2022 DRAGON 5 SYMPOSIUM

MID-TERM RESULTS REPORTING

17-21 OCTOBER 2022

PROJECT ID. 57457

APPLICATION OF SINO-EU OPTICAL DATA INTO AGRONOMIC MODELS TO PREDICT CROP PERFORMANCE AND TO MONITOR AND FORECAST CROP PESTS AND DISEASES

18 OCTOBER, 2022

ID. 243

SINO-EU OPTICAL DATA TO PREDICT AGRONOMICAL VARIABLES AND TO MONITOR AND FORECAST CROP PESTS AND DISEASES [ID#57547]

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Project's framework and objectives/scopes

- Respond to the need to update and optimize the crop biophysical variable retrieval for agricultural soil and crops using current and present generation EO data considering errors and uncertainties in the remote sensing observations
- Exploit different data assimilation approaches into agricultural models that address the issues of the multi-scale and multivariate nature of the retrieved variables

i) Retrieve agricultural topsoil properties, using multivariate techniques or novel machine learning approaches;

ii) Retrieve crop related bio-physical variables by using RTM (also 3D) and empirical models to simulate the interaction of light with vegetation at leaf and canopy levels. Optimization of data assimilation procedures of the multivariate and multi-scale remotely sensed variables into agricultural models for yield, quality and biotic & abiotic disease estimation;

iii) Development of innovative methods for crop pests and diseases monitoring at the regional scale,

iv) Evaluation of parameters potentially predisposing the onset of pests and diseases;

v) Exploits the DIAS systems.

EO Data Delivery

Data access since July 2020 for no. of scenes of high/low bit rate data

ESA	No. Scenes
1. Sentinel-2 (Time series from 2016) on several African countries	Thousands (ftp)
2. Sentinel-2 (Time series (2019-2021) on the Quzhou County (China)	220 (ftp)
3. Sentinel-3 Quzhou County (China)	3
4. Sentinel-1 Quzhou County (China)	2
Total:	1225
Issues:	

ESA Third Party Missions *including national	No. Scenes
1. PRISMA on Quzhou	5
2. PRISMA for Locust diff sites	12
3.	
4.	
5.	
Total:	17
Issues:	

Chinese EO data	No. Scenes
1.	
2.	
3.	
4.	
5.	
Total:	
Issues:	

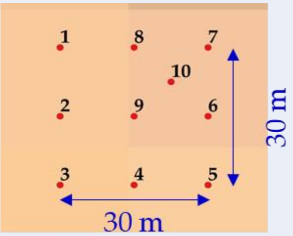
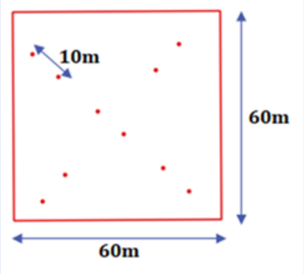
European Young scientists contributions in Dragon 5

Name	Institution	Poster title	Contribution
Francesco Rossi (PhD candidate)	University of Rome "La Sapienza" SIA CNR IMAA	Retrieving topsoil properties through multiplatform and multi- hyper-spectral EO data [ID#161]	Development of a sharpening CNMT code for PRISMA and S-2; MLR for soil properties
Simone Saquella	University of Rome "La Sapienza" SIA		Development of crop mapping procedures based on S-2
Alvise Ferrari	University of Rome "La Sapienza" SIA		Development of processing techniques based on Google Earth Engine
Riccardo Orsi	University of Rome "La Sapienza" SIA		Development of the crop early warning processing chain

Chinese Young scientists contributions in Dragon 5

Name	Institution	Poster title	Contribution
Ruan Chao	Aerospace Information Research Institute, Chinese Academy of Sciences		Developed a forecasting model for wheat yellow rust based on vegetation indices and meteorological characteristics, achieving 88.7% accuracy in forecasting wheat yellow rust.
Xiao Yingxin	Aerospace Information Research Institute, Chinese Academy of Sciences		Proposed a remote sensing forecasting method combining host and habitat conditions to achieve dynamic forecasting of wheat *fusarium* head blight with an accuracy higher than 70%.
Sun Ruiqi	Aerospace Information Research Institute, Chinese Academy of Sciences		Proposed a dynamic prediction model of desert locust presence risk at Somalia-Ethiopia-Kenya, achieving a accuracy of 77. 46%, and the model enables daily dynamic forecasting of desert locust risk up to 16 days in advance.
Yu Ren	Aerospace Information Research Institute, Chinese Academy of Sciences	[ID#161]	Proposed ML retrieval algorithms for retrieving agricultural soil properties

In situ data collection and requirements

Site	Parameters / istruments	period	Sampling strategies
Quzhou County (China)	Soil sampling and wet analysis. SOC, N, P, K, PH	2019/2020	50 polygons/year
Maccarese & Jolanda (IT)	Soil sampling for wet analysis, texture and SOC. Vegetation parameters (LAI2000, Dualex)	April 2021 May 2021 June 2021 January 2022 February 2022	A total of 57 ESU  
Kenya, Transzonia and Vihiga counties	Polygons of the crop field and corresponding crop types were collected	August 2021	25 polygons

Agricultural Topsoil characterization

Objective is to evaluate the capability of hyperspectral imager (e.g. PRISMA etc) to estimate topsoil properties (i.e. organic carbon, clay, sand, silt), in comparison with multispectral sensors (e.g S-2). To investigate the suitability of hyperspectral, a test was carried out using topsoil data collected in China in the in "Quzhou County" in the Hebei province.

Soil imaging spectroscopy of agricultural fields

Importance

- ❖ Better knowledge of agricultural soils spatial variability
- ❖ Precision agronomic practices
- ❖ More sustainable use of soils
- ❖ CAP policies for EU, e.g. carbon farming

Limiting Factors

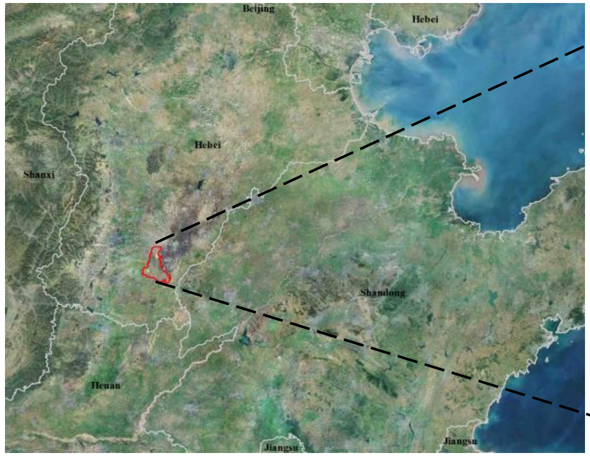
- ❑ Soil moisture
- ❑ Soil tillage
- ❑ Vegetation cover
- ❑ Crop residues
- ❑ Crop rotations
- ❑ Limitation to soil surface

