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Winter wheat, winter rape and poppy crop growth evaluation with the help of remote and proximal sensing measurements

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Abstract. Monitoring of agricultural crops with the help of remote and proximal sensors during the growing season plays important role for site-specific management decisions. Winter wheat, winter rape and poppy are representatives of typical agricultural crops from the family Poacea, Brassicaceae and Papaveraceae, growing in relative dry area of Rakovník district in the Czech Republic. Ten Sentinel 2 satellite images acquired during vegetation season of the crops were downloaded and processed. Crops were monitored with the help of unmanned aerial vehicles (UAV) equipped with consumer grade Red Green Blue (RGB) camera and multispectral (MS) MicaSense RedEdge MX camera. In-field variability was assessed by computing RGB-based vegetation indices Triangular Greenness Index (TGI), Green Leaf Index (GLI) and Visible Atmospherically Resistant Index (VARI) and commonly used vegetation indices as Normalised Difference Vegetation Index (NDVI) and Green NDVI (GNDVI). The results derived from satellite and UAV images were supported with in-situ measurements of hand-held GreenSeeker and Chlorophyll Meter Content sensors. The study showed the usability of individual vegetation indices, especially the TGI index for chlorophyll content estimation, and VARI index for green vegetation fraction detection and leaf area index estimation, in comparison with selected hand-held devices. The results showed as well that leaf properties and canopy structure of typical characteristics of selected families can significantly influence the spectral response of the crops detected in different phenological stages.

Key words: satellite images, unmanned aerial vehicles, vegetation indices, winter wheat, winter rape, poppy.

INTRODUCTION

Monitoring the vitality of agricultural crops during the whole growing season is significant for increasing crop yields and reducing input resources and costs for the agricultural system (Brisco et al., 1998). Knowledges of vegetation indices are fundamental for understanding of agricultural ecosystems as well (Wang et al., 2010). Vegetation indices can describe health and condition of agricultural crops, but each of indices uses different part of electromagnetic spectrum and therefore each of indices has different informative value.

Triangular Greenness Index (TGI) index calculates the triangle area of the reflectance spectrum in red, green and blue wavelengths, allows estimation of chlorophyll concentration in leaves and the canopy (Hunt et al., 2013). Green Leaf Index (GLI) is one of the important indices commonly used for yield forecasting. This spectral index was originally designed for use with RGB camera in data range from 0 to 255 (Gobron et al., 2000; Hunt et al., 2013). Visible Atmospherically Resistant Index (VARI) estimates the fraction of crops in scene with low sensitivity to atmospheric effects (Gitelson et al., 2002). Normalised Difference Vegetation Index (NDVI) is measure of healthy, green vegetation. The combination of it is normalized difference formulation and use of the highest absorption and reflectance regions of chlorophyll make it robust over a wide range of conditions (Rouse et al., 1974). Green NDVI (GNDVI) has similar algorithm to NDVI, but green part of electromagnetic spectrum (in 540 to 570 nm) is measured instead of the red part. GNDVI is more sensitive to chlorophyll content (Gitelson et al., 2002).

Data from Copernicus program can be free downloaded and used for evaluation of crop plots with using commercial software or open access software. Optical satellite imaging have borders in usability for example in cloudy weather (Domínguez et al., 2017). Compared to satellite images, unmanned aerial vehicles represent a much more accurate source of images for crop growth monitoring, especially in terms of spatial and temporal resolution. We can say, that UAVs are the most important technologies in agriculture and their flexibility help scientific sectors development and farmers in praxis (De Rango et al., 2017). One of UAV's benefits is possibility to add various devices for example high resolution multispectral camera, digital camera, thermal camera, LiDAR etc. (Grenzdorffer et al., 2008).

The use of modern technologies in precision agriculture is the reply to new epoch of farming systems, private companies or scientists. Good informations in precision agriculture, especially satellite and UAV's scanning or results from precise measurements, may affect the production function of immediate yield monitoring. That is why the main aim of this study was to evaluate crop growth of winter wheat, winter rape and poppy with the use of proximal and remote sensing measurements. The other objective of this study was to compare the utilization of selected RGB indices with most common spectral indices and prove use for common agricultural practice.

