NOVEL PROXIMAL AND REMOTE SENSING APPROACHES FOR DERIVING VEGETATION INDICES: A CASE STUDY COMPARING PLANT-O-METER AND SENTINEL-2 DATA

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ABSTRACT

With an increasing interest of the agricultural community in precision agriculture, this paper aims to compare two novel sensing approaches for crop monitoring. The recently developed multispectral proximal sensor named Plant-O-Meter and Sentinel-2 satellite, which carries a multispectral optical instrument, are two sensors suitable for agricultural applications. Each of them has pros and cons regarding spatial, spectral and temporal resolutions and their complementary use will surely bring added value compared to information retrieved by a single sensor. In order to correctly address the problem of data fusion, compatibility studies between the two sensors are necessary. In this study, a maize field was sensed on several dates in 2018 growing season using both sensors. Numerous vegetation indices based on different spectral channel combinations were calculated and the results were compared using linear regression analysis. First results showed good positive correlations between the indices obtained by the two sensors.

Keywords*:* crop monitoring, proximal sensing, Sentinel-2, vegetation indices, correlation

1. INTRODUCTION

Recent advances in technology provided an unprecedented opportunity for further development of precision agriculture that has been practiced commercially since 1990's (Mulla, 2013). Both remote and in-field sensors are used for monitoring plant deficiency for nutrients and water, plant health status and soil condition (Lee et al., 2010) and the development of low-cost sensors, as well as the liberalization of data access by data providers such as the European Space Agency (ESA) and NASA, have paved the way for acquisition of vast amounts of sensor data. However, compatibility studies between datasets acquired by different sensors are necessary prior to any kind of data fusion in practice.

Proximal sensing or ground-based remote sensing is performed by sensors at a relatively short distance from the object of interest. Hand-held devices or sensors mounted on tractors and other vehicles are usually referred to as proximal sensors. Their limitation is the small area coverage (Jackson, 1986), but they also have significant advantages, such as high spatial resolution and independent choice of the time of acquisition. Another advantage is that their measurements are not compromised by cloudiness and are ideal for practical applications such as on-the-go variable rate fertilization (Shanahan et al., 2008). Over the years, various different optical proximal sensors found practical applications, such as SPAD meter (Konica Minolta Inc., Osaka, Japan), Hydro N-sensor (Yara International ASA, Oslo, Norway), GreenSeeker (Tribmle Inc., CA, USA), Crop Circle (Holland Scientific, NE, USA), CropScan (Next Instruments, Sydney, Australia), etc.

On the other hand, satellite remote sensing has been used in agriculture since 1970's when the first Landsat satellite was launched. Over the period of nearly half a century, the resolution of satellite images, as well as the revisit frequency, increased dramatically (Mulla, 2013). However, a big drawback of this sensing approach has historically been the high price of satellite imagery. ESA and NASA changed their policies in the last decade and made certain satellite imagery available to general public at no cost (Woodcock et al., 2008; Aschbacher and Milagro-Pérez, 2012). Landsat's 40-year long archive is now freely available together with on-going Landsat missions and state-of-the-art Earth observation program Copernicus operated by ESA on behalf of European Commission. These led to an increased interest of the agricultural community toward satellite remote sensing in the last decade.

Although proximal and remote sensing were extensively studied for assessing crop dynamics (Corti et al., 2018), direct inter-comparison between satellite remote sensing and proximal sensors with respect to crop monitoring has rarely been discussed. Bausch and Khosla (2010) compared QuickBird satellite-derived indices with ground-based Exotech radiometer-derived indices and found good correlation, with highest agreement in green normalized difference vegetation index normalized for reference area (NGNDVI). Caturegli et al. (2015) tested ground-based multispectral measurements (using Licor spectroradiometer and GreenSeeker) and GeoEye-1 satellite images for estimating nitrogen status of turfgrasses. Comparing NDVI values acquired from these instruments, the highest Pearson correlation coefficient was found between GreenSeeker and satellite derived NDVI ($r \approx 1$). Yang et al. (2008) found substantial linear correlation ($r > 0.7$) between NDVI measured from Formosat-2 satellite images and ground portable spectroradiometer GER-2600. Wagner and Hank (2013) revealed Pearson correlation coefficient of 0.85 between RapidEye and YARA-N sensor-derived Red Edge Inflection Point (REIP). Within this study, the necessary modification was made in RapidEye measurements using YARA-N sensor-based model, so that the REIP could be calculated. Bu et al. (2017) confirmed that yields of sugar beet root, spring wheat, corn and sunflower can be predicted with GreenSeeker, Crop Circle and RapidEye red and red-edge imagery.

