

## Yield variability prediction by remote sensing sensors with different spatial resolution\*\*

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**A b s t r a c t.** Currently, remote sensing sensors are very popular for crop monitoring and yield prediction. This paper describes how satellite images with moderate (Landsat satellite data) and very high (QuickBird and WorldView-2 satellite data) spatial resolution, together with GreenSeeker hand held crop sensor, can be used to estimate yield and crop growth variability. Winter barley (2007 and 2015) and winter wheat (2009 and 2011) were chosen because of cloud-free data availability in the same time period for experimental field from Landsat satellite images and QuickBird or WorldView-2 images. Very high spatial resolution images were resampled to worse spatial resolution. Normalised difference vegetation index was derived from each satellite image data sets and it was also measured with GreenSeeker handheld crop sensor for the year 2015 only. Results showed that each satellite image data set can be used for yield and plant variability estimation. Nevertheless, better results, in comparison with crop yield, were obtained for images acquired in later phenological phases, e.g. in 2007 – BBCH 59 – average correlation coefficient 0.856, and in 2011 – BBCH 59-0.784. GreenSeeker handheld crop sensor was not suitable for yield estimation due to different measuring method.

**K e y w o r d s:** satellite images, GreenSeeker handheld crop sensor, plant growth modelling, phenological phases, spectral index

### INTRODUCTION

It is commonly known that crop yield depends on crop growth variability, which is related to multiple factors that can be time-independent (e.g. substrate, topography, soil type and depth) or time-dependent. Annually linked factors may include anomalies in planting, emergence, or weath-

er conditions. Seasonally linked factors can include plant diseases, weed development, severe climatic events or irrigation system malfunctions (Bégué *et al.*, 2008).

Topography is one of the main factors affecting crop variability and crop yield. Godwin and Miller (2003) said that topography was one of the most obvious causes of variation in field crops. Crop variability and crop yield can be affected by the distribution of water on the field. Crops produce more stable yields with a stable water inputs (Schmidt and Persson, 2003), and water redistribution on a field can be modelled by several methods (Marques da Silva and Silva, 2006, Kumhálová and Moudrý, 2014). Topographic wetness index (TWI) is a commonly used algorithm for detecting the water distribution within the field (Kumhálová *et al.*, 2014; Sørensen *et al.*, 2006).

Crop growth and yield can be efficiently monitored using canopy reflectance (Scudiero *et al.*, 2016). Canopy reflectance models have been used widely for investigating the response of vegetation indices to the variation of a number of factors and for understanding the mechanisms of interaction among these factors (Daughtry *et al.*, 2000; Vincini *et al.*, 2014; 2015). Different types of sensors measuring the amount of reflected solar radiation, from low-cost multispectral to high-cost imaging spectrometers, from low spatial to high spatial resolution, and from ground-based to satellite are available (Hunt *et al.*, 2013). Traditional satellite systems such as Landsat have been widely used for agricultural purposes over large areas. The benefit of this system is spectral resolution (over 7 spectral bands) and possibility of freely available remote sensing data (www.usgs.com). Nevertheless one of the disadvantages of these

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**Table 1.** Precipitations and temperatures in different growth stages by BBCH scale recorded on the experimental field in selected years

Growth stage	Winter barley		Winter wheat	
	2007	2015	2009	2011
	Precipitation (mm)			
BBCH 20-29	122.4	81.2	184.2	104.4
BBCH 30-59	2.4	43.7	109.2	39.5
After BBCH 60	146.6	64.6	154.6	257.4
Sum	271.4	189.5	448.0	401.3
Mean	90.5	63.2	149.3	133.8
	Temperature (°C)			
BBCH 20-29	6.9	3.3	4.4	3.4
BBCH 30-59	12.8	12.3	14.3	14.8
After BBCH 60	18.1	17.1	17.7	17.9
Sum	–	–	–	–
Mean	12.6	10.9	12.1	12.0

satellite images is their coarse spatial resolution (Zhang and Pierce, 2013), *i.e.* for Landsat images 30 m, and 16 days the temporal resolution. The new generation of satellites, such as QuickBird (QB) and WorldView-2 (WV-2) (DigitalGlobe, Logmont, Colorado, USA), provide multi-spectral data in the visible to infrared spectra that can be extremely useful in precision agriculture because of their high spatial resolution, 0.6 m for QB and 2 m for WV-2 satellite images (Mulla, 2013). The temporal resolution of these systems is 1 to 3 days for WV-2 and 3-7 days for QB.

