Analysis of moisture conditions in the lowland areas using high resolution spectral data from the Sentinel-2 satellite and the GIS tools

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Abstract. Research concerning agricultural drought issue mainly focuses on the methods based on long-term atmospheric data, temperature, precipitation and evaporation measurements. On the other hand, the scientific bibliography shows the possibilities of using spectral data for description the state of plants. The general availability and increasing resolution of the spectral and temporal data create a chance for monitoring and forecasting deficiencies of soil moisture based on spectral images. Paper presents the results of analysis of the moisture conditions in soil-plant environment in the lowland catchment area using the spectral data obtained from the Sentinel-2 European Space Agency satellite for period February-November 2016. These spectral data were used for the calculation the Normalized Differential Vegetation Index (NDVI) which provided information about moisture conditions in the soil-plant environment. Then, the values of NDVI index were compared with the data obtained from the field investigations. The analyses have showed the spatial and temporal variability of moisture conditions in the soil-plant environment determined on the background of the spectral indicators and the existence of some dependences between climatic and spectral indicators characterizing soil-plant environment.

1 Introduction

The extreme weather events like violent storms, rains and floods, but also droughts caused by rainfall shortages are frequently observed in recent times. They have an influence on the state of plants and moisture conditions in the soil-plant environment. The shortage of precipitation is identified as the main factor causing a decrease in the surface of cereal yields worldwide [12, 20]. NASA recognized that the year 2016 was the hottest year on the northern hemisphere in the XXI century. The mean annual temperature in 2016 was one of the highest in the history of field investigations [11].

Drought is the most complicated climatic phenomenon among the hazards related to weather [9, 15]. Agricultural drought research are focuses on the use of methods based

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on the long-term atmospheric data, temperature, precipitation or evaporation measurements; without taking into account changes in the soil properties and parameters [18, 25]. The water content in the soil-plant environment is the main parameter of many processes occurring on the surface area. The availability of water is also a limiting factor for biomass growth [12].

Moisture deficit is regards as one of the main causes of the reduction of yields' average, their quality, and thus directly influences the financial effects in agricultural production [14, 27]. The occurrence of moisture deficit is considered to be the point which the agricultural drought starts from [16, 21]. Therefore, the soil moisture measurements as a part of the agricultural drought monitoring are necessary in the context of yield forecasting [23]. Monitoring of agricultural drought is based on the field investigations and the use of indicators. The most common is the Climate Water Balance which is defined as a difference between precipitation and evaporation for particular soil types and plant species [2].

Multispectral image used in remote sensing analyses is an image which is a generalization of color photography. The visible spectrum and near infrared, in the range ca. 350–2500 nm is used for the analysis of vegetation. Spectral indicators are calculated based on the dependence of light reflection in individual channels (bands), i.e. reflections of light with given wavelengths [3]. Connecting the reflection of light with the biophysical characteristics of plants allow to use the spectral indicators for assessing the plants' condition, biomass production (including forecasting of yields) and susceptibility of plants organisms to the influence of stressors such as water shortages in the soil. The plants are used as the indicators of moisture conditions in the soil-plant environment in the spectral research [4, 8].

The aim of the presented study is to analyze the relations between remote sensing satellite indicator (NDVI) and meteorological, hydrological parameters in order to determine the possibility of prediction the agricultural drought based on spectral data in the lowland areas in the river valley.

2 Materials and methods

2.1 Study area

Since March 1970, the Institute of Environmental Protection and Development, Wrocław University of Environmental and Life Sciences has been carried out research related to the changes in water conditions on the left bank of the Oder River Valley from city Brzeg Dolny to Malczyce.

