Water Science and Technology

Agricultural biomass monitoring on watersheds based on remote sensed data

--Manuscript Draft--

Manuscript Number:	WST-EM15507R1
Full Title:	Agricultural biomass monitoring on watersheds based on remote sensed data
Article Type:	Research Paper (Editorial Office Upload)
Keywords:	biomass monitoring; remote sensing; drought effects and risks; NDVI; river basin.
Corresponding Author:	János Tamás, D.Sc., Ph.D. University of Debrecen, Hungary Debrecen, HUNGARY
Corresponding Author Secondary Information:	
Corresponding Author's Institution:	University of Debrecen, Hungary
Corresponding Author's Secondary Institution:	
First Author:	János Tamás
First Author Secondary Information:	
Order of Authors:	János Tamás
	Attila Nagy
	János Fehér
Order of Authors Secondary Information:	
Manuscript Region of Origin:	HUNGARY
Abstract:	There is a close quality relationship among the harmful levels of all three drought indicator groups (meteorological, hydrological and agricultural). However, the numerical scale of the relationships among them is unclear and conversion of indicators unsolved. Droughts affecting different areas with different forms of drought cannot be compared. A reliable estimated rate of yield loss is important information for the planned interventions in terms of time and cost. The aim of the project was to develop a process, which could provide information for estimating relevant drought indexes and drought related yield losses more effectively from remote sensed spectral data and to determine congruency of data derived from spectral data and field measurements. The paper discusses a new calculation method, which provides early information on physical implementation of drought risk levels. The elaborated method provides improvement in setting up a complex drought monitoring system, which could assist hydrologists, meteorologists and farmers to predict and quantify yield loss and the role of vegetation in the hydrological cycle. The results also allow the conversion of different purpose drought indices, such as meteorological, agricultural and hydrological ones, as well as more water-saving agricultural land use alternatives could be planned in the river basins.

Agricultural biomass monitoring on watersheds based on remote sensed data

János Tamás [1], Attila Nagy [1] and János Fehér [1,2]
[1] University of Debrecen, Institute of Water and Environmental Management
H-4032 Debrecen, Böszörményi út 138., Hungary (E-mail: tamas@agr.unideb.hu)
[2] FAMIFE Consulting Ltd., H-1221 Budapest, Kiránduló utca 8/B., Hungary

Abstract

There is a close quality relationship among the harmful levels of all three drought indicator groups (meteorological, hydrological and agricultural). However, the numerical scale of the relationships among them is unclear and the conversion of indicators is unsolved. Droughts affecting different areas with different forms of drought cannot be compared. For example, from the evaluation of meteorological drought using the standardized precipitation index (SPI) values of a river basin cannot be stated how many tonnes of maize will be lost during a given drought period. A reliable estimated rate of yield loss would be very important information for the planned interventions (i.e. by farmers or river basin management organisations) in terms of time and cost.

The aim of our research project was to develop a process, which could provide information for estimating relevant drought indexes and drought related yield losses more effectively from remote sensed spectral data and to determine the congruency of data derived from spectral data and from field measurements. The paper discusses a new calculation method, which provides early information on physical implementation of drought risk levels. The elaborated method provides improvement in setting up a complex drought monitoring system, which could assist hydrologists, meteorologists and farmers to predict and more precisely quantify the yield loss and the role of vegetation in the hydrological cycle. The results also allow the conversion of different purpose drought indices, such as meteorological, agricultural and hydrological ones, as well as more water-saving agricultural land use alternatives could be planned in the river basins.

Keywords: biomass monitoring, remote sensing, drought effects and risks, NDVI, river basin.

Introduction

In the hydrological cycle of a watershed the soil covering biomass quantity, its activity as well as the biomass spatial-temporal pattern play a significant role. Biomass is not only affects the water resources through evapotranspiration, but it causes interception, which reduces the intensity of soil reaching rainfall and influences the intensity of run-off, infiltration and erosion.

Notwithstanding, innumerable changes occur in the related hydrological parameters, which could be determined only by approximate methods, because of the numerous crop species grown, wide range of agricultural practices, crop rotations and technologies (plant nutrition, cultivation, plant protection, irrigation, mechanization) applied. The arable field experimental data have significant limitations in hydrological calculations and modelling when they are applied on other areas than the one where the experiment was carried out.

The meteorological drought indices indicate the effect of weather conditions (most commonly the temperature and precipitation) on the intensity of drought. The hydrological drought is associated with the extreme reduction of water resources, while agricultural drought indicates crop loss or vegetation water stress conditions (Niemeyer, 2008). Despite of the fact that there are close quality relationships among the harmful level of all three indicators, the numerical scales of the relationships among them are unclear. Thus, different areas or the same area with different forms of drought cannot be compared. For example, it cannot be stated from the evaluation of meteorological drought standardized precipitation index (SPI) values of a river basin (McKee et al., 1993) how many tonnes of maize will be lost during a given forecasting period. However, the expected rate of yield loss would be very important information for the planned intervention in terms of time and cost. The indexes of meteorological and hydrological drought parameters (temperature, precipitation, humidity, etc.) are based on well-measured and evaluated parameters and widely tested statistical methods (simple and complex index base) (Dai et al., 2004; Sivakumar et al., 2011, Choi et al., 2013). Unlike these, the agricultural drought is influenced by several complex factors, whose measurements are complicated, time and resource intensive and their impact (such as soil drought) is measurable only indirectly or at a later date (i.e. when yield loss is determined). In crop growing practice, for the time being it is not possible to measure exactly (except in laboratory conditions) the relationships among water stress symptoms (stoma resistance, temperature shock, pigment degradation), available soil water content (hydraulic conductivity, field capacity, pF value) and forthcoming yield loss, as well as crop quality degradation. For farming practices and policy-makers the intervention time and the knowledge of spatial extend of the problem is critical for prevention or the reduction of the damage.

