doi: 10.17221/412/2015-PSE

Winter oilseed rape and winter wheat growth prediction using remote sensing methods

J.A. Domínguez[1], J. Kumhálová[1], P. Novák[2]

[1]*Department of Applied Geoinformatics and Spatial Planning, Faculty of Environmental Sciences, Czech University of Life Sciences Prague, Prague, Czech Republic*
[2]*Department of Agricultural Machines, Faculty of Engineering, Czech University of Life Sciences Prague, Prague, Czech Republic*

ABSTRACT

Remote sensing is often used for yield prediction as well as for crop monitoring. This paper describes how Landsat satellite data can be used to derive a growth model calculated from normalised difference vegetation index that can predict winter wheat (*Triticum aestivum*) and winter oilseed rape (*Brassica napus*) phenological state using the Biologische Bundesanstalt, Bundessortenamt und Chemische Industrie scale. Time series of Landsat images were chosen from the years 2004, 2008 and 2012, when winter oilseed rape was grown, and 2005, 2009, 2011 and 2013, when winter wheat was grown in the same experimental field. The images were selected from the whole growing season of both crops. An advantage of this method is the easy availability of the remote sensing and its easy application for deriving a prediction model from vegetation indices. Our results showed that Landsat images, after correct pre-processing, can be used for winter wheat and winter oilseed rape growth model prediction.

Keywords: plant growth modelling; phenological phases; spectral index; atmospheric correction; satellite images

Winter wheat and winter oilseed rape are among the most common and also strategic crops in the Czech Republic (e.g. Krček et al. 2014, Faměra et al. 2015). Periodicity in crop life cycle allows the phenological staging of the crop, although actual development depends on various factors such as the type of crop or weather conditions (Hunkár et al. 2012). Biologische Bundesanstalt, Bundessortenamt und Chemische Industrie (BBCH) scale defines exactly these phases of the crop growth which are actually observed and it has been widely accepted for use in cereals, rape, bean and sunflower (Bleiholder et al. 1989, Lancashire et al. 1991).

The methods of remote sensing can be used for monitoring of phenological phases especially in large plots. Optical remote sensing data was used to estimate crop yields, terms of agro-technical intervention and crop management (Doraiswamy et al. 2004, Kumhálová et al. 2014). Jongschaap and Schouten (2005) reported that wheat area could be estimated with more than 80% users' accuracy and model-based estimates of regional wheat production were in agreement with agricultural statistics.

Spectral reflectance from satellite image data was used to study vegetation cover (Chuvieco 1990). Few vegetation indices have been developed specifically for plant water stress evaluation; several of these indices were based on the relationship between near infrared (NIR) and red bands. An early example is the ratio vegetation index (RVI) (Birth and McVey 1968), defined as the ratio between NIR and red band reflectance. Nowadays the most popular index is normalized difference vegetation index (NDVI) (Rouse et al. 1974), the normalized ratio between NIR and red bands. NDVI is often used for the evaluation of different crops, different purposes and at different scales (Julien et al. 2011, Tornos et al. 2014).

Supported by the Internal Grant Agency, Faculty of Environmental Sciences, Czech University of Life Sciences Prague (CULS Prague), Project No. 42190/1312/3138.

doi: 10.17221/412/2015-PSE

The NDVI was used for the monitoring of vegetation dynamics just computed from digital number bands (Chuvieco 1990, Michener and Houhoulis 1997). This NDVI at the top of the atmosphere is always smaller than at the top of the canopy as it was shown in the simulations using a vegetation/atmosphere radiative transfer model (Myneni and Asrar 1994). The contributions of the atmosphere to NDVI are significant (McDonald et al. 1998), but atmospheric correction is not always necessary in order to perform the classification or to detect the changes (Song et al. 2001). Recently, some models of atmospheric correction have been developed such as quick atmospheric correction (QUAC) (Bernstein et al. 2012) and fast line-of-sight atmospheric analysis of hypercubes (FLAASH) (Li et al. 2014). These models perform the correction using top of atmosphere (TOA) data from the scene only. These processes of atmospheric correction usually consist of two parts. The first one is to convert the digital numbers (DNs) to radiance values. The second one is to convert the radiance data to reflectance. These corrections make it possible to build time series images from different sensors, for example MODIS, MERIS, Landsat or SPOT (Bégué et al. 2008).

