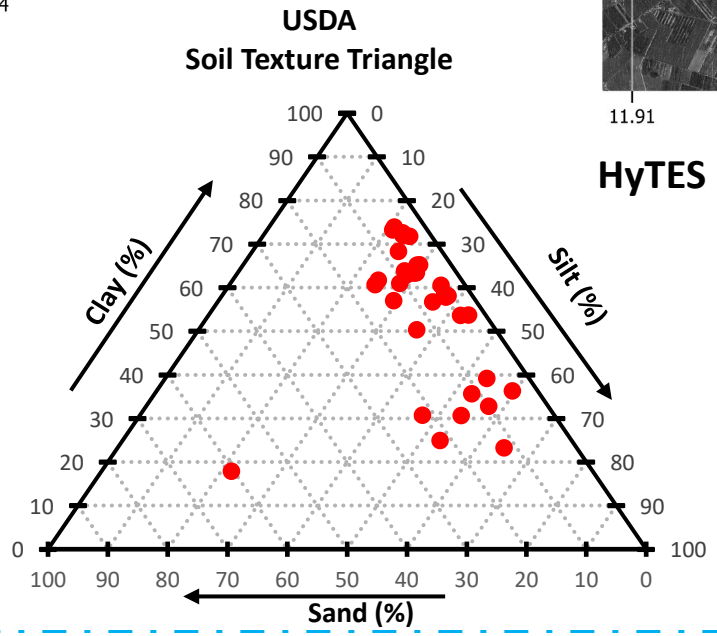
27 JPL lab Nicolet FTIR analysis

XRD on a subset samples for mineralogy



HyTES L1_CORR_IMAA-ICCAAC TES @ 9.81µm

3m ESU	Clay (%)	Silt (%)	Sand (%)	SOC (%)	CaCO3 (%)
Max	17,46	19,65	1,84	0,55	0,00
Min	74,67	78,66	38,85	5,59	11,74
Average	51,44	38,89	9,67	2,54	3,24
STD	14,89	13,59	8,35	1,36	3,07



XRD analysis:

- quartz,
- smectite, chlorite, illite/mica,
- calcite,
- albite and lizardite

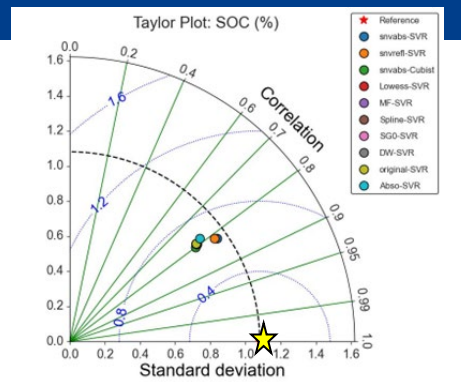
JPL LAB spectra (SSL); HyTES and SBG (LWIR) resampling

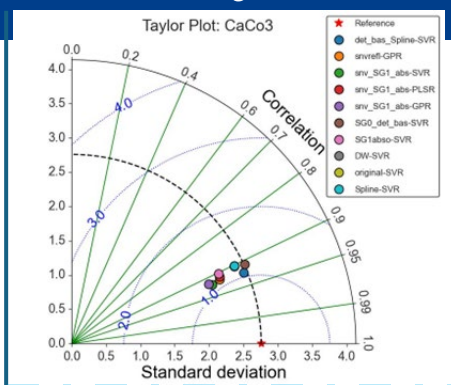
SOC | $CaC0_3$ | Sand (Qz) | Clay (Smectite)

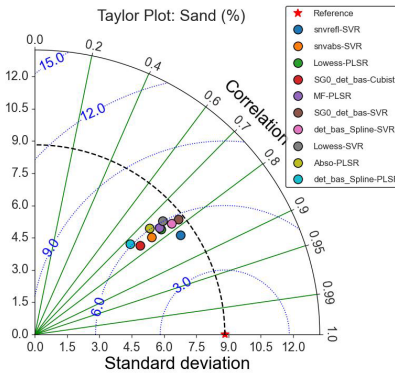
Lab $_{SSL}$

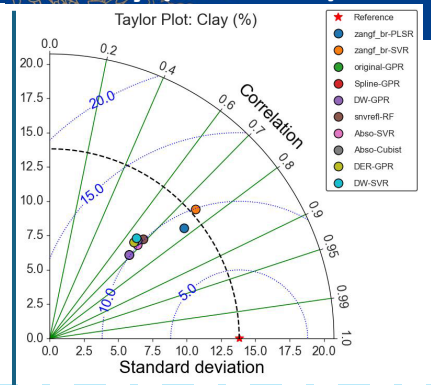
Lab $_{SSL}$ -> HyTES [7.5 -12.0 µm]

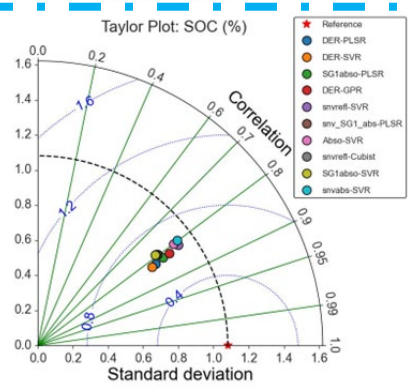
Lab $_{SSL}$ -> SBG-TIR [3.98-12.05 µm]

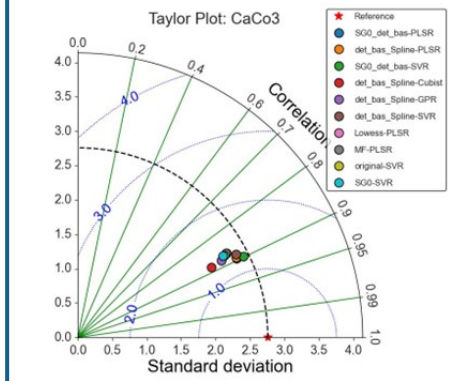


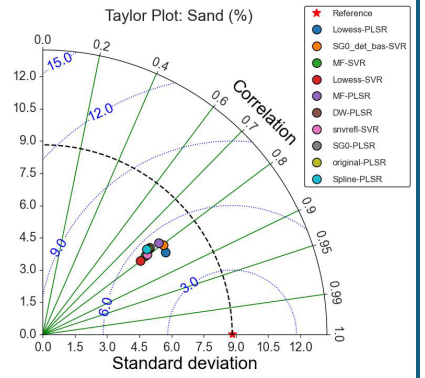


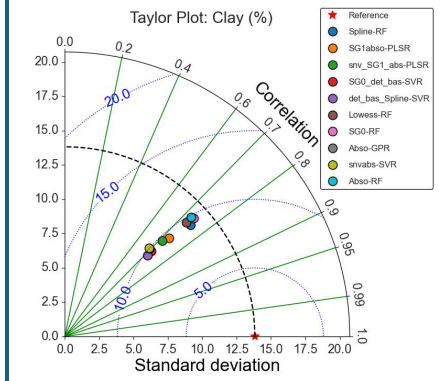


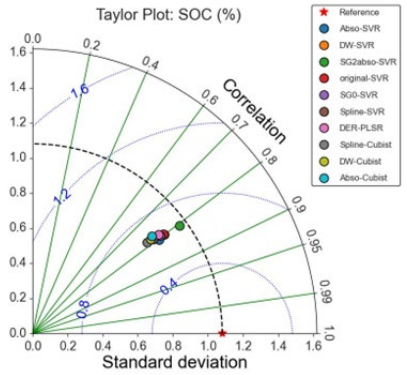


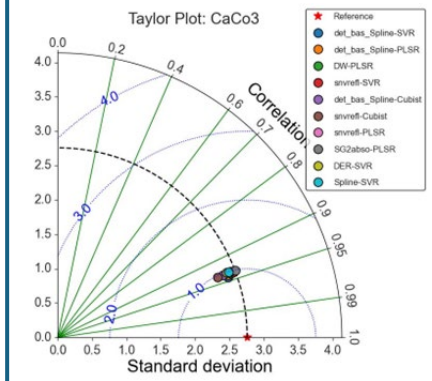


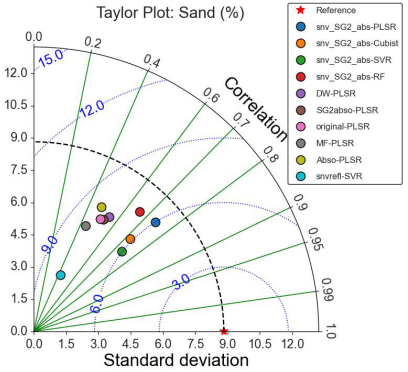


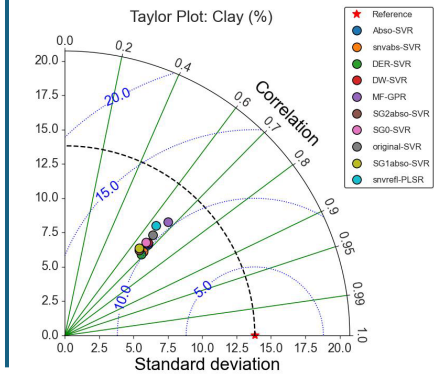


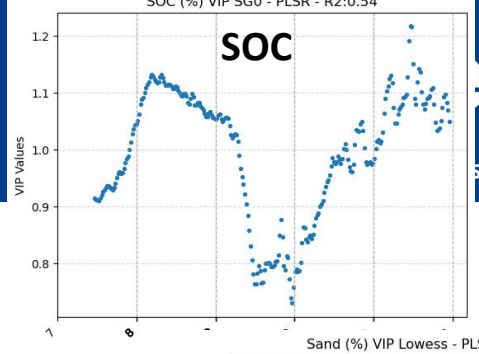


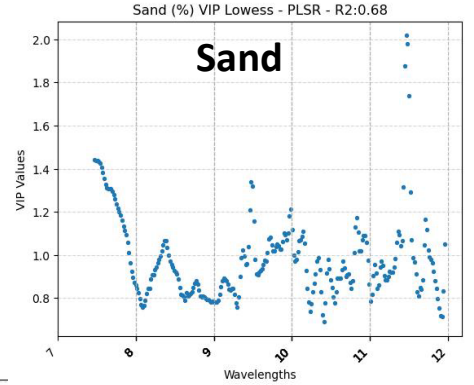


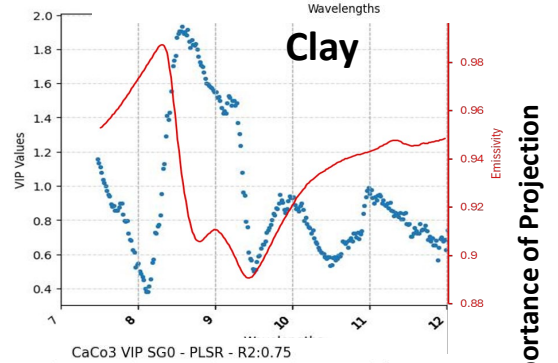


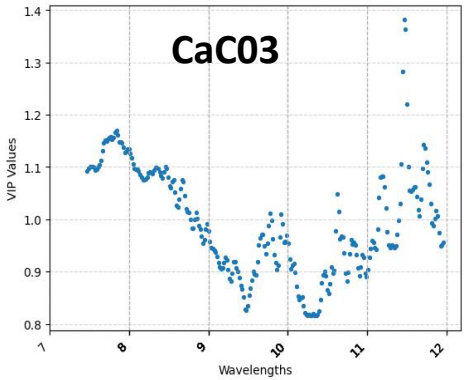






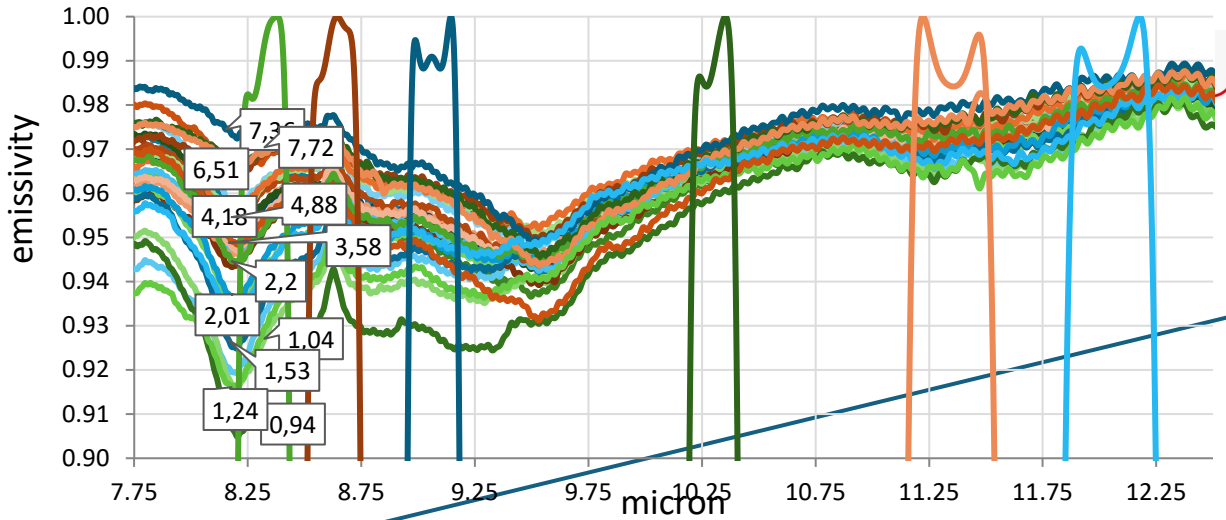




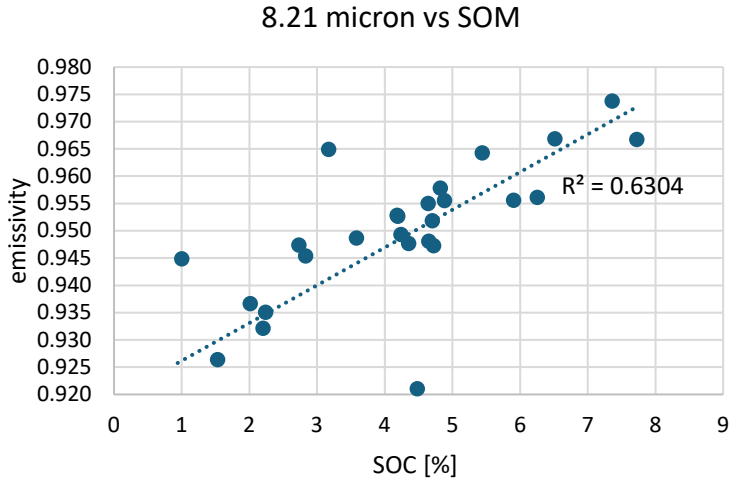


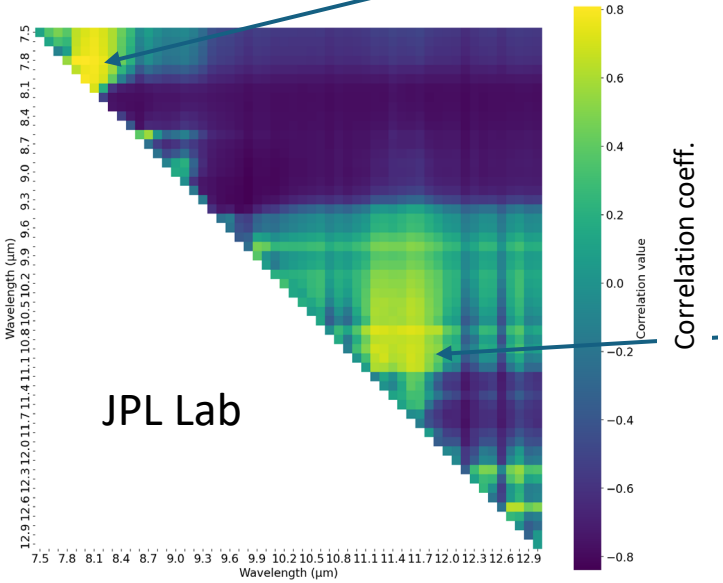
PLSR - Variable Importance of Projection

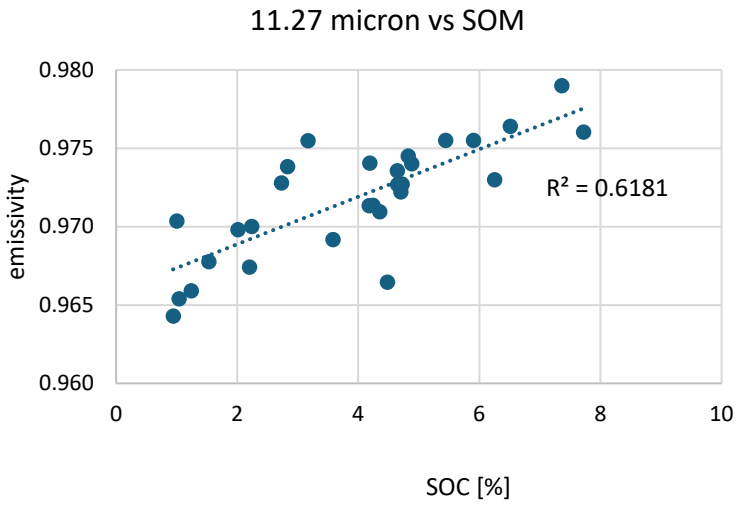
JPL LAB (Nicolet FTIR) vs SOC abundance

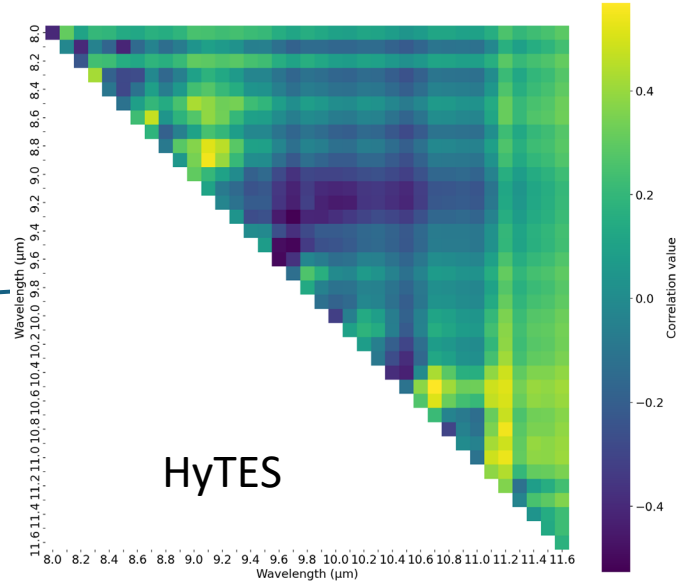


SBG LWIR SRF

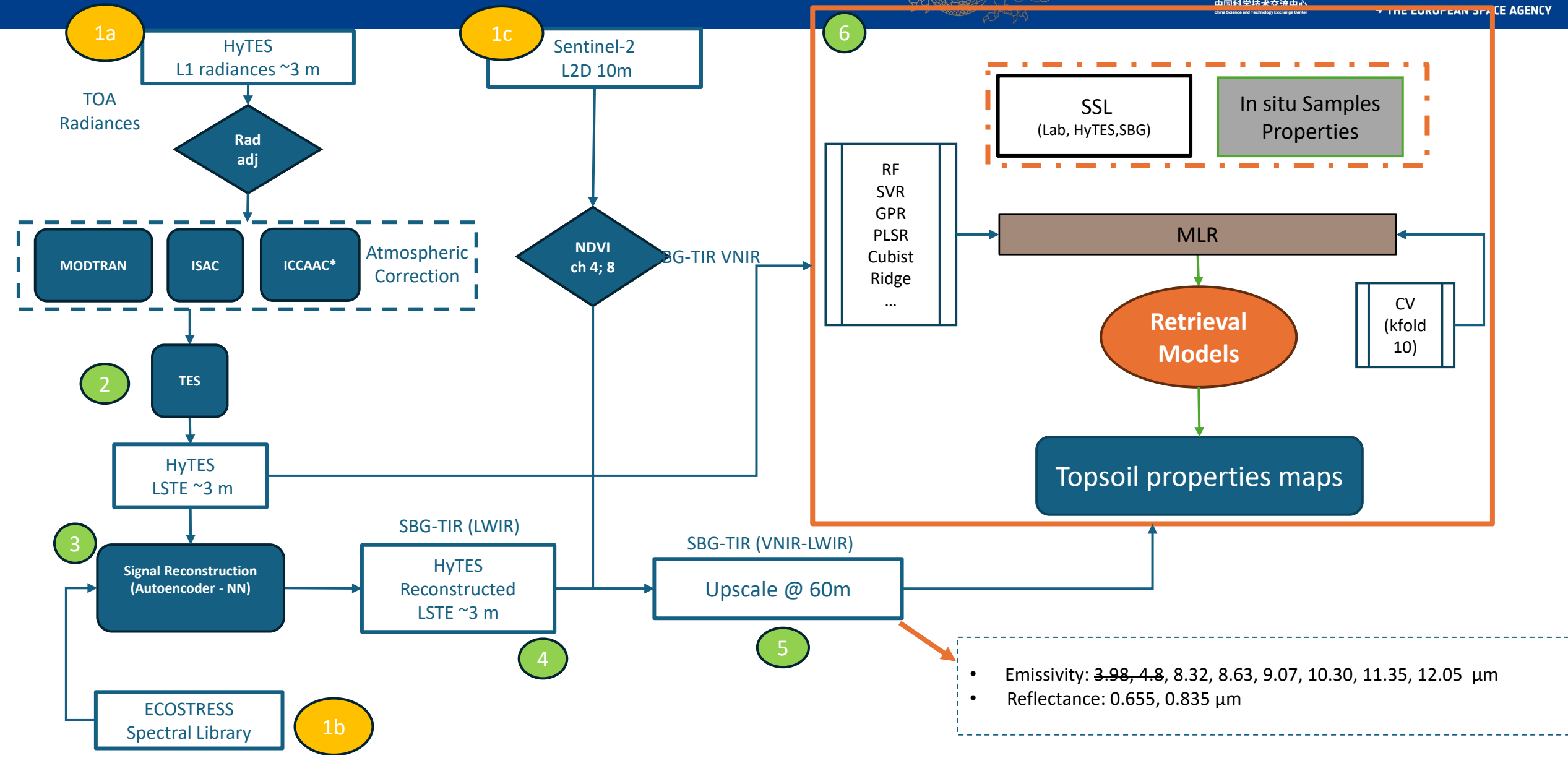








Workflow

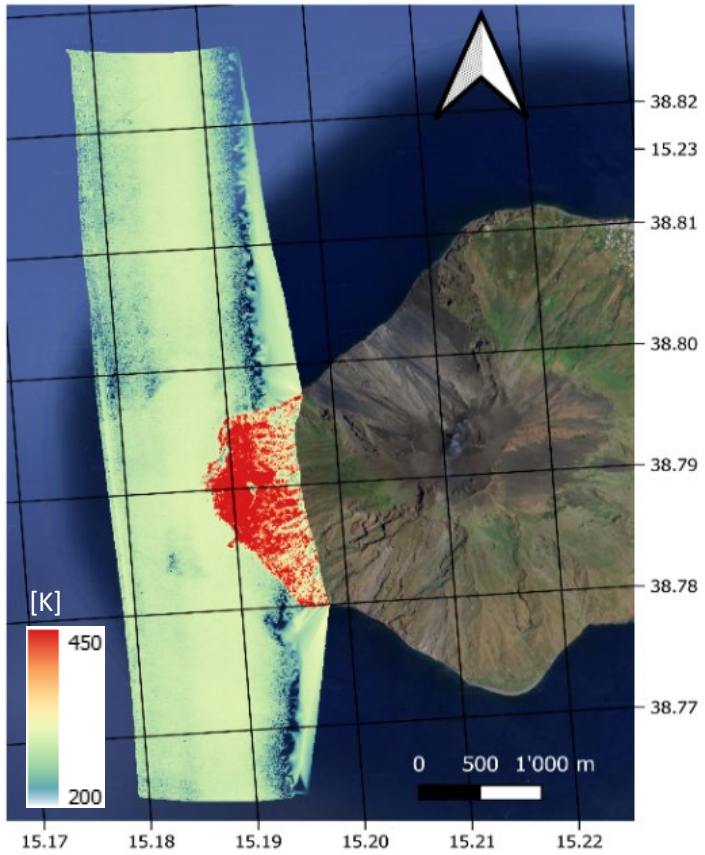


- Emissivity: ~~3.98, 4.8~~, 8.32, 8.63, 9.07, 10.30, 11.35, 12.05 µm
- Reflectance: 0.655, 0.835 µm

