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COMPARISON OF REMOTE SENSING-BASED INDEXES FOR MONITORING DROUGHT IMPACT ON FOREST ECOSYSTEMS

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Boris Markov. COMPARISON OF REMOTE SENSING-BASED INDEXES FOR MONITORING DROUGHT IMPACT ON FOREST ECOSYSTEMS

In the study are tested and compared 7 indexes that can detect indicators of vegetation drought stress – NDII (Normalized Difference Infrared Index), NDWI (Normalized Difference Water Index), MSI (Moisture Stress Index), VSDI (Visible and Shortwave Infrared Drought Index), NMDI (Normalized Multi-band Drought Index), NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index). The indexes are compared by using Landsat 8 image acquired on 23.09.2013, where can be observed drought impact on the forest areas. The study area is Strandja Nature Park. It is characterized by high temperatures and minimum precipitation in the summer months which leads to drought. The indexes are tested in areas with healthy vegetation and dry vegetation. MSI has shown the best ability to distinguish dry vegetation from healthy vegetation. It can identify vegetation drought stress by assessing vegetation water content.

Key words: remote sensing, drought, forest ecosystems.

INTRODUCTION

Drought is a natural phenomenon that can cause serious environmental, social, and economic consequences (Du et. al., 2017). The reasons for drought occurring can be different, but the main reason is associated with low precipitation (Zhang et al., 2013c). Because of its complexity, there are many definitions for drought based on the context (Palmer, 1965).

According to Wilhite and Glantz (1985), there are more than 150 definitions for drought. Based on this definitions, droughts can be classified into four groups – meteorological, agricultural, hydrological and socioeconomic. Meteorological drought is defined by lack of precipitation, while agricultural drought reflects soil moisture deficit. Hydrological drought is affected by a shortage of streamflow and ground-water supplies. Socioeconomic drought is associated with water supply and demand (Hao and AghaKouchak, 2013; AghaKouchak, et al., 2015). Each type of drought can be characterized in three dimensions: severity, duration, and spatial distribution (extent) (Zargar et al., 2011).

Future climate changes are likely to increase the mean temperature, which can lead to significant drying in some regions (Dotzler et al., 2015). Such changes will reduce the soil moisture and impact the forests directly by tree mortalities, and indirectly – by insect outbreaks and fires (Norman et al., 2016). Drought characterization enables drought early warning and assessment of the risk, which allow improved preparation, planning and reducing the damage. (Zargar et al., 2011) Therefore, drought monitoring is crucial for identifying the spatial extent and impact of the drought. Because of the different types of droughts, multiple indicators can be used for its assessment – precipitation, temperature, evapotranspiration, soil moisture, streamflow and groundwater levels (Anderson et al., 2011). The best way to describe the severity of the drought and comparing drought from different regions is by using indexes (Heim, 2002). The indexes are quantitative measures that characterized the level of drought by assimilating data from one or several variables (indicators) in a single numerical value (Zargar et al., 2011). The drought is usually assessing by data from weather stations, like precipitation and temperature, which usually have limited spatial coverage (Gu et al., 2007). Remote sensing can quickly provide inexpensive spatial data for drought investigations (Amalo et al., 2017). Satellite images can provide various information, so remote sensing can be used in many ways to identify drought vulnerability areas with satellite images by assessing water content in vegetation, vegetation phenology, evapotranspiration, temperature etc. (Mildrexler et al., 2016; Liu et al., 2015; Kogan et al., 1995).

There are different types of sensors that can be suitable for drought indicators assessment. Sensors, which operate from visible to shortwave infrared spectrum (400–2500 nm), are suitable for detection of vegetation biophysical parameters and vegetation water content, which are considered as main indicators of plant stress (Ceccato et al., 2001; Govender et al., 2009). The visible spectrum (400–700 nm) has been used for detection of healthy vegetation by the higher absorption in the blue region (400–520 nm) and the red region (630–690 mm). If the vegetation has water deficit the chlorophyll production will decrease and affect the absorption in the blue and red bands. The near-infrared (NIR) spectrum (740–1300 nm) is very sensitive to leaf internal structure and is barely affected by water content. The shortwave infrared (SWIR) spectrum (1300–2500 nm) is strongly affected by vegetation water content, as highest absorption has the range from 1550 to 1750 nm (Zhang et al., 2013b; Tucker, 1980). Thermal infrared sensors (6000–15 000 nm) can provide information for surface temperature. Active sensors can also have application in drought assessment like soil moisture estimation (Ceccato et al., 2001).

