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Comparison of selected remote sensing sensors for crop yield variability estimation

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Abstract. Currently, spectral indices are very common tool how to describe various characteristics of vegetation. In fact, these are mathematical operations which are calculated using specific bands of electromagnetic spectrum. Nevertheless, remote sensing sensors can differ due to the variations in bandwidth of the particular spectral channels. Therefore, the main aim of this study is to compare selected sensors in terms of their capability to predict crop yield by NDVI utilization. The experiment was performed at two locations (Prague-Ruzyně and Vendolí) in the year 2015 for both locations and in 2007 for Prague-Ruzyně only, when winter barley or spring barley grew on the plots. The cloud-free satellite images were chosen and normalised difference vegetation indices (NDVI) were calculated for each image. Landsat satellite images with moderate spatial resolution (30 m per pixel) were chosen during the crop growth for selected years. The other data sources were commercial satellite images with very high spatial resolution – QuickBird (QB) (0.6 m per pixel) in 2007 and WorldView-2 (WV-2) (2 m per pixel) in 2015 for Prague-Ruzyně location; and SPOT-7 (6 m per pixel) satellite image in 2015 for Vendolí location. GreenSeeker handheld crop sensor (GS) was used for collecting NDVI data for both locations in 2015 only. NDVI calculated at each of images was compared with the yield data. The data sources were compared with each other at the same term of crop growth stage. The results showed that correlation between GS and yield was relatively weak at Ruzyně. Conversely, significant relation was found at Vendolí location. The satellite images showed stronger relation with yield than GS. Landsat satellite images had higher values of correlation coefficient (in 30 m spatial resolution) at Ruzyně in both selected years. However, at Vendolí location, SPOT-7 satellite image has significantly better results compared to Landsat image. It is necessary to do more research to define which sensor measurements are most useful for selected applications in agriculture management.

Key words: Remote sensing, crop yield, satellite images, Greenseeker, NDVI.

INTRODUCTION

The concept of Precision Agriculture (PA) has developed as an indispensable reaction to higher population growth over recent decades (Zhang, 2015; United Nations, 2015). Up to 1960s, increasing crop production was enabled by expansion of agricultural areas, however, this trend slowed down when the percentage of arable land reached 9%

of total area worldwide (Moldan, 2015). Vegetation Indices (VI) are one of the tools by which it the concept of PA is currently fulfilled. These mathematical formulas are based on various combinations of reflectance values in specific bands of electromagnetic spectrum. Knowledge of spectral behaviour of vegetation is therefore essential for results interpretation. The method of evaluation canopy characteristics using VI has been gaining importance recently because the whole process operates in a non-destructive mode (Richards, 1993). It is therefore possible to carry out particular analysis repeatedly, for instance in different growth stages (Jones & Vaughan, 2010). A number of studies have been performed to prove the relation between VI and investigated vegetation characteristics, e.g. the study of Hunt Jr. et al. (2013), where triangular greenness index (TGI) was developed and successfully used to indicate leaf chlorophyll content. Prediction models for barley, canola and spring wheat yield were created by Johnson et al. (2016) using Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) data. VI may be also utilized for comparison of different hybrids yield, as Marino et al. (2013) did when studying two hybrids of onion productivity.

NDVI is the basic representative of VI's. The algorithm for NDVI calculation was stated by Rouse et al. (1973) as the ratio of reflectance in near infrared (NIR) and red visible region. NDVI is considered as main indicator of greenness, e.g. of dense and healthy vegetation. Its values range from -1.0 to +1.0, where higher values (0.6–0.9) indicate denser vegetation cover (USGS, 2015). Nevertheless, Huete et al. (2002) stated, that NDVI tend to lose sensitivity as the vegetation cover becomes denser.