MATERIALS AND METHODS

Study area

The study area was located near to Lišany village (N 50° 9'31.57", E 13°44'37.12"), the Czech Republic. Experimental field with winter wheat was in size of 16.48 ha with average elevation of 355.96 m a.s.l. and 3.32% slope. Winter rape field had 19.30 ha with 360.35 m a.s.l. average elevation and 4.14% slope. Poppy field had 18.77 ha with average elevation of 349.25 m a.s.l. and 2.90% slope. Weather condition, total monthly precipitation and temparatures data for the years 2018 and 2019 and then total monthly average of 1961–1990 were provided by the hydrometeorological station Heřmanov in district Rakovník (see Table 1). The experimental fields are owned by Agricultural Company Lupofyt s.r.o. Soil tillage minimalization technology with alternately conventional arable soil technology (ploughing) were used on experimental plots. Since 2015 the crop rotation for the field with winter wheat has been: winter wheat (2015), lupine (2016), winter wheat (2017), winter rape (2018) and winter wheat (2019); for the field with winter rape: winter rape (2015), winter wheat (2016), winter rape (2017), winter wheat (2018) and winter rape (2019); and for the field with poppy: winter rape (2015), winter wheat (2016), winter rape (2017), winter wheat (2018) and poppy (2019).

Table 1. Weather conditions (monthly precipitations and temperatures) for the years 2018 and 2019 and total monthly average of 1961–1990 for hydrometeorological station Heřmanov

	Precipitation (mm)			Temperature (°C)		
Month/Year	2018	2019	Avg 1961–1990	2018	2019	Avg 1961–1990
I.	25.0	34.0	32.0	1.1	1.9	-2.0
II.	2.0	5.0	30.0	2.7	0.5	-0.4
III.	36.0	40.0	36.0	6.9	4.8	3.4
IV.	33.0	26.0	43.0	10.6	8.4	8.1
V.	121.0	41.0	70.0	12.6	13.2	13.0
VI.	27.0	60.0	75.0	16.7	16.5	16.3
VII.	94.0	28.0	72.0	20.1	20.8	17.8
VIII.	64.0	70.0	73.0	16.6	22.1	17.2
IX.	85.0	20.0	46.0	14.7	13.7	13.6
X.	51.0	54.0	36.0	10.6	8.4	8.6
XI.	18.0	64.0	40.0	6.4	6.6	3.3
XII.	31.0	17.0	35.0	2.5	4.9	-0.2
Sum	587.0	459.0	590.0	-	-	-
Mean	49.0	38.0	49.0	10.2	10.1	8.2

Data description

Measurements were performed during vegetation season 2019 on winter wheat, winter rape and poppy crops. Measurements consisted of spectral indices derived from Sentinel 2A/B MSI images, UAV images and handheld devices (GreenSeeker and Chlorophyllmeter). The details can be found in Table 2.

Yield and remote sensing data

Combine harvester New Holland CR9080 was used for yield measurement. This machine was equipped with yield monitor and DGPS receiver. EGNOS correction ensure the accuracy of this system (± 0.1–0.3 m in horizontal and ± 0.2–0.6 m in vertical direction). The yield data were saved every 1 second with coordinates to the external memory. The yield data were processed by basic statistical method in order to eliminate the errors of yield measurement system. The yield data sets were then interpolated to kriging maps (see Fig. 1) using experimental variograms and common procedures. The method is detailed described for example in Kumhálová et al., 2011. Because of problems with poppy yield measurement, the special correction of this yield data set was used. Geographically Weighted Regression (GWR; ArcGIS 10.4.1 SW, ESRI Redlands, CA, USA) with the use of last satellite images from poppy vegetation season (28 June) was used for this correction. GWR is one of several spatial regression techniques increasingly used in geography and other disciplines. GWR provides a local model of the variable or process by fitting a regression equation to every feature in the dataset. GWR constructs these separate equations by incorporating the dependent and explanatory variables of features falling within the bandwidth of each target feature (ESRI, 2019).