The objective of this study is to compare several indexes and find out, which index is the most suitable for monitoring drought impact on forest vegetation in the study area. It will be assessed the abilities of the indexes to discriminate dried vegetation from healthy vegetation and it will be identified threshold values for both types of vegetation.

STUDY AREA

The study area is Strandja Nature Park, which is located in the southeastern part of Bulgaria with a total area of 1163 km^2. The relief is hilly and low mountainous with the highest peak Gradishte (710 m). The area is characterized by Continental Mediterranean climate type with hot dry summer and mild winter. The maximum precipitation is during the winter and the minimum is during the summer. Over the last decades has been observing reducing of the precipitation, which leads to drought in the summer. The longest rivers in the area are Veleka and Rezovska. The soils are represented by 7 main types, of which Luvisols (LV) and Alisols (AL) are most common. About 80% of the territory is occupied by forests. Strandja Nature Park is rich in biodiversity. The forest vegetation has remained tertiary relict and there are many unique and rare species like *Rhododendron ponticum*, *Vaccinium arctostaphylos*, *Ilex colchica* etc.

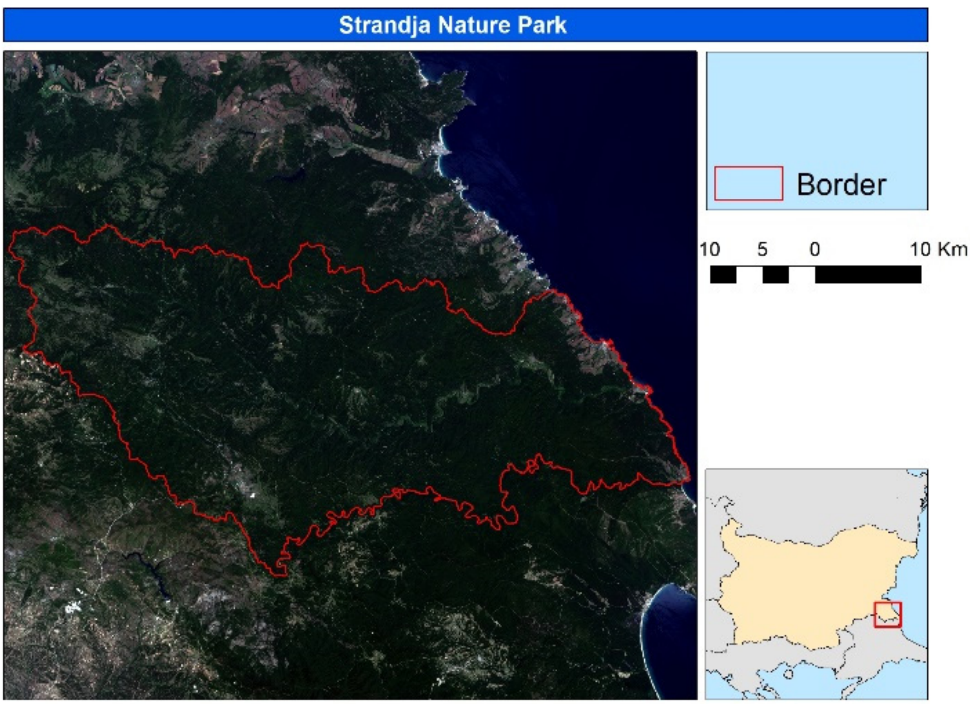

Fig. 1. Study area

DATA

All indexes are compared by using a single Landsat 8 image for the study area (Path/Row – 181/031) acquired on 23.09.2013. The Landsat 8 image has 11 bands (Table 1) with a spatial resolution of 15 m (band 8), 30 m (band 1 to 7 and 9) and 100 m (band 10 and 11). The image is download from the USGS website. This is a standard L1TP product, which is radiometrically, topographic and geometrically corrected (https://landsat.usgs.gov/landsat-8-l8-data-users-handbook-section-4). The image is presented in units of DNs (Digital Numbers), which are converted to surface reflectance by FLAASH algorithm in ENVY 5.8 software. For ground truth, it is used Bing Aerial map layer in Quantum GIS and historical images from Google Earth Pro 7.3.1. For verification, The Bing Aerial map is compared to old images in Google Earth Pro acquired on 19.09.2013, which is 4 days earlier than the Landsat image. By Fishnet tool in ArcGIS 10.4 software, was generated polygons with the same size as Landsat image (30 m) to extract the pixel values for every index.