The use and usefulness of high spatial resolution sensors and the spectral indices derived can be connected with the agricultural knowledge such as the BBCH phenological status scale (Bleiholder et al. 1989). In the literature, some authors have related optical remote sensing data with field data on particular dates (Mistele and Schmidhalter 2008, Laurila et al. 2010). Nevertheless, time series allow the application of statistical models for crop growth development estimation. A time series disadvantage is the need of a large set of images with homogenous atmospheric conditions. It is possible, however, to smooth out the influence of the atmosphere with the help of software tools for atmospheric correction. In the literature, some authors used the atmospheric correction preprocessing (Hunt et al. 2013, Jamali et al. 2015) while other performed no atmospheric correction (Bégué et al. 2008).

The time series analysis is not enough to gain the knowledge of crop development with the aim to make predictions about the phenological status from remote sensing indices such as NDVI. For crop status prediction, a mathematical model must be established. In the past, remote sensing images time series analyses of the natural landscape were used to formulate the mathematical models of gravel pit ponds (Domínguez et al. 2011) and natural vegetation phenology (Chao Rodríguez et al. 2014).

It is clear from this literature review that NDVI has a potential to be used for a prediction of agricultural crops growth. That is why the main aim of this study is to introduce a predictive model for winter wheat and winter oilseed rape growth relating to their BBCH scale phenological status with the use of remotely sensed NDVI. In this paper the suitability of Landsat data atmospheric correction for the needs of agriculture will be assessed. Different methods were compared with the aim to determine which atmospheric correction is the most suitable to carry out the remote sensing of agricultural areas, or whether any atmospheric correction is required at all.

MATERIAL AND METHODS

Study area. The study area selected is an experimental field of 11.5 ha in Prague-Ruzyně (50°05'N, 14°17'30''E), Czech Republic, with soils classified as Haplic Luvisol. Most of the field has a southern aspect and the elevation ranges from 338.5 to 357.5 m a.s.l. Conventional arable soil tillage technology and fixed crop rotation were used on this field. Detailed description of the crop rotation can be found in Kumhálová and Moudrý (2014). Total monthly precipitation and temperature data were provided by the Agro meteorology station at the Crop Research Institute in Prague-Ruzyně for observation years and are summarized in Table 1.

Remote sensing data processing. Landsat 5 and Landsat 7 cloud free images were downloaded from the USGS Global Visualization Viewer (http://earthexplorer.usgs.gov/) for the periods between March and June in years 2004, 2008 and 2012 for winter oilseed rape and in 2005, 2011, 2009 and 2013 for winter wheat (Table 2).

NDVI was calculated using four different methods in the study area (111 pixels): (a) from original images; (b) from images converted to TOA reflectance; (c) from images converted to reflectance using QUAC correction; (d) from images converted to reflectance bands using the FLAASH correction. The remote sensing software used for processing all images in this work was ENVI 5.1 (Excelis, Inc., McLean, USA).

doi: 10.17221/412/2015-PSE

Table 1. Precipitations and temperatures in different growth stages of BBCH scale recorded at the experimental field in the year 2004, 2008, 2012 for winter oilseed rape and 2005, 2011, 2013 for winter wheat

	Winter oilseed rape						Winter wheat					
	precipitation (mm)			temperature (°C)			precipitation (mm)			temperature (°C)		
	2004	2008	2012	2004	2008	2012	2005	2011	2013	2005	2011	2013
0–19 BBCH	52.8	72.0	61.3	16.5	13.5	16.8	20.0	15.2	25.6	9.6	7.9	9.7
20–29 BBCH	103.4	105.3	167.8	5.4	5.3	4.3	83.4	104.4	233.5	4.0	3.4	2.9
30–59 BBCH	157.2	112.6	54.1	14.6	11.8	9.5	90.4	39.5	175.8	13.9	14.8	13.9
After 60 BBCH	46.6	99.6	258.9	19.1	18.9	17.8	207.8	257.4	208.5	18.4	17.9	20.1
Sum	360.0	389.5	542.1	–	–	–	401.6	416.5	634.4	–	–	–
Mean	90.0	97.4	135.5	13.9	12.4	12.1	100.4	104.1	160.9	11.5	11.0	11.7

