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Optimizing data collection in precision agriculture – comparing remote sensing and *in situ* analyses

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Abstract

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Remote sensing has a potential application in assessing and monitoring the plants' biophysical properties using the spectral responses of plants and soils within the electromagnetic spectrum. However, only a few reports compare the performance of different remote sensing approaches against in-situ spectral measurement. The current study assessed potential applications of open data source satellite images (Sentinel 2 and Landsat 9) in estimating the biophysical properties of a crop on a study farm. A Landsat 9 (30 m resolution) and Sentinel-2 (10 m resolution) satellite images with less than 10% cloud cover have been extracted from the open data sources for the period of December 2021 – April 2022. In addition, SpectraVue 710s Leaf Spectrometer was used to measure the spectral response of the crop in April at five different locations within the same field. Results obtained by different data collection methods were compared to evaluate them for applicability in precision agriculture.

Keywords: precision agriculture; vegetation indices; NDVI

Introduction

Agriculture has evolved since its inception for over thousands of years with significant advancement in agricultural practices following the industrial revolution since the 1700s (Thrall et al. 2010).

Despite the benefit of integrating latest advancements from different sectors until now the agriculture sector has been slow to harness the power of these technologies. Adequate application of agricultural practices is highly dependent on information available to the decision-makers. The availability of updated weather data (precipitation and temperature, flood/drought), physically based and remotely sensed crop data, updated market information, and the latest agricultural approaches has been demonstrated to substantially improve production and productivity (Darnhofer et al. 2010).

Remote sensing is a method of capturing, storing, and analyzing the information gathered from a distance without getting in touch with the object (Lillesand et al. 2015). It allows for the analysis of a multispectral images that is useful for identifying and characterizing different Earth features, including soil, vegetation, and water. This technology allows for monitoring of the farming practices, identifying potential plant stress, and selecting and applying different management approaches to optimize the yield (Moussaid et al. 2020).

In spite of remote sensing having been applied in different sectors successfully, its application in agriculture is still limited. The potential application of remote sensing in assessing the soil and crop condition with few input data and acceptable accuracy has been discussed before (Bégué et al. 2015). It also can be applied for estimating nutrient and soil moisture in the absence of physical measurement at acceptable accuracy (Shanmugapriya et al. 2019).

Studies are usually focused on a single remote sensing approach, i.e. using satellite images (Bégué et al. 2015) or UAVs. Most of these studies don't compare the accuracy of remote sensing against field data. Only a few reports compared the remote sensing data against the *in situ* field measurements (Darvishzadeh et al. 2019; Croft et al. 2020; Ulfa et al. 2022).

Several studies have evaluated the application of remote sensing in Bulgaria. Most of them focus on urban and agricultural land management (Kolev & Kozelov 2015; Stoyanov et al. 2019; Dimitrov et al. 2021). (Gikov et al. 2019) demonstrated the Sentinel 2 satellite imagery application for preparing a crop-type map of targeted small regions in Bulgaria. (Dimitrov et al. 2021) extended this work by preparing the crop mapping at a national level. However, studies that compare the accuracy of satellite images to the estimated crop's biophysical properties by the *in situ* field measurement are still very much lacking.

The current study was conducted in a farm field next to the small village of Ovcha Mogila, located in the central part of the Danube hilly lowland about 20 km south of the town of Svishtov.

The objective of this study was to assess the biophysical properties of the crop using a remote sensing approach and *in situ* field measurements and analysis. It contrasts estimation accuracy of satellite images from open data sources to the ones obtained by a leaf sprecrtometer. The biophysical characteristics of the crop have been assessed by applying different vegetation indices where the accuracy of selected vegetation indices from satellites was validated against the field measurement with leaf sprecrtometer.

Materials and Methods

Description of the Study Area

The study was conducted on a farm plot found 1.5 km from the village of Ovcha Mogila, that is located in the central part of the Danube hilly lowland, about 20 km south of the city of Svishtov. The area has a temperate continental climate with an average temperature of 1°C during winter and 22°C during summer. The site has a mean annual precipitation of 615 mm. The choice of the study field was made on the basis of having highly variable soil characteristics – varying slope, soil coloration and depth, water holding capacity, etc. The 5 selected point were chosen as representative for different soil conditions.

In situ Field Measurement

One of the most common approaches to determining the spectral properties of plants is the use of spectroradiometers. The field and laboratory spectroradiometers can provide measurements with a wavelength range of 300 to 1300 nm (Arthur et al. 2012).

