Mapping within-field soil water condition using Sentinel 2

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***Abstract*—Soil and crop water condition monitoring is a fundamental step in agricultural production. There are different methods to measure water stress, some of them are based on soil moisture measurements while others are based on calculations of vegetation indices, evapotranspiration or soil water balance. Currently, the use of remote sensing technologies for the analysis of plant water status comprises a wide range of available methods such as infrared thermometry for canopy temperature measures, microwave radiation for soil water content assessment, and spectral vegetation indices for the study of the reflectance responses of canopies to different environmental conditions. The aim of the presented work is to investigate the applicability of the optical remote sensing in mapping the moisture content within agricultural field.**

Keywords—Sentinel-2, NDVI, NDWI, OPTRAM, water stress monitoring

I. Introduction

Growth and reproduction of crops strongly depends on their environment, and any change in environmental conditions that determines a shift from the crop's optimal state can be considered as stressful. Water is a very important factor in agriculture and plays an essential role in crop production throughout the growing season. Water is required for the germination of seeds and as soon as growth starts water serves as a carrier in the distribution of mineral nutrients. Biomass production is inseparably connected with water demand. Many of the biochemical reactions that are part of growth occur in water or water itself participates in the reactions, e.g: respiration, photosynthesis.

Water is a vital component in the functioning of plants and soil moisture is the dominant factor controlling its supply [1]. So that information on water stress conditions and their analysis is necessary to achieve optimal outputs. Crop water stress monitoring represents a fundamental step in agricultural production, measures of plant water status are required to better understand the mechanisms of plant response and adaptation to water stress, and for the optimisation of crop production [2], through precision irrigation. In order to increase water savings and enhance agricultural sustainability, implementation of suitable irrigation scheduling methods is essential [3], and requires early detection of water stress in crops, before it causes irreversible damage and yield loss.

There are different methods to measure water stress, some of them are based on soil moisture measurements while others are based on calculations of vegetation indices, evapotranspiration or soil water balance. Conventional methods for monitoring crop water stress rely on in situ soil moisture measurements and meteorological variables to estimate the amount of water lost from the plant-soil system during a given period [4]. Other methods of detecting plant water status involve soil water balance calculations, direct and indirect measurement of plant water status, via stomatal conductance and leaf water potential. The disadvantage of measurements based on soil sampling is that these methods are time consuming and produce point information.

Currently, the use of remote sensing technologies for the analysis of plant water status comprises a wide range of available methods such as infrared thermometry for canopy temperature measures, microwave radiation for soil water content assessment, and spectral vegetation indices for the study of the reflectance responses of canopies to different environmental conditions. Soil optical reflection [5, 6], thermal emission [7, 8] and microwave backscatter [9, 10] are highly correlated with soil moisture content, numerous methods for optical, thermal and microwave RS of soil moisture have been developed.

Numerous studies are based on the calculation and analysis of spectral indices and have shown that there is relationship between reflectance values and canopy changes due to water stress. Measures reflectance indices within the VIS and NIR spectral range (e.g.: NDVI, RDVI, OSAVI) to indicate canopy changes due to water stress. Some indices (e.g.: PRI) are sensitive to the photosynthetic pigment changes due to water stress and others are used to measure the reflectance trough in the NIR and SWIR region (WI, SRWI, and NDWI) to represent canopy moisture content.

The so-called "trapezoid" or "triangle" model is one of the most widely applied approaches to RS of soil moisture utilizing both optical and thermal data. The model, hereinafter termed Thermal-Optical TRAapezoid Model (TOTRAM), is based on the interpretation of the pixel distribution within the land surface temperature-vegetation index space [11, 12]. Sadeghi et al. [13] proposed a novel physically-based trapezoid model, so called OPtical TRApezoid Model (OPTRAM), which is based on a relationship between soil moisture and shortwave infrared transformed reflectance. The theoretical basis of OPTRAM, evaluate the predictive capabilities of the universally parameterized OPTRAM with Sentinel-2 and Landsat OLI observations was presented in 2017.