Over the past two decades, remote sensing has emerged as a useful tool for dealing with agricultural drought observation and yield estimation, to complement more traditional approaches such as field trials or simulation models. In particular, remote sensing from airplane- or satellite-mounted sensors can potentially provide observations for every single field in a region for every single growing season (Lobell, 2013).

Numerous approaches exist for estimating crop yields with remote sensing. Several reviews on this topic are available (Moulin et al., 1998 and Gallego et al., 2010). Early efforts relied on simple vegetation indices (VIs) computed from remote sensing measurements of light at red and near-infrared (NIR) wavelengths (Tucker, 1979 and Sellers, 1987), although other parts of the spectrum are commonly utilized in more sophisticated approaches (e.g., Gitelson et al., 2003). Applications with wheat and maize indicated that variations in VI can explain over 80% of the observed variation in crop yields within individual fields (Wiegand and Richardson, 1990 and Shanahan et al., 2001).

There is clear evidence that crop yield estimation is possible with remote sensing, with good accuracies in some cases (Tamás and Bozán, 2009; Nagy and Tamás, 2013). Most evaluations of remote sensing are at scales broader than individual fields, for example by comparing reported yields for counties or crop reporting districts with the average of remotely sensed yields over this domain (Becker-Reshef et al., 2010 and Lobell et al., 2010).

The aim of our study was to develop a model process, which could provide information for estimating the relevant drought indexes and crop losses more effectively. Our study focused on determination of drought effects on watersheds from remote sensed spectral data. The model process identifies those available and most appropriate remote sensing data and GIS transformation, calibration tools, with which remote sensing based agricultural drought monitoring and forecast can be implemented. These steps are synthesized including land use, soil physical, meteorological and satellite data integrating them into a model, which can be a feasible tool for plant specific drought risk evaluation.

This model contains several steps from data acquisition, through processing and calibration to risk mapping and evaluation, which can be carried out in three main steps (Figure 1):

- data acquisition and processing,
- identification and calibration of biomass data and drought risk levels
- drought risk evaluation and mapping.

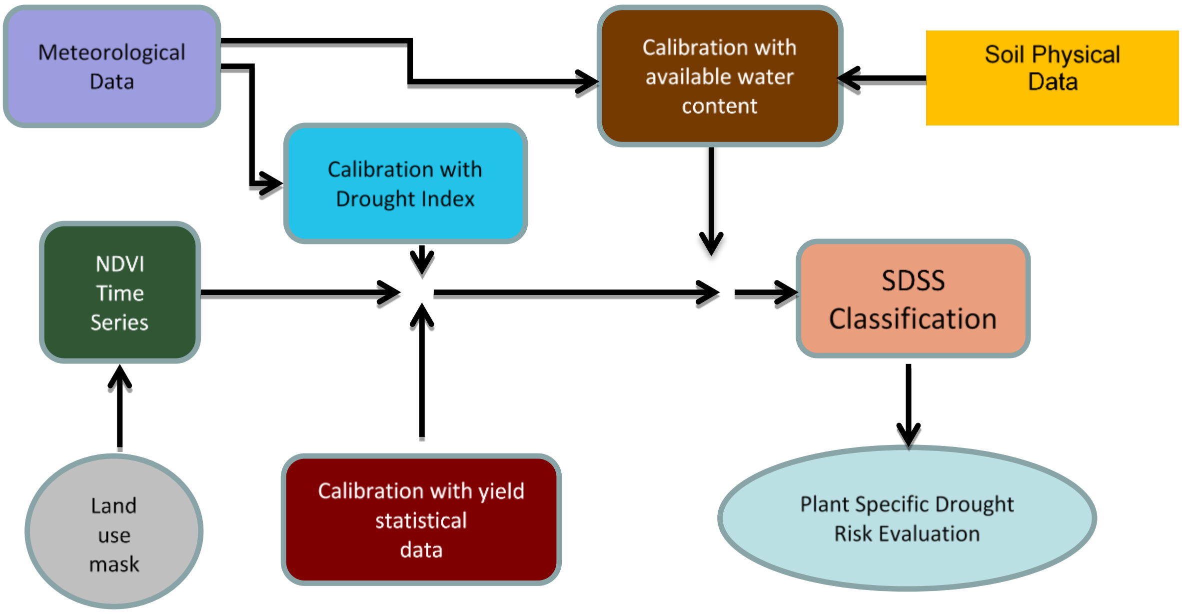


Figure 1. Main steps of the applied model

The study area was the lowland part of the Tisza River Basin, which is located in Central Europe within the Carpathian Basin. Hydrologically the Carpathian Basin is one of the most closed basins on the Earth and the investigated lowland region has semi-arid to arid character. In this region there is intensive agricultural activity where the ratio of arable land is 72%.