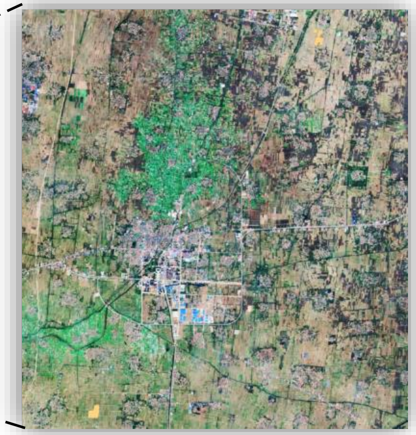
Opportunities

- ➢ Increasing availability of satellite imaging spectroscopy data: PRISMA, EnMAP, GF5 ...
- ➢ Towards operational satellite hyperspectral monitoring: CHIME, SBG ...
- ➢ Repeated observation of the same agricultural fields: temporal variability of soil surface reflectance

Field campaign – topsoil properties

In the first two years of DRAGON 5 the team conducted experiments on topsoil properties at an experimental farm in Quzhou County, Handan City, Hebei Province, China





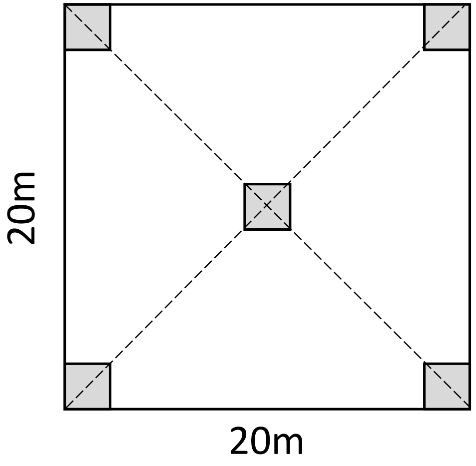
Experimental area 1

Experimental area 2

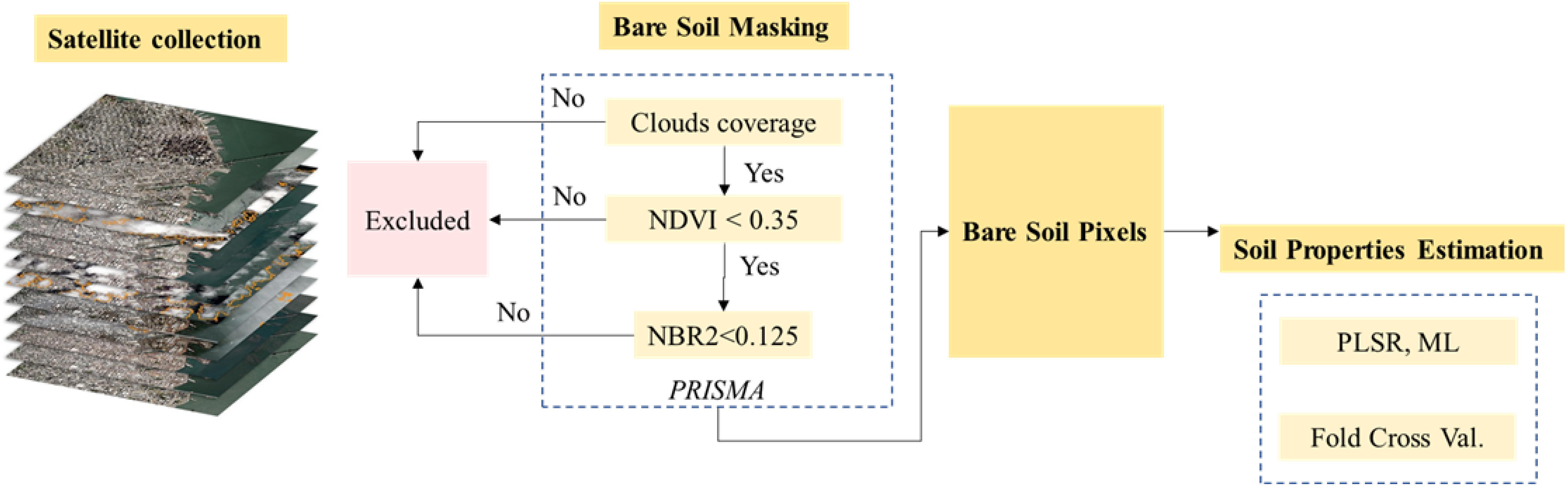
Survey content
PH
Total Nitrogen (%)
Organic Matter (%)
Soil Organic Matter (g/kg)
Soil Nitrogen Content (g/kg)
Effective Phosphorus (g/kg)
Available Potassium (mg/kg)

The topsoil properties were investigated using a five-point sampling method, and for each sampling area the specific sampling locations are shown below. Each sampling area is a 20m X 20m rectangle.

- First remove any plants, stones, etc. from the surface of the soil and dig out small pits using tools.
- Take an appropriate amount of top soil along the cut surface from the bottom upwards, and soil is sampled to a depth of approximately 20cm
- The soil obtained from the five points was mixed well, placed in plastic bags and sent to the laboratory for testing



