WG3 Soil Moisture state monitoring using UASs

Yijian Zeng, Bob Su, Nunzio Romano, Salvatore Manfreda, Eyal Ben-Dor, Brigitta Szabó, Paolo Nasta, Antonino Maltese, Félix Francés García, José Gomis Cebolla, Ruodan Zhuang, János Mészáros, Monica Garcia, George Petropoulos, Giuseppe Ciraolo, David Helman, Anna Brook, and other WG3 colleagues

HARMONIOUS
uas for environmental monitoring

cost
EUROPEAN COOPERATION
IN SCIENCE & TECHNOLOGY

Funded by the Horizon 2020 Framework Programme
of the European Union

WG3: Soil moisture state monitoring using UASs

- Task 3.1. Training schools on the use of the UAS applied to soil moisture.
- Task 3.2. Generating a spectral based model to assess soil property.
- Task 3.3. Inter-comparison among different survey protocols including: definition of the ideal flight time and duration, number of acquisitions in time, and spatial resolution.
- Task 3.4. Inter-comparison among different instruments: ground measurements vs. aerial surveys.

Task 3.1. Training school on the use of the UAS applied to soil moisture estimation.

- ❑ Soil Moisture Dynamics (by Paolo Nasta)

- ❑ Soil Moisture Downscaling With UAS (by Yijian Zeng)

- ❑ Thermal Inertial for Soil Moisture Monitoring via UAS (by Antonino Maltese)

(Thanks to Gernot and Dariia!)

(Carinthia University of Applied Sciences, Villach, Austria, 2020)

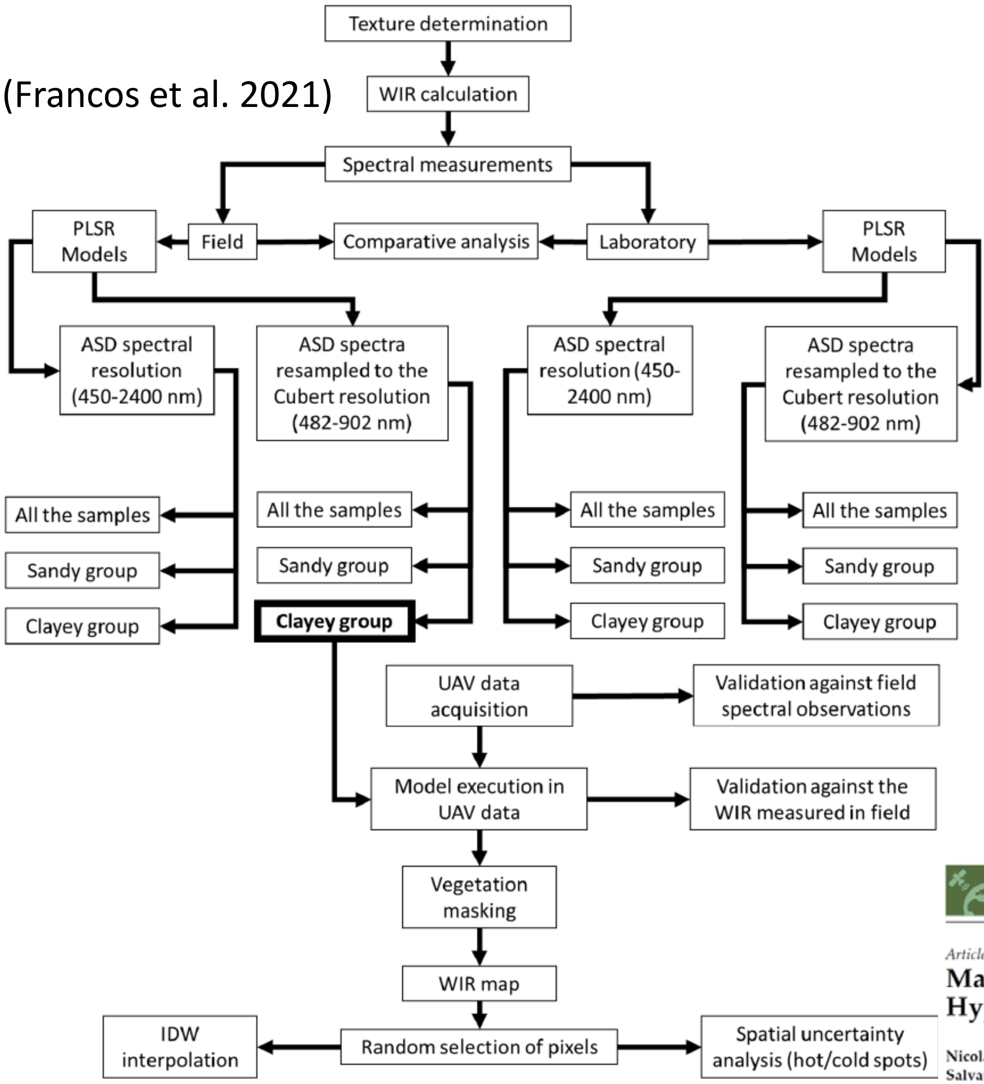
Task 3.1. Training school on the use of the UAS applied to soil moisture estimation: Video Lectures