Table 1

Landsat 8 bands (https://landsat.usgs.gov/what-are-band-designations-landsat-satellites)

	Bands	Wavelength (nanometers)	Resolution (meters)
Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)	Band 1 – Ultra Blue (coastal/aerosol)	435–451	30
	Band 2 – Blue	452–512	30
	Band 3 – Green	533–590	30
	Band 4 – Red	636–673	30
	Band 5 – Near Infrared (NIR)	851–879	30
	Band 6 – Shortwave Infrared (SWIR) 1	1566–1651	30
	Band 7 – Shortwave Infrared (SWIR) 2	2107–2294	30
	Band 8 – Panchromatic	503–676	15
	Band 9 – Cirrus	1363–1384	30
	Band 10 – Thermal Infrared (TIRS) 1	10600–11190	100
	Band 11 – Thermal Infrared (TIRS) 2	11500–12510	100

METHODOLOGY

In this study will be evaluated and compared 7 indexes that can detect indicators of vegetation drought stress. Five indexes (NDII, NDWI, MSI, VSDI, NMDI) are typical drought indexes, which can be used in drought monitoring by assessing the leaf water content of the plants. The other two (NDVI and EVI) are the most common vegetation indexes, which can be used for assessing vegetation condition. The indexes are calculated by Band Math tool in ENVI software.

NDII (NORMALIZED DIFFERENCE INFRARED INDEX)

NDII is developed by Hardisky et al., (1983) and tested with Landsat data. It is based on the NDVI formula, but the red is substitute with SWIR band (1). NIR band (760–900 nm) is sensitive to biomass and SWIR band (1550–1750 nm) is sensitive to water content. The values of NDII range from – 1 to 1, as negative values mean that NIR band values are greater than SWIR band values, which indicates canopy water stress (Sriwongsitanon et al., 2016). This expression can be found with different names, as NDWI (Chandrasekar et al., 2010) or LSWI (Zhang et al., 2013a):

$$NDII = (NIR_{850} - SWIR_{1650}) / (NIR_{850} + SWIR_{1650}). \tag{1}$$

NDWI (NORMALIZED DIFFERENCE WATER INDEX)

The index is proposed by Gao et al., (1996). He used two bands of MODIS data to estimate vegetation water content – NIR (860 nm) and SWIR (1230 nm). Because of the absorption abilities of the leaf water content in the shortwave infrared (1300–2500 nm) spectrum, the index has been modified with different SWIR bands. Chen et al. (2005) and Chandrasekar et al. (2010) have been used the same equation, but with SWIR band centered at 1640 nm ($NDWI_{1640}$) and SWIR band centered at 2130 nm ($NDWI_{2130}$). In this study is used $NDWI_{2130}$ as a combination of NIR band (860 nm) and SWIR band (2130 nm) (2), which corresponds to band 5 (NIR) and band 7 ($SWIR_{2130}$) of Landsat 8 data:

$$NDWI_{2130} = (NIR_{850} - SWIR_{2130}) / (NIR_{850} + SWIR_{2130}) \tag{2}$$

MSI (MOISTURE STRESS INDEX)

MSI is simple ratio index that is used for leaf water content assessment. It is proposed by Hunt and Rock (1987), by using the ratio of SWIR band of around 1600 nm and NIR band at 820 nm (3). The index is inverted relative to other indexes that assess vegetation water content, thus higher values indicate more water stress. The values range from 0 to 3 (Welikhe et al., 2017):

$$MSI = SWIR_{1600}/NIR_{820}. \tag{3}$$

VSDI (VISIBLE AND SHORTWAVE INFRARED DROUGHT INDEX)

VSDI is developed by Zhang et al. (2013b), for monitoring agriculture drought by assessment soil and vegetation moisture. It is applied to MODIS data by using three bands – SWIR (centered at 1640 nm), Red and Blue (4). The SWIR and the Red bands are the moisture-sensitive bands and the Blue band is used as a reference band. The combination of (SWIR – Blue) and (Red – Blue) may maximize the moisture variation and better estimate surface water for different land cover types. Finally, it is subtracted by 1 to make VSDI positively correlated to moisture variation. The values range from 0 (dry) to 1 (wet). Values above one can be related to water bodies and snow or ice cover:

$$\text{VSDI} = 1 - ((\text{SWIR}_{1640} - \text{Blue}) + (\text{Red} - \text{Blue})) \quad (4)$$