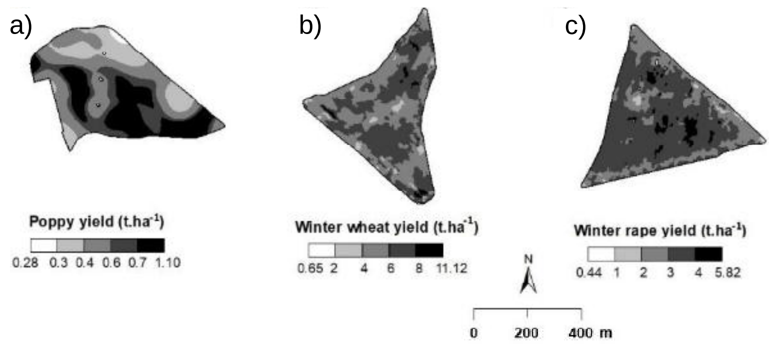

Figure 1. Yield maps (in t ha^{-1}) of poppy (a); winter wheat (b); and winter rape (c).

Table 2. Measurements (date, platform with sensors and spectral indices) used in this study for individual crops for the vegetation season 2019

Date	Platform and sensor	Winter wheat Indices	Winter rape Indices	Poppy Indices
4 April	S2A MSI	GNDVI, NDVI, TGI, VARI	GNDVI, NDVI, TGI, VARI	GLI*, GNDVI*, NDVI*, TGI*, VARI*
12 April	UAV with RGB camera	-	TGI	-
	GreenSeeker	NDVI	NDVI	-
	N-Sensor	NDGI	NDGI	-
	Chlorophyllmeter	CFR	CFR	-
19 April	S2B MSI	GNDVI, NDVI, TGI	GNDVI, NDVI, TGI	GLI*, GNDVI*, NDVI*, TGI*, VARI*
24 April	S2A MSI	GNDVI, NDVI, TGI	GNDVI, NDVI, TGI	GLI*, GNDVI*, NDVI*, TGI*, VARI*
1 May	GreenSeeker	NDVI	-	-
	N-Sensor	NDGI		
	Chlorophyllmeter	CFR		
19 May	S2B MSI	clouds – only parts of the fields usable, not used for the study		
24 May	S2A MSI	GNDVI, NDVI, TGI	Clouds, shadows	GNDVI, NDVI, TGI
3 June	S2A MSI	GNDVI, NDVI, TGI	GNDVI, NDVI, TGI	GNDVI, NDVI, TGI
8 June	S2B MSI	GNDVI, NDVI, TGI	clouds	GNDVI, NDVI, TGI
13 June	S2A MSI	GNDVI, NDVI, TGI	GNDVI, NDVI, TGI	GNDVI, NDVI, TGI
17 June	UAV with MicaSense camera	-	-	GLI, GNDVI, NDVI
18 June	S2B MSI	clouds	GNDVI, NDVI, TGI	clouds
28 June	S2B MSI	GNDVI, NDVI, TGI	GNDVI, NDVI, TGI	GNDVI, NDVI, TGI
30 June	GreenSeeker	-	-	NDVI

**= spectral indices calculated for the bare soil; CFR = Content of Chlorophyll, GLI = Green Leaf Index; GNDVI = Green Normalised Difference Vegetation Index; NDVI = Normalised Difference Vegetation Index; NDGI = Normalised Difference Green Index; TGI = Triangular Greenness Index; VARI = Visible Atmospherically Resistant Index; S2A/B MSI = Sentinel 2A/B Multispectral Instrument.*

The Sentinel 2A or B satellite images for vegetation season of 2019 were downloaded from Copernicus Open Access Hub (https://scihub.copernicus.eu/). The satellite images in level of BOA reflectance (Bottom of Atmosphere) L2A were resampled to 10 m spatial resolution with the help of SW ENVI 5.5 (Excelis, Inv. Mc Lean, USA) or SNAP 6.0.4 (ESA, http://step.esa.int/main/). Aerial survey were performed using common UAV with common RGB camera on 12 April for winter wheat and winter rape monitoring, and using Phantom UAV with MicaSense RedEdge-MX camera (MicaSense, Inc. Seattle, WA, USA) with five spectral bands (RED, GREEN, BLUE, Red Edge and NIR channels) and 1.2 Mpx per EO band sensor resolution on 17 June for poppy monitoring.

