A transfer function to predict soil surface reflectance from laboratory soil spectral libraries

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remote sensing

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Article

Mapping Water Infiltration Rate Using Ground and UAV Hyperspectral Data: A Case Study of Alento, Italy

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Abstract: Water infiltration rate (WIR) into the soil profile was investigated through a comprehensive study harnessing spectral information of the soil surface. As soil spectroscopy provides invaluable information on soil attributes, and as WIR is a soil surface-dependent property, field spectroscopy may model WIR better than traditional laboratory spectral measurements. This is because sampling for the latter disrupts the soil-surface status. A field soil spectral library (FSSL), consisting of 114 samples with different textures from six different sites over the Mediterranean basin, combined with traditional laboratory spectral measurements, was created. Next, partial least squares regression analysis was conducted on the spectral and WIR data in different soil texture groups, showing better performance of the field spectral observations compared to traditional laboratory spectroscopy. Moreover, several quantitative spectral properties were lost due to the sampling procedure, and separating the samples according to texture gave higher accuracies. Although the visible near-infrared–shortwave infrared (VNIR–SWIR) spectral region provided better accuracy, we resampled the spectral data to the resolution of a Cubert hyperspectral sensor (VNIR). This hyperspectral sensor was then assembled on an unmanned aerial vehicle (UAV) to apply one selected spectral-based model to the UAV data and map the WIR in a semi-vegetated area within the Alento catchment, Italy. Comprehensive spectral and WIR ground-truth measurements were carried out simultaneously with the UAV–Cubert sensor flight. The results were satisfactorily validated on the ground using field samples, followed by a spatial uncertainty analysis, concluding that the UAV with hyperspectral remote sensing can be used to map soil surface-related soil properties.

Keywords: water infiltration rate; hyperspectral remote sensing; soil spectroscopy; soil surface; unmanned aerial vehicle

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A transfer function to predict soil surface reflectance from laboratory soil spectral libraries

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Keywords:
Transfer function
Soil spectroscopy
Water-infiltration rate
Soil surface

ABSTRACT

Spectral-based models extracted from laboratory reflectance in the 400–2500 nm spectral range to predict soil attributes may not be applicable to soil spectra acquired in the field. This is because laboratory sampling procedures disturb the natural soil surface's status. We investigated this issue by using the soil surface-dependent property of water-infiltration rate (WIR). We created a dataset with 114 samples collected from six fields with varying textures located in three different Mediterranean countries (Israel, Greece, Italy). Using the field and laboratory spectral datasets, we demonstrated that WIR is better predicted by field vs. laboratory measurements (R^2 = 0.92 and 0.56, respectively). We also developed a transfer function (TF) to predict the field spectral measurements from the laboratory spectra. Use of the TF-processed dataset considerably improved the WIR prediction using laboratory information (from R^2 = 0.56 to 0.76). It was concluded that soil surface reflectance values can be estimated based on laboratory spectra using a TF. The generated TF enables exploiting soil spectral libraries for remote-sensing views and for assessing surface-related soil properties.

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iAqueduct aim to close the gaps between global satellite observation of the water cycle and local needs of information for sustainable management of water resources.

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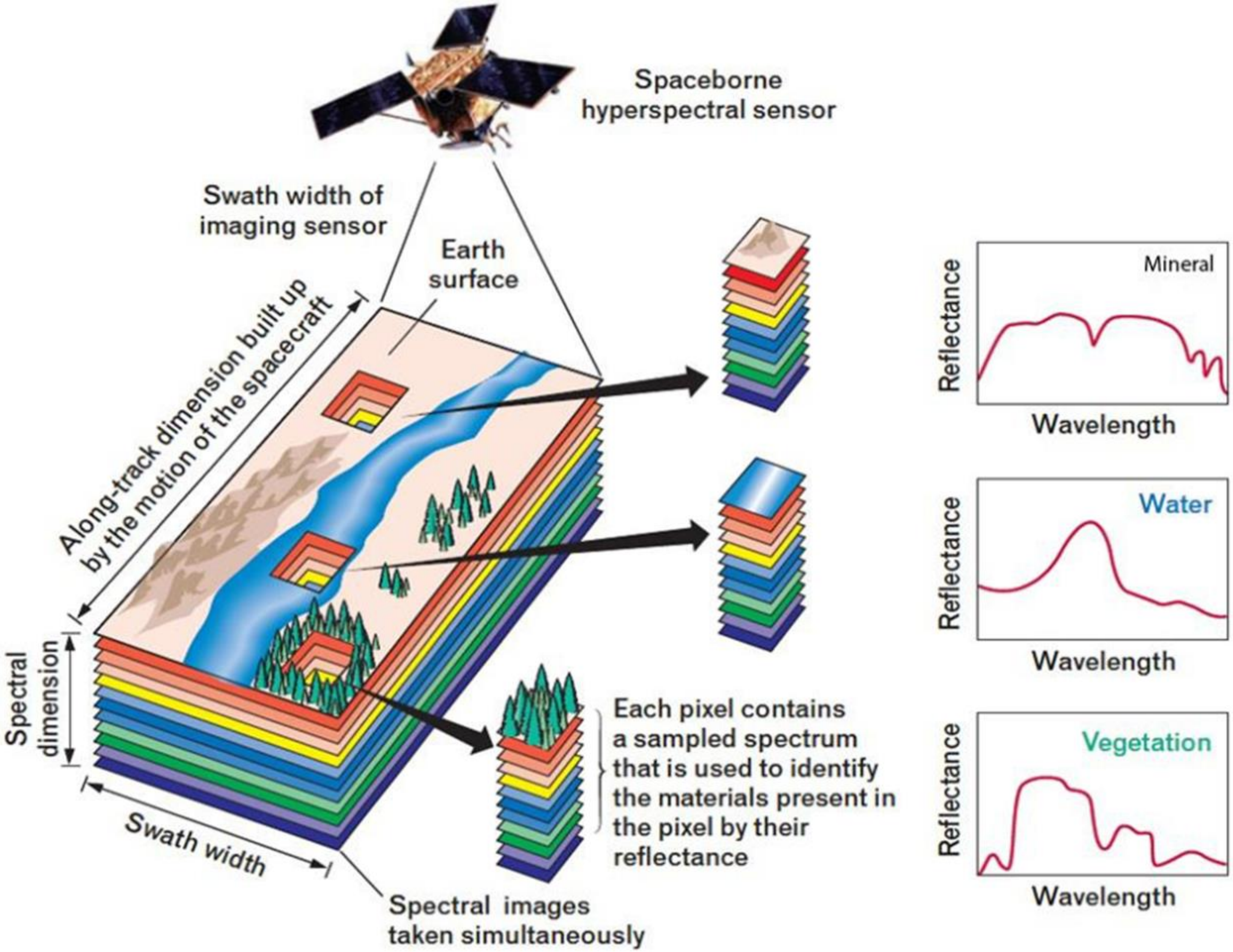
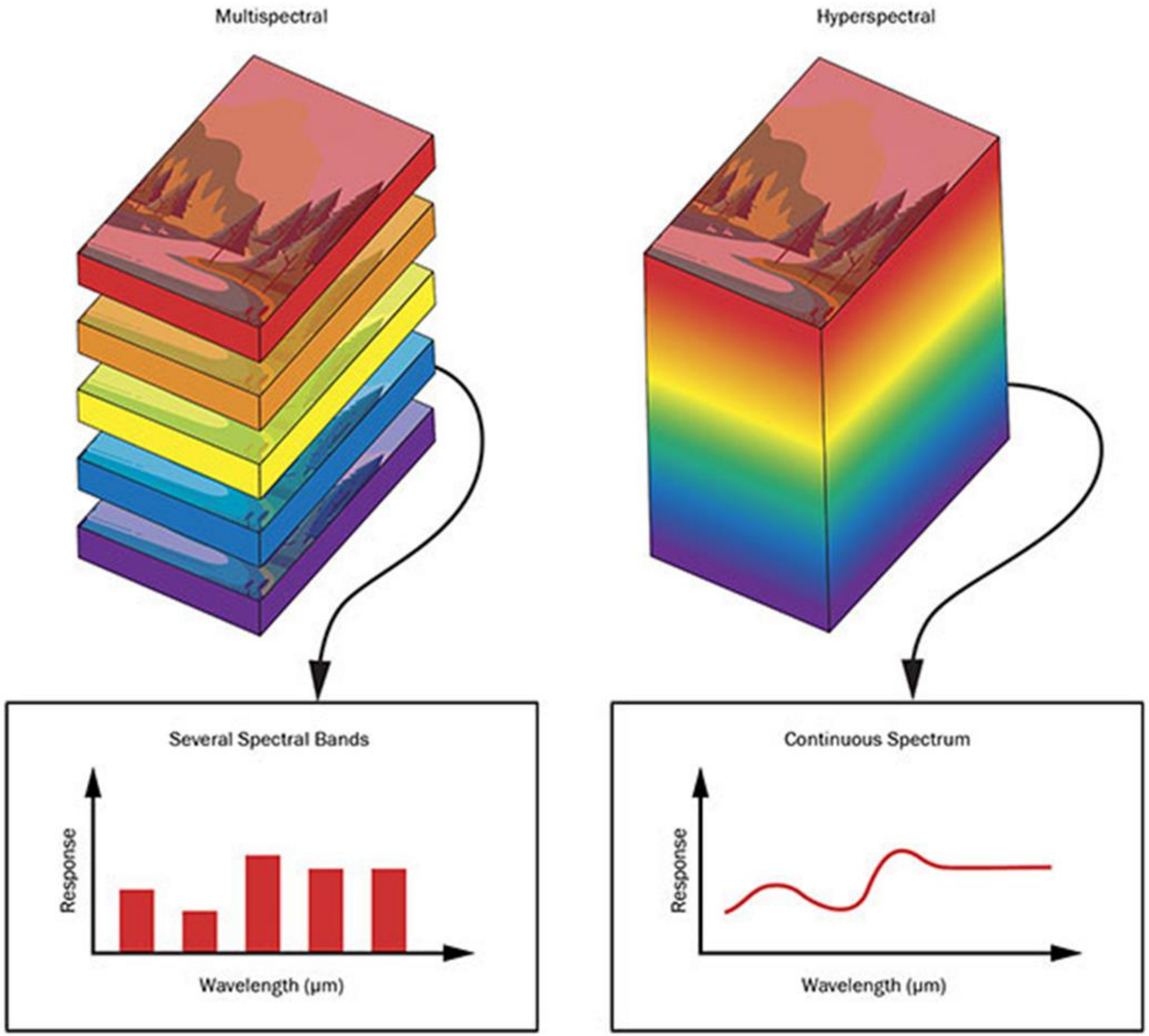
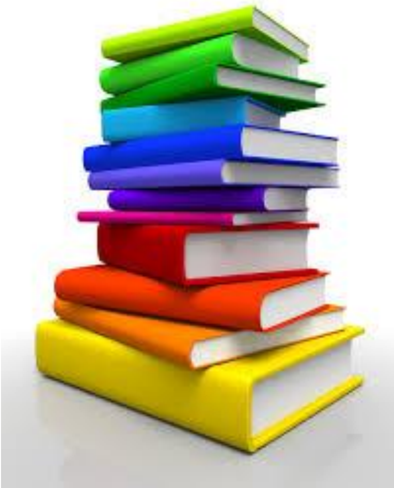


Spaceborne hyperspectral sensor
Swath width of imaging sensor
Earth surface
Along-track dimension built up by the motion of the spacecraft
Spectral dimension
Swath width
Spectral images taken simultaneously
Each pixel contains a sampled spectrum that is used to identify the materials present in the pixel by their reflectance
Mineral
Reflectance
Wavelength
Water
Reflectance
Wavelength
Vegetation
Reflectance
Wavelength


Multispectral
Hyperspectral
Several Spectral Bands
Response
Wavelength (µm)
Continuous Spectrum
Response
Wavelength (µm)

Lab-SSLs



- Soil Spectral Libraries (SSLs) are datasets that contain: Chemical and/or physical soil properties, as well as laboratory spectral measurements.

