EO for Africa Symposium 2024

23 - 26 September 2024
ESA | ESRIN, Frascati (IT)

EO Africa Water Resource Management: support to farmers and planners to improve irrigation water management

24/09/2024

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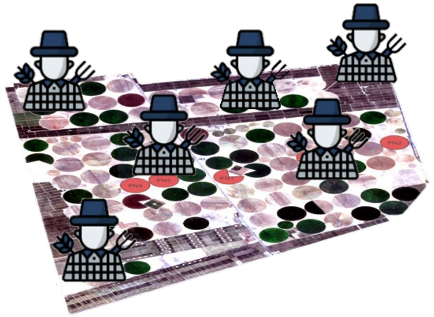


Objectives & Outcomes

Objectives:

- To map the actual evapotranspiration (ETa) and thus the actual water consumption of the cultivated crops
- To estimate the irrigation efficiency at regional scale
- To evaluate the impact of introducing low water consumption rice varieties or innovative irrigation practices

Outcomes:

- Creation of a web platform for the integration of ETa, NDVI and CWSI maps
- An open source ETa model in Python for estimating the ETa during summer and winter seasons
- Compare with actual field measurements for evaluation of the approach

SARE model

ETo varies depending on land cover, elevation, location, weather condition, and Julian day

ETo=Vf∗Lf∗Ef∗Sf∗Tf

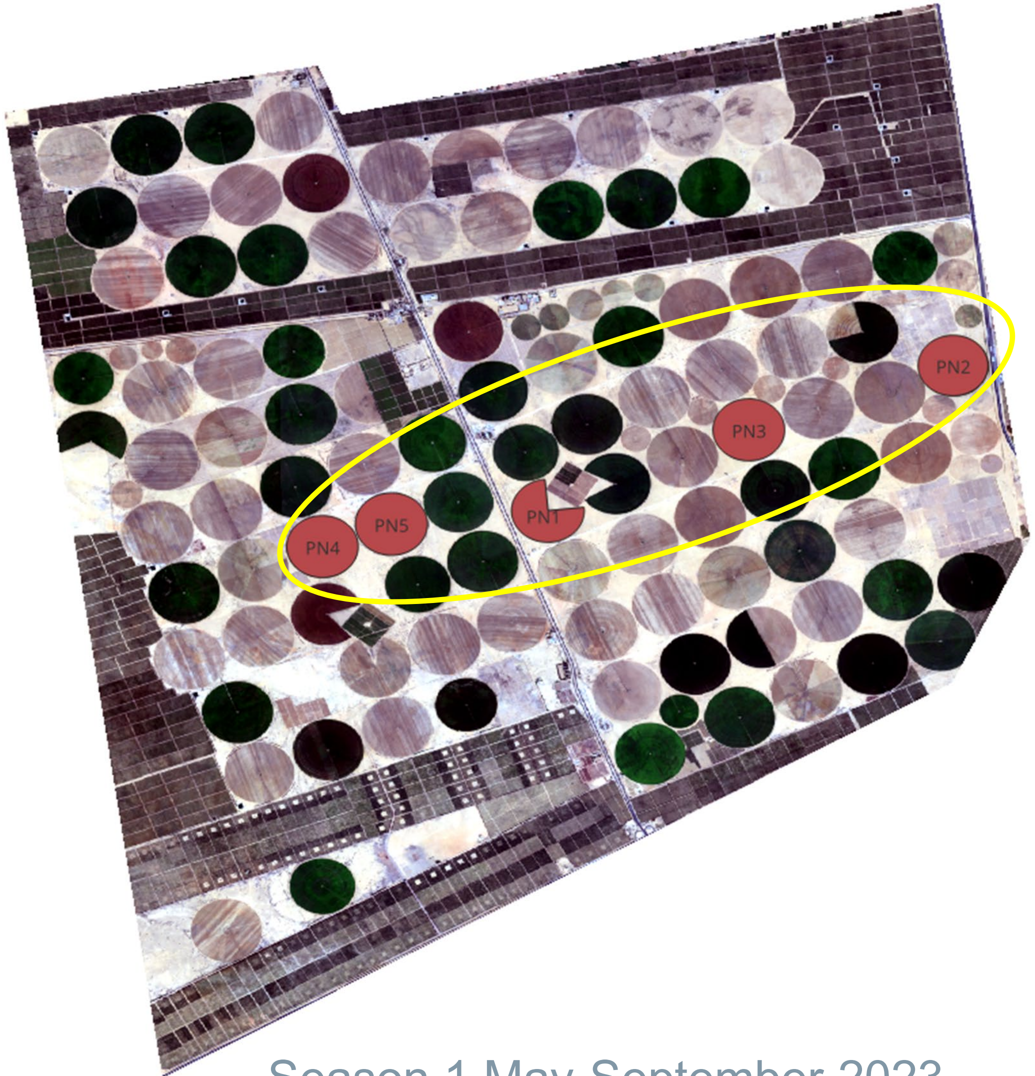
Leading to ETa=ETo*Kc*Ks

The SARE algorithm has been applied for each of the EO data combination:

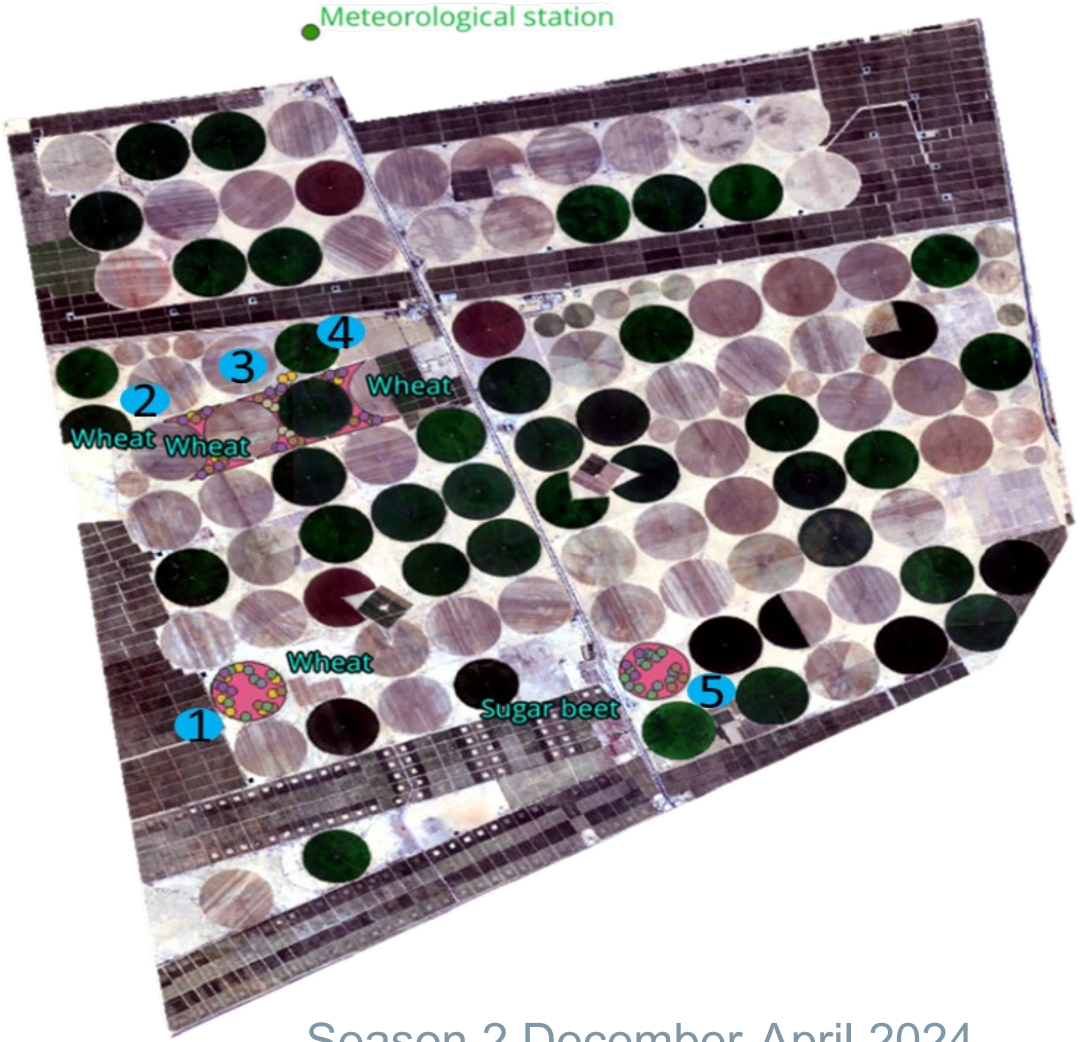
1. Using Sentinel-2 as input for VNIR data and Landsat for TIR data
2. Using Landsat for both VNIR and TIR
3. Using PRISMA as input for VNIR data (using different band configurations) and Landsat for TIR data.

The first two cases have been selected to establish a reference baseline using multispectral sensors to be compared with the results obtained from the hyperspectral sensor .