RESULTS AND DISCUSSION

Atmospheric correction processed with different methods is visualised in Figure 1. The graphs in Figure 1 show that the absence of field spectrum data suggested the use of spectral indices based on field data measures, assuming that the highest and the lowest reflectance values should be similar for the same cover. Of the two atmospheric corrections tested, QUAC was found unsuitable for winter oilseed rape because reflectance spectra behaved differently in images at the same pixel. It determined atmospheric compensation parameters directly from the information contained within the scene (observed pixel spectra), without ancillary information. However, the highest and the lowest reflectance values and the highest NDVI were consistent in all images for the FLAASH atmospheric correction.

NDVI average values (from –0.05 × NDVI average to 0.05 × NDVI average) for each crop and image were plotted with respect to BBCH scale in order to construct a mathematical model that will fit each crop type (Figures 2 and 3). The visual analysis showed the information gap which changed between images randomly. This inaccuracy affected images from the Landsat 7 only. The sensor of Landsat 7 satellite was malfunctioned which caused a lack of information.

NVDI model for winter wheat is shown in Figure 2. Kumhálová et al. (2014) mentioned that the NDVI value of soil without vegetation was 0.25 in this study field. This value is usually influenced by the soil type. Then NDVI increased until the plant reached phenological phase 49 BBCH (end of booting). After the beginning of heading, NDVI value decreased showing the changes in plant spectral reflectance between heading and flowering. NDVI value increased again after the end of flowering (69 BBCH) because of changes in plants structure and colour after the end of flowering. When started the ripening, (80 BBCH) plants changed their colour from green to yellow and the reflectance begun to decrease. Li et al. (2015) reported that NDVI values decreased during the period 51–69 BBCH. They used Zadoks scale instead of BBCH scale.

Table 2. Available Landsat images for the selected years

Crop	Date	Sensor	Satellite
Winter oilseed rape	26-September-2003; 28-Apr-2004; 30-May-2004; 8-Jun-2004; 31-Mar-2008; 2-May-2008; 9-May-2008; 25-May-2008; 10-Jun-2008; 17-Mar-2012; 26-Mar-2012; 27-Apr-2012; 4-May-2012; 19-May-2012; 29-May-2012	ETM+	Landsat 7
Winter wheat	3-Jun-2005; 4-Jun-2011	TM	Landsat 5
	5-October-2004; 16-Apr-2005; 2-May-2005; 3-Apr-2009; 10-Apr-2009; 19-Apr-2009; 26-Apr-2009; 12-May-2009; 13-Jun-2009; 24-Apr-2011; 19-May-2011; 26-May-2011; 18-Jun-2013	ETM+	Landsat 7

