Natural Resources and Sustainable Development **Volume 9, Issue 2, 2019**
DOI: 10.31924/nrsd.v9i2.036

WHEAT YIELD PREDICTION BASED ON MODIS NDVI TIME SERIES DATA IN THE WIDER REGION OF A CEREAL PROCESSING PLANT

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Abstract

The environmental impacts of climate change have been identified as a central issue in of the agriculture because the emergence of drought risk is a growing barrier to crop production and resulting in a decline in the quality and yield of cereals in recent years. In recent years there was a great development made in cereal processing in Hungary. In general, food processing plants requires steady crop supply, therefore it is essential to monitor the possible yield or yield loss of the potential supply area of the new cereal processing plant in Gyöngyösvisonta.

The aerial and satellite images can be used to monitor the response time of areas to biotic and abiotic stress effects, in this study the application of water stress and drought monitoring. We analyzed on the basis of the remote-sensed time series data. In the context of recordings, a number of stress indexes can be calculated to determine the productivity of biomass during a drought period. The study site covers four counties around Gyöngyösvisonta. The source of remote sensed time series data was the 16-day images of MODIS NDVI. The 250 m ground resolution images were downloaded and processed in ArcGIS software using various GIS methods from 2003 to 2018 that area. The sample area was selected that used for the production of wheat from the CORINE database, NDVI, and crop phenology. We applied time series NDVI images using different masking techniques and created the models for wheat yield prediction. During modeling calibration of NDVI data sets was performed by correlation and regression calculations with yield and NDVI data sets. Based on the results moderate correlations (r~0.8), areas with different drought risk levels can be delineated to estimate yield loss with MODIS data in May and June which is the most suitable period for yield loss monitoring before harvest. Calculating these data will allow farmers to determine the appropriate intervention time to avoid territorial degradation.

Key words: MODIS, NDVI, wheat, yield loss

INTRODUCTION

According to the Hungarian climate models, the temperature of the area shows a steady rise (Bartholy et al., 2011), which resulted in the gradual shift of agro-ecological zones (Harnos, Csete, 2008). Precipitation at the national level has decreased by an average of 50 mm per year over the last hundred years, and periods without precipitation have become longer, resulting in more frequent drought (Szász, 1988; Szász, 2005). The environmental impacts of climate change have begun to form a central issue in both humanity and agriculture, since the appearance of too much or too little rainfall can be a major factor in crop yields. Drought is one of the most complex natural hazards in crop production due to its slow onset and impact on yield (Sabău, Brejea, 2016), decreasing cereal quality and yield, and high

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variability over time. Due to drought, agricultural monitoring systems need to start on time. An important tool for climate adaptation is the development of monitoring sensory technologies through the development of precision agricultural technology (Tamás, 2001). Spectral material analysis has also been discovered as a tool for assessing agricultural drought, agricultural water transportation factors and the resulting yield and quality of crops, complementing the traditional research methodology (Atzberger, 2013; Tamás et al., 2015; Nagy et al., 2018). Aerial satellite or terrestrial multi- or hyperspectral recorders have made it possible to record plant quality parameters under field conditions (Neményi, Milics, 2007; Jung et al., 2017). Reflection properties can be observed in the spectrum, which can be supported by the integration of NDVI in wheat plants during the growing season. The MODIS Normalized Vegetation Index (NDVI) satellite image analysis (Gulácsi, Kovács, 2015) is a suitable tool for time series monitoring of the response of plants biotic and abiotic stress effects. From the processed information we can observe the changes of the plant density, the development of the plant diseases and the changes of the yield. With a wide viewing angle of 2.330 kilometers, MODIS captures images in 36 spectral bands around the world in 1-2 days. The sensor also measures the part of the planet's surface covered by clouds almost every day (I1). In practice, MODIS data from Reeves et al., 2005 was used to estimate wheat yields in North Dakota and Montana. The source of the remote sensing data was 16-day MODIS NDVI images. The images show the results of 16 days of chlorophyll intensity and biomass on cloudless, clear images. In addition, MODIS NDVI images have a spatial resolution of 250 m, which is 6.25 ha / pixel, sufficient to monitor field and regional yields in the Central and Eastern Europe region. Spectral data collection provides a rapid surplus of information from the study area, providing the basis for reliable monitoring. During spectral data collection, data on soil-plant-water relationships in the studied area can be recorded up to a resolution of 1 m (Neményi et al., 2010). Plant-specific analysis results may be appropriate to predict NDVI / yield reduction (Rembold et al., 2013). The generated model can provide a good basis for predicting the yield of arable land besides monitoring drought (Nagy et al., 2018). The main is to use spectral technologies to monitor crop yield and yield loss, thereby improving and temporarily intervening in extreme weather conditions, especially drought-prone areas.