Region of interest



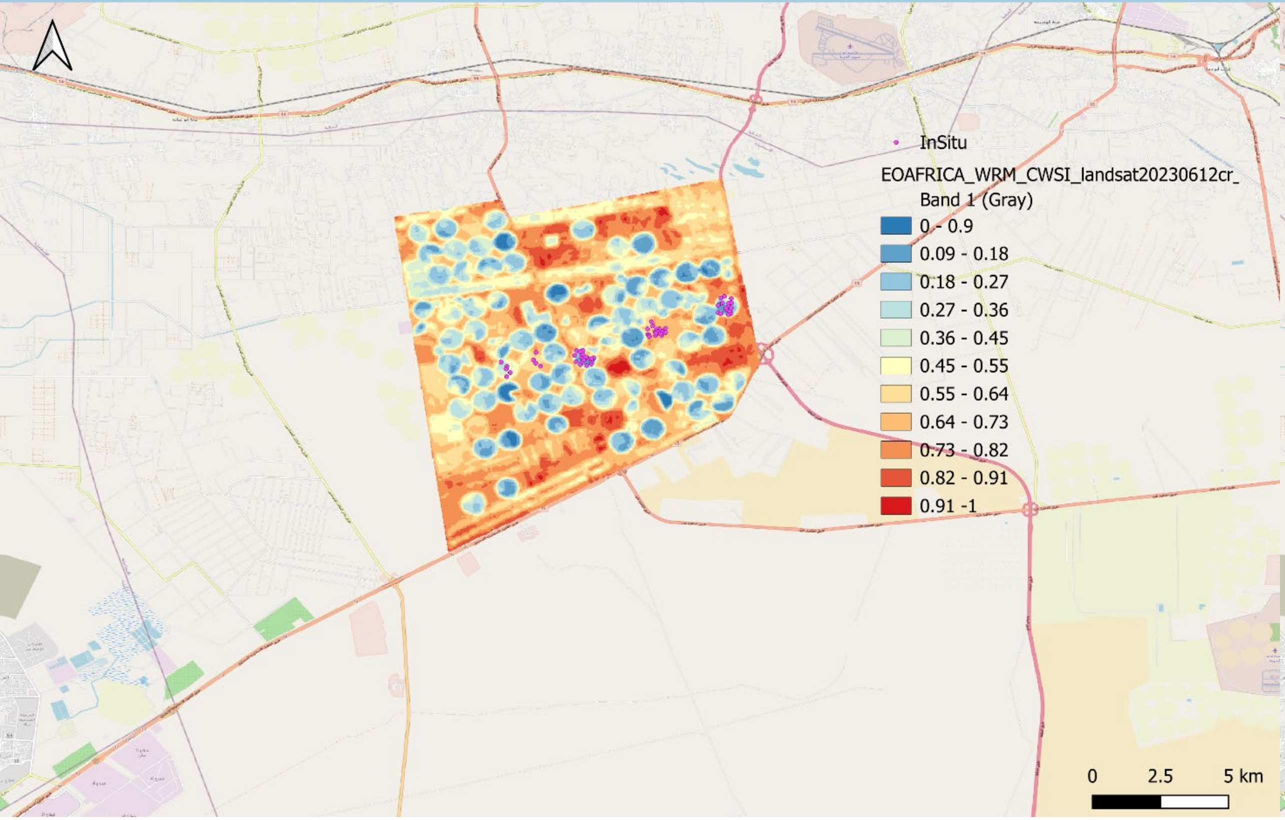
Season 1 May-September 2023

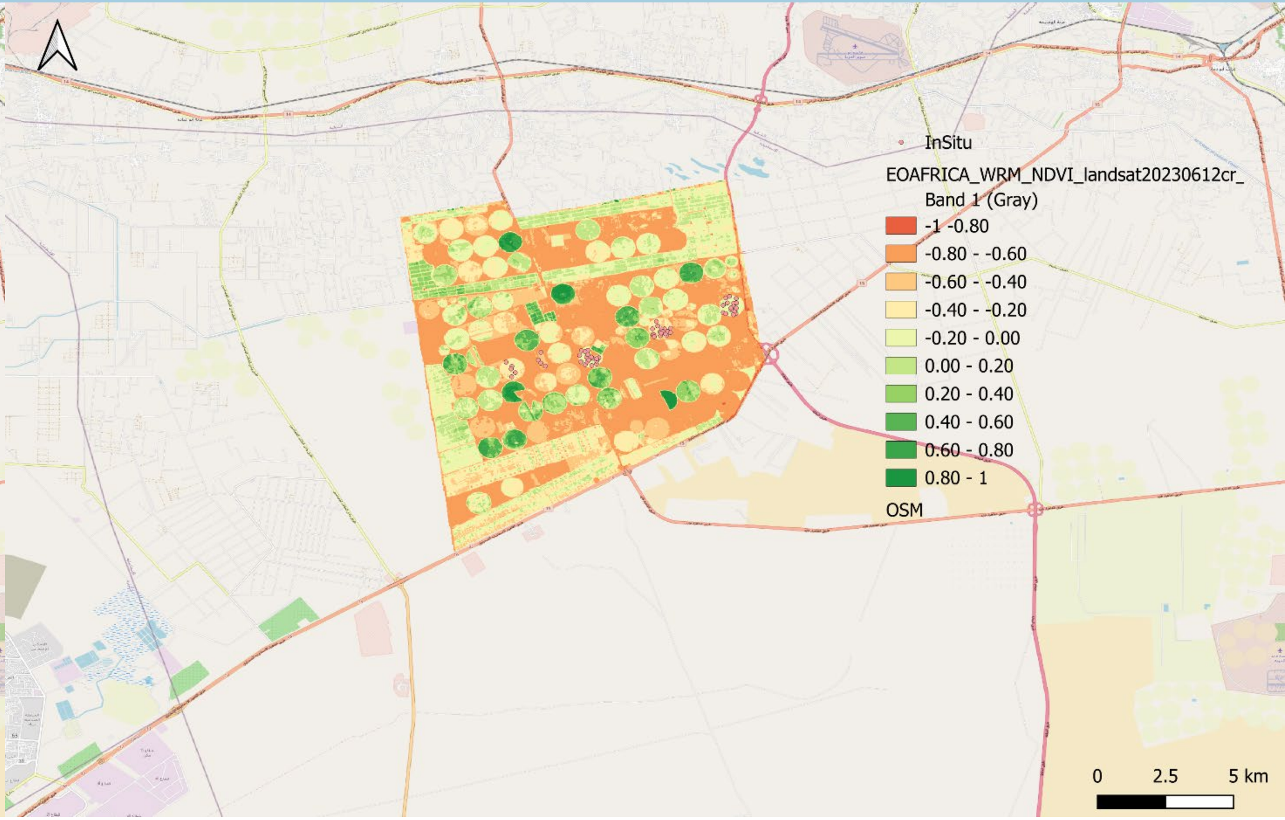


Season 2 December-April 2024

Output Product maps (1/2)

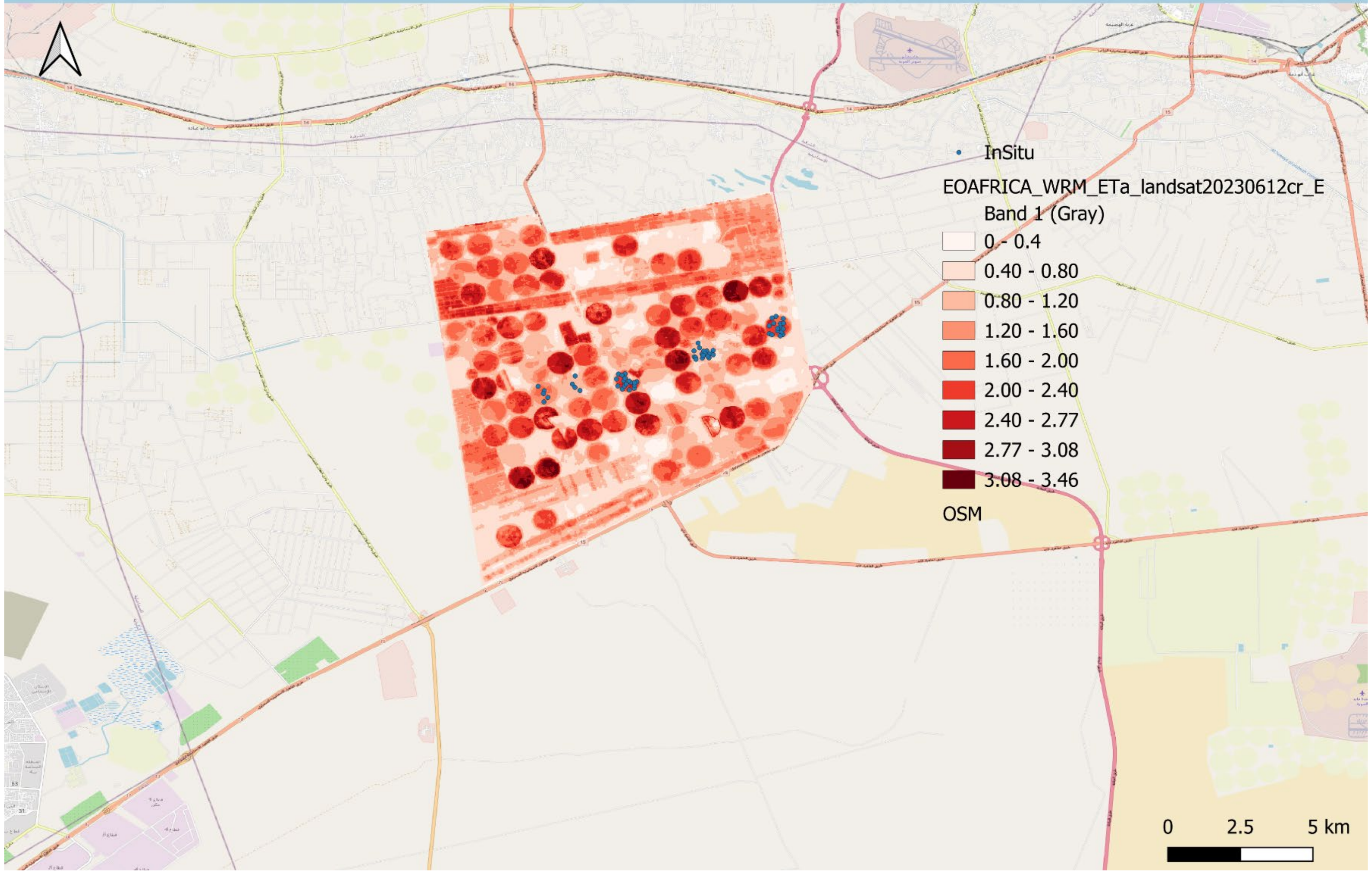
CWSI map	NDVI map





Output Product maps (2/2)