doi: 10.17221/412/2015-PSE

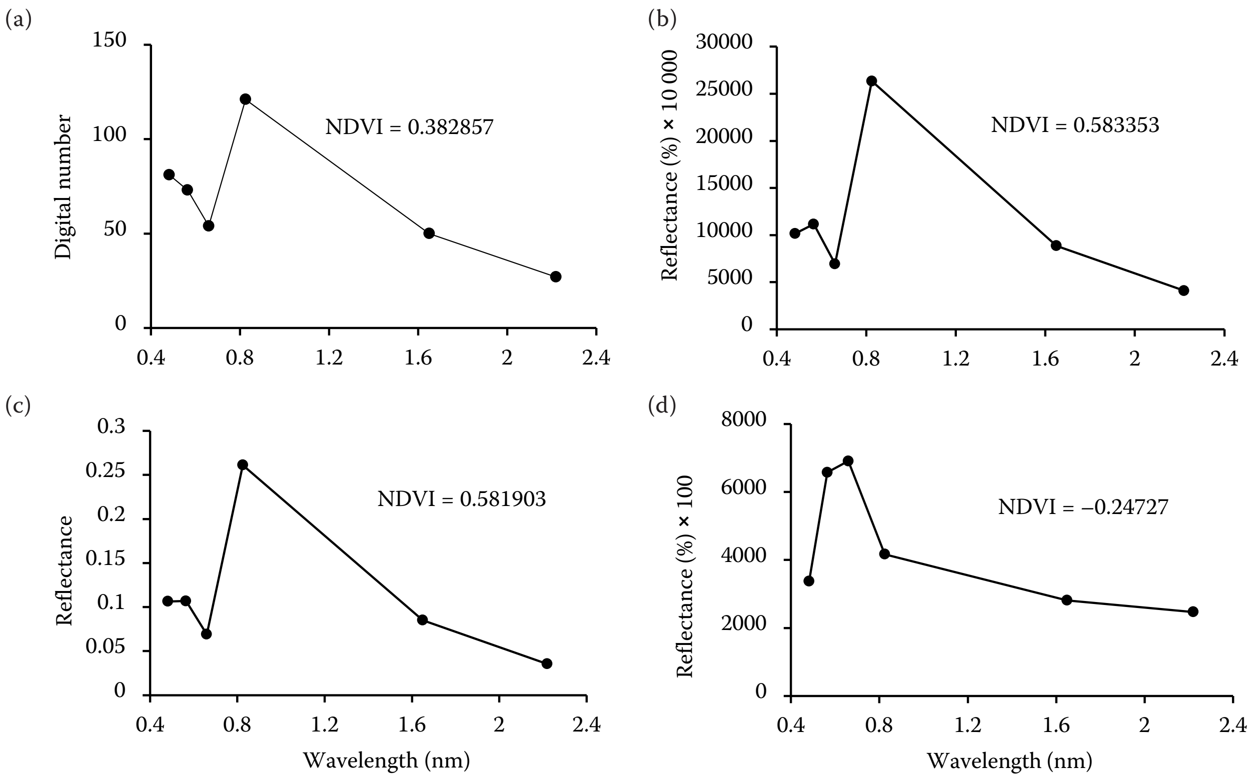

Figure 1. Atmospheric correction processed with different methods: (a) original digital number from sensor (without atmospheric correction); (b) fast line-of-sight atmospheric analysis of hypercubes; (c) top of atmosphere; and (d) quick atmospheric correction

Franch et al. (2015) studied the prediction of harvest on the basis of vegetation indices during the later growth stages and reported that NDVI values decreased to 0.2 before harvest.

In the case of rape available data showed that when the plants began to grow, the NDVI value increased over 0.25 (Figure 3). Changes in NDVI values were similar to winter wheat. As the vegetation continued to grow and the green vegetation covered whole surface, NVDI value increased until flowering (60 BBCH). Behrens et al. (2004) reported that rape plants had major differences in the growth phase during early flowering (60 BBCH) which was caused by uneven development of dif-

