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Assessment of the relationship between spectral indices from satellite remote sensing and winter oilseed rape yield

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Abstract. Winter oilseed rape (*Brassica napus* L.) belongs among the most common and strategic crops in the Czech Republic. Growth and vitality status, yield potential and yield prediction of oilseed rape on plots of different sizes can be effectively examined using remote sensing. That is why the main aim of this study was to discuss a possibility of deriving spectral indices for an assessment which spectral index is more adequate to forecast oilseed winter rape development and consequent yield in the Czech Republic. Information about the winter oilseed rape growth and yield was collected in three years – 2004, 2008, 2012. A relationship between grown crops and selected vegetation indices was evaluated. The Landsat 7 satellite images were selected as a source for deriving spectral indices. The relationship between each spectral index and yield was analysed in 2012 only. Five images on different dates during the whole life of winter oilseed rape were found during this year. The images from the years 2004 and 2008 were cloudier. The spectral indices showing the best relationship with yield from 2012 were then analysed in the images from 2004 and 2008. The results showed that Enhanced Moisture Stress Index is the most acceptable index from the selected indices used in this study. From an agronomical point of view no available index was found to be suitable for the winter rape growth evaluation due to dependence on precipitation conditions. For monitoring of the yield components in winter oilseed rape in conditions of the Czech Republic, it seems necessary to develop a new vegetation index which will reliably describe the winter oilseed rape growth stages during the whole vegetation season.

Key words: Remote sensing, spectral indices, winter oilseed rape, yield rating, Landsat 7 images.

INTRODUCTION

Rapeseed is among the three most important oilseed crops in the world (FAO, 2007). Its oil is used as a raw material to produce industrial and hydraulic oil, cleaners, soap, biodegradable plastics and for animal nutrition (Ghaffari et al., 2014). Besides, it is one of the cultivated medicinal food plants in Middle Asia, North Africa and Western Europe (Saeidnia & Reza, 2012). Rapeseed is also advantageous nutrition and fertilization plant in different soil tillage systems (Růžek et al., 2006). These advantages are the reasons why global cultivation has gradually been increasing over the last 10 years (Schoenenberger & D'Andrea, 2012). Since the 80's rapeseed is the most frequently grown oilseed crop in Europe, above all in the Czech Republic. In this country the area under rapeseed has increased to more than 400 thousand hectares (Krček et al., 2014) and rapeseed has become one of the strategic plants at economic and agricultural levels.

Satellite images are usually used for Earth observation, and many remote sensing applications are devoted to the agricultural sector, mainly in: (1) biomass and yield estimation, (2) vegetation vigour and drought stress monitoring, (3) assessment of crop phenological development, (4) crop acreage estimation and cropland mapping, and (5) mapping of disturbances and land use/land cover (LULC) changes (Atzberger, 2013). Technological advances in remote sensing have enabled the development of new applications in agriculture such as precision agriculture (Zarco-Tejada et al., 2014), irrigation management, time series (Tornos et al., 2015) and crop behaviour (Dominguez et al., 2015).

Only a few studies have been reported on the use of remote sensing methods for assessing winter oilseed rape biophysical parameters (e.g. Pan et al., 2013; Li et al., 2014). The area under winter oilseed rape in the countries of East-Central Europe such as Poland has increased in recent years. This is connected with the intensification of biofuel production. This should lead to the development of methods for the control of the condition of crops and forecasting yields (Piekarczyk et al., 2011). For example Piekarczyk et al. (2011) used hyperspectral radiometer measurements (a hand-held radiometer and multispectral images) for estimation of oilseed-rape yield. They found out that the strongest relationships ($R^2 = 0.87$) between the yield and spectral data recorded by both sensors occurred at early flowering stages.