MATERIAL AND METHOD

The Gyöngyösvisonta plant processes 250.000 tons of Hungarian GMO-free wheat per year using world-class, environmentally friendly, waste-free technology. With this quantity, in a good crop year, the factory can process one-tenth of the wheat to be exported. Hungary is the state-of-the-art wheat starch factory in Central Europe. The wheat growing areas, closest to the farm cannot provide this quantity. Because of this, besides Heves County, the investigated counties include, the Tisza catchment area of Csongrád County, Borsod-Abaúj Zemplén County, Jász-Nagykun-Szolnok County, Békés County, Szabolcs-Szatmár-Bereg County and Hajdú-Bihar County areas and areas with potential wheat production (Fig. 1) (Faragó, Koncz, 2012).

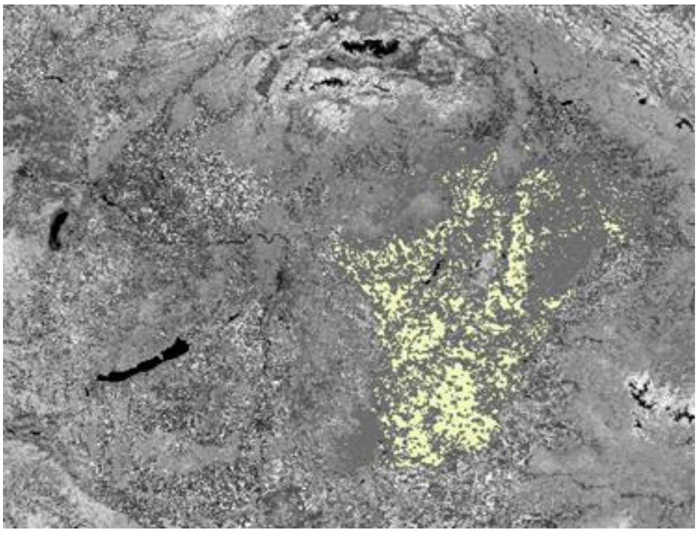

Fig. 1. Arable area of the examined counties

The most frequently influenced weather events are spring frost, drought, heat stress and stormy weather such as strong winds, hail and heavy rainfall (Antal, 2005). From these, the drought period is highlighted, because prolonged drought changes physiological processes, thereby limiting plant growth (Abid et al., 2018). For winter wheat to grow, the average daily temperature during the growing season must reach 2100 ^{o}C (Kismányoky, 2013). According to the National Meteorological Service, the minimum and maximum rainfall between the center of the Great Plain of Debrecen, between 1901 and 2010 was 321 mm and 953 mm. Increasing number of heat days during the ripening of cereals and the lack of precipitation can lead to a significant loss of yield hence to a deterioration in quality. However, too much precipitation can lead to prolonged ripening and lower quality. Due to the increase in crop volatility, the development of storage capacity may be justified in the future. MODIS NDVI images were downloaded from https://earthexplorer.usgs.gov/ for the selected area and year. The downloaded years were 2015, 2016, 2017 and 2018, for which we added data series already processed from 2000 to 2014. TerrSet and ArcGIS geospatial software were used to process the downloaded images. The

MODIS NDVI time series data available were downloaded for the sample site and was prepared for further processing and converted to GeoTiff in a TerrSet software environment. Remote sensing data from the internationally available CORINE 2012 land use database and topographic maps were processed and integrated with digital elevation model data. There are five main steps to calibrate NDVI in the ArcGIS software environment (Fig. 2).