To acquire desired information about specific vegetation characteristic in form of VI, remotely sensed data are utilized. At present, there are a number of sources that provide such kind of imagery. The data may beacquired by spacecraft or aircraft. These carry devices onboard, that capture Earth's surface either actively or passively (Khorram et al., 2016), therefore remote sensing sensors are divided into active and passive as well. Passive sensors exploit the electromagnetic radiation emitted or reflected from Earth's surface, thus the signal detected comes from outside a sensor. Conversely, active sensors collect information per an artificial signal. Energy is emitted from within the sensor and detected after it is reflected from the surface (Wang & Weng, 2013). In literature, differences between active and passive sensors have been intensively studied. Erdle et al. (2011) tested one passive and three active reflectance sensors to examine how they provide the information about nitrogen content and crop biomass. Another study (Elsayed et al., 2015) dealt with the capability of both types of sensor to estimate Normalized Relative Canopy Temperature (NRCT). GS is a representative of the active sensors. Its signal is emitted towards the target and the amount of reflected radiation is detected. GS convert such data into NDVI directly (Trimble, 2017). On the other hand, satellite data in this study were all acquired by passive sensors. There are differences in desired wavelengths between particular sensors.

It is clear from the above literature review that different methods and sensors can be used for crop yield prediction. Therefore, this study aims to compare selected sensors in terms of their capability to predict crop yield by NDVI utilization.

MATERIALS AND METHODS

Study area

The data for this study were obtained from two experimental fields. The first one (Ruzyně) was situated in Prague-Ruzyně (50°05'N, 14°17'30"E), Czech Republic. A larger part of the field has a southern aspect and the elevation ranges from 338.5 to 357.5 m above average sea level (a.s.l). The size of area is 11.5 ha. The average slope of the field is approximately 6%. The soil of this experimental plot can be classified as Haplic Luvisols partially covering fine calcareous sandstones with higher content of coarse silt and lower content of clay particles and clay. The value of cation exchange capacity in the top layer containing clay is 20–35%. The soil profile is neutral and the sorption capacity is from saturated to fully saturated. Content of available minerals is from good to very good. In the slope positions and in loess loam profiles of Luvisols with remnants of alluvial horizon can be found. Some parts where the topsoil directly overlays the parent material of loess loam are strongly eroded. The average precipitation is 526 mm per year and the average temperature is 7.9 °C.

The second field (Vendolí) was located near to Vendolí in Eastern Bohemia (49°43' 47.94"N, 16°24' 14.21"E), Czech Republic, and it has 26.4 ha. The plot is undulated with the average slope approximately 6%. The elevation ranges from 543 to 571 m a.s.l. The soil of this experimental plot can be classified as modal cambisols lying on calcareous sandstone. Some parts, on sloppy terrain especially, are strongly eroded, while big amount of stones is lying on the top parts of the field. The average precipitation is 700 mm per year and the average temperature is between 6–7 °C.

Conventional arable soil tillage technology based on ploughing was used on these fields. Crop rotation system, based on wheat, barley and oilseed rape crops alternation, is common practice in the Czech Republic. Our experiment included the data from the year 2007 and 2015 for Ruzyně with winter barley and 2015 only for Vendolí with spring barley.

Field data

A combine harvester Sampo 2070 equipped with an LH 500 yield monitor (LH Agro, Denmark) with a DGPS receiver with EGNOS correction measured yield in Ruzyně location. The horizontal and vertical accuracy of this system was ± 0.1 to 0.3 m and ± 0.2 to 0.6 m, respectively. Measured yield data were processed by an on-board computer on the combine harvester and saved together with the location data every 3 s. An axial combine harvester New Holland CR9080 equipped with New Holland factory yield monitor and DGPS receiver with correction measured yield in Vendolí location. The precision of this system horizontally was ± 0.1 to 0.3 m and vertically it was ± 0.2 to 0.6 m. The data were saved with the coordinates every 1 s. The grain moisture content was measured continuously in the case of both fields and the yield was recalculated to 14% moisture content. The yield values were corrected using a common statistical procedure; all values that exceeded the range defined as mean ± 3 standard deviations were removed. Because of the large amount of data for both location studied (more than 8,000), the Method of Moments (MoM) was used to compute the experimental variograms. Experimental variograms of yield were computed and modelled by weighted least-squares approximation in GS+ software (Gamma Design Software, St. Painwell, MI, USA). A detailed description of this method can be found in

Kumhálová et al. (2011). Ordinary punctual kriging was done using the relevant data and exponential variogram model parameters for yield data visualisation.