The use of vegetation indices (VIs) is of great importance in monitoring crop dynamics and predicting the yield. Hence, it is essential to quantify the level of similarity between different sensor measurements prior to data fusion. In this paper, various VIs derived from measurements made with a recently developed, active, multispectral proximal sensor named Plant-O-Meter (POM), were compared to VIs derived from Sentinel-2 optical satellite imagery. Although the spatial resolution of POM is higher than Sentinel-2's and more detailed information can be obtained, the latter would be more suitable for covering larger agricultural areas. In this regard, POM measurements could serve as ground-truth or they could be used for on-the-go in-field applications. Nevertheless, both sensors represent modern active optical instruments that are likely to find broader use in the near future.

2. Materials and Methods

The present study was carried out during the 2018 growing season on a commercial field located in Begeč in Serbia (45° 14' 32.712" N and 19° 36' 21.486" E), whose size was 6 ha. The field was sown with "Exxupery" hybrid (R.A.G.T. Semences, France) of maize (Zea mays L.) on 15 April 2018. Seeding was done in 300 m long rows, at the plant distance of 0.2 m within rows and 0.7 m between rows. A total of 300 kg ha^{-1} of 15:15:15 NPK fertilizer was applied at planting.

In-field reflectance measurements were made using POM sensor, recently developed by BioSense Institute (Republic of Serbia). This proximal sensor is connected to Android-operated devices through a user-friendly application and has the ability to record georeferenced point measurements and map the canopy properties of a field crop, using the internal GPS of the Android device. It records the data in four different spectral bands, namely blue (465 nm), green (535 nm), red (630 nm) and nearinfrared (850 nm). Every tenth row of the experimental field was scanned by walking along the rows, holding the sensor directly on top of the crop row with the scanning footprint perpendicular to the row direction. The measuring frequency was 1 Hz, which roughly corresponded to 1 m distance between the POM record points along the row. POM measurements were performed at four different dates and were carried out in the following stages of maize development: 6-leaf growth stage (V6), beginning of tasseling (VT), silking (R1) and at the end of blister stage (R2), (Table 1).

Table 1. Corresponding acquisition dates for POM and Sentinel-2 and development stage of maize.

POM date	Sentinel-2 date	Crop development stage
01.06.2018	30.05.2018	6-leaf (V6)
21.06.2018	24.06.2018	Tassel (VT)
04.07.2018	14.07.2018	Silking (R1)
26.07.2018	29.07.2018	Blister (R2)

Sentinel-2 is a constellation of two identical satellites and the joint revisit time of A and B satellites is 5 days at the equator. Each carries an optical multispectral instrument that provides images in 13 spectral bands with spatial resolutions of either 10, 20 or 60 m (European Space Agency, 2015). Bands used in the experiment are blue (490 nm), green (560 nm), red (665 nm) and NIR (842 nm) bands with a 10 m resolution and the narrow NIR (865 nm) band with a 20 m resolution. With respect to POM measurement dates, corresponding cloud-free satellite images were downloaded and processed. Atmospherically corrected images were downloaded from the official Copernicus Open Access Hub (https://scihub.copernicus.eu/) and processed with official Sentinel-2 Toolbox (SNAP) software and QGIS. Acquisition dates for Sentinel-2 images are given in Table 1.

Since the narrow NIR band of Sentinel-2 images was only available at a 20 m resolution, all images were resampled using the nearest neighbor method. Thus, the blue, green, red and NIR bands from Sentinel-2 images were down-sampled from 10 m to 20 m resolution.

Due to the higher resolution of POM measurements compared to Sentinel-2 images, i.e. several POM measurements points fell within a single Sentinel-2 image pixel (Fig. 1), all POM measurements inside a Sentinel-2 pixel were averaged. By employing this, there was only one corresponding value per POM spectral band for a single image pixel. Hence, 1-1 mapping between measurements of the two sensors was achieved. Using different spectral band combinations, various indices were calculated (Table 2).