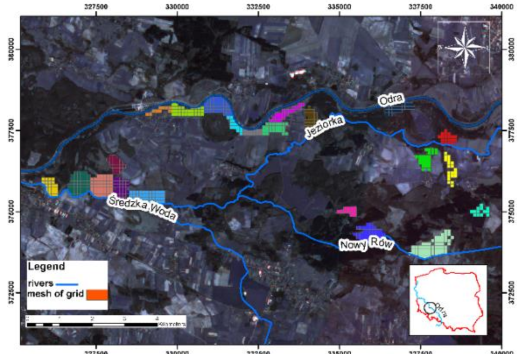

Fig. 1. Location of the investigated area and analyzed grasslands in the left bank of the Oder River Valley down the dam Brzeg Dolny (coordinate system PUWG-92).

Field investigations include measurements of flow rates, water levels, groundwater table and soil moisture contents. The water catchment where the measurements are carried out is mainly under the agricultural use. The water management of plants on the study area is based mainly on the use of water from precipitation. This is related to the fact of lowering the groundwater table in the river valley down the dam Brzeg Dolny [17, 21]. Calculations were made for grasslands located on the study area, with surface 7.73 km^2 (Fig. 1).

2.2 Materials

Hydrological and meteorological data

Daily sums of precipitation [mm], average daily temperatures [°C] for station Wrocław-Strachowice, water levels in the Oder from the gauge stations Brzeg Dolny and Malczyce [cm] were obtained from The Institute of Meteorology and Water Management – National Research Institute on the basis of the act on the re-use of public sector information, which implements the directive 2013/37/UE into Polish law. The Climatic Water Balance (CWB) was calculated on Jaworski method [13], regard to the evapotranspiration rate according to the model of Doroszewski and Górski [9].

Table 1. Specification of meteorological and hydrological data (T. – temperature [°C], P. – precipitation [mm], W. – water level [cm], CWB – climatic water balance [mm]).

Date	T. Mean 5_days before	T. Mean 10_days before	T. Mean 20_days before	T. Mean 30_days before	P. Sum 5_days before	P. Sum 10_days before	P. Sum 20_days before	P. Sum 30_days before	W. Mean 10_days before	W. Mean 20_days before	CWB 5_days before	CWB 10_days before	CWB 20_days before	CWB 30_days before
Feb 6,2016	6.4	6.9	2.8	2.2	5.8	12.9	26.7	41.4	115.0	89.0	7.0	14.7	30.8	46.8
March 17,2016	3.6	3.7	3.3	3.6	6.6	21.5	49.0	71.8	251.0	246.0	-14.0	2.6	30.4	53.6
March 27,2016	6.3	5.8	4.8	4.2	4.5	5.1	26.6	54.1	214.0	232.0	-23.7	-23.3	0.4	27.1
May 6, 2016	12.3	10.1	9.4	9.8	21.2	23.5	33.3	67.6	176.0	204.0	-37.7	-36.5	-36.9	-5.6
June 25, 2016	22.2	20.4	19.4	19.4	4.4	37.4	41.4	46.7	80.0	89.0	-91.5	-60.0	-74.1	-88.7
Aug 4, 2016	21.1	21.7	20.6	20.4	7.4	15.7	30.2	108.1	108.0	119.0	-72.4	-71.8	-68.6	-10.4
Sep 13, 2016	22.1	20.5	20.3	19.7	0.0	15.7	15.7	35.2	63.0	71.0	-63.3	-50.8	-77.2	-81.4
Nov 22, 2016	8.4	5.0	4.6	6.0	0.0	9.2	31.0	35.3			15.2	24.4	35.0	40.7

Remote sensing observations

Spectral data were obtained from the Sentinel-2 European Space Agency satellite [10]. The series consist of two satellites Sentinel – 2A (launched 23th June 2015) and Sentinel – 2B (launched 7 March 2017) which move simultaneously. The main instrument of Sentinel-2 satellite is a single multi-spectral instrument (MSI) with 13 spectral channels, in spectral range 413–2210 nm. The data are the images of reflection in the top of atmosphere and they had to be necessarily processed by radiometric and geometric corrections. In order to obtain the surface reflection, MSI bands were scaled to surface reflectance using Dark Object Subtraction (DOS) methods in Semi-Automatic Classification Plugin for QGIS [7].