The research presented in the article focus on the exploitation of Visible, Near Infrared and Short Wave Infrared

(SWIR) reflectance properties for the construction of vegetation and water indices and use of the optical trapezoid model targeted (OPTRAM) to the estimation of soil water content within field. The aim of the work is to investigate the applicability of the model in the examination and mapping of the moisture content of smaller areas (agricultural field). The model ability to provide plant physiology, vegetation characteristics, and crop water status at the canopy scale can improve the site-specific decision-making process in a precision agriculture.

II. Materials and Methods

The model ability to provide crop water status at the field level was tested on a relatively small agricultural area. From a pedological point of view, the study area has average properties. Its humus content does not exceed 1-2%. The area has varied topographic features, the west part is heavily eroded. During the study period (2017-2018) the area was covered by winter wheat.

A. *Satellite images and data analysis*

Multispectral ESA Sentinel-2 satellite images acquired from the ESA Sentinel Scientific Data Hub were used in this study. A total of 17 cloud-free images were available, but after preliminary interpretation, 7 of them were selected for further processing. Sentinel-2 is a high spatial (10 to 60-m) resolution multispectral satellite having 13 spectral bands covering the visible, NIR and SWIR electromagnetic frequency domains and temporal resolution of ~5-day. The characteristics of the data used in the research include the Table 1.

TABLE I. THE SPECIFICATION OF REMOTE SENSING DATA

Datasets	The specification of RS data	
	Spectral resolution	*Acquisition date*
Sentinel-2	VIS, NIR, SWIR (bands: 3, 4, 8, 12)	2017 (Nov.19, Dec. 19.) 2018 (Jan. 18, Mar. 24, Apr. 13, May 13, Jun. 12)

The data extraction includes the following steps: data pre-processing, multi-level image segmentation, delimitation of indices and the application of the optical trapezoid model OPTRAM. It is important to note that the Sentinel-2 Level-1C processing includes radiometric and geometric corrections including ortho-rectification and spatial registration on a global reference system with sub-pixel accuracy. Calculation of the TOA (the top-of-atmosphere) reflectances also occurs in this process. Hierarchical framework was used to identify the boundary of study area at super-object level and determine the unit of investigation (20 m) at the second level for mapping surface moisture. After pre-processing vegetation index (NDVI) and (STR) were determined. Reflectance at the red band (B4: 665 nm) and the near infrared (B8: 842 nm) were used to calculate the NDVI. Reflectance at the SWIR band (B12: 2190 nm) was used for calculation of the STR following the Sadeghi et al. [14].

By measuring the reflectance of the plants or soil at various wavelengths, it is possible to collect a lot of information about the status of the plants and soil properties. The reflectance of light spectra depends on the land cover type (plant, soil types), water content within tissues, and other intrinsic factors. The reflectance of vegetation is low in the blue and red regions of the visible spectrum, due to absorption by chlorophyll for photosynthesis. It has a peak at the green region which gives rise to the green colour of vegetation. In the near infrared (NIR) region, the reflectance is much higher than that in the visible band due to the cellular structure in the leaves. In the mid infrared (SWIR) there are more water absorption regions (Fig. 1). Those regions are used to examine correlation between root zone soil moisture and the vegetation status.

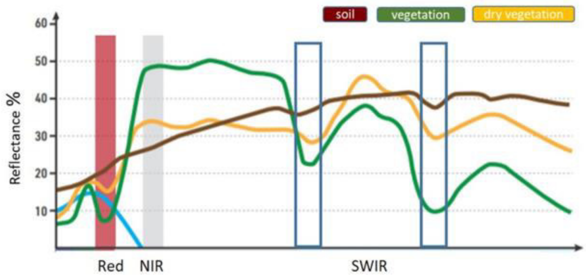

Fig. 1. Spectral reflectance of vegetation and soil with different levels of water content (yellow line: dry vegetation). The spectral bands used to calculate the indices are highlighted.

Based on RED, NIR and SWIR bands different indices are calculated to quantify plant vigour and relate it to root zone soil moisture. The soil moisture status influences the vegetation water status and thereby changes the spectral characteristics of the vegetation.

The most common vegetation index used in the water stress models (e.g.TOTRAM) is the Normalized Difference Vegetation Index (NDVI).

The water-absorption bands in the 1300–2500 nm region show the highest sensitivity to leaf water concentration in most crops. Short infrared is very sensitive to the water contained in the object whether it is soil or vegetation. NDWI (Normalized Difference Water Index) is one of the popular indicators of this kind of investigations.