- Mapping soil properties for UAS-based environmental monitoring
  by Paolo Nasta and Nicolas Francos, https://youtu.be/NYDoIrdB8Bg

- Soil Moisture Retrievals from Unmanned Aerial Systems (UAS)
  by Ruodan Zhuang, https://youtu.be/2_mDpQMnF-o

Task 3.2. Generating a spectral based model to assess soil property.

(Francos et al. 2021)



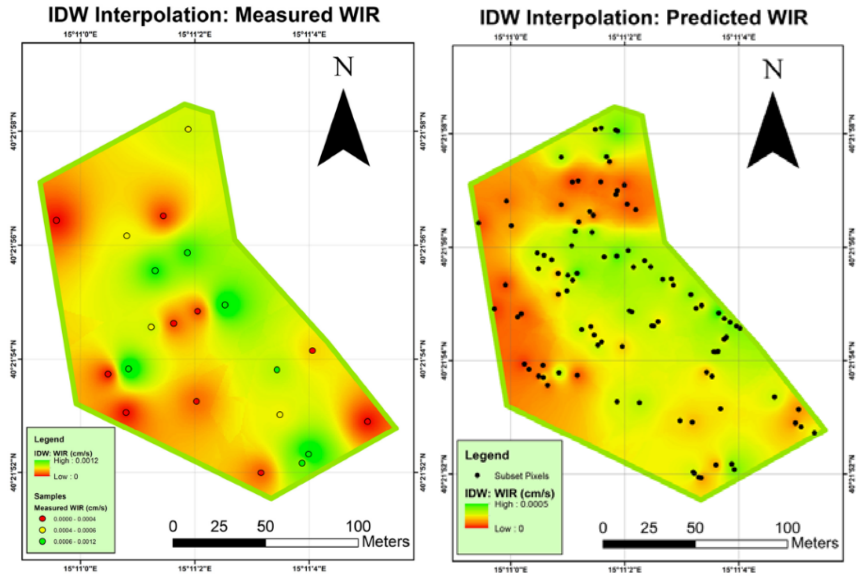


Figure 16. IDW interpolation of the measured WIR in the field using the 21 measurement points in the field assuming no vegetation.

Figure 17. IDW interpolation of the predicted WIR after execution of the spectral-based model on the exposed soil pixels in the hyperspectral image.

30 Mar. 17:05-17:20: Nicolas Francos et al. – Mapping Water Infiltration Rate Using Ground and UAV Hyperspectral Data: A Case Study of Alento, Italy

31 Mar. WG3 meeting, 14:00-14:20 Nicolas Francs et al. – A transfer function to predict soil surface reflectance from laboratory soil spectral libraries

remote sensing

Article

Mapping Water Infiltration Rate Using Grou
Hyperspectral Data: A Case Study of Alento,

Nicolas Francos [1,*], Nunzio Romano [2], Paolo Nasta [2], Yijian Zeng [3], Brig
Salvatore Manfreda [5], Giuseppe Ciraolo [6], János Mészáros [4], Ruodan Zhua
Eyal Ben-Dor [1]

ELSEVIER

Geoderma

Volume 405, 1 January 2022, 115432

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

Nicolas Francos, Eyal Ben-Dor

Task 3.2. Generating a spectral based model to assess soil property.

- Field spectroscopy overperform traditional laboratory spectral measurements, since it preserves the soil-surface status without disruption, which is unavoidable for lab approaches;
- The spectral-based model (based on in-situ measurements) can be used to map soil property, with the hyperspectral imageries from UAS.
- Furthermore, based on the correlation between the field soil spectral library (FSSL), and the traditional laboratory spectral measurement, a transfer function can be established to correct the lab-based spectral measurements, and improve the accuracy in assessing soil property.
- Soil properties (e.g., soil textures, and other physical properties) estimated using spectral-based model could be further combined with Pedotransfer Function to obtain soil hydraulic parameters (e.g., Ksat, SWRC).