Galambošová (2016) stated that another possibility for canopy reflectance measurement is, for example, the use of devices such as N sensor, Crop Spec, Crop Circle ACS, OptRX, ISARIA or Greenseeker. The Greenseeker (GS) as a crop sensor can be in handheld form as well. The GS optical sensor employs a patented technology to measure crop reflectance and to calculate the Normalised Difference Vegetation Index (NDVI). It also predicts yield potential. Nevertheless, the GS sensor is marketed primarily as a biomass sensor, not as N-sensor (Sharma *et al.*, 2015). NDVI spectral index (Rouse *et al.*, 1974) is based on the absorption difference of photosynthetically active tissues in the red and near-infrared wavelengths of the electromagnetic spectrum (Julien *et al.*, 2011). NDVI derived from measurements of canopy reflectance have been widely used for in-season estimation of yield. NDVI is used for the evaluation of different crops for different purposes at different scales (Domínguez *et al.*, 2015; Tornos *et al.*, 2014).

According to the literature, remote sensing sensors are very popular for monitor crop growth and for yield prediction (Scudiero, 2016). Therefore, the main aim of this study was to assess the suitability of selected sensors and their spatial resolution for monitoring crop variability and yield.

## MATERIALS AND METHODS

The experimental data for this study were obtained from an experimental field of 11.5 ha in Prague-Ruzyne (50°05'N; 14°17'30"E), Czech Republic, with a Haplic Luvisol soil. Conventional arable soil tillage technology and fixed crop rotation were used on this field. Yield was measured by a combine harvester equipped with the yield monitor LH 500 (LH Agro, Denmark). Detailed description of the yield measuring device can be found in Kumhálová *et al.* (2011). Experimental variograms of yield were computed by common procedures using an exponential model. The 2009 yield data were not measured because of a sudden failure of the yield monitor.

Total monthly precipitation and temperature data were provided by the Agro meteorology station at the Crop Research Institute in Prague-Ruzyne. Precipitation and temperature for observed years are provided in Table 1.

The topographic data was derived from LiDAR data kindly provided by the Czech office for surveying, mapping and cadastre. Elevation data were interpolated by inverse distance weighting (IDW) in ArcGIS 10.1 to create the DEM. The slope model (SM) and flow accumulation model (FAM) were then derived from the DEM – D8 algorithm. TWI uses SM and FAM raster data as inputs, based on the idea that low-gradient areas will gather water (high TWI values), whereas steep convex areas will shed water (low TWI values). TWI values are non-dimensional relative indices and vary by landscape type and DEM. Detailed description of the TWI can be found in Kumhálová *et al.* (2014).

Winter barley (2007 and 2015) and winter wheat (2009 and 2011) were chosen because of cloud-free data availability in the same period for the experimental field from Landsat satellite images and QuickBird or WorldView-2 images. Landsat satellite images were downloaded from the USGS Global Visualisation Viewer (<http://earthexplorer.usgs.gov/>). WV-2 and QB satellite images were purchased from the ArcDATA Company (Table 2). For atmospheric correction, the Fast Line-of-sight Atmospheric Analysis of Hypercubes was used (Dominguez *et al.*, 2015; Li *et al.*, 2014). All image pre-processing was implemented with ENVI SW (ENVI; version 5.3, Excelis, Inc., McLean, VA, USA).