Technological advances in the spectral data from World War Two to the mid-1960s encouraged scientists to use these data and to explore their applications (Cohen & Goward, 2004). The first spectral indices obtained from these data were developed as the ratio between reflection signals at 740 nm (near-infrared band, NIR) and 650 nm (red band, RED) (see Table 1) and they were used for different vegetation studies and called spectral vegetation index (SVI), simple ratio (SR), ratio vegetation index, formerly known as the environmental vegetation index (EVI) (Birth & McVey, 1968). SVIs are based on the relationship between the leaf structure and electromagnetic radiation reflectance by chlorophyll. A few years later, Landsat 1 was launched with a spectral resolution similar to that used in spectroscopy studies for the visible and NIR bands. SVI was the first spectral index used, however, for studying plant growth it is better to use the normalized difference vegetation index (NDVI), because pigments in plant leaves strongly absorb wavelengths of red light and the leaves themselves strongly reflect wavelengths of near-infrared light (Rouse et al., 1974). However, the NDVI exhibited no good correlation with the chlorophyll content. The best correlation was found in the ratio of the reflection signals at 800 nm (NIR) and 550 nm (green band, GREEN). The resulting spectral index was similar to NDVI, but replaced the red band by the green band. This index was called green normalized difference vegetation index (GNDVI) (Buschmann & Nagel, 1993). The optimized soil adjusted vegetation index (OSAVI) was developed as a modification of NDVI to correct for the influence of soil brightness when the vegetative cover is sparse. The OSAVI is structurally similar to the NDVI but with the addition of a 'soil brightness correction factor' (Rondeaux et al., 1996). Various spectral indices were used for nitrogen determination in maize, such as normalized green ratio (Norm G), normalized red ratio (Norm R), normalized infrared ratio (Norm NIR), and the green optimized soil adjusted vegetation index (GOSAVI) (Sripada et al., 2006). The close relationship between leaf nitrogen content and leaf chlorophyll content was analysed by means of chlorophyll vegetation index (CVI) (Hunt et al., 2011).

Table 1. Spectral range overview of Landsat 7 image

Landsat 7 Bands	Spectral Range	Wavelength (μm)
Band 1	Blue	0.45–0.51
Band 2	Green	0.53–0.59
Band 3	Red	0.64–0.67
Band 4	Near Infrared (NIR)	0.85–0.88
Band 5	Short-wave Infrared 1 (SWIR 1)	1.57–1.65
Band 7	Short-wave Infrared 2 (SWIR 2)	2.11–2.29

Soil and water content are other factors of great importance for plant growth and health. That is why short wavelength infrared bands (SWIR) were used in moisture stress index (MSI) and in enhanced moisture stress index (EMSI) (Rock et al., 1985; Dupigny-Giroux and Lewis, 1999). Water content in the leaves has been studied using the normalized difference water index (NDWI) (Gao, 1996). A modification of NDWI is to replace SWIR1 by SWIR2; this index was called enhanced normalized difference water index (ENDWI) (Chen et al., 2005). During a five-year (2001–2005) history of moderate resolution imaging spectroradiometer (MODIS), the NDVI and the NDWI were used to study drought and allowed to develop a new spectral index – normalized drought difference index (NDDI) and enhanced NDDI (ENDDI). The ENDDI ratio is calculated by dividing the difference of the NDVI and ENDWI between the sums of these spectral indexes (Gu et al., 2007).

It is clear from the above review of literature that remote sensing can be used for the assessment of plant biophysical parameters and a relatively high number of vegetation indexes was introduced. Satellite remote sensing is presented as an auxiliary tool in agriculture. However, it is necessary to analyse the various methodologies in order to obtain optimum performance of this tool and the relationship between satellite remote sensing and yield forecasting. Only a few studies examined biophysical properties of rape in the past despite the fact that rape is an increasingly popular crop under European conditions. Thus, the aim of this study is to fill this gap of knowledge and to assess which spectral index is the best for winter oilseed rape yield forecasting in the Czech Republic.

MATERIALS AND METHODS

Study area

The study area is an experimental field of 11.5 ha in size with Haplic Luvisol located 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 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. Conventional arable soil tillage technology based on ploughing and fixed crop rotation was used in this field. Since 2001 the crop rotation has been as follows: sugar beet (2001), spring barley (2002), winter wheat (2003), winter oilseed rape (2004), winter wheat (2005), oat (2006), winter barley (2007), winter oilseed rape (2008), winter wheat (2009), oat (2010), winter wheat (2011), winter oilseed rape (2012), winter wheat (2013), oat (2014), winter barley (2015) and winter oilseed rape (2016) (Kumhálová & Moudrý, 2014). This crop rotation system is a common practice in the Central Bohemian Region (Czech Republic). Our experiment included the data from the years 2004, 2008 and 2012 only.

Field data

Yield was measured by a combine harvester equipped with an LH 500 yield monitor (LH Agro, Denmark) with a DGPS receiver with EGNOS correction. 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. The grain moisture content was measured continuously 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 every year 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. (2011a). Ordinary punctual kriging was done on a 6.5 m grid using the relevant data and exponential variogram model parameters for yield data visualisation (see Table 2). The data were processed in ArcGIS 10.3.1 software (ESRI, Redlands, CA, USA).

Total monthly precipitation and temperature data were provided by the agro-meteorological station at the Crop Research Institute in Prague-Ruzyne. Precipitation and temperatures for the observed years are also shown in Table 3.