The tested wheat crop leaf's spectral response was measured using the CI-710s SpectraVue Leaf Spectrometer (CID Bioscience). This spectrometer is designed to measure plant's absorption, transmission, and reflection of light over a wide wavelength range. The spectral responses of the tested wheat plants were measured at 5 points inside the farm

Table 1. The different types of vegetation indices used in the present study

Index	Symbol	Formula		Reference
		Landsat-9	Sentinel-2	
Green Normalized Difference Vegetation Index	GNDVI	$\frac{B5-B3}{B5+B3}$	$\frac{B8-B3}{B8+B3}$	(Gitelson et al. 1996)
Normalized Difference Vegetation Index	NDVI	$\frac{B5-B4}{B5+B4}$	$\frac{B8-B5}{B8+B5}$	(Rouse Jr. et al. 1973)
Normalized Difference Moisture Index	NDMI	$\frac{B5-B6}{B5+B6}$	$\frac{B8-B11}{B8+B11}$	(Gao 1996)
Soil Adjusted Vegetation Index	SAVI	$\left(\frac{B5-B4}{B5+B4+0.5}\right)*1.5$	$\left(\frac{B8-B4}{B8+B4+0.5}\right)*1.5$	(Huete 1988)
Structure Insensitive Pigment Index	SIPI	$\frac{B5-B1}{B5+B4}$	$\frac{B8-B1}{B8+B4}$	(Penuelas et al. 1995)
Additional Leaf spectrometer-derived vegetation indices*				
Enhanced Vegetation Index	EVI	$2.5*\frac{(\lambda 800-\lambda 670)}{(\lambda 800+6*\lambda 670)-(7.5*\lambda 490)+1}$		(Huete et al. 2002)
Simple Ratio	SR	$\frac{\lambda 800}{\lambda 670}$		(Blackburn 1998)

* – for the leaf spectrometer-derived vegetation indices exact wavelengths of the reflected light are given.

plot that were visually determined to vary in their soil color, slope and (consequently) the state of the crop. The obtained spectral values were used to calculate a number of vegetation indices according to their empirical formula (Table 1).

Remote Sensing Data

The Landsat-9 satellite images were collected from the USGS Earth Explorer open data source (https://earthexplorer.usgs.gov), setting cloud cover criteria of less than 10%. The Landsat 9 has nine bands with a spatial resolution of 30 m, except for the panchromatic band (15 m) and thermal infrared band (100 m) (Masek et al. 2020). Scaling of Landsat-9 (collection 2, level 2) data was performed before it was used to determine the vegetation indices with a multiplicative scale factor of 0.0000275 and additive offset of 0.2.

The Sentinel-2 satellite images were downloaded from the Copernicus open hub website (https://scihub.copernicus.eu/dhus/#/home) in April. The Sentinel-2 (S2MSI) images have 13 bands with different spatial resolutions. The onboard sensors have spatial resolutions of 10 m, 20 m, and 60 m. Similarly to Landsat-9, a cloud cover percentage of less than 10% was applied to gather quality satellite images for further analysis (Drusch et al. 2012) (Table 2).

Prescreening and clipping the satellite images according to the study area boundary were carried out using QGIS software. The coarser resolution Sentinel-2 bands (20 m and 60 m) were resampled to 10 m using QGIS.

Data Analysis

The several most common broadband vegetation indices were selected, as summarized in Table 1. Based on the wavelength range of each satellite band, the vegetation indices were determined according to their empirical equations. As the leaf spectrometer produces continuous range of data between 360 and 1100 nm the Jupiter Notebook and its built-in Python program were used to determine the vegetation indices. Several python libraries have been used, including NumPy, Pandas, Matplotlib, and Rasterio. The measured leaf spectral responses by the leaf spectrometer in reflectance, transmission, and absorption were used to determine the selected vegetation indices.

