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The impact of drought in 2015 on the health forest condition determined using Landsat-8 OLI images

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Abstract. The main aim of this research was to determine the impact of drought (in 2015) on forests stand condition using remote sensing and statistical techniques. The study was based on the analysis of vegetation indices calculated from a series of Landsat-8 OLI satellite images covering the 2014 and 2015 growing seasons. Various tree biophysical and physical parameters as well as forest habitat characteristics were tested in order to find the most significant factors affecting drought resistance. Three approaches were used: (i) index differences, (ii) PCA analysis, and (iii) ANOVA statistical analysis. All three approaches used in this study indicate that forest biodiversity is the most important factor determining habitat response to stress conditions. Coniferous and mixed tree habitats were less sensitive than deciduous ones. Statistical analysis revealed the relationship between stress and soil types, as those more permeable were less dependent on rainwater. The highest stress was found for precipitation-dependent gley soils. Undergrowth density and height were also indicated as important factors inducing habitat response to a changing weather situation. All the results confirmed the usefulness of mid-infrared based indices for water shortage monitoring in forests. They confirmed that habitat biodiversity has a positive effect on its resistance to stressful conditions. Also forest type (conifer/deciduous) determines it's sensitivity. Precipitation and groundwater shortages have different effects on the forest condition depending on soil type.

Keywords*:* Drought, forest, Landsat-8 OLI, biodiversity, PCA, vegetation indices

1. Introduction

According to the current state of the art, changes in the physiological, structural, functional or demographic properties of forests caused by direct or indirect effects of drought can be reliably detected using remote sensing techniques (Assal et al. 2016). Just as other adverse environmental or man-made factors, water stress influences the condition of trees and increases the risk of greater intensity of disease development. Remotely acquired data could help address all these issues. Vegetation indices are useful tools to detect anomalies. They can be calculated for periods spanning many years; thus, enabling a trend analysis to uncover the spatial distribution and change direction over time.

According to RCP 6 and RCP 8.5 scenarios (Riahi et al. 2011) droughts may become a common phenomenon. Their intensity and duration has increased (Grossiord et al. 2014), as well as the percentage of affected areas throughout the last century (Wang et al. 2014). Examples of local drought occurrence and impact have been studied in Poland for Białowieża Primeval Forest (Michalski et al. 2004), Niepołomice Forest (Bednarz 1994), and Silesian Beskid (Durło et al. 2015). Drought occurrence in Wielkopolska region was described in Kotlarz et al. 2018.

Quercus robur L., is especially vulnerable to water shortages. Summer droughts were found to inhibit their growth. Moreover, recurring droughts can lead to their gradual weakening and dying (Sohar et al. 2014). Increased frequency of droughts caused by global warming will become a crucial factor causing an increase in the mortality of oaks (Urlim et al., 2015).

It should be pointed out that when a drought is investigated using remote sensing techniques, it is not the drought itself that is sensed, but rather what is examined is the potential sensitivity of an area to the factors causing the drought, its occurrence and its effects, which are most frequently manifested by quantitative and qualitative changes in the elements of animate and inanimate nature. Plants use both the water accumulated in soil and precipitation water. All types of disturbances related to the amount of water available to plants can influence their normal physiology and growth. Drought affects all the properties of forest ecosystems, which can be detected and monitored using remote sensing data. The main components of damage to trees include: wilting, stomatal closure, leaf shedding, reduction of photosynthesis, inhibition of cell growth (cell growth, cambial growth, root growth). In particular, an adverse impact on the number and surface area of leaves is readily visible. During the summer, a num-

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ber of newly formed stem units may be affected. Then, if the drought continues, the number of new buds will be significantly reduced (Coder 1999).

Precipitation levels can be monitored using traditional weather stations; it should be pointed out, however, that the availability of digital methods and satellite data has contributed significantly to the development of new tools for area (rather than point/local) monitoring and forecasting of weather parameters, also including precipitation. Among them, it is possible to distinguish the decrease in the surface area of inland waters (an abiotic component), for example, a decrease in the area covered by vegetation (a biotic component) and the deterioration of the vitality of vegetation manifested by its ability to photosynthesize (a biotic component).

