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DROUGHT MONITORING WITH SPECTRAL INDICES CALCULATED FROM MODIS SATELLITE IMAGES IN HUNGARY

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Abstract
In this study a new remote sensing drought index called Difference Drought Index (DDI) was introduced. DDI was calculated from the Terra satellite's MODIS sensor surface reflectance data using visible red, near-infrared and short-wave-infrared spectral bands. To characterize the biophysical state of vegetation, vegetation and water indices were used from which drought indices can be derived. The following spectral indices were examined: Difference Vegetation Index (DVI), Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Difference Water Index (DWI), Normalized Difference Water Index (NDWI), Difference Drought Index (DDI) and Normalized Difference Drought Index (NDDI). Regression analysis with the Pálfai Drought Index (PaDi) and average annual yield of different crops has proven that the Difference Drought Index is applicable in quantifying drought intensity. However, after comparison with reference data NDWI performed better than the other indices examined in this study. It was also confirmed that the water indices are more sensitive to changes in drought conditions than the vegetation ones. In the future we are planning to monitor drought during growing season using high temporal resolution MODIS data products.

Keywords: drought, remote sensing, MODIS, monitoring, spectral indices

INTRODUCTION

Climate change is one of the most significant issues facing the world because it is predicted to alter climate patterns and increase the frequency of extreme weather events. In recent years, the frequency of droughts that are due to global warming-related climate change has increased and is accompanied by a rise in the severity of these phenomena (IPCC, 2013; Trenberth et al., 2014). In our days – also in the Carpathian Basin – one of the environmental problems waiting for solution is water shortage, which is one of the biggest hazards, that causes serious damages especially in agriculture in drought-stricken years (Rakonczai, 2011). We are talking about water shortage if water supply falls short on human demand and wildlife needs. It can be caused by the limitations of available resources or the insufficient level of utilization of those or/and the increase of society's needs. According to the guide of the International Commission on Irrigation and Drainage (ICID), when precipitation cannot satisfy water needs, because there is a big deficit compared to normal or expected, which extends to growing season, or longer periods too, then there is drought.

It is hard to define the beginning and the end of droughts and quantifying its effects. Meteorological drought is characterized by the substantially less rainfall compared to multi-year average, this coupled with air temperatures exceeding the average and low relative humidity. This directly affects agricultural production (agricultural drought), which is most often visible on the physiological condition of plants to the naked eye, or can be seen from satellite above. Depending on the duration and the strength of meteorological drought, the soil moisture content decreases to the fraction of available water capacity (soil drought). If the catchment area is hit by meteorological drought, runoff and water level of reservoirs, lakes and rivers decreases which is called hydrological drought. The magnitude of drought is influenced by local conditions, e.g. more porous, thicker topsoil can absorb and store more usable water (Heim, 2002; Pálfai, 2004; Hao and Singh, 2015).

In addition to the economic damage caused by persistent drought, social damage can occur too (e.g. high prices, restrictions of water usage), as well as drought could amplify the existing vulnerability of the social classes (Wisner et al., 2004). There is socioeconomic drought when demand for economic goods, as the result of deficit connected to water supply, exceeds the human supply (Wilhite and Glantz, 1985). The Hungarian economy is frequently hit by droughts which are partly due to the unexploited water potential.

Drought is a relative rather than an absolute condition that needs to be interpreted separately in every region and on every group of organisms. Every drought differs from one another in intensity, duration and spatial extent. In agricultural point of view, drought is a substantial degree of water shortage of stand of croplands and forests which greatly limits the life processes of

plants. Without a plant drought cannot be interpreted since different plant species react distinctly to the same level of drought (Anyamba and Tucker, 2012).

With the drought assessment in a quick and cost-effective way, with even the possibility of forecasting, it may become possible to increase adaptability of water retention. Optimization of the redistribution of water resources may become possible if location is known where greater need for them is. We could prepare for drought or at least moderate its damages by filling up reservoirs (partially) satisfying irrigation and ecological needs if necessary. Remote sensing methodology provides one of the ultimate tools that support the water management organizations' operational work

VULNERABILITY AND SOME INDICATORS OF DROUGHT

Risk is the combination of the probability of an event and its negative consequences which is the intersection of hazard, vulnerability and exposure. Vulnerability which is inversely related to coping capacity is the characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard (UNISDR, 2009).

In drought monitoring there are many meteorological-statistical method and remote sensing based indices; more than a hundred of them is known (Faragó et al., 1993; Zargar, 2011). The one developed by Palmer (1965) in the US, which is calculated from precipitation, temperature and soil moisture content data, is the so-called Palmer Drought Sensitivity Index (PDSI) that has been used in Hungarian study areas too (Horváth, 2002). For the Standardized Precipitation Index (SPI) at least 30 years long precipitation dataset is needed. The gamma distribution fitted on the empirical probability distribution of the dataset has to be transformed to normal distribution; the probabilities are the SPI values (McKee et al., 1993). This analysis method is very popular (Hayes et al., 2012) in Hungary too (DMCSEE, 2010-14; Blanka et al., 2014).