The vegetation indices of Sentinel-2 and Landsat-9 were extracted to the sampling five locations using the spatial analyst tool of ArcMap and compared with the vegetation indices of CI-710s SpectraVue of the same day. All the vegetation indices values from the satellites were resampled to 10 m to perform further statistical analysis and for the determination of the correlations of the satellite-derived NDVIs the data from 5 points in time (during 4 months) was used. A linear regression analysis was used to compare Sentinel-2, Landsat-9, and spectrometer vegetation indices. The coefficient of determination (R^2) (1) and Root Mean Square Error (RMSE) (2) were used as comparison criteria. The correlation matrix was prepared using Corr and the Seaborn heatmap python libraries among the vegetation indices of different sensors. A Pearson correlation coefficient (r) (3) was used to assess the correlation matrix.

$$R^2 = \frac{\sum\left(\left(Rmeasured - \overline{Rmeasured}\right)\left(Rmodeled - \overline{Rmodeld}\right)\right)^2}{\sum\left(Rmeasured - \overline{Rmeasured}\right)^2 \sum\left(Rmodeled - \overline{\overline{Rmodeld}}\right)^2} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum(Rmeasured - Rmodled))^2}{n}} \quad (2)$$

$$r = \frac{\sum\left(\left(Rmeasured - \overline{Rmeasured}\right)\left(Rmodeled - \overline{Rmodeld}\right)\right)}{\sqrt{\sum\left(Rmeasured - \overline{Rmeasured}\right)^2 \sum\left(Rmodeled - \overline{\overline{Rmodeld}}\right)^2}} \quad (3)$$

where $R_{measured}$ is the measured reflectance value measured by either of Sentinel 2, Landsat 9, or leaf Spectrometer. $R_{modeled}$ is the predicted reflectance value of the sensors to be compared against a specific sensor.

Results and Discussion

Various vegetation indices have found usage in agriculture. However, a number of those are difficult to obtain by remote sensing as they require measurements of either ligh

Table 2. The Landsat-9 and Sentinel-2 satellite images used for the study

Landsat-9			Sentinel-2		
Sensing date	Sensor	Spatial resolution	Sensing date	Sensor	Spatial resolution
24/12/2021	OLI-2	30m	19/12/2021	MSIS2B	10m/20m/60m
			20/01/2022	MSIS2A	10m/20m/60m
10/02/2022	OLI-2	30m			10m/20m/60m
26/02/2022	OLI-2	30m	19/02/2022	MSIS2A	10m/20m/60m
30/03/2022	OLI-2	30m	21/03/2022	MSIS2A	10m/20m/60m
			05/04/2022	MSIS2B	10m/20m/60m
15/04/2022	OLI-2	30m	13/04/2022	MSIS2A	10m/20m/60m

transmission or absorbance by the crop leaves (Bojinov et al. 2022). In our study the vegetation indices of Sentinel-2 and Landsat-9 were first compared to each other by using 6 different points in time during 6-month period preceding the *in-situ* measurement (Table 3). Afterwards satellite NDVIs were extracted to the five points used for data collection with the leaf spectrometer and compared against the vegetation indices based on the measured spectral response using the latter. Several vegetation indices (NDVI, EVI, GNDVI, SAVI, SIPI, SR) were also determined with the leaf spectrometer based on the reflectance values of the study wheat leaves.

Table 3. The coefficient of determination (R^2) and root mean square error (RMSE) for the comparison of Sentinel 2 and Landsat 9 vegetation indices

Vegetation Indices	R^2 values	RMSE
	Sentinel 2 vs Landsat 9	Sentinel 2 vs Landsat 9
NDVI	0.060***	0.076
EVI	0.070***	0.051
GNDVI	0.013***	0.081
MCARI	0.013***	0.081
SAVI	0.056***	0.052
SIPI	0.052***	0.141
CHLG	0.05***	1.00
SR	0.043***	0.832

*** $p < 0.01$, **$p < 0.05$, * $p < 0.1$

As the vegetation indices from the measured leaf spectral response at five sampling points do not include the data from soil reflectance, the spectrometer-derived vegetation indices did not represent the lower range of values determined by the satellite (remote) sensors. For all the vegetation indices, the highest values were observed in the northern part of the study area, while the minimum values were detected in the northeast and southwest part of the field. The Landsat-9 vegetation indices were better aligned with the leaf spectrometer vegetation indices. The GNDVI and NDVI data revealed that Landsat-9 has a better agreement with the leaf spectrometer than Sentinel-2. In general, the leaf spectrometer vegetation indices do not align well with the vegetation indices of satellite vegetation indices (VIs). This might be due to the differences in specific wavelengths used for calculating respective VIs as different satellites vary in their wavelength collection bands (Table 4) while the SpectraVue spectrophotometer collects continuous data throughout the 360–1100 nm spectrum.

Some authors (Ke et al. 2015; Mezera et al. 2022) compared the performance of optical sensors and satellite images vegetation indices and found an average correlation between them. One of the strengths of that research is the frequency of measurement, which is better than the current study. However, others (Polivova & Brook 2021) pointed out that the optical sensor vegetation indices are highly variable compared to the vegetation indices of multispectral images. We found one study (Bareth et al. 2016) that also made comparison on the uncalibrated multispectral images vegetation index with the NDVI from the optical spectrometer. According to the study, no strong correlation was found between the spectrometer NDVI and the multispectral RGBVI.