Drought has various impacts on particular plant species and/or plant communities. Ecosystem functioning is sensitive to biodiversity, and thus, resistance to drought is correlated with species richness (Tilman, Downing 1994; Kotlarz et al. 2018). The research done to date has demonstrated that areas with enhanced biodiversity are less sensitive to drought (Thompson et al. 2009). In general, mixed species forests are less sensitive to water stress than monocultures (Grossiord et al. 2014). Additionally, it is important to account for how different types of trees respond in different ways to the stress caused by water scarcity.

The research done in the Polish forests indicates that the first and foremost reason of oak deaths on a wide scale is changing groundwater level (Kuźmiński et al. 2015; Oszako 2000). Defoliation is a visible effect of the changing water level (Dmyterko, Bruchwald 1998). Therefore, our hypothesis is that by studying the reflectance of the trees' crowns, it is possible to investigate the phenomena that depend on the ground water level and generally drought occurrence.

The aim of our study was to investigate how the drought of 2015 influenced the oak stands on the Krotoszyn Plateau, Central Poland. Furthermore, we investigated the properties of forest stands changing the drought impact on the forests' health.

2. Drought in 2015 in Poland

The results of the measurements carried out by the traditional methods unambiguously demonstrated the occurrence of drought in 2015. The effects of agricultural drought were the greatest in the Wielkopolska region, where its duration exceeded 100 days. The soil drought was also the most intensive there compared with the whole country and the soil water deficit lasted for more than 30 days (Boczoń et al. 2016). Table 1 shows the weather parameters at the Krotoszyn weather station.

The beginning of the growing season was estimated by the archive weather data. In 2014, it started on 28 March, while in 2015, it started on 8 April. All the satellite images considered for this analysis were labelled with the attributable day of the growing season.

3. Materials and methods

Study area

Three research areas were selected from the three forest districts in the southern Wielkopolska: Krotoszyn Forest District, Piaski Forest District and Karczma Borowa Forest District. The main item of interest was oak *Quercus robur* L. The chosen 29 ROIs were internally homogeneous with respect to their composition in terms of species, age, height, and so on. They are described in Table 2, using the informa-

Table 1. Meteorological data: minimum and maximum temperatures and precipitation in Krotoszyn

Year	Month	T_{min} [ºC]	T_{max} [ºC]	Precipitation [mm]
2014	Jan	-0.25	5.90	19.60
	Feb	0.90	8.20	30.47
	Mar	3.77	12.93	37.08
	Apr	6.57	16.23	74.74
	May	9.77	19.37	67.18
	Jun	13.23	23.13	80.87
	Jul	14.73	24.70	55.70
	Aug	14.60	24.33	75.43
	Sep	11.70	20.23	62.70
	Oct	8.40	15.27	54.83
	Nov	4.30	9.77	36.73
	Dec	1.60	6.07	27.90
2015	Jan	-0.17	4.833	22.77
	Feb	0.47	6.833	26.23
	Mar	1.70	10.27	20.03
	Apr	4.87	15.07	29.37
	May	8.37	18.83	22.93
	Jun	12.17	22.90	36.03
	Jul	15.30	26.30	31.77
	Aug	14.97	26.07	37.17
	Sep	11.63	21.33	29.20
	Oct	6.80	14.83	37.37
	Nov	4.23	10.70	34.23
	Dec	1.23	6.833	34.30

tion which was: (i) collected during a few field campaigns during the HESOFF Life+ project, (ii) based on the experience of the project team, (iii) taken from cartographic materials, (iv) gathered at the Forest Data Bank, and (v) taken from the DTM generated from high resolution QUERCUS camera imagery (Kacprzak & Rotchimmel 2016).

Satellite data

Landsat-8 OLI data were used to identify and quantify the effects of the drought in 2015 for 3 forest areas in the Wielkopolska region in Poland (Krotoszyn, Piaski and Karczma Borowa Forests). The values of several major remote sensing vegetation indices were compared with the values of the indices obtained from a two-year dataset. The research was conducted in 29 selected regions of interest (ROIs), shown in Figure 1 against the background of CIR images. In order to assess the changes in the condition of stands, three methodological approaches were tested, resulting in multithematic and multiaspect results, including spectral properties, their statistic, diversity and dependences. First, the differences between the selected vegetation indices (2015 minus 2014) were calculated for each defined ROI. Then, the obtained values were subjected to the PCA analysis and compared with the PCA analysis of the field parameters, in order to determine the relationships between the forest characteristics and the changes found. The most important relationships and factors influencing the obtained results were identified using ANOVA.