Updated European hydraulic pedotransfer functions with communicated uncertainties in the predicted variables (euptfv2)

Brigitta Szabó[1], Melanie Weynants[2], and Tobias K. D. Weber[3]

[1]Institute for Soil Sciences, Centre for Agricultural Research, Herman Ottó út 15, 1022 Budapest, Hungary
[2]European Commission Joint Research Centre, via Enrico Fermi 2749, 21027 Ispra, Italy
[3]Institute of Soil Science and Land Evaluation, University of Hohenheim, Emil-Wolff-Straße 27, 70593 Stuttgart, Germany

Correspondence: Brigitta Szabó (toth.brigitta@atk.hu)

Task 3.3 Inter-comparison among different survey protocols

CHAPTER 8

Soil Moisture Monitoring Using UAS

Ruodan Zhuang [1], Salvatore Manfreda [2], Yijian Zeng[3], Zhongbo Su [3, 4], Eyal Ben Dor[5], George P. Petropoulos[6]

Abstract: Quantification of high-resolution soil moisture (SM) is needed in numerous applications, yet its retrieval remains challenging even today. Unmanned Aerial Systems (UAS) based remote sensing provides a possibility of high-resolution land surface data acquisition. This chapter aims at introducing SM data monitoring approaches using images from sensors mounted on UAS. Four representative approaches (i.e., apparent thermal inertia method, Kubelka–Munk method, simplified temperature-vegetation triangle method, and random forest regression) that differ in the data requirements and applicability, are introduced. The thermal inertia model builds upon the dependence of the thermal diffusion on soil moisture, which can be inferred from thermal infrared (TIR) data. The Kubelka–Munk Model is a spectral model to retrieve surface soil moisture using the available optical (VIS-NIR) data. The simplified temperature–vegetation triangle model can be used to map surface soil moisture and evapotranspiration. In addition, we also introduce a soil moisture downscaling method using the random forest regression model.

Keywords: *soil moisture, (apparent) thermal inertia, Kubelka–Munk model, simplified temperature–vegetation triangle, random forest regression*

remote sensing

MDPI

Review

Current Practices in UAS-based Environmental Monitoring

Goran Tmušić [1], Salvatore Manfreda [2,*], Helge Aasen [3], Mike R. James [4,5], Gil Gonçalves [6], Eyal Ben-Dor [7], Anna Brook [8], Maria Polinova [8], Jose Juan Arranz [9], János Mészáros [10], Ruodan Zhuang [11], Kasper Johansen [12], Yoann Malbeteau [12,13], Isabel Pedroso de Lima [14], Corine Davids [15], Sorin Herban [16] and Matthew F. McCabe [12]

Methods	Input	Output
Thermal Inertia Method	UAS LST, NDVI, albedo, etc.	SSM over bare soil and sparse vegetated area.
Kubelka-Munk Model	Optical (SWIR) reflectance, NDVI, etc	SSM over bare soil area.
Simplified Triangle Model	UAS LST, NDVI, DSM, etc.	SSM over vegetated area and ET.
P dfklqh#Ohduqlqj#) #Ghhs#Ohduqlqj	UAS LST, NDVI, DSM, Coarse resolution Land surface features and SSM, etc.	SSM over bare soil and unshadow area.

31 Mar. WG3 meeting, 15:00-15:20 George Petropoulos et al.: UAS for Soil Water Content and Evaporative Fraction retrievals: An investigation of Ts/VI methods in a Mediterranean setting.

31 Mar. WG3 meeting, 14:20-14:40 Bertalan, L., Holb, I., Pataki, A., Négyesi, G., Szabó, G., Kupásné Szalóki, A., Szabó, S. UAV-based multispectral and thermal cameras to predict soil water content – A machine learning approach

31 Mar. WG3 meeting, 14:40-15:00 Qianqian Han, Lijie Zhang, Ionut Cira, et al.: A ensemble of optimized machine learning algorithms for predicting the soil moisture at global scale.

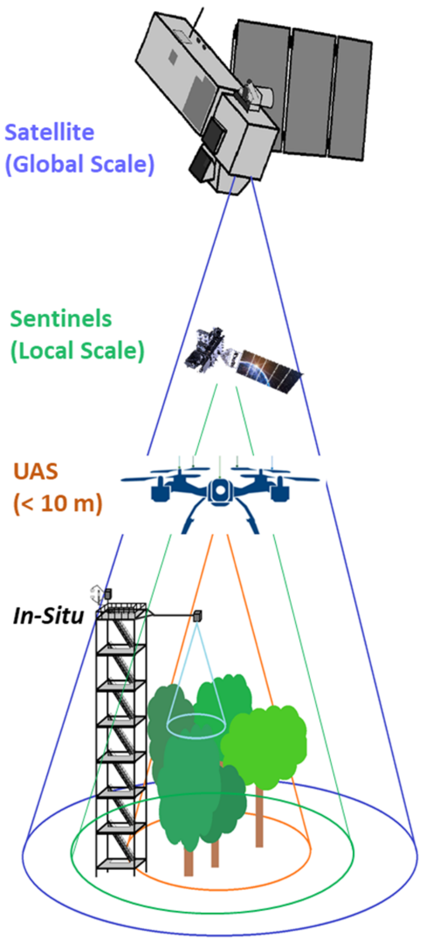
When different SM retrieval models are going to be used, the sensor type and the acquisition time should be well-planned based on the theory and the follow-up processing methodologies.