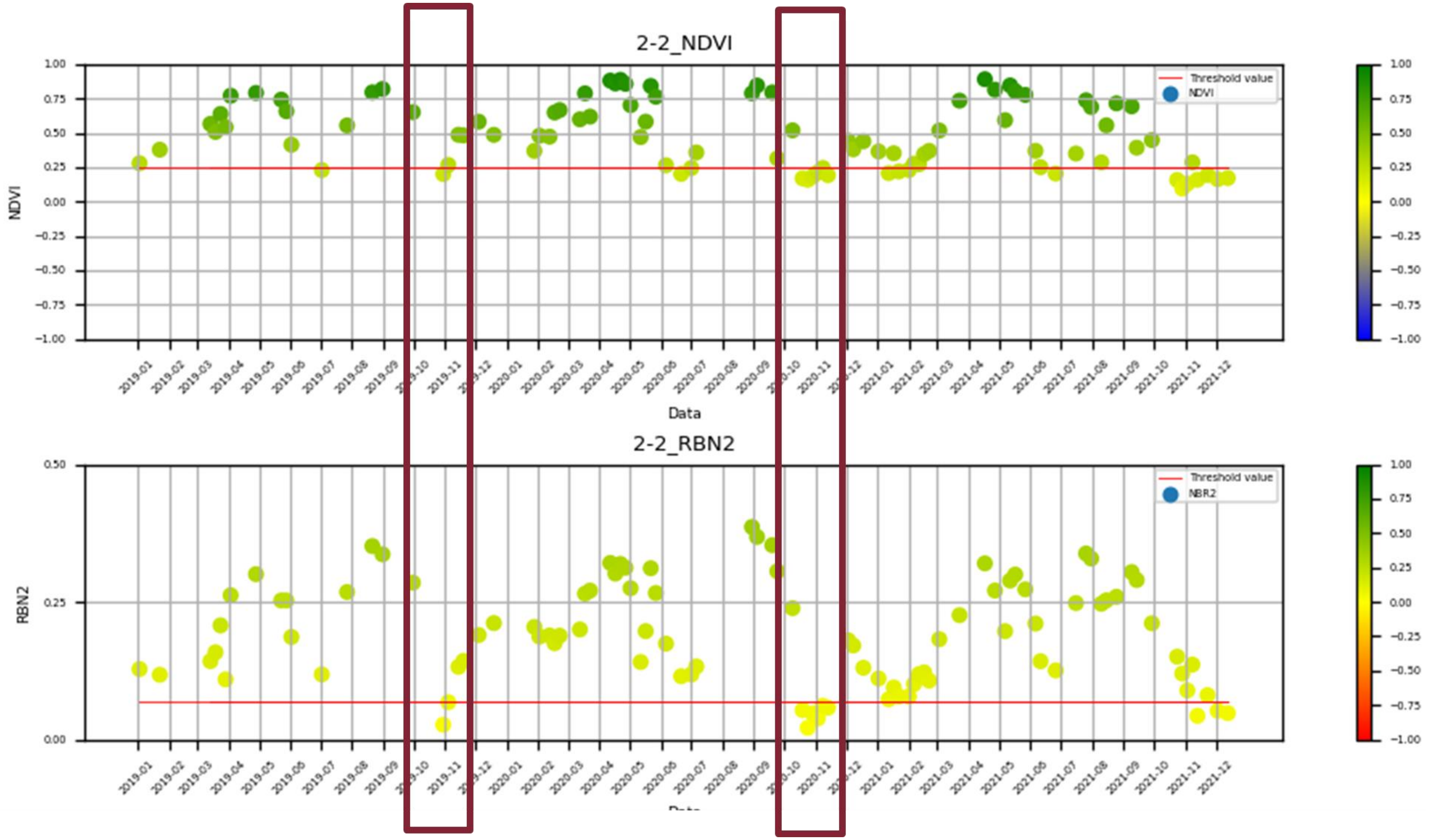
Topsoil characterization: methodology



Topsoil characterization: bare soil date selection

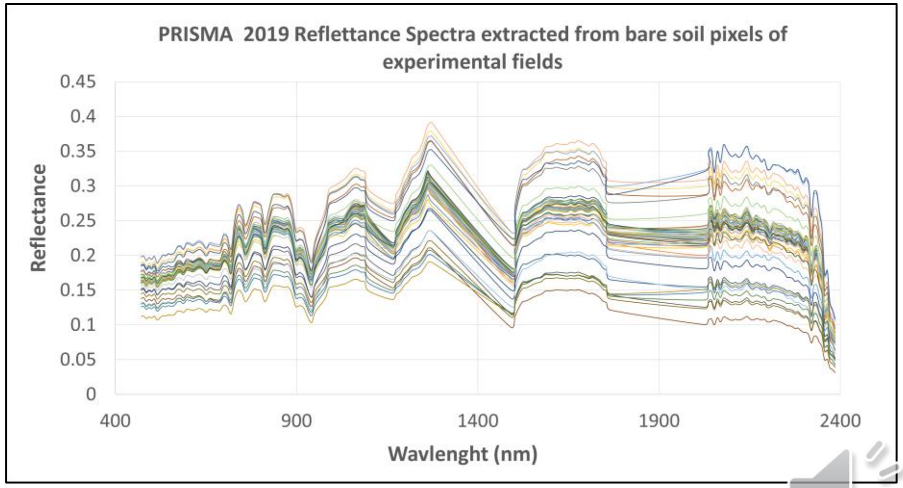
The date with the higher outcrops of bare soil has been selected by analyzing a 2019-2020 S-2 time series of NDVI and NRB2 index. On the base of this result the optimal PRISMA dates have been selected (i.e. 13/10/2019 11/11/2020)

Sentinel 2 NDVI and NBR2 time series analysis



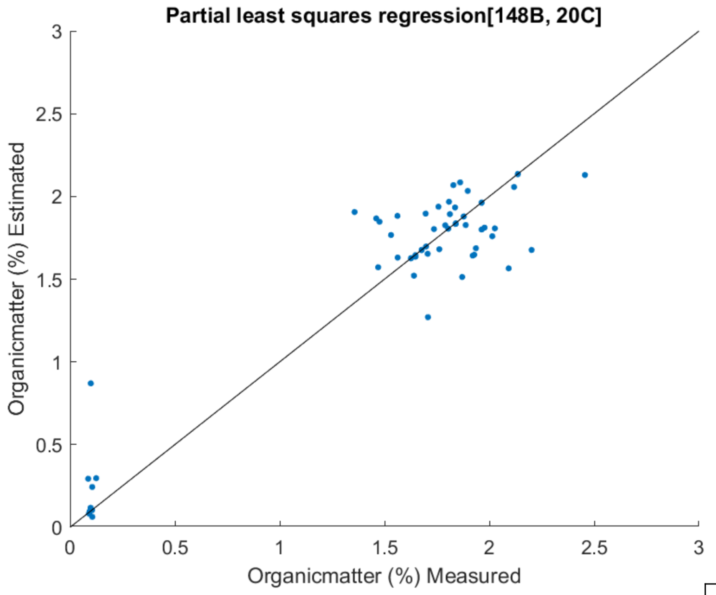
13/10/2019 11/11/2020 PRISMA images

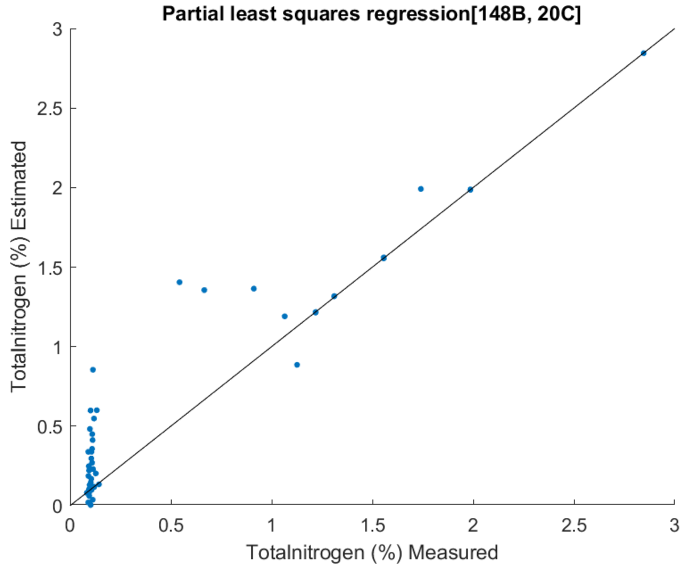
Index	Sentinel-2
NDVI	$\frac{(\rho_{832.8} - \rho_{664.6})}{(\rho_{832.8} + \rho_{664.6})}$
NBR2	$\frac{(\rho_{1613.7} - \rho_{2202.4})}{(\rho_{1613.7} - \rho_{2202.4})}$



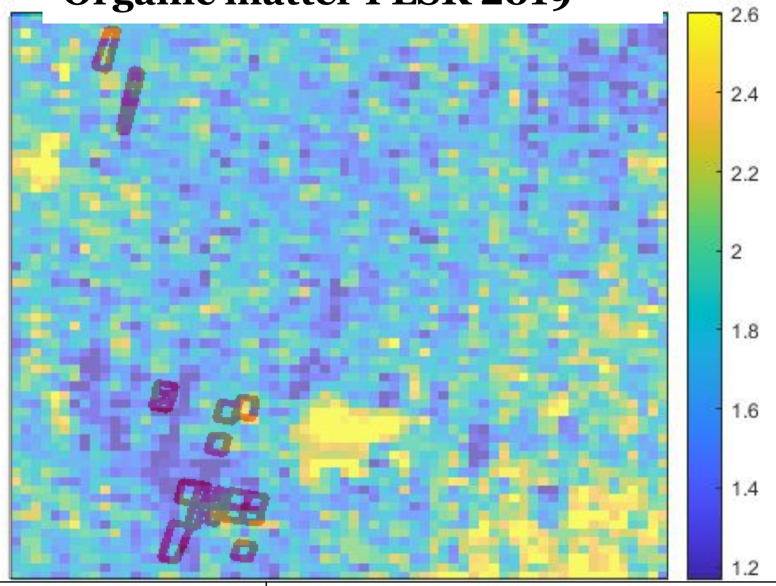
Quzhou PRISMA bare Soil Spectral Library