Table 2. Summary statistics, variogram model parameters and the methods of interpolation used for yield in the experimental field

	Yield 04	Yield 08	Yield 12
Count	10,861.0	8,440.0	9,389
Mean	3.708	2.734	2.809
Median	3.739	2.527	2.942
Mode	3.073	0.677	2.626
Sample variance	0.878	7.283	6.623
Standard deviation	0.937	1.477	1.199
Minimum	0.304	0.059	0.100
Maximum	7.104	7.342	6.623
Skewness	-0.612	0.126	-0.252

Table 2 (continued)

Method of estimation	Method of moments (MoM)		
Variogram model	Exponential		
Distance parameter (r)	28.9	22.7	69.7
Approximate range = 3 r	86.7	68.1	209.1
Nugget variance	0.340	1.040	0.589
Sill variance	0.817	1.750	1.449
Method of interpolation	Kriging	Kriging	Kriging

Table 3. Precipitation and temperatures in different growth stages by BBCH scale recorded on the experimental field in the year 2004, 2008, 2012 for winter oilseed rape

	Precipitation (mm)			Temperature (°C)		
	Winter oilseed rape					
	2004	2008	2012	2004	2008	2012
BBCH 0-19	52.8	72.0	61.3	16.5	13.5	16.8
BBCH 20-29	103.4	105.3	167.8	5.4	5.3	4.3
BBCH 30-59	157.2	112.6	54.1	14.6	11.8	9.5
After BBCH 60	46.6	99.6	258.9	19.1	18.9	17.8
Sum	307.2	317.5	480.8	-	-	-
Mean	102.4	105.8	160.3	13.0	11.9	10.5

Remote sensing data processing

Landsat 7 Enhanced Thematic Mapper Plus (ETM^+) images were obtained from the US Geological Survey (USGS) (http://earthexplorer.usgs.gov/). All cloud-free images (see Table 4) available over the study area from the years 2004, 2008 and 2012 between March and June have been selected (path 191, row 25 and path 192, row 25). ENVI 5.3 (Excelis, Inc., McLean, USA) remote sensing software was used for processing all images.

Table 4. Available Landsat images for the selected years

Crop	Date	Sensor	Satellite
Winter Oilseed Rape	28-Apr-2004, 30-May-2004, 8-Jun-2004, 2-May-2008, 9-May-2008, 10-Jun-2008, 17-Mar-2012, 26-Mar-2012, 27-Apr-2012, 4-May-2012, 19-May-2012,	ETM+	Landsat 7

The images that could not be used because of cloud cover or because of striping with data gaps were also found. This is a problem of Landsat 7 images. It is caused by the scan line corrector anomaly in Landsat 7, which is inconvenient when using remote sensing in some study areas. In fact it was the reason why there were only a few images from Landsat 7 for this area. However, the images available in UGSS allowed analysing the relationship between the spectral index and the yield. Temporal distribution of the images along the observed three years included all the growth stages of winter oilseed rape for each year.

Selected spectral indices (see Table 5) were calculated by means of images converted into reflectance bands using the atmospheric correction model Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) (Li et al., 2014; Dominguez et al., 2015).

Table 5. Spectral indices evaluated in this study

Spectral Index	Algorithm	References
Ratio Vegetation Index (RVI)	(NIR / RED)	Birth & McVey (1968)
Normalized Difference Vegetation Index (NDVI)	(NIR – RED) / (NIR + RED)	Rouse et al. (1974)
Green Normalized Difference Vegetation Index (GNDVI)	(NIR_r – GREEN) / (NIR + GREEN)	Buschmann & Nagel (1993); Gitelson et al. (1996)
Normalized Green (NG)	GREEN / (NIR + RED + GREEN)	Sripada et al. (2006)
Normalized Red (NR)	RED / (NIR + RED + GREEN)	Sripada et al. (2006)
Normalized NearInfrared (NIR)	NIR / (NIR + RED + GREEN)	Sripada et al. (2006)
Chlorophyll Vegetation Index (CVI)	NIR × RED / GREEN)^2	Vincini et al. (2008)
Optimized Soil Adjusted Vegetation Index (OSAVI)	[(NIR – RED) / (NIR + RED +L)] × (1 + L)	Rondeaux et al. (1996)
Moisture Stress Index (MSI)	SWIR1 / NIR	Rock et al. (1985)
Enhanced Moisture Stress Index (EMSI)	SWIR2 / NIR	Rock et al. (1985)
Green Soil Adjusted Vegetation Index (GSAVI)	[(NIR – GREEN) / (NIR + GREEN + L)] × (1 + L)	Stripada et al. (2006)
Normalized Difference Water Index (NDWI)	(NIR – SWIR1) / (NIR + SWIR1)	Gao (1996)
Enhanced Normalized Difference Water Index (ENDWI)	(NIR – SWIR2) / (NIR + SWIR2)	Chen et al. (2005)
Normalized Drought Difference Index (NDDI)	(NDVI – NDWI) / (NDVI + NDWI)	Gu et al. (2007)
Enhanced Normalized Drought Difference Index (ENDDI)	(NDVI – ENDWI) / (NDVI + ENDWI)	Gu et al. (2007)