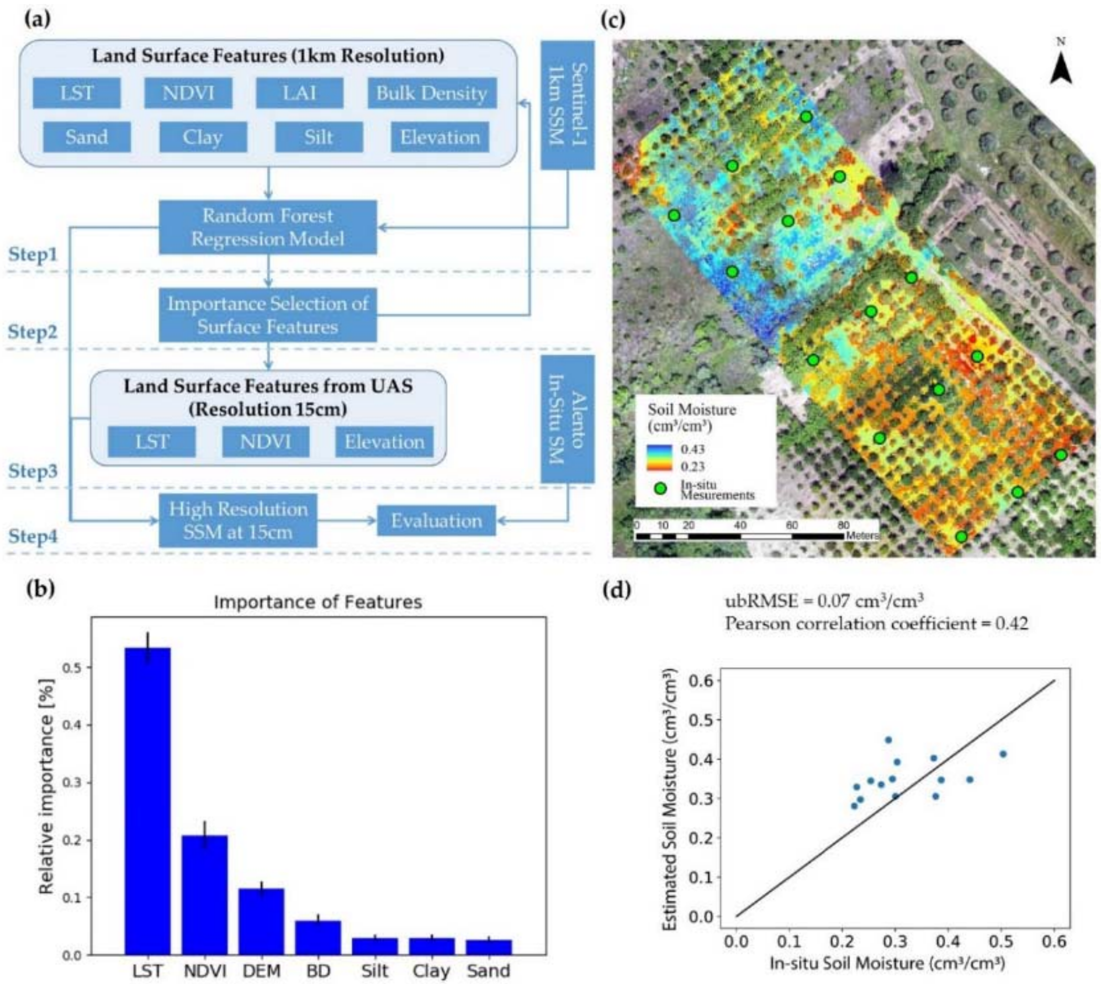
Task 3.3 Inter-comparison among different survey protocols

(Zhuang et al. 2021) Summary of UAS based SM monitoring Methods.