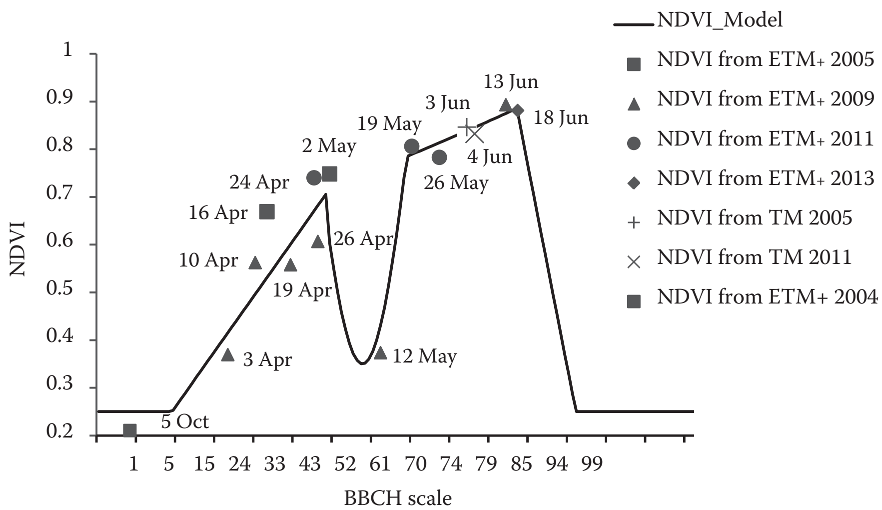

Figure 2. Graph of normalized difference vegetation index (NDVI) and BBCH scale dependency in the case of winter wheat

doi: 10.17221/412/2015-PSE

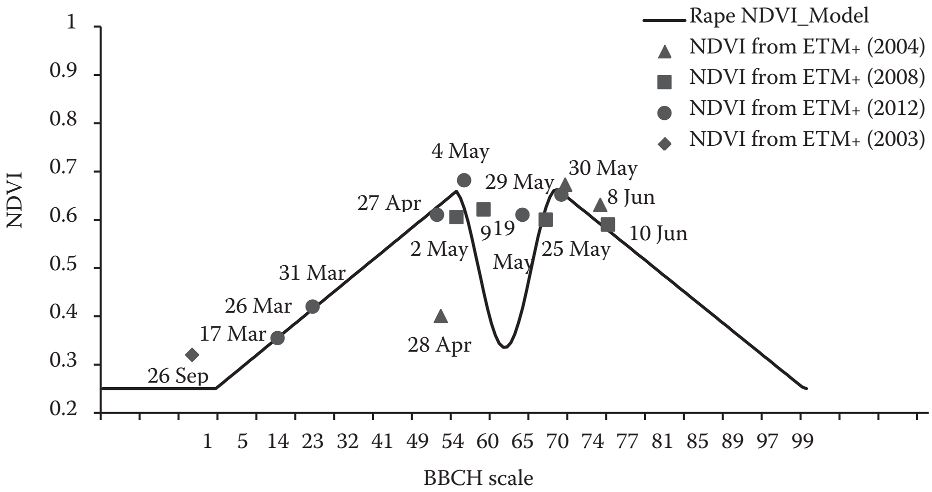

Figure 3. Graph of normalized difference vegetation index (NDVI) and BBCH scale dependency in the case of winter oilseed rape

ferent parts of crop stand. That is typical for i.e. sloping plots. NDVI value was influenced by colour change from green to yellow, decaying to about 0.35 in the phenological phase 65 BBCH (full flowering). After flowering, NDVI values increased again due to colour change from yellow to green, and fallen down again during ripening (Figure 3). NVDI values of rape were discussed by other authors: Pan et al. (2013) indicated a decrease in NDVI values during the full flowering (65 BBCH) to 0.35 and referred to the reduction of NDVI values up to 0.28 during the maturation. Zhu et al. (2008) showed similar results and reported that a decrease of NDVI was caused by change of reflectance.

Linear regression between NDVI from Landsat images and predicted model were visualised in Figure 4. It was found out that NDVI model for winter wheat and winter oilseed rape had an acceptable coefficient of determination (0.93 for winter wheat; 0.77 for winter oilseed rape; at 0.05 significance level).

