Drought Monitoring With Spectral Indices Calculated From MODIS Satellite Images In Hungary

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Abstract and Figures

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Pixel evaluation of MODIS… Created drought categories bas… Performance comparison of…

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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

ration (ET/PET), resp. Normalized Difference Vegetation Index (NDVI), for MODIS sensor data.

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 evapo-

tion) 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

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

(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 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 (1) is derived from NDVI and NDWI (Normalized Difference Water Index):

$$NDDI = (NDVI - NDWI) / (NDVI + NDWI) \quad (1)$$

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

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 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; is the reason we calculated simple difference index without normalization (2):

$$DDI = DVI - DWI \qquad (2)$$

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 (3):

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

where NIR, red and blue band values are atmospheric-corrected (for Rayleigh scattering and ozone absorption) surface reflectance; L is the canopy background adjust-

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

ment 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 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 between DWI and DVI; correlation coefficients vary from 0.88 to 0.95 in June, and 0.92-0.96 in July. Connection between NDWI and NDVI is weaker, correlation coefficients 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

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.

... Calculation of spectral indices. NDVI and NDWI were calculated according to equations (1) and (2): The NDVI was developed by Rouse et al., (1973), which is the normalized refl ectance diff erence between visible and near-infrared refl ectance, and assessment has been described several times during the last decades (Tavazohi & Nadoushan, 2018) for monitoring vegetation cover, chlorophyll and other properties of the plants (Gulácsi & Kovács, 2018b) . The NDVI, which is then normalized refl ectance diff erence between the near-infrared (NIR) and visible red bands, is used extensively in ecosystem monitoring (Gu et al., 2007). ...

... The absorption of healthy vegetation is very high in the visible wavelength range. Dry and unhealthy vegetation canopy has lower NDVI value because refl ectance in the visible RED channel is increased, simultaneously in the NIR parameters, indicators or indices (remote sensing data included) in a single drought classifi cation product is required (Hayes et al., 2012). The Diff erence 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) (Gulácsi & Kovács, 2018b) . Totally 21 indices have been developed by researchers and used around the world for drought, of which the VCI and VHI indices are the most widely used globally. ...

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... It assesses vegetation richness, with higher values indicating better vegetation (Gulácsi and Kovács, 2015) . In this study, barren land and Moderate vegetation have shown maximum number of landslides. ...

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... Researchers from Hungary revealed that there is a moderate to strong relationship between NDVI and NDWI, namely, the coefficients of determination fluctuated between 0.66-0.91 within the growing season, but both indices were applicable for the evaluation of the level of drought [24] . However, our results are in contradiction with this statement, as it was found that there is just a moderate indirect relationship between NDVI and NDWI in the long-term analysis. ...

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... The NDWI values range from −1 to 1, where water surfaces typically fall within the range of 0.2 to 1. Flooding and high humidity are usually within the range of 0 to 0.2, while moderate drought and non-aqueous surfaces are within −0.3 to 0. Drought conditions and non-aqueous surfaces are within the range of −0.1 to −0.3 [24] . ...

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January 2019 · Ying yong sheng tai xue bao = The journal of applied ecology / Zhongguo sheng tai xue xue hui, Zhongguo ke xue yuan Shenyang ying yong sheng tai yan jiu suo zhu ban

Hui Ting Yang · Hanqiu Xu · Tingting Shi · Shan Mu Chen

Remote sensing change detection based on fractional vegetation cover (FVC) has become an important way in the research of vegetation and related ecosystems. It is difficult to meet the requirement for optical remote sensing in subtropical areas because of cloudy/rainy weather conditions. Using images from different seasons in the vegetation change detection will inevitably lead to errors in the ... [Show full abstract]

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Aszályvizsgálat lehetősége MODIS műholdképekből számított spektrális indexekkel Magyarországon

December 2015 · Tájökológiai Lapok

András Gulácsi · Ferenc Kovács

Az aszály hatása a növényzet biofizikai állapotváltozásának jellemzésével, a műholdas távérzé- kelési adatok alapján számítható spektrális vegetáció- és vízindexekkel és az ezekből képezhető aszályindexek- kel számszerűsíthető. A differenciált vegetációindex (DVI), a normalizált differenciált vegetációindex (NDVI) és a továbbfejlesztett vegetációindex (EVI), valamint a differenciált vízindex ... [Show full abstract]

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March 2018 · Hungarian Geographical Bulletin

András Gulácsi · Ferenc Kovács

In this paper, several spectral indices based on spectral reflectance data from the Terra satellite's Moderate Resolution Imaging Spectro-radiometer (MODIS) sensor were evaluated in terms of their practical applicability for quantifying drought intensity and its geographical effects to support the drought monitoring applications. A total number of 358 MODIS 8-day composite images for the period ... [Show full abstract]

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September 2019 · Geosciences

Ferenc Kovács · András Gulácsi

In the next decades, climate change will put forests in the Hungarian Great Plain in the Carpathian Basin to the test, e.g., changing seasonal patterns, more intense storms, longer dry periods, and pests are expected to occur. To aid in the decision-making process for the conservation of ecosystems depending on forestry, how woods could adapt to changing meso- and microclimatic conditions in the ... [Show full abstract]

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