ASSESSMENT OF THE POTENTIAL OF PRISMA HYPERSPECTRAL DATA TO ESTIMATE SOIL MOISTURE

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ABSTRACT

In this research the potential of the PRISMA hyperspectral sensor in comparison with multispectral data (Sentinel-2 MSI and Landsat 8 OLI) was assessed for predicting soil moisture. To this aim, PRISMA, Sentinel-2 and Landsat 8 spectra, resampled according to the spectral bands of each sensor, were simulated from a laboratory soil spectral library.

The soil samples used to create the spectral library were collected from different agricultural areas in Central and Southern Italy. Partial Least Square Regression (PLSR), the Normalized Soil Moisture Index (NSMI) and the Soil Moisture Gaussian Model (SMGM) were employed to calibrate soil moisture (SM) estimation models from the resampled spectra. The prediction accuracy of SM estimation was assessed from statistical metrics.

The best accuracies in retrieving SM were obtained by PLSR using data resampled at PRISMA spectral resolution. A preliminary test of the application of the calibrated models was carried out using real PRISMA and Sentinel-2 data.

Index Terms— soil moisture, PRISMA, PLSR, SMGM, spectral library, hyperspectral

1. INTRODUCTION

Remote sensing approaches for soil moisture (SM) retrieval have shown continuous progress in recent years, both for optical, thermal infrared, and microwave systems [1], [2]. Remotely sensed SM has potential applications in hydrology and agricultural water management, offering spatially continuous observations of SM over vast zones. In this regard, spatialized satellite-based observations can be complementary to point soil moisture measurements collected in situ.

Concerning optical remote sensing, which would offer a higher spatial resolution, as compared to microwave and thermal infrared remote sensing, some studies have proposed and tested a variety of indices for assessing SM [1]. Multivariate chemometric and machine learning methods have been also proposed for modeling SM relationships with remote sensing data [3].

With the current and upcoming availability of hyperspectral satellites data with high signal to noise ratio, such as PRISMA [4], EnMAP [5] and CHIME [6] there are real opportunities to improve the methods to estimate SM from optical sensors. Indeed, the retrieval of topsoil properties in agricultural areas, is an important application domain of these new generation spaceborne hyperspectral sensors, for the improvement of agricultural and environmental management of soils. The retrieval of stable soil properties such as texture and soil organic carbon, is hampered by the confounding effect of soil moisture [7]. Therefore, methods to quantify soil moisture in bare soils, from optical data, are valuable as they could be incorporated in topsoil properties retrieval algorithms for these sensors.

In this study, we calibrated SM estimation models by making use of a specifically developed soil spectral library. We considered two approaches: (i) using PLSR to model SM from laboratory and resampled hyperspectral (PRISMA) and multispectral (Sentinel-2 and Landsat 8) datasets; and (ii) estimating soil moisture content exploiting spectral features via a Soil Moisture Gaussian Model (SMGM) applied to the laboratory dataset and to the dataset resampled at PRISMA resolution. We assess and compare the prediction accuracy for both approaches.

2. MATERIALS AND METHODS

A specific soil spectral library was set-up, for the purpose of calibrating soil moisture retrieval models, therefore including a good diversity of soils in terms of physical and chemical characteristics: clay [5-80%], sand [5-93%], soil organic matter [0.4-6%], $CaCO_3$ [0-22%]. The soil samples were collected in different agricultural fields in Central and Southern Italy, in the areas of Maccarese (41°52’ N, 12°14′ E, 8 m a.s.l.), Castelluccio (42°49’ N, 13°12’E, 1338 m a.s.l.) and Pignola (40°33’ N, 15°45’E, 788 m a.s.l.).

Field campaigns for collecting soil samples in the 0 - 10 cm depth layer were performed over the test sites. In the laboratory, after air-drying and sieving at 2 mm, a subsample was employed for wet analyses in the laboratory and another subsample for spectroscopy measurements. These subsamples were placed in labeled small aluminum bowls, previously painted in black on the interior. They were then thoroughly wetted by carefully pouring water at the edges. Reflectance measurements were performed in a dark room, using an Analytical Spectral Device (ASD) Field Spec Fr Pro covering the 350 – 2500 nm range, equipped with a contact probe with an internal illumination source. The measurements were performed at different dates during the natural soil drying process. At the time of each spectral measurement, the sample weight was recorded. At the end of the measurement cycle, the samples were oven-dried, and the dry weight was recorded, in order to back-calculate the gravimetric soil moisture for each spectral measurement. The protocol used for the measurements strictly followed the Internal Soil Standard (ISS) approach detailed in [8] and [9].