Data acquisition and processing

Landsat (or similar sensors such as SPOT) has been the main source of data with sufficient spatial resolution in most agricultural areas, but with a 16-day gap between successive images, and frequent cloud cover in most cropping regions (with the exception of dry, irrigated areas), it can be difficult to obtain more than one or two clear images within a growing season (Lobel, 2013). Another problem in the accuracy of yield detection is the spatial resolution. Although Reeves et al. (2005) used 1 km Moderate Resolution Imaging Spectroradiometer (MODIS) data to estimate wheat yields in North Dakota and Montana, but an average farm size (which is about 14-15 ha) is smaller in Central East European (CEE) region than in the USA. Therefore the monitoring of agriculturtal drought through possible yield loss of a specified crop is not appropriate with datasets, such as Fraction of Absorbed Photosynthetically Active, Radiation (fAPAR) or AVHRR data, having low spatial resolution (>1 km) (Gobron et al. 2009), because one pixel exceeds the average crop field size in CEE region. Thus in farm and regional scale cloudness time series data with moderate resolution is appropriate.

In this study the source of remote sensing data has been MODIS Normalized Difference Vegetation Index (NDVI) (MOD13 16-day product) data. The images represents 16 day moving average chlorophyll intensity and biomass quantity resulting from cloudless clear images. Further more MODIS NDVI images has 250 m spatial resolution representing 6.25 ha/pixel, which is adequate for yield monitoring in CEE region in field and regional scale.

Internationally available land use (CORINE database, topographic maps) remote sensing data, MODIS NDVI time series images[1], and data of digital elevation models were processed and

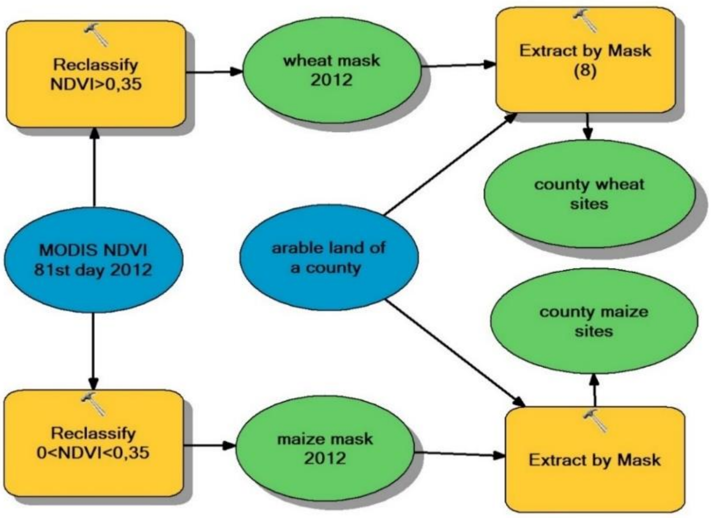
[1] Data source from USGS: http://glovis.usgs.gov/

integrated to determine the water content and consumption of the concerned cultivated plants at different soil types.

The reflected solar radiation in the red (RED=620-670 nm) and near-infrared (NIR=841-876 nm) wave-length bands were used from the MODIS 36 hyperspectral channels and NDVI was calculated with NDVI = (NIR-RED)/(NIR+RED) formula. Five major steps were carried out for NDVI calibration: i) reprojection of MODIS data; ii) mask building for data extraction; iii) extraction of MODIS NDVI time series by masks; iv) acquiring data matrix from NDVI images and v) normalization of extracted NDVI data matrix and yield data.

After reprojection of the MODIS NDVI data sets, a complex model was set up in order to select and delineate arable lands from the whole Carpathian basin. The reason for selecting the concerned sites was to eliminate the disturbing effect of other land use categories on NDVI values. The identification of exact site for winter wheat and maize crops was made based on the time series and NDVI pattern changes of the sites. ArcGIS 10.2 software was used to create models for the data processing of NDVI images. First, those Boolean mask images were produced with which the MODIS data set can be extracted. Masking was based on several data sources of land use and terrain models. USGS Shuttle Radar Topography Mission (SRTM) models were used to select plain areas (below 200 m altitude[2]). The SRTM 90 m DEM's have a resolution of 90 m at the equator, and are provided in 5 deg x 5 deg tiles. Thereafter CORINE Landover datasets (CLC 2006) were used to select arable lands. After all plain areas and arable lands were selected, the layer of plain and arable land was merged together to select overlapping sites. Following these steps the polygons of counties were selected from reference sites and the arable lands were extracted from counties.

NDVI classification process was carried out for every year, based on the NDVI images representing the situation in March (Figure 2). Sites with NDVI values between 0.35 and 1 were classified to wheat, and sites with 0-0.35 NDVI values were classified to maize. Two masks were obtained for a year, one for wheat, one for maize[3]. These masks were used to extract the sites of a given crop from the county-arable land mask. County-arable land mask represents the arable lands of a certain region.



[2] Source USGS http://srtm.usgs.gov/index.php

[3] On 90% of the arable lands wheat and maize are produced. Classification of arable land was carry out with maximum likelihood supervised based on training site, where accurancy was 90%.

Figure 2. ArcGIS model for creating mask and extraction of wheat and maize sites

Then masks for county wheat/maize sites were used to *extract the MODIS NDVI images* to get NDVI data for different crop sites. New models were built for each year for masking (Figure 3.). The model describes the extraction processes of the MODIS NDVI images for a certain year. This model had to be built for every year and run for maize and wheat sites county by county.