NDVI values from GS handheld crop sensor were collected during the winter barley growth in April 23rd, and May 19th 2015 at Ruzyně location, and May 8th, May 30th and June 30th at Vendolí location. Experimental variograms of NDVI values were computed by common procedures using an exponential and spherical model (see Table 1). The data were processed in ArcGIS 10.3.1 software (Esri, Inc., Redlands, CA, USA).

Table 1. Summary statistics, variogram model parameters and the methods of interpolation used for yield and GS in the experimental field

	Yield			GS – NDVI				
Crop	Winter barley		Spring barley	Winter barley		Spring barley		
Location	Ruzyně		Vendolí	Ruzyně		Vendolí		
				2015		2015		
				23-april	19-may	8-may	30-may	20-june
Count	8,808.0	10,974.0	18,537.0	103.0	103.0	110.0	110.0	110.0
Mean	5.618	5.322	4.049	0.779	0.802	0.321	0.697	0.672
Median	5.481	5.385	4.111	0.790	0.810	0.310	0.715	0.680
Standard deviation	1.373	0.836	1.377	0.062	0.030	0.076	0.083	0.068
Minimum	1.109	1.391	0.204	0.390	0.670	0.190	0.440	0.510
Maximum	10.149	9.254	8.733	0.890	0.850	0.580	0.850	0.830
Skewness	0.015	-0.666	-0.025	-2.946	-2.206	0.458	-0.693	-0.567
Methodofinterpolation	Kriging							
Methodofestimation	Method of Moments (MoM)							
Variogram model	Exponential				Spherical			
Distance parameter (r)	22.9	11.0	72.30	205.7	610.9	210.9	297.0	215.9
Approximaterange = 3 x r	68.7	33.0	216.9	617.1	-	-		-
Nugget variance	0.3170	0.4200	0.5390	0.0025	0.0005	0.0044	0.0038	0.0047
Sill variance	1.0100	0.5900	1.9140	0.0051	0.0012	0.0063	0.0077	0.0026

Total monthly precipitation and temperature data were provided by the agro-meteorological station at the Crop Research Institute in Prague-Ruzyně and from weather station Davis in Vendolí. Precipitation and temperatures for the observed year are also provided in Table 2.

Table 2. Precipitation and temperatures in different growth stages by BBCH scale recorded on the experimental fields in the year 2015 for winter and spring barley

	Precipitation (mm)			Temperature (°C)		
	2007	2015	2015	2007	2015	2015
	Ruzyně		Vendolí	Ruzyně		Vendolí
Plant	Winter barley		Spring barley	Winter barley		Spring barley
BBCH 0-19	32.0	48.7	30.4	10.9	11.0	5.5
BBCH 20-29	90.4	100.4	7.6	5.7	3.8	9.7
BBCH 30-59	2.4	43.7	35.8	12.8	12.3	13.0
After BBCH 60	146.6	64.6	132.6	18.1	17.1	18.6
Sum	271.4	189.5	206.4	-	-	-
Mean	90.5	63.2	51.6	12.6	10.9	11.7

Remote sensing data

Landsat satellite images were downloaded directly from the USGS Global Visualization Viewer (http://earthexplorer.usgs.gov/), as free remotely sensed data.Images from Landsat 5 (L-5), Landsat 7 (L-7) and Landsat 8 (L-8) were used for this study. WV-2, QB and SPOT-7satellite images were purchased from the ArcDATA Company. Table 3 provides the bandwidths of red visible (RED) and near infrared (NIR) range of sensors used in this study. For atmospheric correction, the Fast Line-of-sight Atmospheric Analysis of Hypercubes was used (Li et al., 2014; Dominguez et al., 2015). All image pre-processing was implemented with ENVI SW (ENVI; version 5.3, Excelis, Inc., McLean, VA, USA).