NDVI values, as the ratio of reflectance in near infrared (NIR) and RED visible region (Rouse *et al.*, 1974), were computed for every image with ENVI SW. The information about the range of wavelengths, satellite images, sensors and crops used in this study is provided in Table 2.

**Table 2.** Available satellite images for the selected years

Satellite	Sensor	RED range	NIR range	Date	Crop	Growth stage
		nm				
Landsat 5	TM	630-690	760-900	24 May 2007	winter barley	BBCH 59
Landsat 7	ETM+	630-690	750-900	19 April 2009	winter wheat	BBCH 20-29
				26 May 2011	winter wheat	BBCH 59
Landsat 8	OLI	640-670	850-880	18 March 2015	winter barley	BBCH 21-22
		590-710	715-918	22 May 2007	winter barley	BBCH 59
QuickBird				13 April 2009	winter wheat	BBCH 20-29
				31 May 2011	winter wheat	BBCH 59
WorldView-2		630-690	705-895	23 March 2015	winter barley	BBCH 21-22

All images were then exported into ArcGIS SW (ArcGIS; version 10.3.1, Esri, Inc., Redlands, CA, USA) for further processing. Selected images (WV-2 and QB), yield and TWI raster were resampled by changing the cell size according to satellite image outputs to 30, 0.6, and 2 m, and then to 4 m according to average measured yield point (*ca.* 16 m<sup>2</sup>) and 15 m as a control of spatial resolution. The number of pixels used for evaluation was different for each of the evaluated years. It was caused by the fact that experimental plot boundary changed slightly between the years because of management practices. Only the pixels completely inside the boundaries were used for the evaluation.

GreenSeeker (version 1.00, Rev B, 2012, Trimble Navigation Limited, USA) uses the red (660 nm, ~25 nm FWHM) and infrared (780 nm, ~25 nm FWHM) bands and converts reflected data into NDVI directly (Trimble, 2017). NDVI values from Greenseeker handheld crop sensor were collected during the winter barley growth on April 23rd, and May 19th 2015. Experimental variograms of NDVI values were computed by common procedures using an exponential and spherical model.

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

## RESULTS AND DISCUSSION

Correlation coefficients (R) between NDVI (from original and resampled data sets of Landsat, QB and WV-2 satellite images with different spatial resolution), TWI and yield were calculated for individual image data and plant species (Table 3). Summary statistics of crop yield and GS for selected dates and years are given in Table 4. Summary statistics for NDVI calculated from original and resampled satellite images for selected crops are in Table 5.

Correlation matrices between NDVI from GS crop sensor, Landsat satellite images, yield and TWI were then calculated for individual data sets of winter barley (Table 6).

Winter barley was grown in 2007 and 2015. In 2007, yield and TWI had higher R (0.433 for SR of Landsat and 0.530 for QB) (Table 3). That year was drier in comparison with other years (Table 1). Low precipitation (2.4 mm) in the growth stage BBCH 30-59 can cause a significant displacement of relatively higher yield to water-accumulating depressions. This fact is confirmed also by correlations presented in Table 3, where R between NDVI and yield had average value of 0.856 and R between TWI and NDVI had average value of 0.419 for all spatial resolutions (Fig. 1). The movement of higher yield to concave areas in 2007 was also validated by summary statistics presented in Table 4, whereby both standard deviation and min-max range were higher than in 2015. In our previous articles (Kumhálová *et al.*, 2011; 2014), the influence of topography on yield in drier years was also found. Table 5 and Fig. 2 show that the NDVI values depended on the sensor used.