NMDI (NORMALIZED MULTI-BAND DROUGHT INDEX)

NMDI is proposed by Wang and Qu (2007) as an improvement to other NIR-SWIR indexes that estimate water content. It is based on three bands, one in the NIR centered approximately at 860 nm, and two in the SWIR centered at 1640 nm and 2130 nm (5). The index is designed to detect drought for both vegetation and soil. The NIR band is insensitive to leaf water content and SWIR bands are used for water absorption bands. Thus, the combination of the two SWIR bands allows enhancing detection of water content for both vegetation and soil. The values for NDMI range between 0 and 1. For soil, the values range from 0.7–0.9 for a very dry soil to 0.3 for extremely wet soil. For vegetation the values usually ranging from 0.4–0.6 – greater than 0.6 wet vegetation and less than 0.4 dry vegetation (Wang et al., 2008):

$$\text{NMDI} = \text{NIR}_{860} - (\text{SWIR}_{1640} - \text{SWIR}_{2130}) / \text{NIR}_{860} + (\text{SWIR}_{1640} - \text{SWIR}_{2130}). \quad (5)$$

NDVI (NORMALIZED DIFFERENCE
VEGETATION INDEX)

NDVI is the most popular remote sensing-based vegetation index (6). It is strongly correlated with healthy vegetation (Tucker, 1979). The red band is very sensitive to chlorophyll and other pigments in the leaves and the cell structure of the leaves has high reflectance in the NIR band (Karnieli et al., 2013). Therefore, the chlorophyll and other pigments absorb radiation in the red band, which leads to higher NDVI value. On the other hand, when vegetation is unhealthy the values of the red band is increasing, which decrease the NDVI values (Zargar et al., 2011). The values range from –1 to 1. Higher values indicate healthy vegetation, values around 0 represent bare soil, and negative values are associated with water bodies:

$$\text{NDVI} = (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red}). \quad (6)$$

EVI (ENHANCED VEGETATION INDEX)

The EVI is developed as an improvement of NDVI. It is more sensitive to biomass and can reduce some atmospheric influence. For the first time, EVI is used as MODIS product as a combination of three bands – Blue band, Red band and NIR band (Huete et al., 2002). EVI is defined as (7): where L is a soil adjustment factor, and $C1$ and $C2$ are coefficients used to correct aerosol scattering in the red band by the use of the blue band. The Blue, Red, and NIR bands represent reflectance at the Blue (450–520 nm), Red (600–700 nm), and Near-Infrared (NIR) wavelengths (700–1100 nm), respectively. In general, G=2.5, $C1$=6.0, $C2$=7.5, and L=1 (Matsushita et al., 2007):

$$EVI = G \times ((NIR - Red) / (NIR + C1 \times Red - C2 \times Blue + L). \quad (7)$$

RESULTS

Two category pixels have been used for the comparison of the indexes – 10 pixels of dry vegetation (Table 2) and 10 pixels of healthy vegetation (pixels with high NDVI values) (Table 3). Additional, to measure the maximum, minimum, and average values of the dried vegetation has been assessed the values of several patches of dry vegetation (84 pixels), which includes those 10 pixels of dry vegetation (Table 4).

Table 2

Ten pixels with dry vegetation

Pixels	NDII	$NDWI_{2130}$	MSI	VSDI	NMDI	NDVI	EVI
1	0.16	0.48	0.71	0.79	0.45	0.69	0.43
2	0.19	0.52	0.67	0.79	0.46	0.68	0.42
3	0.18	0.51	0.68	0.75	0.45	0.65	0.43
4	0.17	0.50	0.70	0.81	0.46	0.62	0.35
5	0.10	0.43	0.81	0.79	0.40	0.59	0.32
6	0.15	0.49	0.72	0.79	0.43	0.61	0.36
7	0.15	0.49	0.72	0.73	0.44	0.60	0.40
8	0.11	0.44	0.79	0.74	0.42	0.58	0.36
9	0.18	0.51	0.69	0.77	0.46	0.66	0.42
10	0.15	0.47	0.73	0.76	0.45	0.62	0.38
Mean	**0.15**	**0.48**	**0.72**	**0.77**	**0.44**	**0.63**	**0.38**