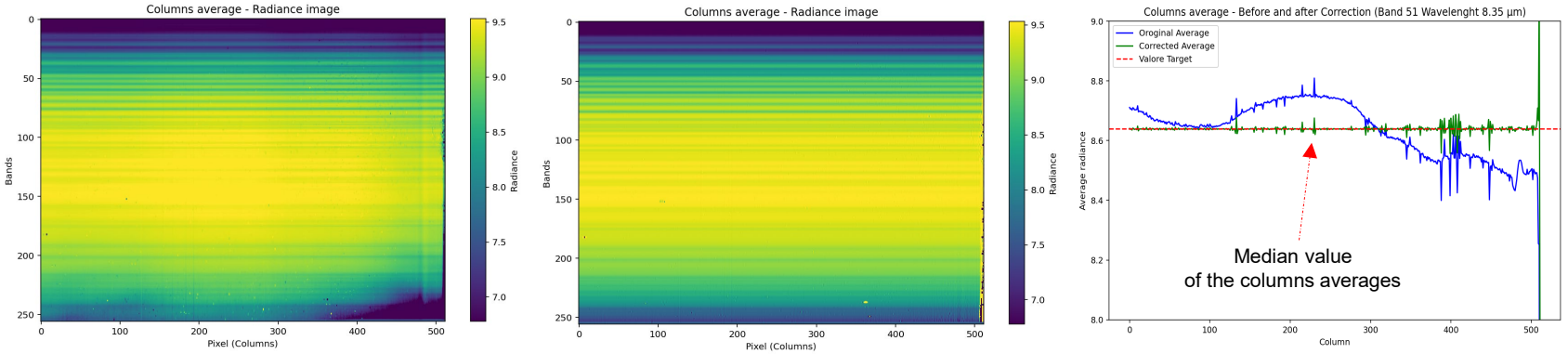
*Wang, Du, et al. "*Airborne thermal infrared hyperspectral image temperature and emissivity retrieval based on inter-channel correlated automatic atmospheric compensation and TES*." Remote Sensing of Environment 315 (2024)

HyTES ad hoc processing: spatial pattern correction

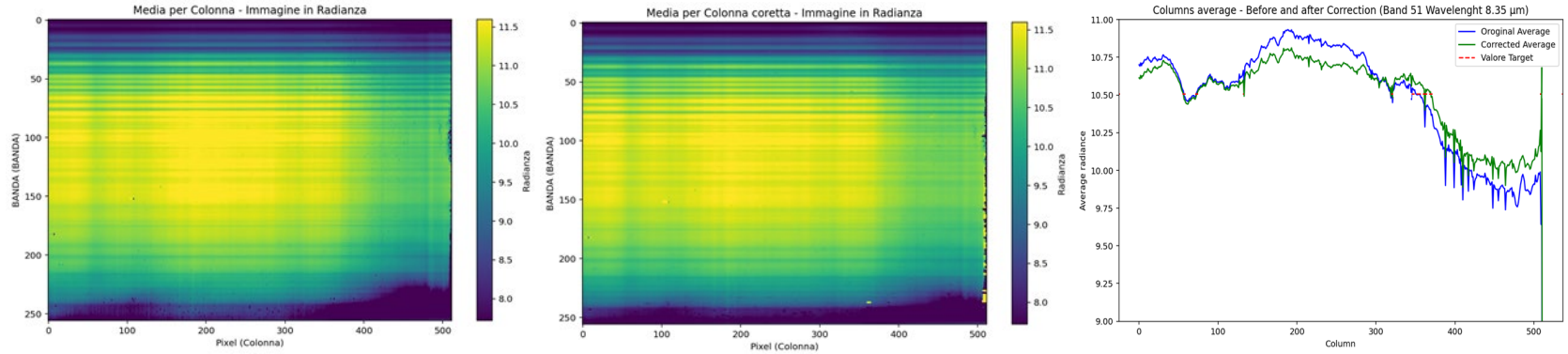
HyTES survey Stromboli L2 product of Stromboli 04/07/23.
Deep sea water as been used as reference homogeneous target.



The average radiance value of each column for an open sea region should be roughly constant. Any differences have been attributed to the sensor. A correction coefficient matrix [bands x columns] has been calculated to minimize these spatial structures and applied them to the Jolanda survey.

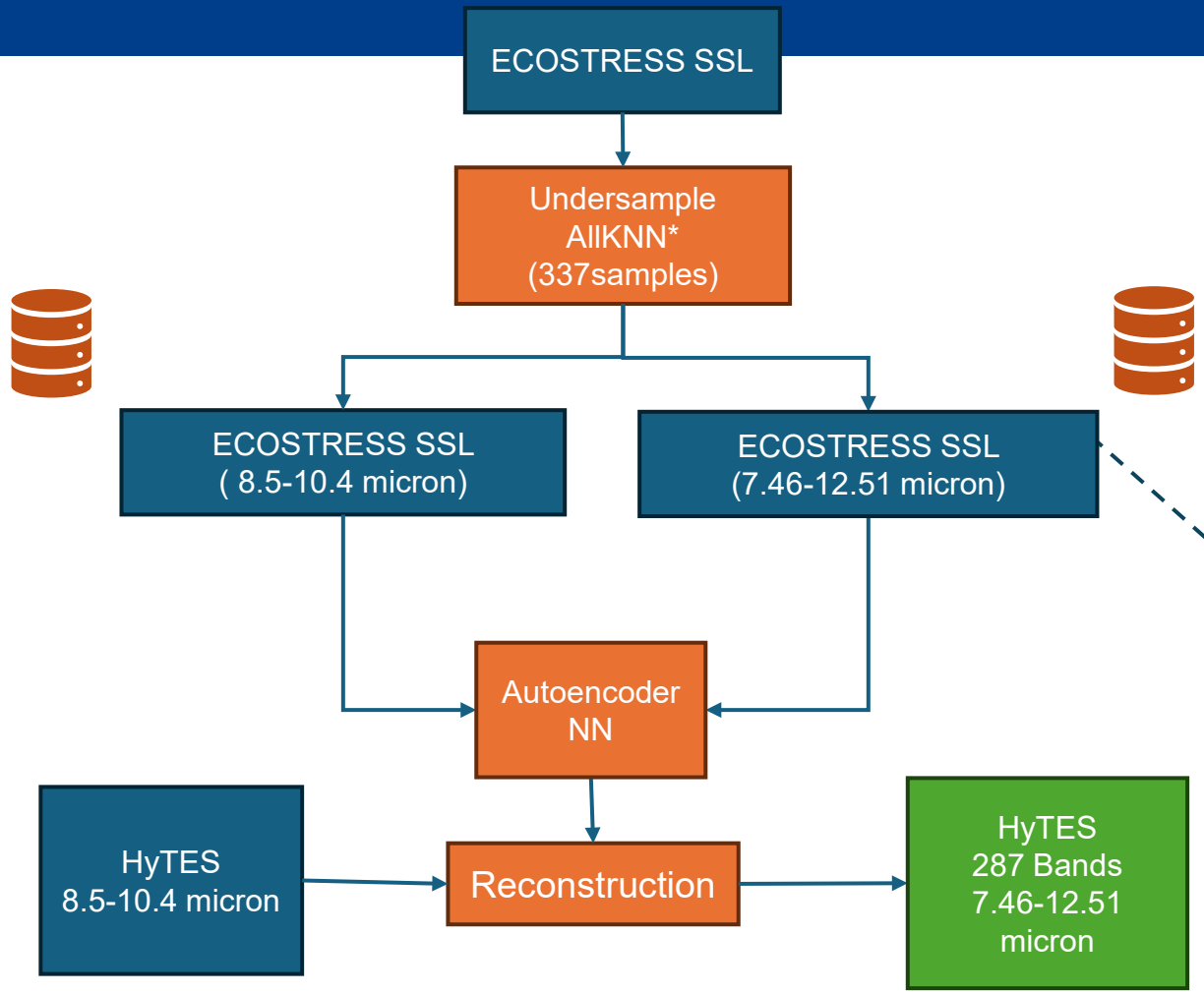


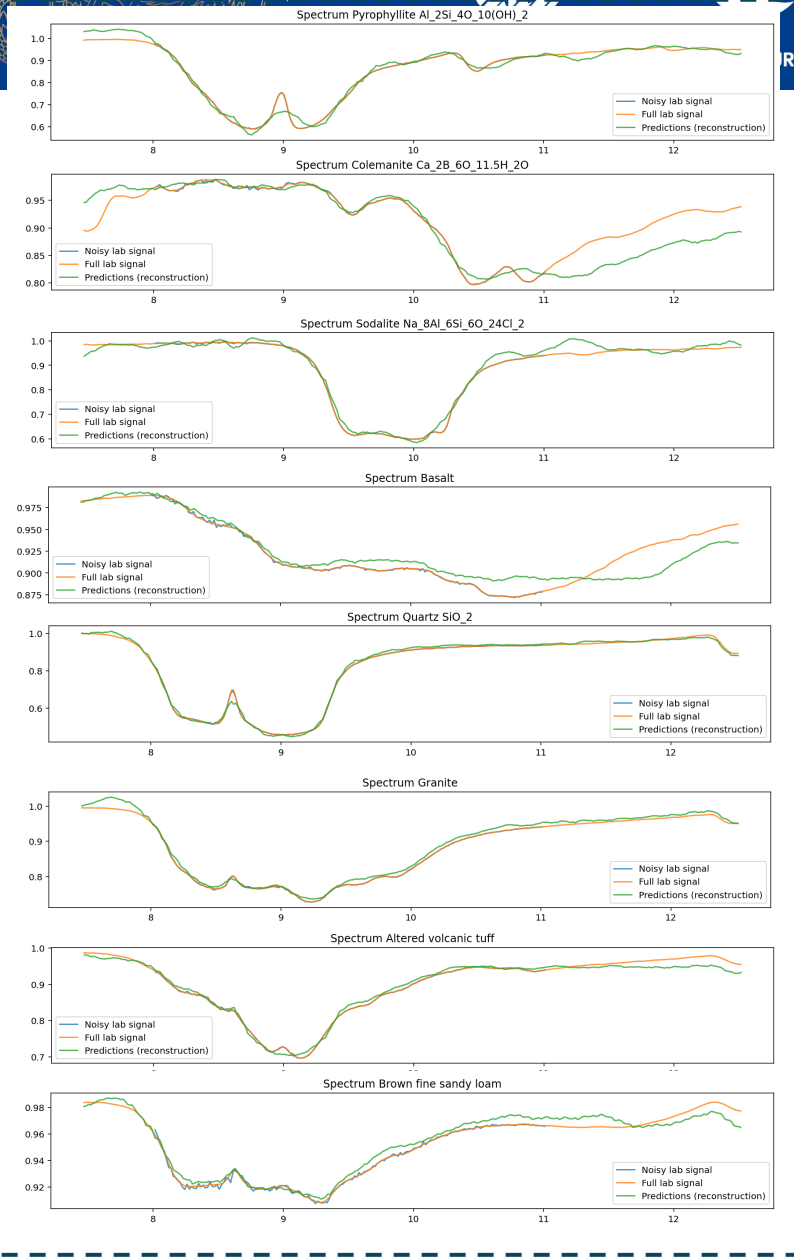
deep sea Stromboli radiance subset



Jolanda radiance

HyTES Regression for Emissivity

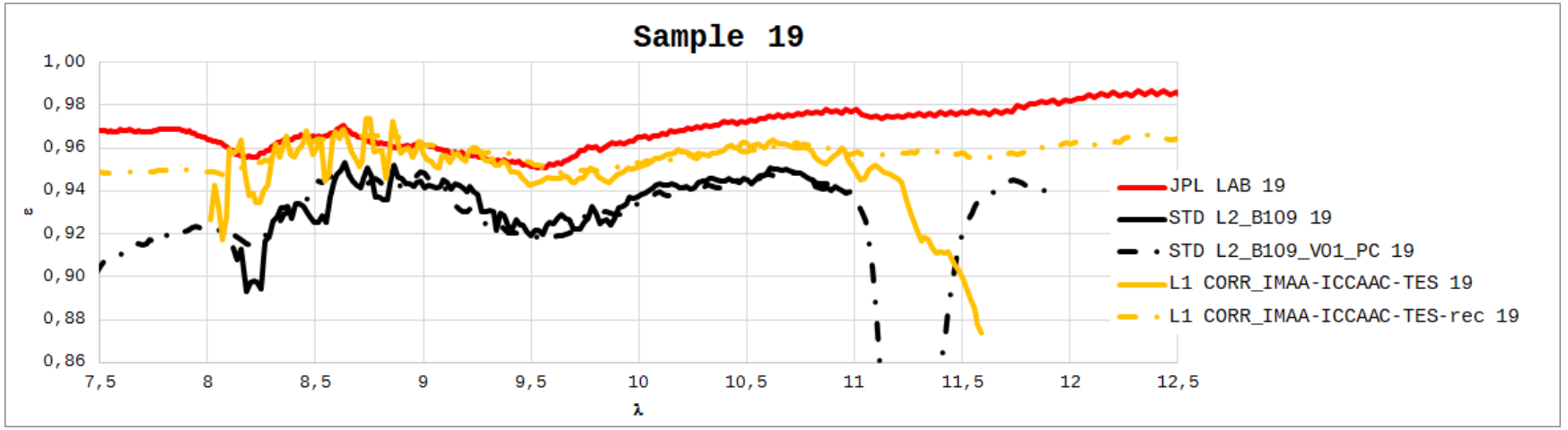


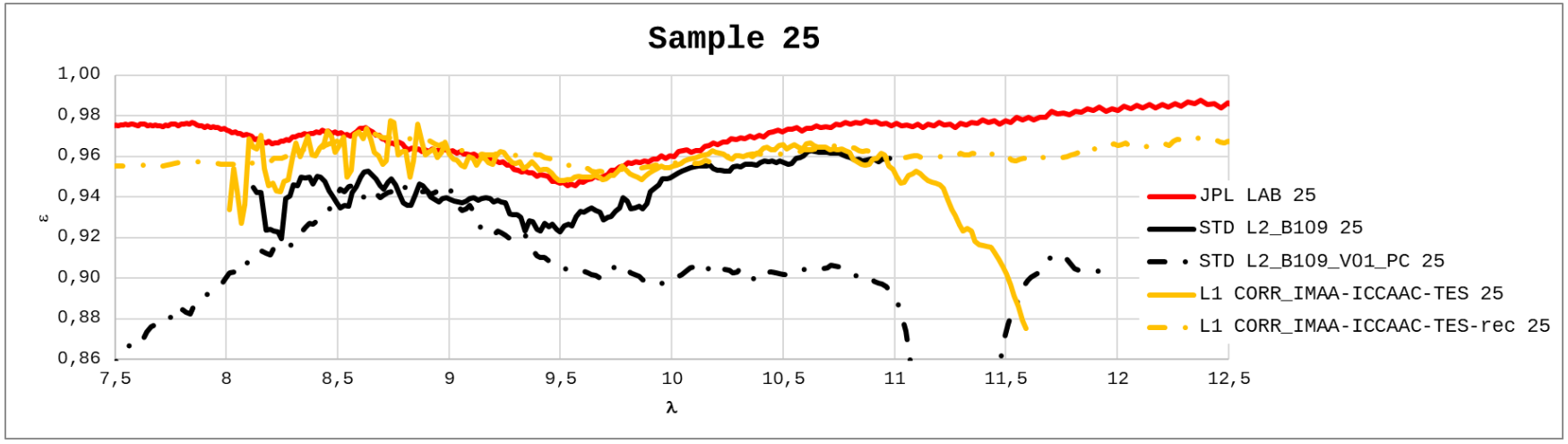


* I. Tomek, “An Experiment with the Edited Nearest-Neighbor Rule,” IEEE Transactions on Systems, Man, and Cybernetics, vol. 6(6), pp. 448-452, June 1976.

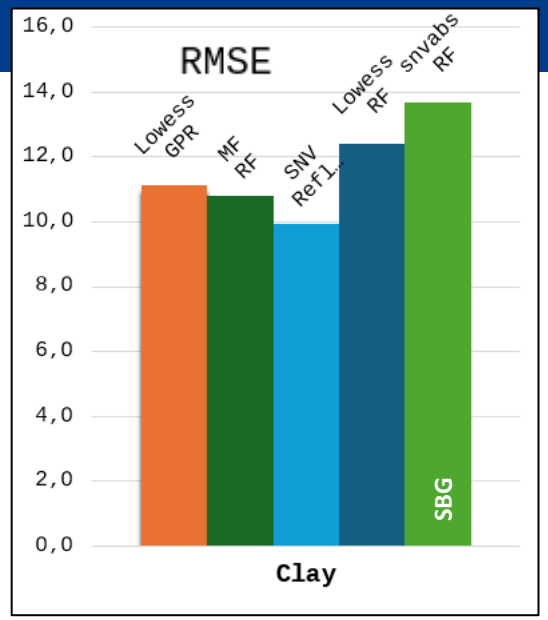
Emissivity spectra comparison

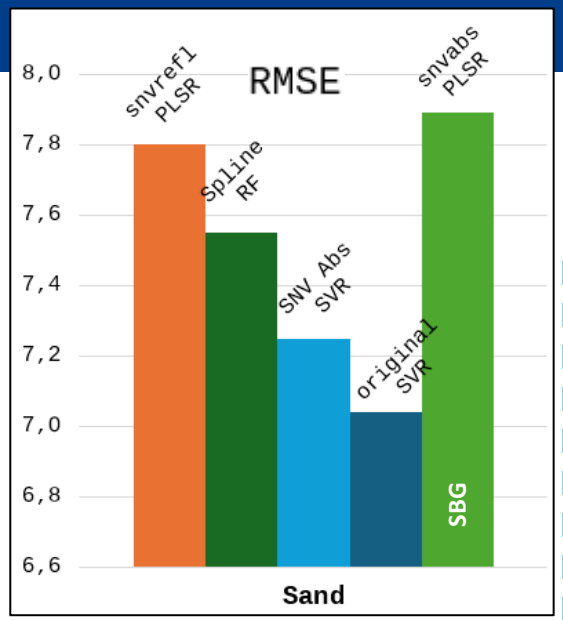
Q_ID	Sample ID	Q_point_ID	Clay (%)	Silt (%)	Sand (%)	OM (%)	SOC (%)	pH	CaCO3 (%)	Longitude (deg)	Latitude (deg)
BF-SBG 53	19	10	50.1	38.59	11.31	5.9	3.422	7.39	2.85	11.9198	44.8397
BF-SBG 59	25	1	62.15	22.96	14.89	7.72	4.478	7.44	1.29	11.9180	44.8438