In 2015, winter barley yield and TWI had lower R values (0.242 for Landsat and 0.148 for WV-2) (Table 3). The year 2015 was the driest among the years analysed in our study. The precipitation distribution was uneven during the winter barley growth (in BBCH 20-29, 81.2 mm only). On the contrary, the precipitation distribution in BBCH 30-59 (43.7 mm) could probably cause the later crop to be beaten. In that year, harvesting losses caused by crop beating decreased the yield. This fact was confirmed by low R values between yield and NDVI (Table 3), although the NDVI values were relatively high during BBCH 21-22 and crops were in a good condition (Table 5). Winter wheat was grown in 2009 and 2011. Unfortunately, in the year 2009 the yield was not measured. Table 3 shows that the R between TWI and NDVI from QB was very weak. It corresponds with more precipitation distribution (Table 1) on the date of satellite data acquisition. The differences between

**Table 3.** Correlation coefficients between normalised difference vegetation index (NDVI) (from original and resampled Landsat (L), QuickBird (QB) and WorldView-2 (WV-2) satellite images with different spatial resolution (SR)), topographic wetness index (TWI) and resampled yield (to different SR) of selected crops and years

Parameter	Yield		NDVI					
	Winter barley							
	2007							
Satellite	L 5 TM	QB	L-5	QB	QB	QB	QB	QB
SR (m)	30	0.6	30	0.6	4	15	30	
Yield	1	1	0.861***	0.861***	0.859***	0.865***	0.835***	
TWI	0.433***	0.530***	0.485***	0.427***	0.428***	0.444***	0.313***	
	2015							
Satellite	L 8 OLI	WV-2	L-8	WV-2	WV-2	WV-2	WV-2	WV-2
SR (m)	30	2	30	2	4	15	30	
Yield	1	1	0.264**	0.133***	0.134***	0.119**	-0.018	
TWI	0.242*	0.148***	0.360***	-0.030***	-0.045***	0.158***	-0.055	
	Winter wheat							
	2009							
Satellite	L 7 ETM+	QB	L-7	QB	QB	QB	QB	QB
SR (m)	30	0.6	30	0.6	4	15	30	
TWI	–	–	0.495***	-0.033***	-0.026*	-0.041	0.109	
	2011							
Satellite	L 7 ETM+	QB	L-7	QB	QB	QB	QB	QB
Yield	1	1	0.821***	0.785***	0.781***	0.792***	0.739***	
TWI	0.498***	0.630***	0.515***	0.397***	0.393***	0.409***	0.250*	

Levels of statistical significance: \* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$ .

sensors response can be seen between NDVI from Landsat and QB in Tables 3 and 5 as well. Landsat images showed noticeably higher values in all cases than the QB images in each spatial resolution.

In the year 2011, Table 3 shows higher R between winter wheat yield and TWI (0.498 for Landsat and 0.630 for QB). The precipitation distribution was uneven during the winter wheat growth (after BBCH 60 - 257.4 mm) (Table 1). Correlation coefficients between yield and TWI reached high values (Table 3). This crop response was probably caused by low precipitation during the growth stages BBCH 30-59. Again, low precipitation can cause a significant displacement of relatively higher yield to water-accumulating depressions (Kumhálová *et al.*, 2011; 2014). The summary statistics presented in Table 4 confirmed again the

yield inequality. On the contrary, the summary statistics of NDVI presented in Table 5 showed similar values obtained by sensors used in this study.

GS measurements on April 23rd (BBCH 31) and May 19th (BBCH 55), 2015, and comparisons between NDVI from GS and Landsat images, yield and TWI in Table 6 are in good accordance with previous statements about crop development during the year 2015. Nevertheless, R between NDVI from GS and Landsat images were weak. It could be caused by the different method of data collection.

NDVI derived from Landsat and QB data showed similar results for later sensing (BBCH 59). For early sensing stage (BBCH 20-29), significant differences between the results from Landsat and QB were found (Table 3). It could be influenced by the soil sensing between the crops.