- The number of SSLs is increasing because these datasets have an important potential to train machine learning algorithms that can monitor soil properties from the sky.

- SSLs are created under lab conditions, so it is unclear if they can be used to infer field conditions.

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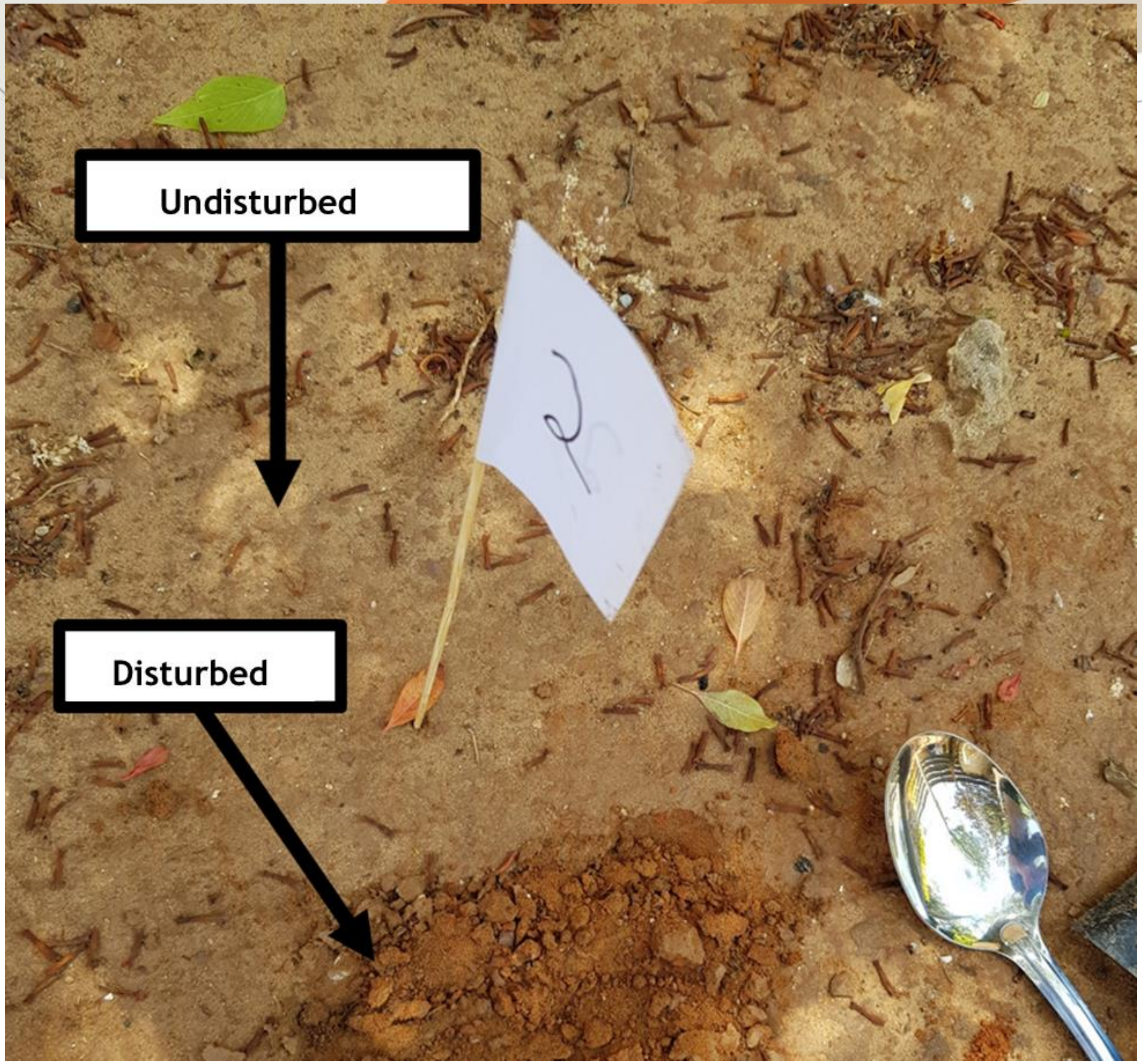
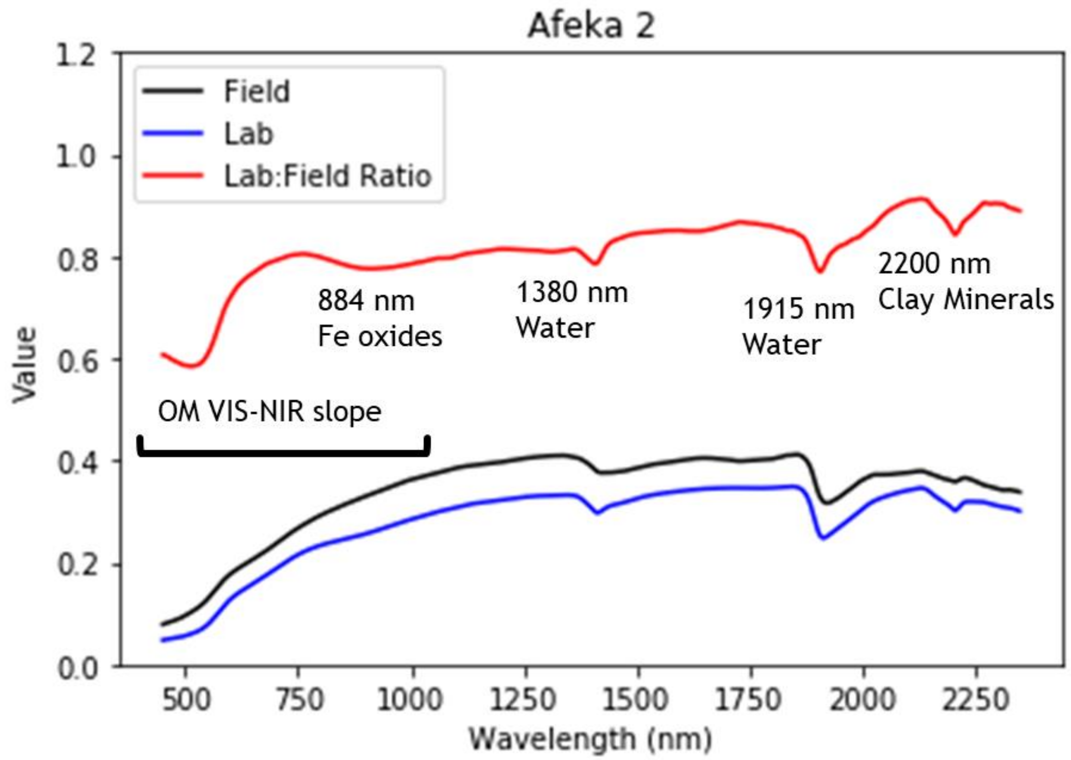
Why Use Water Infiltration Rate (WIR)

- **WIR may be defined as “*the meters (length units) per unit time of water entering into the soil regardless of the types or values of forces or gradients*” (Kirkham, 2014)**

- WIR is a very important hydrological parameter, which is strongly dependent on soil surface conditions.
- Thus, WIR is an excellent soil property to investigate the gap between lab and field spectral observations


Undisturbed
Disturbed


Afeka 2
Field
Lab
Lab:Field Ratio
884 nm
Fe oxides
1380 nm
Water
1915 nm
Water
2200 nm
Clay Minerals
OM VIS-NIR slope
Value
Wavelength (nm)
1.2
1.0
0.8
0.6
0.4
0.2
0.0
500
750
1000
1250
1500
1750
2000
2250

The Gap between the Field and the Lab

- In different areas of the Mediterranean Basin, we will measure WIR using a Mini Disk infiltrometer.
- Next, we measured the spectral signature in the field and in the lab.
- The field spectra were measured using an ASD connected to SoilPro (Ben Dor et al., 2017) in order to get optimal spectral signatures in the field.