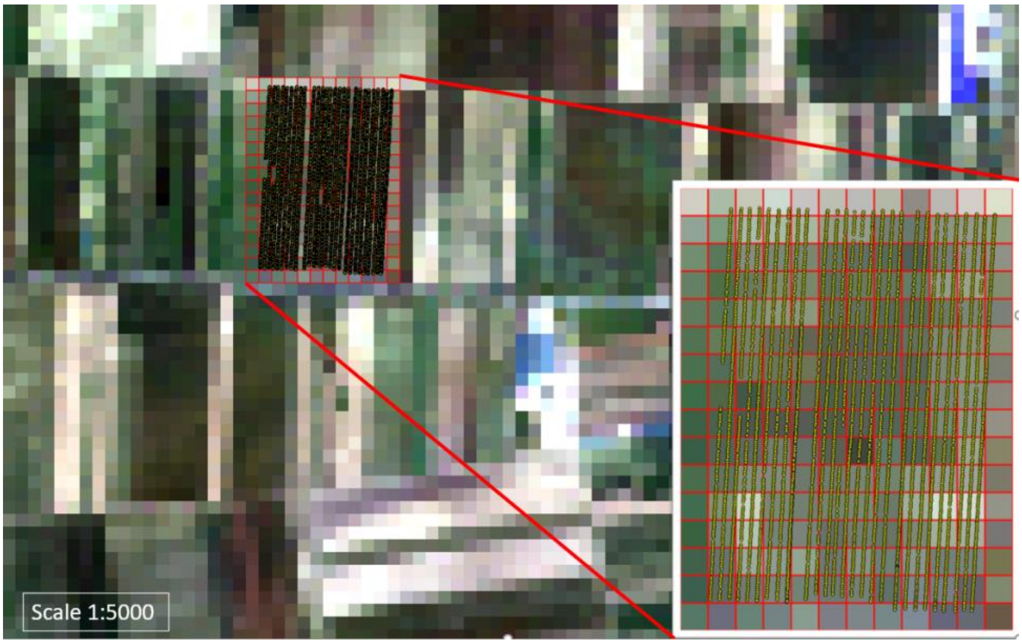

Figure 1. Sentinel-2 image of the experimental field in Begeč at 20 m resolution where yellow dots represent POM measurement points.

Pixels that were known to be outliers were manually excluded from further analysis. Those were either border pixels, contaminated by the features outside the field, or pixels contaminated by other objects located inside the parcel.

3. Results and Discussion

The analysis of the Sentinel-2 image acquired on 24 June 2018 provided poor results due to the significant effect of a layer of clouds over the experimental field. Therefore, this date was excluded from the analysis. This is a good example of the constraints of the use of optical satellite images as they highly depend on the weather (Mulla, 2013).

Table 2. Coefficient of determination (r^2) and Root Mean Square Error (RMSE) form the regression between indices calculated from Sentinel-2, using the wide range NIR band, and POM.

date	01-06-2018		04-07-2018		26-07-2018	
	r^2	RMSE	r^2	RMSE	r^2	RMSE
NDVI	0.680	0.075	0.162	0.093	0.036	0.093
SR	0.612	0.905	0.147	4.283	0.045	4.616
IPVI	0.668	0.045	0.162	0.047	0.036	0.046
NDVIg	0.616	0.058	0.102	0.209	0.008	0.210
NDVIb	0.652	0.103	0.050	0.096	0.000	0.134
SIPI	0.546	0.527	0.059	0.266	0.000	0.267
EVI	0.325	0.182	0.002	0.719	0.000	1.327
GSAVI	0.614	0.091	0.105	0.319	0.008	0.318
GOSAVI	0.615	0.058	0.103	0.210	0.008	0.210
GCI	0.574	0.500	0.087	4.625	0.028	4.611
NLI	0.478	0.014	0.124	0.006	0.060	0.004
TDVI	0.672	0.115	0.167	0.091	0.034	0.089
WDRVI	0.648	0.120	0.156	0.226	0.041	0.230
GRNDVI	0.659	0.062	0.177	0.236	0.022	0.239
GBNDVI	0.676	0.061	0.097	0.244	0.008	0.274
RBNDVI	0.700	0.131	0.143	0.152	0.010	0.184
PNDVI	0.686	0.082	0.155	0.259	0.017	0.288
Average	**0.580**	**0.179**	**0.111**	**0.677**	**0.020**	**0.736**

Table 3. Coefficient of determination (r^2) and Root Mean Square Error (RMSE) form the regression between indices calculated from Sentinel-2, using the narrow range NIR band, and POM.