Table 3

Ten pixels with healthy vegetation (vegetation with high NDVI values)

Pixels	NDII	$NDWI_{2130}$	MSI	VSDI	NMDI	NDVI	EVI
1	0.41	0.71	0.41	0.82	0.59	0.89	0.73
2	0.43	0.72	0.38	0.88	0.62	0.88	0.61
3	0.40	0.71	0.41	0.83	0.59	0.89	0.72
4	0.42	0.73	0.40	0.84	0.60	0.89	0.70
5	0.45	0.74	0.37	0.85	0.63	0.88	0.69
6	0.39	0.70	0.43	0.83	0.58	0.89	0.71
7	0.50	0.76	0.33	0.93	0.66	0.89	0.46
8	0.42	0.72	0.39	0.86	0.61	0.89	0.64
9	0.39	0.69	0.43	0.85	0.59	0.89	0.63
10	0.40	0.71	0.41	0.76	0.59	0.90	0.81
Mean	**0.42**	**0.71**	**0.39**	**0.84**	**0.60**	**0.88**	**0.67**

Table 4

Values of patches of dry vegetation (84 pixels)

	Min	Max	Mean	SD
NDII	0.10	0.28	0.19	0.03
NDWI	0.43	0.61	0.52	0.03
MSI	0.55	0.81	0.67	0.05
VSDI	0.71	0.84	0.78	0.02
NMDI	0.40	0.52	0.46	0.02
NDVI	0.58	0.78	0.66	0.04
EVI	0.32	0.52	0.41	0.04

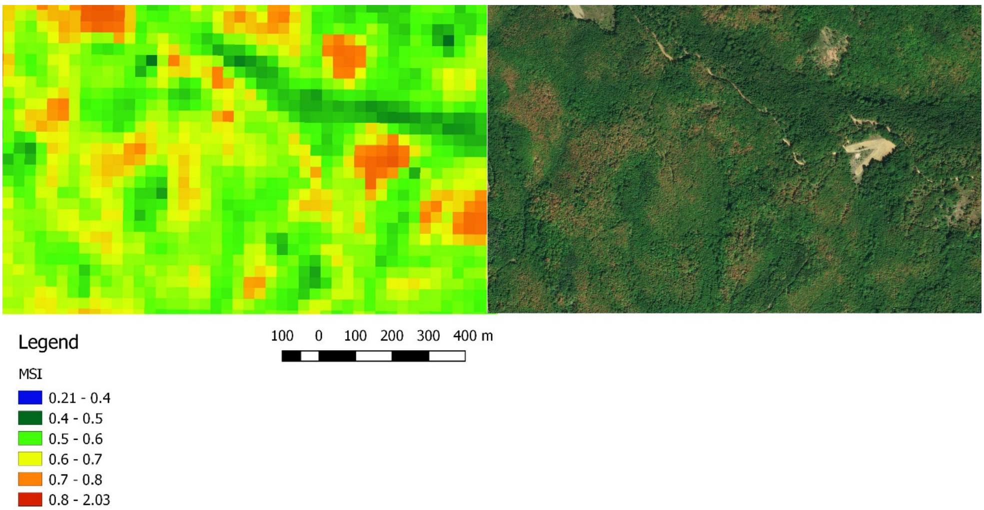

Fig. 2. Threshold values of MSI

The best ability to distinguish healthy from dry vegetation has MSI. NDVI shows good results too. The values of EVI show a large variation in both dry and healthy vegetation. NDWI and NDII, which use similar equation but different SWIR band, show a high correlation between the values. Indexes that use more than 2 bands, such as NMDI and VSDI, have less ability to distinguish dry from healthy vegetation.

Table 4 shows that MSI values range from 0.55 to 0.81 for dry vegetation. High values are associated with pixels with only dry vegetation, while low values are associated with mixed pixels with dry and healthy vegetation. Figure 2 shows that in the middle of the dried patches has highest values, gradually decreasing towards pixels with healthy vegetation.

So it can be concluded that it can be used the threshold values from around 0.4 to 0.8 for drought assessment on broadleaf forest areas in the study area:

- Values around 0.4 or less are indicative of healthy forest vegetation.

