From Spectral Time Series Analyses To Drought Monitoring –GWP IDMP

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ABSTRACT

The World Meteorological Organization (WMO) and Global Water Partnership (GWP) have launched a joint Integrated Drought Management Programme (IDMP) to improve monitoring and prevention of droughts. In the frame of this project this study focuses on identification of agricultural drought characteristics and elaborates a monitoring method (with application of remote sensing data), which could result in appropriate early warning of droughts before irreversible yield loss and/or quality degradation occur. The spatial decision supporting system to be developed will help the farmers in reducing drought risk of the different regions by plant specific calibrated drought indexes.
For the investigations normalized difference vegetation index (NDVI) was used calculated from 16 day moving average chlorophyll intensity and biomass quantity data. The study area was the Tisza River Basin, which is located in Central Europe within the Carpathian Basin. The results offer concrete identification of remote sensing and GIS data tools for agricultural drought monitoring and forecast, which eventually provides information on physical implementation of drought risk levels. As a result, five drought risk levels were developed to identify the effect of drought on yields: Watch, Early Warning, Warning, Alert and Catastrophe.
In the frame of this innovation such a data link and integration, missing from decision process of IDMP, are established, which can facilitate the rapid spatial and temporal monitoring of meteorological, agricultural drought phenomena and its economic relations, increasing the time factors effectiveness of decision support system. This methodology will be extendable for other Central European countries when country specific data are available and entered into the system.

Keywords: MODIS NDVI, Yield loss, Drought, Drought mapping, Hungary

1. INTRODUCTION

The World Meteorological Organization (WMO) and Global Water Partnership (GWP) have launched a joint Integrated Drought Management Programme (IDMP) in March of 2013, to improve monitoring and prevention of one of the world's greatest natural hazards. GWP is responding to the climate change challenge through a portfolio of programmes and projects aimed at building climate resilience through better water management (Kindler and Thalmeinerova, 2012). In the frame of GWP DEE IDMP, this study focuses on identification of agricultural

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drought characteristics and elaborate and signaling agroinformatic method, which could result in appropriate early warning of droughts before irreversible yield loss occur.

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 condition (Niemeyer, 2008). Despite the fact that there is a close quality connection among the harmful level of all three indicators, the numerical scale of the relationships among them is 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) (McKee et al., 1993) values of a river basin, 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.

Over the past decade, the number of Earth observation satellites increased by several orders of magnitude and the spectral and spatial resolution of data they collect improved. Multispectral remote sensing technology is widely used in agriculture and is appropriate for vegetation analysis (Polder & van der Heijden, 2001; Sabins, 1997).Vegetation has characteristic spectra, often showing characteristic absorption maxima or minima at particular wavelengths. Most vegetation indices are based on the sharp increase in reflectance from vegetation that occurs around 700 nm (the red-edge), a change that is characteristic of green vegetation and not found for most other natural surfaces that show relatively slow changes of reflectance with wavelength over this region (Jones and Vaughan, 2010). In particular, since 2002 new opportunities for better data for calculations can be gained from the MODIS Aqua and Terra satellites which provide free 36-band number, with 1 day repeating cycle and 250 to 500 m pixel size time series data sets (Tucker, 1985). For agricultural water management today, remote sensing time series analysis (RS- TSA) is one of most important solutions for measuring agricultural droughts and its effects (Tamás et al., 2009). Technologically, the broad application of remote sensing (RS) has few barriers, although the accumulated knowledge on RS is slowly being implemented into practice. While it is possible to continuously gather spectral physical data on plant water content, the direct interpretation of these data is not feasible practical for farmers. Using field or other meteorological reference data for calibration of remotely sensed spectral data, real plant water demand can be quickly and effectively mapped in both space and time on the surface (Lei and Peters, 2003).

The aim of our study was to develop a process, which could provide information for estimating the relevant drought indexes and crop losses more effectively, and to help fill the knowledge gap in this field, in order to develop agricultural drought-related decision parameters and applications in practice from spectral MODIS satellite time series datasets.

2. MATERIAL AND METHODS

Our study focused on determination of drought effects on watersheds from remote sensed spectral data. For the investigations normalized difference vegetation index (MODIS NDVI) was used calculated from 16 day moving average chlorophyll intensity and biomass quantity data. 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 Earth and the investigated lowland has semi-arid to arid character. In this region there is intensive agricultural activity where the ratio of arable land is 72%.