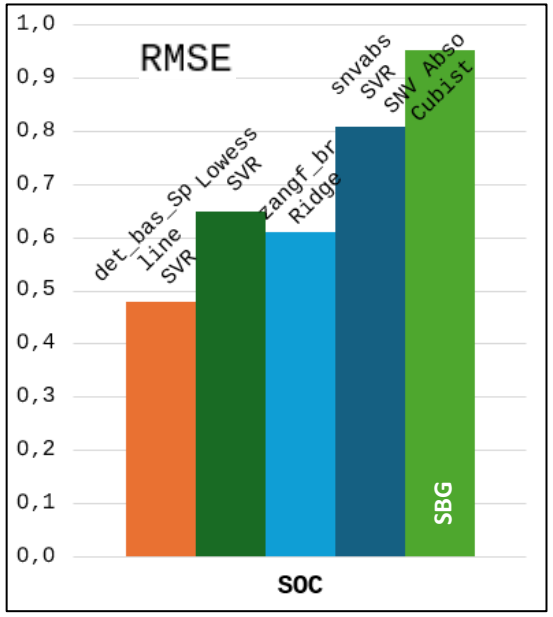


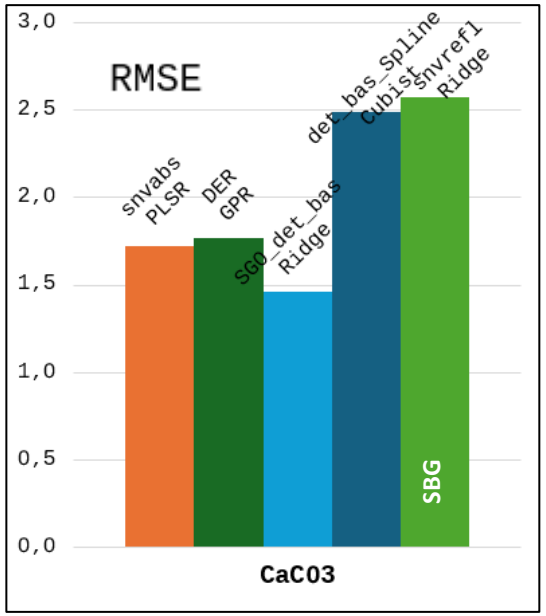


Regression Results – HyTES/SBG-TIR

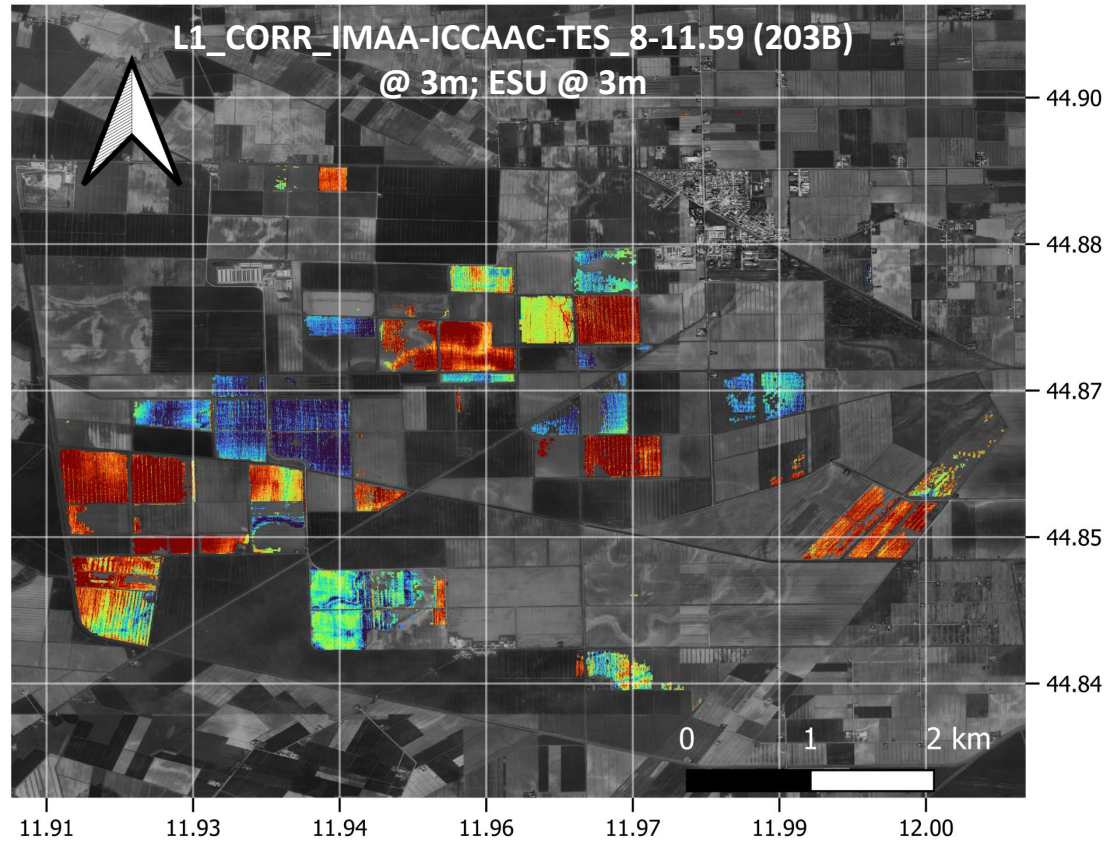






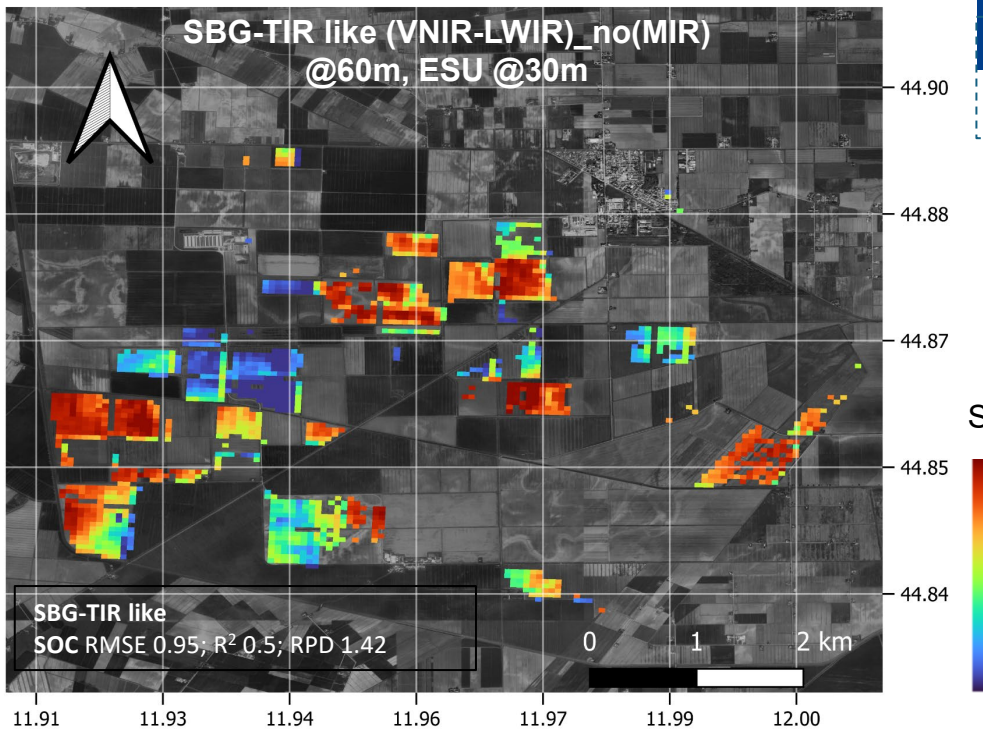


L2_B109_V01_EMIS_LST_8.6-10.4(107B) @3m
L2_B109_V01_EMIS_PC (256B) @3m
L1 CORR_IMAA-ICCAAC-TES_8.6-10.4 (107B) @3m
L1 CORR_IMAA-ICCAAC-TES_8-11.59 (203B) @3m
SBG-TIR (VNIR-LWIR)_no(MIR) @60m, ESU @30m

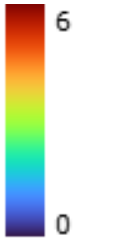


Prep	Alg	RMSE	R2	RPD
snvabs	SVR	0,81	0,64	1,68

SBG-LIKE (VNIR-LWIR) topsoil parameter retrieval

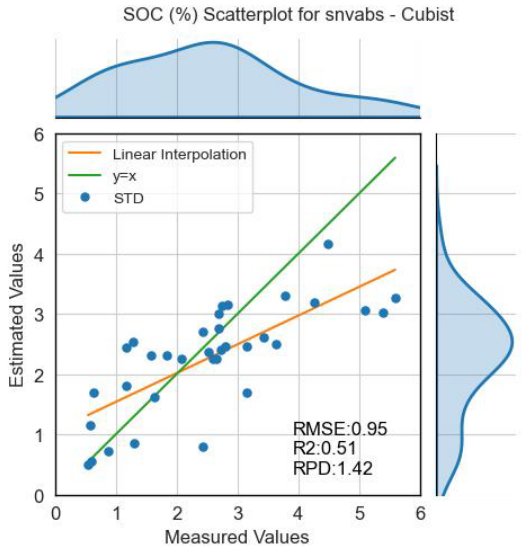


SOC (%)



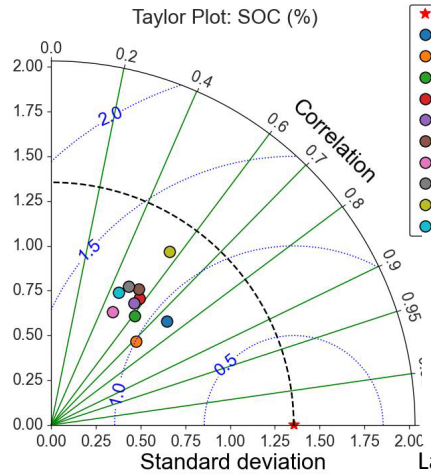
SBG channels applied for SOC retrieval

- Emissivity: ~~3.98, 4.8~~, 8.32, 8.63, 9.07, 10.30, 11.35, 12.05 µm
- Reflectance: 0.655, 0.835 µm

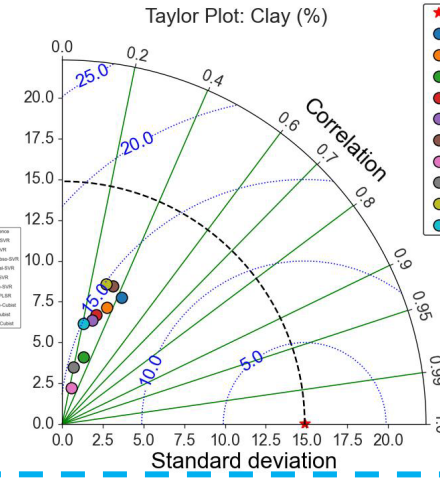


Taylor diagrams provide a graphically way to summarize how closely a pattern matches observations.

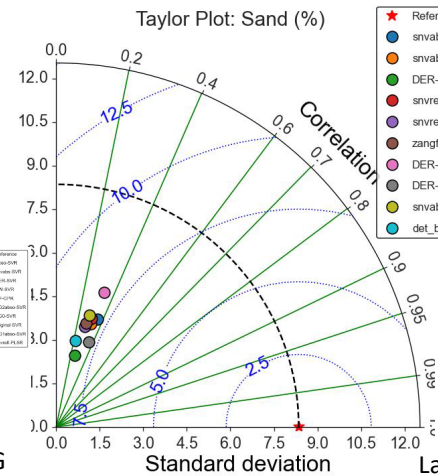
The similarity between two patterns is quantified in terms of their correlation, their centered root-mean-square difference and the amplitude of their variations (represented by their standard deviations)



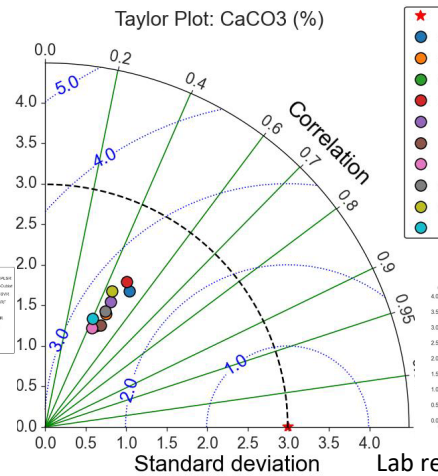
Lab resampled SBG



Lab resampled SBG



Lab resampled SBG



Lab resampled SBG

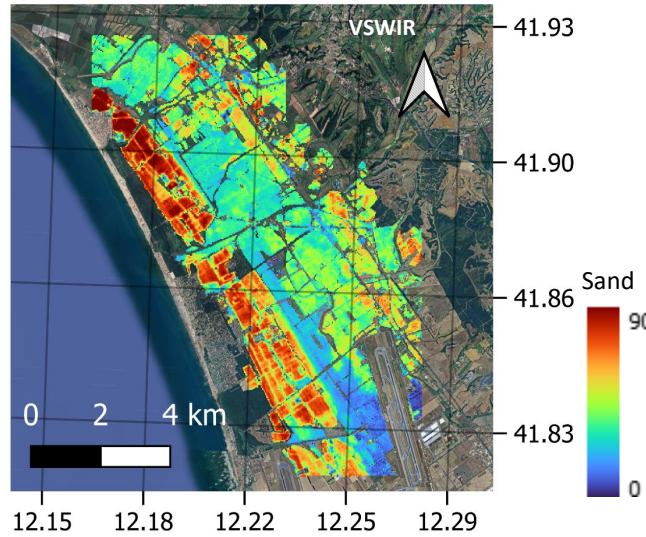
Conclusion

- HyTES LWIR spectral range is suitable to predict topsoil characteristics; ML procedures shows a feasible topsoil spatial pattern at a field scale;
- Local to Global is still an issue if we apply ML techniques;
- The performance of the models is severely affected by the quality of the HyTES survey. The same applies to atmospheric correction and TES;

- SBG-TIR (VNIR+LWIR) enables the prediction of SOC at Jolanda; however, $CaCO_3$, sand and silt do not yield satisfactory results. The low prediction values for the coarser soil fractions are due to the small amount of coarser material present (i,.e. narrow paleo-channels).

Still to be explored:

- ECOSTRESS time series on Jolanda;
- Parametric regression as alternative to ML for Global application;
- SBG-TIR simulation starting from emissivity map and using RTM (we are exploring RTTOV);
- LST, NDVI combination to identify bare soil pixel and NPV (day/night time series);
- Sinergy with VSWIR (CHIME) also taking advantage of the higher SBG/LSTM revisit time;
- To test for sand retrieval, a test site with wider sandy soil is required



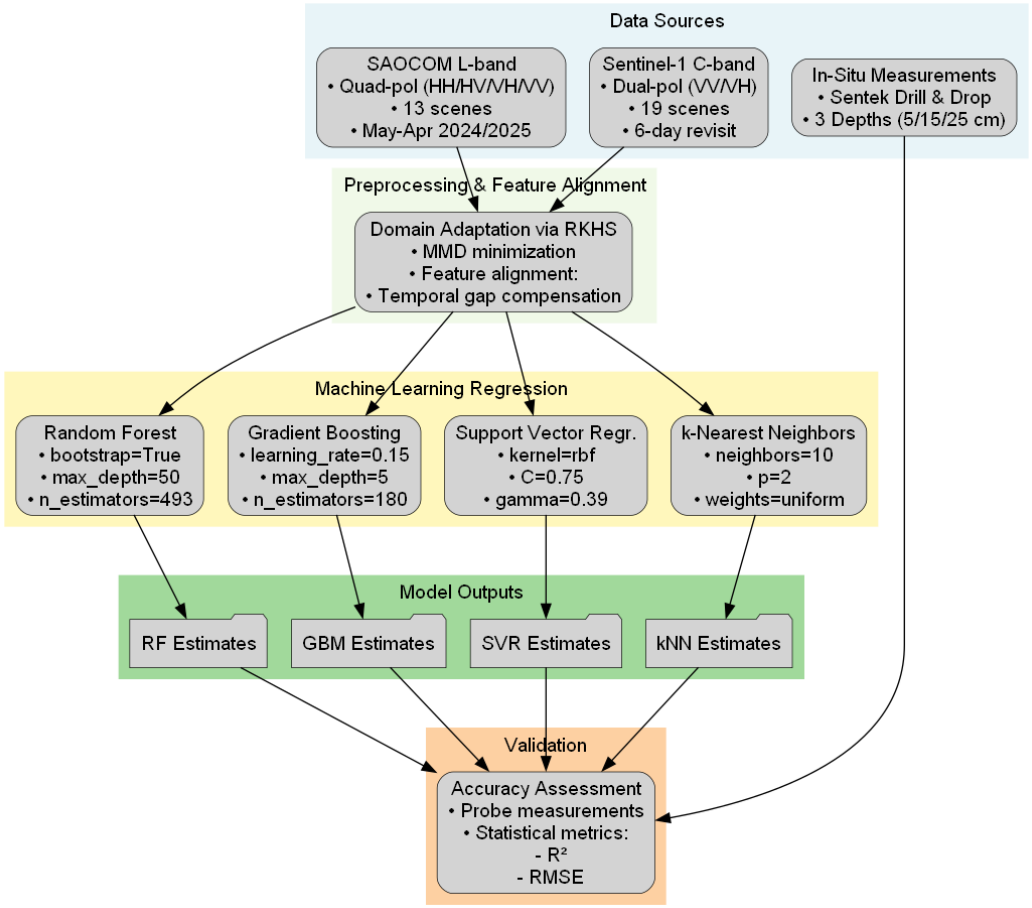

CSTEC
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Sentinel-1
Sentinel-2
Sentinel-3
Sentinel-5p
Earthcare
3rd objective:
Machine Learning Driven Multi-Frequency SAR Fusion for Surface Soil Moisture Retrieval
AIR
SAPIENZA
UNIVERSITÀ DI ROMA

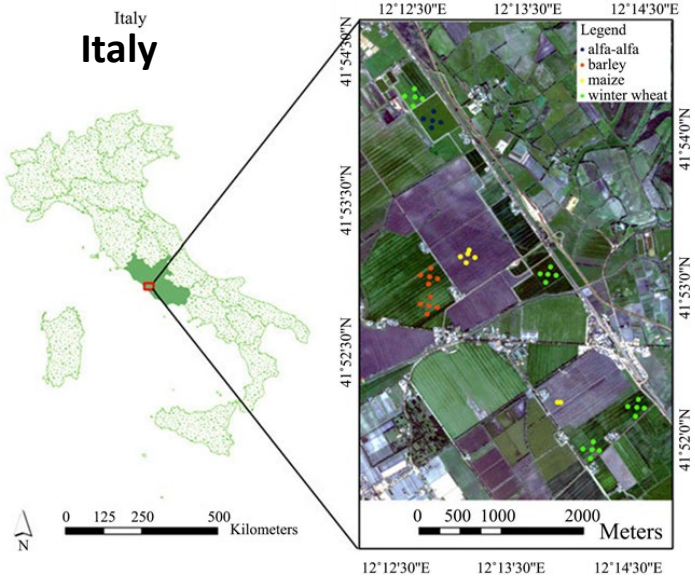
Soil moisture

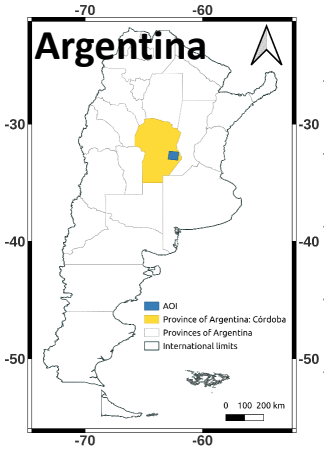
Machine Learning Driven Multi-Frequency SAR Fusion for Surface Soil Moisture Retrieval

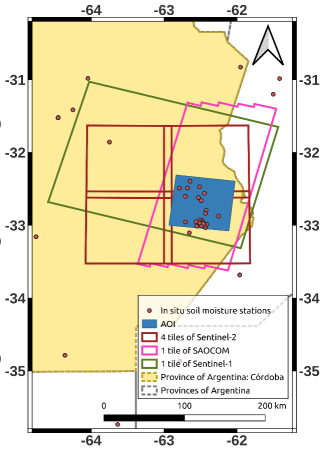
Methodology: Fusion of multi-frequency SAR (L/C-band), optical (NDVI), and meteorological data with ML (LSTM/RF) sets a new standard for SSM retrieval, resolving vegetation saturation, temporal hysteresis, and cross-sensor inconsistencies.

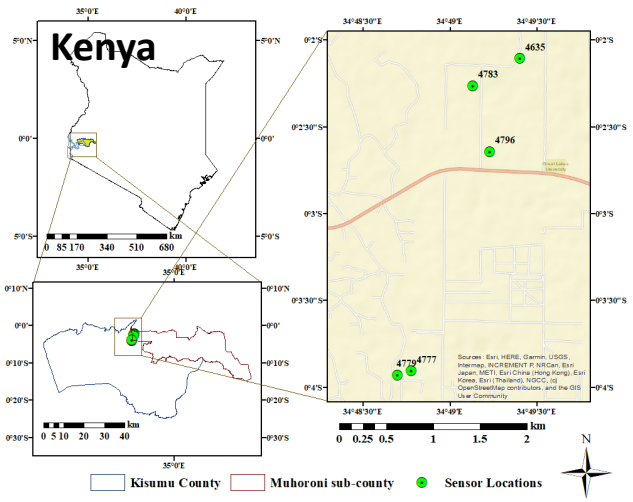
Operational frameworks support precision irrigation (water savings), drought early warning, and carbon flux modeling. The open-source implementations provide benchmarks for hydrological agencies.

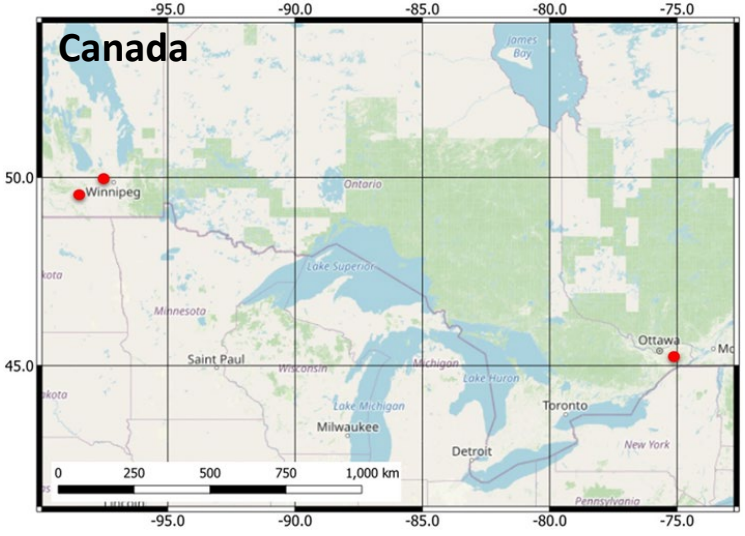












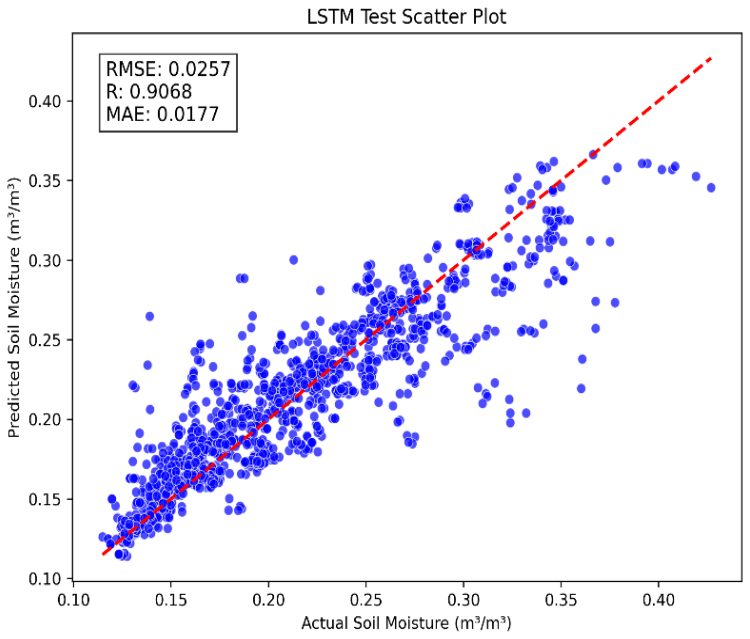
Soil moisture

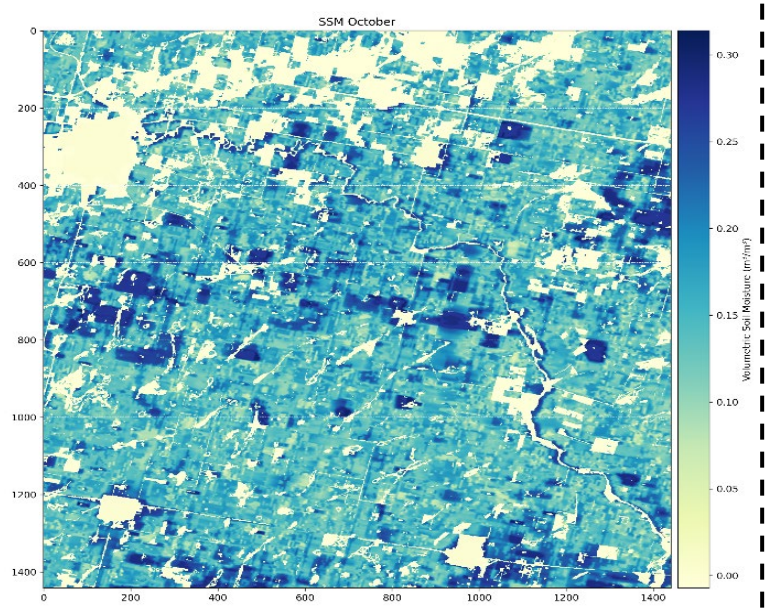
Machine Learning Driven Multi-Frequency SAR Fusion for Surface Soil Moisture Retrieval

NDVI and meteorological data compensation to model performance

Excluded Features	R^2	R^2 Decrease (%)	RMSE m^3/m^3	RMSE Increase (%)	MAE m^3/m^3	MAE Increas (%)
None (All features)	0.84	0.00%	0.024	0.00%	0.016	0.00%
NDVI	0.81	3.57%	0.026	8.33%	0.017	6.25%
Surface Temperature	0.76	9.52%	0.029	20.83%	0.020	25.00%
Precipitation	0.74	11.90%	0.031	29.17%	0.021	31.25%
NDVI + Temp + Precipitation	0.75	10.71%	0.030	25.00%	0.020	25.00%

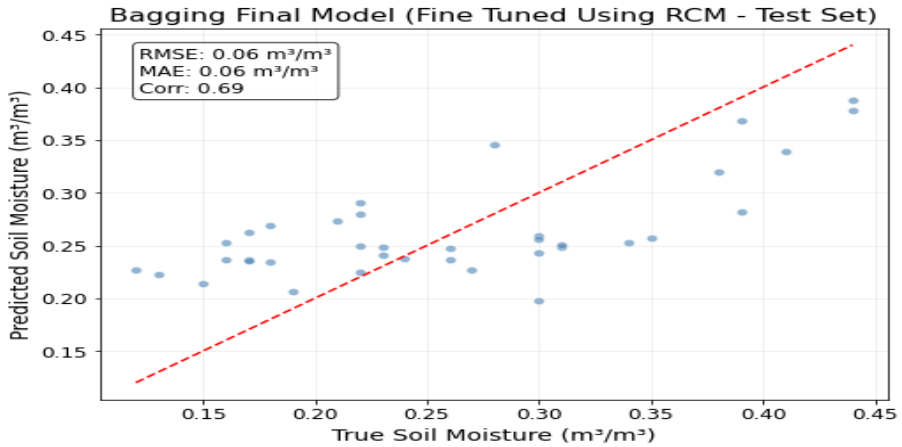
Fusion of C band and L band using LSTM MODEL

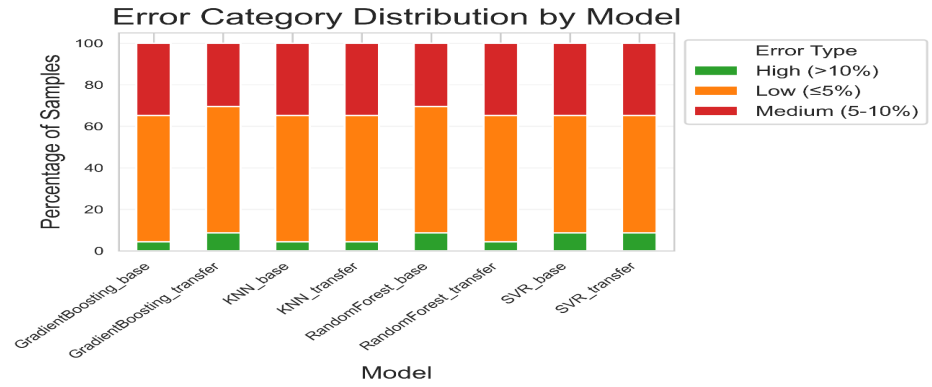




Cross frequency calibration

- kernel-based domain adaptation framework aligned non-coincident (L-band) and (C-band) acquisitions.
- The model was trained first using L band features, then domain adaptation was used to align C band features to L band space, the model was then fine-tuned using C band features .