Mu et al. (2013) used a drought index called Drought Severity Index (DSI), which can be generated from the ratio of evapotranspiration and potential evaporation (ET/PET), resp. Normalized Difference Vegetation Index (NDVI), for MODIS sensor data.

The basic version of Pálfai Drought Index (PAI), which is commonly applied in Hungary, is calculated from meteorological (daily temperature and precipitation) datasets and we get its actual value when we multiply its base value with empirical correction factors (Pálfai, 1989). Fiala et al. (2014) are analyzing the simplified version of PAI (PaDI) in Hungarian and Serbian areas with GIS processing; PaDI is calculated from monthly average temperature and monthly average precipitation dataset.

Spectral indices derived from measurements of multispectral sensors like the ones analyzed in our study could be a great addition to their method as well. Kovács (2007) and Ladányi et al. (2011) identified high drought risk areas based on time series of biomass productivity from Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI)

DATA AND STUDY AREA

Drought indices calculated from Terra MODIS satellite images may become suitable in monitoring short term spatiotemporal variations in drought intensity at regional scale. High temporal resolution allows analyzing environmental change processes. In the course of data processing, several pre-calibrated and evaluated products are manufactured which are available free of charge (e.g. GLOVIS database). MODIS-composites are compiled from the optimal selection of pixel values of satellite images recorded during the period of 8 or 16 days. Cell values of composites are always made of the best data quality pixels available (Huete et al., 2002; Vermote and Kotchenova, 2008). Selection covers the viewing and illumination geometry, the state of the atmosphere and the amount of cloud cover e.g. the first half of July is one of the most suitable dates, because precipitation in this month has the maximum weight since plants require a lot of water in July. In addition, the occurrence of a drought is the most likely in this month (Pálfai, 2004). However, after harvest it is inappropriate to choose a date, because harvested croplands can be classified as drought-stricken (e. g. time range of wheat

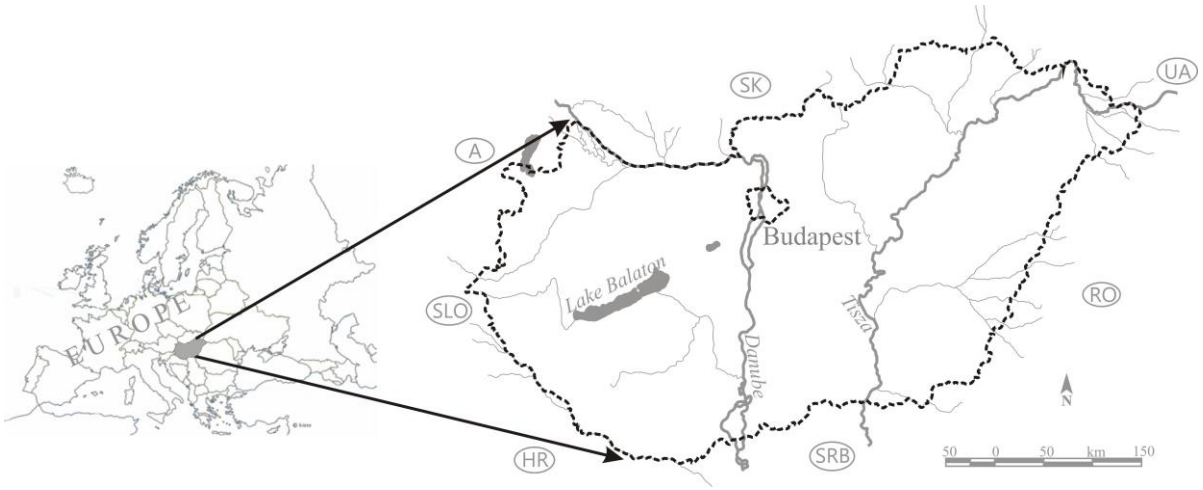

Fig. 1 Hungary, the study area

harvest in Hungary is from the end of June to middle of July). For our analysis we have chosen two dates: one from June and another one from July (Fig. 1).

For the calculation of spectral indices MOD09A1 (Collection 5) 500 m resolution 8-day surface reflectance composite images (Surface Reflectance 8-Day L3 Global 500m SIN Grid) between 2000 and 2014 were used (Table 1). Spectral band values are multiplied by a factor of 10,000. Images are from the 9-16th (resp. 10-17th) of June (resp. 10-17th) and the 12-19th (resp. 11-18th) of July. In some instances different periods were chosen because of high cloud cover. The 16-day 500 m resolution EVI composite images (MOD13A1 EVI, Vegetation Indices 16-Day L3 Global 500m SIN Grid) were obtained for the period of 9-24th (resp. 10-25th) of June and of 11-26th (resp. 12-27th) of July. Records from the MODIS catalog H/V 19/4 (Lat/Long 45/21.1) were downloaded from GLOVIS database [1]. The composites are not allowing observing changes on daily scale or less than 8 or 16 days long time periods, but they are still very good at monitoring changes for longer periods.