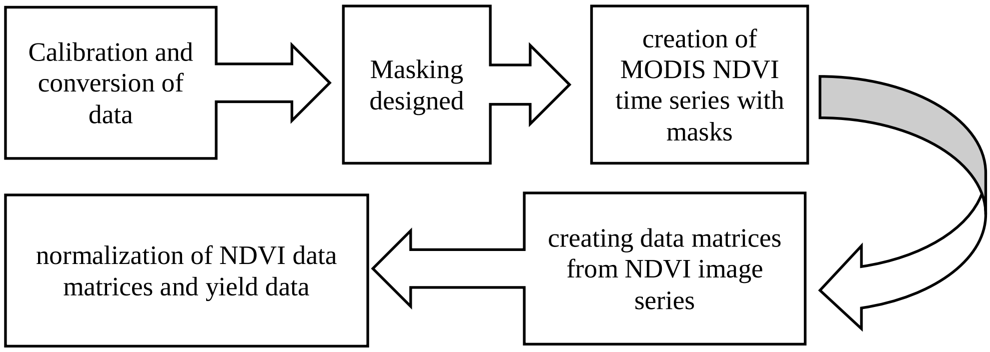

Fig. 2. NDVI calibration steps

MODIS NDVI data for April and July of each year were used to represent the wheat fields in the Tisza catchment areas. Based on the classification of the images, we made Boolean masks based on two images / year. After the images are sorted into a logical mask, they indicate the density of vegetation and the barren locations during the vegetation period. This eliminated the areas covered by alfalfa, maize and industrial crops in the case of wheat. The United States Geological Survey (USGS) used the Shuttle Radar Topography Mission (SRTM) models to select lowland areas and then used the CORINE Landcover dataset to select arable land. After sorting the arable land, the layers were merged and delimited by counties. The county - arable mask shows the arable areas of a county. We integrated the county arable mask and wheat-covered classified areas. Each year we received potential wheat growing areas for the county. After extraction, a data matrix of the average NDVI values was created, and the obtained values provides the basis for the calibration of the NDVI images (Tamás et al., 2015). The calibration was performed by linear regression of the average wheat yield (t / ha) available from the Central Statistical Office (CSO) until 2000-2016, and the results were validated with the data of 2017-2018. According to the literature, remote sensing time series of at least 6 years should be used for crop analysis (Dempewolf et al., 2014; Nagy et al., 2018). Using the regression equations, we estimated the estimate yields by county. The accuracy of the prediction was evaluated by the coefficient of accuracy index (R^2) (1) and for the validation of the model we calculated the root mean square error (RMSE) (2) values for the analysis of the prediction and the regression. NRMSD facilitates the comparison between datasets or models (3).

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

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

$$NRMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - y_i')^2}{n} / (\max(y_i) - \min(y_i))} \quad 3)$$

where: y_i: measured data for the sample
y_i': estimated yields of the sample
$\bar{y}$: average yield
n: number of samples used for validation
max (yi): maximum measured data for the sample
min (yi): minimum measured data for the sample

RESULTS AND DISCUSSION

Processing of MODIS NDVI data series for Heves County in June

The predictions of the yields were made by linear regression of the estimated yield values of the examined years, which were compared with the yield data available according to the Central Statistics Office. The R^2 values were calculated on the basis of preliminary studies with NDVI and CSO yields for June 10 and June 26, which was $R^2 = 0.386$ on June 10 and $R^2 = 0.508$ on June 26 (Fig. 3). These values give a medium value for further evaluation. The regression equations were computed with the NDVI values to obtain the projected yield values for the year.