From the laboratory spectral data, four different datasets were obtained: (i) the full spectral data provided by the spectroradiometer (ASD), (ii) spectra resampled according to the PRISMA hyperspectral sensor bands (PRISMA), (iii) spectra resampled according to the Sentinel-2 MSI bands (Sentinel-2), and (iv) spectra resampled to the Landsat 8 OLI bands (Landsat-8).

SM estimation models were calibrated using Partial Least Square Regression (PLSR). A subset of 75% of the data was used for calibration of the model, whereas 25% was used for validation. The subsets were obtained by using a k-means spectral sampling procedure in the R package prospectr. The following spectral pre-treatments were tested: Savitzy-Golay (SG), standard normal variate (SNV), standard normal variate detrend (SNV-detrend), first derivative (FD), and conversion to absorbance (ABS).

For the calculation of normalized difference features, the Normalized Soil Moisture Index (NSMI) was calculated based on the normalized difference values of the wavelengths 1800 and 2119 nm [10]. Subsequently, following the approach by [11], SM content was estimated through fitting an inverted Gaussian function to the continuum in soil spectra, using the SMGM function from the hsdar package in R. The SMGM estimates the water content by fitting a Gaussian function to the continuum points of the spectra in the spectral region between approximately 1500 to 2500 nm. This approach could only be employed for hyperspectral laboratory and resampled PRISMA datasets.

The metrics used for the assessment of the models included relative bias (rBias), coefficient of determination (R^2), root mean squared error (RMSE) and relative RMSE (rRMSE), ratio of performance to deviation (RPD) and ratio of performance to inter-quartile range (RPIQ).

A preliminary validation test was carried out using real PRISMA and Sentinel-2 data, obtained during a ground campaign carried out at Braccagni (Grosseto, Central Italy) on June 4th 2021, in which gravimetric soil moisture was measured on the same day as the satellites overpass. Airborne AVIRIS-NG data were also acquired on the same day.

3. RESULTS AND DISCUSSION

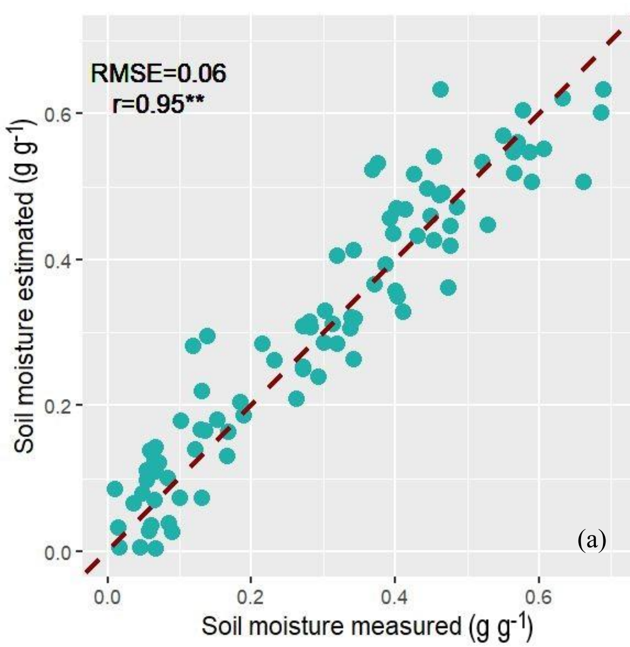
The results of the estimation of SM from laboratory (LAB) and resampled PRISMA, Sentinel-2 MSI and Landsat 8 OLI based on PLSR models are presented in Table 1.