2.3 Methods

Remote sensing vegetation index was determined based on the multispectral images from the Sentinel-2. Indicators have provided the information about the current status of plants and their response to water conditions in the environment. At the same time, a set of hydrological and climatic data, regarding the conditions of environment in the study area were analyzed.

The procedure included two steps: 1) selection of grasslands from other types of land cover and calculation of the NDVI for grasslands, 2) comparison and description of the relationship between time series of spectral and in situ data and condition of plants represented by NDVI values [8, 14, 22].

Corine Land Cover 2012 data set (CLC 2012) was used for differentiation of grasslands from other types of land cover. Analyses were done on 22 areas with surface larger than 150m^2. The selection of areas was under the assumption that their condition depends only on the availability of water resources, not on the growth stages as is the case of cereals [19]. Calculations were made in a grid, with mesh size 10 m (Fig. 1) which is consistent with the spatial resolution of Sentinel-2 data.

Analyses were performed for eight dates during the growing season in 2016. For each dates the maximum and minimum NDVI values were calculated and the median value was determined. NDVI was computed for every mesh of the grid using equation 1.

$$NDVI = \frac{(NIR-VIS)}{(NIR+VIS)} \quad (1)$$

Normalized Difference Vegetation Index – NIR – near infrared, Sentinel-2 band no. 8, VIS – visible spectrum, Sentinel-2 band no. 4.

NDVI represents the difference between reflectance in the near-infrared and red bands normalized by the sum of both of them [26]. It specifies the condition of plants basing on the amount of chlorophyll in the cells [5].

In the second step a statistical analyses were performed in the Statistica 13.1 software. Before basic statistical analyzes the necessary preliminary tests were done. It has been tested, if the independent variables had a normal distribution according to the Shapiro-Wilk test. Then for the dependent variables NDVI median, and independent variables with normal distribution, Pearson's linear correlation coefficients were determined, and for non-normal variables the non-parametric Spearman correlation coefficients were determined, 95% confidence interval was applied.

3 Results

The increase of NDVI value was observed between Feb 6th and Jun 25th, from the beginning of the growing season through the phase of intensive plant growth. A reduce in the NDVI value was observed from Jun 25th to Nov 11th when the vegetation decrease on the grasslands. It was also found that the median values were accepted above 0.6 in the period from May to September which corresponded to the good condition of plant species. The smallest differences between the recorded maxima and the median were also observed in this period (Tab. 2).

The box-plot (Fig. 2) shows the temporal variability of the NDVI values for study area in the particular dates, the median of which is clearly shaped as sinusoid. NDVI values presented a normal distribution. The analysis showed that the value of the third quartile in Feb 6st was 0.43, March 17th was 0.47, March 27th was 0.48 and all the values were within the range lower than 0.5. It means that 75% of the observations were lower than 0.5. Such values of the NDVI allowed to state that the plants in this area could be characterized as dry or weak [5]. Whereas the NDVI values for the first quartile in May 6th, Jun 25th and Sep 4th were respectively 0.51, 0.58 and 0.57 and they were higher than 0.5. It means that only 25% of the observed values of the indicator were lower than 0.5. It allowed to state that plants were in good condition [5]. Similarly the state of vegetation on Sep 13th was good, when the value of the first quartile was 0.47 and was slightly less than 0.5. In Nov 22th first quartile had a value 0.41, while the third one was 0.51. According to the adopted methodology, it was concluded that the vegetation was characterized as dry or weak.

Table 2. NDVI value for the studied area in 2016. Data obtained from sentinel-2.