Spectral indices (see Table 3) were calculated from each of Sentinel 2 image (see Table 2). The images were acquired for the whole vegetation season with the aim to reach essential growth stages (see Fig. 2 and Table 4).

Table 3. Vegetation indices used in this study

RGB Spectral Index	Algorithm	References
Normalized Difference Vegetation Index	$NDVI = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R}}$	(Rouse et al., 1974)
Green Normalized Difference Vegetation Index	$GNDVI = \frac{\text{NIR} - \text{G}}{\text{NIR} + \text{G}}$	(Gitelson et al., 1996)
Green Leaf Index	$GLI = \frac{(\text{G} - \text{R}) + (\text{G} - \text{B})}{2\text{G} + \text{R} + \text{B}}$	(Gobron et al., 2000; Hunt et al., 2013)
Visible Atmospherically Resistant Index	$VARI = \frac{\text{G} - \text{R}}{\text{G} + \text{R} - \text{B}}$	(Gitelson et al., 2002)
Triangular Greenness Index	TGI =G-0.39×R-0.61×B	(Hunt et al., 2013)

Where g = G/(R+G+B); b = B/(R+G+B); r = R/(R+G+B); and green (G), red (R), blue (B) and NIR are the reflectance values of each band.

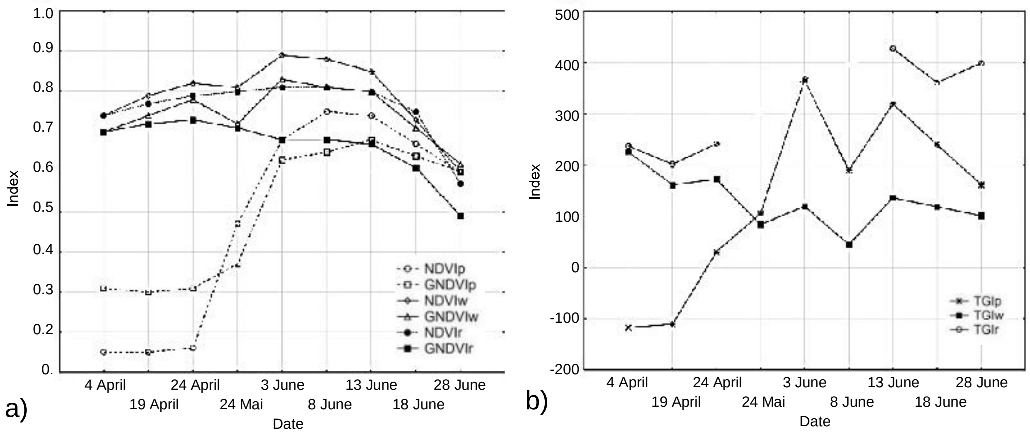

Figure 2. Graphs of Normalised Difference Vegetation Index (NDVI), Green NDVI (GNDVI) (a); and Triangular Greenness Index (TGI) (b) for winter wheat, winter rape and poppy calculated from Sentinel 2 images for vegetation season.

Table 4. Growth stages of monitored crops, expressed in BBCH scale

BBCH	Winter wheat	Winter rape	Poppy
0–19	21.9.2018–10.11.2018	6.8.2018–31.3.2019	25.3.2019–20.4.2019
20–29	11.11.2018–10.4.2019	-	21.4.2019–10.5.2019
30–59	11.4.–31.5.2019	1.4.–15.4.2019	11.5.2019–15.6.2019
60–89	1.6.2019–27.7.2019	16.4.–24.7.2019	16.6.2019–28.7.2019

Data were compared for each of the selected crop (winter wheat, winter rape and poppy). Correlation coefficients (R) were calculated between generally known and used NDVI and GNDVI spectral indices and TGI index for Sentinel 2 images, and then these indices derived from Sentinel 2 images were compared with other measurements (Chlorophyllmeter, GreenSeeker, N-Sensor, indices derived from UAV images and yield data).