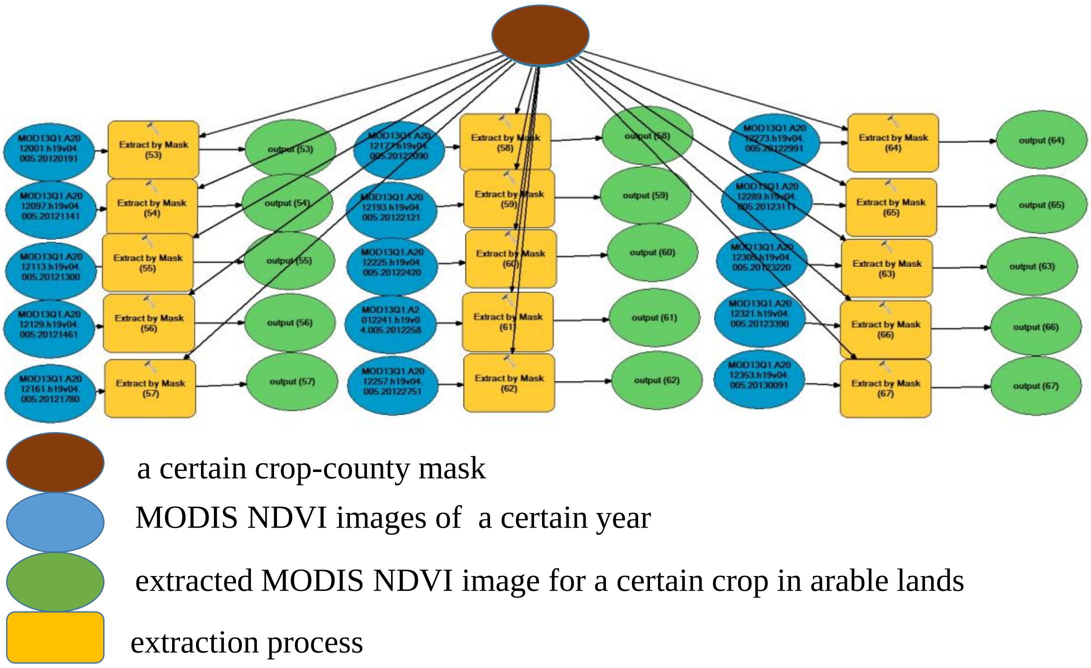


Figure 3. ArcGIS model for extraction process of a certain crop-county mask from MODIS NDVI images

After extractions *data matrix* of the mean NDVI values had to be created. The mean NDVI values were gathered from every extracted NDVI image covering the whole timescale concerning the examined counties in the study areas. The data matrix of the mean NDVI values was the basis of the NDVI image calibration.

Next issue was to harmonize NDVI and yield data (t/ha), which was easily solved by the *normalization* of the datasets. In this way the two datasets became dimensionless between 0-1 values, so that statistics can be made from them. Normalization was made as follows:

$$\text{Normalized value} = (\text{Value} - \text{Value}_{min})/(\text{Value}_{max} - \text{Value}_{min})$$

where *max* and *min* refer to the values for dense vegetation and for the lowest vegetation cover, respectively. During normalization maximum and minimum values were chosen from the whole NDVI dataset.

Identification and calibration of drought risk level

NDVI based drought risk levels were calibrated by yield and meteorological data. MODIS NDVI time series dataset, yield data were available from 2000 – 2012. Concerning the yield dataset, in the case of both maize and wheat severe yield losses were detected in 2000, 2002, 2003, 2007, and 2012, remarkable yield amounts were detected in 2001, 2005, 2006, and average in 2010 and 2011 (Figure 4.). These findings are strongly related to the SPI and meteorological data, except for year 2010, when extreme amount of precipitation (900-1300 mm/year) was observed on the low land of the Tisza River Basin and due to the surplus drainage water cover on the fields for long period and plant diseases, the quantity of the yields remained average.