The direct potential supplier of the grain processing plant is Heves County, therefore the results for the county were evaluated separately. The June 10 and June 26 values obtained by calculating the regression equations were averaged and compared to the yields reported by the CSO (Fig. 4). Our prediction gave almost the same results, with the biggest differences observed in 2002 and 2010. 2010 was considered to be a very rainy year, which may have reduced yields.

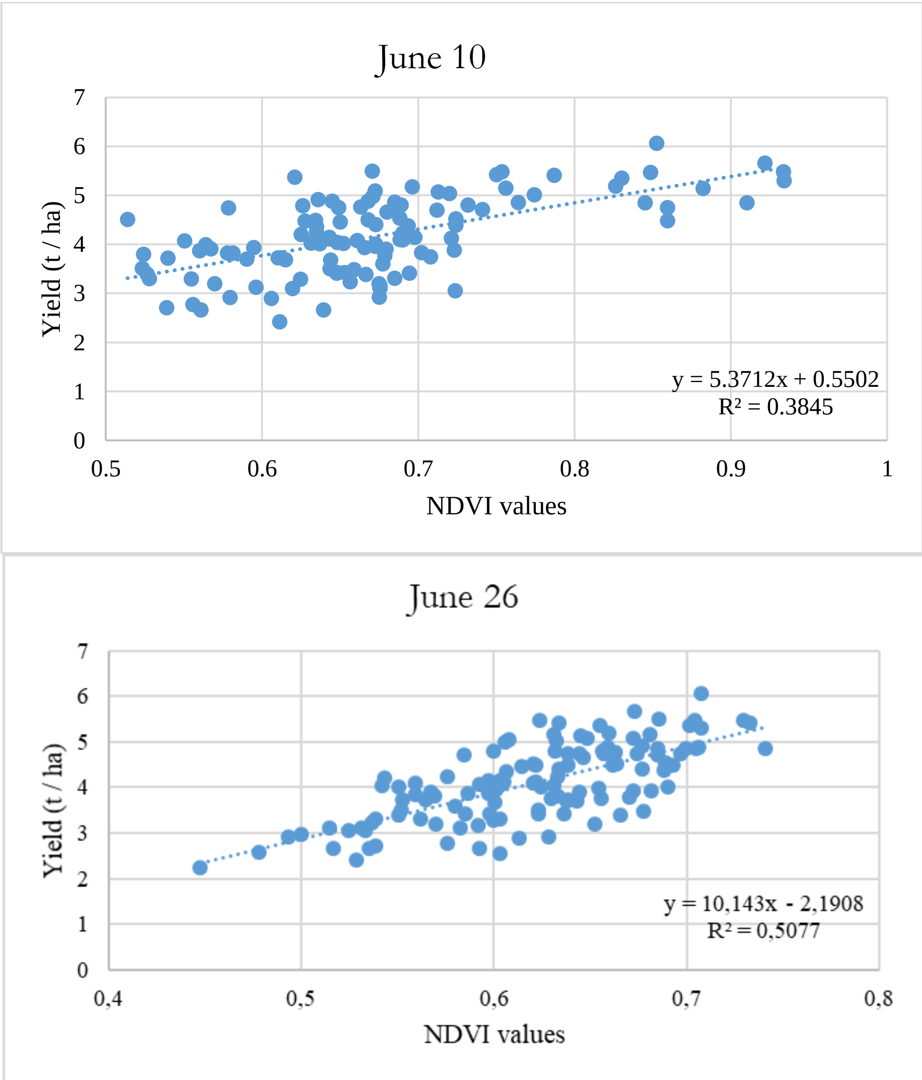

Fig. 3. Relationship between NDVI values and yield

The RMSE error of the Heves County forecast was 0.43 on June 10 and June 26, as well. The projected value deviation from fair values was 8.45 % on June 10, with the largest deviation in 2007 and the lowest in 2015. In 2007, Hungary was characterized by a prolonged, highly drought-like climate, which explains and supports the high yield loss. As of June 26, the forecasted value deviation from fair value was 1.95 %, with the largest deviation in 2012 and the lowest in 2014. Taking into account the 3-year time horizon for Heves County, the deviation from the projected value to the fair value was 14.4%, and the deviation from the projected value to the fair value at the 6-year average was 10.75 % based on June 10 values. As of June 26, the 3-year forecasted value deviation from fair value was 10.97 %

and the 6-year forecasted value deviation from fair value was 8.42 % (Fig. 5). With the exception of the 14.4 % obtained on the basis of the 3-year average deviations at 10 June, the other values are close to or less than the accepted maximum of 10 %.