This research consisted of an analysis covering two years and the satellite data were taken from the Landsat ESPA Ordering Interface. This analysis was based on the vegetation indices acquired from surface reflectance bands. (Department of the Interior, U.S. Geological Survey 2016). The acquisition (and growing season) dates of the Landsat scenes used in the analysis (path 190, row 24) were as follows: for 2014–92(6), 140(54), 156(70), 188(102); and for 2015–111(14), 127(30), 223(126).

Vegetation Indices

We used 14 remote sensing vegetation indices (VI). It was not assumed that any of the indexes describe better drought impact on trees health; all available were used.

Table 2. Bands and their middle wavelengths of vegetation indices used in the analysis

no.	Index	ESPA	Calculations	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7	Band 8	Band 9	Bibliography
				The middlewavelength [nm]									
				440	480	560	655	882.5	1610	2200	590	1370	
1	EVI	+		*				*			*		Huete et al. 1997
2	MSAVI	+					*	*					Qi et al. 1994
3	NBR	+						*		*			Key, Benson 2006
4	NBR2	+							*	*			Key, Benson 2006
5	NDMI	+						*	*				Hardisky et al. 1983
6	NDVI	+					*	*					Rouse et al. 1974
7	SAVI	+					*	*					Huete 1988
8	SR	+					*	*					Jensen 1986
9	GNDVI		+			*		*					Gitelson et al. 1996
10	ARVI		+		*		*	*					Kaufman, Tanre 1992
11	BNDVI		+		*			*					Hancock, Dougherty 2007
12	MSI		+					*	*				Hunt, Rock 1989
13	BG		+		*	*							Shimada et al. 2012
14	GR		+			*	*						Gitelson et al. 2002

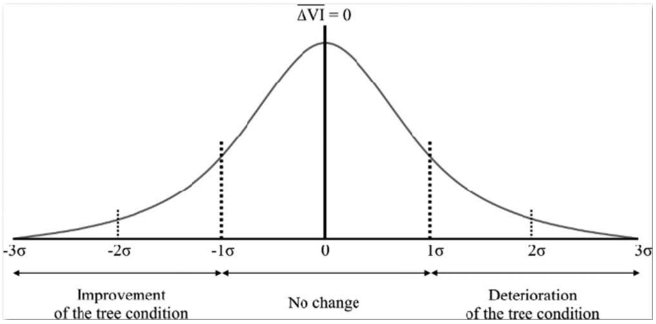

Figure 1. The location of the study area and chosen regions of interests (yellow squares)

They were calculated using surface reflectance bands. In order to check for the variations of indices that show disturbances in the forest conditions, change-detection differential analyses were performed for all the selected regions of interest. The amount of indices was chosen to enable the classification of the results into several resistance classes, and also to conduct a PCA analysis. ANOVA statistical analysis gives the possibility to distinguish their respective utility (Table 3).

Change analysis

The analysis was based on the vegetation indices image differencing method (Volcani et al. 2005). For all the indices, the values for 2015 were subtracted from the values for 2014. The mean and standard deviation values (σ) were calculated, taking into account the differences for each pixel in all the ROIs for all the available data. The mean value was detracted from the acquired differences (2014–2015) and this result was divided by the standard deviation. The output table (Table 4) presents the differential vegetation indices (ΔVI) for all the analysed indices for each ROI.

Table 3. Values of the Differential Vegetation Indices (ΔVI) for all the remote sensing indices calculated for Krotoszyn, Piaski and Karczma Borowa Forests