ETa map



Hyperspectral satellite capabilities(PRISMA)

PRISMA (band # & range)	Sentinel-2 (band # & range)	Landsat (band # & range)
Red: 32–35 (647–685 nm) NIR: 11–22 (778–905 nm)	Red: #4 (650–680 nm) NIR: #8 (785–899 nm)	Red: #4 (638–673 nm) NIR: #5 (772–898 nm)

PRISMA bands selected for "RED" (central wavelength in nm)	PRISMA bands selected for "NIR" (central wavelength in nm)
655.4	785.7
664.9	796.1
674.5	806.7
	817.3
	827.9
	838.5
	849.2
	860.0
	870 .7
	881.5
	892.1

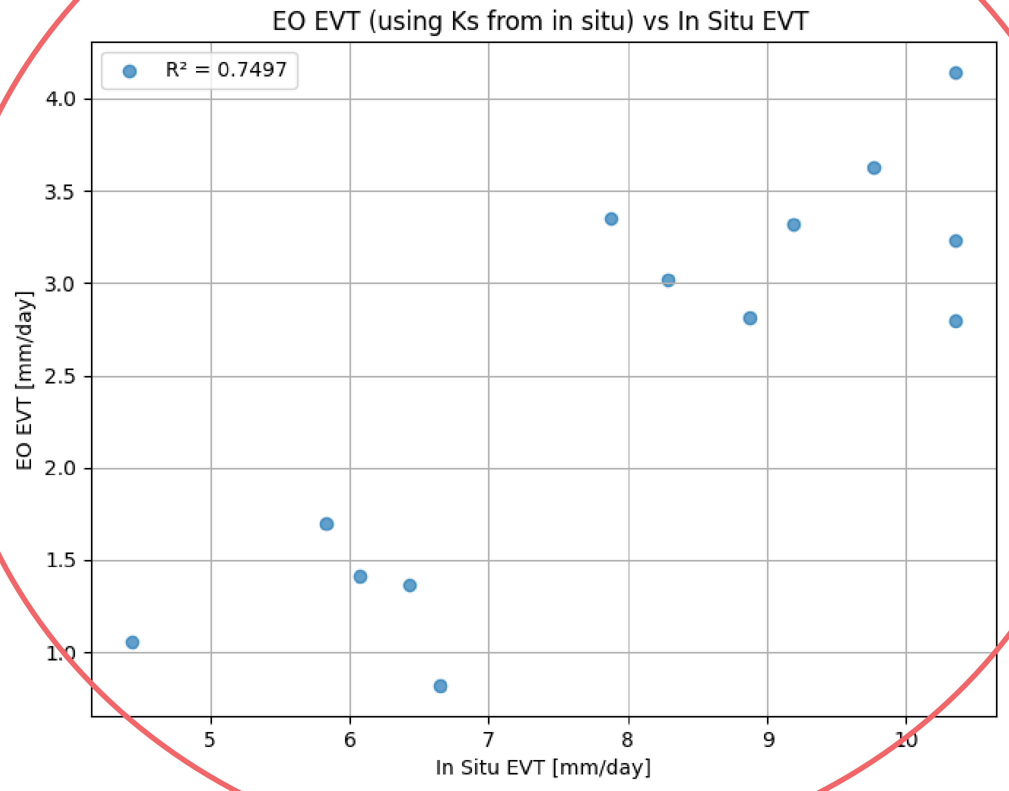
Approach 1: Combination of multiple bands
We selected multiple bands in the Red and NIR part of the PRISMA spectrum to match the Red and NIR bands of Sentinel-2 (i.e., Red: 650–680nm; NIR: 785–899nm) and Landsat (i.e., Red: 638–673nm; NIR: 772–898nm)

Approach 2: Central wavelength band
We selected a single PRISMA band centered at 664.9 nm (for Red) and at 806.7 nm (for NIR)