Table 1 Spectral bands of MOD09A1 surface reflectance 8-day composites (Vermote and Kotchenova 2008)

MOD09A1 bands	wavelength (nm)
1 (visible red)	620-670
2 (near infrared)	841-876
3 (visible blue)	459-479
4 (visible green)	545-565
5 (SWIR 1)	1230-1250
6 (SWIR 2)	1628-1652
7 (SWIR 3)	2105-2155

SWIR: short-wave infrared

Quality Control and State Flag created for the spectral bands provide information about each pixel's data quality, accuracy and consistency (e.g. cloud cover and cloud shadow, dead detector and data interpolated, value out of bounds, aerosol quantity of the air, zenith angle of sun). The quality control and state bands are storing metadata as decimal numbers which have to be converted into 16, resp. 32 bit binary series to extract information needed for pixel evaluation.

Before using MODIS data, incorrect, inaccurate or inconsistent pixel values have to be excluded from analysis. The processing tools (LDOPE Tools and MODIS Reprojection Tool) provided by the MODIS land quality assessment group (Roy et al., 2002) were applied at the extraction of quality, cloud cover and cloud shadow mask from the 16/32 bit binary quality and state bands. General rule is that the lower the value, the better the quality. Zero means that there are no quality issues. The pixel values defined as incorrect were overwritten by the pre-defined no data value of spectral bands (−28,672). For the execution of this operation a program was written in C language (named MODIS Quality Control Tool) which reads in data in ASCII grid file format. We have taken the following bits into consideration with the conditions for pixel evaluation shown in Table 2. The predefined no data value for MOD13A1 data is −3000. The strictness of specified conditions in case of MOD09A1 and MOD13A1 data are very much alike. Data accuracy is determined by inaccuracies of cloud filtering, variable viewing and illumination geometry, different amount of cloud filtered data for averaging, inaccuracy of atmospheric correction. Database can also be cleaned if we are not taking into consideration satellite passes with higher than 40° zenith angle or providing less than 25% data coverage (Huete et al., 2002).

Data processing and analysis was performed in open-source geospatial software environment, the following programs were used: SAGA GIS 2.1, QGIS 2.4-Chugiac (Python 2.7.5, GDAL 1.11.0 and GRASS GIS 6.4.3 integrated into QGIS), R for Windows 3.1.2, MODIS Reprojection Tool 4.1, LDOPE Tools 1.7, and own programs written in C language in Code::Blocks 10.05 environment. Processing was automatized by the use of scripts.

METHODS

Characterization of spectral indices

A new method for drought delineation using MODIS surface reflectance data was presented in the paper by Gu et al. (2007). It is called Normalized Difference Drought Index (NDDI). NDDI (Eq. 1) is derived from NDVI and NDWI (Normalized Difference Water Index):

$$NDDI = (NDVI - NDWI) / (NDVI + NDWI) \quad \text{(Eq.1)}$$

where:
$NDVI = (NIR_{858\ nm} - red_{645\ nm}) / (NIR_{858\ nm} + red_{645\ nm})$,
$NDWI = (NIR_{858\ nm} - SWIR_{2130\ nm}) / (NIR_{858\ nm} + SWIR_{2130\ nm})$,
NIR: near infrared, SWIR: short wave infrared.

Table 2 Pixel evaluation of MODIS satellite images using the quality assessment bands

MOD09A1	MOD13A1
State Flags: 0-1. bits: Cloud State (=0) 2. bit: Cloud Shadow (=0) Quality Control: 2-5. bits: 1st band's data quality (=0) 6-9. bits: 2nd band's data quality (=0) 26-29. bits: 7th band's data quality (=0)	VI Quality detailed QA: 0-1. bits: VI Quality (MODLAND QA bits) (<=1) 2-5. bits: VI Usefulness (<=4) 15. bit: Possible shadow (=0) Pixel reliability QA summary (<=1).

NDVI was developed by Rouse et al. (1973), and it has been in use for decades for monitoring vegetation cover, chlorophyll content and other properties of the plants. Absorption of healthy vegetation is very high in the visible wavelength range. On the other hand, the near infrared channel is located at the high reflectance plateau. Dry and unhealthy vegetation canopy has lower NDVI value because reflectance in the visible red channel is increased, simultaneously in the NIR channel decreased. If chlorophyll content is high, then it means that the plant is photosynthetically very active, which means high absorption in visible red and high reflectance in NIR channels.

NDWI represents the water content in vegetation canopies. Absorption by vegetation liquid water around 858 nm (NIR channel, at the high reflectance plateau of vegetation canopy) is negligible, while at around 2130 nm it is very high. If water content decreases, then in SWIR channels reflectance increases significantly, therefore the NDWI value decreases showing dry vegetation under drought stress.

Chen et al. (2005) used spectral indices calculated from $NIR_{858\ nm}$ and $SWIR_{1640\ nm}$, respectively $SWIR_{2130\ nm}$ bands of MODIS reflectance data for the estimation of moisture content of corn and soybeans. Both showed potential in estimating vegetation moisture content. This NDWI is the variation developed by Gao (1996). The study conducted by Gu et al. (2007) showed that NDWI has a stronger response to drought conditions than NDVI. The average of NDVI and NDWI were consistently lower (NDVI<0.5 and NDWI<0.3) under drought conditions than under non-drought conditions (NDVI>0.6 and NDWI>0.4)

At shallow, turbid waters the water-leaving reflectance at NIR is not negligible, and is not only related to phytoplankton abundance, but also to suspended sediment concentration. Atmospheric correction of MODIS (the "clear water" assumption) fails in the presence of even modest quantities of suspended particle matter, because NIR water-leaving reflectance is not negligible, and is not related to phytoplankton abundance (Chen et al., 2013; Wang et al., 2013). Because of that, some parts of water surfaces are being classified as drought-stricken in case of NDWI and the drought indices. It is the reason why the area of Lake Balaton was excluded from our analysis.

