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Abstract

Surface soil moisture evaluated from satellite multispectral optical data through Visible and Shortwave Drought Index and its comparison with microwave-based soil moisture products †

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Abstract: Soil moisture is a key parameter in several applications, from land management to emergency response. Microwave-based soil moisture products are already provided daily, yet at 1 km resolution. Optical remote sensing could be a complementary source of information at higher spatial resolution (10-100 m), but most studies have been limited to highly homogeneous scenarios. In this paper, the potential of optical images to assess soil moisture in a highly-fragmented scenario is investigated. Landsat-8 optical data were processed to retrieve the Visible and Shortwave Drought Index (VSDI) over an area with heterogeneous land cover. Results were compared with the Copernicus Soil Water Index (SWI) product, showing a moderate correlation (Pearson coefficient equal to 0.402) that however increases to 0.668 if only bare soil pixels are selected.

Keywords: Earth Observation, soil moisture, optical data, Landsat-OLI, multitemporal analysis, agro-forestry applications

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1. Introduction

Soil moisture is a key parameter in several application fields, from water supply management to agriculture, from prevention and mitigation of extreme events like floods, fires, droughts, to climatological and hydrological studies [1].

Remote sensing techniques offer considerable advantages for providing information useful to assess soil moisture content and for monitoring its distribution and temporal evolution from regional to global scale. Microwave (MW) remote sensing techniques and methods can be regarded as an already well-established tool to assess soil moisture content, although in some cases the results can be affected by vegetation cover and soil roughness [2]. While methods based on microwave remote sensing from satellite have already achieved a high degree of maturity providing daily soil moisture products at 1 km spatial resolution, optical remote sensing has been proposed as a complementary source of information at higher spatial resolution (10-100 m) in several studies. The latter, however, have mainly been conducted in controlled conditions or very specific scenarios [3]. Thus, the actual capability of optical remote sensing in a complex, highly fragmented real case scenario is still an open issue.

In this paper, we analyze a multitemporal sequence of Landsat-8 images to compare the performances of the Visible and Shortwave Infrared Drought Index (VSDI) that in a previous study [4] resulted to be the most promising among others indexes for soil moisture evaluation in an agricultural area with heterogeneous land cover. In particular, here we compare the performance of VSDI with the Soil Water Index (SWI) Copernicus product [5] that has a higher spatial resolution (1 km) with respect to Global Land Data

Assimilation System (GLDAS) 2.1 used in [4].

2. Materials and methods

2.1. Study area

The study area (Figure 1a) is an agricultural area, featuring cultivated fields and also forested patches and it is located in the South-Western Tuscany, near Grosseto, Italy (Long. 11.2515-11.519 E, Lat. 42.525-42.00 N). It corresponds to an area of about 20 km x 20 km.

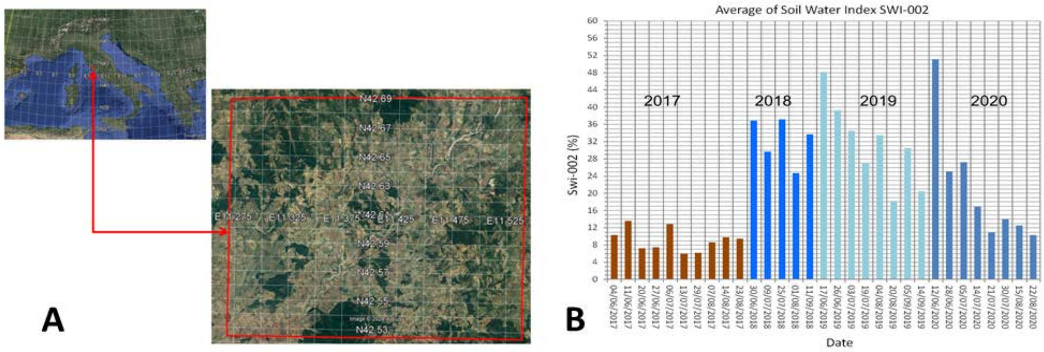

Figure 1. a) Study area. b) Average SWI-002 surface moisture of the study area.

2.2. Data

The dataset is a multi-temporal sequence of 31 images acquired over the study area in the summer season (June to September) from 2017 to 2020 by the Operative Land Imager (OLI) sensor. The latter operates on board the Landsat-8 and has a spatial resolution of 30 m with 9 spectral channels in the visible, near infrared and the Short Wavelength Infrared (SWIR). The images, have already been preprocessed at L2 level by NASA. All the images have a cloud coverage lower than 10%.

The validation dataset is constituted by the surface moisture information provided daily by the Copernicus SWI-002 (Soil Water Index at surface level) product, based on the MW images acquired by the ASCAT and SAR sensors operating on the METOP and Sentinel-1 platforms, respectively, as described in [5]. Figure 1b shows the average value of surface soil moisture evaluated in the study area by the SWI-002 index in correspondence with the Landsat acquisition days during the summer season of 2017-2020.