ROI No.	ForestDistrict	Δ Vegetation Indices														Resistance-class
		ΔEVI	ΔMSAVI	ΔNBR	ΔNBR2	ΔNDMI	ΔNDVI	ΔSAVI	ΔSR	ΔGNDVI	ΔARVI	ΔBNDVI	ΔMSI	ΔBG	ΔGR	
Krotoszyn		**0.69**	**0.91**	**0.91**	**1.05**	**0.77**	**1.07**	**0.98**	**0.62**	**1.11**	**1.02**	**1.10**	**0.71**	**-0.40**	**0.01**	
1	Con	-0.17	0.07	0.22	0.44	0.04	0.90	0.39	-0.38	1.01	0.75	1.08	-0.09	-0.14	-0.14	Con3
2	Con	-0.57	-0.17	0.62	0.66	0.43	0.81	0.16	-0.48	0.89	0.67	0.98	0.39	-0.08	-0.15	Con3
3	Dec	0.51	0.54	0.55	0.88	0.42	0.44	0.45	0.84	0.40	0.56	0.26	0.34	-0.17	0.05	Dec3
4	Dec	1.78	2.04	0.67	1.18	0.39	1.45	1.89	1.42	1.58	1.25	1.62	0.28	-0.75	0.06	Dec1
5	Dec	1.26	1.32	1.14	1.29	0.97	1.44	1.41	0.85	1.44	1.36	1.51	0.90	-0.66	0.08	Dec1
6	Dec	1.09	1.10	0.95	1.03	0.87	1.24	1.19	0.77	1.31	1.22	1.24	0.81	-0.36	0.03	Dec1
7	Dec	1.92	1.95	1.58	1.52	1.46	1.68	1.94	1.11	1.65	1.65	1.65	1.63	-0.78	0.11	Dec1
8	Mix	-0.01	0.39	0.88	0.97	0.68	0.98	0.59	0.14	1.04	0.90	1.06	0.63	-0.34	-0.05	Mix3
9	Dec	0.99	1.20	1.10	1.17	1.05	0.92	1.09	1.04	0.93	0.92	0.88	1.02	-0.44	0.05	Dec1
10	Dec	0.89	1.31	1.47	1.55	1.36	1.32	1.31	1.06	1.33	1.29	1.32	1.30	-0.57	0.07	Dec1
Piaski		**0.19**	**0.18**	**0.59**	**0.30**	**0.85**	**0.06**	**0.04**	**0.77**	**-0.14**	**0.26**	**-0.22**	**0.88**	**0.05**	**0.06**	
11	Dec	0.28	0.30	0.67	0.29	1.02	0.03	0.11	1.11	-0.23	0.23	-0.23	1.02	-0.16	0.13	Dec2
12	Con	-0.83	-0.77	-0.12	-0.07	-0.07	-0.41	-0.70	-0.38	-0.41	-0.36	-0.44	-0.21	0.35	-0.16	Con3
13	Con	-1.03	-0.98	-0.59	-0.51	-0.62	-0.69	-0.90	-0.70	-0.65	-0.69	-0.66	-0.72	0.63	-0.23	Con3
14	Dec	0.14	0.17	0.43	0.39	0.60	0.06	0.00	0.91	0.05	0.27	-0.21	0.52	0.31	0.00	Dec3
15	Dec	0.58	0.45	1.06	0.38	1.39	0.45	0.36	0.68	-0.02	0.76	-0.02	1.75	-0.11	0.16	Dec2
16	Dec	0.67	0.57	1.16	0.82	1.45	0.36	0.41	1.03	0.10	0.66	-0.05	1.46	0.01	0.13	Dec2
17	Dec	0.13	0.24	0.24	0.20	0.55	-0.30	-0.06	1.25	-0.29	-0.20	-0.40	0.31	0.07	0.01	Dec3