**Table 4.** Summary statistics and method of interpolation used for plant yield ( $t\ ha^{-1}$ ) in selected years and for NDVI from GreenSeeker (GS) sensor

Parameter	Winter barley		Winter wheat	GS	
	2007	2015	2011	23 April 2015	19 May 2015
Count	8808.0	10974.0	7548.0	103.0	103.0
Mean	5.618	5.322	7.053	0.779	0.802
Median	5.481	5.385	7.218	0.790	0.810
Standard deviation	1.373	0.836	1.953	0.062	0.030
Minimum	1.109	1.391	0.589	0.390	0.670
Maximum	10.149	9.254	13.458	0.890	0.850
Skewness	0.015	-0.666	-0.141	-2.946	-2.206
Method of interpolation	Kriging				
Method of estimation	Method of moments (MoM)				
Variogram model	Exponential			Spherical	
Distance parameter ( $r$ )	22.9	11.0	45.3	205.7	610.9
Approximate range = $3 \times r$	68.7	33.0	135.9	617.1	-
Nugget variance	0.3170	0.4200	1.3800	0.0025	0.0005
Sill variance	1.0100	0.5900	3.2600	0.0051	0.0012

Domínguez *et al.* (2015) discussed in their study how the phenological phase of the crop could influence the NDVI values during the crop growth. They developed NDVI models for winter wheat and winter rape crops from seeding to later phenological phases of selected crops. The results of our study are in accordance with the study of Domínguez *et al.* (2015). Scudiero (2016) noted that more research is needed to define, by geographical region, which sensor measurements are most useful for improving soil and crop management. Images resampled to different spatial resolutions showed similar mean but decreasing min-max range with decreasing spatial resolution. This fact was confirmed for each year studied. The spatial resolution of images used in this study did not play any crucial role for yield variability prediction. It could be an important property for crop evaluation in a small scale, for example for weed detection (Wu *et al.*, 2011). Based on our results, the GS device is not suitable for yield estimation. This is in contrary with Walsh *et al.* (2013). They noted that GS NDVI was a better predictor of final winter wheat yield in a dry site-year. On the other hand, Updike and Comp (2010) stated that many of the differences in analysis of results can be explained by the differences in the sensors themselves. Vincini *et al.* (2015) discussed that experimental datasets can be affected by experimental error, due for example to imperfect sampling. It corresponds with the study of Ciganda *et al.* (2012). Those authors determined the number of leaf layers sensed by red-edge chlorophyll index. They found that vertical distribution of chlorophyll contents in leaves significantly influenced remote sensing techniques. Those techniques need to meet very stringent requirements for this reason.

Zhang (2016) also highlighted that some differences exist between sensor systems. These differences can be caused by the variations in bandwidth of the particular spectral channels of the measuring systems. Mather and Koch (2011) described that one of the problems met in remote sensing is that the spectral reflectance of a given Earth-surface cover type is influenced by a variety of confusing factors. Casa *et al.* (2015) stated that small geometric registration errors typically do occur between the sensors used, even when an accurate calibration is performed.

## CONCLUSIONS

1. On the basis of presented results it may be concluded that each satellite image data source used in this study can sufficiently explain yield variability regardless to spatial resolution of the images. Better results, in comparison with crop yield, were obtained for images acquired in later phenological phases. Images acquired in early phenological phases showed differences according to sensor used. The sensors usually differ in bandwidth. Other reason of variations can be early scanning of the crop (when soil is visible between the plants).
2. GreenSeeker handheld crop sensor is not suitable for yield estimation of the whole agriculture plot due to high workload of this procedure based on long time required for data collection and the necessity of using the interpolation method to obtain the map. In contrast, satellite image is acquired in a relatively very short time.
3. Results obtained in this study can be helpful for the selection of suitable sensor with adequate spatial resolution for yield estimation.