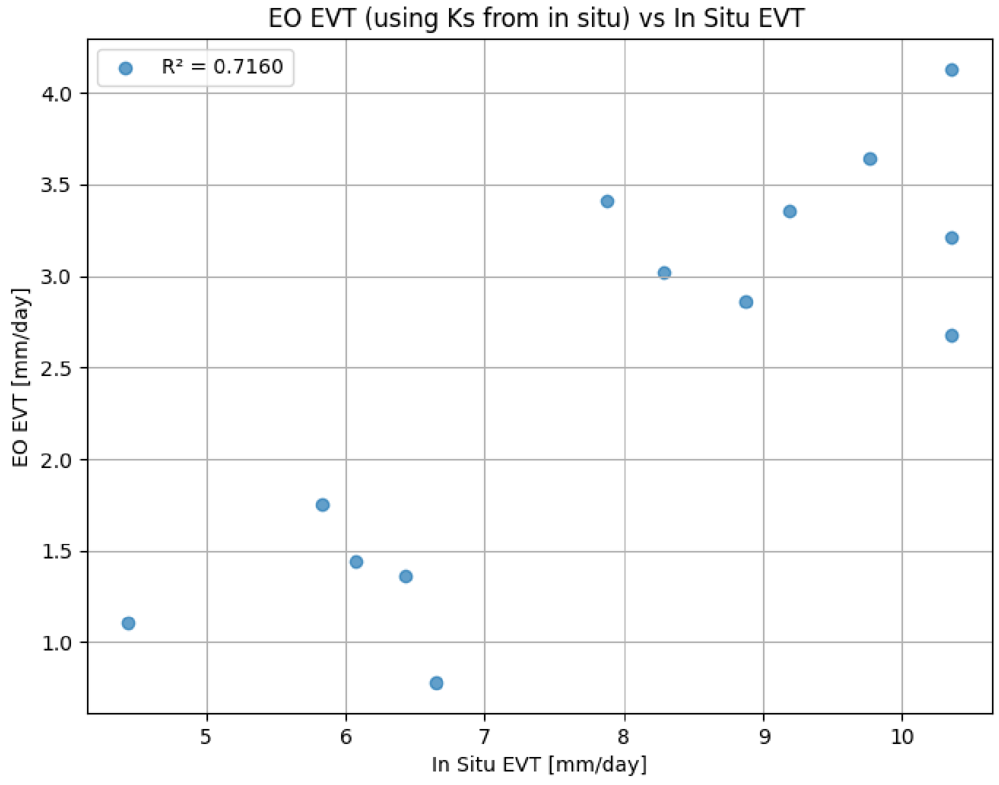
Prisma's central bands

21/07/23 Prisma's band combination selections

Red at 664.9 nm, NIR at 806.7 nm

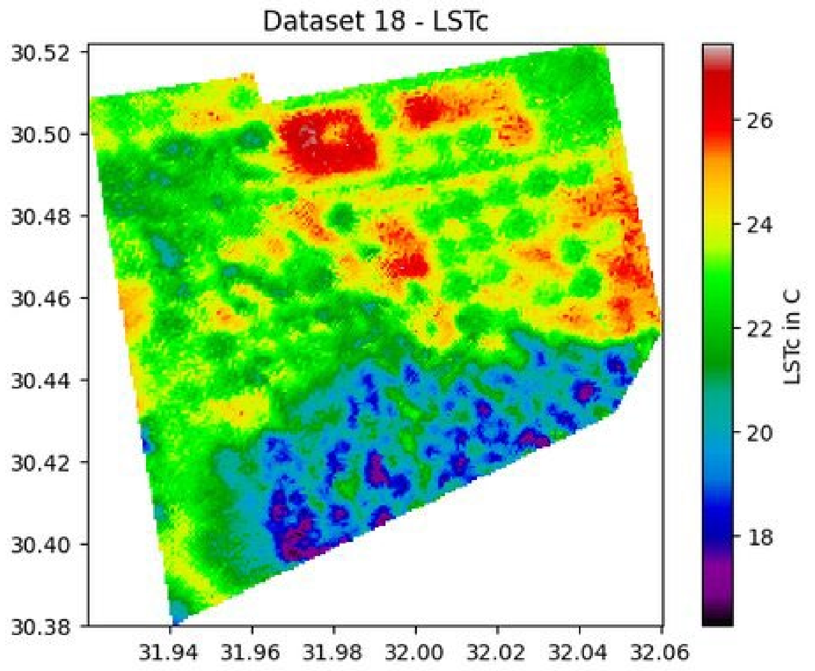


Red at 655.4 nm , NIR 785.7 nm

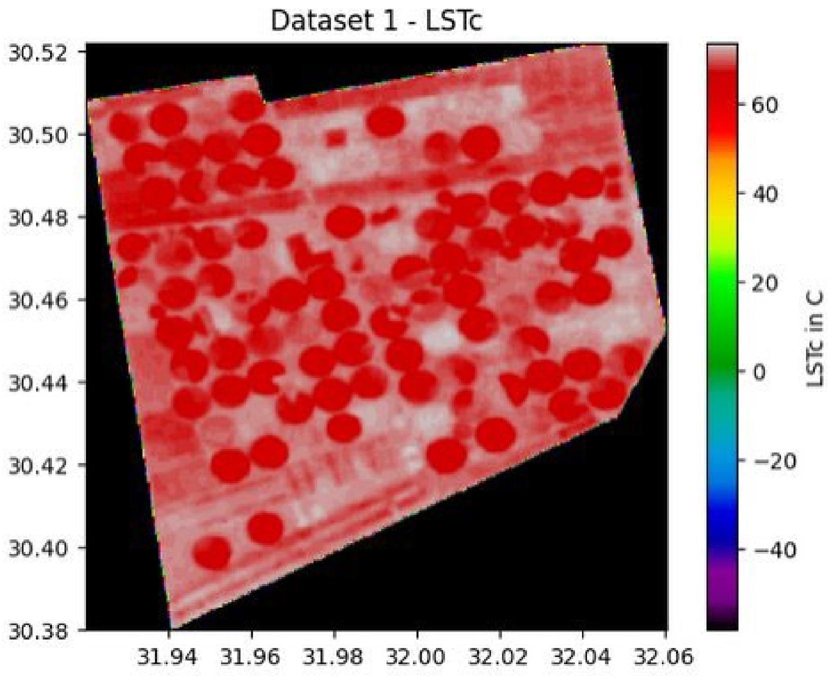


The ECOSTRESS challenge

- ECOSTRESS data are not usable because the acquisitions over the Area of Interest (AOI) occurred at night during the days of in-situ measurements. Using thermal measurements taken at night introduces too much uncertainty into the estimation of Ks.
- ECOSTRESS sensor in not operational – Giving historical data without the option to choose ascending/descending orbit's data, cloud coverage etc.
  - **16/06 Ecostress (night time) LST**



16/06 Landsat LST



Ks complexity

The stress coefficient Ks value can be estimated using a linear relationship with the air-surface temperature difference as the main parameter.

Challenge

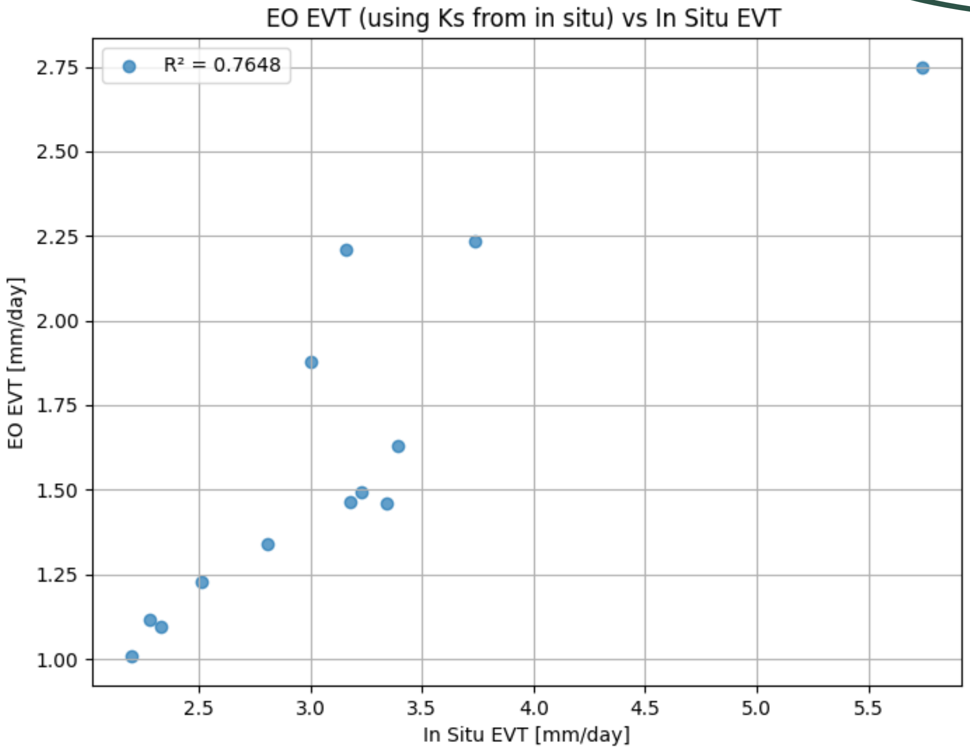
- Calibrating this linear function requires knowing the points of maximum and minimum phenological stages of crop due to water stress. This information is not easily obtainable, and uncertainties in this knowledge can introduce errors into the estimation.

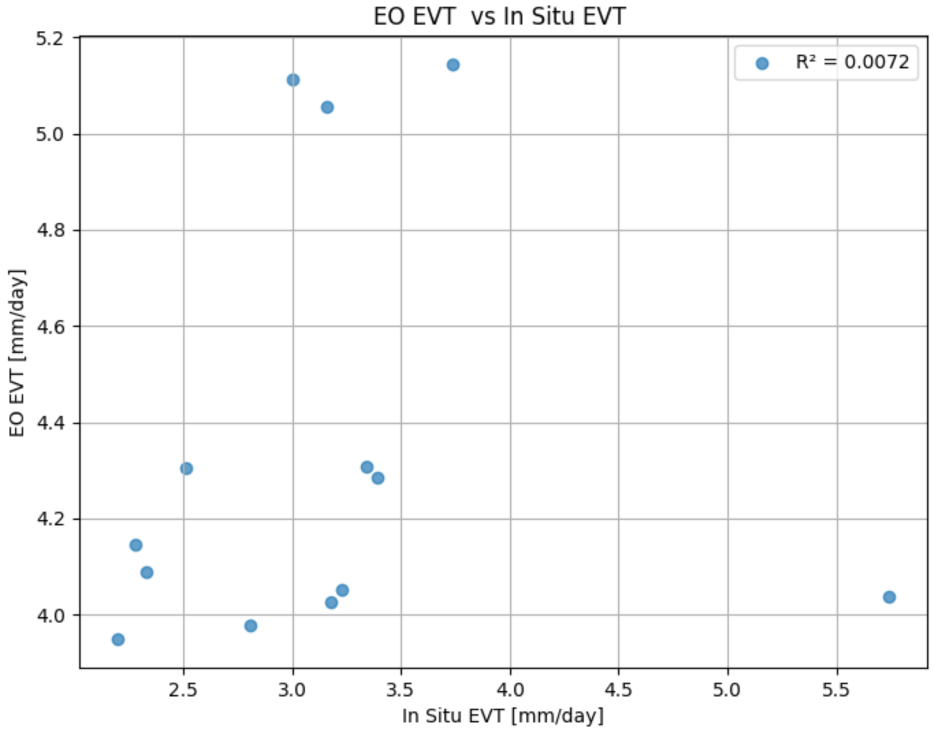
Solution

- To minimize sources of uncertainty and enhance the reliability of the subsequent comparisons and analyses with EO data from PRISMA, Sentinel-2, and Landsat sensors. , the Ks value was directly taken from in-situ measurements. This method was chosen to eliminate any potential inaccuracies that could arise from using remote thermal measurements, which can be affected by various atmospheric and sensor-specific factors or introduced by the methodology used to derive the Ks.

In situ validation (1/5)

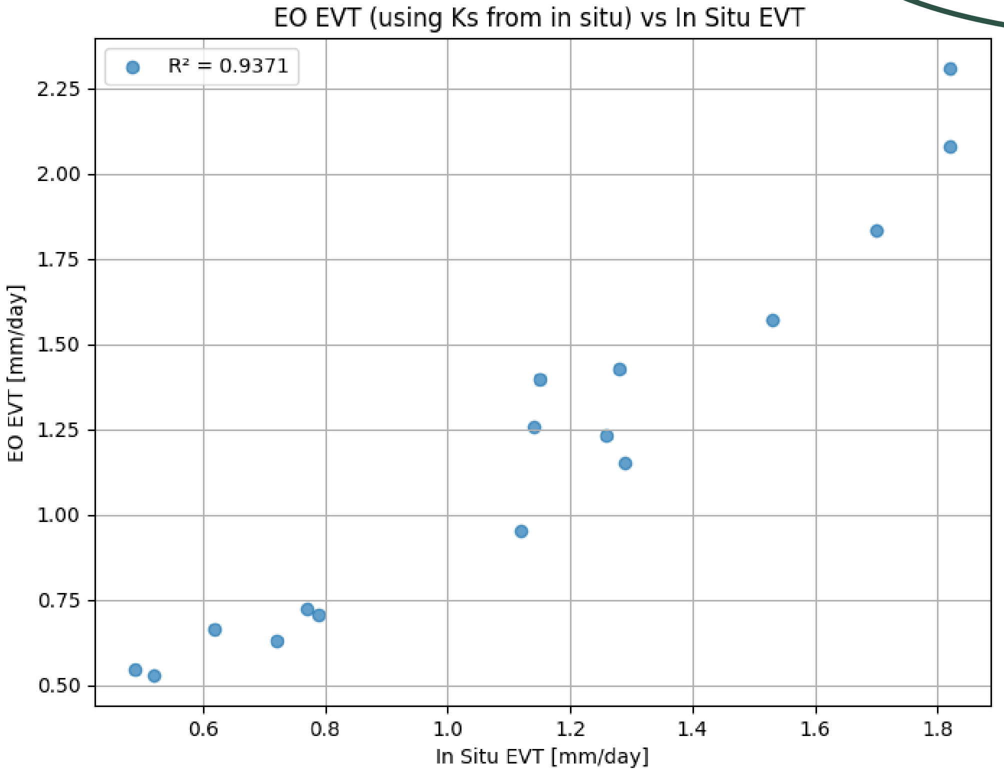
16/06/23 Prisma VNIR & Landsat Thermal data