Methods	Sensors; Acquisition Time	Land Surface Information	Conditions; Strength; Limitation
Apparent Thermal Inertia method	-TIR; Sunrise & Noon. - Optical (Red, Green, NIR); Noon.	- LST - NDVI - Albedo	- Surface SM over bare soil and sparsely vegetated areas; - Reliable; - In-situ measurements are required.
Kubelka-Munk method	- Optical (SWIR); Noon.	- Reflectance	- Surface SM; - Simplicity; - Hyperspectral sensor required.
Simplified Temperature-vegetation Triangle method	-TIR -Optical (Red, NIR); Noon.	- LST - NDVI	- Surface SM and evapotranspiration over densely and heterogeneous vegetated areas; - Not require any ancillary parameters and land surface model; - UAS based applications can be developed more.
Random Forest Regression	- TIR - Optical (Red, Green, NIR); Noon.	- LST - NDVI - DSM, etc.	- Surface SM; - Fully use all available data; - Difficult to validate.

Task 3.4 Inter-comparison among different instruments: ground measurements vs. aerial surveys.





water

MDPI

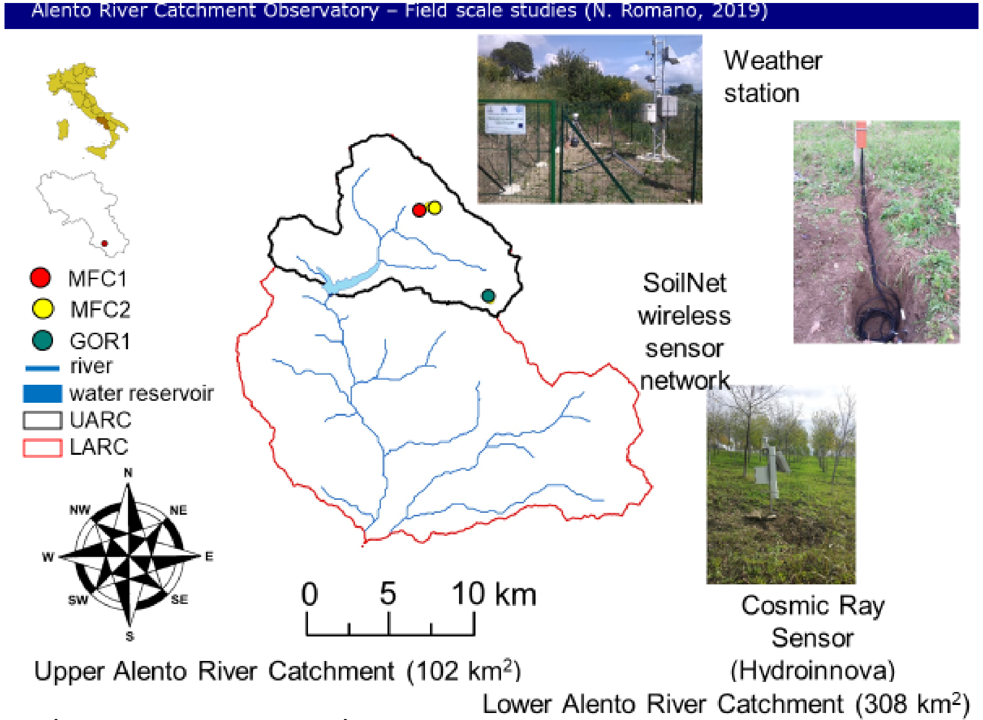
Concept Paper

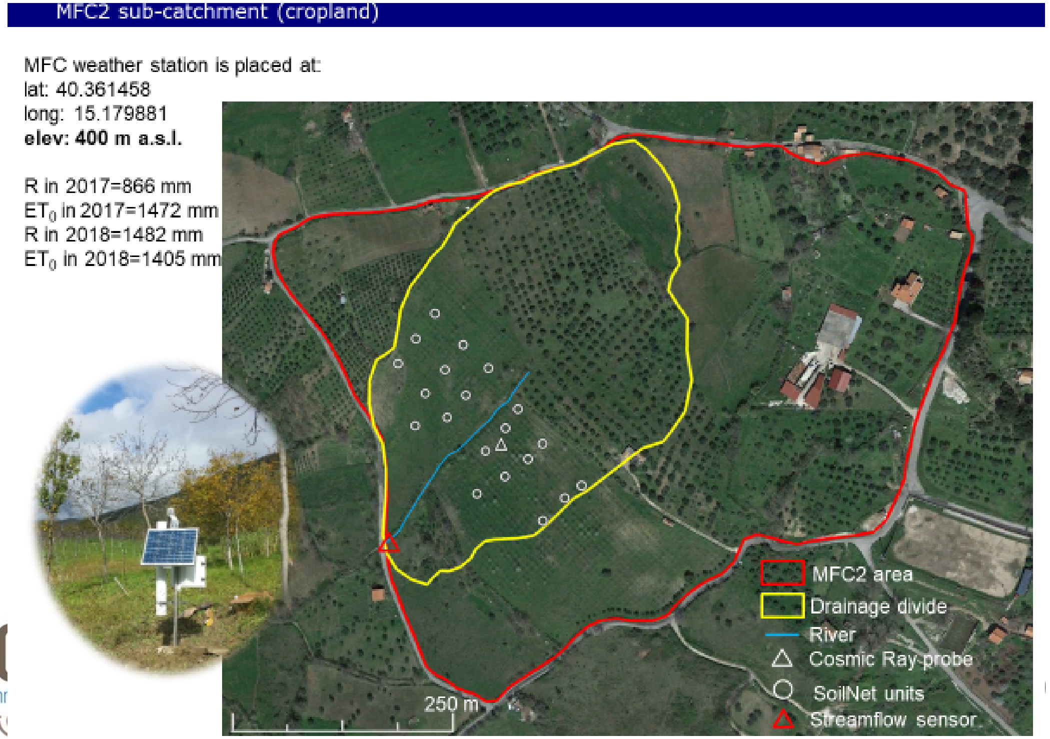
An Integrative Information Aqueduct to Close the Gaps between Satellite Observation of Water Cycle and Local Sustainable Management of Water Resources