date	01-06-2018		04-07-2018		26-07-2018	
	r^2	RMSE	r^2	RMSE	r^2	RMSE
NDVI	0.710	0.069	0.162	0.100	0.045	0.103
SR	0.644	0.863	0.135	4.791	0.058	5.615
IPVI	0.696	0.042	0.162	0.050	0.045	0.052
NDVIg	0.630	0.059	0.106	0.217	0.012	0.224
NDVIb	0.676	0.099	0.044	0.101	0.002	0.141
SIPI	0.579	0.522	0.057	0.265	0.001	0.264
EVI	0.344	0.176	0.003	0.715	0.000	1.312
GSAVI	0.627	0.093	0.108	0.331	0.012	0.339
GOSAVI	0.629	0.060	0.107	0.218	0.012	0.225
GCI	0.595	0.515	0.094	5.015	0.032	5.349
NLI	0.493	0.014	0.116	0.006	0.097	0.004
TDVI	0.702	0.106	0.167	0.096	0.043	0.098
WDRVI	0.677	0.114	0.153	0.243	0.052	0.261
GRNDVI	0.683	0.057	0.178	0.248	0.029	0.260
GBNDVI	0.696	0.056	0.095	0.255	0.017	0.293
RBNDVI	0.728	0.124	0.136	0.162	0.022	0.200
PNDVI	0.710	0.076	0.151	0.274	0.028	0.313
Average	**0.603**	**0.175**	**0.110**	**0.733**	**0.028**	**0.842**

The linear regression analysis provided an insight of which indices calculated using POM are in better agreement with the same ones calculated using Sentinel-2 satellite images. The differences were mainly due to the deviations in the operating wavelengths for the two sensors and in the different sensitivity of each sensor at different bands. Sentinel-2 provides two measurements in the NIR channel: wide (785 – 900 nm) and narrow (855 – 875 nm) range. According to the statistical analysis, using the narrow range NIR in calculations of Sentinel-2 indices provided better correlation to the POM indices (Tables 1, 2; Figure 2). This was expected since the measuring range for the two bands, narrow NIR band of Sentinel-2 and NIR band of POM, is much closer.

In general, good positive correlations were obtained for most of the indices measured by the two sensors at V6 growth stage of maize (01-06-2018; Tables 2 and 3). This is an indication that POM has a high potential for providing reliable measurements of the canopy reflectance and plant status during maize growing stages, and it can serve as a good alternative to the satellite sensors, having the benefits that the active proximal sensors offer: high spatial resolution, flexibility in the measurement timing and independence from cloudiness, as given by (Bu et al., 2017).

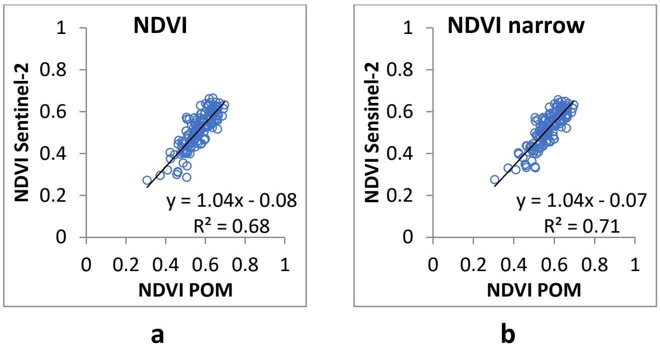

Figure 2. Linear regression between the NDVI calculated from POM measurements and Sentinel-2 satellite images using wide (a) and narrow (b) bands, at V6 maize growth stage.

POM measurements at the V6 growth stage showed good correlation with Sentinel-2 results, mainly due to the uniformity of the color of the canopy across the field. Concerning the NDVI, which is the most widely used vegetation index (Tagarakis and Ketterings, 2017; Hatfield et al., 2008), the linear regression showed significant correlation for the narrow band (r^2= 0.71, RMSE = 0.069; Table 3, Figure 2) showing a 1:1 relationship; the slope of the linear model was almost 1 and the constant approached 0 (Figure 2). After tasselling, the measurements showed considerably lower correlation between the two sensors explained by the mixture of colors after the tassels appear, and the different shades of the canopy from green to yellow as the plants approach maturity. Due to the large difference in the spatial resolution of the measurements of the two sensors in the study, this random mixture of colors affected the results of each sensor differently.

4. Conclusions

Ground based proximal sensing provides comparable results to the indices calculated from Sentinel-2 satellite images. Cloudiness is an important limiting factor of satellite remote sensing. POM active proximal sensor can be an alternative to satellite images, as it provides comparable measurements at a high spatial resolution, independent of weather and illumination conditions. The plant development stage plays an important role in the agreement between the indices derived by POM and Sentinel-2 due to the large difference in spatial resolution of the measurements.

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