In the case of data processing and transformations five major steps should be done in order to make the NDVI calibration:

- Reprojection of MODIS data
- Mask building for data extraction
- Extraction of MODIS NDVI time series by masks
- Acquiring data matrix from NDVI images
- Normalization of extracted NDVI data matrix and yield data

After reprojection of the MODIS NDVI data time series, a complex models for mask building and data extraction were established in order to select and delineate arable lands from the whole Charpathian basin. The reason for selecting the concerned sites was to eliminate the disturbing effect of other landuse categories on NDVI values. ArcGIS 10.2 software was used to create models for the data processing of NDVI images. Boolean mask images were produced for the selection of plain fields and arable lands with which the MODIS data set can be extracted. The Boolean masks were made based on the CORINE Land Cover (CLC2006) and SRTM 90 m DEM data. After creating these masks, a set of models were created for the extraction of MODIS NDVI datasets.

The models resulted NDVI images, representing arable lands on plains in a certain region. On the other hand the extracted NDVI images cannot be used directly for maize and winter wheat yield loss calibration, because the images represent arable lands and not the production area of the maize and wheat. Therefore further data was needed concerning the production area. Since there is no available data for the exact localization of the production area of maize and wheat, further mask models were built to separate the winter grains (wheat) and maize from each other (Figure 1.).

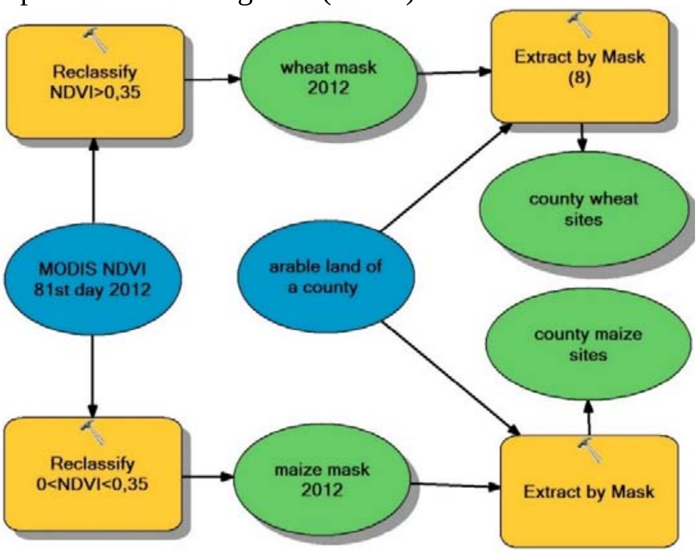

Figure 1. ArcGIS model for creating mask and extraction of wheat and maize site at a ROI

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The bases of the mask models was that the winter wheat has ground cover in March, and fields dedicated to maize production is still bare, since the appropriate date for maize seeding is the middle of April on the Great Plain. Concerning crop rotation, NDVI classification process was made for every year, based on the NDVI images representing March, in our case the 81st day of the year. In the case of wheat, sites with 0.35-1 NDVI values were classified to wheat, and sites with 0-0.35 NDVI value were classified to maize. After the classification, two masks were obtained for one year, one for wheat, one for maize. After that 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. As a result, wheat and maize mask were produced for every year for a certain county.

The masks for county wheat/maize sites were then used to extract the MODIS NDVI images to get NDVI data for the different crop sites. For masking, new models were built for each years (Figure 2.). 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.