Topsoil characterization - results

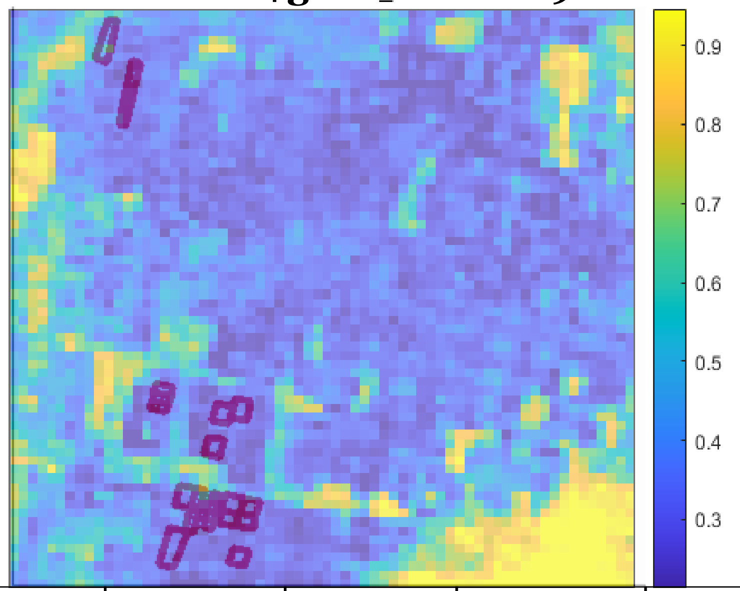




Organic matter PLSR 2019



Total Nitrogen PLSR 2019



Variable	MLRA	RMSE	RRMSE	NRMSE	R	R2
Organic Matter (%)	Partial least squares regression	0.17	11.97	7.05	0.98	0.95
	Canonical Correlation Forests	0.26	18.95	11.17	0.95	0.91
Total Nitrogen (g/kg)	Canonical Correlation Forests	0.24	54.05	8.64	0.96	0.92
	Partial least squares regression	0.28	62.58	10.01	0.93	0.86
Phosphorous (g/kg)	Canonical Correlation Forests	2.50	63.10	10.49	0.91	0.83
	Partial least squares regression	2.98	75.36	12.53	0.87	0.76
Available Potassium (g/kg)	Canonical Correlation Forests	37.56	27.45	14.79	0.73	0.54
	Partial least squares regression	56.72	41.46	22.33	0.61	0.37
pH	Canonical Correlation Forests	0.07	0.87	16.02	0.68	0.46
	Partial least squares regression	0.12	1.56	28.72	0.36	0.13

Crop Early Warning - objectives

- The crop early warning aims to assist the user to quickly identify the onset and evolution in time and space of crop stress conditions due to weather anomalies.
- The monitoring considers both meteorological conditions and vegetation status and then analyze the impacts of weather anomalies on crops.
- Conditions of stress on crop can have different causes: <u>weather conditions</u>, <u>spread of pests and diseases</u>.
- Crop stress due to meteorological adverse conditions can develop rapidly, but they also can end up quickly if deficits in the precipitation are relatively small. Deficits in net water supply accompanied by extreme temperature values may eventually **impact crop growth** and productivity.
- To issue an alert, a check is carried out on the phenologic state. Phenology maps are computed.

Crop Early Warning: Precipitation Alert - PrI

Based on historical values of precipitation (10 years, from 2008 to 2017, have been considered) the forecasted precipitation amount is evaluated.

This forecast-type product, allows to forecast locations over the Area Of Interest (AOI), which receive an anomalous amount of precipitation with respect to the previous ten years in the same period and the same area. This information will be combined with the other two described below to issue an early warning.

Crop Early Warning: Temperature Anomaly Alert - TAI

Evapotranspiration is, however, a more direct indicator of crop growth since it is a measure of the amount of water actually used by the crop. Based on historical temperature values (10 years, from 2008 to 2017, have been considered) the forecasted temperature conditions are evaluated.

This forecast-type product, allows to forecast locations over the AOI, exhibit anomalous temperature levels with respect to the ones registered in the previous ten years in the same period and the same area.

This information will be combined with the precipitation and products concerning the vegetation status to issue an early warning.

Crop Warning: NDVI Alert – VCI/NDVIA

NDVI is used as a proxy for crop status. NDVI anomaly, with respect to the averaged NDVI values, is a key variable within the crop monitor activities.

Two indices, representing an anomaly of the vegetation status, are used:

- **VCI** (Vegetation Condition Index) by Copernicus Land Service
- **NDVIA** (NDVI Anomaly) provided by USGS.

The VCI has been used to produce the low-resolution vegetation early warning maps (1km). The VCI maps produced by Copernicus Land Service has been discontinued in June 2020, but it was replaced by using Sentinel-3 images with a resolution of 300 m.

NDVIA based on Sentinel-2 images has been used to produce the medium resolution vegetation early warning maps with respect the NDVI statistics of the previous six years demonstrating the feasibility of a high-resolution crop early warning product.

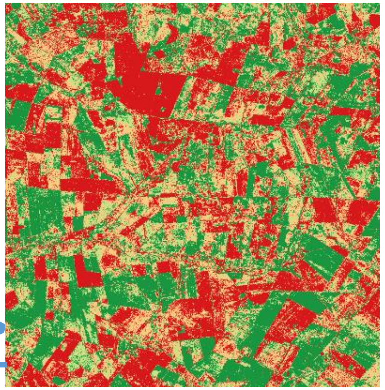
Crop Early Warning production – CREW

The Crop Early Warning production (CREW) is based on the combination of three different indices:

- Vegetation Condition Index (VCI) / Normalized Difference Vegetation Index Anomaly (NDVIa)
- Temperature Anomaly Index (TAI)
- Precipitation Index (PrI)

A phenology map is also used to determine whether we are within the phenological cycle of the crop, and then, if to consider the state of the vegetation for the analysis.

VCI ->

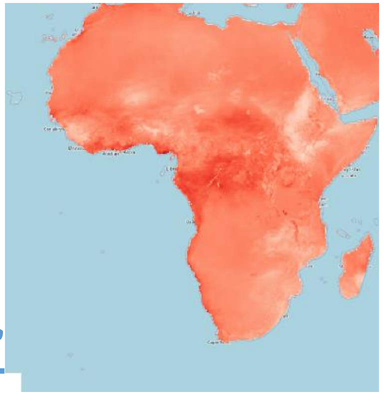


+

TAI ->

+

PrI ->



CREW

Crop Early Warning Results – CREW

From the comparison between the vegetation data, TAI, PrI and the verification of being within the phenological cycle, **four level** of warning are generated (that increase with the level).