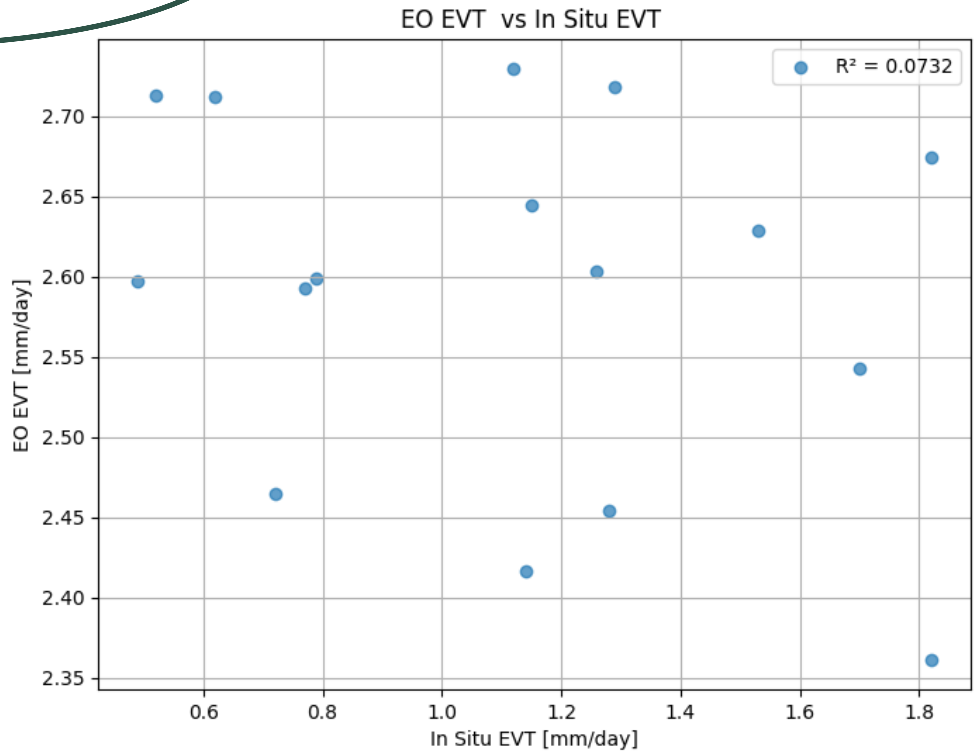




In situ validation (2/5)

05/01/24 Prisma VNIR & Landsat Thermal data

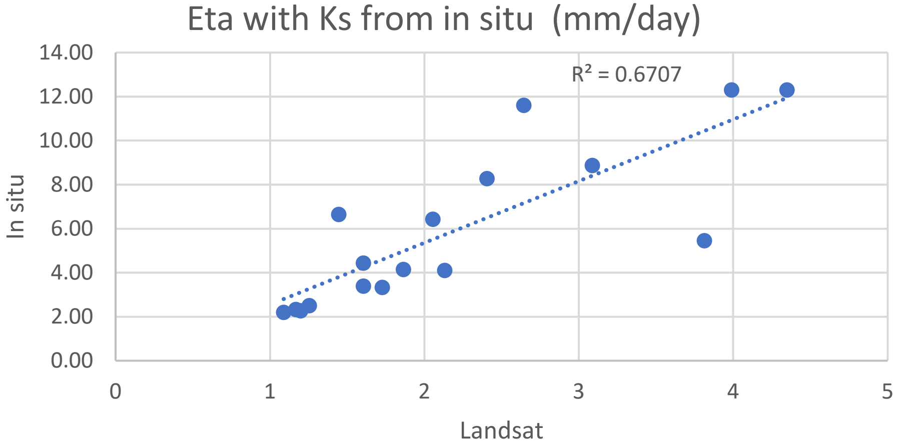




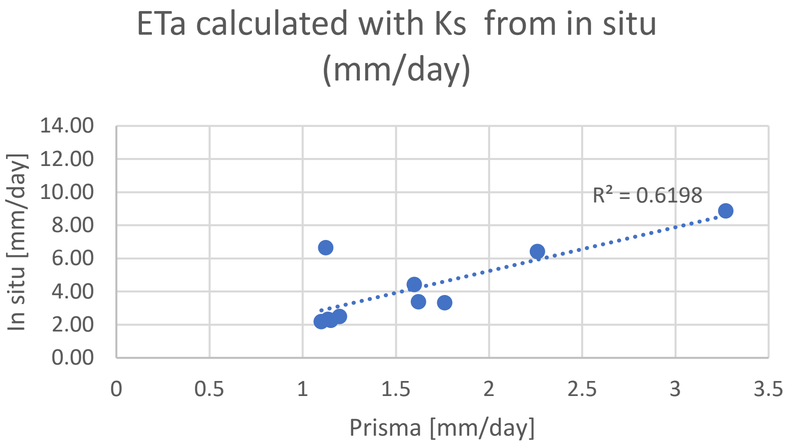
In situ validation (3/5)

Per Pivot comparison Season 1 (May-September 2023)