Zhongbo Su [1,*], Yijian Zeng [1,*], Nunzio Romano [2,3], Salvatore Manfreda [4], Félix Francés [5], Eyal Ben Dor [6], Brigitta Szabó [7], Giulia Vico [8], Paolo Nasta [2], Ruodan Zhuang [9], Nicolas Francos [6], János Mészáros [7], Silvano Fortunato Dal Sasso [9], Maoya Bassiouni [8], Lijie Zhang [1], Donald Tendayi Rwasoka [1], Bas Retsios [1], Lianyu Yu [1], Megan Leigh Blatchford [1] and Chris Mannaerts [1]

Task 3.4 Inter-comparison among different instruments: ground measurements vs. aerial surveys.

HARMONIOUS/iAqueduct Research Bed (Alento):





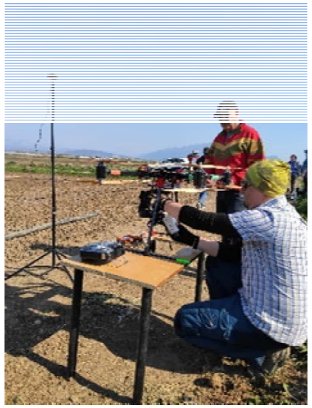
(N. Romano, 2019)

COST EUROPEAN COOPERATION IN SCIENCE & TECHNOLOGY

HARM UAS for environ

Task 3.4 Inter-comparison among different instruments: ground measurements vs. aerial surveys.

Field survey in the area of Sele river catchment (Mar. 20-25, 2022) photos by Brigitta Szabó