- Values of 0.4–0.55 indicate the level of water stress.
- Values around 0.55–0.80 show the drought impact – from pixels with healthy and dried vegetation, to pixels with only dried vegetation.
- Values above 0.8 may in forest areas be associated with severe drought and/or low canopy density.
- Values above 1 are associated with pixels without tree vegetation.

CONCLUSIONS

In this study, the 7 remote sensing-based indexes were tested for dry forest vegetation assessment. The results show that MSI is the most appropriate. It can identify vegetation drought stress based on vegetation water content. It was defined threshold values from around 0.4 for healthy vegetation to around 0.8 for dry vegetation. The values between them can show the level of drought impact.

An improvement can be made, by using images with higher spatial resolution (like Sentinel-2), which can detect less mixed pixels. A single index can't be suitable for full drought characterization but can give information about a particular drought indicator. Combination of several indexes for different indicators, as well as meteorological data, can be more efficient for drought monitoring.

REFERENCES

AghaKouchak, A., A. Farahmand, F. Melton, J. Teixeira, M. Anderson, B. Wardlow, C. Hain. 2015. Remote Sensing of Drought: Progress, Challenges and Opportunities. – *Reviews of Geophysics*, 53 (2), 452–480.

Amalo, L., R. Hidayat, R. Harris. 2017. Comparison between remote-sensing-based drought indices in East Java. – *Earth and Environmental Science*, 54.

Anderson, M., C. Hain, B. Wardlow, J. Mecikalski, W. Kustas. 2011. Evaluation of Drought Indices Based on Thermal Remote Sensing of Evapotranspiration over the Continental United States. – *American Meteorological Society*, 24, 8, 2025–2044.

Ceccato, P., S. Flasse, J. Gregoire, S. Tarantola, S. Jacquemoud, J. Gregoire. 2001. Detecting vegetation leaf water content using reflectance in the optical domain. – *Remote Sensing of Environment*, 77, 22–33.

Chandrasekar, K., M. Sai, P. Roy, R. Dwevedi. 2010. Land Surface Water Index (LSWI) response to rainfall and NDVI using the MODIS Vegetation Index product. – *International journal of remote sensing*, 31(15), 3987–4005.

Chen, D., J. Huang, T. Jackson. 2005. Vegetation water content estimation for corn and soybeans using spectral indices derived from MODIS near- and short-wave infrared bands. – *Remote Sensing of Environment*, 98, 225–236.

Dotzler, S., J. Hill, H. Buddenbaum, J. Stoffels. 2015. The Potential of EnMAP and Sentinel-2 Data for Detecting Drought Stress Phenomena in Deciduous Forest Communities. – *Remote Sensing*, 7, 14227–14258.

Du, L., N. Song, K. Liu, J. Hou, Y. Zhu, X. Wang, L. Wang, Y. Guo. 2017. Comparison of two simulation methods of the temperature vegetation dryness index (TVDI) for drought monitoring in semi-arid regions of China. – *Remote Sensing*, 9, 2, 177.

Gao, B. 1996. NDWI – A normalized difference water index for remote sensing of vegetation liquid water from space. – *Remote Sensing of Environment*, 58, 257–266.

Govender, M., P. Dye, I. Weiersbye, E. Witkowski, F. Ahmed. 2009. Review of commonly used remote sensing and ground-based technologies to measure plant water stress. – *Water SA*, 35 (5), 741–752.

Gu, Y., J. Brown, J, Verdin, B. Wardlow. 2007. A five-year analysis of MODIS NDVI and NDWI for grassland drought assessment over the central Great Plains of the United States. – *Geophysical Research Letters*, 34, 6, 1–6.

Hao Z., A. AghaKouchak. 2013. Multivariate Standardized Drought Index: A Parametric Multi-Index Model. – *Advances in Water Resources*, 57, 12–18.