Data	**Feb 6th (1)**	**Mar 17th (2)**	**Mar 27th (3)**	**May 6th (4)**	**Jun 25th (5)**	**Aug 4th (6)**	**Sep 13th (7)**	**Nov 11th (8)**
Min.	0.14	0.06	0.05	0.22	0.14	0.16	0.19	0.05
Median	0.38	0.42	0.42	0.62	0.69	0.66	0.61	0.46
Max.	0.63	0.66	0.68	0.82	0.87	0.85	0.85	0.65

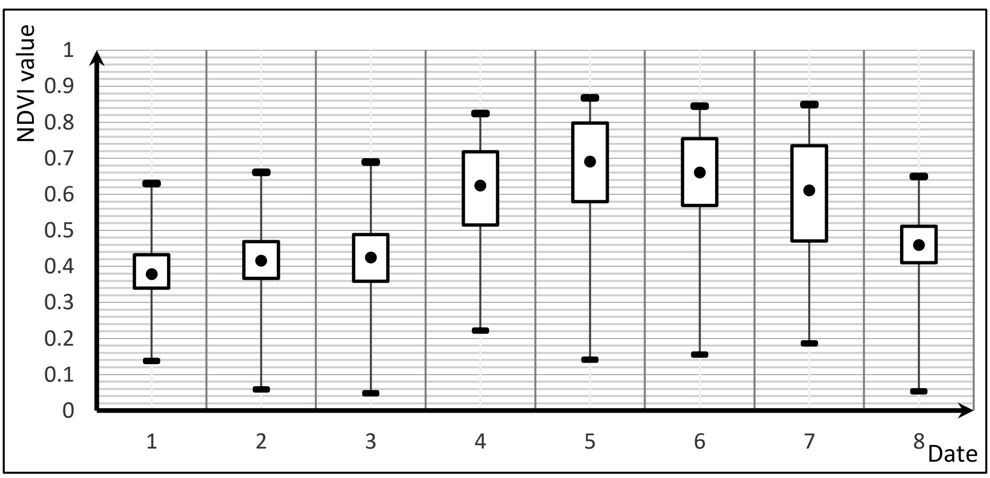

Fig. 2. Temporal variability of the NDVI values within the study area.

The assessment of the plants condition on grassland fields for analyzed area in 2016 using NDVI showed that the median values increased and reached the maximum in the summer months, and then decreased with the approaching the winter period. The maximum NDVI values had a similar trajectory, but this trend was not observed in the case of minimum value.

The strongest correlation (almost full correlation, r = <0.9; 1.0), red colour) between NDVI median and Temperature mean from 5 days before was showed. Very strong correlation (r = <0.7; 0.9), green colour) was obtained for Temperature mean from 20 and 30 days before, and also for CBW from 5, 10 and 30 days before. Correlation between NDVI and Temperature mean from 10 days before and CBW from 20 days before was on the limit very strong and strong. Strong correlation (r = <0.5; 0.7), blue colour) between the

Precipitation sum and Water level Mean from 10 days before was achieved. However, no correlation (r < 0.5) was obtained neither for Precipitation sum from 5, 20 and 30 days before nor mean Water level Mean from 20 days before (Table 3). Linear regression diagrams for correlation the variables with normal distribution shows Figure 3.

Table 3. Correlation between the NDVI values and the independent variables (meteorological and hydrological).

	T. Mean 5_days before	T. Mean 10_days before	T. Mean 20_days before	T. Mean 30_days before	P. Sum 5_days before	P. Sum 10_days before	P. Sum 20_days before	P. Sum 30_days before	W. Mean 10_days before	W. Mean 20_days before	CWB 5_days before	CWB 10_days before	CWB 20_days before	CWB 30_days before
	Variables with normal distribution - Pearson's linear correlation coefficient													
NDVI median	0.92	-	-	-	-	0.63	-0.05	0.31	-0.60	-0.43	-0.89	-0.88	-	-0.84
	Variables which didn't show normal distribution - Spearman's non-parametric R correlation coefficient													
NDVI median	-	0.71	0.85	0.88	0.04	-	-	-	-	-	-	-	-0.71	-