Bartoszek (2014) introduced a general assessment of the winter oilseed rape vegetation state over a larger area; remote sensing can constitute the only credible source of information. Bartoszek (2014) further stated that remote sensing allows the determination of phenological stage of plants in areas of different dimensions and areas separated from each other, as well as the determination of

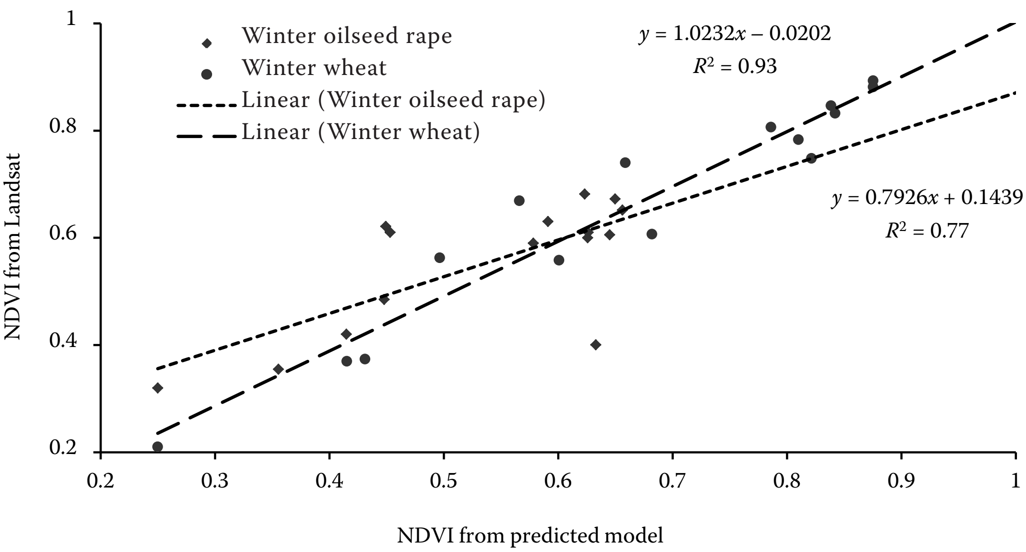

Figure 4. Dependence between normalized difference vegetation index (NDVI) from Landsat Images and NDVI from predicted model

doi: 10.17221/412/2015-PSE

the growth and development of winter oilseed rape using NDVI from satellite data.

Differences between the model and real crop conditions were found in our data and in other papers as well. Jongschaap and Schouten (2005) introduced that these differences are presumably associated with management practices, such as soil conditions and fertilizer application. The use of a remote sensing run-time calibration method for dynamic simulation models may result in increased simulation accuracy. The advantage of our proposed models is that they are simpler and use reflectance to determine NDVI. Jongschaap and Schouten (2005) used DN values to determinate NDVI in their study.

Through the use of BBCH scale the relationship between NDVI and BBCH is independent on agricultural field geographic location and period of the year (Peltonen-Sainio et al. 2010, Pan et al. 2013).

It may be concluded on the basis of the presented results that Landsat TM/ETM$^+$ images can be used for the modelling of plant growth estimation with the help of prediction model. Landsat TM/ETM$^+$ images can be also used for deriving NDVI for those purposes as well, although several limitations appeared during the images processing. Applicability of images from ETM+ sensor was one of these limitations. Landsat 7 (ETM+) sensor had a failure of the Scan Line Corrector and therefore several images had wedge-shaped gaps since May 31st, 2003. Other limitations are related with cloud-free images availability in a growing season and with the use of atmospheric correction. It was concluded that to make an atmospheric correction (FLAASH) of selected images for correct images processing and then for NDVI calculation is necessary. This is in a good agreement with Haboudane et al. (2004) who stated that substantial efforts were expended in improving the NDVI and in developing new indices aiming to compensate for soil background influences, as well as for atmospheric effects. Vegetation indices still have definite intrinsic limitations; they are not a single measure of a specific variable of interest such as pigment content, plant geometry, or canopy architecture.

Acknowledgement

Deep thank to the Crop Research Institute, v.v.i. for providing yield and meteorological data.

REFERENCES

Bartoszek K. (2014): Usefulness of MODIS data for assessment of the growth and development of winter oilseed rape. Žemdirbystė (Agriculture), 101: 445–452.

Bégué A., Todoroff P., Pater J. (2008): Multi-time scale analysis of sugarcane within-field variability: Improved crop diagnosis using satellite time series? Precision Agriculture, 9: 161–171.