During calculation of NDDI, most of the values are transformed into an interval between −1 and +1, however in spite of quality control extreme out of range values are generated too that makes statistical analysis useless. With the use of difference drought index (DDI) the emerging of extreme out of range values was avoided. It is the reason we calculated simple difference index without normalization (Eq. 2):

$$DDI = DVI - DWI \quad \text{(Eq. 2)}$$

where:
DVI (Difference Vegetation Index) = $NIR_{858\ nm} - red_{645\ nm}$,
DWI (Difference Water Index) = $NIR_{858\ nm} - SWIR_{2130\ nm}$.

The lack of normalization, which gets rid of the differences in spectral radiance resulting from different illumination angle and slope, is the only disadvantage DDI has, but the greater part of Hungary is lowlands with the dominant land use of croplands, therefore it is a small concern.

The Enhanced Vegetation Index (EVI), as an optimized hybrid index, combines the characteristics of the Atmospheric Resistant Index (ARVI) and the Soil Adjusted Vegetation Index (SAVI). EVI is an NDVI variant with correction factors for minimizing atmospheric effects and removing soil-brightness induced variations (Solano et al., 2010). The EVI formula is written as (Eq. 3):

$$EVI = G \cdot ((NIR_{858\ nm} - red_{645\ nm}) / (NIR_{858\ nm} + C_1 \cdot red_{645\ nm} + C_2 \cdot blue_{469\ nm} + L)) \quad \text{(Eq. 3)}$$

where NIR, red and blue band values are atmospheric-corrected (for Rayleigh scattering and ozone absorption)

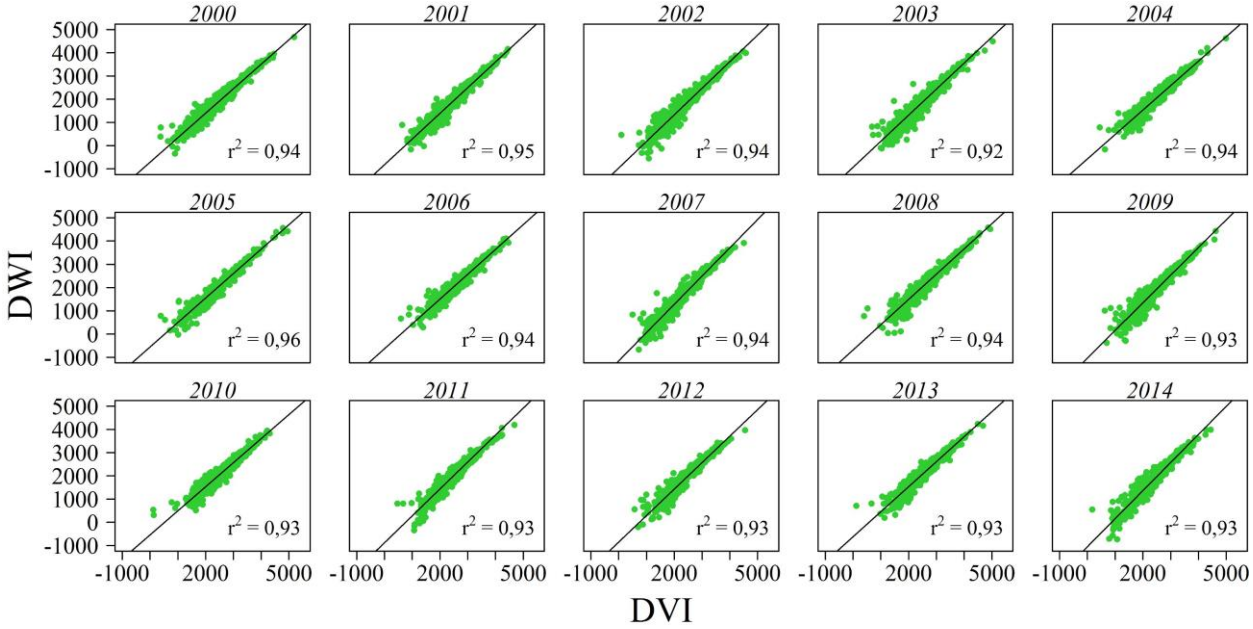

Fig. 2 The connection between DVI and DWI on the examined date in July

surface reflectance; L is the canopy background adjustment for correcting nonlinear, differential NIR and red radiant transfer through a canopy; C_1 and C_2 are the coefficients of the aerosol resistance term (which uses the blue band to correct for aerosol influences in the red band); and G is a gain or scaling factor. The coefficients adopted in the EVI algorithm are, L=1, C_1=6, C_2=7.5, and G=2.5.