Field Spectral Measurements using ASD connected to SoilPRO

The Mini-disk Infiltrometer

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Data Acquisition

▶ This dataset contain samples of 6 different fields along the Mediterranean Basin:

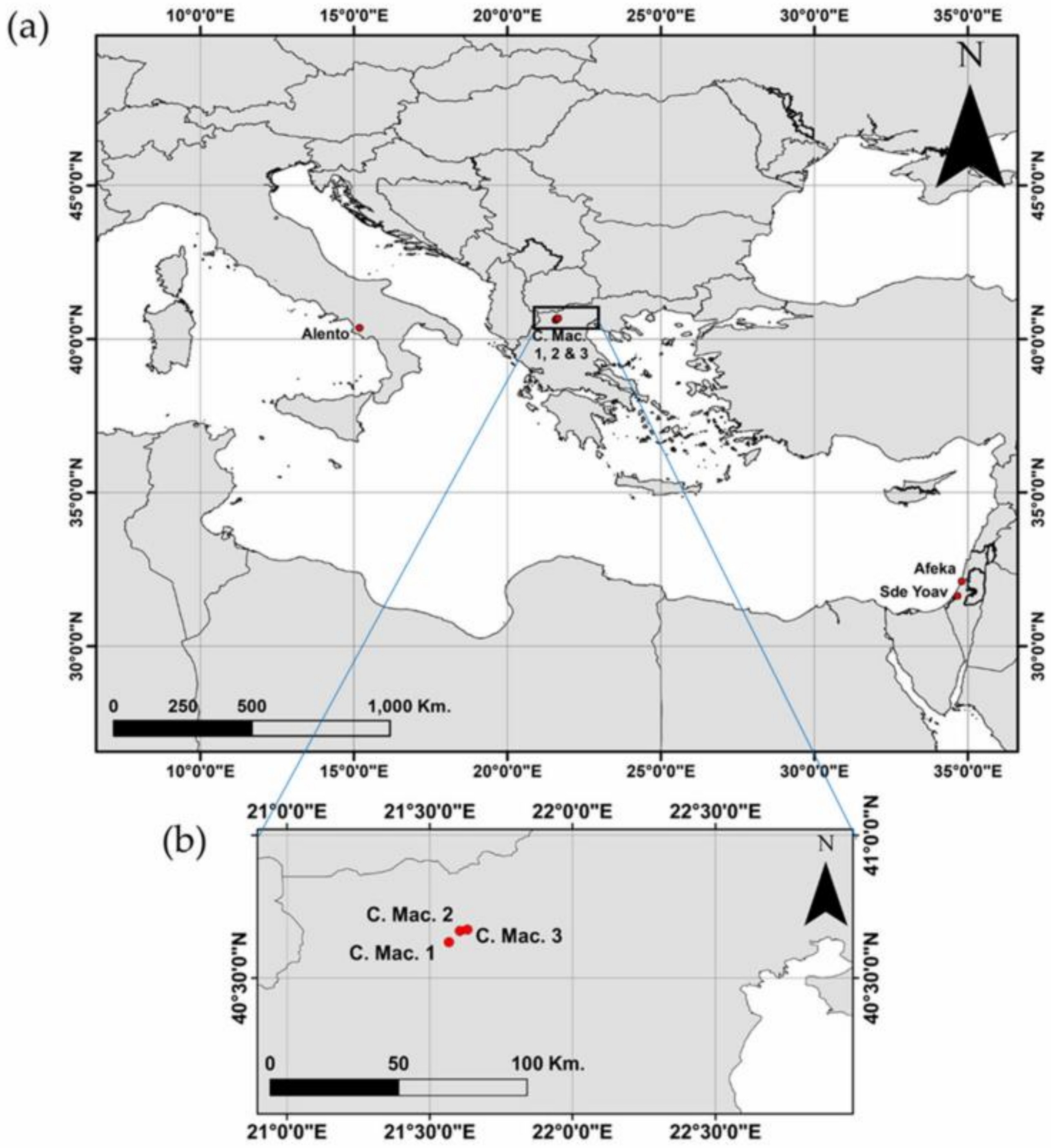
i) Kibbutz Sde Yoav, Israel (30 Samples)

ii) Afeka, Tel Aviv, Israel (18 Samples)

iii) Alento, Italy (21 Samples)

iv) Aminteo, Greece (45 Samples of 3 different fields)

Data Acquisition



Data Acquisition

The texture prediction is necessary to estimate WIR, and was performed following the ***diagram of Thien*** in field.

As the WIR is considerably affected by the soil texture, the samples were grouped into two textural categories to examine whether fine-tuning according to their texture would provide better accuracy. Thus, three groups were evaluated as follows:

I. The whole dataset: samples collected from all sites (114 samples).

II. The "sandy" dataset: samples from Afeka (Tel Aviv), Israel and from the three fields in Central Macedonia, Greece (58 samples).

III. The "clayey" dataset: samples from Sde Yoav, Israel and Alento, Italy (46 samples).

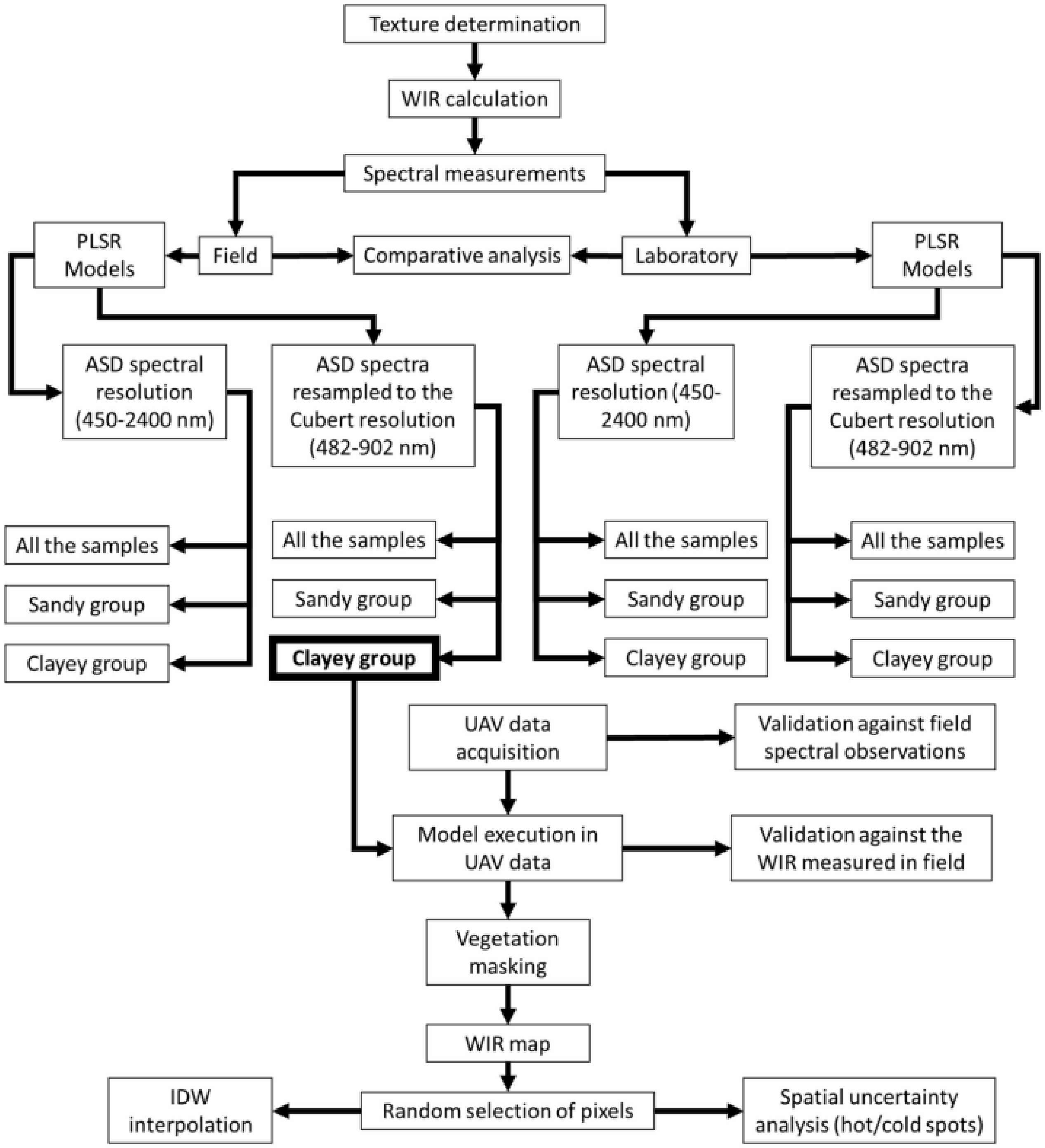
Experiment Design

- Both, the lab and the field based datasets, were resampled according the spectral configuration of Cubert UHD 185.
- PLSR models were generated to predict WIR using different groups.
- We applied the best model to an UAV hyperspectral image.
- The predicted values of the pixels that were mapped as bare soil, were randomly subset to 100 points and interpolated using IDW. Then, a Getis-Ord* hotspot analysis was performed.
- The measured values were also interpolated to compare.

The UAV Platform

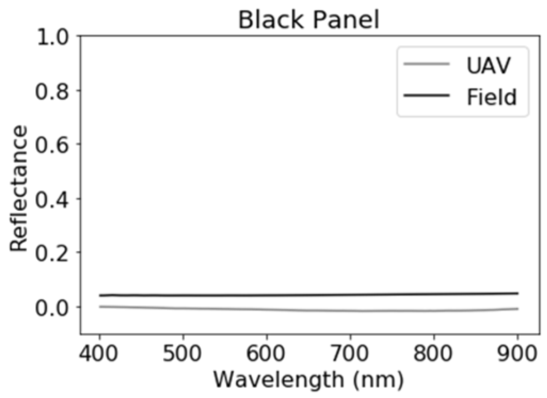
- For the UAV mission, we used a Cubert UHD-185® which is a HRS snapshot sensor onboard a CarbonCore Cortex X8 UAV.
- Cubert UHD-185 measures the reflectance across the 450-950 spectral range with 125 bands.
- The images were acquired on a sunny day (13/06/2019) between 9:57 and 10:30 in an agricultural field of Alento, Italy.
- The mission took place from an altitude of 138 meters providing a pixel size of 5 cm/pix approx.
- For the mosaic, we used 468 images in which we applied an 80% of forward overlap and 65% of side-lap.