In our experiment correlation coefficients of the NDVIs, obtained from the two satellite images and from the CI-710s SpectraVue leaf spectrometer had various degrees of agreement. The most surprising result of the current study was that the VIs from the two satellites had a very strong negative correlation (-0.77) (Figure 1). This explains why these indices also had very different correletions to the ones calculated from the data from leaf spectrometer. While the NDVI obtained from Landsat 9 had a low-to-average negative correlation the same VI obtained from Sentinel 2 had very low, but positive correlation to the NDVI obtained from leaf spectrometer.

There are several factors that may have contributed to these seemingly contradictory results. First of all, the two satellites gather data from somewhat varying bands for calculating NDVI (Table 4). Combined with the differences in the resolution of the two sensors, this could lead to substantial variation in the end result. Second, the satellite images

Table 4. The wavelength range and spatial resolution of Sentinel-2 and Landsat 9 satellites used in the study.

Sentinel-2			Landsat 9		
Band	Resolution (m)	Wavelength range (nm)	Band	Resolution (m)	Wavelength range (nm)
Band 2(blue)	10	458–523	Band 2(blue)	30	452–512
Band 3(green)	10	543–578	Band 3(green)	30	533–590
Band 4 (red)	10	650–680	Band 4 (red)	30	636–673
Band 8 (NIR)	10	785–900	Band 5 (NIR)	30	851–879
Band 8A (NIR)	20	855–875			
B11(SWIR-1)	20	1565–1655	Band 6	30	1566–1651
B12(SWIR-2)	20	2100–2280	Band 7	30	2107–2294

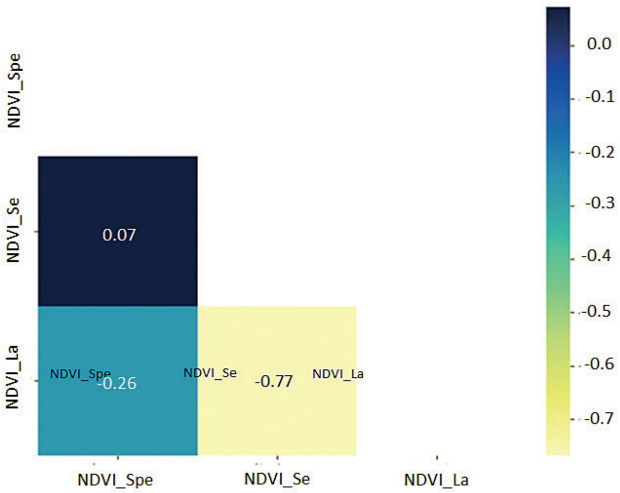

Figure 1. Correlation coefficients between NDVIs calculated by using 3 different sensors (Spe – CI-710s SpectraVue; La – Landsat)

unavoidably contain both background reflectance of the soil, that is missing in the data from the leaf spectrometer. Third, the satellite images also unavoidably contain data from the weeds, that might have been present in their relatively large “pixels” of respective images, which is also avoided in the leaf spectrometer data. Nonetheless, the results revealed that most of the values of vegetation indices obtained from different sensors are within the standard range (data not presented). The Leaf Spectrometer does not capture the lower limits of most vegetation indices since it measures only plant responses (without the background soil reflectance that satellite data collection inevitably also includes). On the other hand, NDVI (Figure 1), EVI, and GNDVI (data not shown) from the Landsat-9 showed a better agreement with the leaf spectrometer.

Conclusions

The initial comparison of the NDVIs obtained from the 2 satellites at 6 different points in time during 4 month period preceeding the *in-situ* measurement showed that the correlation between the two was very low (0.072-0.26). The comparison of vegetation indices from different sensors based on the five sampling points showed that Sentinel-2 has better agreement for NDVI to the Leaf spectrometer than Landsat-9. On the other hand, NDVI, EVI, and GNDVI from the Landsat-9 showed a better agreement with the leaf spectrometer. Therefore, data from any particular satellite source should be taken with precaution and best compared with reference data from *in situ* measurements for obtaining reliable assessment of the crop condition.

Further studies with increased numbers of leaf spectral response measurements are required to improve the predicting capacity of both satellite and leaf spectrometer indices.

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