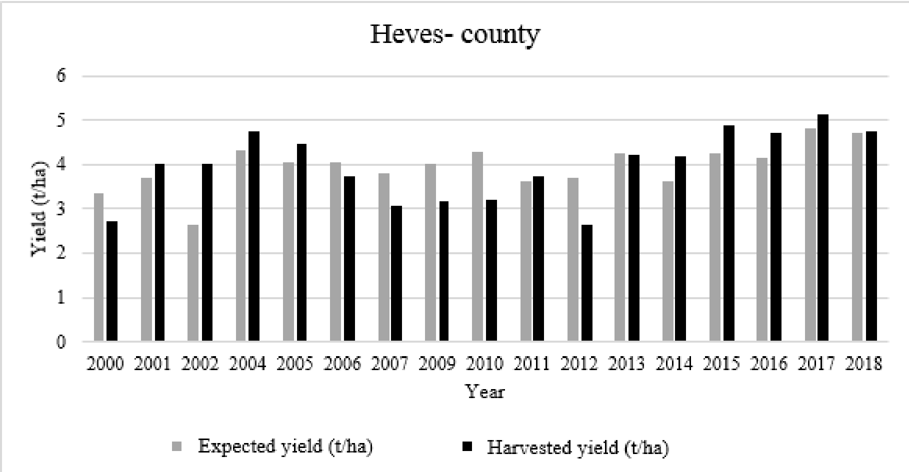

Fig. 4. Expected yield data for Heves County

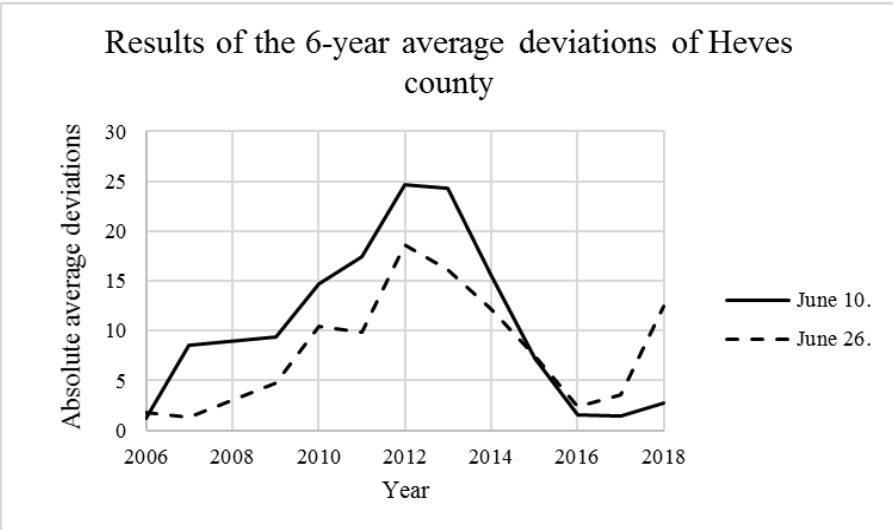

Fig. 5. Mean deviation values for 3 and 6 years for Heves County

Processing of MODIS NDVI data series for June for the 7 counties in the Tisza catchment area

Using the average deviations from the projected value from the fair value, we examined the relationships between the estimated yield and the harvested yield values over a 3- and 6-year period for all years and counties examined. The 1-year average deviation from the projected value as at June

10 is 10.9 %, the 3-year average deviation from the forecast value is 11.67 %, and the 6-year forecast deviation from fair value is 11.97 %. As of June 26, the average deviation from fair value over the 1-year projected value is 9.9 %, the average deviation from the fair value over the 3-year projected value is 10.34 %, and the average deviation from the 6-year forecast value is 10.08 % (Fig. 6). Our values are slightly above the acceptable tolerance of 10 %, so these data can be used for future wheat crop prediction. With the forecasting method used, yields can be estimated 4 weeks before harvest. Accurate application of the model requires accurate application of the appropriate software and accurate data recording.