NDVI were computed for every image with ENVI SW. All images were then exported into ArcGIS SW for further processing. Very high resolution (VHR) images (WV-2, QB and SPOT-7) were resampled according to Landsat satellite image outputs to 30 m. Yield data were resampled according to satellite images to spatial resolution of 0.6 m, 2 m, 6 m and 30 m. Data from GS were resampled according to Landsat images to 30 m spatial resolution for further processing.

Pearson's correlations between the yield maps and NDVI derived from satellite images and GS sensor were calculated using Statistica 13 (StatSoft Inc., Tulsa, USA) procedure.

Table 3. Bandwidths of red visible (RED) and near infrared (NIR) range of selected satellites and sensors

Satellite	Sensor	RED range (nm)	NIR range (nm)
L-5	TM	630–690	760–900
L-7	ETM+	630–690	750–900
L-8	OLI	640–670	850–880
QB		590–710	715–918
SPOT-7		625–695	760–890
WV-2		630–690	705–895
	GS	660, ~25 nm FWHM	780, ~25 nm FWHM

RESULTS AND DISCUSSION

Correlation coefficients (*R*) between NDVI (from original and resampled data sets of Landsat, QB, WV-2 and SPOT-7 satellite images) and yield were calculated for individual image data and plant species in selected locations (see Table 4). Correlation matrices between NDVI from GS crop sensor, Landsat satellite images and yield were then calculated for individual data sets (see Table 5). Summary statistics for NDVI calculated from original and resampled satellite images for selected crops are in Table 6. Summary statistics of crop yield and GS for selected dates only for 2015 provides Table 1.

Winter barley was grown in 2007 and 2015 in Ruzyně location. The year 2007 was drier up to BBCH 60 phenological stage in comparison with the year 2015 in Ruzyně location (see Table 2). Low precipitation in the growth stage BBCH 30-59 (2.4 mm) can cause a significant displacement of relatively higher yield to water-accumulating depressions. This fact is confirmed also by correlations presented in Table 4, where *R* between NDVI a yield had average value 0.856. The movement of higher yield to terrain concave areas in 2007 was also validated by summary statistics presented in Table 1, whereby both standard deviation and min-max range were higher than in 2015. In our previous articles (Kumhálová et al., 2011; Kumhálová et al., 2014), the influence of topography to yield in drier years was also found.

Table 4. Correlation coefficients between normalised difference vegetation index (NDVI) (from original and resampled L, QB and WV-2 satellite images with different spatial resolution (SR)) and yield of selected crops and years (levels of statistical significance: * *p < 0.05*; ** *p < 0.01*; *** *p < 0.001*)

Year	Yield		Growth stage	NDVI	
2007	Ruzyně		BBCH 59	Winter barley	
Satellite	L-5 TM	QB	L-5	QB	QB
SR	30 m	0.6 m	30 m	0.6 m	30 m
Date	May 24	May 22	May 24	May 22	May 22
Yield	1	1	0.861***	0.861***	0.835***
2015			BBCH 21-22		
Satellite	L-8 OLI	WV-2	L-8	WV-2	WV-2
SR	30 m	2 m	30 m	2 m	30 m
Date	March 18	March 23	March 18	March 23	March 23
Yield	1	1	0.264**	0.133***	-0.018
2015	Vendolí		BBCH 75	Spring barley	
Satellite	L-8 OLI	SPOT	L-8	SPOT-7	SPOT-7
SR	30 m	6 m	30 m	6 m	30 m
Date	July 1	July 4	July 1	July 4	July 4
Yield	1	1	0.341**	0.565***	0.501***

The year 2015 was drier year in sum of precipitation than the year 2007, but the precipitation distribution was more balanced during the growth stages (see Table 2). On the contrary, the precipitation distribution in BBCH 30–59 (43.7 mm) could probably cause the later crop beaten. In this year, harvesting losses caused by crop beating decreased the yield (see Table 1). This fact was confirmed by low *R* values between yield and NDVI (see Table 5); although the NDVI values were relatively high during BBCH 21–22 and crops were in a good condition (see Table 6). GS measurements on April 23rd (BBCH 31) and May 19th (BBCH 55) and comparisons between NDVI from GS and Landsat images and yield in Table 5 are in good accordance with previous statements. Nevertheless, *R* between NDVI from GS and Landsat images were weak (see Table 5).