Behrens T., Kraft M., Wiesler F. (2004): Influence of measuring angle, nitrogen fertilization, and variety on spectral reflectance of winter oilseed rape canopies. Journal of Plant Nutrition and Soil Science, 167: 99–105.

Bernstein L.S., Jin X.M., Gregor B., Adler-Golden S.M. (2012): Quick atmospheric correction code: Algorithm description and recent upgrades. SPIE Optical Engineering, 51: doi:10.1117/1.OE.51.11.111719.

Bleiholder H.T., Boom V.D., Langelüddecke P., Stauss R. (1989): Einheitliche Codierung der phänologischen Stadien bei Kultur und Schadpflanzen. Gesunde Pflanzen, 41: 381–384.

Birth G.S., McVey G.R. (1968): Measuring the colour of growing turf with a reflectance spectrophotometer. Agronomy Journal, 60: 640–643.

Chao Rodríguez Y., el Anjoumi A., Domínguez Gómez J.A., Rodríguez Pérez D., Rico E. (2014): Using Landsat image time series to study a small water body in Northern Spain. Environmental Monitoring and Assessment, 186: 3511–3522.

Chuvieco E. (1990): Fundamentals of remote sensing. Madrid, Ediciones Rial S.A. (In Spanish)

Domínguez J.A., Marcos C., Chao Y., Delgado G., Rodríguez D. (2011): Freshwater study using remote sensing. Madrid, UNED. (In Spanish)

Doraiswamy P.C., Hatfield J.L., Jackson T.J., Akhmedov B., Prueger J., Stern A. (2004): Crop condition and yield simulations using Landsat and MODIS. Remote Sensing of Environment, 92: 548–559.

Faměra O., Mayerová M., Burešová I., Kouřimská L., Prášilová M. (2015): Influence of selected factors on the content and properties of starch in the grain of non-food wheat. Plant, Soil and Environment, 61: 241–246.

Franch B., Vermote E.F., Becker-Reshef I., Claverie M., Huang J., Zhang J., Justice C., Sobrino J.A. (2015): Improving the timeliness of winter wheat production forecast in the United States of America, Ukraine and China using MODIS data and NCAR growing degree day information. Remote Sensing of Environment, 161: 131–148.

Haboudane D., Miller J.R., Pattey E., Zarco-Tejada P.J., Strachan I.B. (2004): Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. Remote Sensing of Environment, 90: 337–352.

Hunkár M., Vincze E., Szenyán I., Dunkel Z. (2012): Application of phenological observations in agrometeorological models and

doi: 10.17221/412/2015-PSE

climate change research. Quarterly Journal of the Hungarian Meteorological Service, 116: 195–209.

Hunt Jr.E.R., Doraiswamy P.C., McMurtrey J.E., Daughtry C.S.T., Perry E.M., Akhmedov B. (2013): A visible band index for remote sensing leaf chlorophyll content at the canopy scale. International Journal of Applied Earth Observation and Geoinformation, 21: 103–112.

Jongschaap R.E.E., Schouten L.S.M. (2005): Predicting wheat production at regional scale by integration of remote sensing data with a simulation model. Agronomy for Sustainable Development, 25: 481–489.

Jamali S., Jönsson P., Eklundh L., Ardö J., Seaquist J. (2015): Detecting changes in vegetation trends using time series segmentation. Remote Sensing of Environment, 156: 182–195.

Julien Y., Sobrino J.A., Jiménez-Muñoz J.-C. (2011): Land use classification from multitemporal Landsat imagery using the yearly land cover dynamics (YLCD) method. International Journal of Applied Earth Observation and Geoinformation, 13: 711–720.

Krček V., Baranyk P., Pulkrábek J., Urban J., Škeříková M., Brant V., Zábranský P. (2014): Influence of crop management on winter oilseed rape yield formation – Evaluation of first year of experiment. In: Proceedings of the Conference Mendelnet 2014, Brno, 57–63.

Kumhálová J., Moudrý V. (2014): Topographical characteristics for precision agriculture in conditions of the Czech Republic. Applied Geography, 50: 90–98.