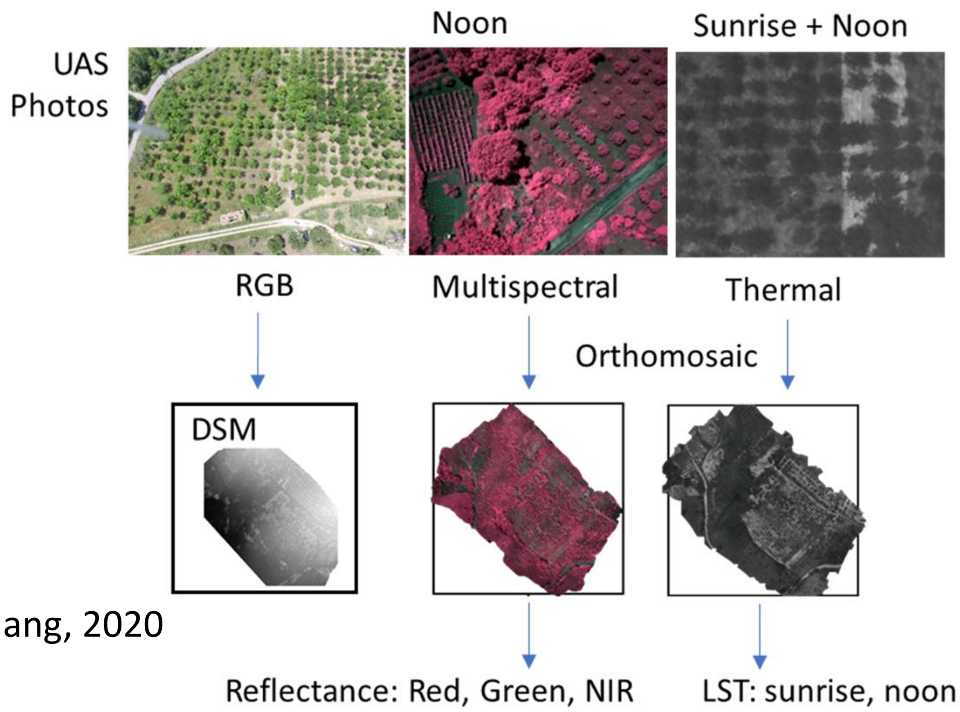




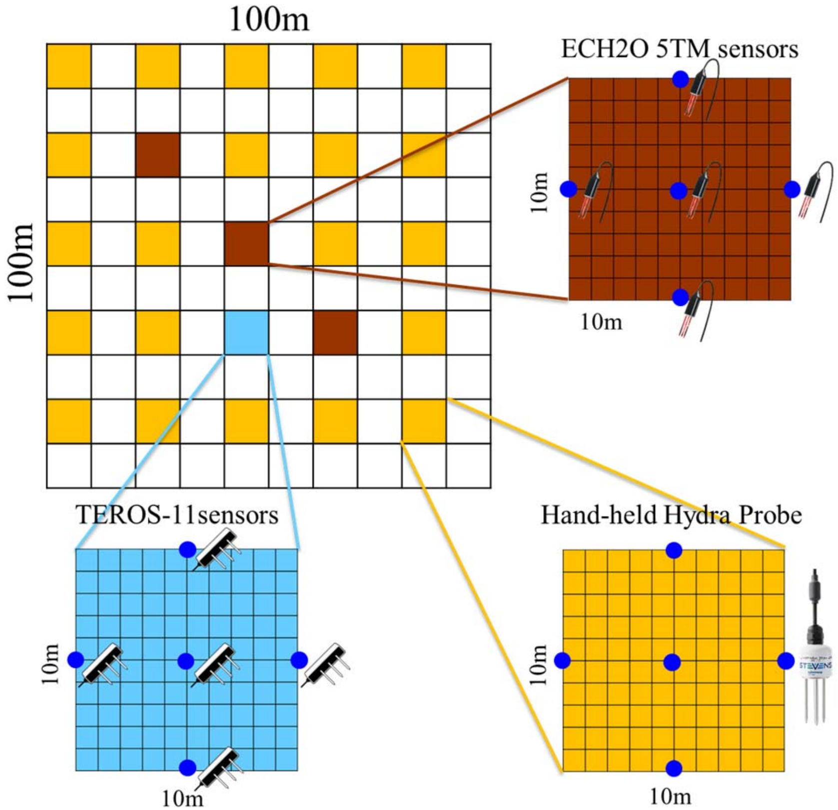



Task 3.4 Inter-comparison among different instruments: ground measurements vs. aerial surveys.

Field survey in the area of Sele river catchment (Mar. 20-25, 2022)



(Zhuang, 2020



WG3: Soil moisture state monitoring using UASs

- *Main aim:* Define a shared methodology to understand the spatial and temporal behaviour of soil moisture over different scales.
- Deliverables 3.1: Guidelines for soil water content monitoring (standard operating procedure) and for comparison of ground measurements with UAS data.