Statistical connections between DWI-DVI and NDWI-NDVI

Relationships between DWI-DVI and NDWI-NDVI were unfolded using linear regression analysis which we run for a random sample of 500-600 pixels. We used the same random pixels for each date. There is a strong link between DWI and DVI; coefficients of determination vary from 0.88 to 0.95 in June, and 0.92-0.96 in July. Connection between NDWI and NDVI is weaker, coefficients of determination show greater variability (r^2 are 0.66-0.85 for June and 0.78-0.91 for July) (Fig. 2).

NDVI has been applied for decades in vegetation monitoring (Rouse et al., 1973). High correlation has proved water indices to be capable of quantification of droughts. There is a strong connection between chlorophyll and moisture content of vegetation canopy for which are vegetation and water indexes proxies that proves the usability of water indices.

RESULTS

Spatial extent of drought-stricken areas based on DDI and NDWI

When defining the value range of drought classes one huge advantage cluster analysis or other automatic classification algorithms have that we extract information from data without subjective interference. We used a cluster analysis method by Forgy (1965) called Iterative Minimum Distance for DDI data. Best results were obtained when setting eight outgoing clusters. Before the first iteration data was normalized with standard deviation. Separate classes were created, each containing pixels with similar drought intensity.

We calculated the DDI average for each date and the average of all June and July records between 2000 and 2014 (DDI_{June}=505.67 and DDI_{July}=520.95). If DDI mean exceeds these thresholds than the given time period is considered to be drought-stricken. Based on the rule June was drought-stricken in 2000, 2001, 2002, 2003 and 2009, and in case of July in 2000, 2001, 2002, 2003, 2007, 2009, 2012 and 2014. After that we averaged the DDI averages of drought years (DDI_{June}=578.86 and DDI_{July}=586.25) to get the drought threshold limits of DDI. The cluster mean of drought clusters exceeds these threshold limits. The difference between the average of drought and non-drought years referring to time series of the two months is 122 and 140 (June and July respectively). Based on class means we separated 4 drought intensity categories from the classes in the examined periods (Table 3). The DDI threshold of July (650) based on the cluster means between drought and non-drought is higher than the average of DDI (586) in drought years. The average of DWI, which is one of the factors influencing DDI values, is 1856 in drought years while it is 2197 in mild and wet years in July. In case of DVI, the other factor, these values are 2442 and 2639 respectively. By the differences DWI reacts more sensitively to drought condition than DVI. In case of the June values compared to the July ones DWI shows less, but still higher difference (189) between drought (2082) and non-drought (2271) average than DVI (difference is 107. Water indices are more sensitive to drought conditions than the vegetation ones. In order to utilize the high sensitivity of water indices we calculated the drought categories based on the vegetation liquid water content for NDWI too (Table 3).

Table 3 Created drought categories based on DDI and NDWI

DDI categories	Description
DDI <0	wet, water cover
0<= DDI <650	no drought
650<= DDI <812	weak drought
812<= DDI <1053	moderate drought
1053<= DDI <1319	strong drought
1319<= DDI	very strong drought

NDWI categories	Description
0.7<= NDWI	very high moisture content
0.6<= NDWI <0.7	high moisture content
0.6<= NDWI <0.5	moderate moisture content
0.4<= NDWI <0.5	low moisture content
0.3<= NDWI <0.4	weak drought
0.2<= NDWI <0.3	moderate drought
0<= NDWI <0.2	strong drought
NDWI <0	very strong drought

After defining drought categories for NDWI, we excluded the weak drought class because compared to DDI we would have overestimated the spatial extent of droughts. In case of NDWI pixels with value under 0.3 are considered to be drought-stricken. The results from DDI and NDWI coincide very well (r^2=0.91). Spatial extent of droughts for July is shown in Fig 3.

Average spatial extent of drought according to DDI was 22,778 km^2 in July. Average area was exceeded in 2000, 2001, 2002, 2003, 2007, 2009, 2012 and 2014. Spatial extent of drought was lowest (7,669 km^2) in 2005 according to DDI, but in case of NDWI in 2004 (7,454 km^2). The biggest drought was in 2007 which hit 42,452 square kilometers according to DDI. On the other hand NDWI showed that the spatial extent of drought was greatest in 2000 (35,846 km^2), however area hit by strong and very strong drought peaked in 2007 (in case of DDI the moderate drought areas culminated as well). In the ranking 2007 and 2000 are followed by 2003 and 2002 in July.