B. *The vegetation and water indices*

During the quantitative interpretation of remote sensing information from vegetation can be created by extracting vegetation information using individual light spectra bands or a group of single bands for data analysis. Vegetation indices use various combinations of multispectral satellite data to produce single images representing the amount of vegetation present, or vegetation vigour. They can reduce the data volume for analysis and provide combined information that is more strongly related to changes than any single band. The construction of VI algorithms are effective tools to measure vegetation status. Vegetation information from remote sensed images is mainly interpreted by differences and changes of the green leaves from plants and canopy spectral characteristics. The data from near infrared (0.7–1.1 m) and red (0.6–0.7 m) or other bands are combined in different ways according to their specific objectives. As the population of plants increases, the amount of biomass causes an increase in the overall near-infrared reflectance and a reduction in the red reflectance. From previous research, there are known relationships between the indices using those two regions of the spectrum and the amount of vegetation. By calculating the Normalized Difference Vegetation Index (NDVI we can get information on the crops' vigour (Fig. 2). Low index values usually indicate little healthy vegetation while high values indicate much healthy vegetation.

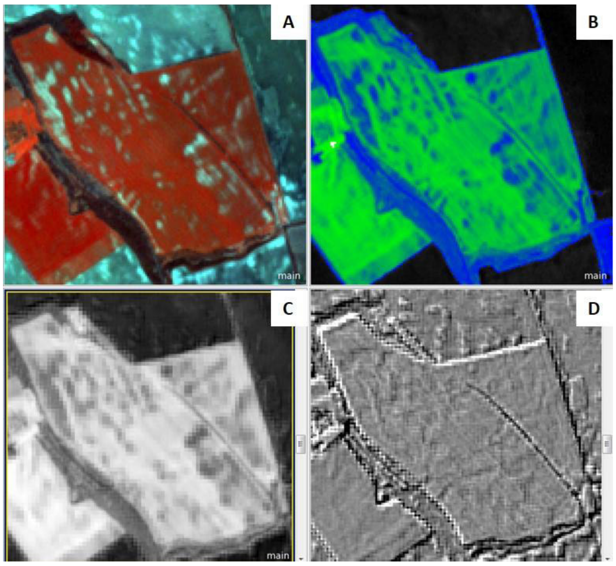

Fig. 2. A: Satellite image (Sentinel 2: fals coloure composition), B: NDVI, C: NDMI, D: NDRE (Normalised Difference Red Edge Index).

The NDWI is used to monitor changes related to water content in water bodies. As water bodies strongly absorb light in visible to infrared electromagnetic spectrum, NDWI uses green and near infrared bands to highlight water bodies. Index values greater than 0.5 usually correspond to water bodies. Vegetation usually corresponds to much smaller values.

NDWI index is often used synonymously with the NDMI index, often using NIR-SWIR combination as one of the two options. NDMI seems to be consistently described using NIR-SWIR combination (Fig. 2). As the indices with these two combinations work very differently, with NIR-SWIR highlighting differences in water content of leaves, and GREEN-NIR highlighting differences in water content of water bodies.

NDRE (Normalized Difference Red Edge) this index is more appropriate than NDVI index for intensive management applications throughout the crop growing season. It is a modification of the NDVI index, however works as a better measure of vegetation health than NDVI especially for mid-late season crops that have elevated levels of chlorophyll because VRE bands are more translucent to leaves than red light and hence is seldom completely absorbed by a canopy.

C. The optical trapezoid model (OPTRAM)

The traditional trapezoid model, TOTRAM, is based on the pixel distribution within the Land Surface Temperature-Vegetation Index space (LST-VI). An inverse linear relationship between surface soil moisture and LST is then assumed (Fig. 3).

The OPtical TRApezoid Model (OPTRAM) was developed for Soil Water Content (SWC) estimation making use of optical satellite data, and is based on the linear physical relationship between soil moisture and Shortwave Infrared Transformed Reflectance (STR) [14].