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4th & 5th & 6th objectives:

Vegetation pests & diseases monitoring and forecasting for food and ecological security

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Kiwifruit Vine Decline Syndrome (KVDS)

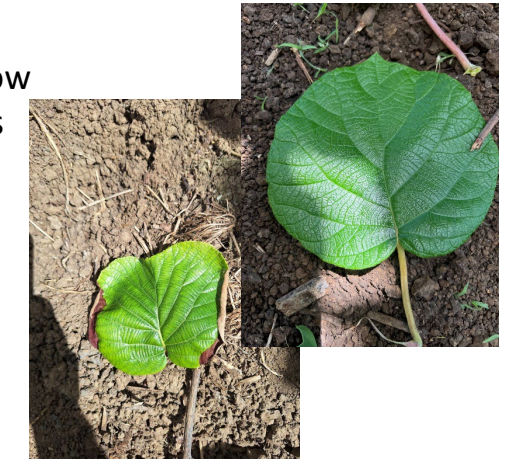




- Italy is the world's second-largest kiwi producer
- KVDS in Italy since 2012, in Lazio Region since 2016.
- 7000 ha lost in Lazio Region and 200 millions euro damage due to lost production.
- Plants die because of root system damage
- A **soil-related** problem that takes into account biotic and abiotic factors
- The idea is to investigate the relationship between the disease incidence in different areas in Lazio region and the soil properties from satellite multispectral images.



Sentinel 2 image NDVI clearly showing very low NDVI in diseased areas (Latina, Lazio, Italy)



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4th objective:

Crop phenology and growth status monitoring

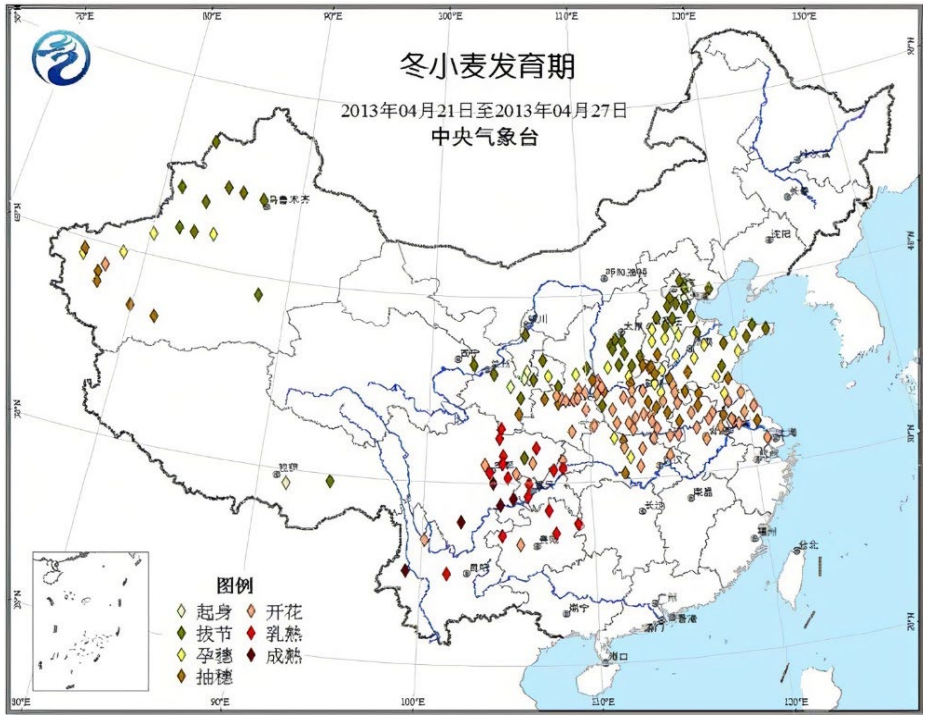


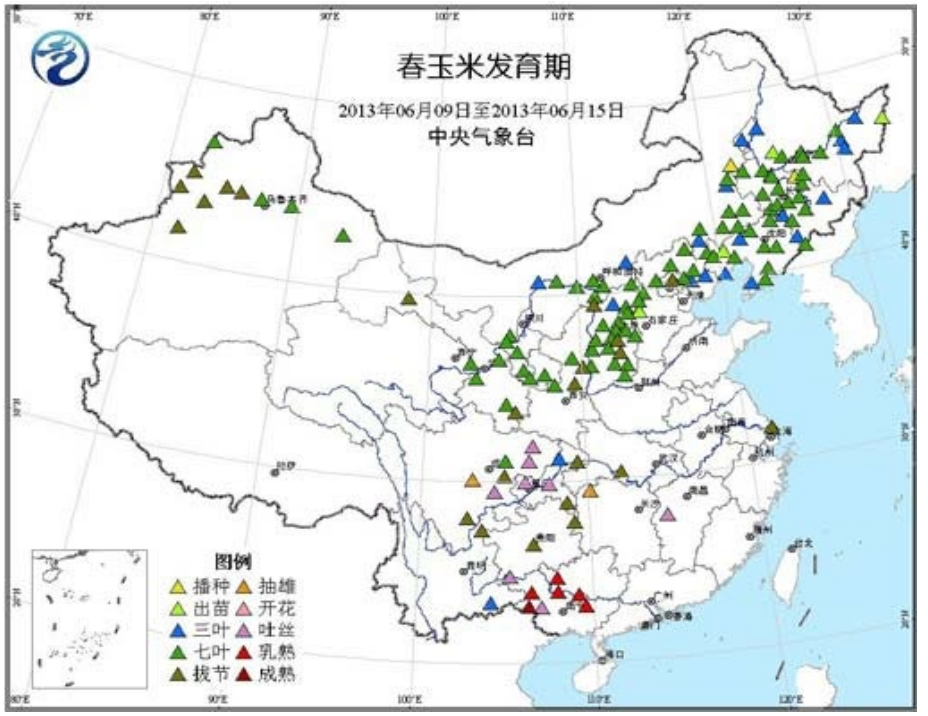




Regional Crop Phenology Monitoring

Challenge: Significant differences in phenological phases severely affect quantitative diagnosis of crops using remote sensing



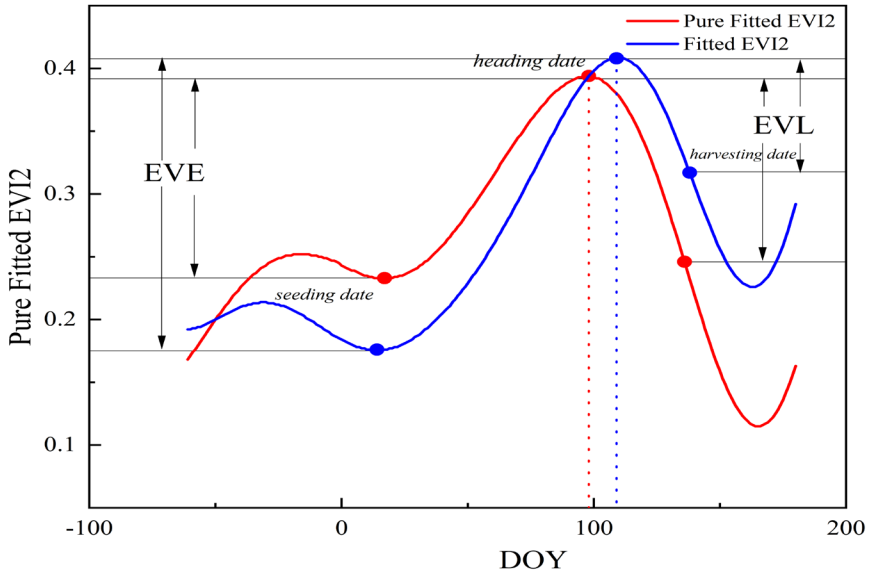


Large-scale crop phenological differences are the primary source of uncertainty affecting quantitative remote sensing diagnosis!

Synchronous phenological differences: Winter wheat: ~60 days; Maize: ~50 days

Heading stage monitoring of winter wheat

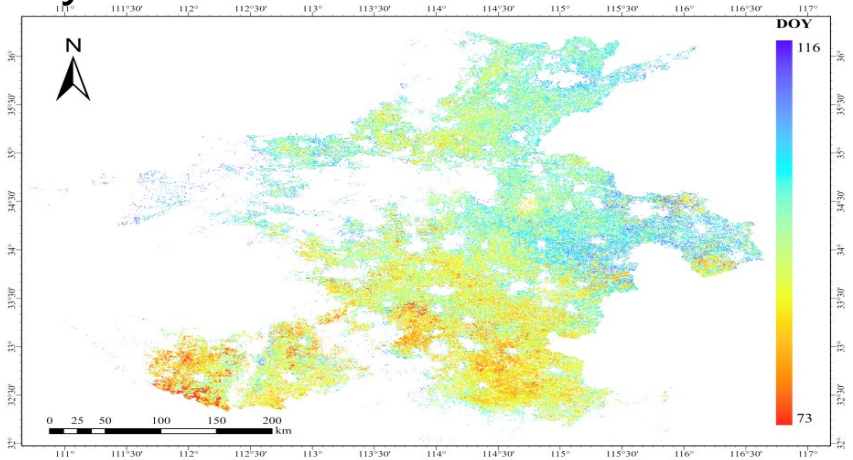
A large-scale winter wheat heading stage extraction method using machine learning was established. Compared with traditional heading stage extraction methods based on time-series curve feature points, this approach significantly improved monitoring accuracy

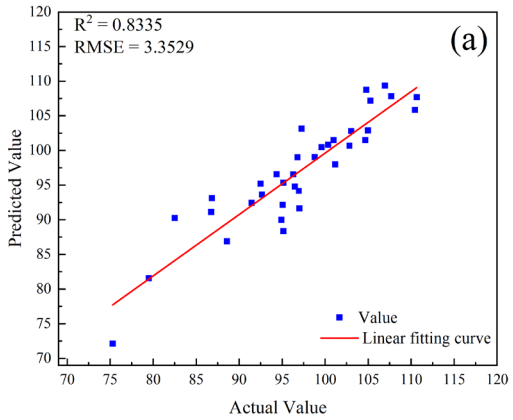


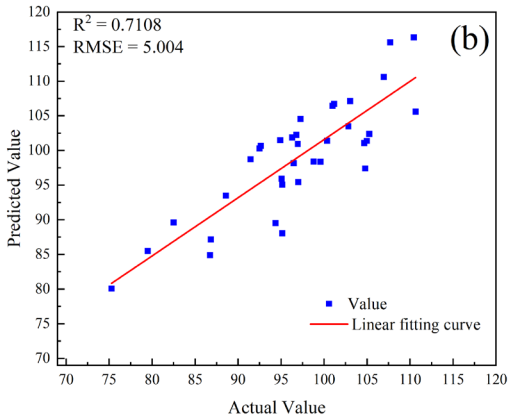
$$EVE = (EVI2_{heading} - EVI2_{seedling}) + (EVI2_{\max 1} - EVI2_{\min 1})$$

$$EVL = (EVI2_{heading} - EVI2_{harvesting}) + (EVI2_{\max 2} - EVI2_{\min 2})$$

A phenological feature-based training set extraction method was constructed

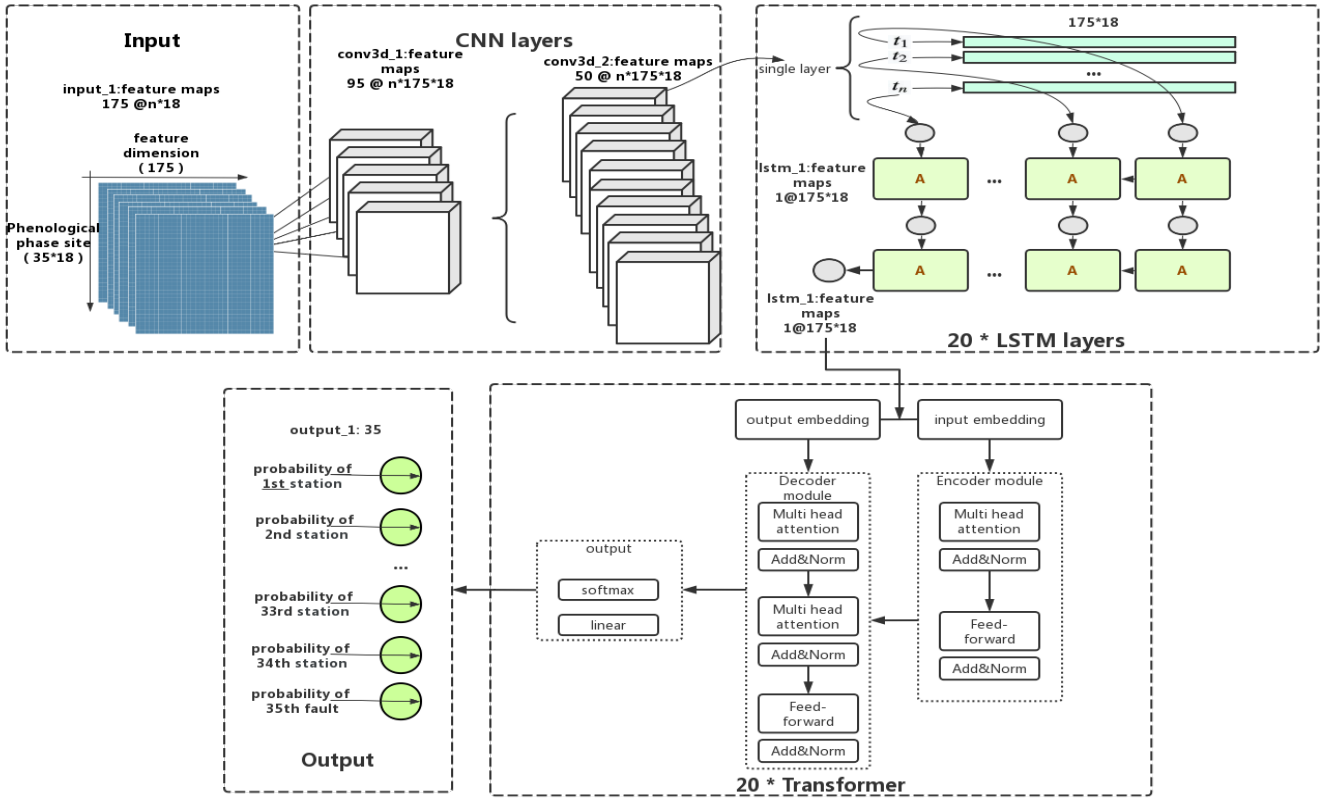




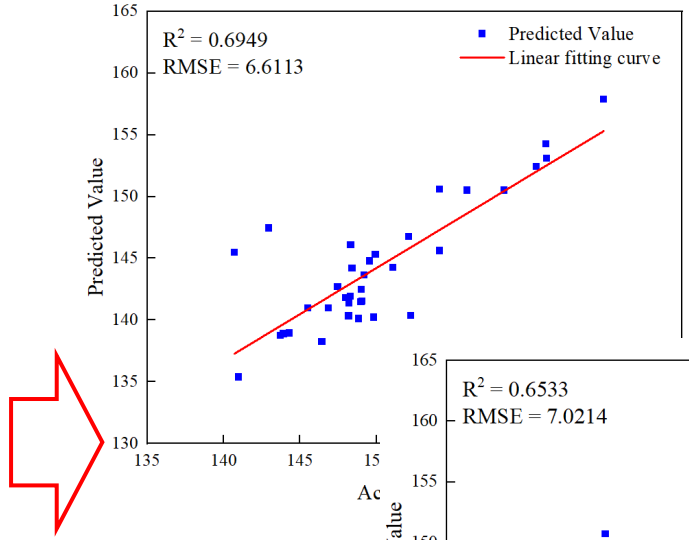


Maturity stage prediction of winter wheat

A winter wheat maturity stage prediction method was established using multi-source meteorological factor data and the CNN+LSTM+Transformer deep learning model based on time-series data



Maturity Date - CNN + LATM + Transformer

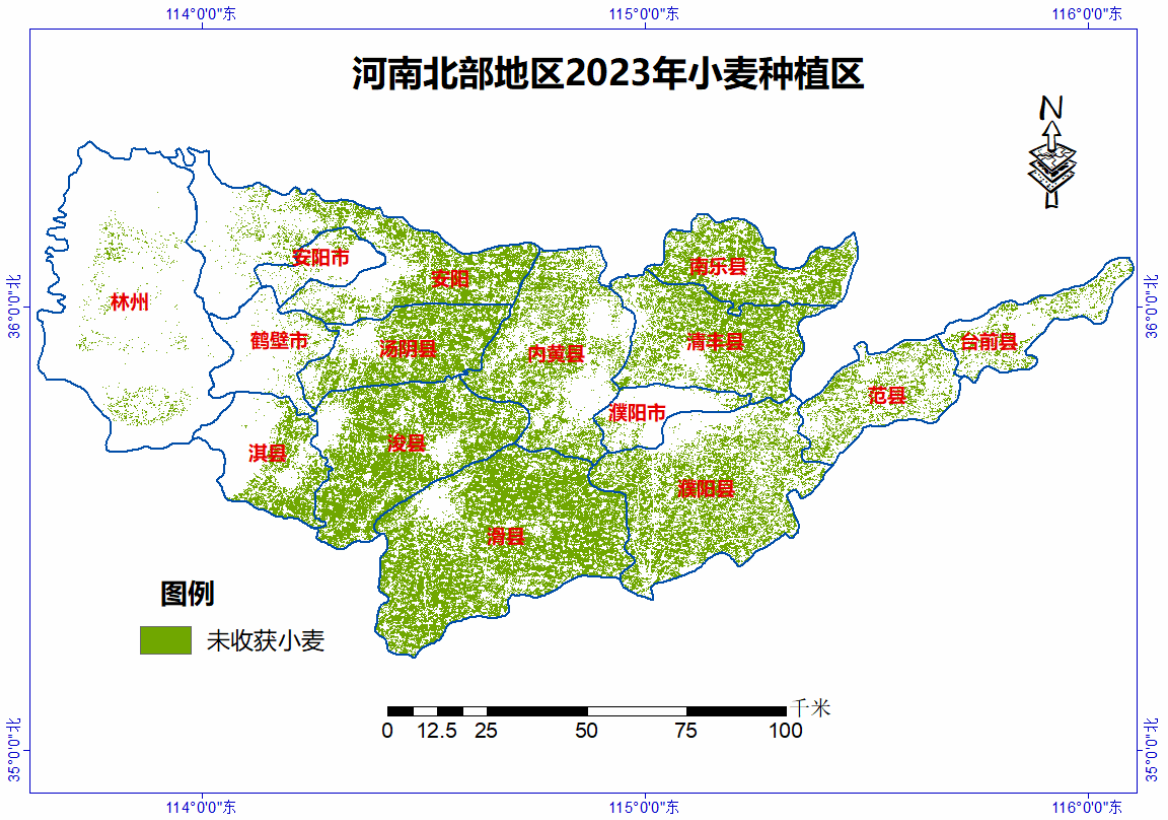


CLT model

Average Growing Degree Day (GDD) method

Regional Crop Phenology Monitoring

Harvest progress monitoring in northern Henan Province



City	County	Harvest Percentage On June 6 (%)	Harvest Percentage On June 11 (%)		
			Stem Harvest	Ear Harvest	Total Harvest
Anyang	Linzhou	19.74	91.57	5.56	97.13
	Anyang (county)	9.77	73.03	23.02	96.05
	Anyang (city)	14.76	51.60	39.29	90.89
	Neihuang	23.14	56.47	40.95	97.42
	Tangyin	25.46	77.46	20.89	98.35
	Hua	21.71	71.93	26.61	98.55
Puyang	Nanle	4.52	48.50	50.99	99.48
	Taiqian	5.18	26.72	59.10	85.82
	Qingfeng	10.36	38.51	60.28	98.80
	Fan	9.36	23.46	70.96	94.42
	Puyang (city)	6.58	37.65	58.34	95.99
	Puyang (county)	9.47	54.08	44.26	98.34
Hebi	Hebi	19.89	55.85	39.36	95.21
	Jun	15.93	75.86	23.34	99.20
	Qi	42.13	89.36	9.45	98.82

Satellite remote sensing images from Henan Province show that, as of June 9, 2023, the wheat harvest in the areas south of the Yellow River has essentially been completed, while the areas north of the Yellow River have entered the peak harvest period. The wheat harvest progress in areas such as Hebi, Puyang, Anyang, and Xinxiang has reached nearly 50%. Monitoring was focused on the wheat harvest progress in key areas of Henan Province, including Hebi, Puyang, Anyang, and Xinxiang.