FLAASH correction consists of two parts. The first is conversion of digital numbers (DNs) to radiance values. This is calculated by the following formula:

$$L_\lambda = (Gain_\lambda \times DN7) + bias_\lambda \tag{1}$$

where L_λ is the calculated radiance [in W/(m^2 × sr ×μm)], DN7 is the Landsat 7 ETM$^+$ DN data or the equivalent calculated in step, and the gain and bias are band-specific numbers. The latest gain and bias numbers for the Landsat 7 ETM+ sensor are given in Chander et al. (2009).

The second part is to convert radiance data to reflectance data. Top of Atmosphere (TOA) Reflectance was calculated using the following expression:

$$R_\lambda = \frac{\pi L\lambda d2}{Esun\lambda \sin(\Theta SE)} \tag{2}$$

where R_λ is the reflectance (unitless ratio), L_λ is the radiance calculated in the preceding step according to formula 1, d is the Earth-Sun distance (in astronomical units), $Esun_\lambda$ is the band-specific radiance emitted by the Sun, and ΘSE is the solar elevation angle.

The FLAASH module from ENVI software was used to correct Landsat data with the metadata file for each Landsat image (scene centre location, sensor altitude, pixel size, flight date and time), atmospheric model (Mid-Latitude Summer), aerosol model (rural), initial visibility (30 km) and aerosol retrieval [2-Band (Kaufman)].

The relationship between each spectral index and yield was analysed in 2012 only because in that year 5 images taken on different dates during the whole winter oilseed rape life were found. The spectral indices showing the best relationship with yield were then analysed in the images from 2004 and 2008. The statistical analysis of data was done by Statistica 8.0 software (StatSoft Inc., Tulsa, OK, USA).

RESULTS AND DISCUSSION

The correlation coefficients (R) between different spectral indices and yield in different years are shown in Table 6. The correlation coefficients were calculated for a 5% significance level. Winter oilseed rape yield in all the three growing seasons is represented in Fig. 2. All basic differences between yield data can be seen in Table 2. Fig. 3 shows the dependence between the EMSI spectral index and yield on three dates of crop monitoring in 2008 and Fig. 4 documents the same dependence on five dates of crop monitoring in 2012.

Table 6. Correlation coefficients (R) between different spectral indexes and yield in the years 2004 in terms:(1) 28–Apr, (2) 30–May, (3) 8–Jun; 2008: (1) 2–May, (2) 9–May,(3) 10–Jun; 2012: (1)17–March, (2) 26–March, (3) 27–Apr, (4) 4–May, (5) 19–May (5% significance level)

	NDVI	GNDVI	CVI	OSAVI	MSI	EMSI	NDWI	ENDWI	NDDI	ENDDI
2004										
(1)	0.07	0.007	0.005	0.0004	0.000	0.0001	0.0007	0.0006	0.007	0.009
(2)	0.0005	0.07	0.08	0.056	0.042	0.19	0.034	0.047	0.003	0.0004
(3)	0.013	0.09	0.09	0.07	0.077	0.08	0.085	0.05	0.002	0.047
2008										
(1)	0.009	0.004	0.033	0.01	0.005	0.02	0.0025	0.022	0.026	0.033
(2)	0.05	0.027	0.012	0.07	0.216	0.04	0.216	0.044	0.17	0.1
(3)	0.147	0.112	0.012	0.147	0.277	0.61	0.0314	0.192	0.2	0.013
2012										
(1)	0.32	0.18	0.11	0.31	0.22	0.46	0.22	0.24	0.23	0.06
(2)	0.25	0.30	0.17	0.22	0.33	0.52	0.28	0.32	0.20	0.06
(3)	0.24	0.20	0.08	0.20	0.28	0.56	0.27	0.22	0.21	0.15
(4)	0.002	0.006	0.01	0.002	0.006	0.036	0.01	0.0001	0.004	0.06
(5)	0.01	0.07	0.05	0.10	0.18	0.65	0.25	0.15	0.38	0.02