Hardisky, M., V. Klemas, R. Smart. 1983. The influence of soil salinity, growth form, and leaf moisture on the spectral radiance of Spartina alterniflora canopies. – *Photogrammetric. Engineering and Remote Sensing*, 49, 77–83.
Heim, R. 2002. A Review of Twentieth-Century Drought Indices Used in the United States. – *Bulletin of the American Meteorological Society*, 83, 8, 1149–1165.
Huete, A., K. Didan, W. van Leeuwen, T. Miura, E. Glenn. 2011. MODIS vegetation indices. – *Remote Sensing and Digital Image Processing*, 11, 579–602.
Hunt, E., B. Rock. 1989. Detection of changes in leaf water content using near- and middle-infrared reflectances. – *Remote Sensing Environment*, 30, 43–54.
Karnieli, A., Y. Bayarjargal, M. Bayasgalan, B. Mandakh, Ch. Dugarjav, J. Burgheimer, S. Khudulmur, S. Bazha, P. Gunin. 2013. Do vegetation indices provide a reliable indication of vegetation degradation? A case study in the Mongolian pastures. – *International Journal of Remote Sensing*, 34, 17, 6243–6262.
Kogan, F. 1995a: Droughts of the late 1980s in the United States as derived from NOAA polar orbiting satellite data. – *Bulletin of American. Meteorological Society*, 76, 655–668.
Liu, S., Y. Peng, W. Du, Y. Le, L. Li. 2015. Remote Estimation of Leaf and Canopy Water Content in Winter Wheat with Different Vertical Distribution of Water-Related Properties. – *Remote Sensing*, 7, 4626–4650.
Matsushita, B. W. Yang, J. Chen, Y. Onda, G. Qiu. 2007. Sensitivity of the Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) to Topographic Effects: A Case Study in High-density Cypress Forest. – *Sensors*, 7, 2636–2651.
Mildrexler, D., Z. Yang, W. Cohen, D. Bell. 2016. A forest vulnerability index based on drought and high temperatures. – *Remote Sensing of Environment*, 173, 314–325.
Norman, S., F. Koch, W. Hargrove. 2016. Review of broad-scale drought monitoring of forests: Toward an integrated data mining approach. – *Forest Ecology and Management*, 380, 346–358.
Palmer, C. 1965. Meteorological drought. US Weather Bureau Res, Washington DC, Paper No. 45, 1–58.
Sriwongsitanon, N., H. Gao, H. Savenije, E. Maekan, S. Saengsawang, S. Thianpopirug. 2016. Comparing the Normalized Difference Infrared Index (NDII) with root zone storage in a lumped conceptual model. – *Hydrology and Earth System Sciences*, 20, 3361–3377.
Tucker, C. 1979. Red and photographic infrared linear combination for monitoring vegetation.– *Remote sensing of environment*, 8, 127–150.
Tucker, C. 1980. Remote Sensing of Leaf Water Content in the Near-Infrared. – *Remote Sensing of Environment*, 10, 23–32.
Wang, L., J. Qu, X. Hao. 2008. Forest fire detection using the normalized multi-band drought index (NMDI) with satellite measurements. – *Agriculture and Forest Meteorology*, 148, 11, 1767–1776.
Wang, L., J. Qu. 2007. NMDI: A Normalized Multi-Band Drought Index for Monitoring Soil and Vegetation Moisture with Satellite Remote Sensing. – *Geophysical Research Letters*, 34, 1–5.
Welikhe, P., J. Quansah, S. Fall, W. McElhenney. 2017. Estimation of soil moisture percentage using LANDSAT-based moisture stress index. – *Journal of Remote Sensing and GIS*, 6, 200.
Wilhite, D., M. Glantz. 1985. Understanding the drought phenomenon: the role of definitions. Drought Mitigation Center Faculty Publications, Paper 20.
Zargar, A., R. Sadiq, B. Naser, F. Khan. 2011. A review of drought indices. – *Environmental Reviews*, 19, 333–349.
Zhang, N., Y. Hong, Q. Qin, L. Liu. 2013a. Evaluation of the visible and shortwave infrared drought index in China. – *International Journal of Disaster Risk Science*, 4 (2), 68–76.
Zhang, N., Y. Hong, Q. Qin, L. Liu. 2013b. VSDI: a visible and shortwave infrared drought index for monitoring soil and vegetation moisture based on optical remote sensing. – *International Journal of Remote Sensing*, 34 (13), 4585–4609.
Zhang, Y., P. Changhui, L. Weizhong, F. Xiuqin, Z. Tinglong, Z. Qiuan, C. Huai, Z. Pengxiang. 2013c. Monitoring and estimating drought-induced impacts on forest structure, growth, function, and ecosystem services using remote-sensing data: recent progress and future challenges. – *Environmental Reviews*, 21, Number 2, 103–115.
https://landsat.usgs.gov/landsat-8-l8-data-users-handbook-section-4 (Accessed on 22.03.2018)
https://landsat.usgs.gov/what-are-band-designations-landsat-satellites (Accessed on 22.03.2018)

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