**Table 5.** Summary statistics for NDVI calculated from original and resampled satellite images for selected years and crops

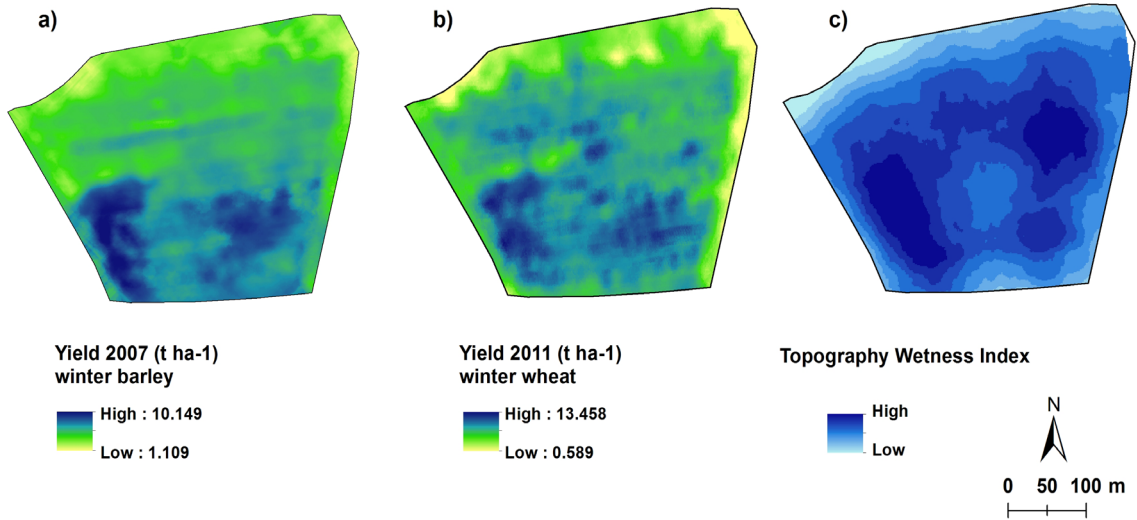
Satellite	L-5		QB		L-8			WV-2		
Winter barley										
Parameter			2007					2015		
SR (m)	30	0.6	4	15	30	30	2	4	15	30
Count	115	306704	6880	485	115	102	26684	6627	469	102
Mean	0.756	0.635	0.636	0.635	0.635	0.528	0.414	0.414	0.414	0.418
Median	0.759	0.638	0.638	0.637	0.635	0.532	0.416	0.415	0.413	0.418
Standard deviation	0.077	0.041	0.041	0.041	0.039	0.046	0.057	0.058	0.058	0.056
Minimum	0.556	0.477	0.490	0.495	0.544	0.315	0.185	0.191	0.219	0.269
Maximum	0.876	0.799	0.750	0.728	0.721	0.626	0.619	0.597	0.559	0.559
Skewness	-0.664	-0.401	-0.408	-0.420	-0.138	-1.047	-0.153	-0.160	-0.242	-0.353
Winter wheat										
Satellite	L-7		QB		L-7			QB		
2009										
SR (m)	30	0.6	4	15	30	30	0.6	4	15	30
Count	107	300157	6722	482	107	101	293279	6562	464	101
Mean	0.774	0.591	0.591	0.591	0.583	0.800	0.773	0.774	0.773	0.775
Median	0.782	0.591	0.592	0.592	0.585	0.808	0.780	0.781	0.779	0.782
Standard deviation	0.044	0.043	0.042	0.043	0.041	0.055	0.044	0.044	0.044	0.044
Minimum	0.492	0.301	0.305	0.333	0.325	0.616	0.550	0.580	0.607	0.616
Maximum	0.833	1.050	0.761	0.726	0.651	0.876	1.076	1.018	0.932	0.887
Skewness	-2.920	-1.029	-1.077	-1.093	-2.509	-1.189	-0.957	-0.935	-0.872	-0.932

Explanations as in Table 3.