Total precipitation was average and mean temperature was higher in comparison with the other years during the 2004 winter oilseed rape growing season (Kumhálová et al., 2013). In that year, winter oilseed rape yield significantly differed from the other observed years (see Fig. 1). The yield was much more uniform overall field area and the mean of the yield was calculated to be 3.708 t ha^{-1}, which was about by 1 t ha^{-1} more than in the other two years (see Table 2). Relatively high yield and its uniformity were very probably caused by favourable water availability in the BBCH 30-59 development stages of winter oilseed rape. Sufficient available water caused the steady growth of plants on drier areas of the field. Less rainfall (see Table 3) was observed after the beginning of flowering. Nevertheless, this decrease of water availability hardly had any influence on the yield. The highest decrease in yield was observed at the headlands. It was probably caused by technogenic soil compaction at the headlands and other factors (pest attacks) (*Meligethes aeneus, Scierotinia scierotiorum*). It is quite clear from Table 6 that the correlation coefficients are generally very low. This fact may indicate that it is not possible to establish a relationship between selected indices in table 5 and rape yield. This is probably caused by specific development and leaf structure of rapeseed plants in comparison with grain plants. Another reason could be changes in the vegetation reflectance during the different rape phases, because rape changes rapidly the growth phases during the spring (Domínguez et al., 2015). That is why the spectral index values varied considerably. It is also clear from Table 6 that EMSI is the best index among the selected ones. EMSI is a spectral index that evaluates moisture stress and compares the relationships between band 4 (in Landsat 7 images), which contains information about the structure of the plant, and band 7, which contains data about water in the cells of the plant. EMSI showed low variability in band 4 and high variability in band 7 (Pan et al., 2013). Higher values of this index indicate greater water stress and lower water content. This fact could be seen in 2008 and 2012 in the later phase, but this dependence was very weak in 2004. Only three dates were evaluated in the 2004 season. The date 28.4.2004 was influenced by a change in the colour of vegetation during the BBCH 60 growth stage (beginning of flowering). Correlation coefficients (see Table 6) were very low for the other two dates in 2004. Both dates could be affected by the shooting stage, when due to the weather conditions water drops (dew in the morning during hot weather) were present on the leaves and reflectance values significantly changed. A significant relationship was found between the values of vegetation indices and yield in the 2004 season. Low correlation coefficients determined on 8. 6. 2004 could be caused by the weather conditions in the growth period after BBCH 60. This period was affected by dry and warm weather (see Table 3).

Average total precipitation and lower temperatures were observed in the 2008 growing season in comparison with the other observed years (Kumhálová et al., 2013). That year was good for plant mass production in the autumn season. Rape plants grew too large for winter. This consequently caused high infestation by fungal diseases (Kumhálová et al., 2011b), which significantly affected the yield on areas with standing water in the studied field. The field terrain probably had a negative effect on yield due to a positive effect on the plant disease development (Kumhálová et al., 2013). The average yield was 2.734 t ha^{-1}. Fig. 1 shows the influence of terrain topography and the influence of losses caused by fungal diseases on yield.

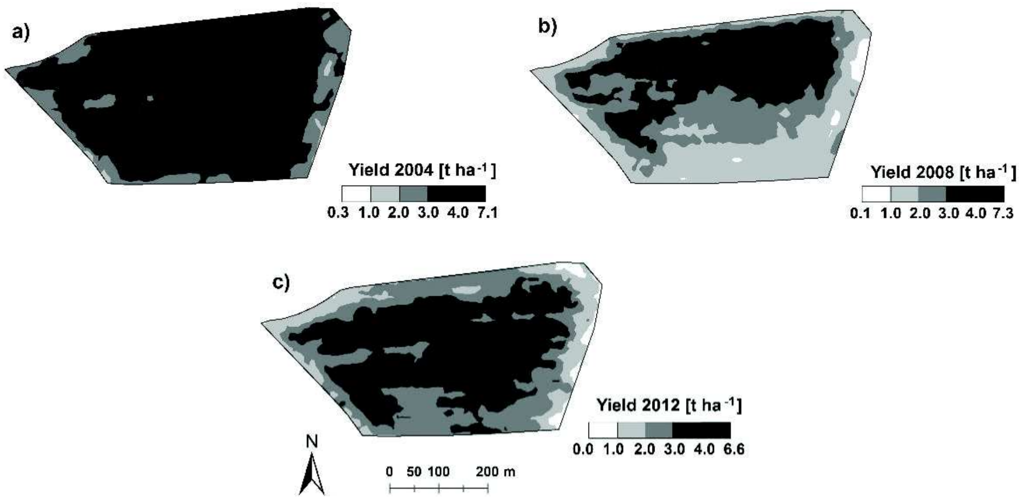

Figure 1. Winter oilseed rape yield.