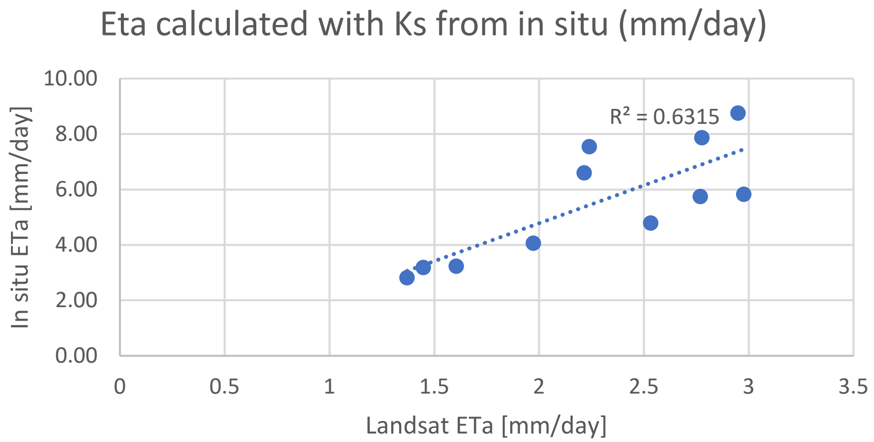
Landsat



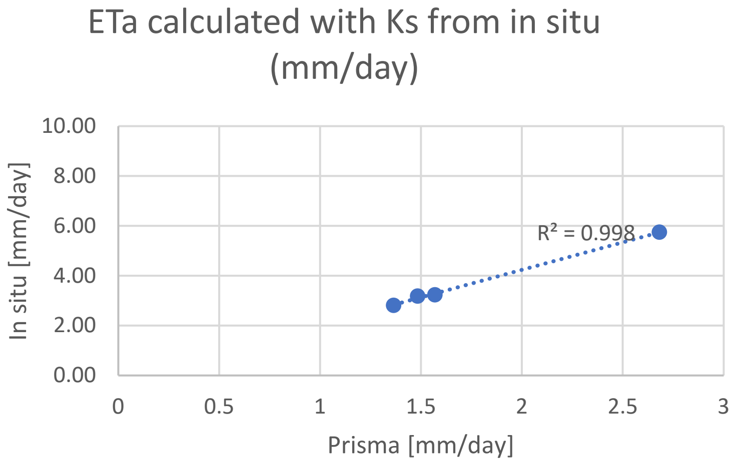
Prisma



PN1

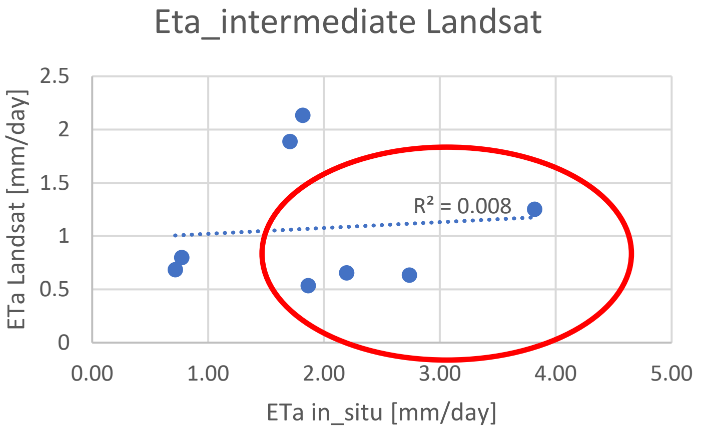


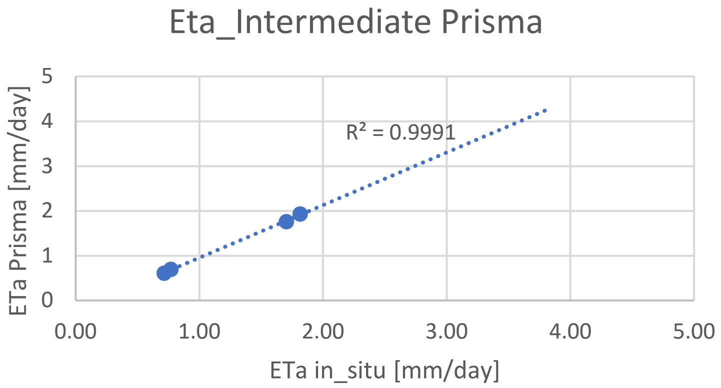
PN2

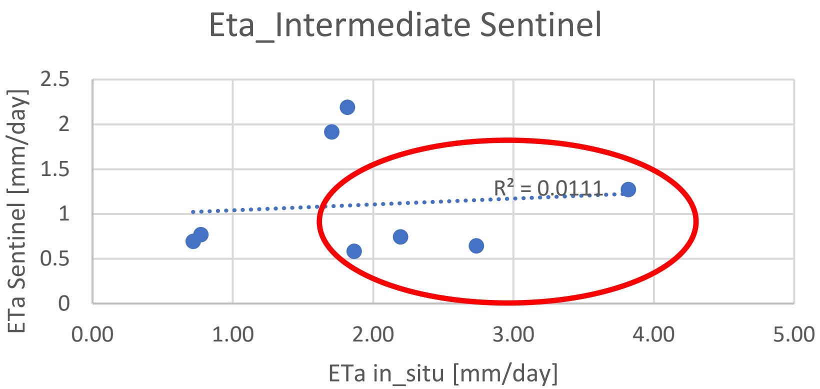


Per Pivot comparison Season 2 (December-April 2024)

Challenge : Very few field measurements ! Many missing dates ! High in situ EVT values paradox ??





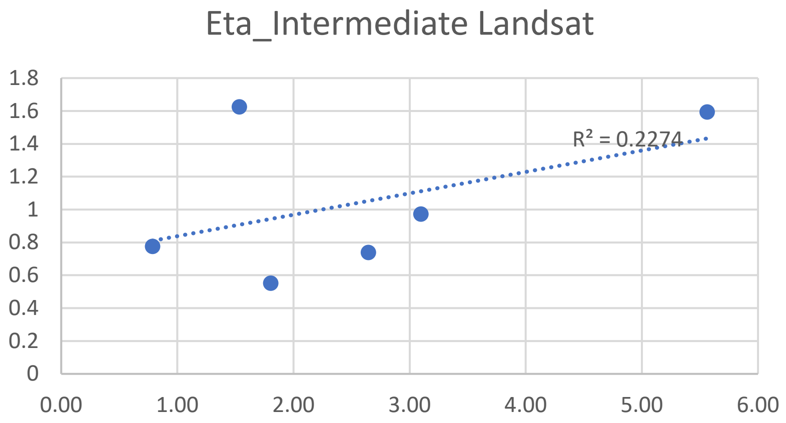


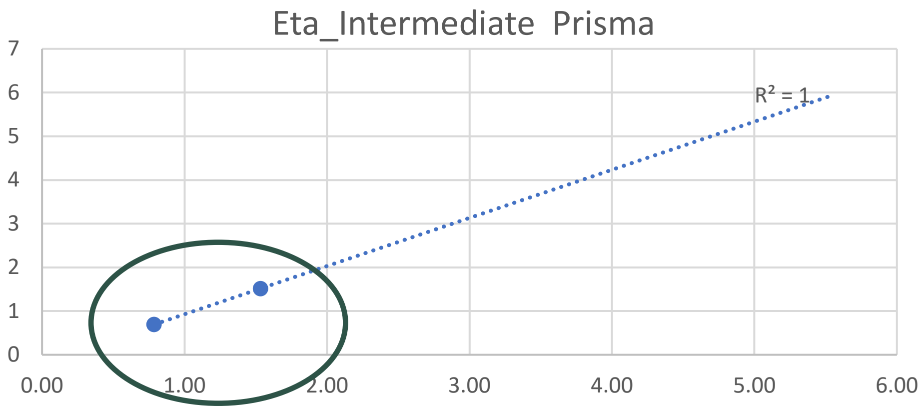
06/01/24 & 03/04/24 field measurements for PN2.

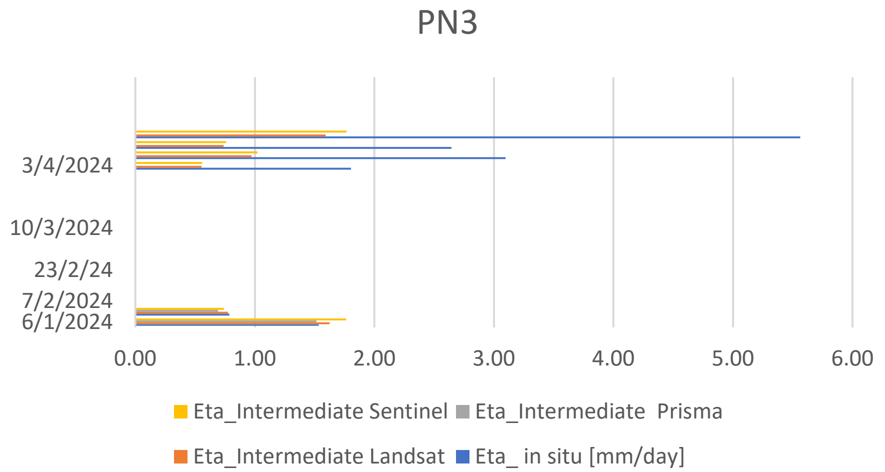
In total 4-8 data points to compare, where 03/04/24 in situ ones really high

In situ validation (5/5)

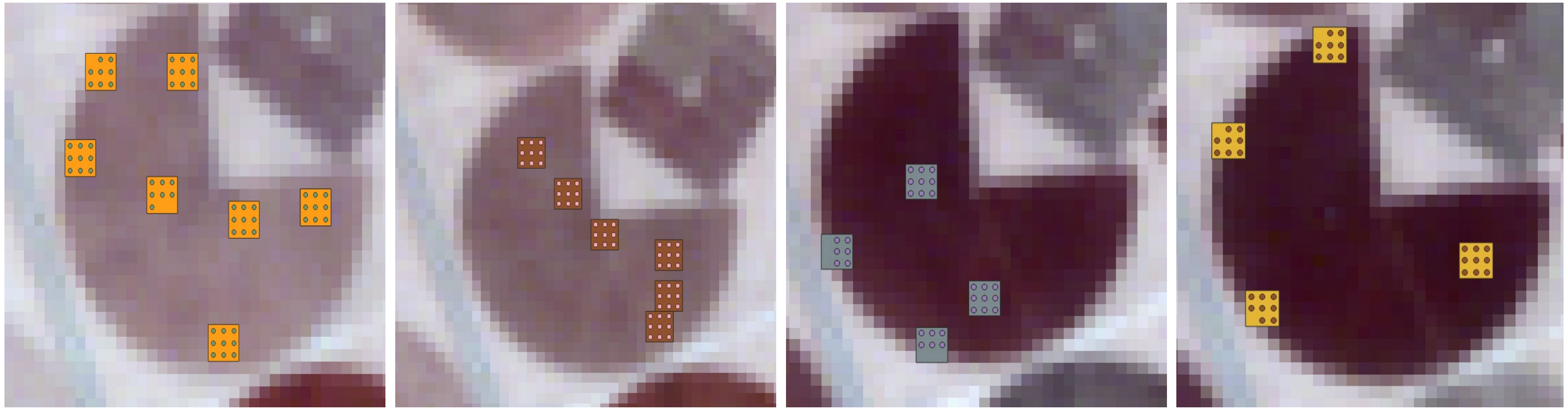
In total 2-6 data points to compare, where 03/04/24 in situ ones really high for PN3







ML Approaches
Data collection and dataset building



Date	Sample sites [n°]	Sampled pixels [n°]
06/06	7	87
16/06	21	117
14/07	13	182
22/07	13	113

Location data

Date	Pivots	Sample	Lat	Long
06_06	PN1	F2S1	30.4539	31.9965
06_06	PN1	F2S1	30.4539	31.9965
06_06	PN1	F2S1	30.4539	31.9965
06_06	PN1	F2S1	30.4539	31.9965
06_06	PN1	F2S1	30.4539	31.9965
06_06	PN1	F2S1	30.4539	31.9965
06_06	PN1	F2S1	30.4539	31.9965

Prisma – VNIR - SWIR

06_06_NIR_1	06_06_NIR_2	06_06_NIR_3	06_06_NIR_4	06_06_NIR_5	06_06_NIR_6	06_06_NIR_7
3563	3291	4122	4341	4831	5279	5627
2995	2829	3089	3246	4412	4569	4760
4246	4089	4958	4661	6066	6834	6703
3271	3235	3528	3465	4713	5061	5056
3804	3149	3439	3378	4643	4659	4871
3187	2972	3085	3276	4392	4475	4596
3169	3541	4262	4307	5018	5353	5634