Adjusted CBA-Wheat model for predicting aboveground biomass in winter wheat

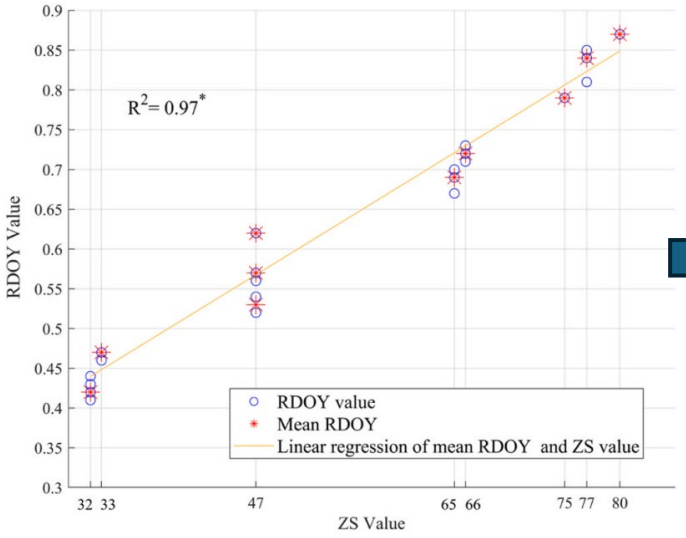
•Proposing the concept of the relative day of the year (RDOY) to replace the traditional Zadoks stage (ZS), thereby optimizing the CBA-Wheat model for predicting aboveground biomass (AGB) in winter wheat, and comparing the performance of the CBA-WheatRDOY model with machine learning models, including Partial Least Squares Regression (PLSR) and Random Forest (RF).

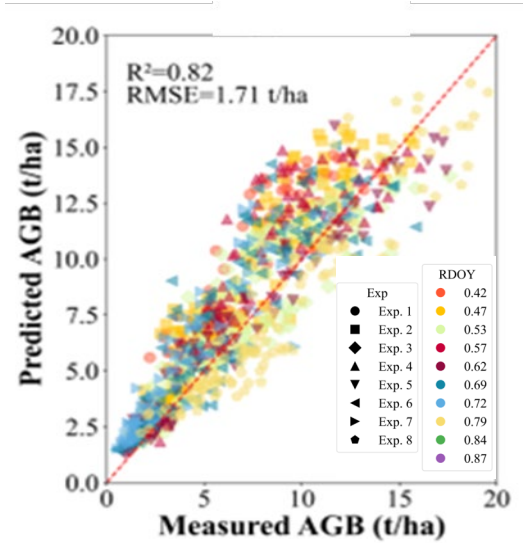
$$RDOY = \frac{DOY_a - DOY_b}{DOY_c - DOY_b}$$

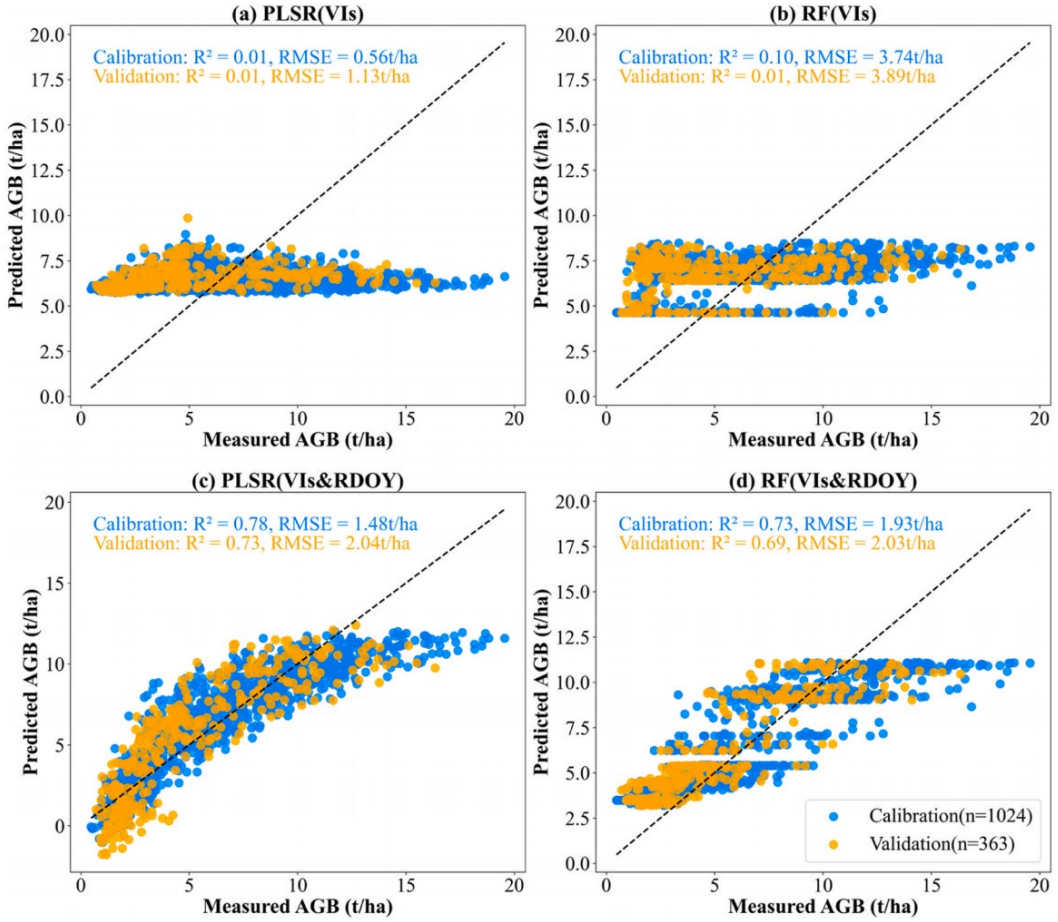
$$AGB = \beta \times VI + \alpha$$

$$\beta = \gamma_1 e^{\gamma_2 RDOY}$$

$$\alpha = \gamma_3 RDOY - \gamma_4$$



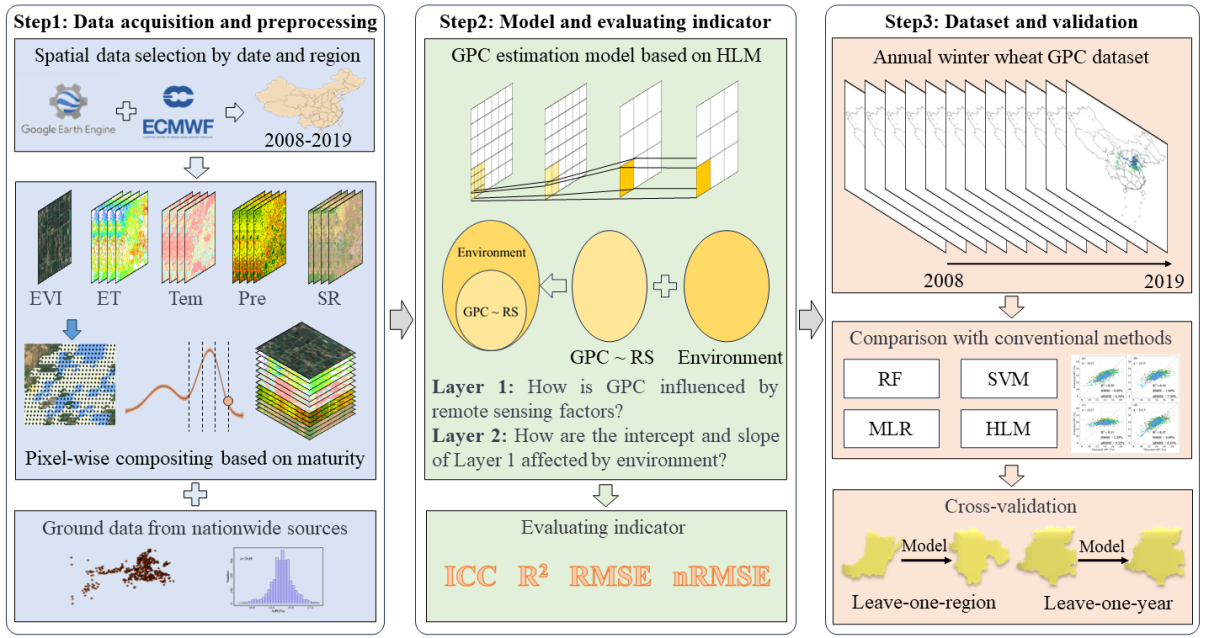


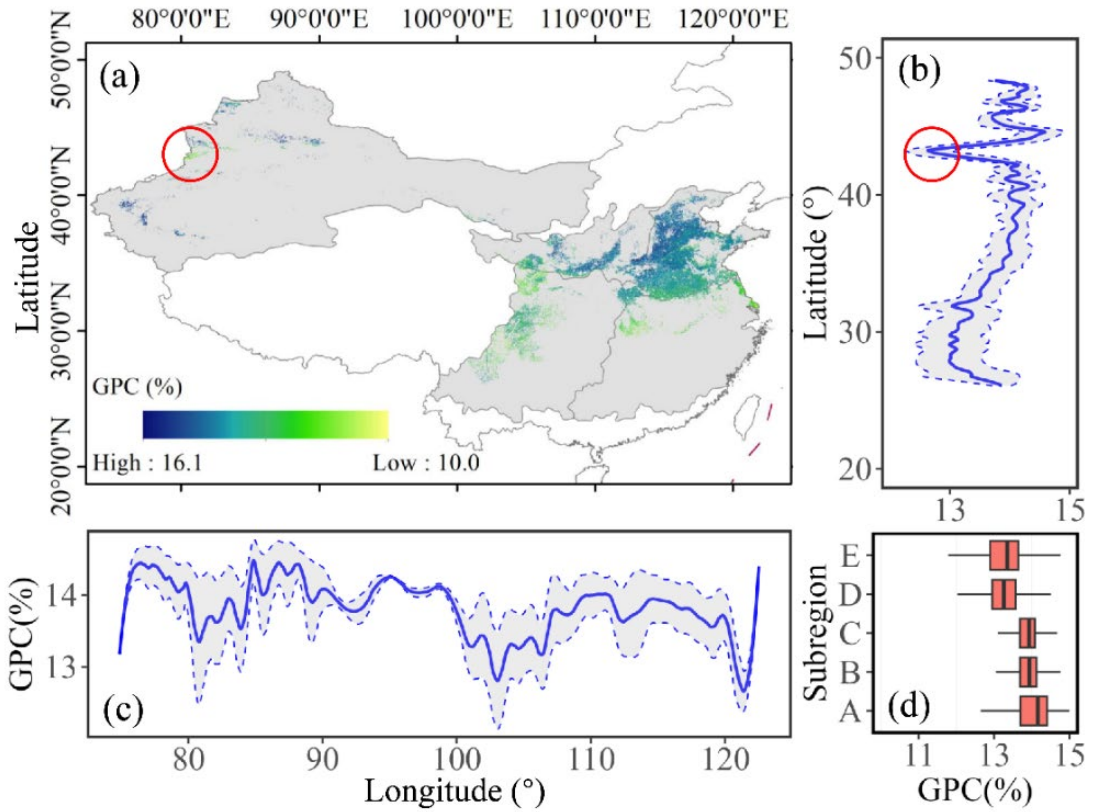


CBA-Wheat$_{RDOY}$ has advantages in estimating winter wheat biomass.

Adjusted CBA-Wheat model for predicting aboveground biomass in winter wheat

- Using multi-source climate and remote sensing data from 2008 to 2024, an estimation model of wheat grain protein content (GPC) with strong spatial-temporal migration was developed based on hierarchical linear model (HLM).
- Using this model, the first set of wheat GPC dataset cnwheatgpc-500 with 500 meter resolution and long time series in China was generated.





The grain protein content of Winter Wheat in China is typically high in the north and low in the south.

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Desert Locust Forecasting

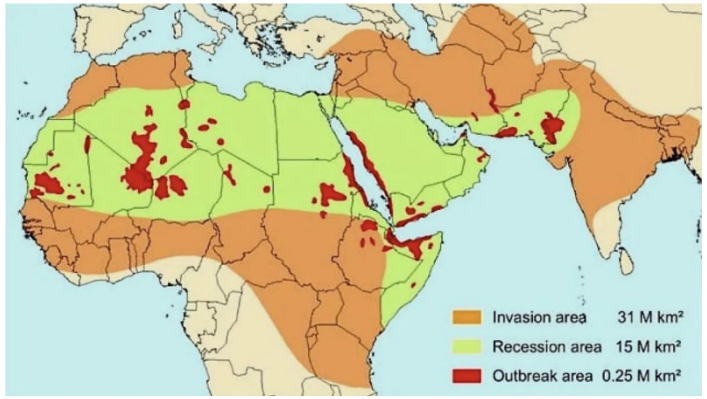
Backgroud

The desert locust is one of the world's most important migratory pests, posing a serious threat to food security, ecological health and regional stability, and early warning of the risk of its occurrence is of great importance.

Objectives

Coupling ground data and remote sensing data to quantitatively analyse the time lag characteristics of key indicators of desert locust occurrence, and to study the extraction methods of indicators.

Developing the remote sensing dynamic forecasting model of desert locust occurrence coupled with multiple indicator factors to achieve early warning of desert locus.



Michel Iecoq, 2020



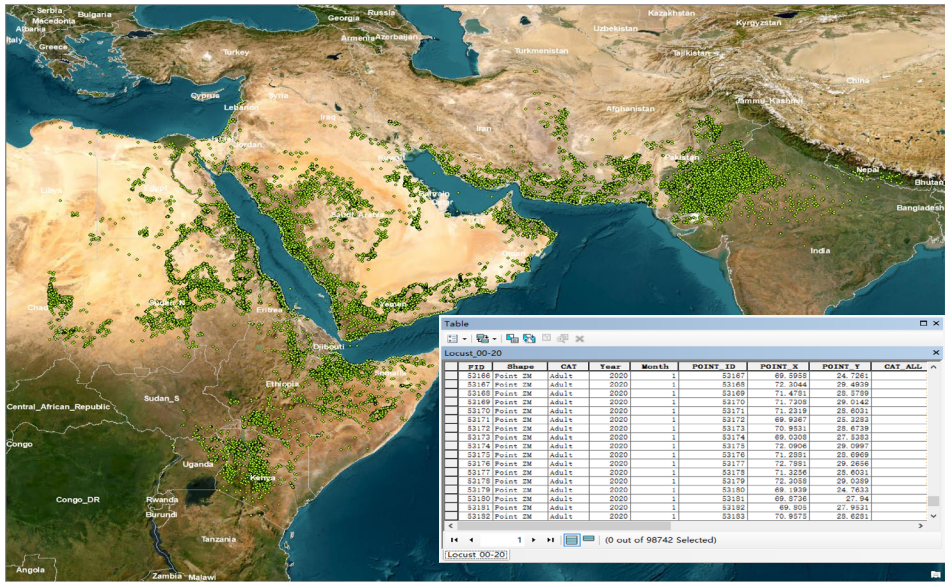
Research content

- Extraction of multivariate indicators required for early warning of desert locust occurrence
- Analysis of the lagged response of desert locust occurrence to indicators
- Early warning of the risk of desert locust occurrence

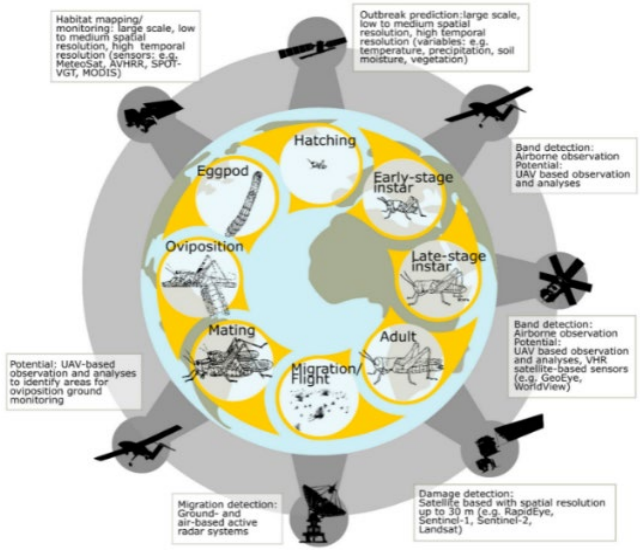
Desert Locust Forecasting

Desert locust migration warning indicators

The occurrence and development of desert locusts are characterized by explosiveness, migratory and destructiveness . Under suitable conditions, it usually takes only about 75-150 days for the nymphs that break out of the soil to develop into adult locusts . The desert locust is one of the most widespread and destructive migratory locusts. Its distribution range covers arid and semi-arid areas in Africa, Asia and the Middle East . Its distribution and activities are affected by factors such as climate, environment and terrain.



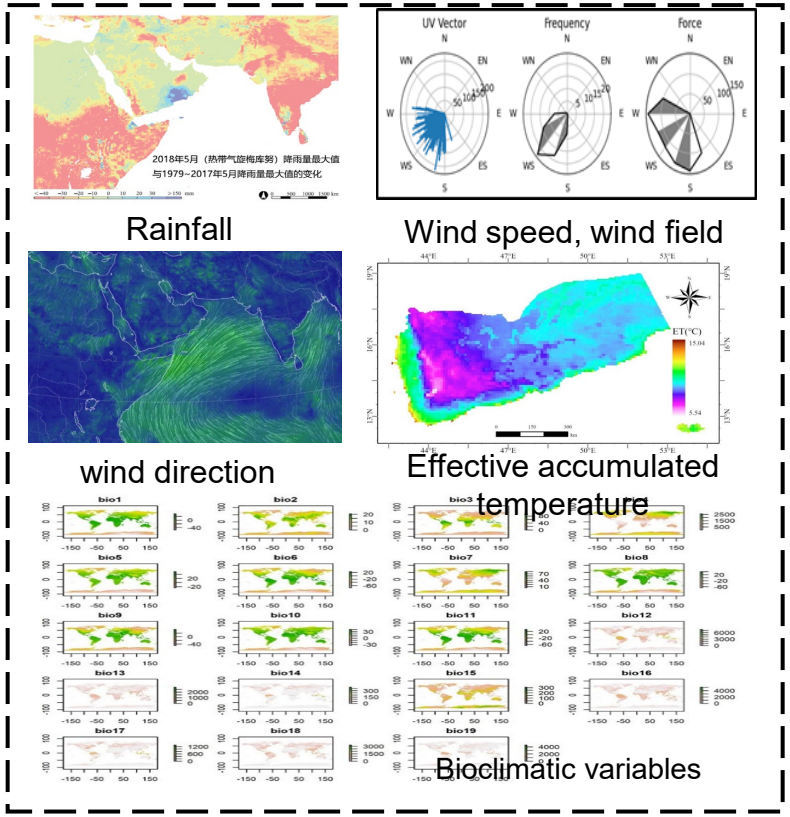
Global distribution of desert locusts

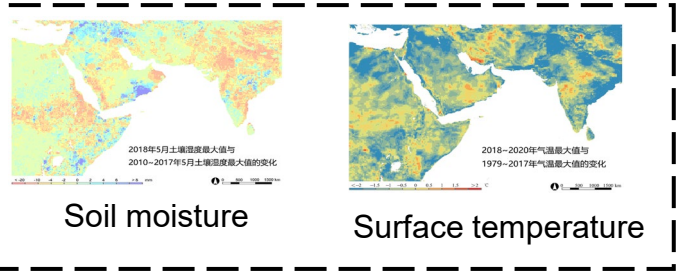


The role of satellite remote sensing technology in different stages of locust occurrence and development

Desert Locust Forecasting

The occurrence mechanism of desert locust is a complex multi-factor interaction process. The insect source, host and environment are the three factors that affect the occurrence and development of locusts. This project obtains the habitat factors that comprehensively characterize the host and environmental elements in a continuous space and time based on multi-source remote sensing data , and constructs a desert locust monitoring and early warning indicator system.



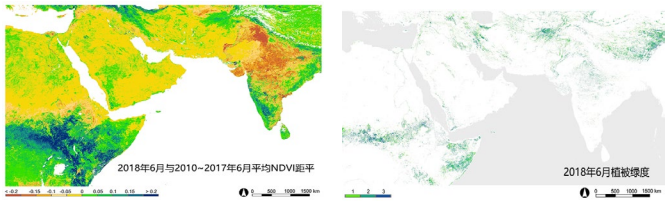


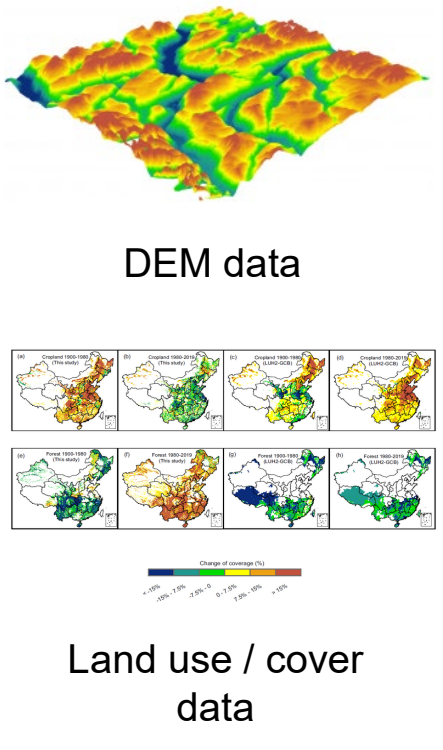
soil

Meteorological

Terrain

Host





Pest indicator set

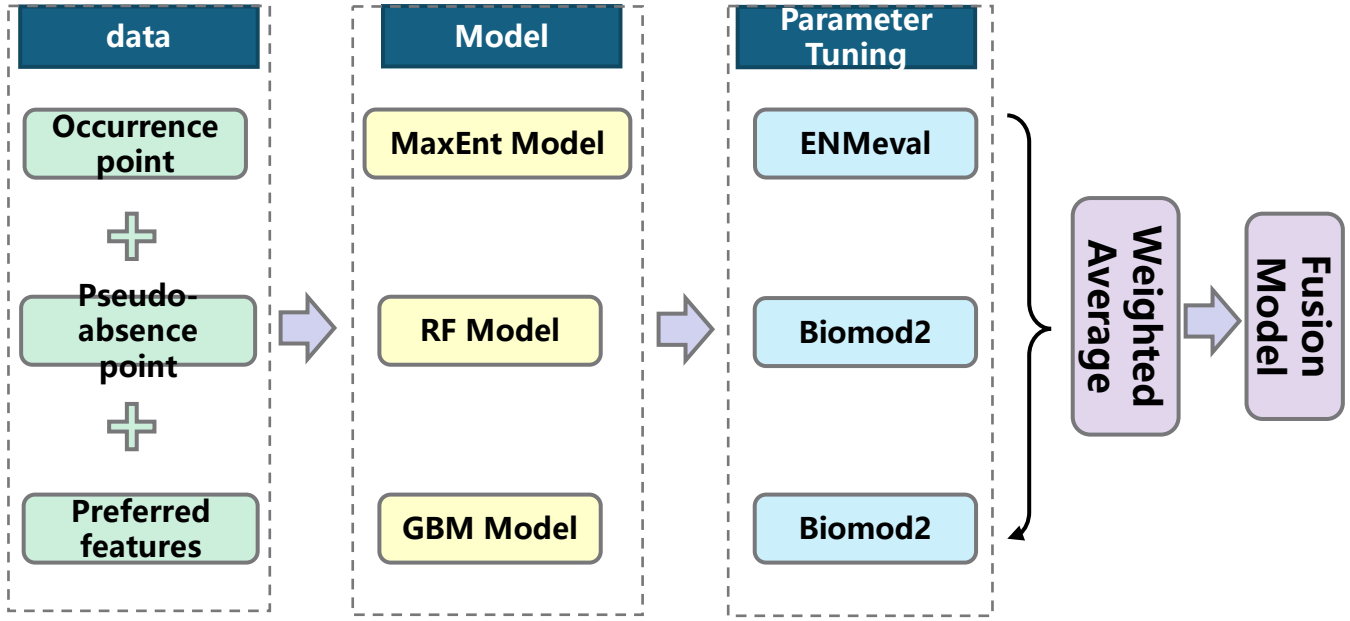
- **Meteorology:** rainfall, wind speed, wind direction, effective accumulated temperature, world bioclimatic variables
- **Host:** NDVI , surface greenness, etc.
- **Soil:** soil moisture, ground surface temperature
- **Terrain:** DEM data, land use / cover data
- …

Insect source, host and environment are the three factors that affect the occurrence and development of locusts

Desert Locust Forecasting

Ecological niche model (ENM) for desert locust

- Desert locust: Based on locust location data and selected monitoring features , three ecological niche models, MaxEnt , RF and GBM , were constructed and their parameters were optimized. Then, a weighted average synthesis strategy was adopted to construct a fusion ecological niche model.