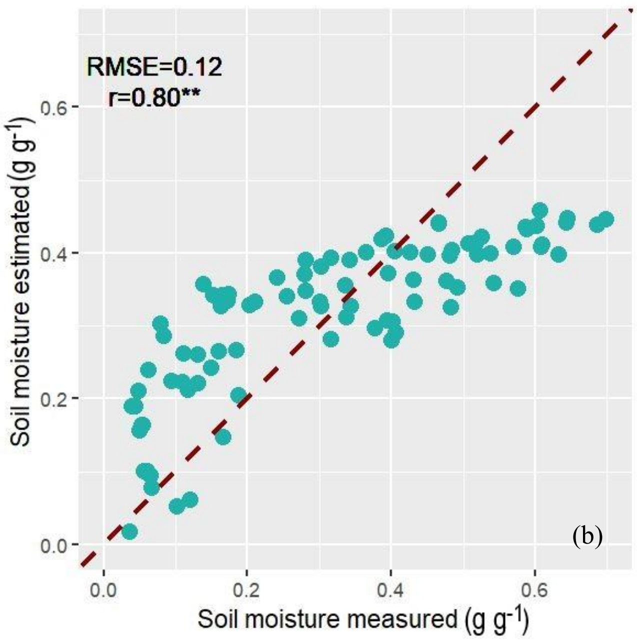
Table 1. Results of soil moisture estimation from PLSR on the validation subset for lab spectra resampled to the different sensor bands.

Sensor	n. comp.	rBias	R^2	RMSE	rRMSE	RPD	RPIQ
		[%]	[-]	[-]	[%]	[-]	[-]
LAB (ASD)	11	0.26	0.93	0.06	4	3.79	6.47
PRISMA	10	-0.69	0.91	0.06	5	3.19	5.07
Sentinel-2	6	1.85	0.64	0.12	11	1.64	2.88
Landsat 8	4	4.87	0.70	0.11	9	1.75	3.07

In the absence of noise, the spectra resampled to PRISMA bands had significantly better results than those resampled to multispectral sensors. Results for the PRISMA data ranged from 0.92 to 0.95 for r and from 0.06 to 0.07 for RMSE, considering the different applied pre-treatments. The best pre-treatment, reported in Table 1, was for SNV. These results are in the same range as the ASD laboratory spectra delivering an r ranging from 0.92 to 0.96 and an RMSE at the level of 0.06 - 0.08.

For the multispectral datasets, Sentinel-2 MSI showed worse results than Landsat, with an R^2 of 0.64 and an RMSE equal to 0.12. However, Landsat data showed a higher bias. Looking at the scatterplots of the predictions (Fig. 1) it is apparent that for the multispectral datasets there is an overestimation for low-medium SM values and an overestimation for high SM values. This does not appear for PRISMA and ASD spectra.





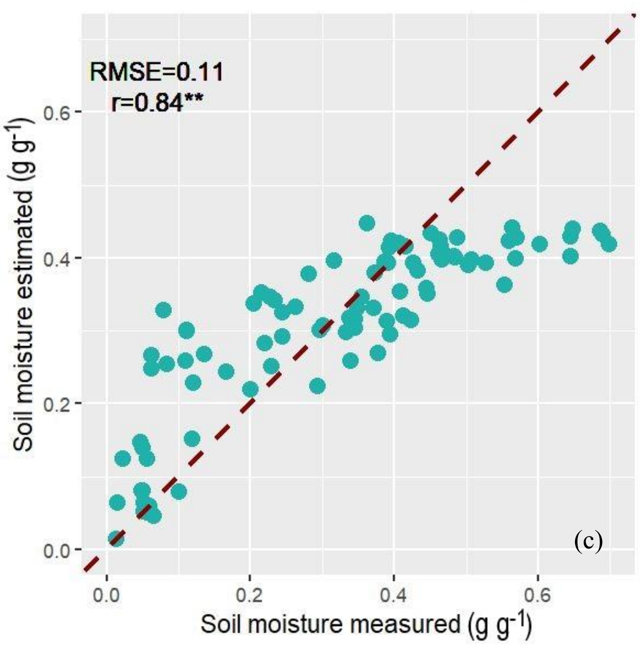


Figure 1. SM model predictions for PRISMA (a), Sentinel-2 (b) and Landsat-8 (c) resampled datasets with PLSR.

Table 2 presents the results obtained using the NSMI for all datasets.