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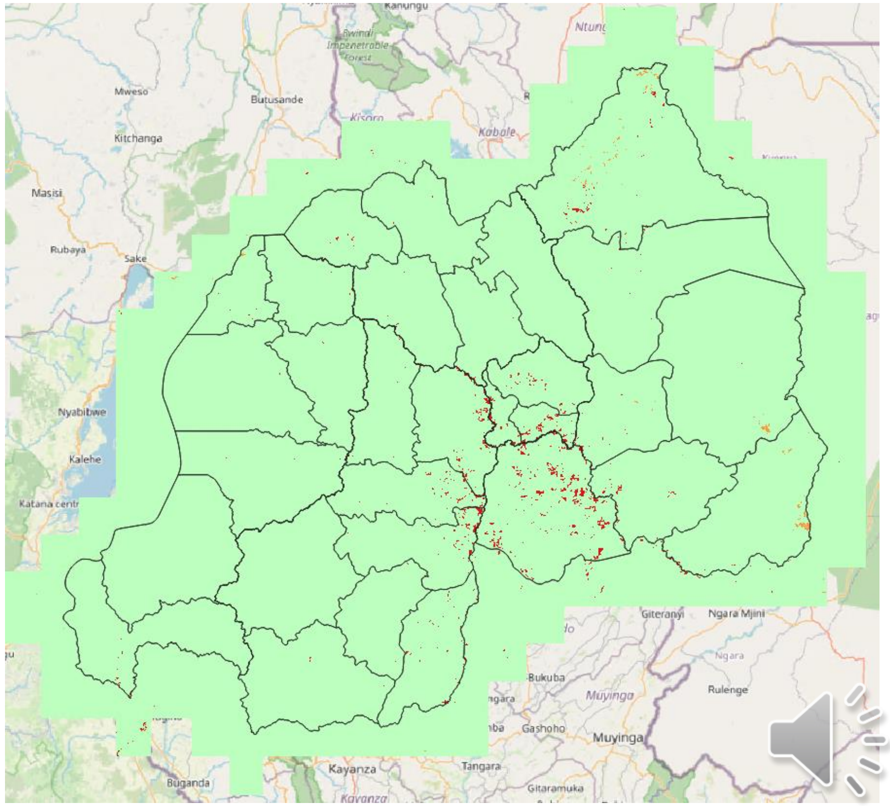
1 Level 1: only vegetation stress persistence

2 Level 2: vegetation stress + temperature anomaly

3 Level 3: vegetation stress + rain deficiency

4 Level 4: vegetation stress + temperature anomaly + rain deficiency



NDVI anomalies without prior thermal and or precipitation anomalies could be representative of vegetation stress not caused by weather conditions, that is, pests, diseases, etc.

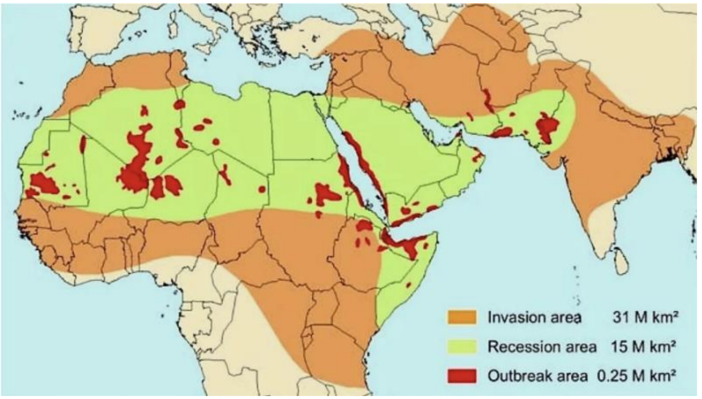
Pest Early Warning – Desert Locust

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 locust.



Michel lecoq, 2020

Research content

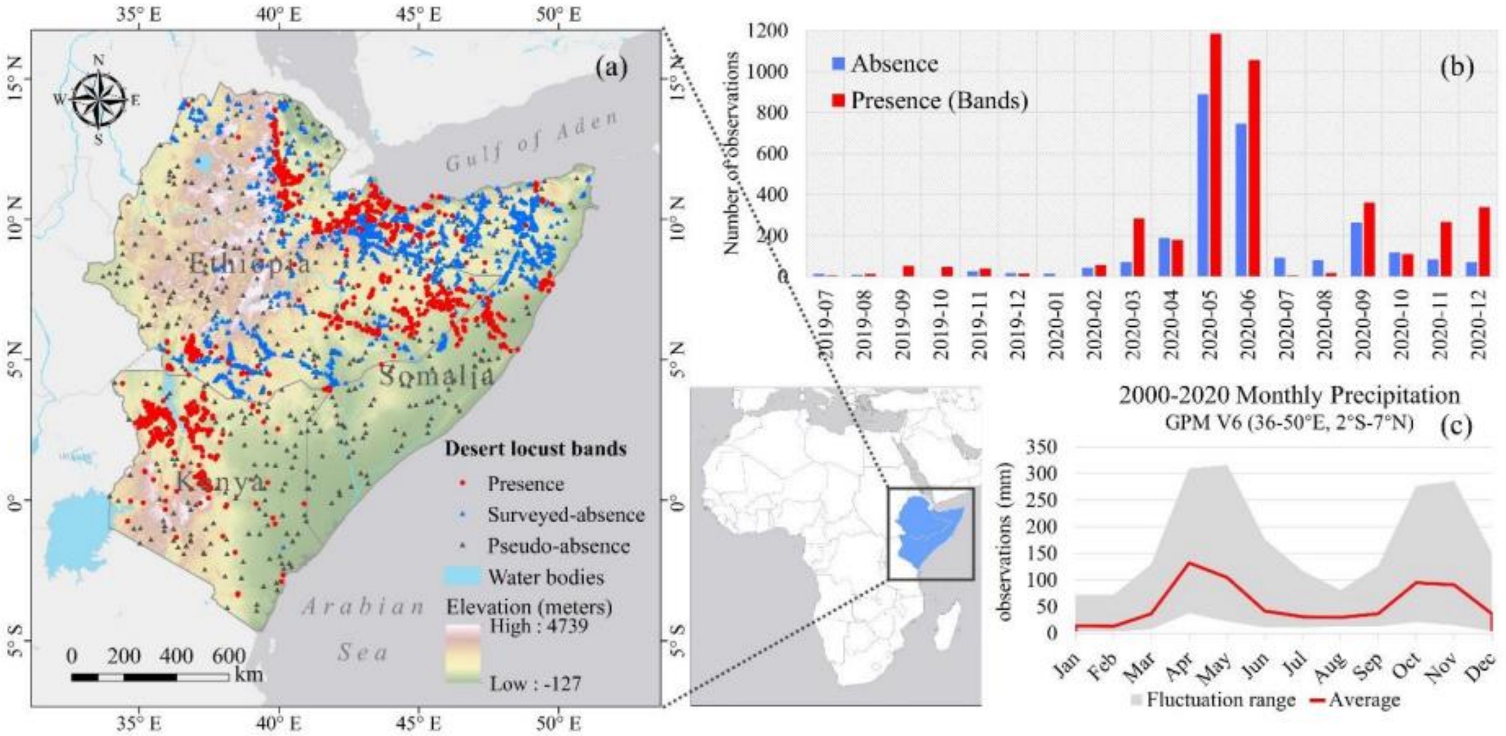
- Extraction of multivariate indicators required for early warning of desert locust occurrence
- Analysis of the lagged response of desert locust occurrence to indicators
- Early warning of the risk of desert locust occurrence

Desert Locust Early Warning – Study Area

This study concerns Somalia, Ethiopia, and Kenya in the Great Horn of Africa. SEK can form complementary breeding areas activated by either spring, summer, or winter rains.