Flowchart

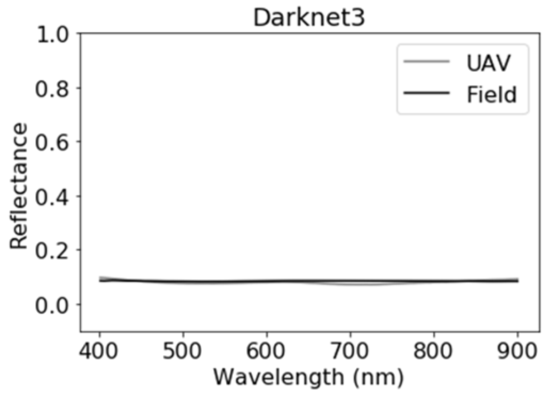


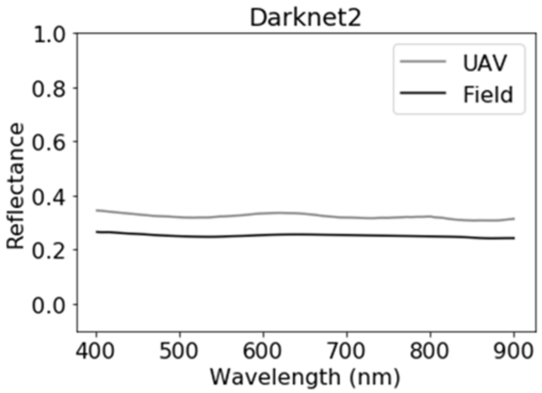
Texture determination
WIR calculation
Spectral measurements
PLSR Models
Field
Comparative analysis
Laboratory
PLSR Models
ASD spectral resolution (450-2400 nm)
ASD spectra resampled to the Cubert resolution (482-902 nm)
ASD spectral resolution (450-2400 nm)
ASD spectra resampled to the Cubert resolution (482-902 nm)
All the samples
Sandy group
Clayey group
All the samples
Sandy group
Clayey group
All the samples
Sandy group
Clayey group
All the samples
Sandy group
Clayey group
UAV data acquisition
Validation against field spectral observations
Model execution in UAV data
Validation against the WIR measured in field
Vegetation masking
WIR map
IDW interpolation
Random selection of pixels
Spatial uncertainty analysis (hot/cold spots)

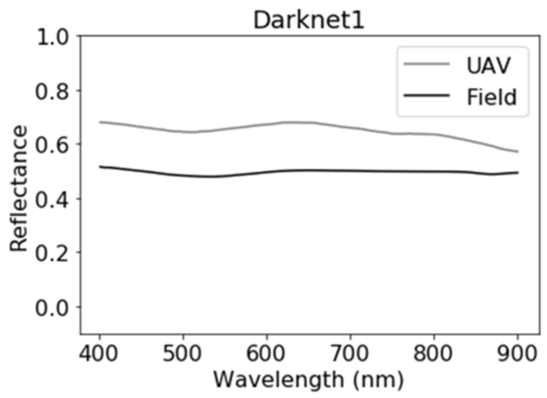
- The DN values were calibrated to a halon WR before the flight
- In order to validate the correction, the average sum of deviation squared (ASDS) was calculated for 5 different targets with increasing reflectance

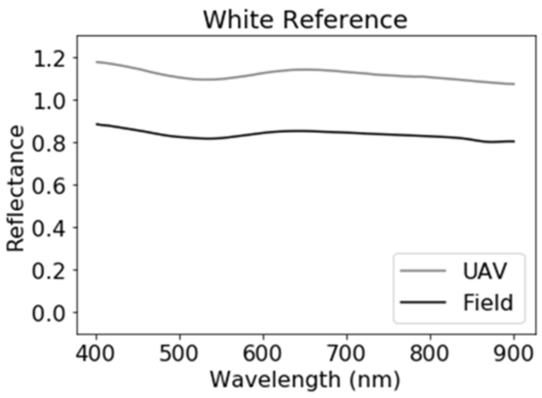


Sample	ASDS
BlackPanel	0.003
DarkNet3	0.000
DarkNet2	0.003
DarkNet1	0.011
WhitePanel	0.024









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Results

ASD resolution (400-2450 nm)

Group	Parameter	Field	Laboratory
Whole dataset	RPIQ (Cal)	10.83	5.26
	R^2 (Cal)	0.98	0.92
	RMSE (Cal)	0.0001	0.0002
	No. of samples (Cal)	83	83
	RPIQ (Val)	2.26	1.87
	R^2 (Val)	0.70	0.57
	RMSE (Val)	0.0004	0.0004
	No. of samples (Val)	21	21
	p-Value (Val)	0.0000	0.0001
	No. of components	9	9
	Spectral preprocessing	1st derivative	
Sandy dataset	RPIQ (Cal)	4.24	1.8
	R^2 (Cal)	0.90	0.48
	RMSE (Cal)	0.0002	0.22
	No. of samples (Cal)	46	46
	RPIQ (Val)	3.19	1.84
	R^2 (Val)	0.82	0.22
	RMSE (Val)	0.0004	0.0007
	No. of samples (Val)	12	12
	p-Value (Val)	0.0001	0.123
	No. of components	5	5
	Spectral preprocessing	Absorbance and 1st derivative	
Clayey dataset	RPIQ (Cal)	17.66	4.96
	R^2 (Cal)	0.99	0.89
	RMSE (Cal)	5.86	0.0002
	No. of samples (Cal)	37	37
	RPIQ (Val)	3.14	2.85
	R^2 (Val)	0.81	0.7
	RMSE (Val)	0.0003	0.0004
	No. of samples (Val)	9	9
	p-Value (Val)	0.0004	0.0025
	No. of components	6	6
	Spectral preprocessing	1st derivative	

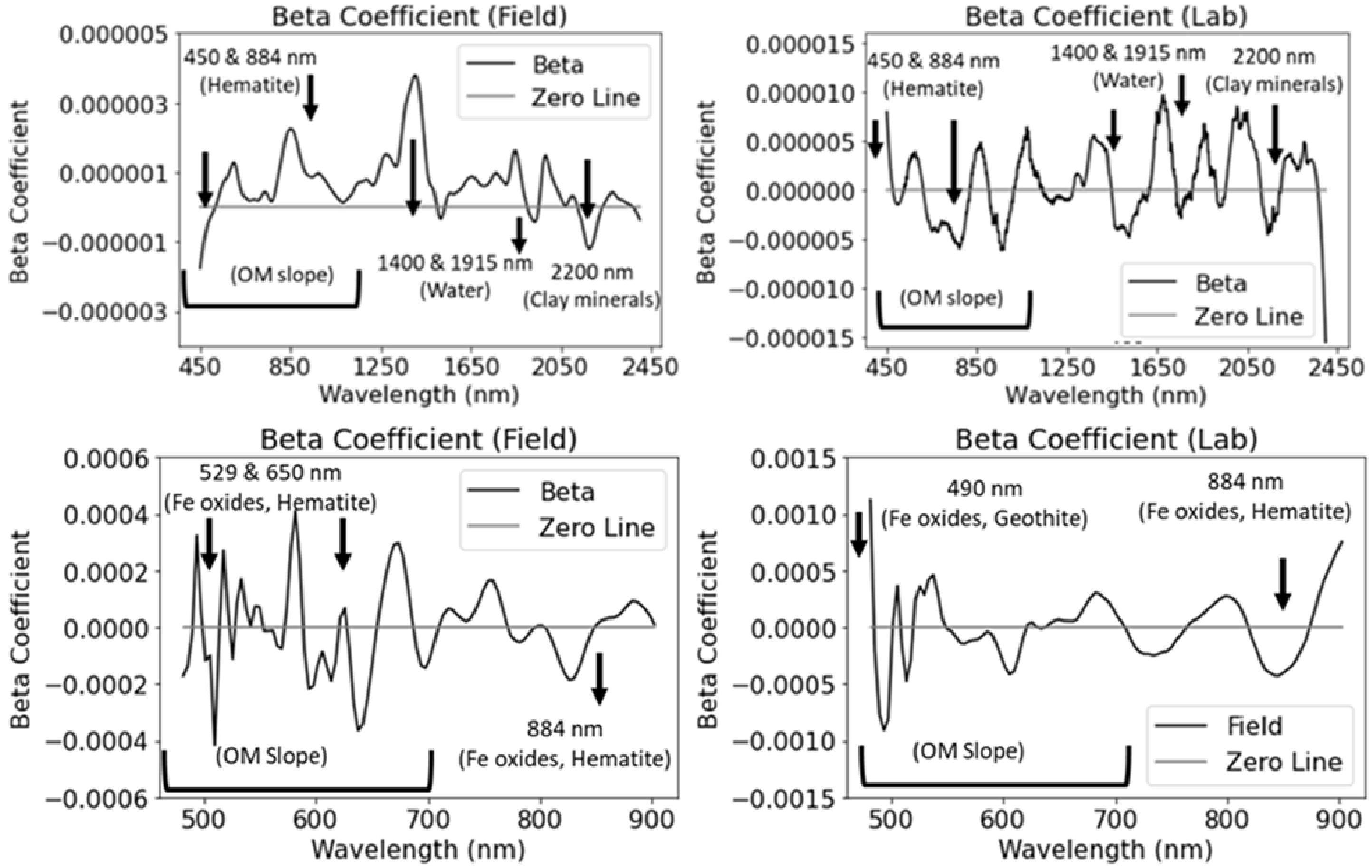
CUBERT resolution (450-950 nm)

Group	Parameter	Field	Laboratory
Whole dataset	RPIQ (Cal)	2.26	2.05
	R^2 (Cal)	0.52	0.41
	RMSE (Cal)	0.0005	0.0006
	No. of samples (Cal)	83	83
	RPIQ (Val)	1.06	1.02
	R^2 (Val)	0.36	0.30
	RMSE (Val)	0.0007	0.0007
	No. of samples (Val)	21	21
	p-Value (Val)	0.0038	0.0106
	No. of components	10	10
	Spectral preprocessing	Absorbance and 1st derivative	
Sandy dataset	RPIQ (Cal)	2.36	2.59
	R^2 (Cal)	0.63	0.55
	RMSE (Cal)	0.0005	0.0005
	No. of samples (Cal)	46	46
	RPIQ (Val)	2.7	1.66
	R^2 (Val)	0.83	0.45
	RMSE (Val)	0.0003	0.0005
	No. of samples (Val)	12	12
	p-Value (Val)	0.0000	0.0169
	No. of components	11	11
	Spectral preprocessing	Absorbance and 1st derivative	
Clayey dataset	RPIQ (Cal)	2.26	2.05
	R^2 (Cal)	0.66	0.47
	RMSE (Cal)	0.0004	0.0005
	No. of samples (Cal)	37	37
	RPIQ (Val)	3.67	2.18
	R^2 (Val)	0.86	0.49
	RMSE (Val)	0.0003	0.0005
	No. of samples (Val)	9	9
	p-Value (Val)	0.0001	0.0048
	No. of components	6	6
	Spectral preprocessing	1st derivative	