Kumhálová J., Zemek F., Novák P., Brovkina O., Mayerová M. (2014): Use of Landsat images for yield evaluation within a small plot. Plant, Soil and Environment, 60: 501–506.

Lancashire P.D., Bleiholder H., van den Boom T., Langelüddecke P., Stauss R., Weber E., Witzenberger A. (1991): A uniform decimal code for growth stages of crops and weeds. Annals of Applied Biology, 119: 561–601.

Laurila H., Karjalainen M., Kleemola J., Hyyppä J. (2010): Cereal yield modeling in Finland using optical and radar remote sensing. Remote Sensing, 2: 2185–2239.

Li P., Jiang L., Feng Z. (2014): Cross-comparison of vegetation indices derived from Landsat-7 enhanced thematic mapper plus (ETM^+) and Landsat-8 operational land imager (OLI) sensors. Remote Sensing, 6: 310–329.

Li X.M., He Z.H., Xiao Y.G., Xia X.C., Trethowan R., Wang H.J., Chen X.M. (2015): QTL mapping for leaf senescence-related traits in common wheat under limited and full irrigation. Euphytica, 203: 569–582.

McDonald A.J., Gemmell F.M., Lewis P.E. (1998): Investigation of the utility of spectral vegetation indices for determining information on coniferous forests. Remote Sensing of Environment, 66: 250–272.

Michener W.K., Houhoulis P.F. (1997): Detection of vegetation changes associated with extensive flooding in a forested ecosystem. Photogrammetric Engineering and Remote Sensing, 63: 1363–1374.

Mistele B., Schmidhalter B. (2008): Spectral measurements of the total aerial N and biomass dry weight in maize using a quadrilateral-view optic. Field Crops Research, 106: 94–103.

Myneni R.B., Asrar G. (1994): Atmospheric effects and spectral vegetation indices. Remote Sensing of Environment, 47: 390–402.

Pan Z., Huang J., Wang F. (2013): Multi range spectral feature fitting for hyperspectral imagery in extracting oilseed rape planting area. International Journal of Applied Earth Observation and Geoinformation, 25: 21–29.

Peltonen-Sainio P., Jauhiainen L., Trnka M., Olesen J.E., Calanca P., Eckersten H., Eitzinger J., Gobin A., Kersebaum K.C., Kozyra J., Kumar S., Marta A.D., Micale F., Schaap B., Seguin B., Skjelvag A.O., Orlandini S. (2010): Coincidence of variation in yield and climate in Europe. Agriculture, Ecosystems and Environment, 139: 483–489.

Rouse J.W., Haas R.H., Schel J.A., Deering D.W. (1974): Monitoring vegetation systems in the Great Plains with ERTS. In: Proceedings of the Third ERTS-1 Symposium, NASA Goddard, NASA SP-351, 309–317.

Song C., Woodcock C.E., Seto K.C., Lenney M.P., Macomber S.A. (2001): Classification and change detection using Landsat TM data: When and how to correct atmospheric effects? Remote Sensing of Environment, 75: 230–244.

Tornos L., Huesca M., Dominguez J.A., Moyano M.C., Cicuendez V., Recuero L., Palacios-Orueta A. (2014): Assessment of MODIS spectral indices for determining rice paddy agricultural practices and hydroperiod. ISPRS Journal of Photogrammetry and Remote Sensing, 101: 110–124.

Zhu L., Xu J.F., Huang J.F., Wang F.M., Liu Z.Y., Wang Y. (2008): Study on hyperspectral estimation model of crop vegetation cover percentage. Spectroscopy and Spectral Analysis, 28: 1827–1831. (In Chinese)

Received on June 25, 2015
Accepted on July 28, 2015

Corresponding author:

Mgr. Jitka Kumhálová, Ph.D., Česká zemědělská univerzita v Praze, Fakulta životního prostředí, Katedra aplikované geoinformatiky a územního plánování, Kamýcká 129, 165 21 Praha-Suchdol, Česká republika
e-mail: kumhalova@fzp.czu.cz