Since 2018, the Indian Ocean Dipole has experienced extreme positive phases, with tropical cyclones, Sagar, in May 2018, and Pawan, in late 2019, taking turns to hit coastal regions.

They brought SEK extraordinary rainfall, providing suitable conditions for desert locust breeding. Mass migration of swarms from the Arabian Peninsula since June 2019 has culminated in an outbreak of desert locusts in SEK.



Spatial and temporal distribution of ground points of the desert locust band used for this study in the SEK region.

(a) geographical location of SEK with band (swarm) observations in 2000-2020; the red dot represents (swarm) band presence while the blue triangle refer to surveyed-absence and the grey one indicates pseudo-absence.

(b) monthly count of bands from July 2019 to December 2020.

(c) monthly observations of Global Precipitation Measurement (GPM) V6 in the central SEK region for 20 years(2000-2020); the red line indicates monthly mean rainfall; the grey area indicates the fluctuation interval.

Desert Locust Early Warning – Indicators

Analysis of time lagged 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

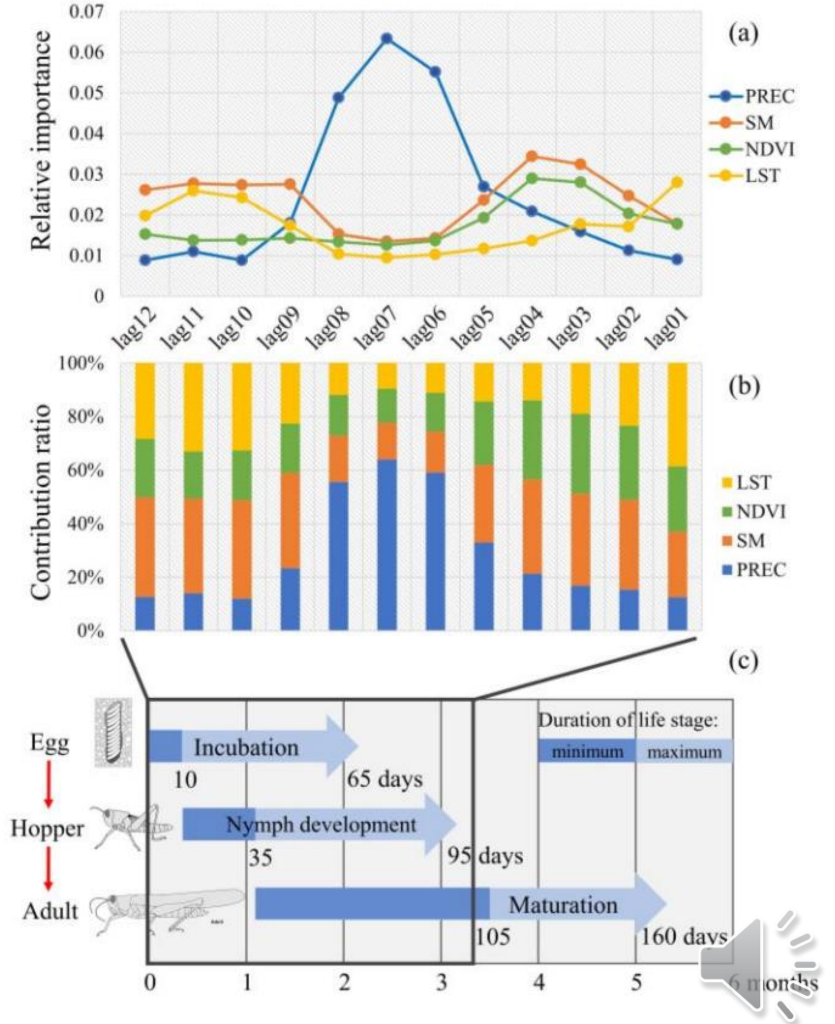
The increase in soil moisture from 73-80 days before occurrence to 33-40 days before occurrence is a booster of locust egg hatching and an early signal of vegetation growth

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



Desert Locust Early Warning – Forecast

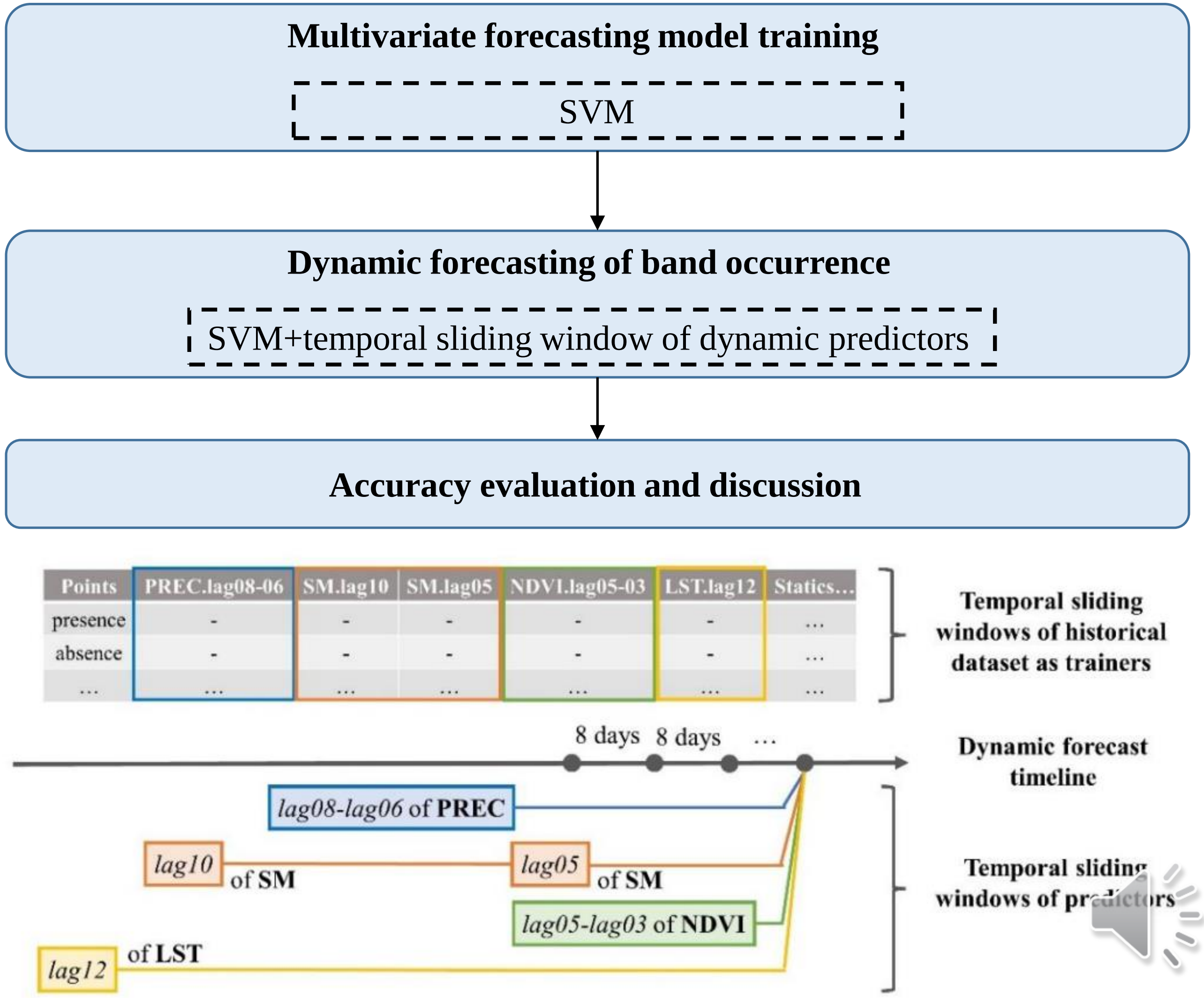
Model for Forecast Based on a Temporal Sliding Window