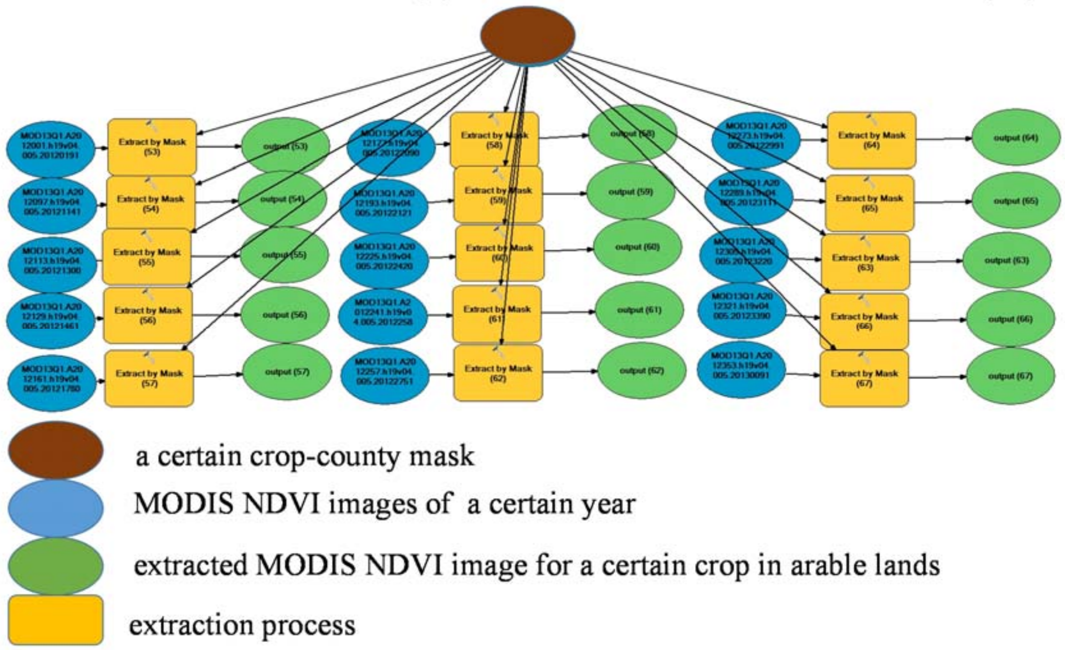

Figure 2. ArcGIS model for extraction process of a certain crop-county mask from MODIS NDVI images

After extractions the main aim was to create the data matrix of the mean NDVI values. The mean NDVI values were gathered from every extracted NDVI images, from the whole timescale concerning the ten examined counties (7 counties in Hungary, 2 counties in Slovakia and 1 county in Romania). The collection of mean NDVI values were made in ArcGIS 10.2 software ambient as well, by using band collection statistics tools. 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. Normalization was made as follows:

Normalized value = (Value – $Value_{min}$)/($Value_{max}$ – $Value_{min}$)

where in the case of NDVI images the subscripts max and min refer to the values for dense vegetation and for the lowest vegetation cover. During normalization maximum and minimum values were chosen from the whole NDVI dataset regardless regions of interest. This provides us data uniformity for the whole river basin.

3. RESULTS AND DISCUSSION

As it was described earlier NDVI based drought risk levels were calibrated by yield and meteorological data. As well as MODIS NDVI time series dataset, yield data is also available from 2000 – 2012. Concerning the yield dataset, in the case of maize and wheat severe yield loss were detected in 2000, 2002, 2003, 2007, and 2012, remarkable yield amount were detected in 2001, 2005, 2006, and average in 2010 and 2011 (Figure 3.).

These findings are strongly related to the SPI and meteorological data, except for year 2010, when extreme amount of precipitation (900-1300 mm) fell on the plains of the Tisza river basin and due to the surplus water occurrences and diseases the quantity of the yields remained average. Furthermore the weather contributed to the spread of weed coverage.

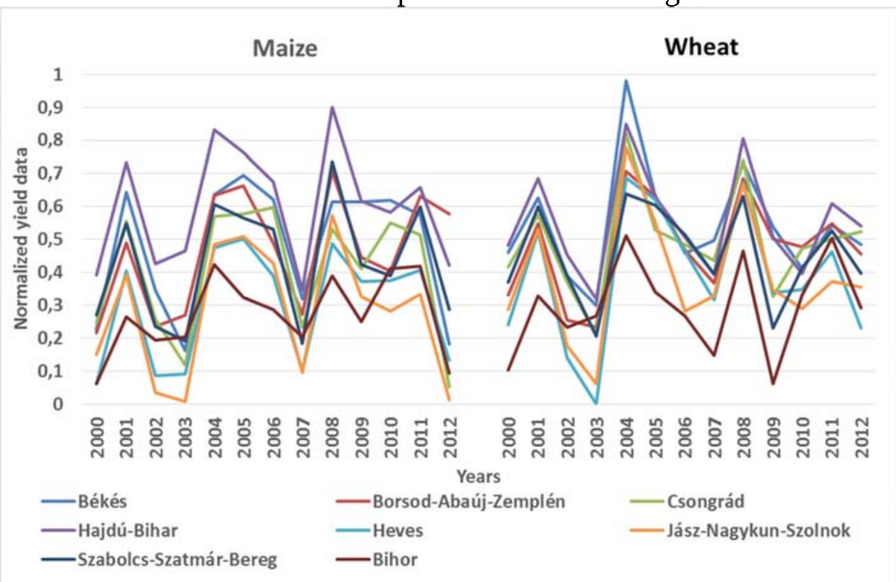

Figure 3. Yield changes of maize, wheat, 2000-2012 (based on KSH and INSSE data)

Beside the fluctuation of yield, yield differences also detected between counties. Regardless the drought situation the largest maize and wheat yield production levels reveal generally 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. 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.