Table 2. Results of soil moisture estimation using the Normalized Soil Moisture Index from linear regression models applied to the validation subset for lab spectra resampled to the different sensor bands.

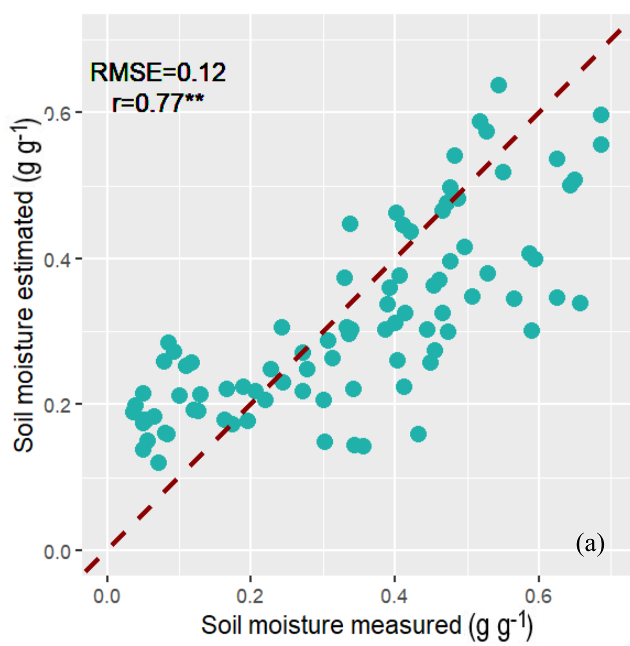
Sensor	Bias	R^2	r	Signif.	RMSE	rRMSE	MAE	RPD	RPIQ
	[%]	[-]	[-]	[-]	[-]	[%]	[%]	[-]	[-]
ASD	1	0.84	0.92	**	0.09	7	29.60	2.38	4.12
PRISMA	0	0.80	0.90	**	0.09	6	30.15	2.27	4.11
Sentinel-2	0	0.72	0.85	**	0.12	10	37.37	1.81	3.43
Landsat 8	-2	0.70	0.84	**	0.11	9	38.29	1.81	2.95

There results were slightly worse than those obtained by PLSR for the hyperspectral datasets, but slightly better for the multispectral datasets. However, by looking at the scatterplots (not shown here for space reasons) it was still apparent that in the multispectral datasets there was a similar behavior as that observed for PLSR, which did not appear for hyperspectral datasets.

The estimation models based on SMGM methods for both laboratory and PRISMA (Table 3) resampled data display a lower estimation accuracy than that of the PLSR based models. In this case, an overestimation occurred at low SM values and an underestimation for high SM values (Figure 2). Haubrock et al. [10], following the same SMGM approach while estimating SM of field-collected samples from laboratory spectral measurements, found similar results (R^2 of 0.61) with NSMI combining reflectance values at 1800 and 2119 nm.

Table 3. Estimation accuracy of soil moisture models derived from laboratory and PRISMA resampled spectra in SMGM estimation models.

Sensor	Bias	R^2	r	Signif.	RMSE	rRMSE	MAE
	[%]	[-]	[-]	[-]	[-]	[%]	[%]
ASD	3	0.59	0.77	**	0.12	10	39.84
PRISMA	1	0.54	0.73	**	0.14	11	41.67



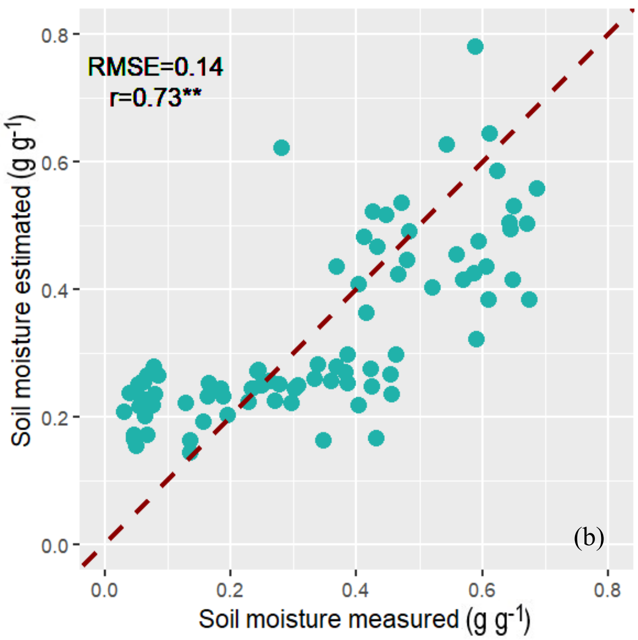


Figure 2. Soil moisture predictions for laboratory (a), and PRISMA (b) resampled dataset in SMGM estimation models.