ROI No.	ForestDistrict	Δ Vegetation Indices														Resistance-class
		ΔEVI	ΔMSAVI	ΔNBR	ΔNBR2	ΔNDMI	ΔNDVI	ΔSAVI	ΔSR	ΔGNDVI	ΔARVI	ΔBNDVI	ΔMSI	ΔBG	ΔGR	
Karczma Borowa		**-0.39**	**-0.50**	**-0.64**	**-0.62**	**-0.66**	**-0.54**	**-0.49**	**-0.55**	**-0.50**	**-0.58**	**-0.47**	**-0.68**	**0.17**	**-0.02**	
18	Dec	-0.58	-0.59	-0.30	-0.36	-0.29	-0.18	-0.45	-0.13	-0.11	-0.24	-0.09	-0.30	0.35	-0.14	Dec3
19	Dec	-0.06	0.12	-0.37	-0.20	-0.49	0.01	0.13	0.07	-0.03	-0.12	0.14	-0.47	-0.13	-0.10	Dec3
20	Con	-2.24	-2.07	-1.18	-1.17	-1.00	-0.87	-2.05	-2.00	-0.81	-0.83	-0.75	-1.23	-1.91	1.60	Con5
21	Con	-0.71	-0.72	-0.80	-0.68	-0.94	-0.38	-0.52	-0.94	-0.28	-0.58	-0.06	-0.97	0.35	-0.27	Con3
22	Dec	0.00	-0.21	-0.33	-0.46	-0.26	-0.36	-0.25	-0.02	-0.36	-0.30	-0.45	-0.23	0.33	-0.13	Dec3
23	Dec	0.06	-0.07	-0.11	-0.25	-0.12	-0.23	-0.04	-0.48	-0.23	-0.28	-0.17	-0.05	0.32	-0.18	Dec3
24	Dec	0.10	-0.09	-0.48	-0.27	-0.64	-0.16	-0.06	-0.02	-0.10	-0.19	-0.11	-0.70	0.24	-0.15	Dec3
25	Mix	-1.59	-1.96	-1.58	-1.65	-1.45	-1.96	-1.95	-1.59	-1.88	-1.89	-1.96	-1.51	1.48	-0.42	Mix4
26	Con	-0.39	-0.92	-2.13	-1.97	-2.24	-2.38	-0.95	-2.19	-2.21	-2.48	-2.19	-2.15	1.47	-0.57	Con5
27	Dec	0.18	-0.01	-0.44	-0.27	-0.55	-0.23	-0.02	-0.06	-0.14	-0.27	-0.16	-0.66	0.31	-0.16	Dec3
28	Dec	-0.20	-0.09	-0.30	-0.28	-0.34	-0.29	-0.16	0.12	-0.24	-0.41	-0.16	-0.36	0.05	-0.14	Dec3
29	Dec	0.16	-0.03	-0.33	-0.41	-0.30	-0.18	-0.05	-0.01	-0.18	-0.21	-0.17	-0.21	0.18	-0.12	Dec3

Explanations: Con – coniferous, Dec – deciduous, Mix – mixed forests. The minus sign before the name of the index means that it has been multiplied by -1 to achieve comparable change range values

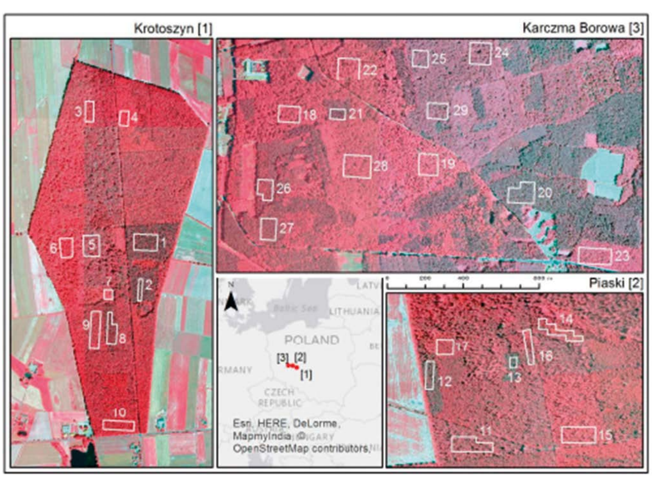

Figure 2. Interpretation of the results of the differential index distribution

Principal Component Analysis

Environmental variables were analysed using the principal component analysis (PCA) method in order to find the reasons for the varied vulnerability and changes/stability of the forests due to weather conditions. PCA is a mathematical procedure which uses covariance or correlation matrices of observed reflectance, and linear algebraic methods to transform a large number of optical channels (data dimension) into a smaller number of variables called principal components (PC) (Nandi et al. 2015). PCA is also used for multi-date image series transformations (Byrne et al. 1980; Coppin et al. 2001; Dronova et al. 2015). PCA was applied to two data sets: in-situ data from the Forest Data Bank (ROIs diversity) and remote sensing Differential Vegetation Indices (ΔVI). Two main eigenvectors from the PCA analysis conducted on 17 quantitative field parameters of ROIs