Fungal diseases produce a coating on the leaves and physiological changes in the structure of plants. The influence of fungal diseases was much smaller in later growth stages (after BBCH 60). In the 2008 season there were two dates (May 2, May 9) of the flowering phenophase (BBCH 60-65 stage). A change in the colour of vegetation from green to yellow made it impossible to evaluate a relationship between yield and values of vegetation indices. The rape stand in terms of the growth phase was not quite uniform. Drier sites began to flower earlier than wetter ones. This corresponds to the variation in dependences between the yield and EMSI index (see Fig. 2). The value of correlation coefficient between the yield and EMSI index in the phase after BBCH 70 (June 10, 2008) increased to 0.61, which is acceptable for the evaluation of yield. This value is in agreement with other studies evaluating i.e. oat and wheat yield when the values of MSI index reached -0.68 or -0.60 for oat and -0.65 or -0.82 for winter wheat (Kumhálová et al., 2014). The rape stand at this time is light green with fully developed pods. Correlations between yield and other indices were generally very low on June 10, 2008.

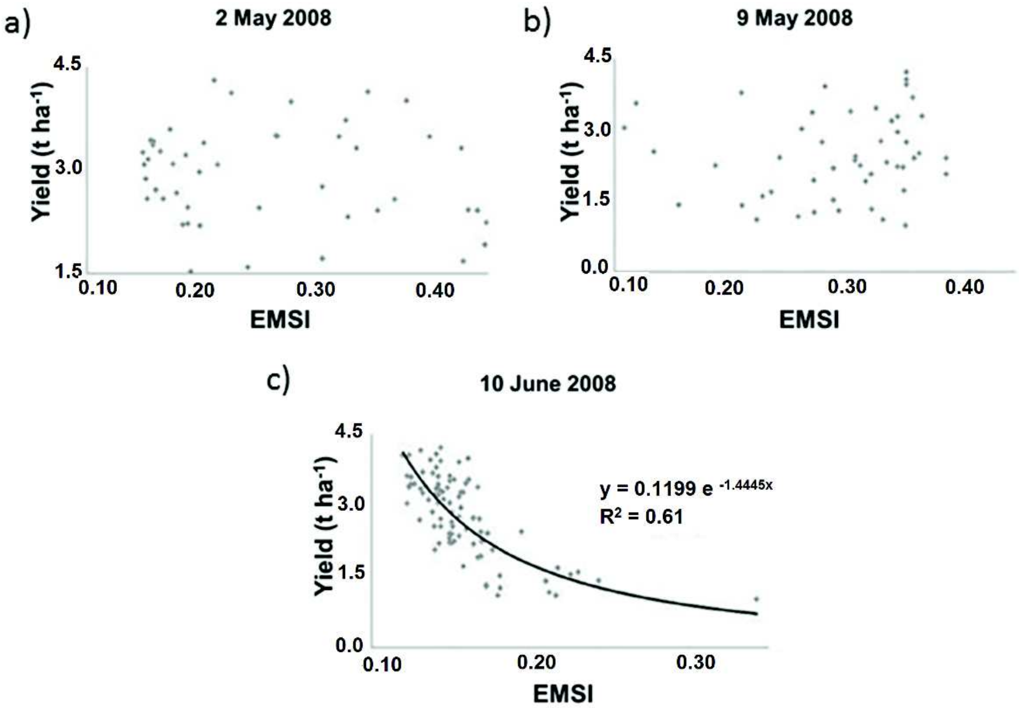

Figure 2. Relationship between EMSI on different dates and yield in 2008.

The year 2012 was the coldest and richest in precipitation. This weather pattern probably caused that the rape crop prospered well in the autumn season (especially in BBCH 10-19 stages). Nevertheless, the worst uptake of nitrogen fertilization at drier places of the field was probably caused by relatively low precipitation during flowering (BBCH 60-69). Kumhálová et al. (2013) described the influence of topography, which can be seen in the southwestern part of the field (see Fig. 1). The influence of soil compaction at the headlands can be seen.