Technical route for building desert locust model

Suitability (M) factor	1 (Not suitable)	2 (generally suitable)	3 (suboptimal)	4 (very suitable)
Vegetation coverage	<10% or >80%	10%～15% or 70% to 80%	50%～70%	15%～50%
Land cover type	Artificial surfaces, bare land, forest land, water bodies, other	arable land	grassland	Wetlands
Soil moisture content	-	<10% or >25%	19%～25%	10%～19%
Surface temperature	<20℃ or >40℃	25℃～28℃	34℃～40℃	28℃～34℃

Suitability classification of habitat factors of East Asian migratory locust

Desert Locust Forecasting

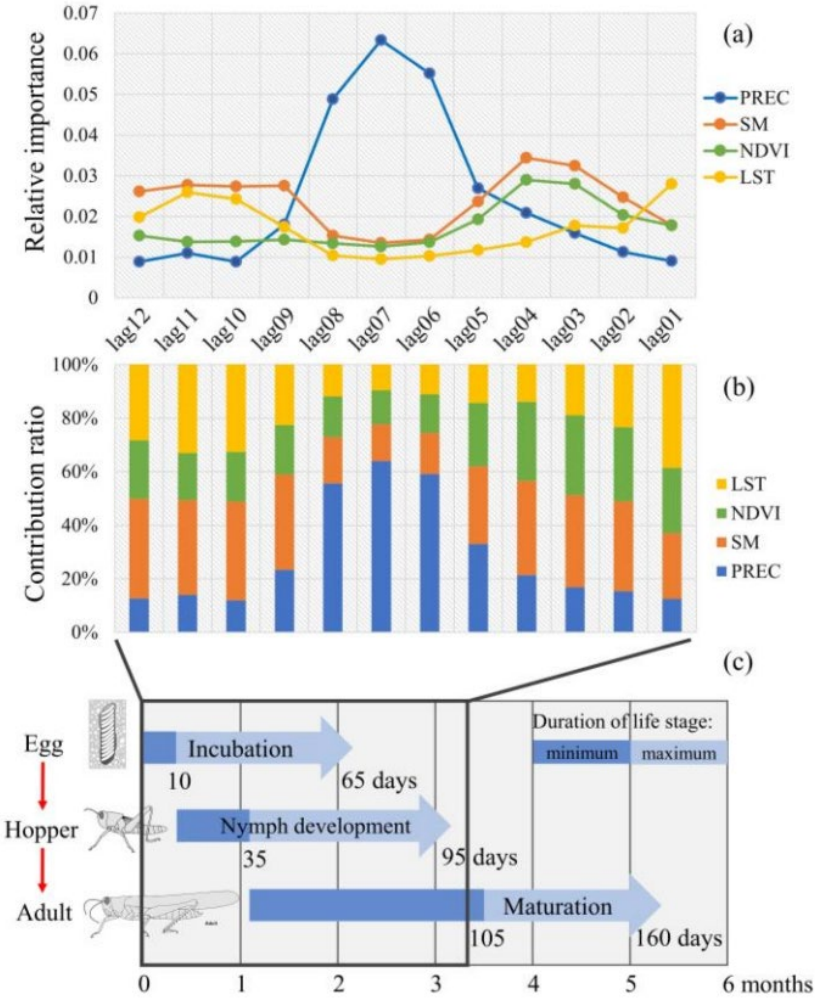
Analysis of time labeled effects of indicator factors

Rainfall The surge in rainfall observed 41-64 days before the onset of the desert locust is a signal for females to lay eggs and can also promote vegetation growth, which ultimately affects locust corm growth and development

Soil moisture The increase in soil moisture from 73-80 days before occurrence to 33-40 days before occurrence is a booster of locust egg hatching and an early signal of vegetation growth

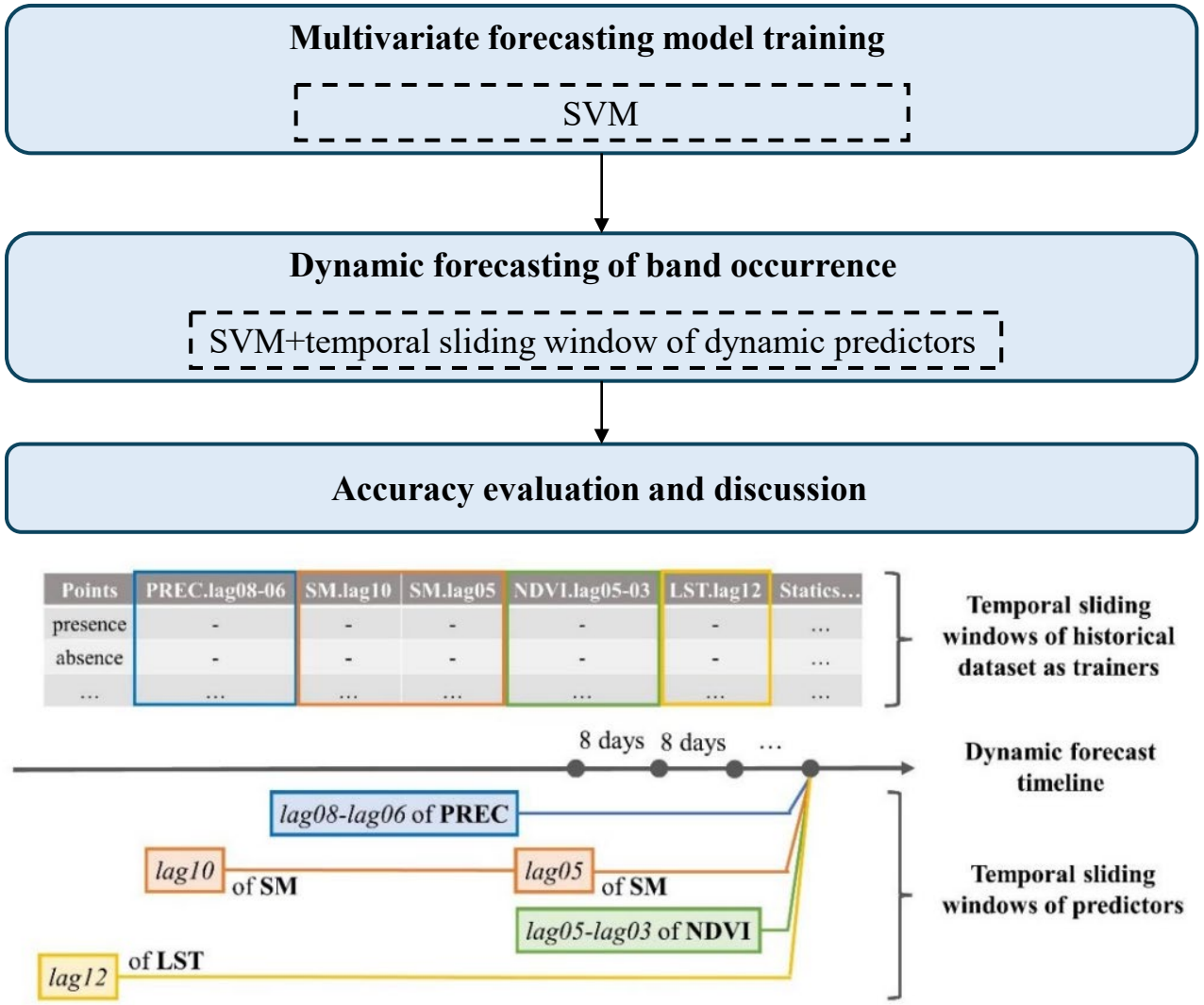
NDVI The increase in NDVI during the 17-40 days prior to locust infestation acts as a food source and habitat for locust cysts during their developmental phase, influencing their growth, development and distribution and aggregation, as well as an ecological response to meteorological conditions such as precipitation

LST The 89-96 days and 17-24 days of LST prior to locust infestation influenced egg hatching rates, mortality and development rates, and therefore acted on both the pre- and post-desert locust development process



Model for Forecasting Based on a Temporal Sliding Window

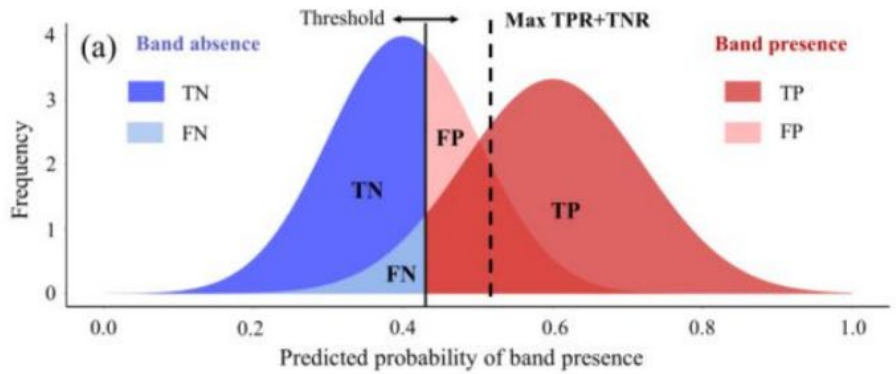
W e use SVM as the fundamental model for the forecast for a better overall accuracy throughout the year. For dynamic indicators, a temporal sliding window selector was invented to choose trainers and predictors dynamically based on the time lag information mining from the historical ground survey information and long time series of satellite. Lagging variables of dynamic indicators with lower significance were removed and those that contributed highly survived. We then combined other static indicators for model training and prediction. Thus, we proposed a data-driven multivariate approach combining machine learning and a temporal sliding window to predict band occurrence for early.

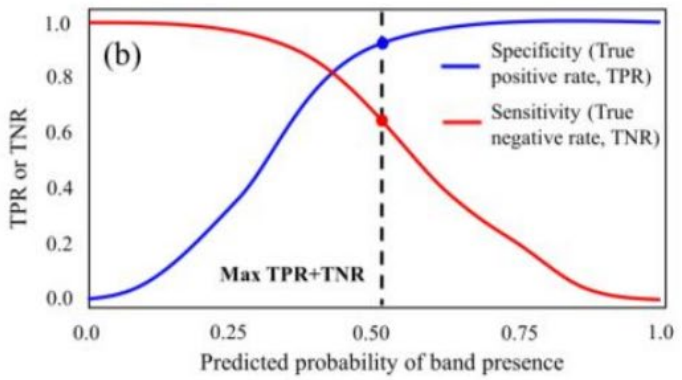


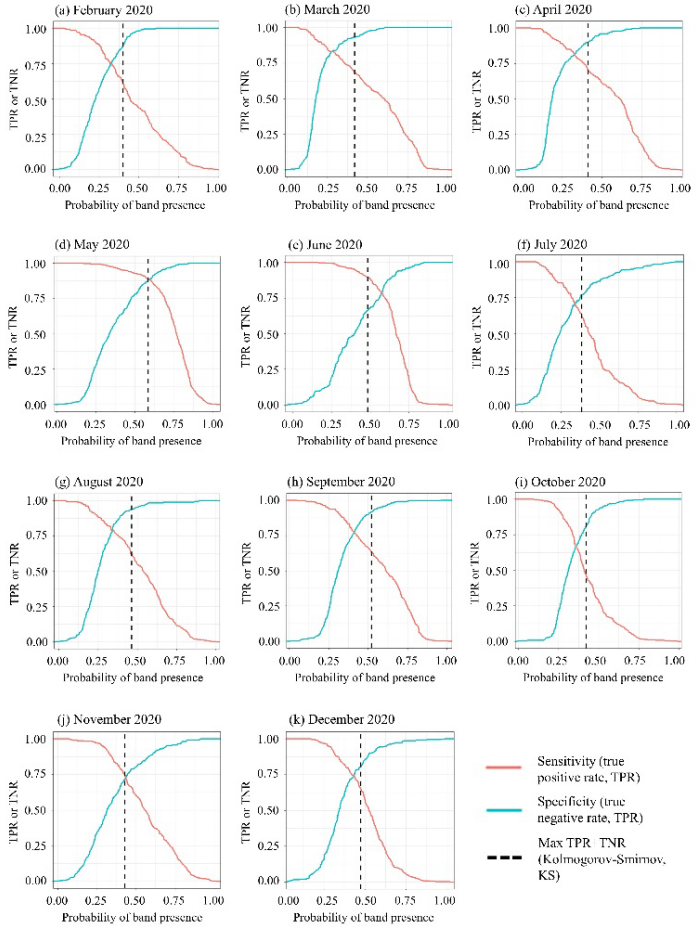
Model Evaluation and Accuracy Assessment

Dynamic optimal segmentation → Confusion matrix construction → Calculation of precision indicators

- **Dynamic optimal segmentation:** the probability threshold corresponding to the KS statistic (max TPR+TNR) of the training model is used as the optimal segmentation point to map the prediction results to binary classification results (with/without risk)
- **Confusion matrix construction:** the occurrence points of each month reserved from the training set are superimposed on the classification results as ground truths, and the occurrence points falling into the risk zone are recorded as true positives; the absence points falling into the non-risk zone are recorded as true negatives
- **Calculation of precision indicators:** accuracy, sensitivity, specificity, ROC-AUC, precision and F1 score were selected as indicators





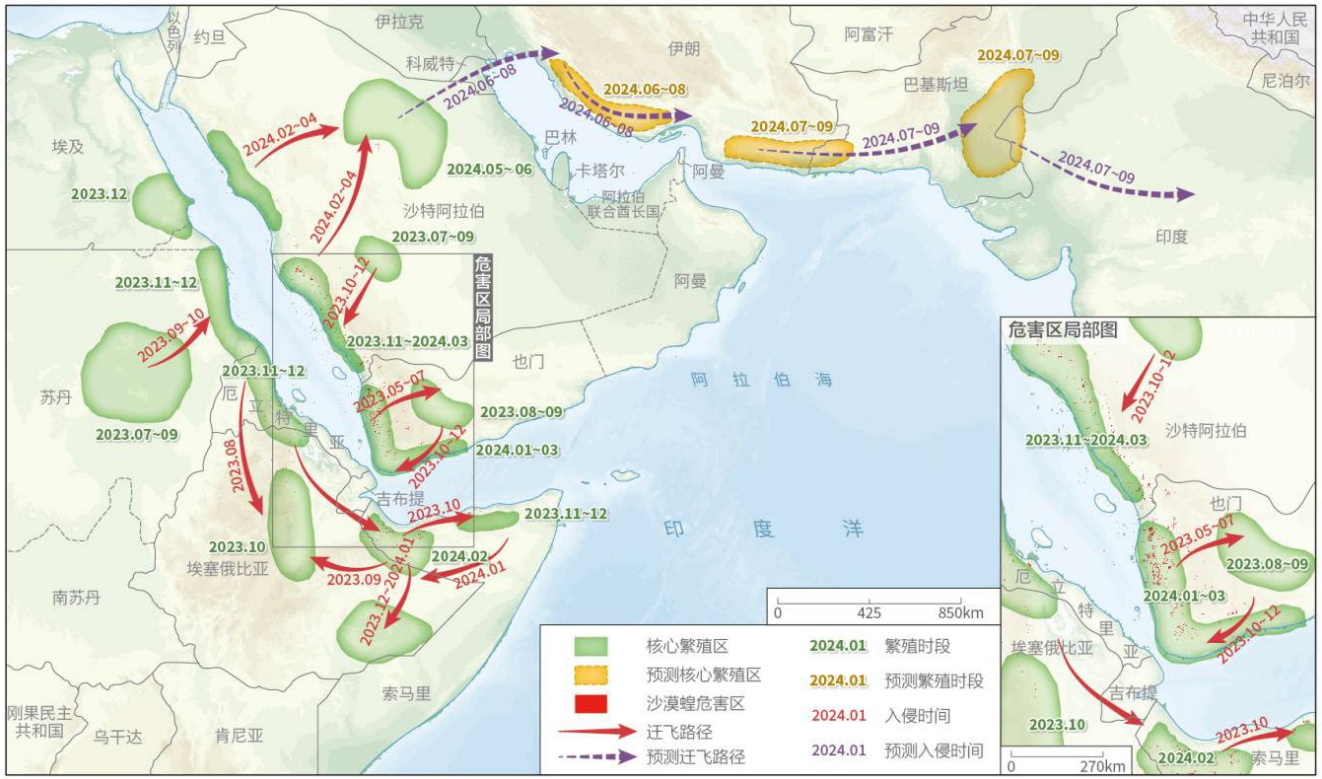


Desert Locust Forecasting

Dynamic Forecasting of Desert Locust

In response to the serious damage caused by desert locusts in early 2024-2025, we carried out migration route forecasts 10-30 days in advance , and provide support for sentinel early warning in major grain-producing countries where desert locusts invade .

- **From October to December 2024 , the Red Sea coast is expected to have abundant rainfall and good vegetation growth. Locusts in inland areas will migrate to coastal areas suitable for reproduction.**
- **From March to May 2025 , locusts in the Red Sea coastal areas in northern Saudi Arabia are expected to migrate inland for spring breeding, and the number of locusts in the Red Sea coastal areas will decrease.**



Desert locust migration route monitoring and prediction





Grasshopper Forecasting

Background

Grasshoppers can greatly interfere with agriculture and husbandry, and they will breed and grow rapidly in suitable habitats.



Objectives

The environmental factors, including meteorological, vegetation, topographic, and soil factors, that affect the developmental stages of grasshoppers ;

extracted the grasshopper potential suitable habitat associated with meadow and typical steppes;

Analysis spatial-temporal characteristics of the grasshopper potential suitable habitat

Explored the effects of the habitat factors in two steppe types.



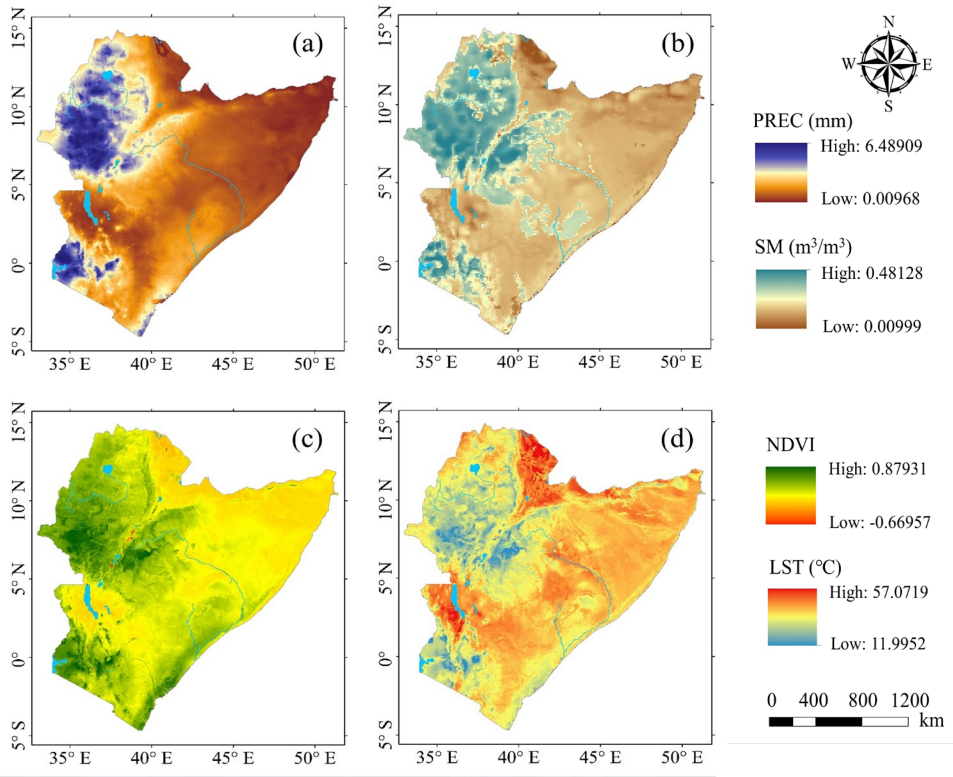
Research content

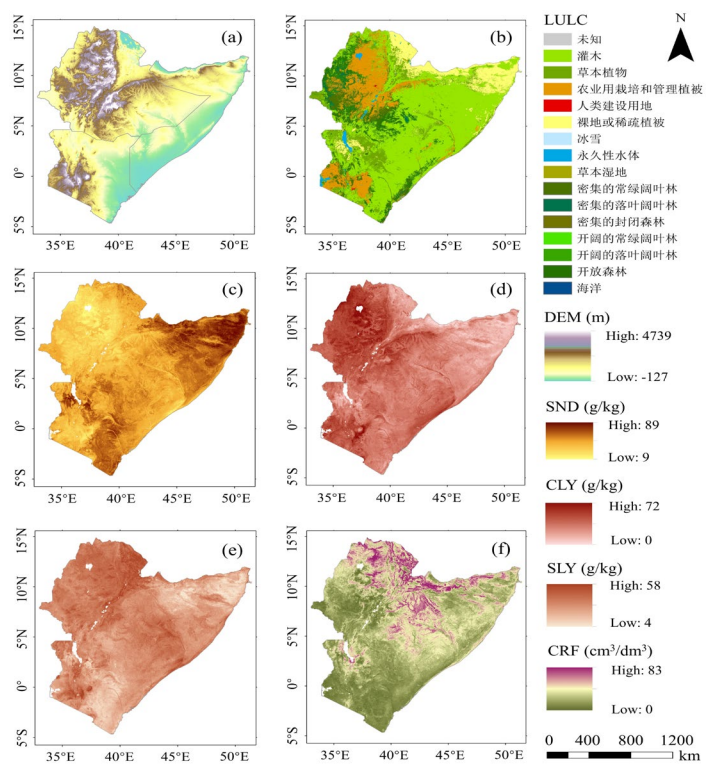
- extract the distribution of the grasshopper potential habitat
- analyze the spatial-temporal characteristics of the grasshopper potential habitat
- detect the different effects of key environmental factors in the meadow and typical steppe

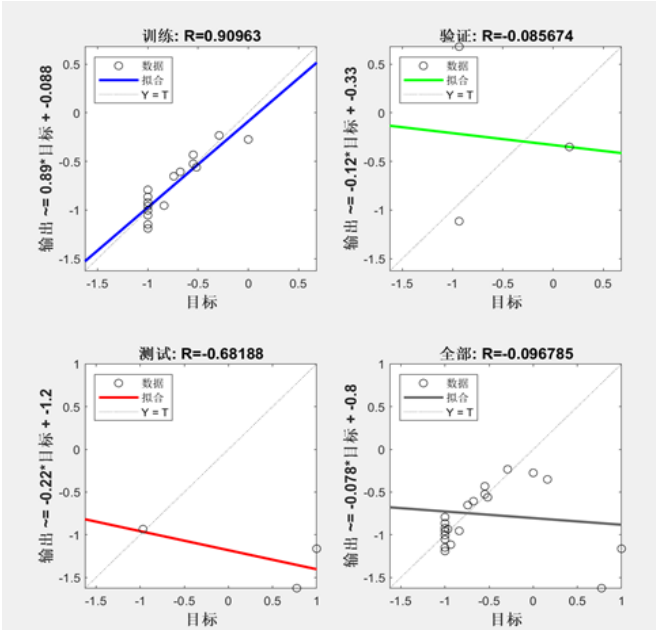
Grasshopper Forecasting

Grasshopper habitat monitoring factors

- Based on the grassland cross-border invasive insect habitat monitoring dataset, combined with the growth and development mechanisms of each dominant species, statistical analysis, machine learning and deep learning algorithms were used to screen grassland cross-border invasive warning indicators, covering a total of 12 factors including NDVI, precipitation, LST, LULC, DEM, etc.