Landsat

Landsat_B1	Landsat_B2	Landsat_B3
10549	11406	14276
10329	11097	13815
10775	11622	14616
10356	11160	13671
10525	11361	14221
10464	11247	14055
10521	11403	14358
10200	11007	13763

In-situ

TDR	ET0	Kc	Ks	ETa
11.5	8.1	0.7	0.49	2.79
11.5	8.1	0.7	0.49	2.79
11.5	8.1	0.7	0.49	2.79
11.5	8.1	0.7	0.49	2.79
11.5	8.1	0.7	0.49	2.79
11.5	8.1	0.7	0.49	2.79
11.5	8.1	0.7	0.49	2.79

- 4 different dates
- 54 sample sites
- pixel sampled for both Landsat8 and PRISMA images

Algorithms and preliminary results

2 algorithms used:

- Light Gradient Boosting Model (LGBM) regressor;
- Random Forest (RF) regressor;

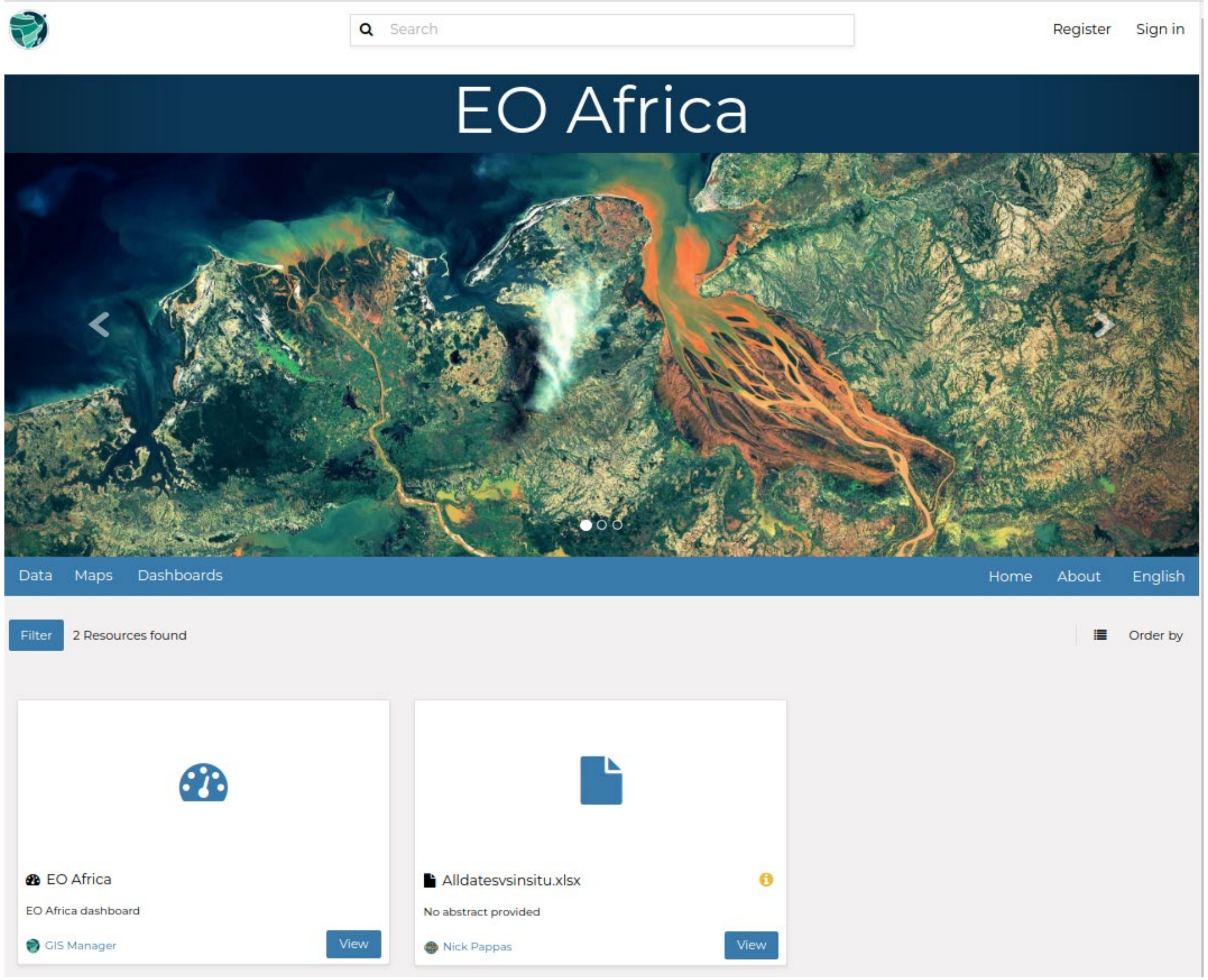
- R^2 used for prediction accuracy estimation;

Algorithms	Accuracy R-squared		
	Kc	Ks	ETa
LGBM	0.88	0.15	0.73
RF	0,88	0,05	0.54

Importance x predicted parameter

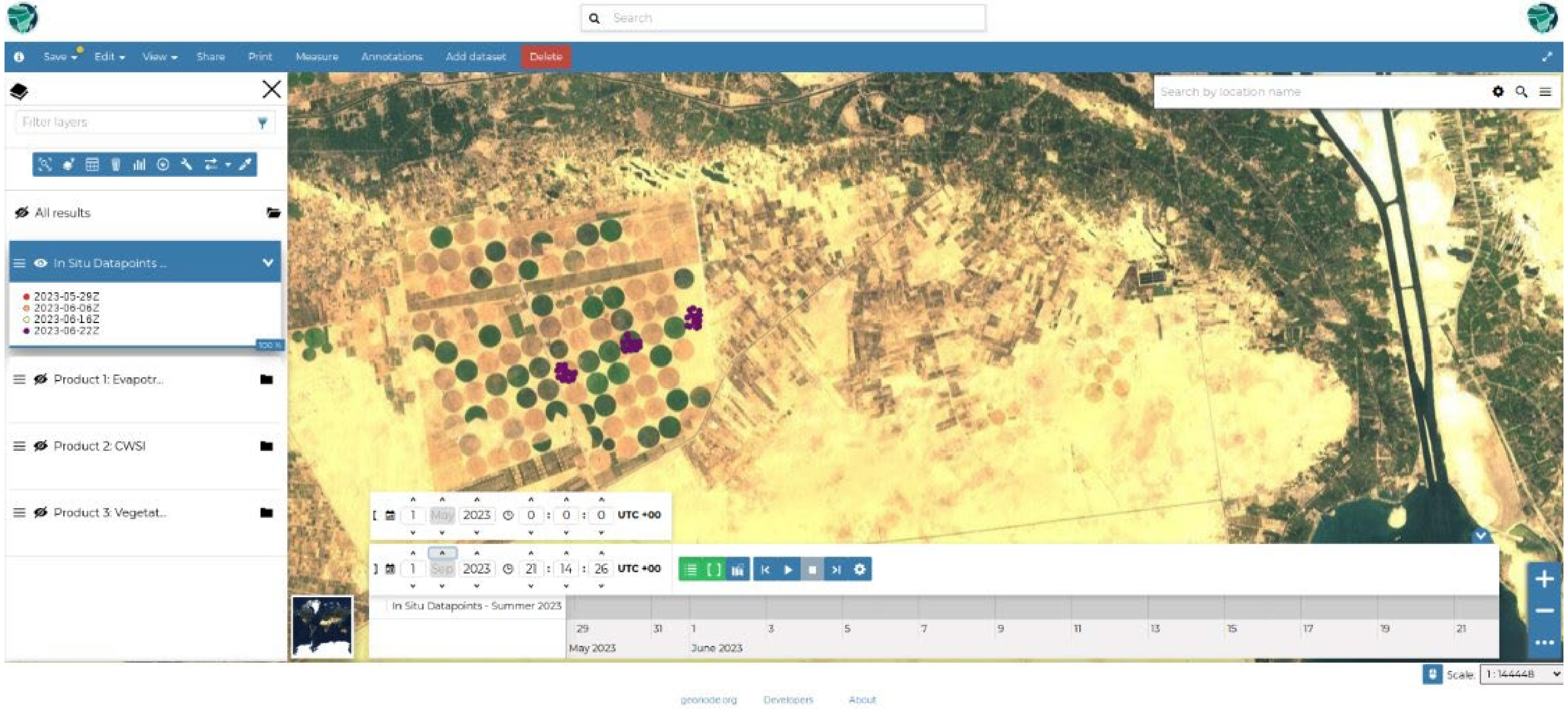
	LGBM				RF			
	Kc	Ks	ET0	ETa	Kc	Ks	ET0	ETa
Band/Hyperspectral index	Landsat_B10	ndmi	ndmi	Landsat_B10	VNIR_24	VNIR_4	VNIR_24	LST
	VNIR_1	SWIR_41	Landsat_B10	VNIR_40	VNIR_23	VNIR_3	VNIR_21	Landsat_B10
	ndmi	VNIR_40	SWIR_49	SWIR_102	VNIR_25	ndmi	VNIR_23	ndmi
	VNIR_40	SWIR_97	VNIR_39	ndmi	VNIR_22	SWIR_86	VNIR_25	SWIR_49
	SWIR_99	SWIR_40	VNIR_1	wi	SWIR_22	Landsat_B10	VNIR_27	SWIR_50
	VNIR_42	SWIR_89	SWIR_93	SWIR_42	SWIR_41	SWIR_42	VNIR_28	srwi
	SWIR_3	Landsat_B10	srwi	SWIR_95	VNIR_19	SWIR_136	VNIR_29	VNIR_1
	CSWI	SWIR_35	VNIR_40	SWIR_101	SWIR_49	srwi	ndvi	VNIR_2
	SWIR_49	SWIR_98	VNIR_9	CSWI	ndmi	LST	LST	VNIR_3
	srwi	SWIR_91	VNIR_6	SWIR_97	VNIR_20	VNIR_2	ndmi	VNIR_4