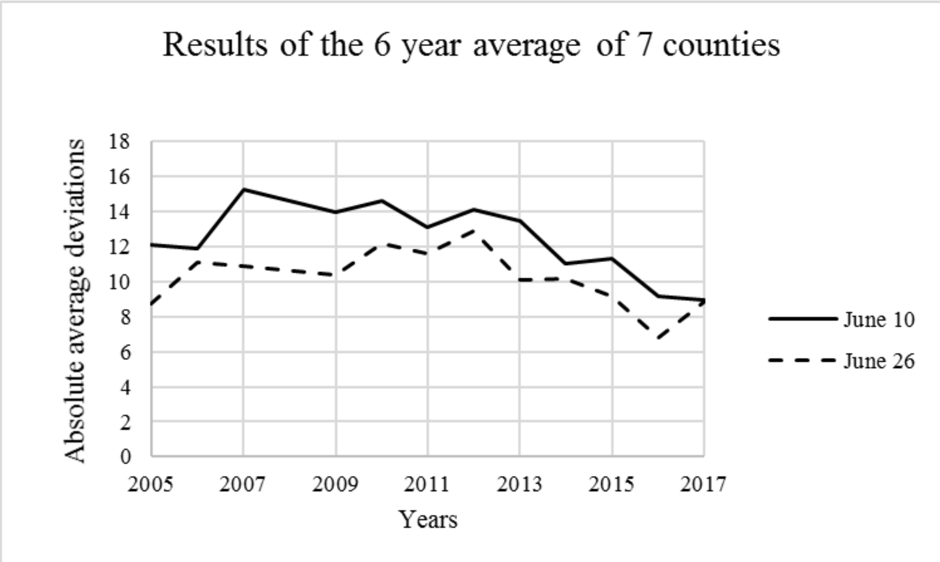

Fig. 6. Values of absolute mean deviations

Between 2000 and 2018, the RMSE error for the forecast for the seven counties examined was 0.38 on June 10 and 0.34 on June 26. RMSE / year values were further calculated from the forecast RMSE error values for the 7 surveyed counties of all years, from which RMSE /% yields were calculated using real yield data (Table 1).

Table 1

RMSE / % yield minimum, maximum and average values

	June 10.	June 26.
Minimum RMSE / Yield %	7.96	4.41
Maximum RMSE / Yield %	25.55	27.58
Average RMSE / Yield %	14.65	13.78

CONCLUSIONS

Our investigations show that MODIS NDVI time series data images can be used to develop and calculate crop prediction. Crop prediction helps field workers and farmers to be prepared in time for the expected yield changes and their possible quantitative changes. Providing and developing a monitoring base can be an important step in improving the yield patterns of the Tisza River Basin, including both wheat and maize. The developed monitoring system for wheat can be based on the processing of the June values, within which we can apply the values of absolute average deviations in 6-year intervals, which can give approximate results up to 4 weeks before the wheat harvest. With this method we can support the yield of the potential supply areas of the grain processing plant built in Gyöngyösvisonta and their development, helping to get more and better-quality grain into the food chain in the future. Compared to climate data, it can help you to recognize early the effects of water stress caused by plant water scarcity or prolonged rainfall.

Acknowledgment

The research was financed by the Higher Education Institutional Excellence Programme (NKFIH-1150-6/2019) of the Ministry of Innovation and Technology in Hungary, within the framework of the 4th thematic programme of the University of Debrecen., Research of complex rural economic and sustainable development, elaboration of its service networks in the Carpathian basin (EFOP-3.6.2-16-2017-00001).

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Received: October 31, 2019
Revised: November 28, 2019