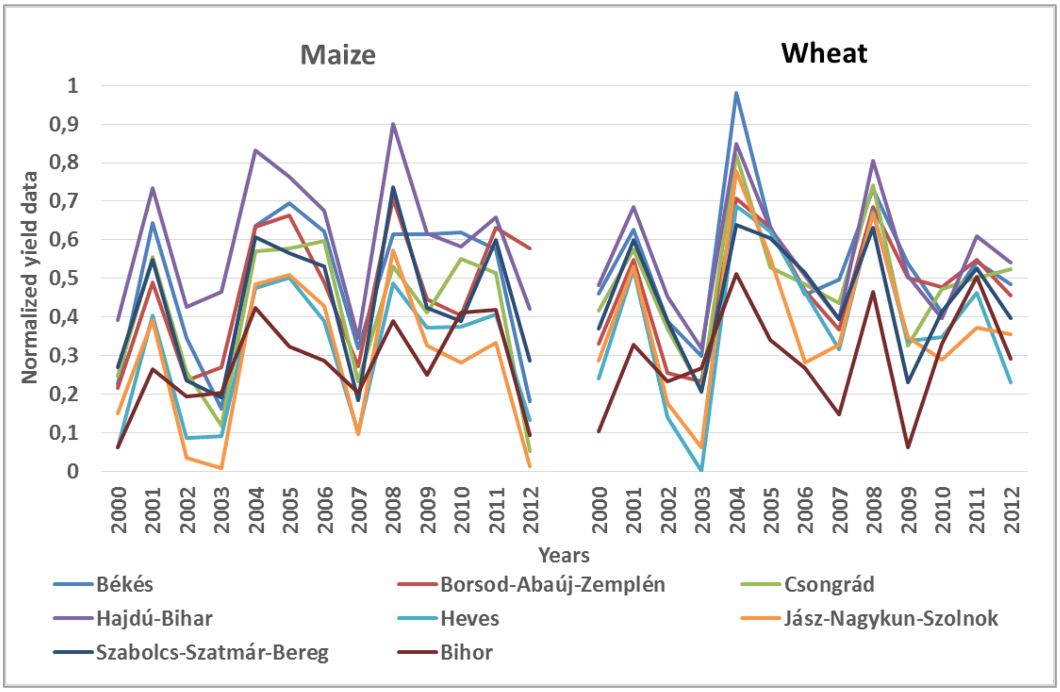


Figure 4. Yield changes of maize, wheat, 2000-2012 (based on KSH and INSSE data)

Beside the yield fluctuation, yield differences were also detected between counties in Hungary. Regardless of the drought situation, the largest maize and wheat yield production levels were observed in Hajdú-Bihar and Békés counties out of the examined counties, while Jász-Nagykun-Szolnok, Heves and Bihor (Romania) counties showed the worst yield results. The reason for this is the differences in soil characteristics (Várallyay et al., 1994). Hajdú and Békés counties have the highest rates of chernozem soils with very good water management characteristics, while Heves and Szolnok counties have relatively more clay and loamy clay soils, which are very sensitive to drought (Figure 5).

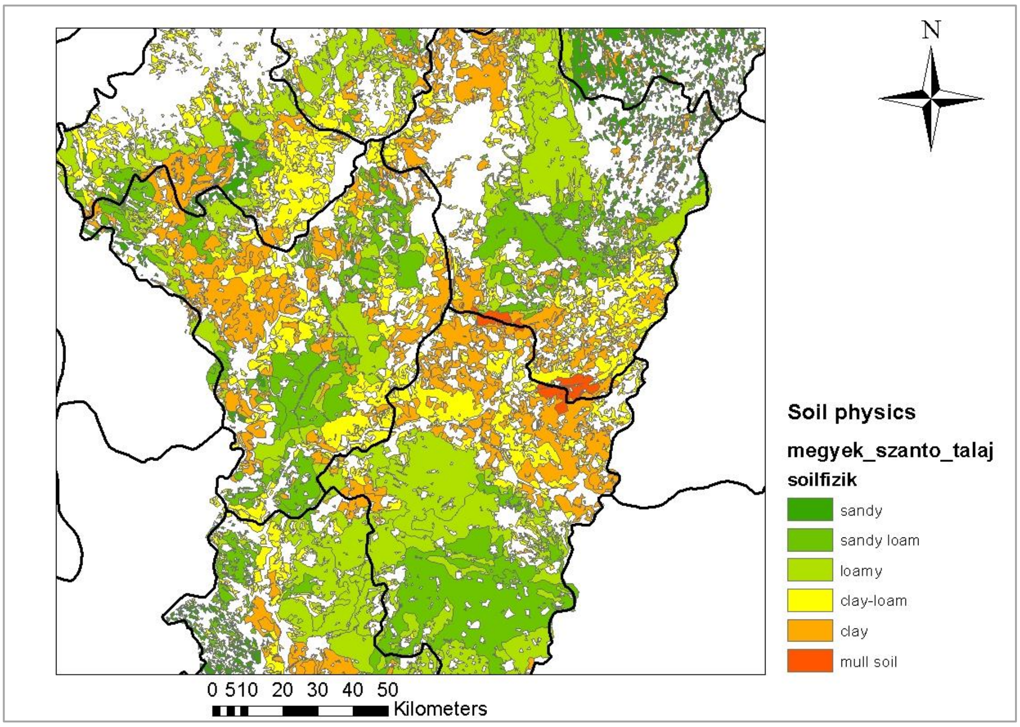


Figure 5. Soils of the concerned counties in Tisza river basin (based on the agro-topographic map of Hungary)

The calibration of NDVI datasets were carried out by calculating correlation and regression between yield and NDVI datasets. Since we had one yield value for one year for each county, but several mean NDVI values could be revealed within a year, first, the collected and normalized NDVI datasets had to be grouped. The basis of the grouping was the date within a year, than all data were arranged to one matrix with 13 year data. The matrix contained variables for normalized NDVI data in certain dates (the number of variables were different for each plant species based on the vegetation period of the certain crop) and one variable for the yield. The reason for establishing these matrices was to select those significant normalized NDVI time scales or intervals, which can be used for reliable yield or yield loss forecasting. Significant correlations were found between normalized NDVI values and maize yields from the middle of June, to the end of August, including the most drought sensitive blooming period (July) of this crop. In the case of wheat, only June was found to be reliable for yield prediction and forecasting (Table 1.). These results also suggest, that the effect of soil on yield appears through the NDVI values. If it is not the case, significant correlation cannot be detected at all. On the other hand, the fair and moderate correlation can also be explained by the effect of soil. Since we have yield data only for counties, and not for catchments or polygons of soil types, than yield data represents the effect of various soil type.