RESULTS AND DISCUSSION

The coefficients of correlation for selected parameters are shown in Table 5, 6 and 7. The coefficients of correlation were calculated for a 5% significance level.

Table 5. Coefficients of correlation between Triangular Greenness Index (TGI) and Normalized Different Vegetation Index (NDVI) a Green NDVI (GNDVI) derived from Sentinel 2 images for the vegetation season of winter wheat, winter rape and poppy (at 5% significance level)

		Winter wheat		Winter rape		Poppy	
Date	Index	NDVI	GNDVI	NDVI	GNDVI	NDVI	GNDVI
4 April	TGI	-0.14	-0.28	0.59	0.47	-0.04	-0.64
	VARI	-0.31	-0.25	-0.48	-0.43	0.61	0.84
19 April	TGI	-0.34	-0.50	0.63	0.51	0.10	-0.43
24 April	TGI	-0.33	-0.49	0.55	0.37	0.11	-0.41
24 May	TGI	0.80	0.80	-	-	0.85	0.74
3 June	TGI	-0.19	-0.32	0.17	-0.10	0.82	0.52
8 June	TGI	-0.10	-0.39	-	-	0.85	0.73
13 June	TGI	0.12	-0.16	0.45	0.15	0.74	0.70
18 June	TGI	-	-	0.42	0.53	-	-
28 June	TGI	0.70	0.49	0.47	-0.12	0.78	0.60

Table 5 showed comparison between RGB indices (TGI and VARI) and NDVI and GNDVI spectral indices with near-infrared band, mostly used in literature (e.g. Domínguez et al., 2017) for crop vigor evaluation. The indices were calculated for Sentinel 2 images only. The results showed that TGI index developed for chlorophyll estimation calculated using RGB spectral bands had the strongest correlations with NDVI and GNDVI for poppy crops in comparison with the other (winter wheat and winter rape). Higher values of correlations in 24 May and 8 June were probably caused by light condition over the experimental field (clouds shadows on crop canopy). Nevertheless, results from 3 June, when the images was clear, showed that correlation between NDVI and TGI in case of poppy was relatively high as well. It means that the shadows affect the measured values to some extent, but the trend is generally maintained. Generally, correlations between TGI and NDVI were more significant for poppy (calculated from end of April – see BBCH scale in Table 4) and winter rape. On the contrary, winter wheat crops showed more significant dependence between TGI and GNDVI during the growth season, when the plants were green. The last image captured on 28 June showed opposite results because of partly matured canopy. As the results on 4 April in case of winter wheat and winter rape showed, VARI index developed for vegetation faction and leaf area estimation could be used only for early growth stages evaluation, when canopy is uneven. The development of NDVI and GNDVI indices calculated from Sentinel 2 images are given in the Fig. 2, a. The graph showed relatively similar development of the values of these spectral indices. Early values of crop growth were evaluated only in case of winter wheat and winter rape canopy (see Table 4). On the contrary, TGI index in Fig. 2, b showed uneven development of this index and plant growth during the time which is probably caused by light condition over the experimental field (clouds shadows on crop canopy) how it is explained higher.

Table 6. Coefficients of correlation between handheld sensors (CFR = Chlorophyllmeter; N-Sensor a GreenSeeker = GSK) and UAV images (Triangular Greenness Index = TGI) used in this study and spectral indices (NDVI, GNDVI, TGI and VARI) derived from Sentinel 2 (S2) images for winter wheat and winter rape and crop yield (at 5% significance level)