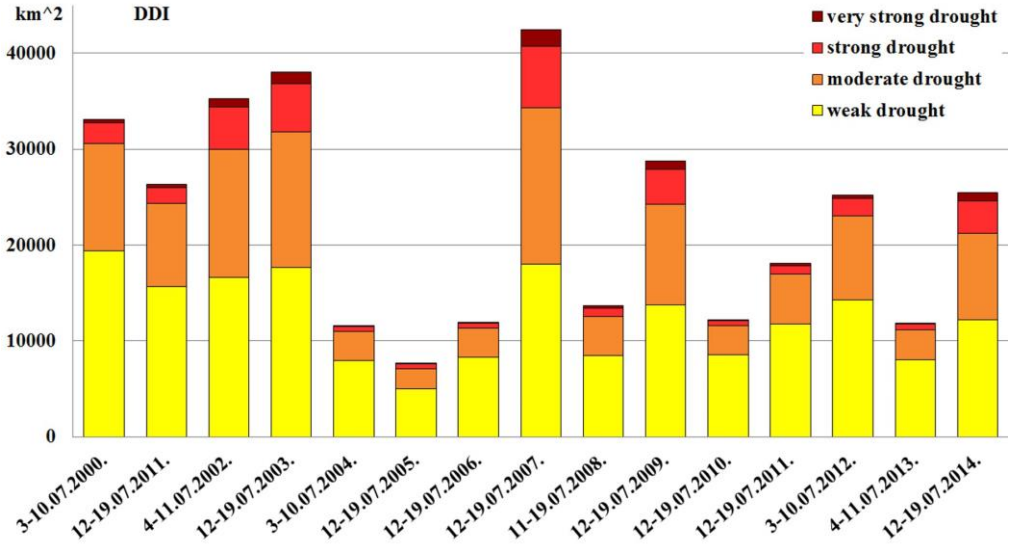

Fig. 3 Extent of drought affected areas in July according to DDI

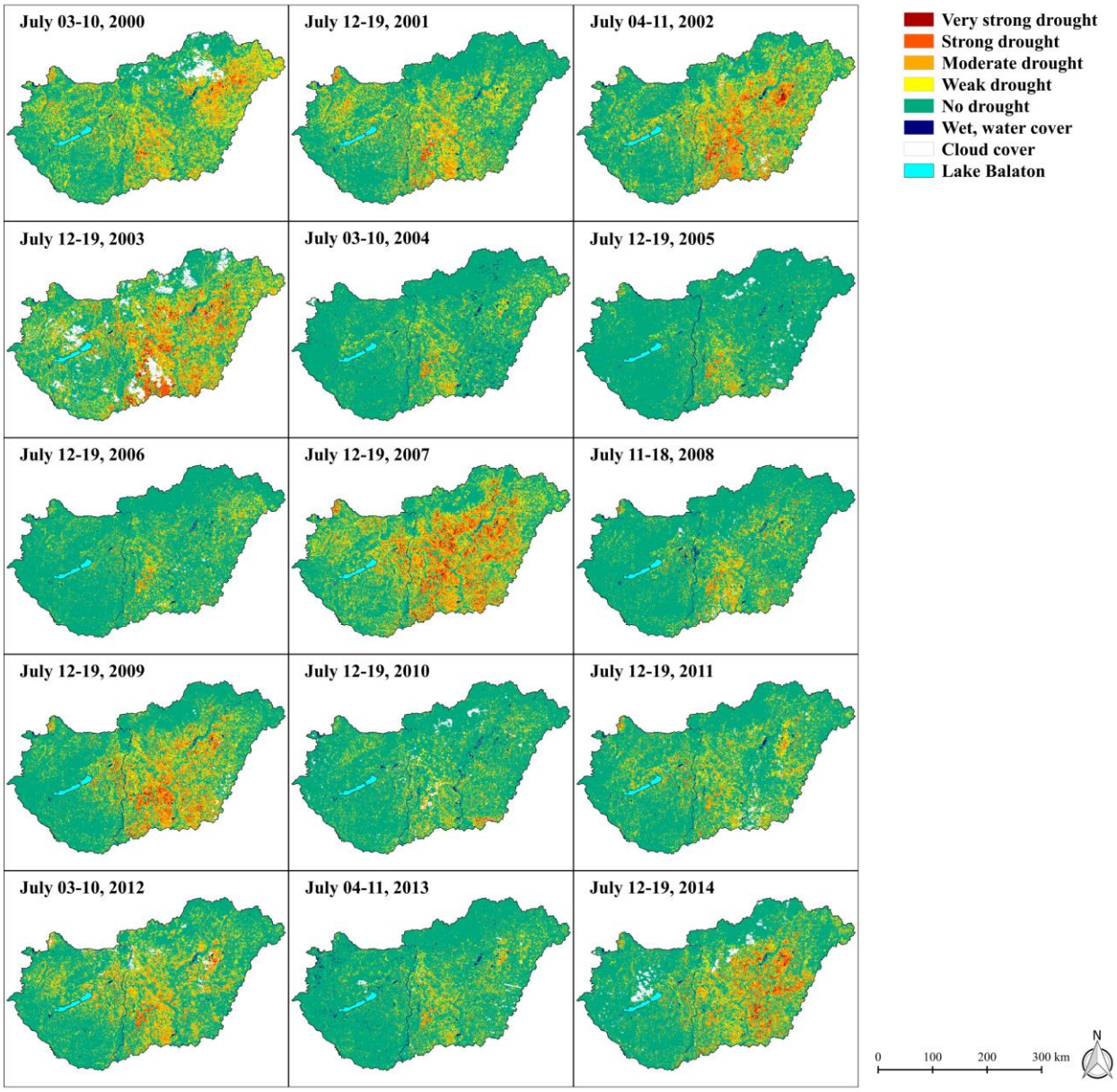

Fig. 4 Geographic distribution of drought areas according to DDI in July

DDI averages in June and in July show a great divergence in 2007 indicating that drought appeared first in July. In contrast, drought in 2003 was noticeable too. The difference between consecutive years stands out in 2003-2004 and in 2006-2007. In addition, higher annual variability between 2006 and 2010 is worth for mentioning. Geographical distribution of drought based on DDI and NDWI in July are shown on Fig. 4 and *5* where the high vulnerability of Danube–Tisza Interfluve stands out very well.