Spring barley was grown in 2015 in Vendolí location. The precipitation distribution during the growth stages were balanced except the BBCH 20–29. The precipitation distribution was lower during these growth stages (7.6 mm) – see Table 2. Nevertheless, this weather running could lead to higher *R* (0.613) between yield and NDVI calculated from Landsat image in 30th May (see Table 5). It is validated by summary statistics presented in Table 1 as well, whereby standard deviation reached higher value. The precipitation distribution over the all growth stages could cause displacement of higher yield to places with better growth conditions. GS measurements were carried out on May8th (BBCH 35), May 30th (BBCH 55) and June 20th (BBCH 65). *R* between NDVI from GS and Landsat images was weak in early growth stage (8th May). On the contrary, the *R* value reached 0.679 between these two (GS and Landsat satellite) measurement methods in 30th May. The last measurements NDVI on 20th June with GS and on 20th

with Landsat were similar in comparison with yield, but the *R* between the measurement methods reached the value 0.453 only. These differences can be caused by other measurement method used and other spatial distribution of values measured. SPOT-7 image, acquired on 1st July, was chosen for crop evaluation. Very high resolution image in late date was available only, because of very cloudy scene during the crop growth. The *R* between yield and Landsat and SPOT-7 images was different. The Landsat image was cloudy in northern part of the experimental field. That is why 38 pixels from this part of field had to be removed (see Table 6).

Table 5. Correlation coefficients between normalised difference vegetation index (NDVI) from GS sensor, Landsat images and crop yield (levels of statistical significance: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$)

		Winter barley – Ruzyně			
2015	Date/SR	GS NDVI	GS NDVI	L-8 NDVI	L-8 NDVI
Date		April 23	May 19	April 19	May 14
Yield	30m	0.011	0.022	0.260**	0.145
L-8 NDVI	April 19	0.310*	-	-	-
L-8 NDVI	May 14	-	0.359***	-	-

		Spring barley – Vendolí					
2015	Date/SR	GS NDVI	GS NDVI	GS NDVI	L-7 NDVI	L-8 NDVI	L-8 NDVI
Date		May 8	May 30	June 20	April 29	May 30	June 24
Yield	30m	0.323***	0.458***	0.387***	0.001	0.613***	0.415**
L-7 NDVI	April 29	0.035	-	-	-	-	-
L-8 NDVI	May 30	-	0.679***	-	-	-	-
L-8 NDVI	June 24	-	-	0.453***	-	-	-

L-8 – Landsat 8 OLI image; L-7 – Landsat 7 ETM+; SR – spatial resolution.

Table 6. Summary statistics for NDVI calculated from original and resampled satellite images for selected years and crops

Year	2007 – winter barley			2015 – winter barley			2015 – spring barley		
	Ruzyně						Vendolí		
Satellite	L-5	QB	QB	L-8	WV-2	WV-2	L-8	SPOT-7	SPOT-7
SR	30 m	0.6 m	30 m	30 m	2 m	30 m	30 m	6 m	30 m
Count	115	306704	115	102	26684	102	231	6311	269
Mean	0.756	0.635	0.635	0.528	0.414	0.418	0.888	0.802	0.797
Median	0.759	0.638	0.635	0.532	0.416	0.418	0.901	0.809	0.809
Standard deviation	0.077	0.041	0.039	0.046	0.057	0.056	0.095	0.044	0.055
Minimum	0.556	0.477	0.544	0.315	0.185	0.269	0.519	0.623	0.531
Maximum	0.876	0.799	0.721	0.626	0.619	0.559	1.087	0.886	0.876
Skewness	-0.664	-0.401	-0.138	-1.047	-0.153	-0.353	-0.413	-0.732	-0.763