The Whole Dataset

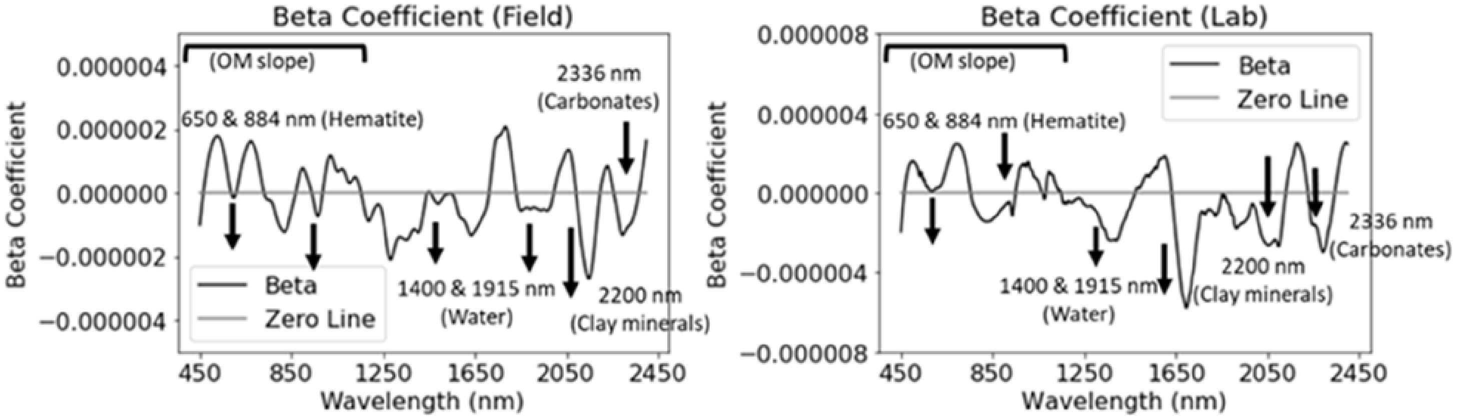
ASD SPECTRAL RESOLUTION (VIS-NIR-SWIR)

CUBERT UHD-185 SPECTRAL RESOLUTION (VIS-NIR)

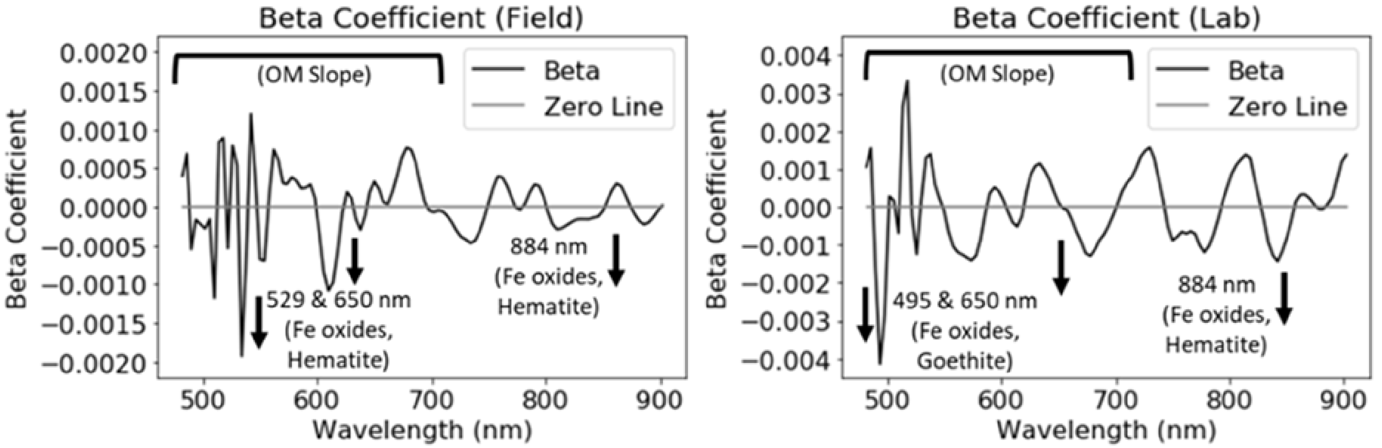


The Sandy Soils

ASD SPECTRAL RESOLUTION (VIS-NIR-SWIR)



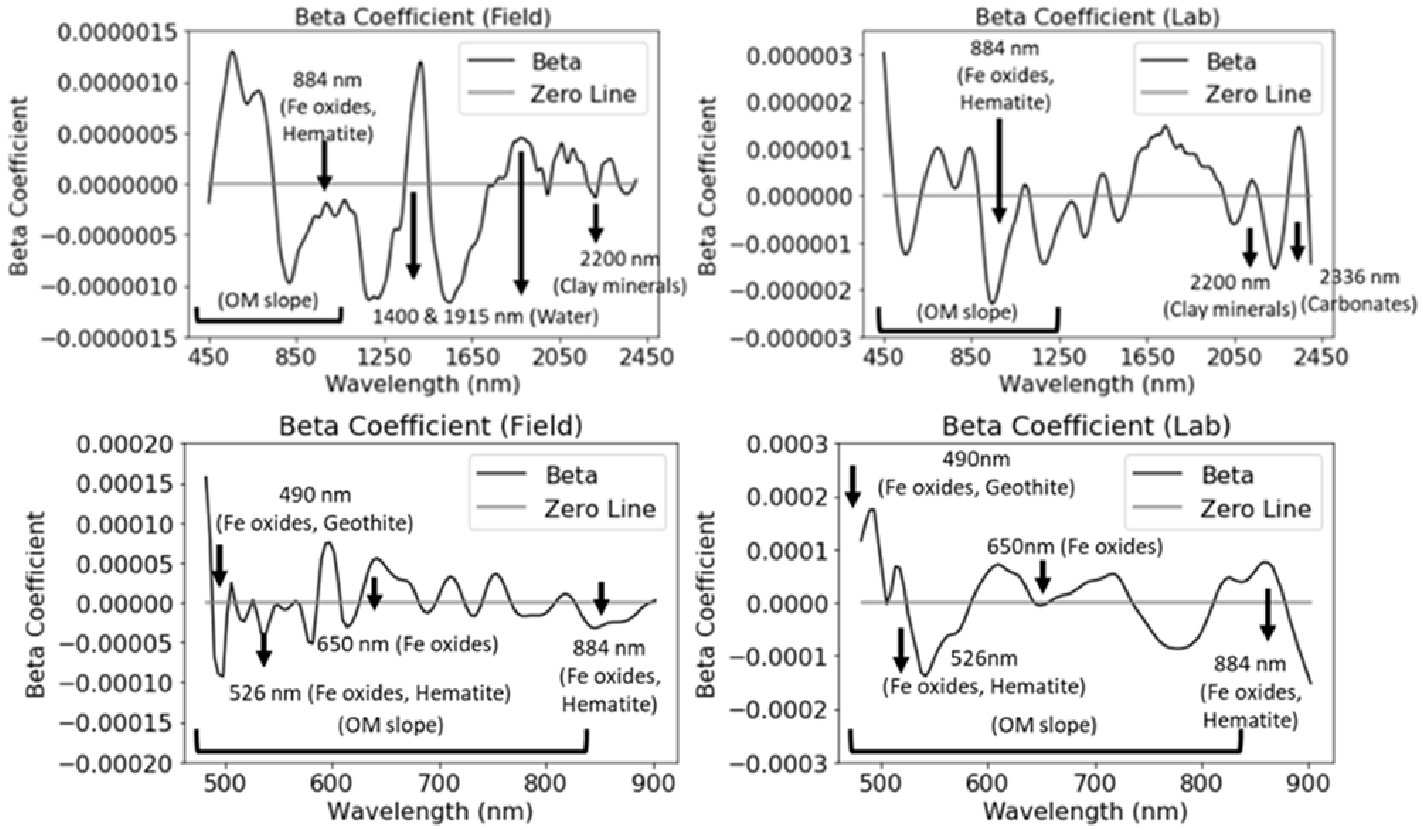
CUBERT UHD-185 SPECTRAL RESOLUTION (VIS-NIR)

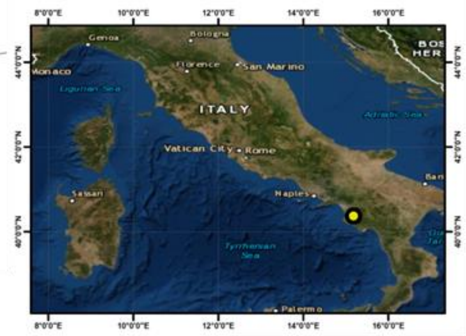


The Clayey Soils

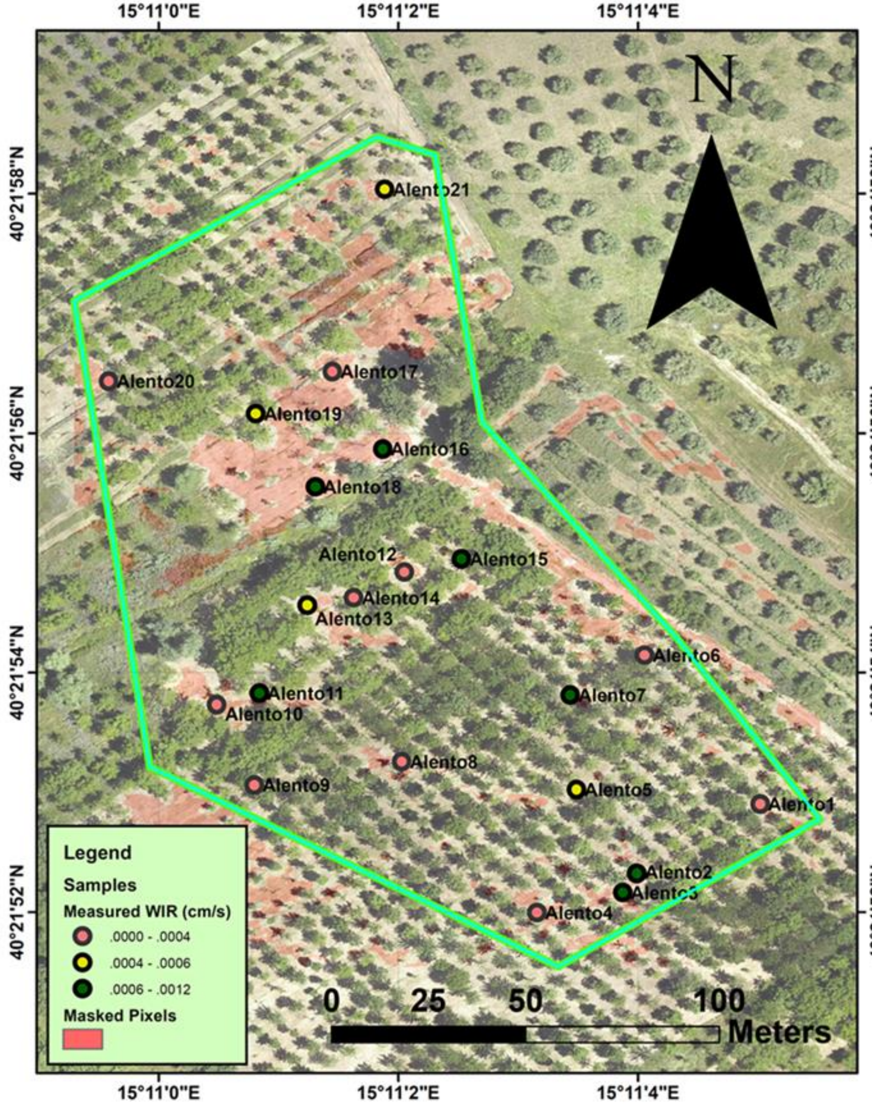
ASD SPECTRAL RESOLUTION (VIS-NIR-SWIR)