Table 1. Correlation between normalized NDVI values and yield in the case of wheat and maize

	9-Jun	25-Jun	11-Jul	27-Jul	12-Aug	28-Aug
Maize		0.65*	0.70*	0.69*	0.68*	0.54*
Wheat	0.51*	0.63*				

*significant (p<0.05)

Based on the linear regression results, yield and descriptive statistics of normalized NDVI, reference spectral curves were generated in order to determine the Watch, Early warning, Warning, Alert and Catastrophe levels of NDVI (Figure 6.):

Watch: When plant water stress is observed in sensitive phenological phases.

Early Warning: When relevant plant water stress is observed. The available soil moisture is close to critical, and it is suggested for farmers to start preparation of intervention. Predicted potential yield loss is up to 10%.

Warning: When plant stress translates into significant biomass damage, and there is time to start the intervention actions. Potential yield loss is up to 20%.

Alert: When farmers expect irreversible vegetation damage with real negative profit, and they have to consider to give up additional cultivation actions in crop production in that actual vegetation period. Potential yield loss is up to 30%.

Catastrophe: When serious damages and profit loss mitigation is necessary. Potential yield loss is up to 40%.

After generating these reference curves, the normalized NDVI was back scaled and transformed into real NDVI values. As a result of this process, concrete NDVI levels and thresholds could be calculated for yield and yield loss.

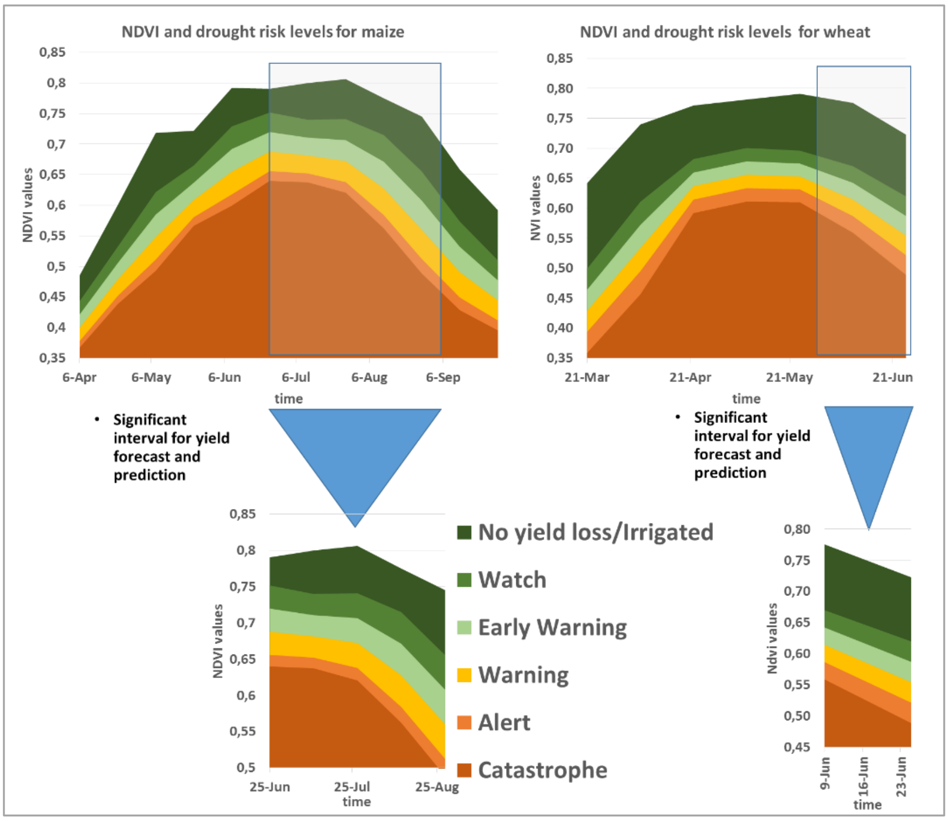


Figure 6. Drought risk and signalling NDVI levels for maize and wheat

It has to be mentioned, that the genetic potential of different species or hybrids can highly influence yields. Earlier species of maize has less yield than those which mature in autumn. FAO maturity group 100 hybrids could produce 1 t/ha more yield in average in this region. However, it has to take into consideration that the later harvested species or hybrids enhance the risk of yield loss, because their blooming period is directly in the middle of the most drought risk affected summer months.

There is also a need to understand why significant correlation can only be found in the middle and the final phenological phases of the crops. The answer is in the recovering ability of the plants. The later the droughts appear, the less is the possibility of the recovery of a certain crop. For example, if the emergence of wheat are weak or there is a period of drought in early spring with wet autumn before, than there is still a possibility to have good wheat yield, if there was enough rains in the winter or in the second half of spring.

After calibrating NDVI by yield, the validation was made by meteorological data, as well. Higher yearly mean temperature and less precipitation cause an earlier vegetation cycle. Concerning this and regarding climate change, one can expect lower yearly average NDVI values in the future for Tisza river basin. The large NDVI values tend to occur in wet conditions, while low NDVI values imply warm-dry climate conditions. This phenomenon regarding to the NDVI values is mainly observable in August: i.e. average year, excess water and/or drought hazarded extreme year. From the agricultural point of view and because of being one of the input data of several drought indices, such as SPI, soil water content were used to calibrate NDVI data. According to the results, moderate significant correlation (r^2=0.62 p=0.008) was found between available soil water content and NDVI values. These moderate values were highly due to the origin of soil moisture data, which were based on soil samples. Thus these point data cannot represent properly a site, or larger, heterogeneous area.