Fig. 3 shows the dependence between the EMSI index and yield on several dates of taking images (in 2012). A good agreement was found between the values of EMSI and yield in the majority of the spring growth stages from the beginning of stem elongation (BBCH 30) to ripening. The correlation coefficients in 2012 between EMSI and rape yield gradually increased during the plant development from 0.46 (March 17) to 0.65 (May 19). It corresponds with the amount of precipitation in the BBCH 30-59 growth stages (54.1 mm) in 2012. As it was described in Kumhálová et al. (2011a), topography and weather conditions affected the yield in this field. On the contrary, the correlation coefficient dropped sharply on May 4, 2012. It was due to the beginning of the flowering stage (BBCH 60), when the colour of plants is changed in the individual storeys, which influences also reflectivity. Therefore in the flowering stage it is not possible to evaluate the rape stand by this index. The highest value of correlation can be seen in the evaluation of the images from May 19, 2012. At that time rape was at the BBCH 70 stage. The upper parts of plants were after the end of flowering. The development of pods occurred at this stage.

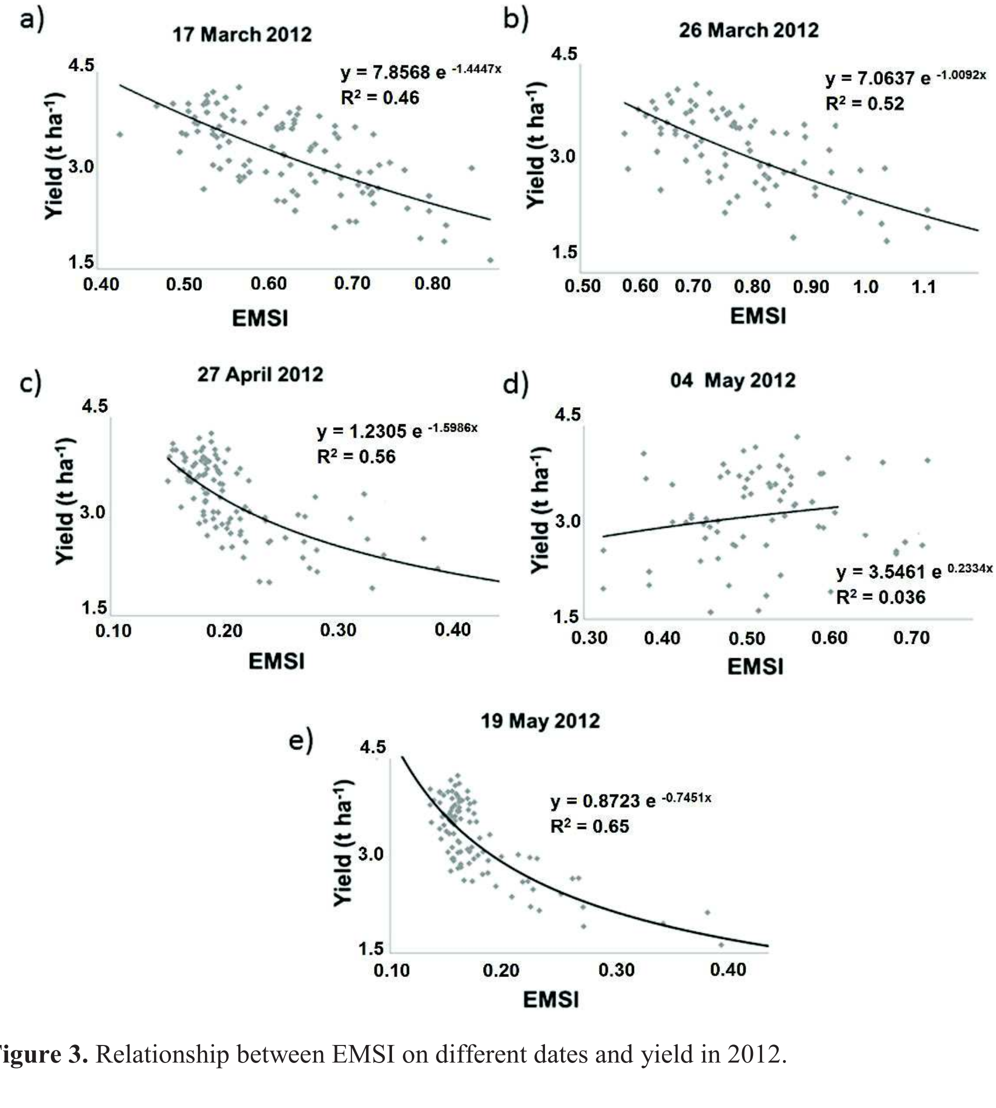

Figure 3. Relationship between EMSI on different dates and yield in 2012.