The calibration of NDVI dataset 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 the data were arranged to one matrix with data of 13 year. 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 or fruit) and one variable for the yield. The reason for establishing these matrices was to select those significant normalized NDVI time scale or interval, which can be used for reliable yield or yield loss forecasting. Based on the results significant correlation were found between normalized NDVI values and maize yield 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 is found to be reliable for yield prediction and forecasting (Table 1.). These results also suggest, that the effect of soil on yield through the NDVI values appears, 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 for counties, and not for catchments or polygons of soil types, yield data represents the effect of various soil type at the same time on the county yield data. The effect of the rate of the major soil type on yield can be detectable.

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 results of linear regressions, 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 4.):

1. *Watch*: When plant water stress is observed in sensitive phenological phases
2. *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%.
3. *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%.
4. *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%.
5. *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.

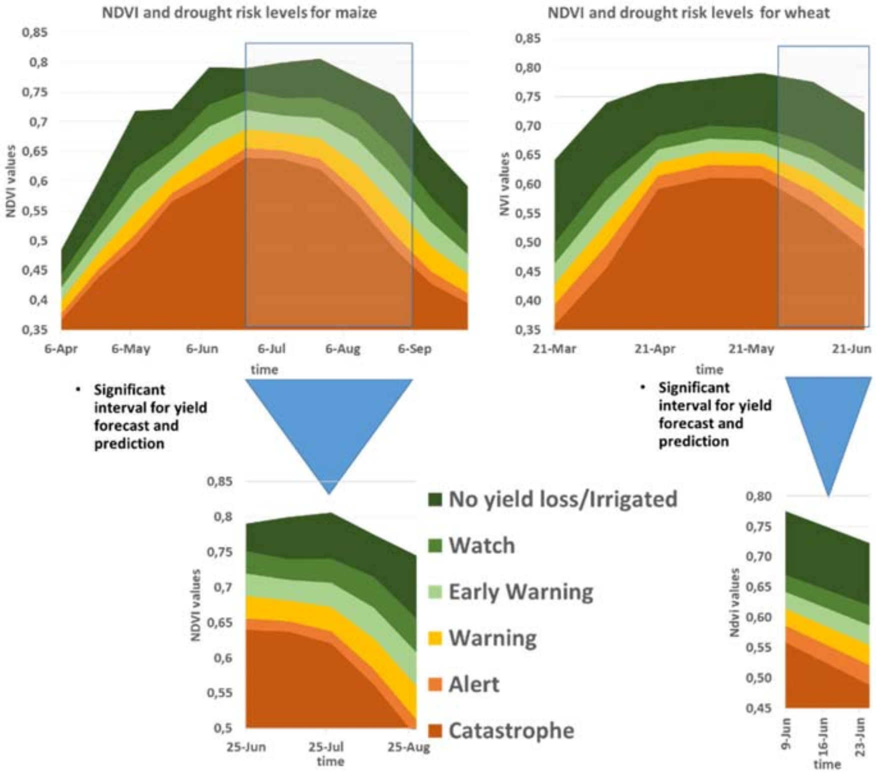

Figure 4. Drought risk and signaling NDVI levels for maize and wheat

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. However, it has to take into consideration, that later ripening 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 that why significant correlation can only be found in the middle of and the final phenological phase of the crops. The answer is in the recover ability of 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, there is still a possibility to have good wheat yield, if there was enough rains in winter or in the e 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, we 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 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.

This new drought risk monitoring and forecasting method is an improvement for hydrologists, meteorologists and farmers, allowing to set up a complex drought monitoring system, where for a given period and respective catchment area the expected yield loss can be predicted, and the role of vegetation in the hydrological cycle could be more precisely quantified. Based on the results more water-saving agricultural land use alternatives could be planned on drought areas.

4. ACKNOWLEDGEMENTS

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