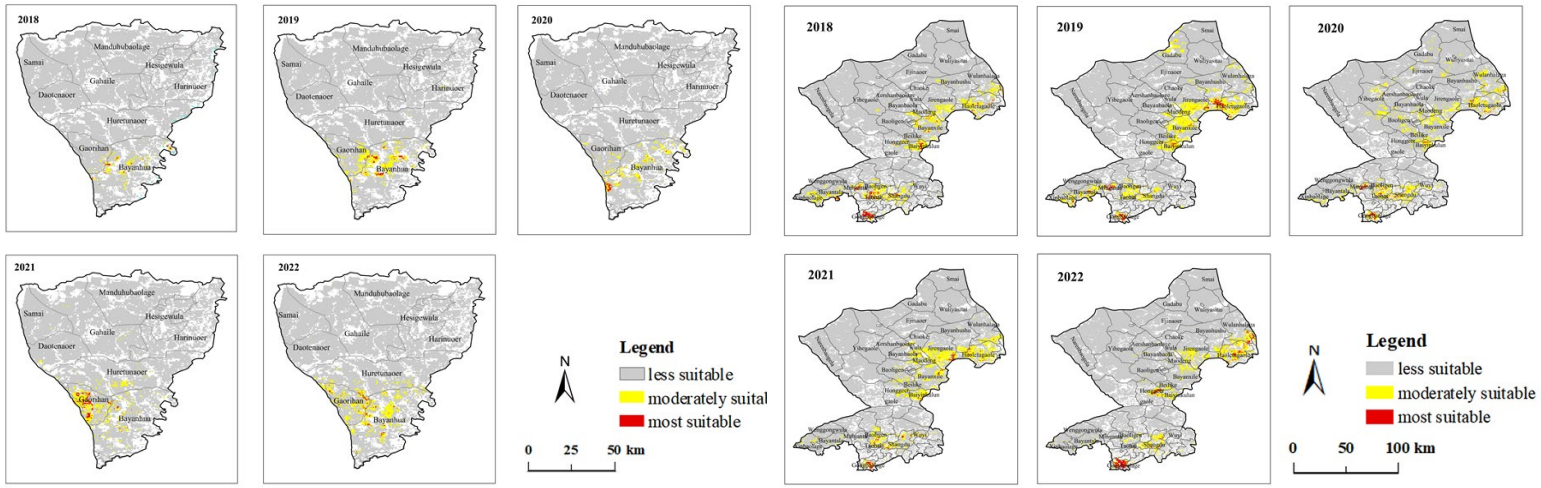


BP neural network model fitting

Grasshopper Forecasting

Extraction Method of Grasshopper Potential Suitable Habitat

- MaxEnt was applied to extract the distribution of grasshopper potential suitable habitat.
- Grasshopper potential suitable habitat maps were generated using the **bootstrap approach** with replicates set to **50** ;
- the training (70%) and testing (30%) datasets for each year ;
- Model accuracy was evaluated in terms of the omission rate and predicted area (ORPA) and the area under the curve (AUC) of the receiver operating characteristic (ROC) curve;
- Three levels of possibility were set: less suitable (0–0.5), moderately suitable (0.5–0.7), and most suitable (0.7–1).



Spatial distribution of the GPHs in the meadow and typical steppe

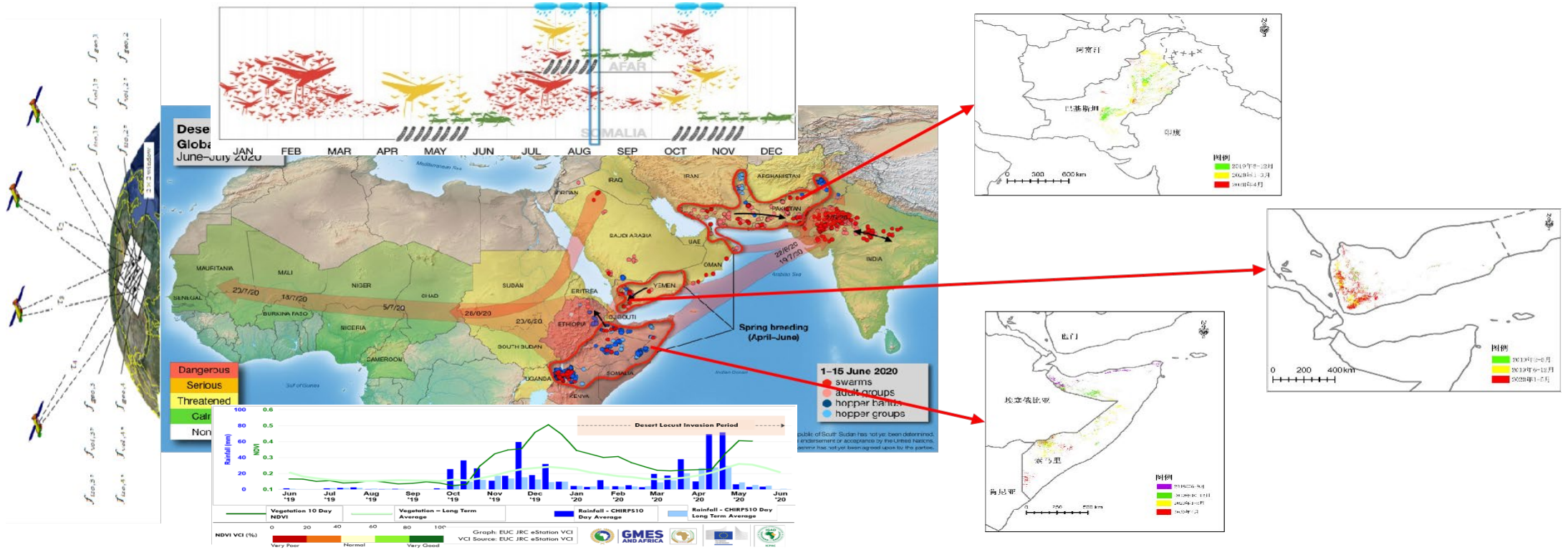
Year	Area of Meadow Steppe (km²)			Area of typical Steppe (km²)		
	Most Suitable	Moderately Suitable	Less Suitable	Most Suitable	Moderately Suitable	Less Suitable
2018	44	407	32,853	1091	8829	110,098
2019	101	1135	32,068	1055	12,460	106,503
2020	64	691	32,549	686	10,341	108,991
2021	192	1218	31,894	672	10,854	7491
2022	102	1622	31,580	1192	7491	111,335

Areas of each suitability level in the meadow and typical steppes from 2018 to 2022.

Grasshopper Forecasting

Early warning technology for cross-border invasive grasshopper

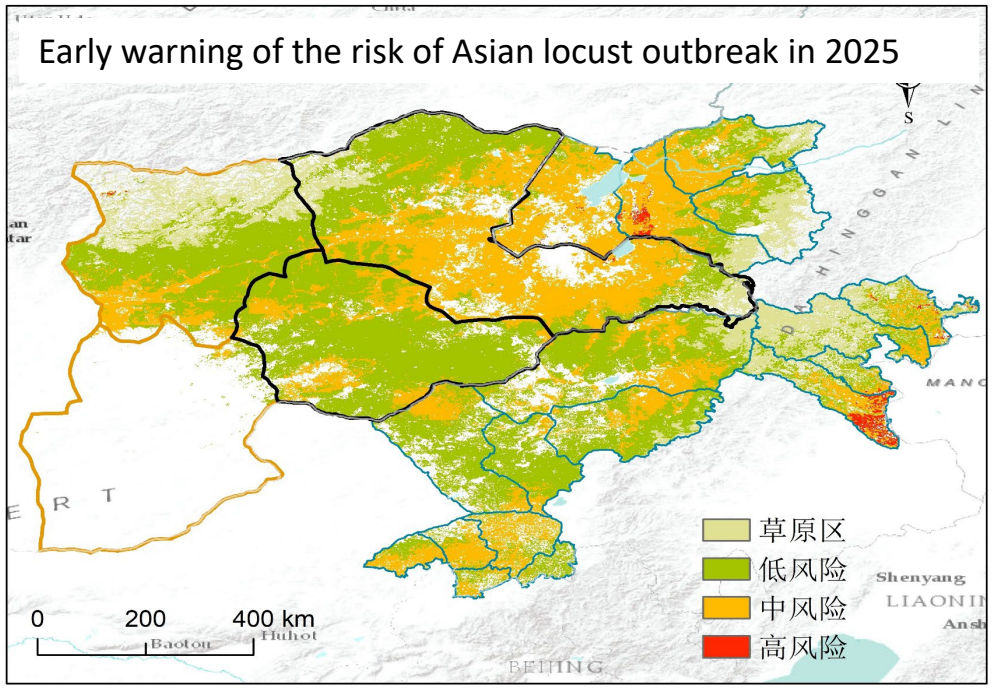
On the basis of suitability monitoring, factors affecting the migration and spread of dominant species in border areas are considered, and models such as **WRF** are used, combined with local vegetation growth status and type characteristics to determine whether the territory meets the growth and development of grassland cross-border insects, identify potential spread areas, invasion trajectories and channels, and achieve sentinel early warning of grassland cross-border invasive grasshopper.



Grasshopper Forecasting

Potential suitable habitat monitoring and risk prediction of grasshopper

Based on grassland locust early warning indicators, and taking into full consideration the population ecological characteristics and migration and diffusion mechanisms of invasive insects from abroad, sentinel early warnings are achieved in locust migration and diffusion areas, sentinel early warning areas, and key monitoring areas within the country.

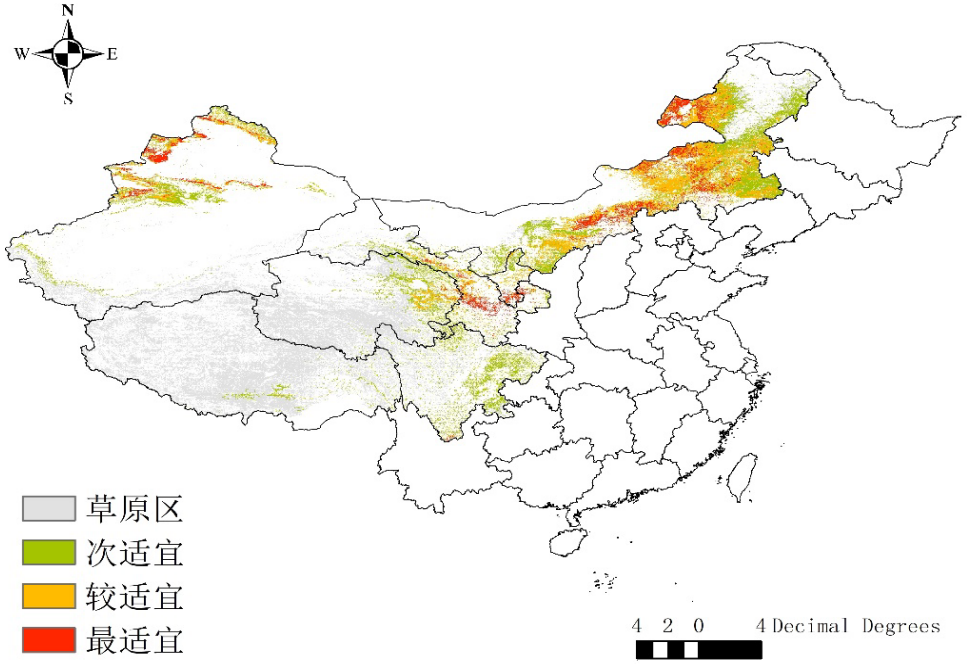


Not suitable

Generally suitable

Suboptimal

Very suitable

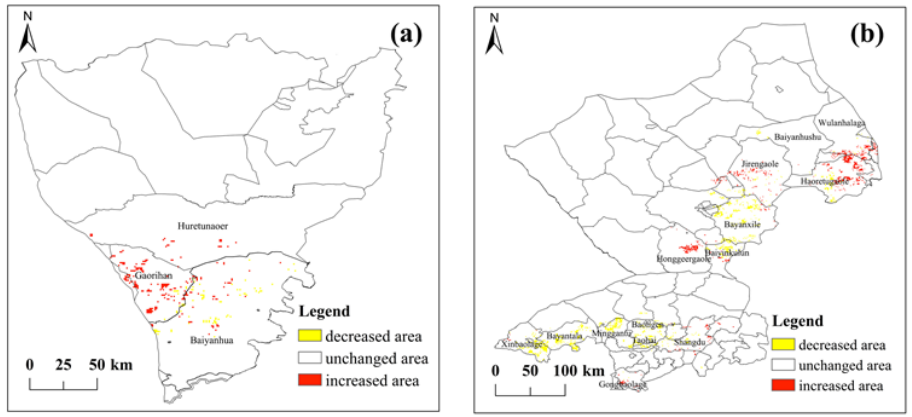


Monitoring results of grassland locust suitable habitats in 2025

Grasshopper Forecasting

Temporal Variation Characteristics of Grasshopper Potential Suitable Habitat

- the suitability index changes corresponding to each pixel were analyzed;
- the significance of these changes was tested according to the F value from 2018 to 2022.
- Only the trends that passed the F test had significant p values, meaning that the trend of the suitability index changed. The p value selected for this study was 0.1, meaning that at this level, the trend at least marginally significantly changed.



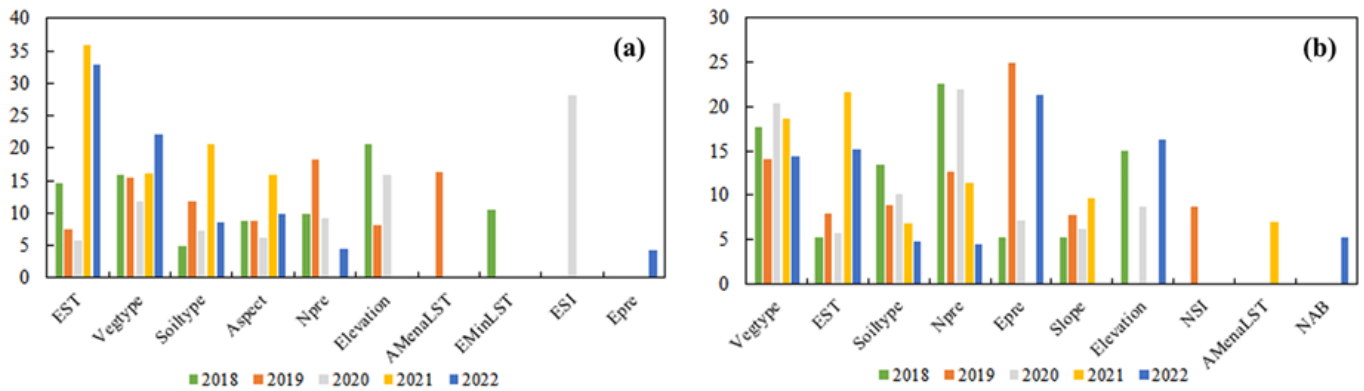
(**a**) The trends of the suitability index in meadow grasslands; and (**b**) typical steppe.

Main Influencing Factors in the Meadow and Typical Steppes

- We regarded the factors with cumulative contributions exceeding 80% as the main influence factors.
- EST, soil type, vegetation type are the same important factors for two steppes ;

In the meadow steppe, the EST, vegetation type, soil type, and aspect were the vital factors

In the typical steppe, the vegetation type, EST, soil type, and NPre were the vital factors



environmental factors contributions from 2018 to 2022 in the (**a**) meadow steppe, and (**b**) typical steppe.

Pine Wilt Disease Monitoring and Forecasting

Background

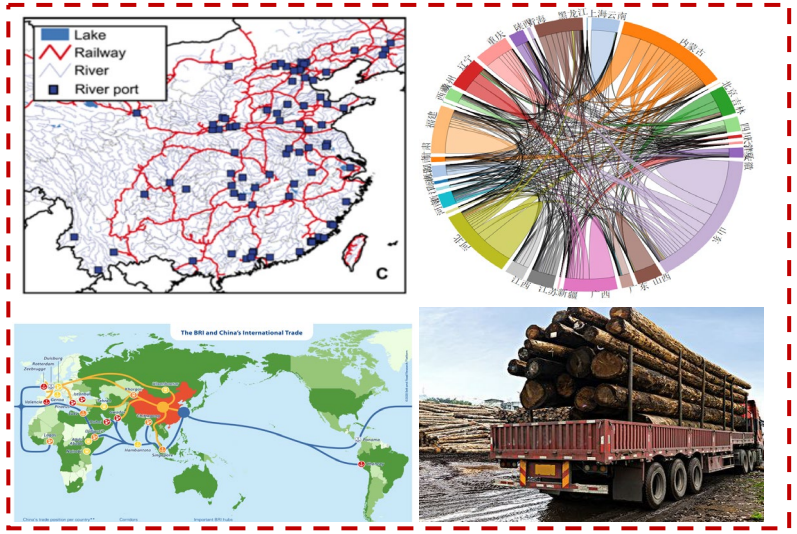
Pine wilt disease (PWD) is the most serious forest disaster in China. The annual direct economic and ecological service value loss caused by pests and diseases in China exceeds two hundred billion yuan.

The spread of PWD has not only caused serious damage to pine forest resources and threatened the ecological security, but it has also had a significant impact on import and export trade.

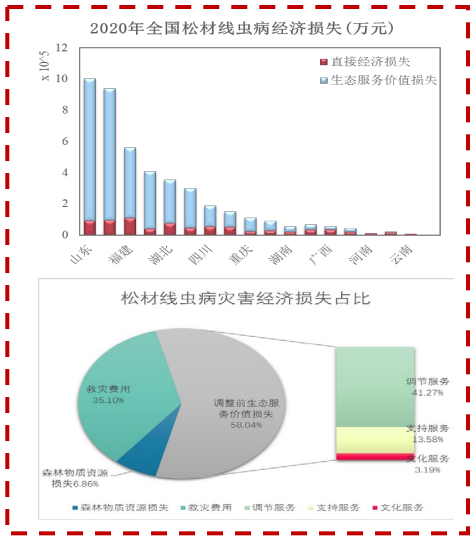
Therefore, it is urgent to monitor the induced trees and forecast the spreading area to control the disease.



Pine wilt disease causes damage of pine trees



Distribution and transmission in China and around the world



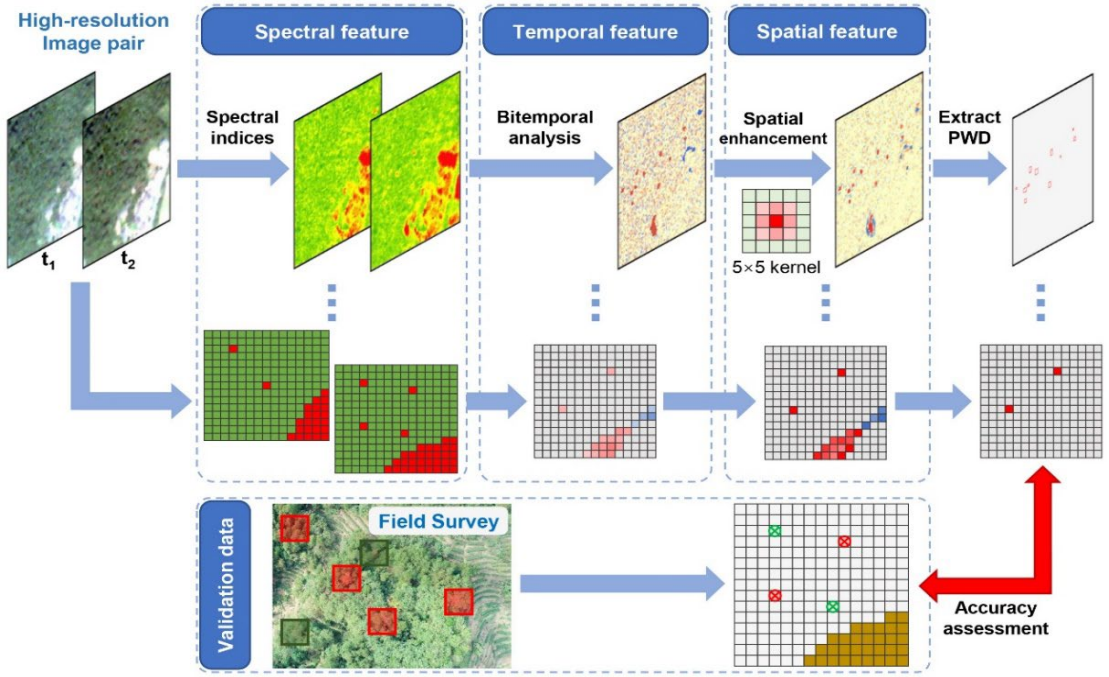
Economic losses

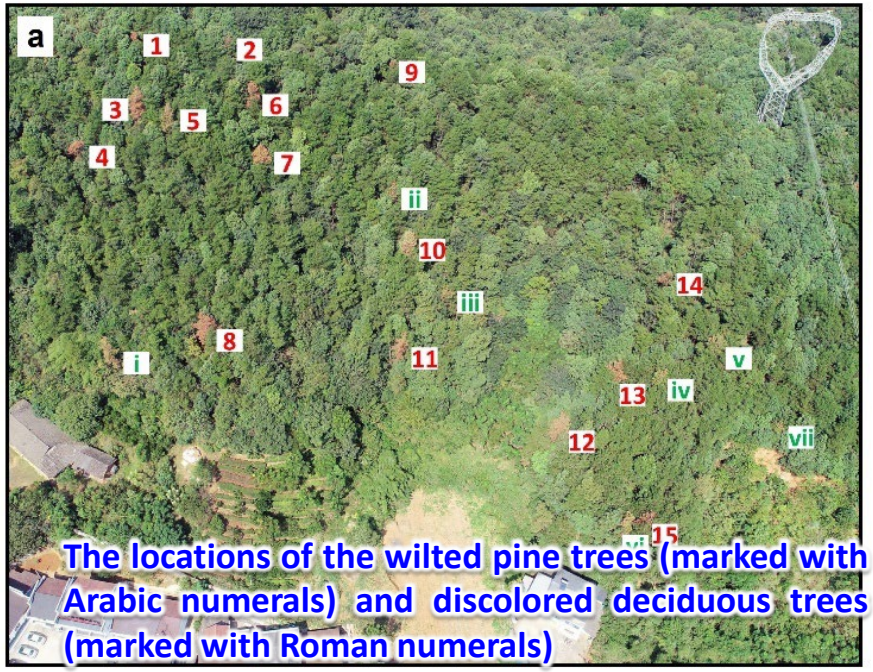
Pine Wilt Disease Monitoring and Forecasting