Drought risk evaluation and mapping

After the yield loss specified signalling levels of drought identified, the implementation the results were carried out. The evaluation of yield loss specific drought risk levels was generally based on classification and mapping of MODIS NDVI images and identification of the most drought effected region by calculating the area of the sites with different drought risk levels. Within the drought risk evaluation and mapping deliverables the purpose of the results is suitable for identification of drought affected sites and the delineation of drought sensitive areas, forecasting of yields in the case of extreme drought situation at a certain place and calculation of possible yield loss.

Drought maps were generated by the classification of the NDVI image based on the drought risk levels. Mapping were made for a drought affected year with severe yield loss and for a year with good meteorological circumstances with average yield. Drought risk evaluation and mapping of yield loss were carried out for maize and wheat in 2003 and in 2008. The yield loss forecast were based on the NDVI image from 6th of June for heat, and 1th of July for maize. The drought risk maps show the spatial distribution of yield loss pixel by pixel for the whole production area in Tisza catchment. There can be seen the severe different in yield loss between the drought affected, and not affected year. Since the drought risk map is raster, first the vectorization should be made, in order to calculate the area. Before area calculation sites with the same drought risk category has to be merged to achieve one polygon for each risk category. After that the rates (%) of different drought risk affected sites and yield loss were also calculated for both wheat and maize. (Table 2.).

Table 2. Rates (%) of different drought risk affected sites for wheat and maize (100% is the concerned investigated area)

	2003 (drought affected)				**2008 (average year)**			
Risk levels	Tisza catchment (T.c.)	Hungarian part of T.c.	Jász-Nagykun-Szolnok	Hajdú-Bihar	Tisza catchment (T.c.)	Hungarian part of T.c.	Jász-Nagykun-Szolnok	Hajdú-Bihar
	Wheat (area %)							
Catastrophe	38.44	45.38	59.08	34.80	11.99	13.42	15.73	4.77

Alert	8.25	8.27	7.84	7.70	5.05	5.23	5.40	3.30
Warning	8.29	7.96	6.99	8.03	0.45	4.41	4.62	3.04
Early Warning	10.59	9.75	7.50	10.69	8.30	8.09	8.75	6.13
Watch	7.18	6.42	4.51	7.82	10.14	9.69	10.57	9.06
No yield loss	27.25	22.22	14.07	30.96	64.07	59.15	54.92	73.70
	Maize (area %)							
Catastrophe	51.77	51.86	66.06	20.92	24.54	19.85	21.24	10.74
Alert	2.94	8.06	2.11	1.80	2.78	1.90	2.15	1.27
Warning	8.93	8.11	6.62	7.03	9.92	6.87	6.92	4.97
Early Warning	8.93	7.83	6.46	8.92	11.90	8.83	9.73	6.77
Watch	8.38	2.51	5.99	10.18	12.46	10.61	11.52	9.54
No yield loss	19.05	21.63	12.76	51.16	38.39	51.94	48.44	66.70

In the case of wheat the rate of drought risk was calculated, thus the severe differences between the years can easily be identified numerically. This identification is also appropriate for detecting the differences between sites, or regions and even between catchments. Drought risk was calculated for Jász-Nagykun-Szolnok (JNSz) and Hajdú-Bihar (HB) counties. The reason for selecting these counties was that even in drought affected years, Hajdú-Bihar had the best, and Jász-Nagykun-Szolnok gave the worst results for yield. The risk map resulted the same, since in 2003 a little less than 60% of JNSz area had catastrophic wheat yield production (more than 40%), on the other hand "only" 35% of the area of HB was catastrophic. The same results can be found in 2008 as well, and HB had far better results in "No yield loss" in both years. This statement is valid for maize as well, but the differences between the counties are much larger, than in the case of wheat. The reason is the differences in soil characteristics; the rate of sandy and very often salt effected clay soils with bad water management and waterholding capacities are huge in JNSz, and much less in HB. The soil characteristics influence the biomass, which reflects in NDVI values. The result suggest, that JNSz county is much more sensitive for droughts, than other counties. In this way, drought sensitive sites can easily be selected based on NDVI data.

Conclusions

With the assistance of the developed Agricultural Drought Monitoring and Yield Loss Forecasting Method, the yield loss of maize and wheat can be predicted 4-6 weeks before harvest and the sites affected by droughts can be delineated more accurately. The impact of droughts on agriculture can be diagnosed far in advance of the time of harvest, which is critical for stakeholders in terms of food security and trade in Central East European region. The information gained through this monitoring can facilitate drought intervention activities, reduce impacts of drought on possible stock uncertainty, and can support decision makers in more accurate planning for mitigation measures for a specific region.
The data gained from an Agricultural Drought Monitoring and Yield Loss Forecasting Method provides critical information regarding droughts and crop growth. This is a valid complement to data outlining weather parameters, which also influence crop growth. Agricultural drought monitoring, and its consequent identification of intervention levels is thus a convenient tool to capture our understanding of yield loss. Together with GIS, it provides a framework to process diverse data, which is geographically linked. Currently, monitoring, signalling and intervention levels for agricultural droughts can provide information on regional crop distribution and yield

loss. This can be coupled with crop simulation models in a number of ways. These include: (a) direct use of MODIS NDVI as a forcing variable, (b) re-initialising or re-calibrating MODIS NDVI by yield data; and (c) using yield calibrated NDVI to estimate thresholds for drought (yield loss) categories, and using MODIS NDVI and thresholds in mapping of yield loss forecast.