Comparison of results with reference data

To test the validity of spectral indices we analyzed their relationship with the Pálfai Drought Index (PAI) for the whole country and for the Great Plains only. Based on Pálfai (2011) the western border of the Great Plains was set to the midstream of River Danube. PAI data was obtained from the discussion paper of the National Drought Strategy (Hungarian Ministry of Rural Development 2012).

We compared the spectral index averages with the following reference data provided by CSO [2, 3]: crop yields of cereals (wheat, durum wheat, rye, barley, oat, triticale, corn, maslin (mixture of wheat and rye), rice, other cereals (indian rice, millet, canary seed, sorghum, buckwheat)) between 2000 and 2013, corn and wheat yields between 2000 and 2012 and irrigation water use of agriculture (labeled as „all sold water for irrigation, rice production included"). These data only applies to agricultural land, therefore we clipped DDI data with the area of the „non-irrigated arable land" category of the Corine Land Cover Database (CLC2012) [4]. In our current study we could only relate yields of different crops and irrigation data to the area of croplands based on CLC2012. Because of the lack of available data we could not differentiate between the fields of different cereals. Croplands can be identified in the knowledge of the dataset, since crops with similar growing cycle develop in a similar matter in a given year (Kern et al., 2014).

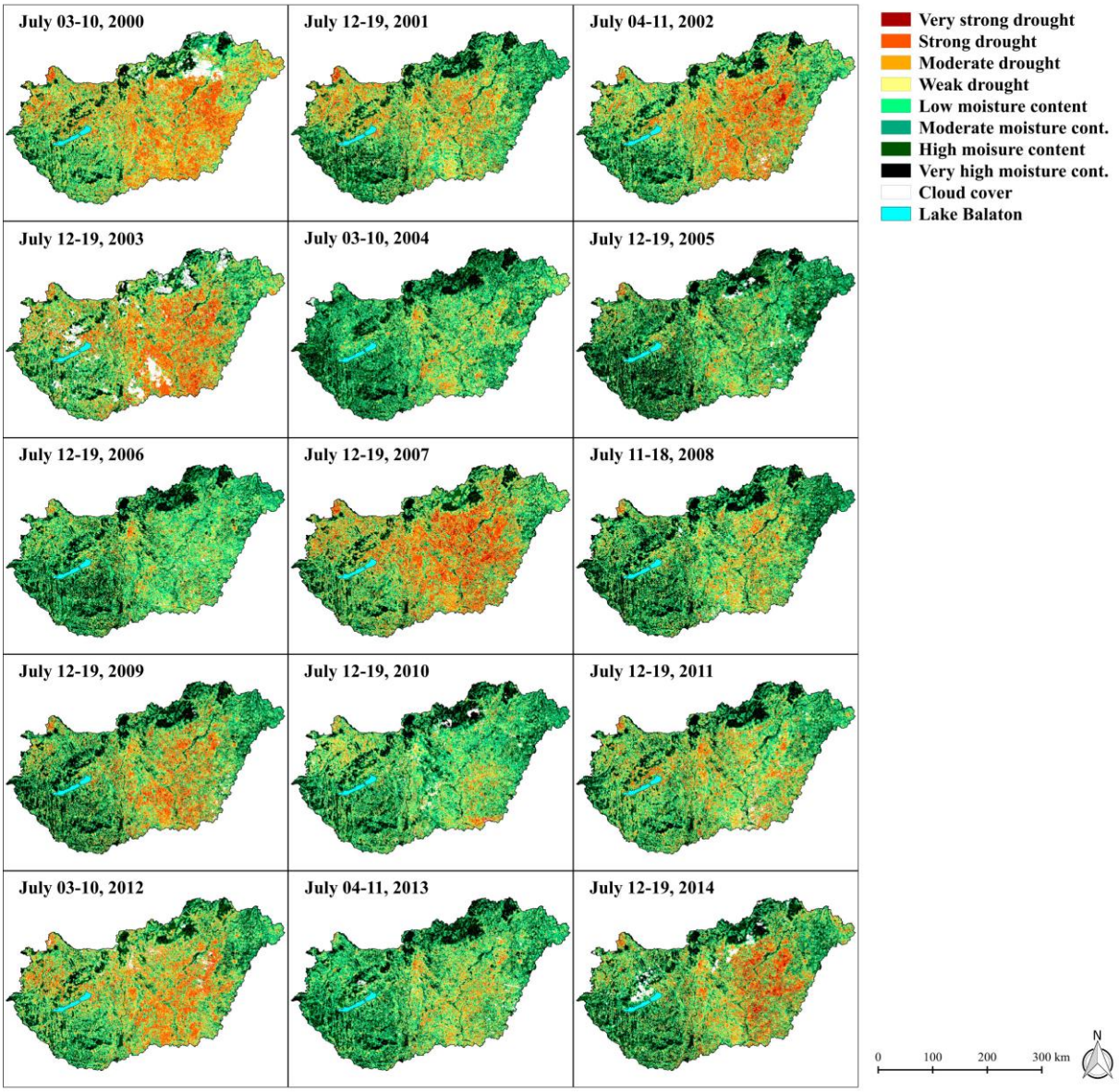

Fig. 5 Geographic distribution of drought areas according to NDWI in July

The spectral index values in June did not perform as well as the July ones. The spectral index-PAI relationships were weak and statistically insignificant except for DDI and NDDI, which performed slightly better (between DDI and countrywide PAI r^2=0.54, while between NDDI and PAI for the Hungarian Plain r^2=0.52). The correlations with yield data were very low, except for wheat-EVI (r^2=0.62) and wheat-DWI (r^2=0.62) correlations. No link was found with irrigation water use.

On the other hand, spectral indices performed well in July. The drought indices show positive trend with PAI; in contrast, vegetation and water indices a negative trend. Drought indices and crop yields are inversely related. Irrigation water use is directly proportional to DDI and NDDI. The opposite is true for vegetation and water indices: direct proportion to PAI and to crop yields and inverse proportion to water use. Normalized difference indices have a stronger link with reference data compared to simple difference indices, except for DDI which performed similar to NDDI (Table 4).

Based on the coefficients of determination in July, not the drought indices performed best, but NDWI. NDWI has the strongest link with PAI in case of the area of the Hungarian Plain, plus a strong one for the whole country as well. Strong statistical connections with all cereals' and corn yields were observed. In addition, NDWI has a moderate high correlation with agricultural water use. DWI is not far behind except for water use.

DDI has a strong link with PAI, but a weak one with agricultural water use; DDI shows moderate strong correlations with all cereals and corn yields.

PAI-DVI and PAI-EVI links were the weakest among the indexes, but EVI and DVI show a bit stronger link with corn yield data then DDI or NDDI. The NDVI-PAI relationship is stronger; in case of all cereal and corn yield data NDVI performed similar to DVI. Connections with irrigation water use were mostly weak; highest in case of NDVI and NDWI. In the harvesting period of wheat, we compared the spectral index averages of the harvested fields with the yields too, so the regression results for wheat which are statistically insignificant are not valid for July.