We use SVM as the fundamental model for the forecast for a better overall accuracy throughout the year.

We proposed a data-driven multivariate approach combining machine learning and a temporal sliding window to predict swarm occurrence for early.

For dynamic indicators, a temporal sliding window selector was introduced 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.

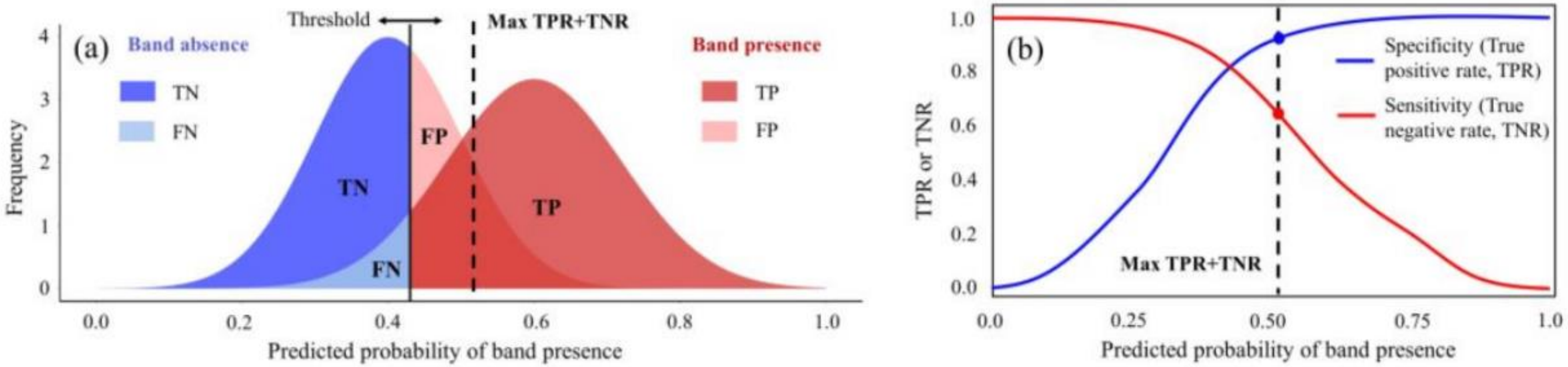
Lagging variables of dynamic indicators with lower significance were removed and those that contributed highly preserved. We then combined other static indicators for model training and prediction.