CUBERT UHD-185 SPECTRAL RESOLUTION (VIS-NIR)

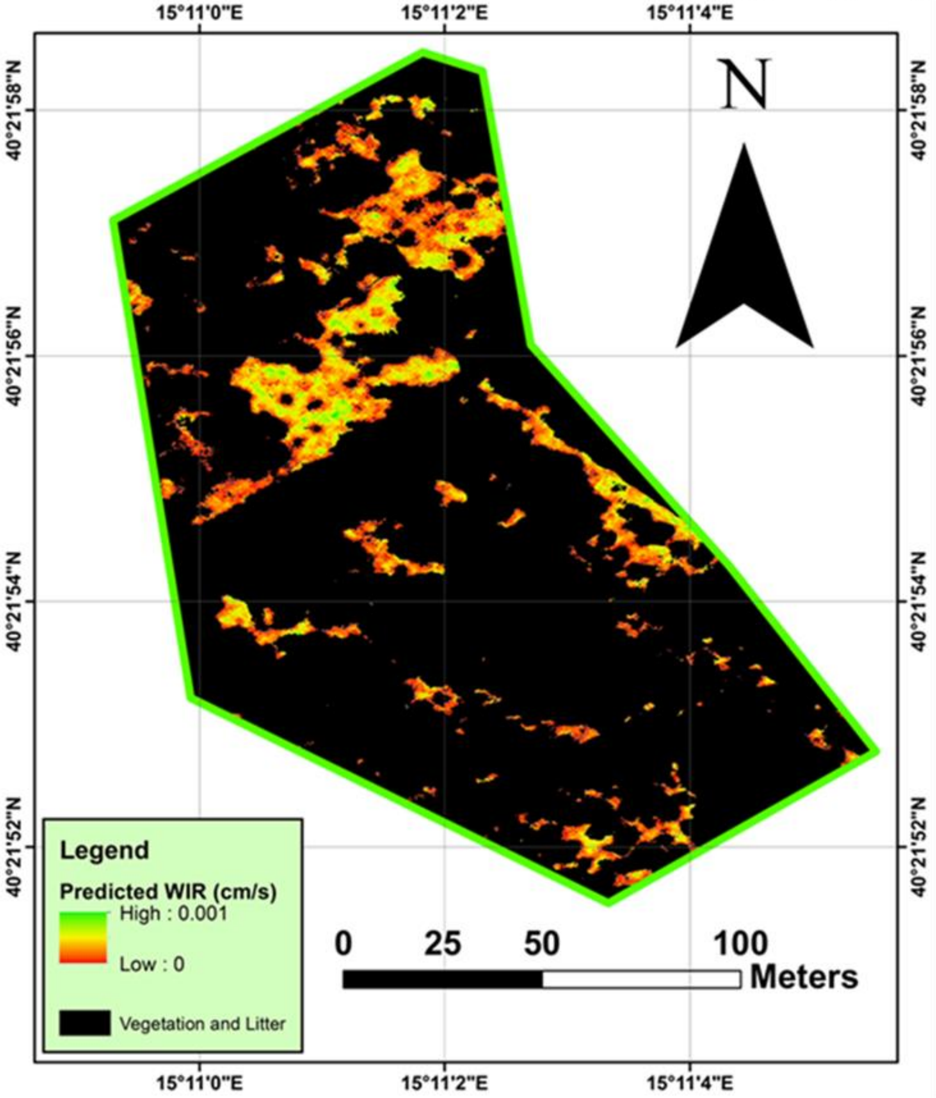




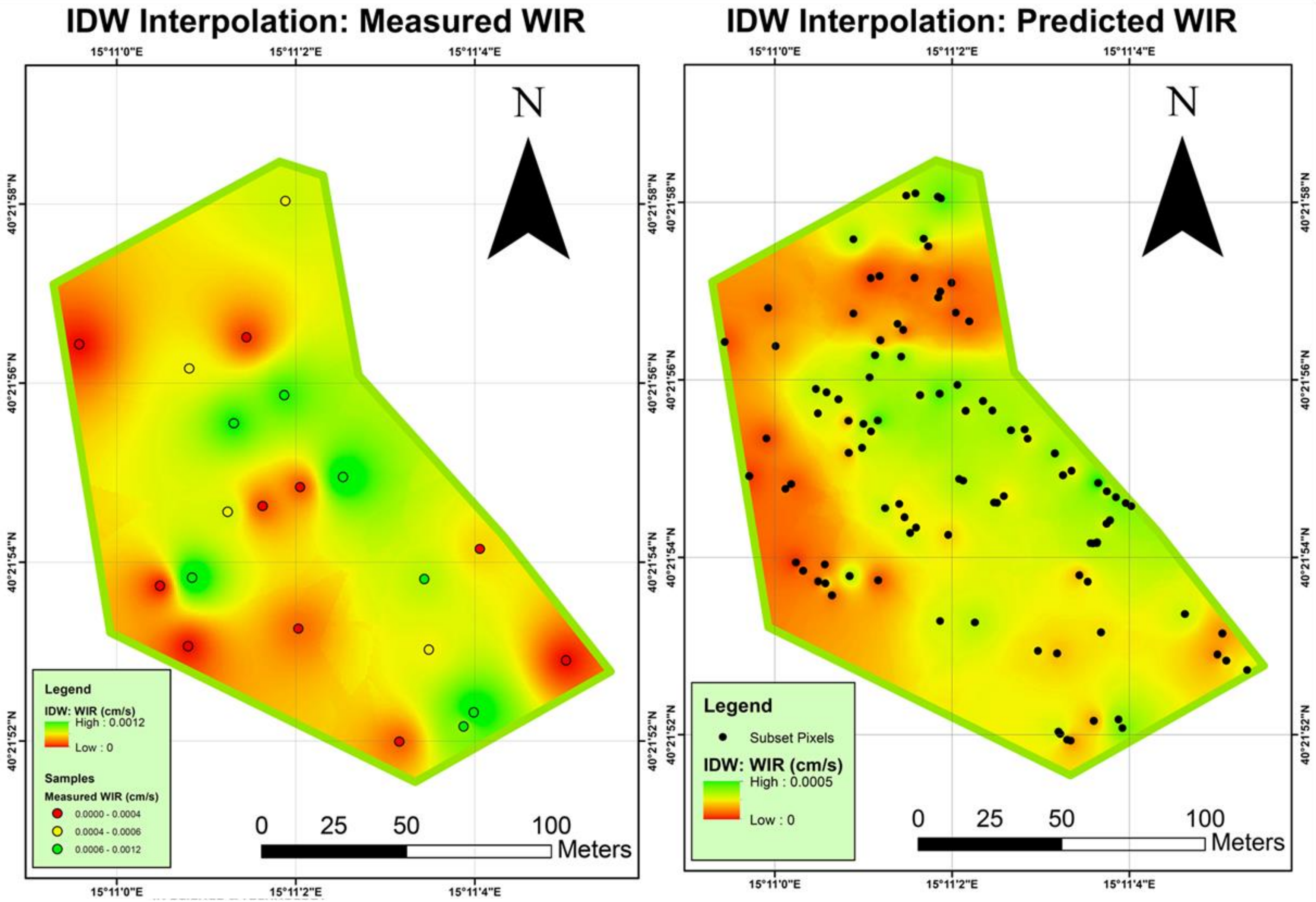
RGB Image with Field Samples



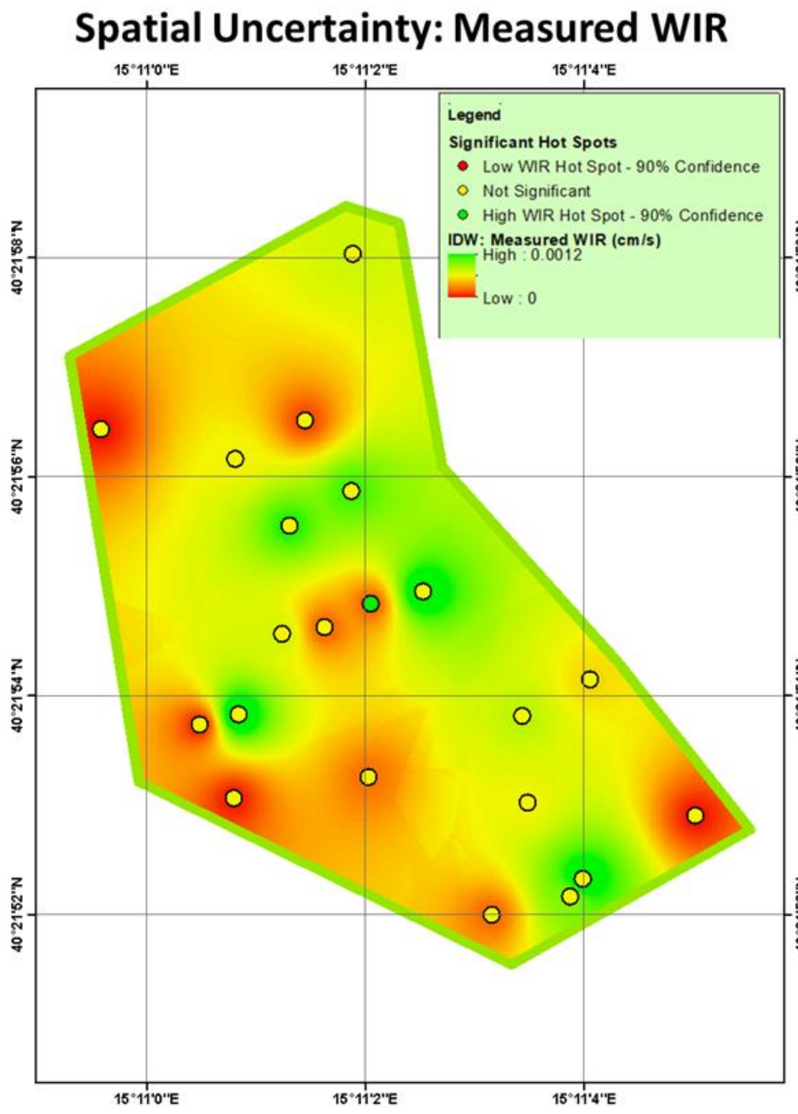
Predicted WIR

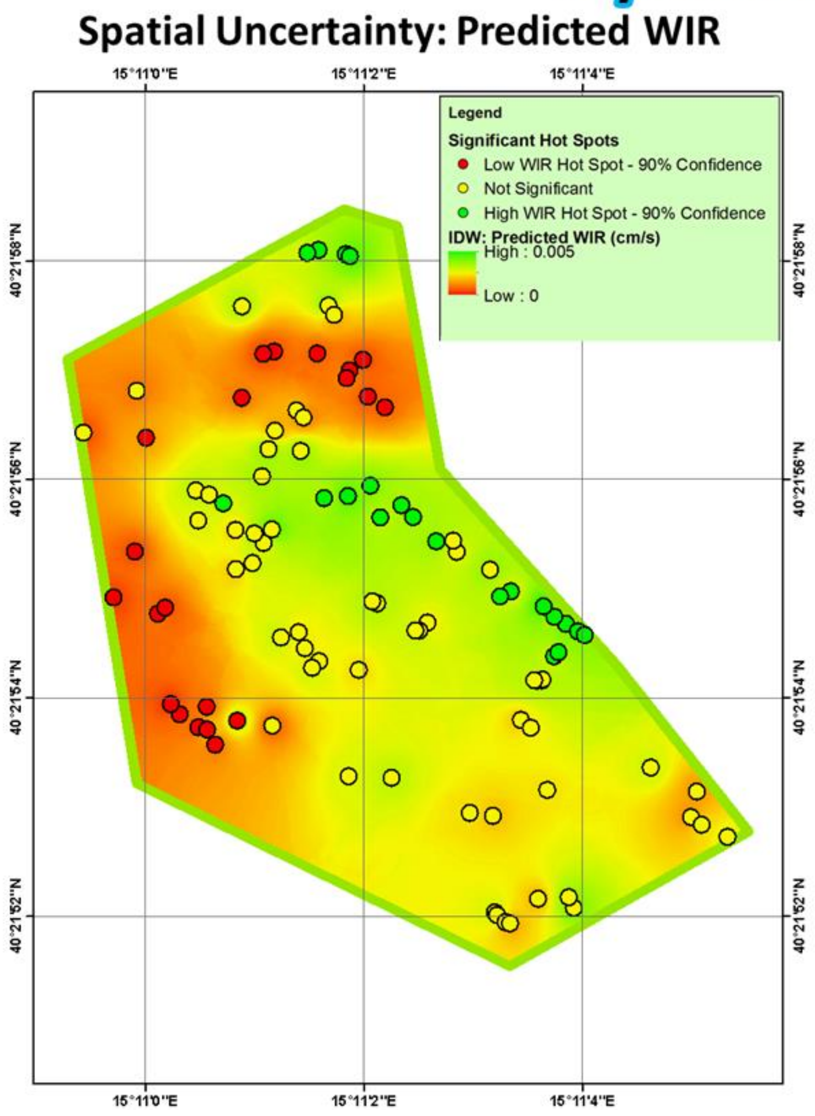


Measured vs Predicted WIR (IDW)

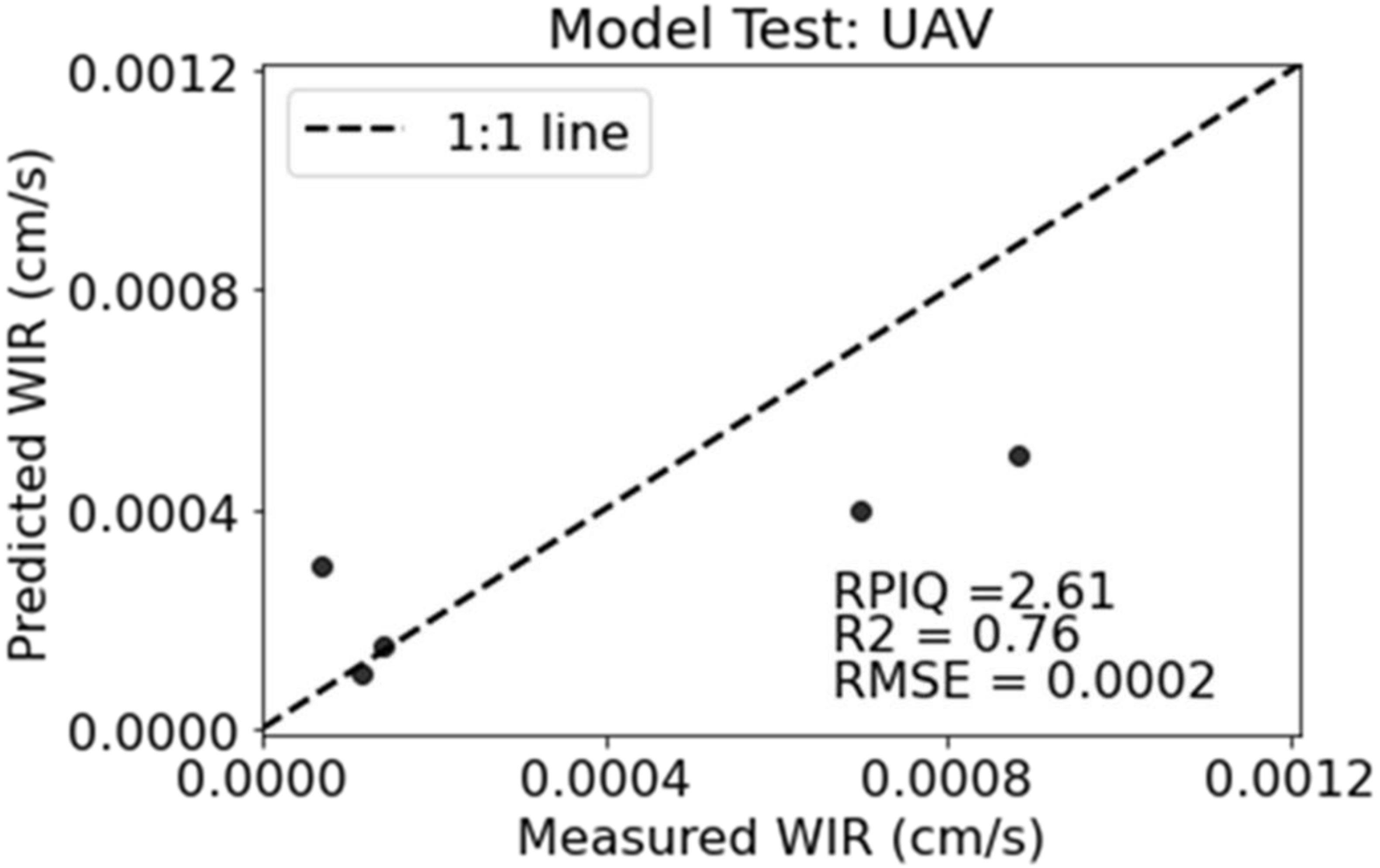


Getis-Ord Gi* Hot Spot Analysis





Validation



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Conclusions

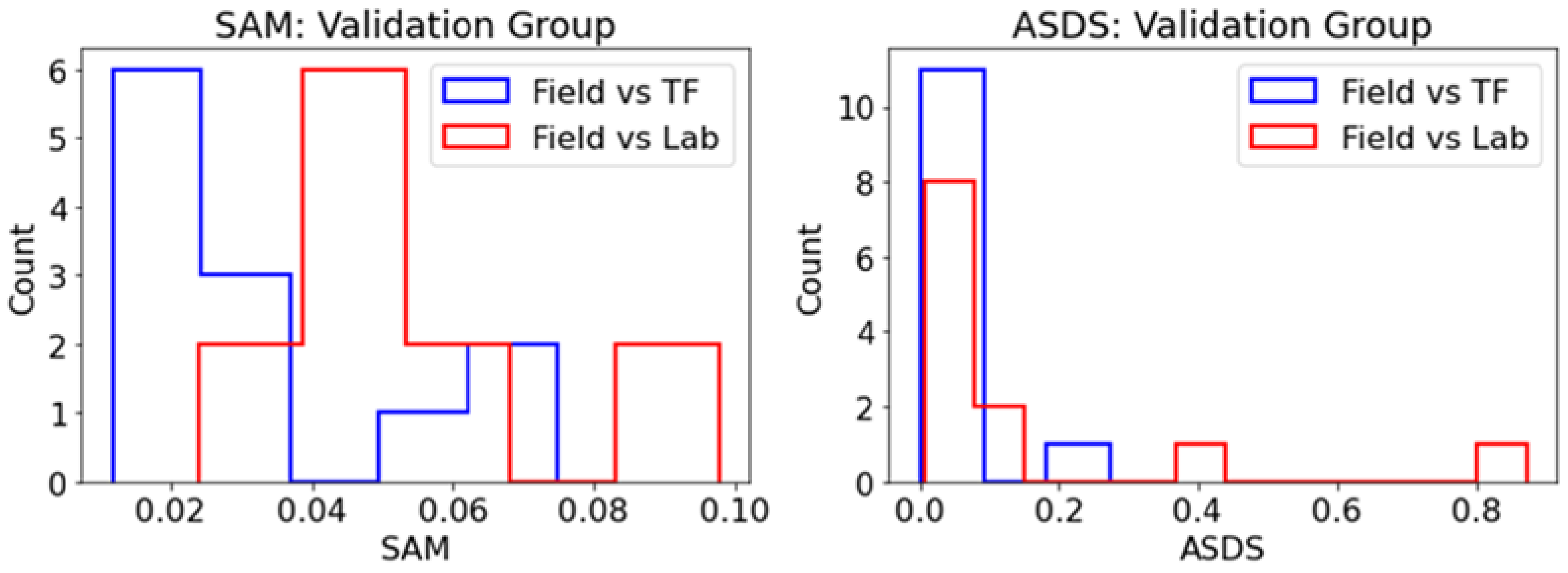
- This study showed that soil surface reflectance is a good tool to predict soil WIR.
- The beta coefficients revealed that quantitative spectral properties of Fe oxides and OM may be lost once the soil samples are collected and measured in the laboratory.
- The field-based models showed better results than the lab level in all the cases.
- Soil surface reflectance showed a very good generic model including all the samples when the SWIR range was considered.
- A field-based model was adapted to a UAV sensor. Then, the results were successfully validated in the field.

A Transfer Function to Predict Soil Surface Reflectance from Lab Soil Spectral Libraries

- In order to predict the field reflectance in every band, we used the lab reflectance values in all the bands.
- Field-spectra was predicted by programming a "loop" in which the number of models is equal to the number of the bands to predict in the field spectra.
- For this task the random forest algorithm (Breiman, 2001) was used for every prediction. Then, the predicted spectra were smoothed using the Savitzky Golay (Savitzky and Golay, 1964) method.

