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ASSESSMENT OF A YIELD PREDICTION METHOD BASED ON TIME SERIES LANDSAT 8 DATA

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The active biomass of cultivated plants and average yield decreases as a result of biotic and abiotic stress effect. The extent of the reduction can be quantified on the basis of remotely sensed data. The aim of this research is to evaluate the suitability of Landsat 8 data for a wheat yield estimation. We processed Landsat 8 recordings for the period 2013–2019 and generated NDVI data. Time series NDVI data were calibrated and validated with observed wheat yield averages. The agricultural plots around Karcag, Hungary, were our research area. The relation between Landsat NDVI data and yield was strongest and highest in the total biomass period ($R^2 = 0.53\text{--}0.54$) and the estimation error based on RMSE is between $0.48\text{--}0.7\text{ t}\cdot\text{ha}^{-1}$.

Keywords: Landsat 8, crop, yield prediction

There has been an increase in the concern about food security and sustainable agricultural development in the world today, of which the actual estimation of supply and demand of major crops such as wheat is the main component. Wheat is the third most grown cereal after maize and rice with a production of $3.78\text{ t}\cdot\text{ha}^{-1}$ globally (FAOSTAT, 2018). In Hungary, the temperature keeps increasing and this can be characterized by a decrease in precipitation and an increasing frequency of droughts (Szász, 2005). For this reason, monitoring the agricultural areas is essential. Remote sensing-based agricultural monitoring systems are able to provide timely information on the status, phases and expected yields of crop production (Bolton, Friedl, 2013; Tewkesbury et al. 2015; Vicente-Serrano et al., 2015), complementing the traditional methodology (Atzberger, 2013; Tamás, Nagy, Fehér, 2015; Nagy, Fehér, Tamás, 2018). This is important because the farmers can easily identify areas where changes in crop yields are expected (Clement et al., 2013). We aim to analyse and apply a yield estimation monitoring system based on Normalized Difference Vegetation Index (NDVI) data derived from Landsat 8 satellite imagery. The interest in using satellite remote sensed data for crop monitoring and crop production forecasting today has tremendously increased due to its potential to produce data synoptically, with much spatial coverage, potentially at global scale. Moreover, remote sensing is capable of providing timely (and potentially real-time) and objective data on crop growth at relatively small cost. We have calculated the NDVI and developed a model to monitor a crop yield. The NDVI as an indicator of photo synthetically active vegetation provides important information for farmers, as the value obtained correlates

with the specific chlorophyll content and biomass content of the vegetation covering in the area (Bolton, Friedl, 2013; Panda, Ames, Panigrahi, 2010; Dempewolf et al., 2014; Mkhabela et al., 2011; De la Casa et al., 2018).

Material and method

We have processed satellite images prepared by Landsat 8 OLI, from which we have calculated the time series NDVI data of the area and compared to the real yield averages for the period 2013–2019, for our research. The Landsat 8 satellites orbit the Earth in a 16-day repetition cycle. Landsat captures approximately 740 scenes every 8 days on the Worldwide Reference System-2 (WRS-2) sequence system with a scene size of $185 \times 180\text{ km}$. Landsat 8 OLI/TIRS C1 Level-1 images with a cloud covering less than 50% were downloaded from <https://earthexplorer.usgs.gov/>. The downloaded files contain a total of 11 spectral bands at different wavelengths of visible, near-infrared and shortwave infrared, of which the data of B4 (red) and B5 (NIR) bands with 30 m spatial resolution were used for further processing in this study. The first calculation of the NDVI index (1) was performed in ArcGIS software with Raster Calculator according to the following formula.

$$NDVI = (NIR - RED)/(NIR + RED) \quad (1)$$

The average yield data ($\text{t}\cdot\text{ha}^{-1}$) required for the research were provided by the Karcag Research Institute of Agriculture in Hungary. Wheat yield data from 16 arable lands (Figure 1) for the period 2013–2019 were used to calibrate the time

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Figure 1 Location of the examined plots
Source: Google Earth

series NDVI data derived from Landsat 8 OLI and to validate the prepared model.