Summary statistics in Table 6 show that NDVI derived from Landsat images had higher mean and maximum values than NDVI derived from other satellites used in this study. This fact may support the conclusion, that Landsat images are more sensitive to crop biomass content. It can be explained by the differences in RED and NIR bandwidth among the sensors (see Table 3). QB, WV-2 and SPOT-7 have wider band range, than any of Landsat sensors. When comparing available Landsat sensors, L-5 and L-7 have similar calibration in contrast with L-8 (see Table 3). Studies dealing with this different

L-8 setting were also performed (Holden et al., 2016; Roy et al., 2016).GS handheld sensor and L-7 provide data in approximately same wavelengths. Nevertheless, there is a difference between GS and L-8. Despite this fact, L-8 data are very well correlated both with GS NDVI ($R = 0.679$, 30th May 2015 at Vendolí) and also with yield ($R = 0.613$, 30th May at Vendolí). However, this may be also caused by measuring date accordance. Differences in red band wavelengths are not so substantial in any case.

Another cause of differences may be input data resampling. Apart from Landsat, all satellite data were resampled to 30 m spatial resolution. Table 6 shows summary statistics for both, original and resampled data. Resampling seems to have no influence on QB data, all categories of summary statistics differ very slightly and mean values are even equal. WV-2 and SPOT-7 original and resampled data differ more in summary statistics than other sources. Each sensor was used to evaluate different dataset. Results that are more accurate may be gained when evaluating selected sensors by calculating NDVI from the same dataset. In addition, Bégué et al. (2008) stated that single date images may be unsatisfactory for yield prediction.

As mentioned above, there is the opinion that NDVI may be poor indicator of crop biomass when the canopy becomes denser (Huete et al., 2002). Gao et al. (2000) stated, that Enhanced Vegetation Index (EVI) tend not to be saturated over dense vegetation, like NDVI does, and seems to be sensitive enough to plant structural characteristics.In study by Zhu et al. (2016) similar issue was studied. L-5, L-7 and L-8 imagery were used to calculate NDVI and EVI for land cover changes evaluation in the city of Guangzhou, China. Due to the different wavelength setting, EVI was chosen as better indicator of greenness. Erdle et al. (2011) compared utilization of active and passive sensors. According to their study, made on seven wheat cultivars, active sensors disadvantage is that they are capable to measure limited number of VI. Conversely, passive sensors perform a possibility to develop different VI. Above that, GS measures only two fixed bands, while another active sensor Crop Circle is capable to capture three user configurable bands, e.g. green, red edge and NIR.As stated in Cao et al. (2015) study, indices derived from Crop Circle perform significantly better, than indices acquired by GS. Ali et al. (2014) examined the potential of yield prediction on dry direct-seeded rice using GS and then chlorophyll meter (SPAD) and simple leaf colour chart. Their result allegation was that all of these methods can be used for in-season yield prediction. Thus, according to that, GS is comparable with more simple measurement methods.

CONCLUSION

The results showed that all satellite images used in this study can sufficiently explain crop variability in given dates and can be used for yield prediction and crop growth evaluation. NDVI spectral index seemed to be good tool for simple and fast evaluation of the agriculture crop, because several data sourceswere possible to use for its calculation. Passive remote sensing sensors were compared with GS active sensor. Nevertheless, not very consistent results were acquired. VHR images were resampled to 30 m spatial resolution according to Landsat images in order to examine possible influence of spatial resolution on information evaluated. However, various bandwidths in RED and NIR region of selected images made the correlations between yield and NDVI different. The greatest difference in such evaluation was found between L-8 OLI sensor and WV-2 and SPOT-7 sensors. On the base of the results obtained in this study, it is necessary to undertake more research to define which of selected sensors is the most capable for yield prediction under conditions of the Czech Republic.

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