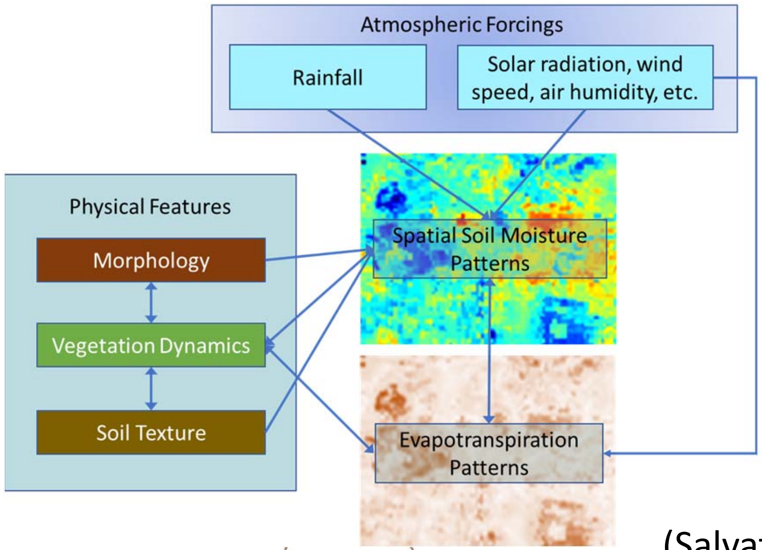
CHAPTER 8

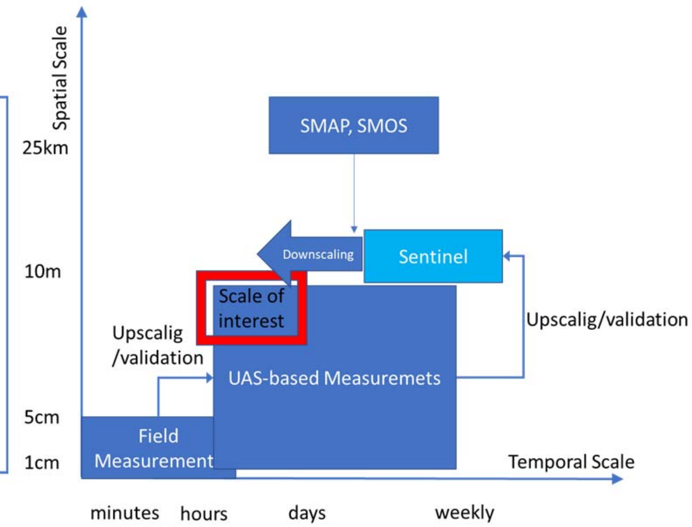
Soil Moisture Monitoring Using UAS

Ruodan Zhuang [1], Salvatore Manfreda [2], Yijian Zeng[3], Zhongbo Su [3, 4], Eyal Ben Dor[5], George P. Petropoulos[6]

Abstract: Quantification of high-resolution soil moisture (SM) is needed in numerous applications, yet its retrieval remains challenging even today. Unmanned Aerial Systems (UAS) based remote sensing provides a possibility of high-resolution land surface data acquisition. This chapter aims at introducing SM data monitoring approaches using images from sensors mounted on UAS. Four representative approaches (i.e., apparent thermal inertia method, Kubelka–Munk method, simplified temperature-vegetation triangle method, and random forest regression) that differ in the data requirements and applicability, are introduced. The thermal inertia model builds upon the dependence of the thermal diffusion on soil moisture, which can be inferred from thermal infrared (TIR) data. The Kubelka–Munk Model is a spectral model to retrieve surface soil moisture using the available optical (VIS-NIR) data. The simplified temperature–vegetation triangle model can be used to map surface soil moisture and evapotranspiration. In addition, we also introduce a soil moisture downscaling method using the random forest regression model.

Keywords: *soil moisture, (apparent) thermal inertia, Kubelka–Munk model, simplified temperature–vegetation triangle, random forest regression*





(Salvatore Manfreda, 2019, at ITC)

Application of SM for calibrating ecohydrological model (TETIS)

	Surface soil moisture	Objective functions	Optimization algorithm	SSM included
Configuration 1	-----	Q (NSE)	SCE-UA	no
Configuration 2	SSM (1km)	Q (NSE) + SSM (NSE)	MOSCEM-UA	Spatially
Configuration 3	SSM (30m)	Q (NSE) + SSM (SPAEF)	MOSCEM-UA	Spatially

From: José Gomis Cebolla, Félix Francés García, Nunzio Romano, and Nasta Paolo.

2015-2016 calibration		2017-2019 validation			
Q	SSM	Q	SSM	ET	Water balance

10 hydro + 2*9 veg

SSM (1km) → SSM (30m)

RF (LST, NDVI, P)

- The inclusion of SSM in model calibration increases the robustness of the model performance.
- Considering different SSM spatial resolutions has an impact in model performance.
- Higher spatial resolution SSM provided better Q performance. In terms of spatial patterns, no clear conclusion is obtained.
- SSM products are not free from errors and inconsistencies.

31.03.2022, 14:00-15:30, WG3 Meeting
https://meet.google.com/nug-kboa-ozm

- **14:00-14:15**: Nicolas Francs et al. – A transfer function to predict soil surface reflectance from laboratory soil spectral libraries
- **14:15-14:30**: Bertalan, László et al. - UAV-based multispectral and thermal cameras to predict soil water content – A machine learning approach.
- **14:30-14:45:** Danyang Yu et al. - Improving sugarcane growth simulations by integrating multi-source observations into a crop model
- **14:45-15:00**: Qianqian Han, Lijie Zhang, Ionut Cira, et al.: A ensemble of optimized machine learning algorithms for predicting the soil moisture at global scale.
- **15:00-15:20**: George Petropoulos et al.: UAS for Soil Water Content and Evaporative Fraction retrievals: An investigation of Ts/VI methods in a Mediterranean setting.
- **15:20-15:30**: Open Discussion