The research institute has provided us with the average yields of real wheat harvested/plot and a vector database of an arable land. We have performed the additional necessary calculations in the ArcGIS software environment. In the first step, we selected the mean NDVI values for each plot between March and August. The resulting average NDVI values/plot were calibrated with the actual yield average data. The calibration was performed by a linear regression (2) and we calculated the deterministic coefficient and estimation equations, the RMSE (Root Mean Square Error) (3) and NRMSE (Normalized Root Mean Square Error) (4) values were calculated to analyse the reliability of the regression and to validate the estimation equations. The calibration was based on data from the first 6 years (2013–2018), while the validation was based on data from 2018–2019, similarly to the research of Dempewolf et al. (2014) and Nagy, Fehér, Tamás (2018), where a minimum of 6-year remotely sensed time series were used for the yield analysis. In addition, we calculated the relative (5) and absolute (6) deviations of the estimated value from the actual harvested value.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - y'_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - y'_i)^2}{n}} \quad (3)$$

$$NRMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - y'_i)^2}{n}} / (\max(y_i) - \min(y_i)) \quad (4)$$

$$Relative\ deviation = \frac{y'_i - y_i}{\bar{y}} \cdot 100 \quad (5)$$

$$Absolute\ deviation = \left| \frac{y'_i - y_i}{\bar{y}} \cdot 100 \right| \quad (6)$$

where:

- y_i – data measured on the sample ($t \cdot ha^{-1}$)
- y'_i – estimated yield of the sample ($t \cdot ha^{-1}$)
- average yield ($t \cdot ha^{-1}$)
- n – number of samples ($t \cdot ha^{-1}$)

Results and discussion

Based on the results of the linear regression, the deterministic coefficient values calculated on the basis of the NDVI values at the end of May and the first half of June period have a stronger correlation (Figure 2) with the yield averages (on days 150, 154, 160 and 163). It is noteworthy that the NDVI data on days 154 and 160 showed the strongest relation with the yield averages ($R^2 = 0.542$ and $R^2 = 0.536$) (Figure 2).

After calculating the estimation models, we validated the models based on the relative deviation, absolute deviation, RMSE and NRMSE% values based on the NDVI and yield data of period 2018–2019. The RMSE and NRMSE% values for the years are shown in the Table 1. The validated 2-year mean RMSE was $0.713 t \cdot ha^{-1}$ on day 150, $0.547 t \cdot ha^{-1}$ on day 154, $0.489 t \cdot ha^{-1}$ on day 160, and $0.491 t \cdot ha^{-1}$ on day 163. The mean NRMSE (%) values based on 2 validated years were 13.09% on day 150, 10.04% on day 154, 8.99% on day 160, and 9.01% on day 163.

The relative deviation of the forecast value from fair values was -6.87% on day 150, on day 154 it was -5.05%, on day 160 it was -5.06%, and on day 163 it was -5.31%. Concerning the absolute differences, the difference on day 150 was 8.37%, on day 154 it was 7.51%, on day 160 it was 6.35% and on day 163 it was 6.14% (Figure 3).

Figure 2 Determination coefficients of NDVI versus yield (A) and linear regression of NDVI and yield on days 154 (B) and 160 (C)

Table 1 Yield estimation models from 2018 to 2019

Day	Equation	Year	RMSE	NRMSE (%)
150.	$y = 9.5592 \cdot \text{NDVI}_{150} + 0.792$	2018	0.865	15.87
		2019	0.519	9.54
154.	$y = 8.1785 \cdot \text{NDVI}_{154} + 1.4639$	2018	0.455	8.35
		2019	0.626	11.49
160.	$y = 9.791 \cdot \text{NDVI}_{160} + 1.2619$	2018	0.439	8.07
		2019	0.535	9.82
163.	$y = 9.1427 \cdot \text{NDVI}_{163} + 1.7047$	2018	0.401	7.36
		2019	0.566	10.39

Based on the relative differences, it can be stated that the predicted yield values are just slightly smaller than the measured yield values. The values of the absolute deviation were not much

higher than the 5% threshold accepted in the literature (Ferencz et al., 2004). The closest to the 5% threshold was the 160th day with the highest R^2 , which differed barely by 1%.

Conclusions

In this study, the Landsat derived vegetation indices during the flowering stage of the wheat development were found to be significantly correlated with the wheat yield in whole study site. In agreement with previous studies, the current study has demonstrated correlations between NDVIs during the flowering/fruiting spike period and crop yields (Marti et al., 2007; Labus et al., 2002; Mkhabela et al., 2011; Tiecheng et al., 2019), which has been admitted as the most critical period for most crops yield forecasting. The NDVI of 160th day of the year was verified to fit for the wheat yield prediction with the highest R^2 the best. Our study concludes that the Landsat 8-OLI time series data are suitable for forecasting the crop yield. The analysis of satellite images will help farmers to forecast the crop yield, as the NDVI can be used to estimate the expected yield before harvest. Climate change models predict that Hungary will experience more serious drought events. Therefore, timely information on potential yield losses helps farmers or decision makers to minimize the impacts of droughts and take appropriate mitigation measures.

Figure 3 Relative and absolute deviations of the predicted value from the actual values

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