Validation: ASDS & SAM

- For validation, the spectral similarity between the field and lab (before and after the correction) spectra in all the samples was evaluated using their average sum of deviations squared (ASDS) (Ben-Dor et al., 2004) and SAM (Kruse et al., 1993) values.
- This evaluation was performed in a selected group of validation samples that represented 10% of the dataset and was not used to train the transfer function.

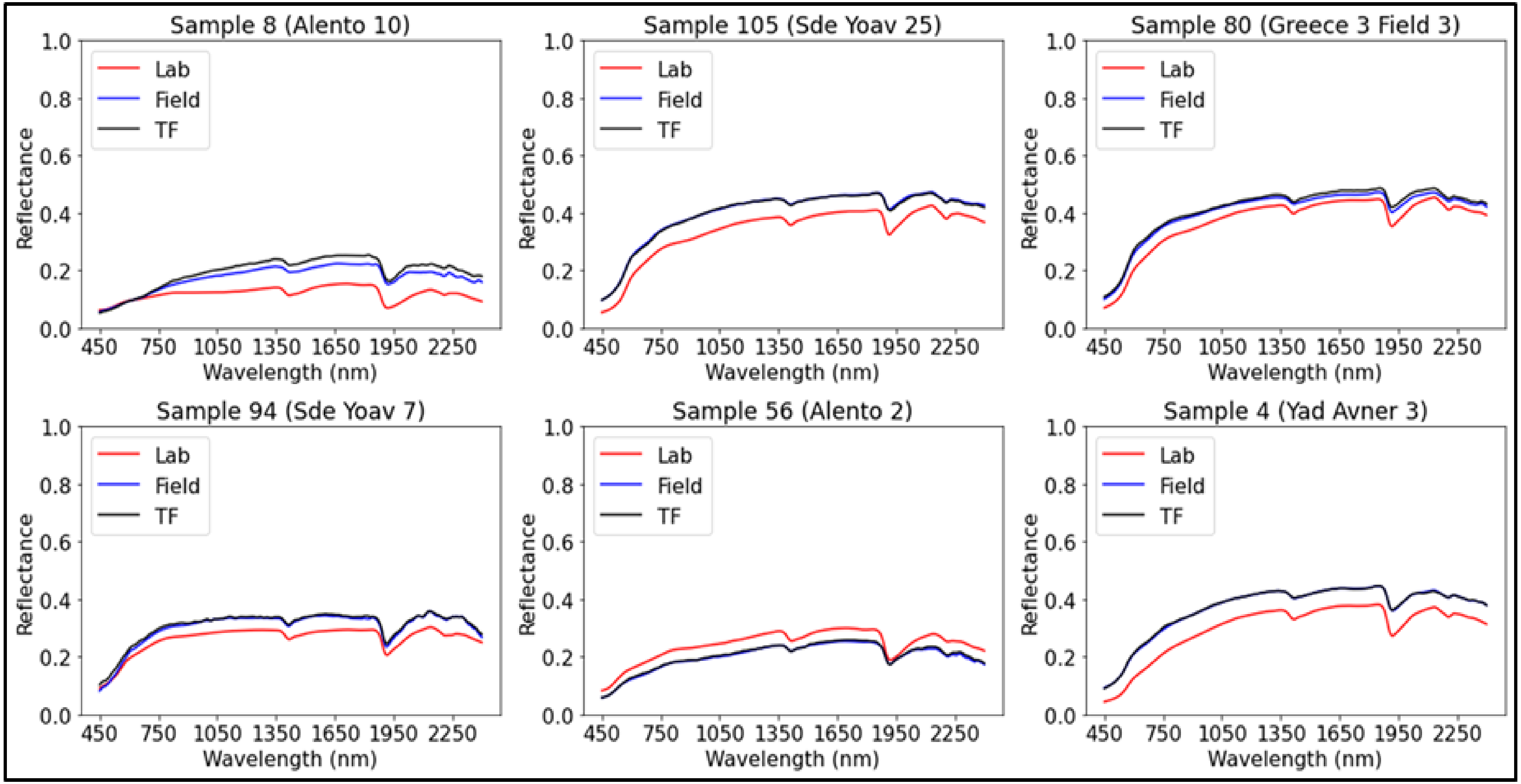


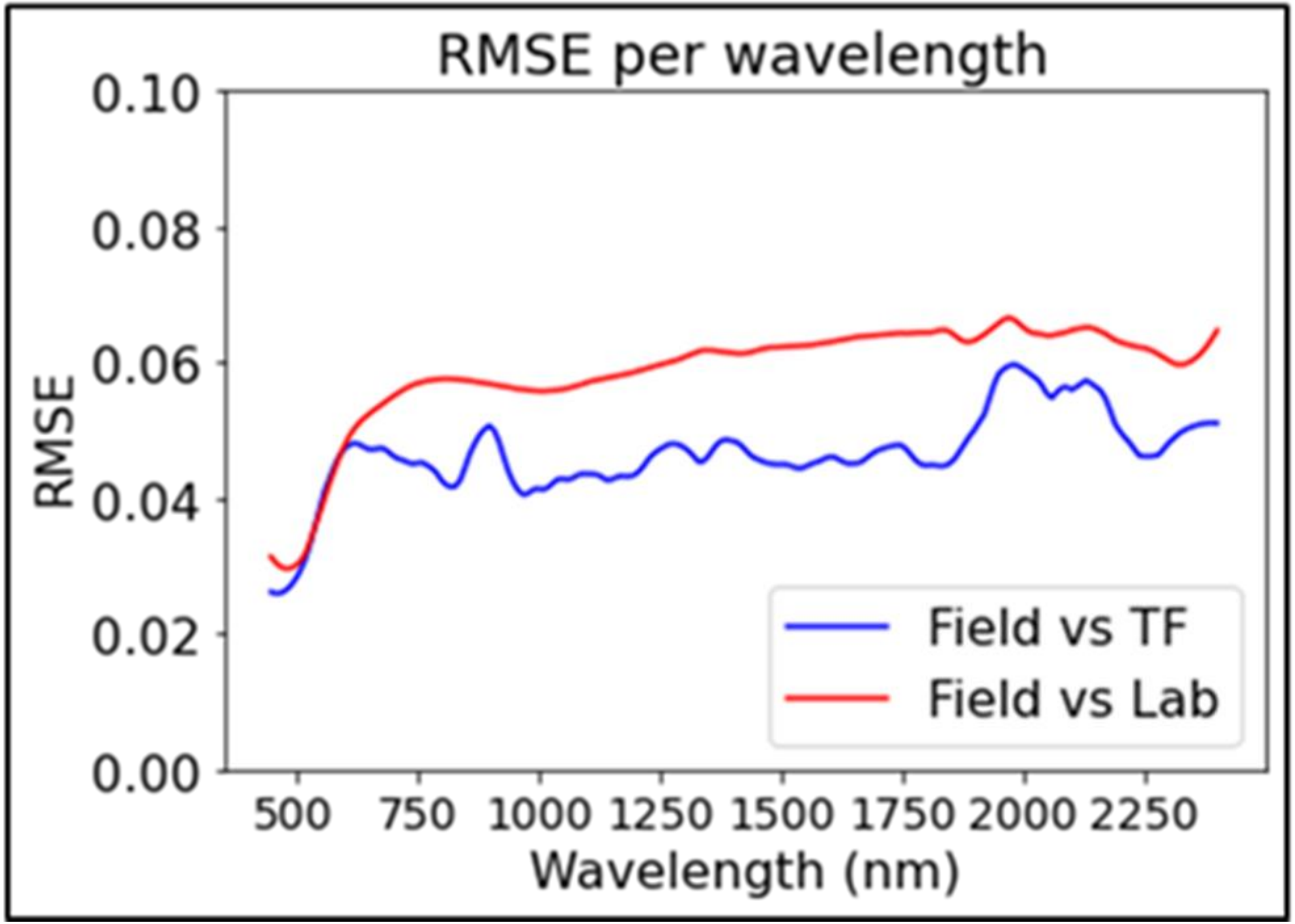
SAM

Parameter	Field vs TF	Field vs Lab
Mean	0.034	0.055
Max	0.075	0.098
Min	0.012	0.02
S. Deviation	0.021	0.021

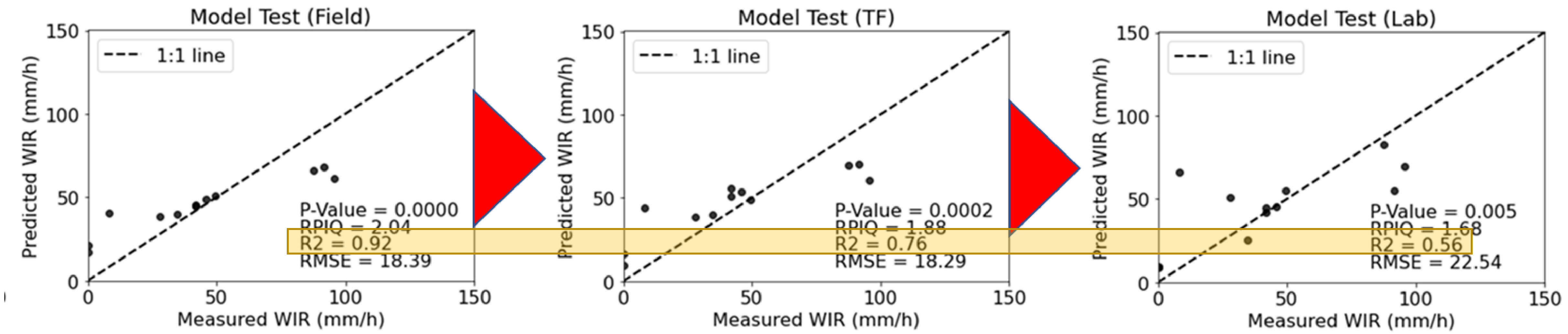
ASDS

Parameter	Field vs TF	Field vs Lab
Mean	0.028	0.144
Max	0.28	0.87
Min	0.006	0.0003
S. Deviation	0.077	0.247


Sample 8 (Alento 10)
Sample 105 (Sde Yoav 25)
Sample 80 (Greece 3 Field 3)
Sample 94 (Sde Yoav 7)
Sample 56 (Alento 2)
Sample 4 (Yad Avner 3)
Lab
Field
TF
Reflectance
Wavelength (nm)
0.0
0.2
0.4
0.6
0.8
1.0
450
750
1050
1350
1650
1950
2250


RMSE per wavelength
0.10
0.08
0.06
0.04
0.02
0.00
RMSE
500
750
1000
1250
1500
1750
2000
2250
Wavelength (nm)
Field vs TF
Field vs Lab

WIR Assessment using Random Forests



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