Detecting discolored trees caused by PWD

Single-date image classification methods often yield false detections caused by deciduous trees, brown herbaceous, and sparsely vegetated regions, resulting in low users accuracy

Therefore, a spatiotemporal change detection method was proposed to reduce false detections in tree-scale PWD monitoring using a pair of PlanetScope 3-m resolution images in complex landscapes





The locations of the wilted pine trees (marked with Arabic numerals) and discolored deciduous trees (marked with Roman numerals)

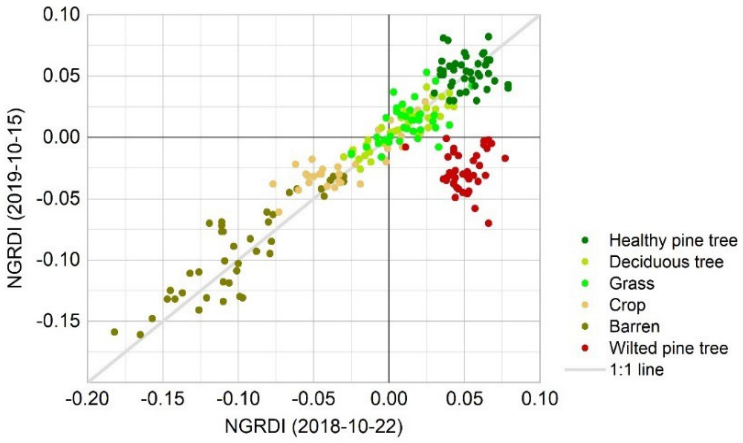
Pine Wilt Disease Monitoring and Forecasting

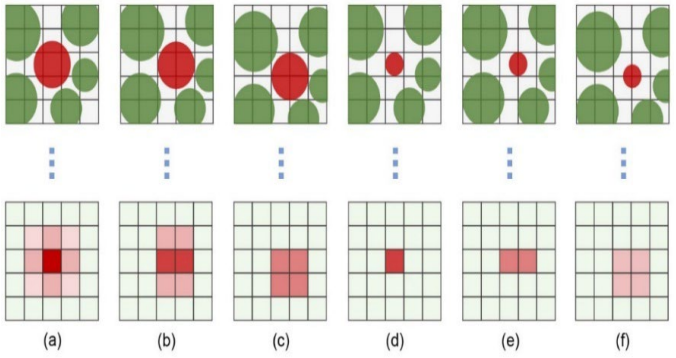
Detecting discolored trees caused by PWD

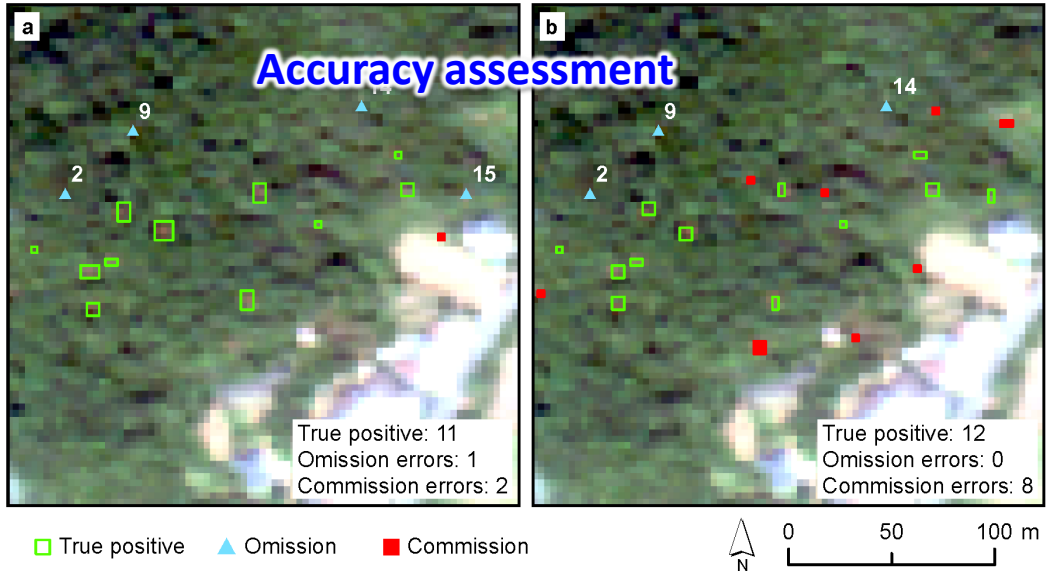
Compared with single-date image classification, the spatiotemporal change detection method can effectively eliminate the discolored broad-leaved trees, and significantly improved user's accuracy (81.2% vs. 67.7)

Bitemporal change detection

Spatial convolution







Site	Total Wilted Trees for Validation	True Positive (Tree Count)	Omission Errors (Tree Count)	Commission Errors (*BB* Count)	Producer's Accuracy	User's Accuracy
A	12	11	1	2	91.7%	84.6%
B	6	5	1	2	83.3%	71.4%
C	90	79	11	15	87.8%	83.0%
D	28	22	6	4	78.6%	84.0%
E	67	55	12	14	82.1%	78.1%
Total	203	172	31	37	84.7%	81.2%

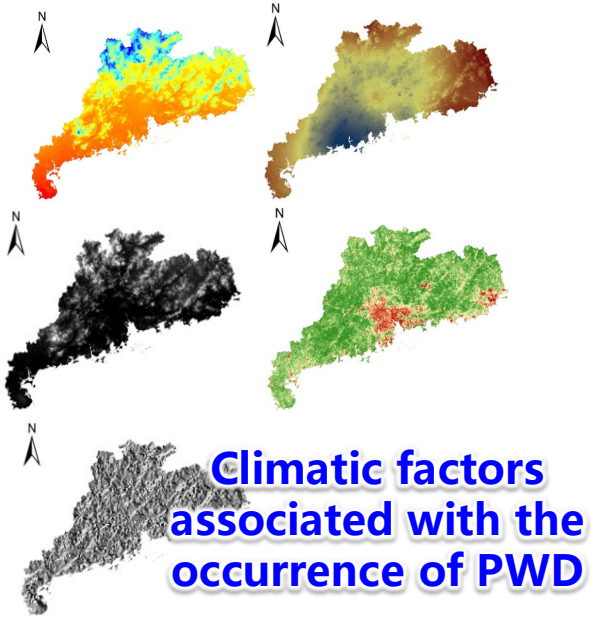
Site	Total Wilted Trees for Validation	True Positive (Tree Count)	Omission Errors (Tree Count)	Commission Errors (*BB* Count)	Producer's Accuracy	User's Accuracy
A	12	12	0	8	100.0%	60.0%
B	6	5	1	4	83.3%	55.6%
C	36 *	30	6	16	83.3%	63.6%
D	11 *	9	2	6	81.8%	60.0%
E	67	53	14	16	79.1%	76.1%
Total	132	109	23	50	82.6%	67.7%

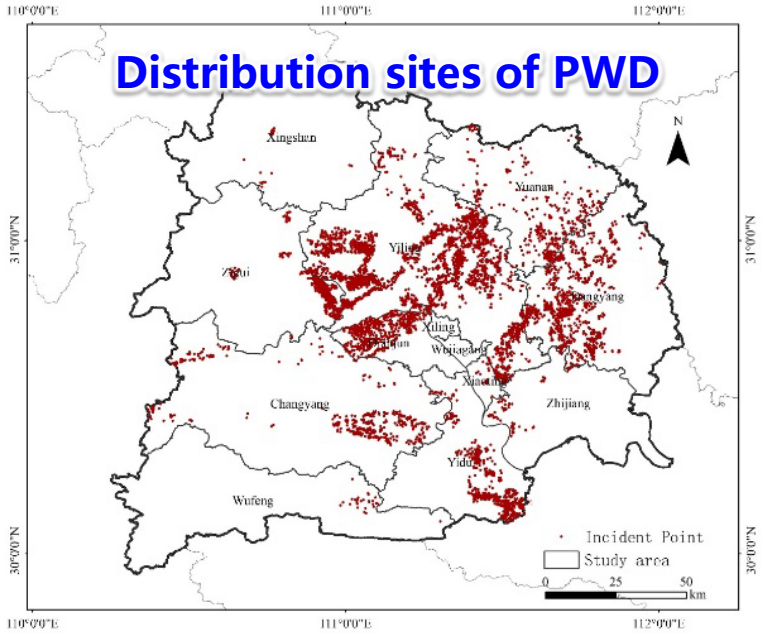
Pine Wilt Disease Monitoring and Forecasting

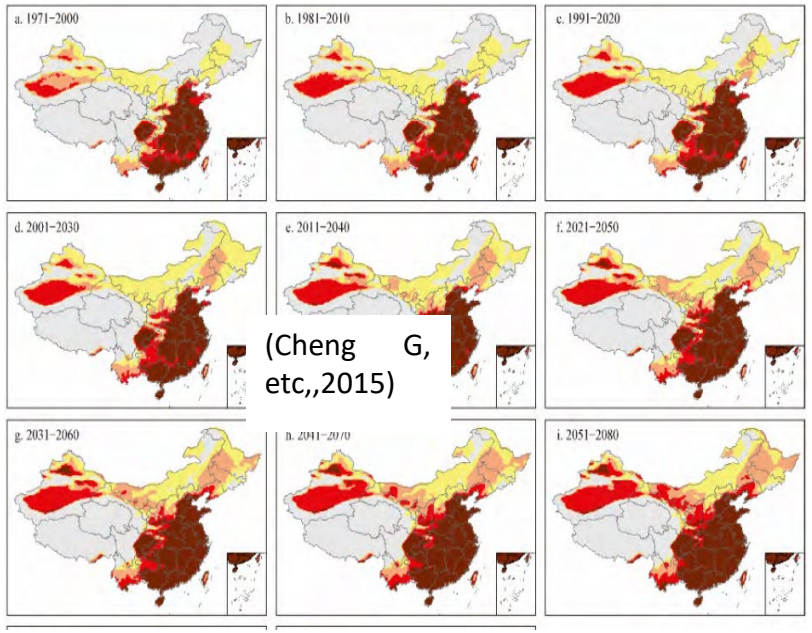
PWD Suitable Habitat Monitoring

Suitable area extraction is the process of linking the species with environmental variable to determine the relationship between the species distribution and environmental variables, and to estimate the distribution of the target species.

Within the suitable area, as long as host pines are present, other climatic factors meet the conditions for invasion and pathogenesis of PWD.







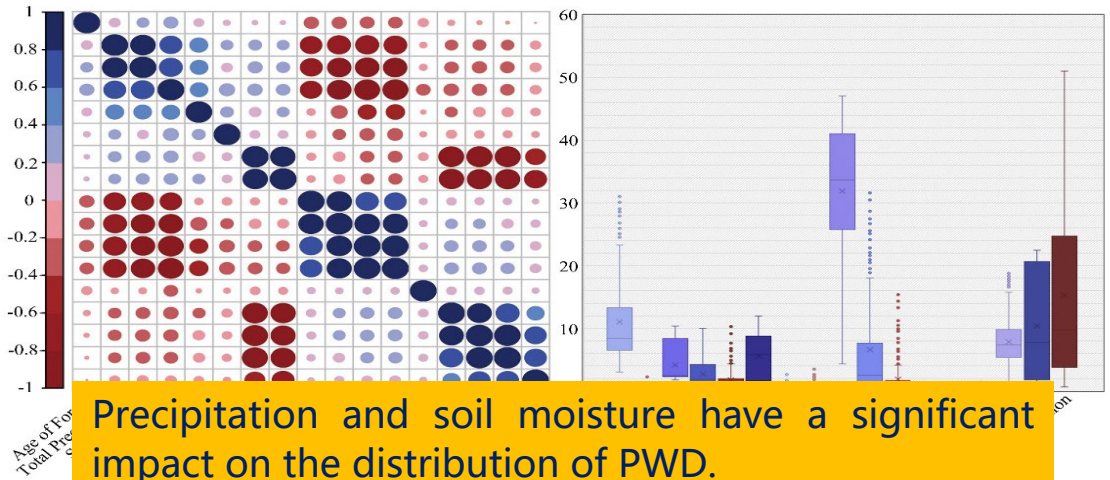
(Cheng G, etc,,2015)

Pine Wilt Disease Monitoring and Forecasting

PWD Suitable Habitat Monitoring

Variable Selection

- To enhance the **representativeness** of the study variables and improve the **interpretability** of the model, a correlation analysis was conducted on the research variables, and factors with correlation coefficients exceeding **0.7** were prioritized and screened based on their importance

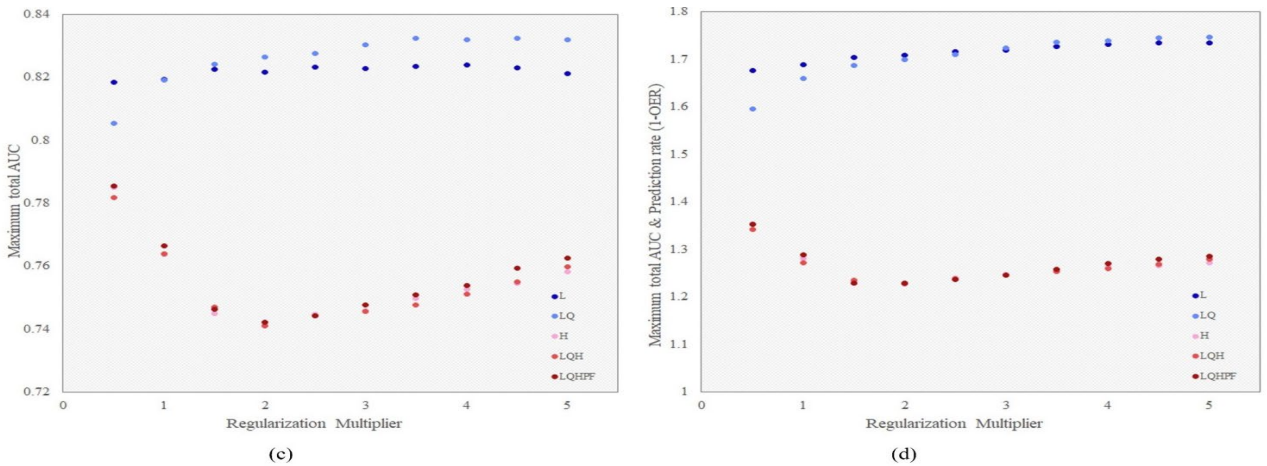


Precipitation and soil moisture have a significant impact on the distribution of PWD.

Elevation is highly correlated with temperature and precipitation.

Model

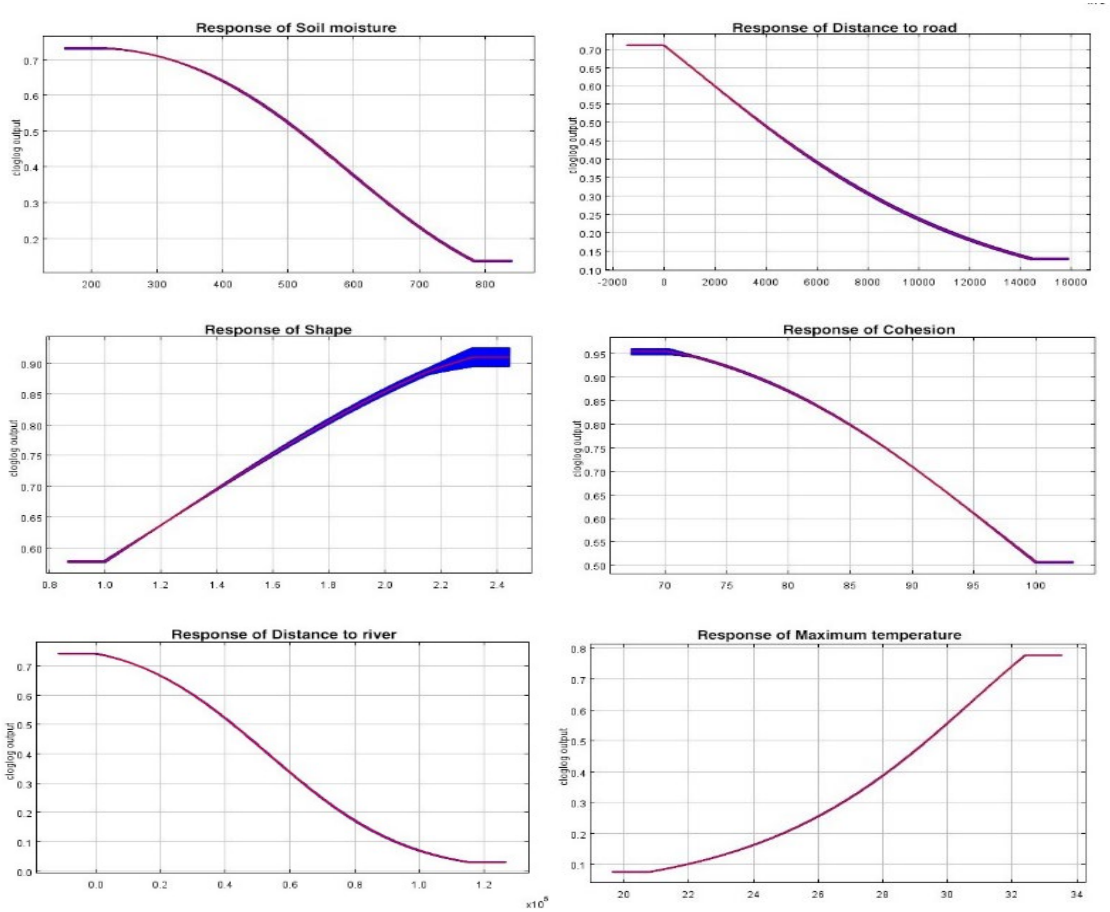
- This study employed the **Maxent** model, and accuracy validation was conducted using the Maximum Total AUC and Prediction Rate (1-OER), **with (1-OER) + AUC** serving as the evaluation standard for the model.
- The model predictions are influenced by two parameters: the **regularization multiplier (RM)** and **feature combinations (FC).**

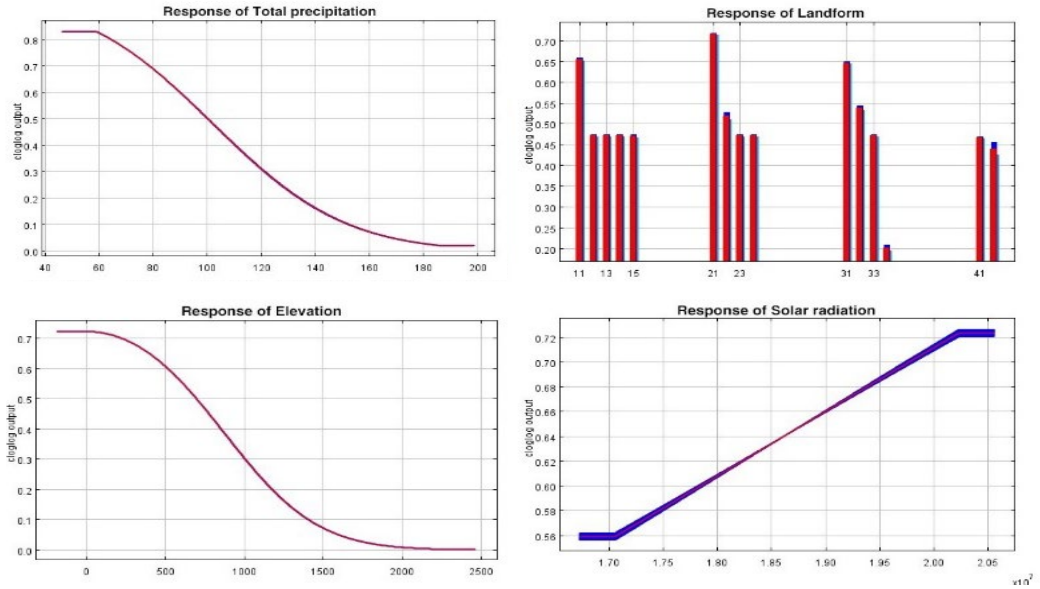


Pine Wilt Disease Monitoring and Forecasting

PWD Suitable Habitat Monitoring

- Response Curve Analysis was conducted between the selected study variables and the probability of PWD occurrence.
- All variables exhibited clear trends with the probability of PWD occurrence.





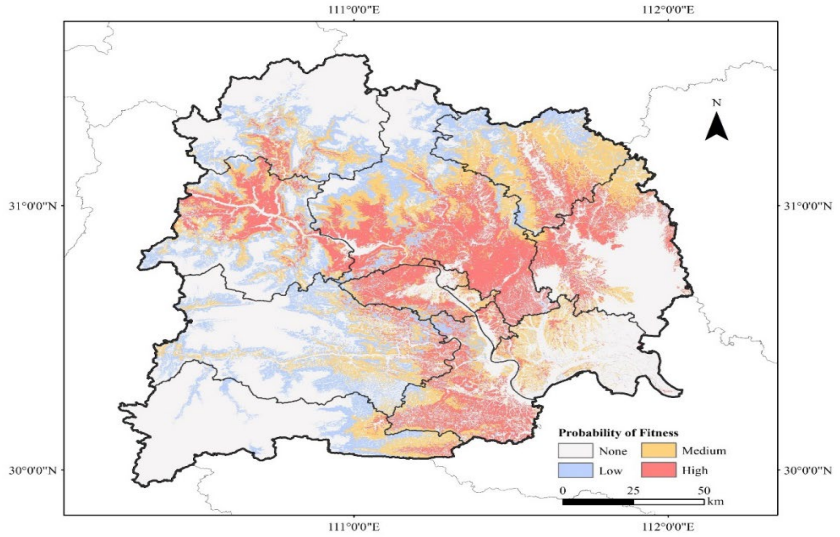
[3] Hao, Z., et al., Risk Prediction and Variable Analysis of Pine Wilt Disease by a Maximum Entropy Model. Forests, 2022. 13(2).

Pine Wilt Disease Monitoring and Forecasting

PWD Suitable Habitat Monitoring

- The distribution of suitability zones in Yichang City can be primarily categorized into three parts.
- The highly suitable zone exhibits a Y-shaped distribution, with the northern and southern regions being unsuitable zones, while the highly suitable and moderately suitable zones are concentrated in the eastern part.

Influence factors	Jackknife test	Chang-yang	Urban area	Dang-yang	Wu-feng	Xing-shan	Yidu	Yiling	Yuan'-an	Zhi-jiang	Zigui
Landform	Without variable										
	With only variable										
Cohesion	Without variable										
	With only variable										
Distance to river	Without variable										
	With only variable										
Elevation	Without variable										
	With only variable										
Age of forest	Without variable										
	With only variable										
Maximum temperature	Without variable										
	With only variable										
Distance to road	Without variable										
	With only variable										
Shape	Without variable										
	With only variable										
Soil moisture	Without variable										
	With only variable										
Solar radiation	Without variable										
	With only variable										
Total precipitaion	Without variable										
	With only variable										



Under different climate environments, transportation conditions, and landscape patterns, the importance of variables influencing PWD distribution has undergone changes.

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Thank you!