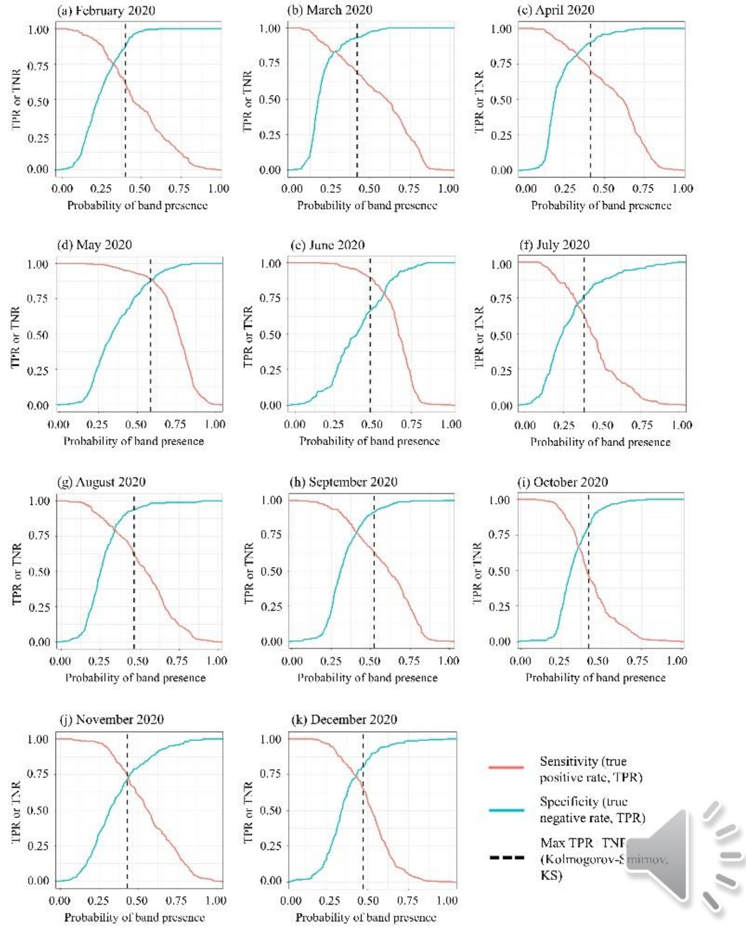


Model Evaluation and Accuracy Assessment

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



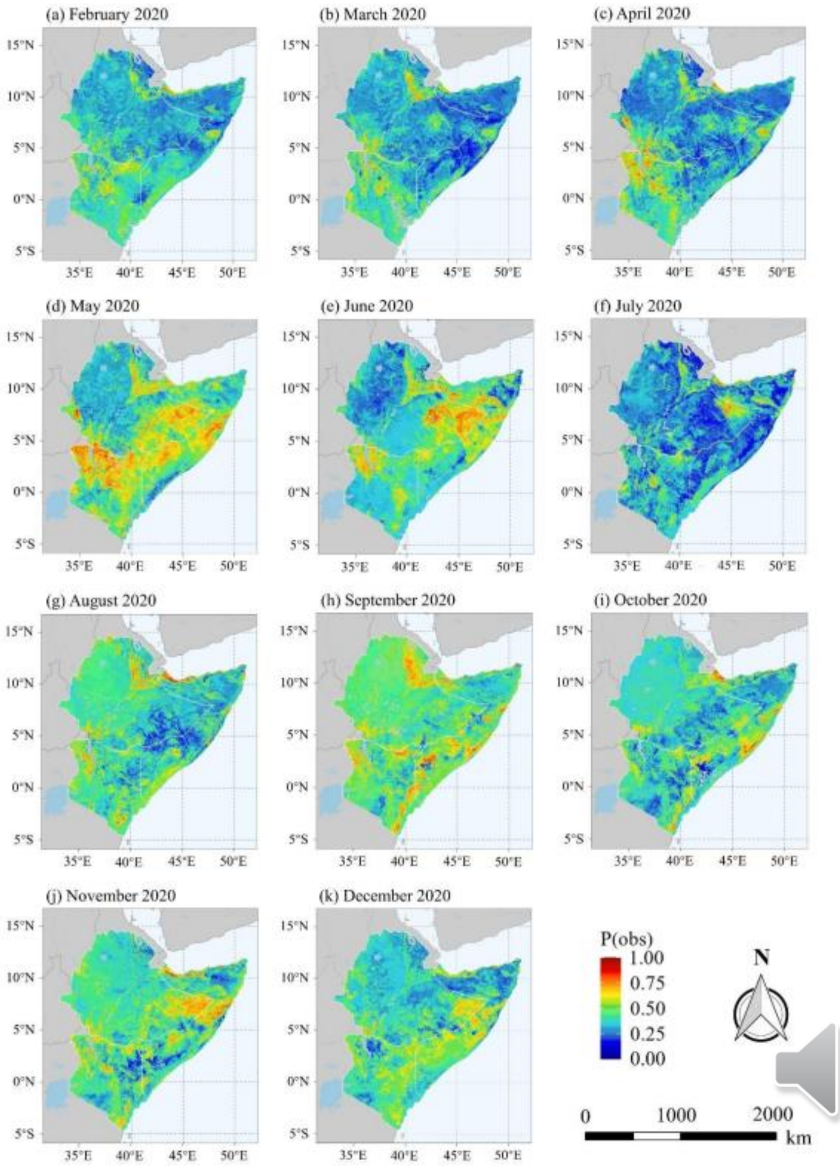


Desert Locust Early Warning – Results

Dynamic Forecast of Desert Locust

Eleven forecast experiments from February to December 2020 demonstrated satisfactory overall performance with an average accuracy of **77.46%**, a ROC-AUC value of **0.7666**, and an F-score close to **0.7715**. The forecast accuracies for March, April, May, and June were exceptionally high, above 0.8.

Date	Evaluation Metrics				
	Accuracy (%)	Sensitivity	Specificity	ROC-AUC	F-Score
February 2020	74.44	0.6047	0.8759	0.7403	0.7792
March 2020	80.15	0.6934	0.9329	0.8131	0.7930
April 2020	82.59	0.7264	0.9002	0.8133	0.7811
May 2020	88.68	0.8886	0.8814	0.8850	0.9218
June 2020	85.31	0.8971	0.6667	0.7819	0.9081
July 2020	70.00	0.6167	0.7714	0.6940	0.6549
August 2020	76.99	0.6238	0.9412	0.7825	0.7453
September 2020	79.81	0.6314	0.9203	0.7759	0.7258
October 2020	66.77	0.5988	0.7419	0.6704	0.6515
November 2020	73.41	0.7500	0.7116	0.7308	0.7673
December 2020	73.95	0.7087	0.7816	0.7451	0.7586
Average	77.46	0.7036	0.8296	0.7666	0.7715



Level and training of YS

University courses

- SATELLITE REMOTE SENSING: ACQUISITION SYSTEMS AND DATA PROCESSING, University of Rome «La Sapienza»
- RADAR SYSTEMS FOR ASTRONAUTICS - University of Rome «La Sapienza»
- MACHINE LEARNING - Universita' di Roma Tor Vergata

PhD based course

- 2ND-INNEO Space HUB, SUMMER SCHOOL 25-29 July 2022
- DATA FUSION OF REMOTELY SENSED AND GEOSPATIAL DATA -IEEE Educational Activities
- MACHINE LEARNING, Data Science and Deep Learning with Python-Sundog Education by Frank Kane

project's schedule, planning & contribution

2023: YS visiting period @ AIR, time TB verified according to restrictions that could occur

partners	Contribution in 2023	Schedule/semestr
IMAA-CNR	Conclude to soil characteristics algorithms retrieval by using single image of ms and/or hys and time series. Scientific publication on topsoil retrieval	1° semester retrieval algorithms consolidation 2° join publication on Quzhou county results
AIR-CAS	Tuning of the SEK prediction model	1° Dynamic prediction model of desert locust presence risk at SEK 2° data validation
UNIRM1 SIA	Test CREW algorithim on SEK areas, DIAS	1° CREW configuration and model running 2° validation activities, join publication
NERCITA	Optimization of data assimilation procedures of the multivariate and multi-scale RS variables into agricultural models for yield	1° identification of the agricultural parameters to retrieve (e.g. N, LMA, CHL) 2°model configuration and test experiments
UNITUS	Preparation of dry and wet SSL on EU sites on which test the retrievals algorithms and moisture evaluation	1° protocol definition for wet SSL 2° data analysis amd Marmite model testing

Publications 2020-2022

- Pignatti, S.; Casa, R.; Laneve, G.; Li, Z.; Liu, L.; Marzialetti, P.; Mzid, N.; Pascucci, S.; Silvestro, P.C.; Tolomio, M.; Upreti, D.; Yang, H.; Yang, G.; Huang, W. Sino–EU Earth Observation Data to Support the Monitoring and Management of Agricultural Resources. *Remote Sens*. **2021**, *13*, 2889. https://doi.org/10.3390/rs13152889
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- Laneve, Giovanni, et al. "Dragon 4-Satellite Based Analysis of Diseases on Permanent and Row Crops in Italy and China." *测绘学报(英文版)* 3.4. **2021**: 98-109.
- Upreti, D.; Pignatti, S.; Pascucci, S.; Tolomio, M.; Huang, W.; Casa, R. Bayesian Calibration of the Aquacrop-OS Model for Durum Wheat by Assimilation of Canopy Cover Retrieved from VENμS Satellite Data. *Remote Sens*. **2020**, *12*, 2666. https://doi.org/10.3390/rs12162666
- Upreti, D.; Pignatti, S.; Pascucci, S.; Tolomio, M.; Li, Z.; Huang, W.; Casa, R. A Comparison of Moment-Independent and Variance-Based Global Sensitivity Analysis Approaches for Wheat Yield Estimation with the Aquacrop-OS Model. *Agronomy* **2020**, *10*, 607. https://doi.org/10.3390/agronomy10040607

- G. Laneve, S. Saquella, R. Orsi, W. Huang, SINO–EU Earth Observation Data To Support The Monitoring And Management Of Agricultural Resources, **IGARSS 2022**, Kuala Lumpur.
- Casa, R., Pignatti, S., Pascucci, S., Huang, W., & Pepe, M. (2020, September). Effect of Spatial Resolution on Soil Properties Retrieval from Imaging Spectroscopy: An Assessment of the Hyperspectral Chime Mission Potential. **IGARSS 2020**, (pp. 4906-4909). IEEE.