2.3. Methodology

The images were co-registered with SWI-002 moisture maps and segmented in four classes (bare soil, vegetation, clouds, cirrus, cloud shadow areas). The images were processed with a low-pass filter with an adequate transfer function to simulate an acquisition with a spatial resolution of 1 km, consistent with SWI-002 Copernicus images. The images were then masked in order to retain only bare soil and vegetated areas.

3. Results

The whole dataset – constituted by 31 images - was used to generate surface moisture maps by applying the VSDI algorithm [6]. The whole set of VSDI values was compared to the corresponding whole set of SWI values (pixel by pixel, for each map) and the correlation of the whole VSDI dataset was evaluated against the whole SWI dataset by means of the Pearson coefficient. The same procedure was also applied to the three data subsets: (1) only vegetated pixels, (2) bare soil and poorly vegetated pixels, and (3) only bare soil pixels. These subsets were selected by means of suitable Normalized Difference Vegetation Index (NDVI) threshold values applied to the dataset [7, 8, 9].

Table 1 reports the Pearson correlation coefficients obtained for the whole dataset and for the three additional sub-sets containing different proportions of vegetated and of bare soil pixels. It is apparent that the correlation between the (optical-based) VSDI data and the (MW-based) SWI data increases considerably when applied to bare soil areas: Pearson correlation coefficient increases up to 0.668 for the bare soil pixels subset.

Table 1. Pearson correlation coefficient between SWI and VSDI for the whole dataset and different data subsets with different number of pixels corresponding to bare soil areas.

	VSDI	VSDI NDVI>0.4	VSDI NDVI≤0.4	VSDI NDVI≤0.35
Dataset	whole dataset	only vegetated areas	bare soil and poorly vegetated areas	bare soil
Pearson coefficient	0.402	0.419	0.630	0.668
Number of pixels	17305	10379	6866	3250

The normalized VSDI values and the SWI values, ranging from 0 to 1 and from 0 to 100 respectively, were divided into 20 classes. Figure 2 shows three-dimensional SWI-VSDI scatterplots that report the number of pixels (z-axis) of the whole dataset belonging to each SWI-VSDI class pair. These scatterplots highlight the lower correlation for the whole dataset (Figure 2a) compared to the subset with bare soil pixels (Figure 2b) that has a lower data dispersion. Vegetation effects have further been investigated and accounted for by assimilating vegetation-related parameters, leading to preliminary results with an improvement of the Pearson correlation coefficients up to 0.80.

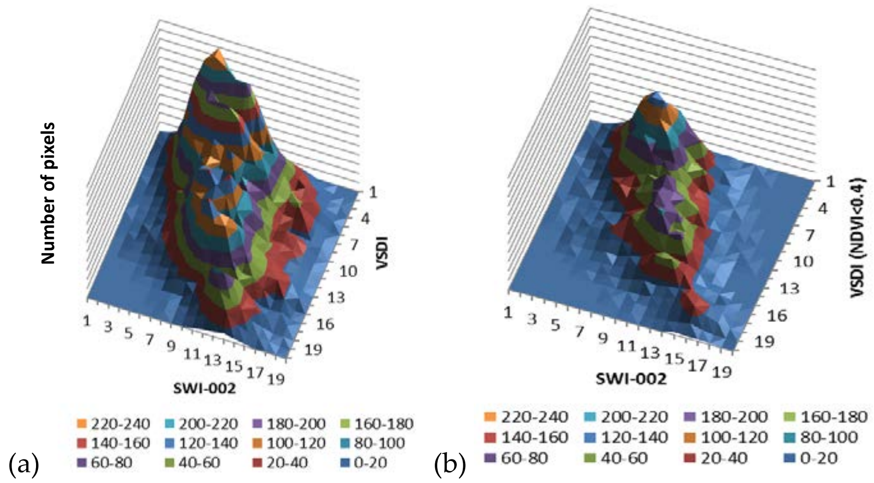

Figure 2. 3D scatterplots of SWI-VSDI classes for: (a) whole dataset, and (b) only bare soil pixels.

4. Conclusions

VSDI values calculated on a multitemporal sequence of Landsat images, acquired in an agricultural area with heterogeneous land cover, showed a moderate correlation (Pearson coefficient equal to 0.402) with Copernicus-provided SWI data at a spatial resolution of 1 km. The correlation however increased considerably if only bare soil pixels are selected, reaching a value of 0.668. This demonstrated a considerable effect of vegetated areas on the results. In the next steps, the assimilation of vegetation-related parameters will be considered to mitigate this effect and improve the correlation between optical-based and MW-based soil moisture data.

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Data Availability Statement: The original data presented in the study are openly available at https://earthexplorer.usgs.gov and https://land.copernicus.eu/en/products/soil-moisture?tab=soil_water_index.

Conflicts of Interest: The authors declare no conflicts of interest.

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