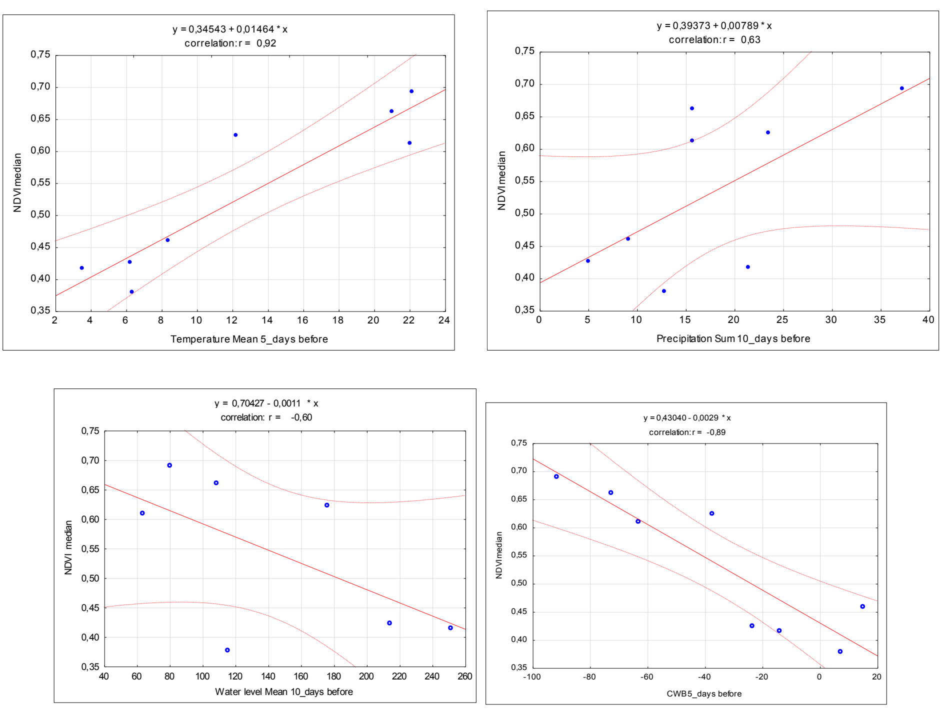

Fig. 3. Diagrams of linear regression with chosen independent variables.

4 Discussion and conclusion

The aim of the study was to analyze the relationship between the values of remote sensing satellite indicators and parameters meteorological and hydrological in order to assess the moisture conditions in soil-plane environment. In-situ measurement of soil moisture is considered as the most accurate method for drought monitoring but available for only small scales and limited areas [6]. Analyzes carried out by other researchers shows high relevance of using the spectral data for assessing the plants condition and biomass production [4, 8, 18]. The well-described indicator, NDVI was used in this work [5, 22]. NDVI characterize the condition of plants basing on the amount of chlorophyll in the cells [22]. However, many environmental factors from the hydrological system (soil-vegetation-atmosphere) can affect the amount of the chlorophyll in the cells. This factor can have a bigger impact on changes the value of NDVI than water shortages [18, 24]. Nichols showed that correlation between Vegetation supply water index (based on NDVI and Surface temperature) and precipitation, occurred only after 60 days without precipitation. On the other hand, Xiang tried to find relation between Process-based Accumulated Drought Index (PADI, based on spectral and in-situ data) and Standardized Precipitation Index (SPI) and received only short-term correlations in his research [28]. Aguilara's indicates the possibility of using NDVI for evaluation precipitation input [1]. Research on the assessment of plants' condition and yield amount using NDVI was conducted in Poland by Dąbrowska-Zielińska [8], however, using spectral satellite data with a spatial resolution of 1 km.

It cannot be clearly determined which environmental parameter effects in the best way on the plants condition represented by the NDVI. It is natural to correlate NDVI with thermal conditions relative to the growing season and climatic water balance (depending on temperature), especially in 2016. Using NDVI the soil moisture analyzes as well as prediction of the agricultural drought could be impossible, due to the lack of the correlation between this indicator and the sum of precipitation and the hydrological regime of water course. In order to find the relation between spectral data and the condition of the environment, as well as the water regime, other spectral indicators should be analyzed by the geostatistical further analysis.

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