The EO Africa Platform



Login/Landing Page

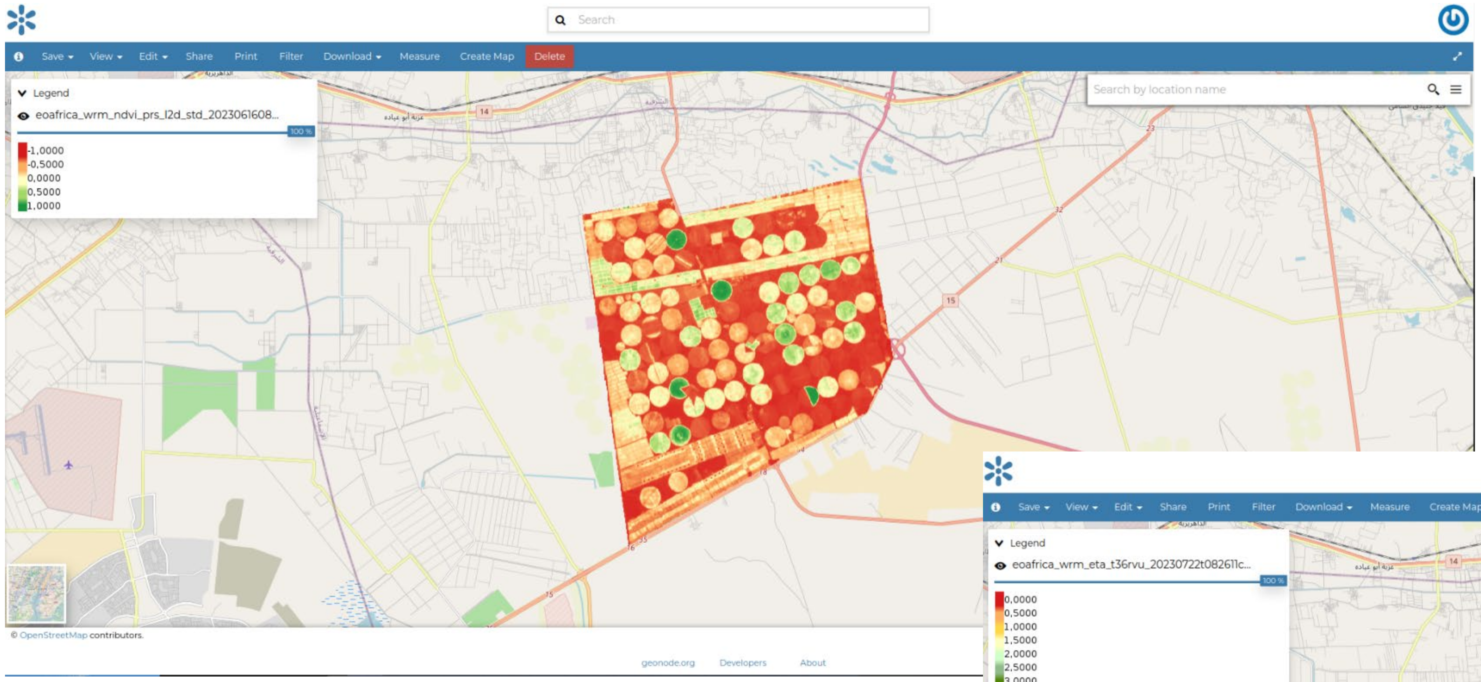
The EO Africa Platform

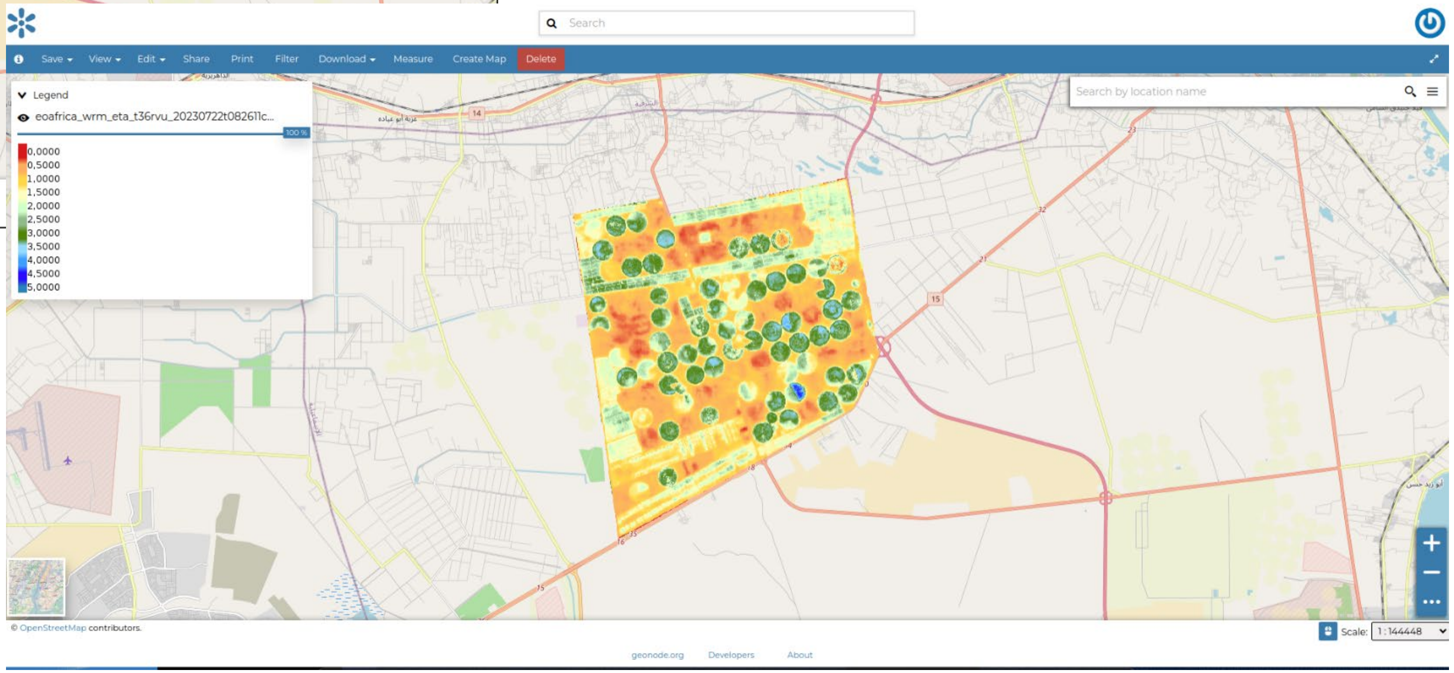


Time series selection

The EO Africa Platform

Product selection





Challenges (1/2)

- The ECOSTRESS challenge
- Few data points in each field visit. One field visit at each visit gives 4-7 field measurements to compare.
- Timing Discrepancy in Data Collection: The limited number of monitoring dates, influenced by the specific pivot being considered, highlights a critical challenge in synchronizing Earth Observation (EO) data acquisitions with in-situ data collection.
- Phenological Stage-Dependent Monitoring Needs: Crop growth stages exhibit varying monitoring requirements. Early stages may need less frequent monitoring, whereas advanced stages, particularly during peak irrigation demands, require more frequent satellite overpasses to capture critical data.
- In-Situ Data Accuracy Challenges: Low coefficients of determination between EO and in-situ data can stem from inaccuracies in traditional in-situ data collection methods.

Challenges (2/2)

- Discrepancy in Soil Moisture Measurements: There is a notable mismatch between soil moisture levels obtained via EO thermal data (CWSI) and in-situ measurements (TDR probe). This discrepancy may be attributed to factors like soil water retention, solar radiation, or wind speed, which impact the relationship between soil moisture and vegetation health.
- Impact of Spatial Resolution on Leaf Temperature Assessment: Leaf temperature, derived from satellite data, is effective for assessing crop water status. However, the 30-meter spatial resolution may introduce errors, particularly at the endpoints of pivots, where the influence of bare soil can distort land surface temperature values, complicating the identification of “hot” and “cold” spots in vegetation.

Conclusions/Future steps

- Hyperspectral sensors give promising results and provide an alternative in terms of wavelength choices , giving the opportunity to adjust/work with different bands and indexes

- Understand the Season 1 and Season 3 similarities and find a common perspective for each season to use as calibration

- Leverage the good R^2 ML approach gives so far .
  - Either use the ML results as calibration parameters to the SARE model approach results
  - Either use some algorithms from the LGBM model and customize to the developed algorithm
  - Tries to be independent from Ks index as this introduces many risks in terms of prediction no matter the method used regarding EO data

Thank you !