Date	Sensor	Winter wheat				Winter rape			
		NDVI S2	GNDVI S2	TGI S2	VARI S2	NDVI S2	GNDVI S2	TGI S2	VARI S2
12 April		4 April – S2 images				4 April – S2 images			
	CFR	-0.21	-0.25	0.07	-0.01	-0.20	-0.21	-0.07	0.15
	NDGI N-Sensor	-0.19	-0.21	0.02	0.03	-	-	-	-
	NDVI GSK	0.47	0.50	-0.41	-0.08	0.52	0.53	0.18	-0.34
	TGI UAV	-	-	-	-	0.36	0.33	0.22	-0.18
12 April		19 April – S2 images				19 April – S2 images			
	CFR	-0.02	-0.03	0.00	-	-0.15	-0.16	-0.08	-
	NDGI N-Sensor	0.05	0.06	-0.07	-	-	-	-	-
	NDVI GSK	0.29	0.31	-0.36	-	0.47	0.46	0.23	-
	TGI UAV	-	-	-	-	0.34	0.29	0.19	-
1 May		24 April – S2 images							
	CFR	-0.09	-0.07	0.08	-	-	-	-	-
	NDGI N-Sensor	-0.02	0.00	-0.18	-	-	-	-	-
	NDVI GSK	0.19	0.17	0.00	-	-	-	-	-
		28 June – S2 images				28 June – S2 images			
	Yield	0.37	0.31	0.27	-	0.10	-0.15	0.41	-

Table 6 described the coefficients of correlation between selected handheld sensors and UAV images, and spectral indices (NDVI, GNDVI, TGI) calculated from Sentinel 2 images. The dependences between selected variables were relatively low. Nevertheless, more significant correlations (R = 0.47/0.50 – NDVI /GNDVI for winter wheat; 0.52/0.53 NDVI/GNDVI for winter rape on 12 April vs. 4 April) were found between NDVI measured with GreenSeeker and indices derived from Sentinel 2. Similarly higher correlations between NDVI measured by GreenSeeker on 30 June and Sentinel 2 spectral indices (28 June) derived for poppy are given in Table 7. Significantly higher correlations (around the R values of 0.6 for NDVI and GNDVI; and around 0.46 R value for TGI) between spectral indices calculated from UAV images (from 17 June) and Sentinel 2 images (13 June) are given in Table 7 as well. Comparison between last satellite images (see Fig. 3) and crop yield are given in Table 6 for winter wheat and winter rape, and Table 7 for poppy.

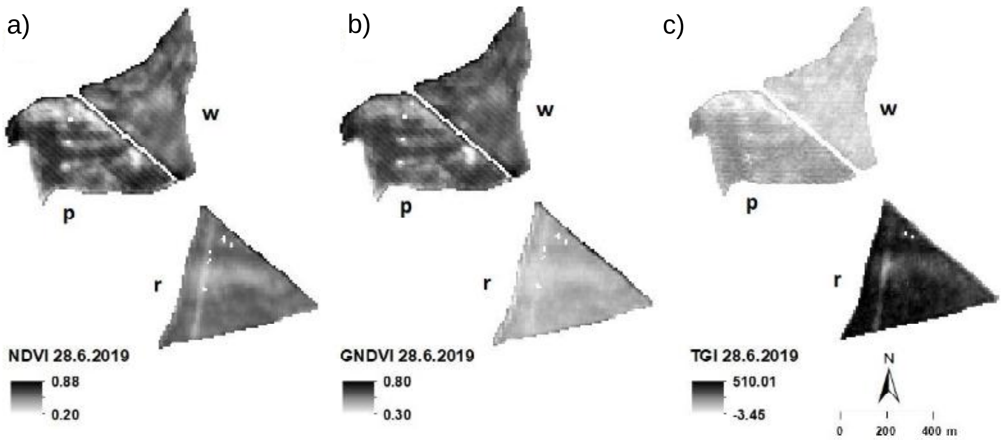

Figure 3. Normalised Difference Vegetation Index (NDVI) a); Green NDVI (GNDVI) (b); Triangular Greenness Index (TGI) (c) for winter wheat (w), winter rape (r) and poppy (p).