This new method is an improvement for hydrologists, meteorologists and farmers, allowing to estimate yield loss and the role of vegetation in the hydrological cycle more precisely. Based on the results more water-saving agricultural land use alternatives could be planned on drought areas.

Acknowledgement

The authors acknowledge that the research work was partly funded by the joint Integrated Drought Management Programme of GWP (Global Water Partnership), WMO (2011-2014) as well as by the EU FP7 programme financed Changehabitats2 (*Network for Habitat Monitoring by Airborne-supported Field work – an innovative and effective process in implementation of the Habitat Directive*) project, the OTKA project K 105789, and TÁMOP 4.2.4. A/2-11-1-2012-0001, for the "National Excellence Program – Elaborating and operating an inland student and researcher personal support system." project.

References

Becker-Reshef, I., Vermote, E., Lindeman, M., Justice, C. (2010): A generalized regression-based model for forecasting winter wheat yields in Kansas and Ukraine using MODIS data. *Remote Sens. Environ*. 114: 1312–1323.

Choi, M., Jacobs J.M., Anderson, M.C., Bosch, D.D. (2013): Evaluation of drought indices via remotely sensed data with hydrological variables. *Journal of Hydrology*, 476: 265–273.

Dai, A., Trenberth, K.E., Qian, T. (2004): A Global Dataset of Palmer Drought Severity Index for 1870–2002: Relationship with Soil Moisture and Effects of Surface Warming. *Journal of Hydrometeorology* 5: 1117-1130.

Gallego, J., Carfagna, E., Baruth B. (2010): Accuracy, Objectivity and Efficiency of Remote Sensing for Agricultural Statistics. Agricultural Survey Methods John Wiley & Sons, Ltd., West Sussex, United Kingdom 193–211.

Gitelson, A.A., Viña, A., Arkebauer, T.J., Rundquist, D.C., Keydan, G., Leavitt B. (2003): Remote estimation of leaf area index and green leaf biomass in maize canopies. *Geophys. Res. Lett*. 30: 1248.

Gobron, N. and Verstraete, M.M. (2009): Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) Global Terrestrial Observing System NRC, Food and Agriculture Organization of the United Nations (FAO) Rome. 14.

Lobell D.B. (2013): The use of satellite data for cop yield gap analysis. *Field Crops Research* 143: 56–64.

Lobell, D.B., Ortiz-Monasterio, J.I., Lee A.S. (2010): Satellite evidence for yield growth opportunities in Northwest India. *Field Crops Research* 118: 13–20.

McKee, T.B., Doesken, N.J., and Kleist, J. (1993): The relationship of drought frequency and duration to time scale. *In: Preprints Eighth Conference on Applied Climatology, American Meteorological Society*, Anaheim (Ca), 17-22 January 1993. AMS, 179-184.

Moulin, S., Bondeau, A., Delecolle, R. (1998): Combining agricultural crop models and satellite observations: from field to regional scales. *Int. J. Remote Sens*. 19 1021–1036.

Nagy, A. and Tamás, J. (2013): Non-invasive water stress assessment methods in orchards. *Communications in Soil Science and Plant Analysis*, 44(01-04): 366–376.

Niemeyer, S. (2008): New drought indices. *In: López-Francos A. (ed.) Drought management: scientific and technological innovations*. Zaragoza: CIHEAM, 2008. p. 267-274. *Options Méditerranéennes: Série A. Séminaires Méditerranéens; n. 80. 1. International Conference on Drought Management: Scientific and Technological Innovations*, 2008/06/12-14, Zaragoza, Spain

Reeves, M.C., Zhao, M., Running, S.W. (2005): Usefulness and limits of MODIS GPP for estimating wheat yield. *Int. J. Remote Sens*. 26: 1403–1421.

Sellers, P.J. (1987): Canopy reflectance, photosynthesis, and transpiration. II. The role of biophysics in the linearity of their interdependence. *Remote Sens. Environ*., 21: 143–183.

Shanahan, J.F.,. Schepers, J.S, Francis, D.D., Varvel, G.E., Wilhelm, W.W., Tringe, J.M., Schlemmer, M.R., Major, D.J. (2001): Use of remote-sensing imagery to estimate corn grain yield. *Agron. J*. 93: 583–589.

Sivakumar, Mannava V.K., Raymond P. Motha, Donald A. Wilhite and Deborah A. Wood (Eds.) (2011): Agricultural Drought Indices. *Proceedings of the WMO/UNISDR Expert Group Meeting on Agricultural Drought Indices*, 2-4 June 2010, Murcia, Spain: Geneva, Switzerland: World Meteorological Organization. AGM-11, WMO/TD No. 1572; WAOB-2011. 197.

Tamás, J. and Bozán, Cs. (2009): Biomass productivity on the Békés-Csanád loess plateau. *Cereal Research Communications*. 37 (4): 505-508.

Tucker, C.J. (1979): Red and photographic infrared linear combinations for monitoring vegetation. Remote Sens. Environ., 8: 127–150.

Várallyay, Gy., Szabó, J., Pásztor, L., Michéli, E. (1994): SOTER (Soil and Terrain Digital Database) 1:500 000 and its application in Hungary. *Agrokémia és Talajtan*. 43: 87–108.

Wiegand, C.L. and Richardson, A.J. (1990): Use of spectral vegetation indexes to infer leaf-area, evapotranspiration and yield. *Results Agron. J*. 82: 630–636.