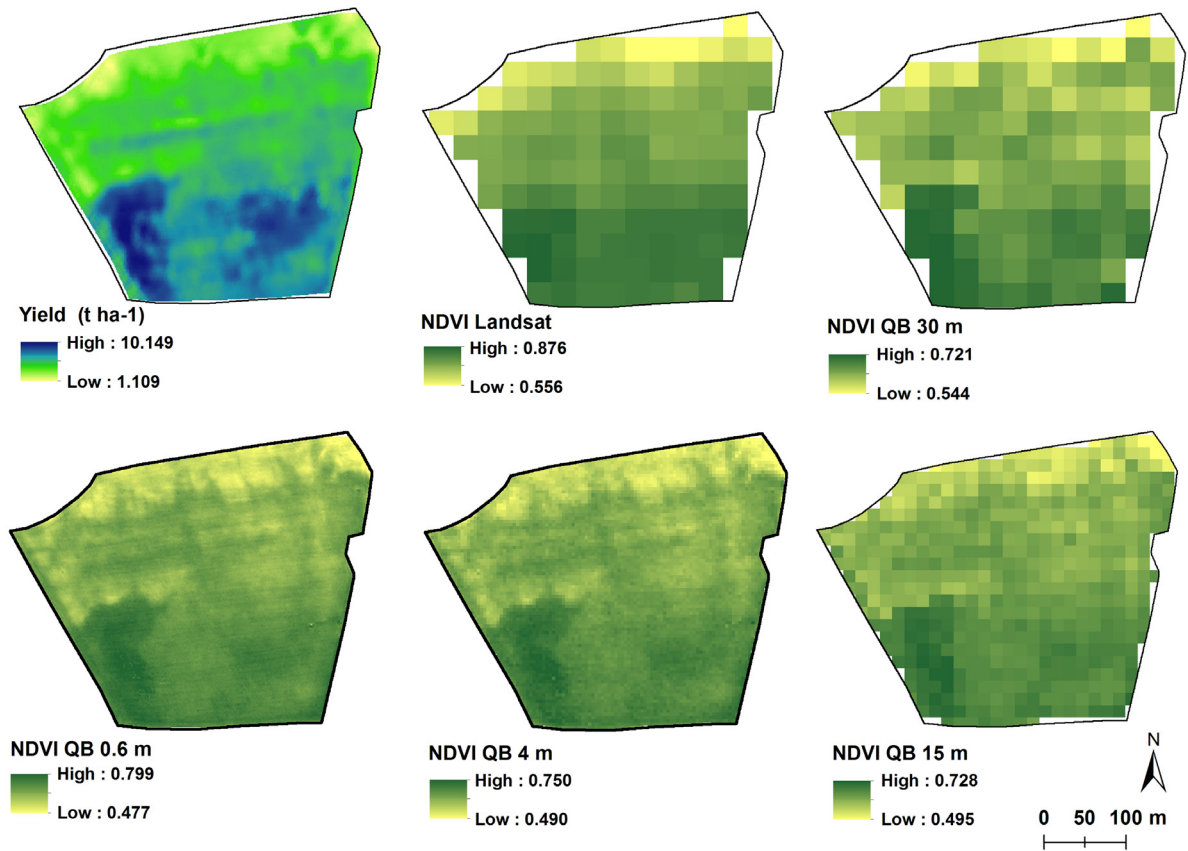
**Table 6.** Correlation coefficients between normalised difference vegetation index (NDVI) from GreenSeeker (GS) sensor, Landsat images, crop yield and TWI of winter barley

2015	Date/SR (m)	GS NDVI	GS NDVI	L-8 NDVI	L-8 NDVI
Date		April 23	May 19	April 19	May 14
Yield	30	0.011	0.022	0.260**	0.145
TWI	30	0.075	0.041	0.411***	0.165
L8 NDVI	April 19	0.310*	–	–	–
L8 NDVI	May 14	–	0.359***	–	–

Levels of statistical significance: \* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$ .



**Fig. 1.** Maps of kriged yield predictions in the experimental field during the observed years: a – 2007 – winter barley, b – 2011 – winter wheat, and c – topographic wetness index model map.



**Fig. 2.** Normalised difference vegetation index (NDVI) values according to sensor used (Landsat and QuickBird (QB)), together with QB images resampled to different spatial resolution, and winter barley yield (t ha<sup>-1</sup>) for the year 2007.

**Conflict of interest:** There is no conflict of interest which could influence the content of the article.

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