DISCUSSION

Although DDI performed adequately in drought detection, it may not be the best choice. On the whole, NDWI shows stronger links to reference data then the other spectral indices.

At the evaluation of results we have to take into consideration that crop yields are influenced by a number of environmental factors besides droughts: harvesting date is not constant it varies annually depending on how much precipitation there is, growing degree units plants get, coping capacity or tolerance of different crops, e.g. Besides drought, cold and wet weather, inland excess water, pest or an extreme weather event like rainstorm or hailstorm can also damage crop yields. Coping capacity of the plants is different; soil properties like fertility, water holding capacity, permeability have an influence on the yield too. Strength of the link between spectral indices and crop yields varies between months or years and between different areas as well.

The Difference Drought Index detects agricultural drought (via biophysical changes of the plants) whereas the Pálfai Drought Index rather detects meteorological drought (through precipitation and temperature time series). Moreover, the distance between meteorological stations is great (up to more than 10 kilometers) so the geometrical resolution of data is significantly less than 500 meters that MODIS reflectance data provides. Differences of spatial resolution may have influenced the tightness of linear fit. On the other hand, because of atmospheric effects some of the pixels had to be excluded from analysis may increase uncertainty of results. For our analysis we have chosen satellite images recorded in a relative cloud-free 8 day periods in order to keep errors originating from atmospheric effects at the lowest level possible.

CONCLUSIONS

The new remote sensing based difference drought index (DDI) performed above expectations during the analysis which is proven by the strong link between DDI and the PAI. Even though they combine water and vegetation

Table 4 Performance comparison of indices according to values of the coefficients of determination (r^2) in July

	Index	PAI (Hungarian Plain)	PAI (whole country)	All cereals [kg/ha]	Corn [kg/ha]	Wheat [kg/ha]	Irrigation water [million m^3]
MOD09A1	DDI	0.87	0.81	0.67	0.63	0.37	0.51
	NDDI	0.85	0.77	0.65	0.64	0.31	0.48
	DWI	0.81	0.75	0.79	0.77	0.47	0.52
	NDWI	0.90	0.80	0.80	0.78	0.48	0.64
	DVI	0.60	0.62	0.69	0.68	0.42	0.42
	NDVI	0.78	0.71	0.72	0.73	0.44	0.64
MOD13A1	EVI	0.63	0.67	0.81	0.76	0.41	0.35

indices, DDI and NDDI did not performed better compared to NDWI which is an ultimate vegetation moisture index. Our results imply that NDWI, which is a proxy for changes in moisture content of the canopy, reacts to drought conditions more sensitively than NDVI (or the other indices), because in case of a drought water loss occurs sooner than the reduction of chlorophyll content of vegetation. Because of its advantages, NDWI may become widespread in Hungary.

In the future we are planning to monitor drought during growing season using high temporal resolution MODIS data products in order to see how spectral indices react to seasonal variations of photosynthetic activity and moisture content of vegetation canopy in more detail.

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