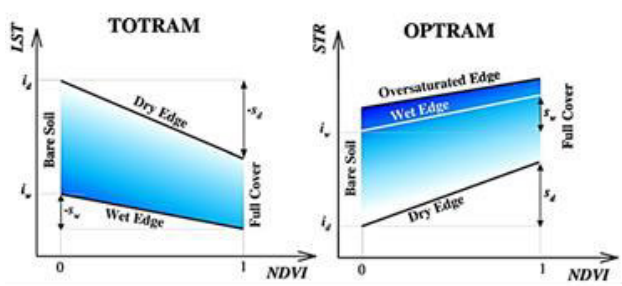

Fig. 3. Sketch illustrating parameters of the traditional thermal-optical trapezoid model (TOTRAM) and the new optical trapezoid model (OPTRAM) [14].

OPTRAM requires a parametrization at a given location based on the pixel distribution within STR-NDVI space (Fig. 3), where STR is the Shortwave Infrared Transformed Reflectance defined as follow:

$$STR = (1 - R_{SWIR})^2 / (2 R_{SWIR}) \quad (1)$$

The model parameters can be obtained for a specific location from the dry and wet edges of the optical trapezoid depicted in (Fig. 3)

$$STR_d = i_d + sd_{NDVI} \quad (2)$$

$$STR_w = i_w + swNDVI \quad (3)$$

where STR_d and STR_w are the STR at θ_d and θ_w, respectively.

The soil moisture for each pixel can be estimated as a function of STR and NDVI:

$$W = \frac{i_d + s_d NDVI - STR}{i_d - i_w + (s_{d} - s_w)NDVI} \quad (4)$$

where i_d, s_d, and i_w, s_w are dry and wet edges parameters.

III. Results and Discussion

The OPTRAM model Eq. (4)] was parameterized based on the pixel distribution within the STR-NDVI space. The model was run separately for each available images, also one integrated trapezoid incorporating pixel distributions from all selected images was used to try universally parameterized.

During the work dry (id and sd) and wet (iw and sw) edges were determined by visual inspection of the STR-NDVI spaces so that the trapezoids surrounded the majority of the pixels (Table 2). From id and sd (dry edge parameters) and iw and siw (wet edge parameters), the normalized moisture content, W, was estimated for each pixel with Eqs. (1,2,3,4). The results are illustrated in the Fig. 4.

TABLE II. OPTRAM parameters obtained for the study area (agricultural field) based on Sentinel-2 (2018)

Data	Dry edge i_d	Dry edge s_d	Wet edge i_w	Wet edge s_w
2018.01.18	3.8	1.2	4.6	0.9
2018.04.08	0	0.5	1.8	2.9
2018.06.12	3.5	1	4.6	2.4

Pixel distributions within the STR-NDVI space for 2 images (as example) are depicted in Fig. 4. Corresponding model parameters are listed in Table II. According to the study results a trapezoidal shapes were formed by the pixels in the

STR-NDVI space in all cases. The normalized moisture content (W), was estimated for each images.

Soil moisture variability within the field are clearly detected by using this model. However, far-reaching conclusions cannot be drawn. Further research is needed. Currently, additional agricultural areas have been included in the research, and devices suitable for meteorological measurements have been placed in the area. Field measurements are absolutely necessary to continue the study and validate the results.

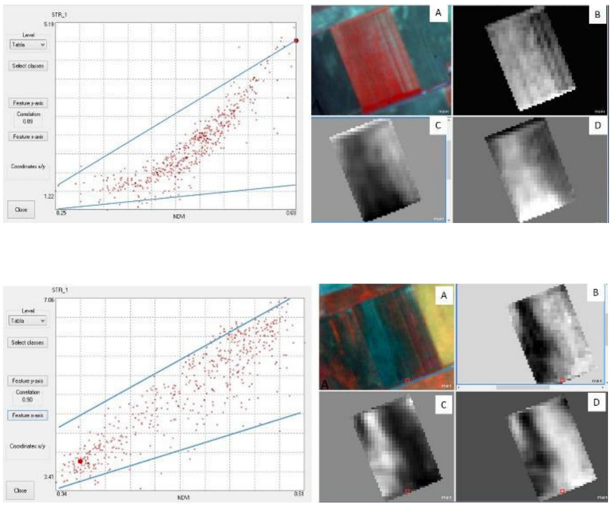

Fig. 4. Pixel distributions within the STR-NDVI space for images (2018 Apr. and Jul.) A: false colour composition, B: NDVI, C: B12 values, D: W values (OPTRAM)

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