Table 7. Coefficients of correlation between handheld sensors and UAV images used in this study and spectral indices derived from Sentinel 2 (S2) images for poppy and crop yield (at 5% significance level)

Date	Sensor	Poppy			
		NDVI S2	GNDVI S2	TGI S2	
		13 June – S2 images			
17 June	GLI UAV	0.61	0.57	0.46	
	GNDVI UAV	0.64	0.61	0.46	
	NDVI UAV	0.63	0.59	0.47	
		28 June – S2 images			NDVI GSK 30 June
30 June	NDVI GSK	0.47	0.31	0.68	-
	Yield	0.62	0.54	0.58	0.48

These results showed that normalised indices calculated from UAV images could suitably complement the time series of satellite images, if any are missing, for example due to cloud cover. This statement is in accordance with study of Cucho-Padin et al. (2019). They tested usability of agricultural UAV based remote sensing methods to increasing productivity with high-quality multispectral camera and open-access software. Their study proved high usability and higher accuracy of UAV images than satellite images from Sentinel 2. The development of high-precision agricultural techniques has been observed for at least two decades (e.g. Moran et al., 1997). However, our results show that even low-cost cameras can be useful for crop scanning.

Hunt et al. (2005), Lelong et al. (2008), Sakamoto et al. (2011), Lebourgeois et al. (2012) wrote in their studies about UAV's with multispectral camera, that can be quickly deployed to acquire data. Because of agricultural purposes, data from UAV had to be processed quickly for providing recommendations. These findings are supported by our research. Based on our measurements during season, we found UAV with multispectral camera as a good source of data to assess the health of the crop and crop predict yield as well. Compared to data collection from Sentinel 2, we are able to obtain data with higher spatial resolution without the risk of cloudy. On the other hand our results are similar as conclusion by Hunt & Stern (2019) that RGB spectral indices (TGI and VARI) derived from UAV camera are crucial dependent on lighting conditions. Barbosa et al. (2019) confirmed the dependence of scanned vegetation on light conditions as well.

Handheld devices like GreenSeeker, Chlorophyllmeter or N-sensor can be useful especially for quickly determining the current state of the crops at selected locations. Because of in-situ measurements, it is hard to select the representative leaf for measurements. Kumhálová & Matějková (2017) used in their study GreenSeeker to find out the usability of this handheld crop sensor for estimation of winter barley crop condition and yield. They presented that GreenSeeker handheld crop sensor is not suitable for large area of crops estimation due to point measurement. Our results are in accordance with theirs.

On the other hand our results confirm the usability of UAV with multispectral camera to evaluate and predict the yield. The results also show a more suitable use of the TGI index to cereals and poppy than winter rape. Domínguez et al. (2017) found, that NDVI are more accuracy to cereals than winter rape as well. It can be caused by different canopy and leaves structure of agricultural crops of different family (in our case Poacea, Brassicaceae and Papaveraceae). Jelínek et al. (2019) found it, that according to Sentinel 2 image to estimate crop structure from 96% for winter wheat. Hunt et al. (2013) researched topic of a visible spectrum band indices. They described TGI as a significant spectral index for crop evaluation. This theory has also been confirmed by our research, primarily for winter wheat and poppy than winter rape. Broge & Leblanc (2000) compared TGI index and canopy reflectance and their results indicated strong correlation, mainly for NDVI, SAVI indices. Although Masoni et al. (1996) found, that high TGI index may be a symptom of other problems. These conclusions are mostly in accordance with ours. Among other crops, our study focused on poppy monitoring as a crop that is relatively commonly cultivated in the Czech Republic, especially for the food or technical purposes, but at the same time it is not allowed worldwide for legislative reasons. Our study can be useful for agricultural practice. Nevertheless next year of poppy monitoring could be useful for making our results more significant.

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CONCLUSIONS

Our research showed solution with the use of visible spectral indices (GLI, TGI and VARI) derived not only from Sentinel 2 images, but from UAVs with common used multispectral or low-cost RGB camera as well. Nevertheless the highest coefficient of correlation between TGI index and NDVI derived from Sentinel 2 images is for poppy in average 0.69, with the maximum of 0.85. This points to the use of the TGI index in case of poppy as an alternative to NDVI when only common RGB camera is available. Generally, the results showed potential in UAV data collection as provide high spatial resolution, lower weather independence and select the best term of imaging. The devices used in this study need to be more used and proved in selected terms during the crop growth in the future.

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