Some correlations between yield and the NDVI and MSI indices reached relatively high levels, but this cannot be generalized. The MSI index, due to the type of rape root system, does not have such an influence as e.g. in shallow rooted cereals. The behaviour of the CVI index is analogical. It is sensitive to the content of chlorophyll in plants. The highest values of all indices in 2012 were a general phenomenon.

In the literature, the studies about a relationship between spectral indices and crop yield are often mentioned. Many authors evaluated various crops grown on plots of different size and they used different sources of remote sensing data. In the last decades there has also been a rapid development of remote sensing systems, especially for targeted application. For agricultural purposes, it is possible to use remote sensing methods from hyperspectral to multispectral systems, from unmanned aerial vehicles or planes, spectroradiometers to satellite systems for monitoring the crop variability. For our study satellite remote sensing was chosen, Landsat 7 satellite data were used due to a good access to the database of Landsat images and a possibility of using several spectral bands, despite of their coarse spatial resolution. The spatial resolution of these images is 30 m. This resolution could limit the monitoring of spatial variability of crops. Nevertheless, Kumhálová et al. (2014) concluded that Landsat TM/ETM$^+$ images can be used for deriving spectral indices which can sufficiently explain plant variability in a field of 11.5 ha in size. Similar results were obtained for example by Chao Rodríguez et al. (2014) in the evaluation of a small water body (11.5 ha). They found out that the Landsat historical archives may still provide a wealth of environmental information. Wu et al. (2015) also used an experimental plot of 36.9 ha in size in their study to estimate the high-resolution Leaf Area Index from synthetic Landsat data (Landsat-7 ETM$^+$).

Many studies have indicated that remotely sensed vegetation indices can be used for crop variability monitoring (e.g. Vincini et al., 2008; Hunt et al., 2013) like in our study with winter oilseed rape. Vegetation indices can also be used to monitor the green vegetation component. At the leaf scale, leaf pigment concentration, leaf water content and leaf structure cause variations in leaf reflectance, transmittance and absorption (van Leeuwen & Huete, 1996). Reflectance and transmittance properties have been observed to be different between dicotyledonous and monocotyledonous leaves, because of differences in the mesophyll structure (Sinclair et al., 1971) and differences between adaxial (leaf face) and abaxial (leaf back) leaf scattering properties (e.g. Woolley, 1971). Van Leeuwen & Huete (1996) described that reflectance differences between vegetation and litter can be attributed to histological and optical properties. Senescence of plant components occurs during or after plant maturity or can be caused by stress factors like lack of water and nutrients or extreme temperatures. Senescence and decomposition of leaves will finally cause the breakdown of all pigments. These events may occur especially in winter oilseed rape and this corresponds with our research. Most vegetation indices tend to be species specific and therefore they are not robust enough when applied across different species, with different canopy architectures and leaf structures (Viña et al., 2011). For our research we chose traditional vegetation indices that were usually applied in other studies to evaluate plant and yield variability. Our results are then in good agreement with the findings of Piekarczyk et al. (2006). They found out that a very poor relationship between spectral data and all agronomic parameters of oilseed rape at the beginning of the spring growing season was caused by the presence of leaf litter on the ground. The spectral properties of plant litter affect vegetation indices and can cause errors in their response to the green vegetation cover. Optical remote sensing seems to be weak tool for oilseed rape evaluation. Huang et al. (2015) noted that a recently proposed alternative has used active microwave remote sensing, otherwise referred to as radar. Active microwave observations can be used to provide complementary information on vegetation properties, such as vegetation structures or level of vegetation growth. Radar vegetation index (RVI) can also be correlated well with the vegetation water content, Leaf Area Index and NDVI (Dinesh Kumar et al., 2013).

CONCLUSIONS

In this paper vegetation indices were evaluated in the stand of rape during three seasons. Very low levels of correlations were detected between vegetation indices and yield. The best results were obtained in the EMSI index even though the EMSI index fluctuated strongly in dependence on the growth phase and other conditions. In practice it appears problematic to use these indices for the rape stand evaluation. In further research it will be necessary to derive appropriate vegetation indices in optical part of spectrum or use RVI, along with their verification and presentation of model situations of a relationship to different stages of rape plant development. Indices in the SWIR 2 band seem promising. Despite the possible adjustment of indices it will not be possible in the future to evaluate oilseed crops during flowering with optical remote sensing methods. Despite the shortcomings mentioned in this article remote sensing used for the assessment of rape stands is a promising technique. European Sentinel mission (especially Sentinel 1) seems to be very promising way from this point of view.

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