The preliminary applications with real PRISMA and Sentinel-2 data seemed encouraging. However, during the field sampling date, the soil surface was rather dry and a wider range of soil moisture observations would be required for a more in-depth assessment of the applicability of the models calibrated on the spectral soil library to real data.

4. CONCLUSION

This work investigates the potential of the recently launched hyperspectral satellite PRISMA for the estimation of SM by using PLSR and SMGM models.

We compared the estimation accuracy using resampled spectra according to spectral characteristics of the multispectral (Landsat 8 and Sentinel-2) and the hyperspectral (PRISMA) satellite imagers. We concluded that hyperspectral characteristics of the satellite mission can improve the estimation of SM as compared to the current multispectral imagers, especially using multivariate calibration techniques such as PLSR.

5. ACKNOWLEDGEMENTS

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5. REFERENCES

[1] J. Yue, J. Tian, Q. Tian, K. Xu, and N. Xu, “Development of soil moisture indices from differences in water absorption between shortwave-infrared bands,” ISPRS J. Photogramm. Remote Sens., vol. 154, pp. 216–230, Aug. 2019.

[2] W. Liu, F. Baret, G. Xingfa, T. Qingxi, Z. Lanfen, and Z. Bing, “Relating soil surface moisture to reflectance,” Remote Sens. Environ., vol. 81, no. 2–3, pp. 238–246, 2002.

[3] A. M. Mouazen, R. Karoui, J. De Baerdemaeker, and H. Ramon, “Characterization of Soil Water Content Using Measured Visible and Near Infrared Spectra,” Soil Sci. Soc. Am. J., vol. 70, no. 4, pp. 1295–1302, Jul. 2006.

[4] S. Cogliati et al., “The PRISMA imaging spectroscopy mission: overview and first performance analysis,” Remote Sens. Environ., vol. 262, no. April, 2021.

[5] L. Guanter et al., “The EnMAP spaceborne imaging spectroscopy mission for earth observation,” Remote Sens., vol. 7, no. 7, pp. 8830–8857, 2015.

[6] R. Casa, S. Pignatti, S. Pascucci, W. Huang, and M. Pepe, “Effect of spatial resolution on soil properties retrieval from imaging spectroscopy: an assessment of the hyperspectral CHIME mission potential,” in IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium, Submitted, 2020.

[7] F. Castaldi, A. Palombo, S. Pascucci, S. Pignatti, F. Santini, and R. Casa, “Reducing the Influence of Soil Moisture on the Estimation of Clay from Hyperspectral Data: A Case Study Using Simulated PRISMA Data,” Remote Sens., vol. 7, no. 11, pp. 15561–15582, Nov. 2015.

[8] E. Ben Dor, C. Ong, and I. C. Lau, “Reflectance measurements of soils in the laboratory: Standards and protocols,” Geoderma, vol. 245–246, pp. 112–124, 2015.

[9] S. Chabrillat et al., “Preparing a soil spectral library using the Internal Soil Standard (ISS) method: Influence of extreme different humidity laboratory conditions,” Geoderma, vol. 355, no. December 2018, 2019.

[10] S. N. Haubrock, S. Chabrillat, C. Lemmnitz, and H. Kaufmann, “Surface soil moisture quantification models from reflectance data under field conditions,” Int. J. Remote Sens., vol. 29, no. 1, pp. 3–29, 2008.

[11] M. L. Whiting, L. Li, and S. L. Ustin, “Predicting water content using Gaussian model on soil spectra,” Remote Sens. Environ., vol. 89, no. 4, pp. 535–552, Feb. 2004.