Table 4. Two main eigenvectors of PCA (PC1 and PC2) of in-situ data [%]. column titles according to Table 1

	dmg	tds	uds	dcd	cnf	SW	age	dmt	h1	h2	wth	nsp	nlc	nsn	nbu	nun	dtm
PC1	0	0.3	-0.7	11.7	43.4	-47	-50	13.9	7.5	-33	15.7	30.2	14.3	1.5	8.1	-2.4	-22
PC2	0	-5.2	-4	2.6	19.8	-21	29.1	37	-41	-8.9	10.5	-31	-28	23	0.7	50.8	-14

are presented in Table 5 and Figure 3. The two main eigenvectors based on 14 remote sensing indices of ROIs that were used for PCA are presented in Table 6 and Figure 4.

In order to compare these results with in-situ data, each ROI was described as the sum of its PCA coordinates, with the values for the negative category equal to more than 1.0 and the values for the positive category equal to less than 0.5. Fig. 5 shows a comparison of the results.

ANOVA Analysis

ANOVA analysis: In the next step, the impacts of selected environmental factors on the Differential Vegetation Indices were examined. For this purpose the multi-factor analysis of variance (ANOVA) was used. Changes in each index were analysed depending on five variables: forest type, biodiversity (the number of main tree species and understory species),

Table 5. Two main eigenvectors of PCA (PC1 and PC2) of Differential Vegetation Indices (ΔVI) [%]

	ΔEVI	ΔMSAVI	ΔNBR	ΔNBR2	ΔNDMI	ΔNDVI	ΔSAVI	ΔMSI	ΔSR	ΔGNDVI	ΔARVI	ΔBG	ΔGR	ΔBNDVI
PC1	0	28.8	-19.4	-2	62.4	-4.1	23	-29.1	6.9	11	49.1	-7.8	-14.5	-25.4
PC2	0	4.5	24	12.5	-34.4	-7.7	34.9	-29.1	13.7	0.1	25.5	-44.4	55	3.9

Table 6. ANOVA results for environmental variables with differential indices. P-values lower than 0.05 are bold and those under 0.005 are underlined

	ΔEVI	ΔMSAVI	ΔNBR	ΔNBR2	ΔNDMI	ΔNDVI	ΔSAVI	**ΔSR**	**ΔGNDVI**	**ΔARVI**	**ΔBNDVI**	**ΔMSI**	**ΔBG**	**ΔGR**
Type of trees	**0.0057**	**0.0054**	**<u>0.0079</u>**	**0.0131**	**<u>0.0017</u>**	0.0602	**0.0203**	**<u>0.0000</u>**	0.1185	**0.0277**	0.1752	**<u>0.0045</u>**	0.0545	**<u>0.0006</u>**
Number of main tree species	0.1728	0.0573	**0.0270**	**0.0182**	**0.0168**	**0.0340**	0.0802	**<u>0.0000</u>**	**0.0409**	**0.0290**	**0.0447**	0.0586	**0.0091**	**<u>0.0000</u>**
Number of understoryspecies	0.1565	0.1318	0.0553	0.0456	**0.0168**	0.2742	0.2035	**<u>0.0001</u>**	0.3408	0.1534	0.4598	**0.0438**	**0.0049**	**<u>0.0000</u>**
Soil	0.3566	0.1580	**0.0074**	**0.0129**	**<u>0.0015</u>**	0.0567	0.2107	**<u>0.0000</u>**	0.0783	**0.0312**	0.1047	**0.0059**	0.0556	**<u>0.0006</u>**
DTM	0.4173	0.2946	0.5474	0.2550	0.3674	0.1976	0.2372	0.1438	0.1491	0.3024	0.1290	0.4590	0.1984	0.3437
Type of trees : Number of main tree species	0.5461	0.2970	0.1000	0.1189	0.0697	0.0750	0.2627	**0.0107**	0.0863	0.0752	0.0770	0.1552	0.0473	**0.0368**
Type of trees : Number of understory species	0.4541	0.4395	0.8897	0.7690	0.7228	0.9906	0.6228	**0.0157**	0.9271	0.9593	0.9602	0.8028	0.4098	0.1908
Number of main tree species : Number of understory species	0.7994	0.8773	0.7110	0.8138	0.5512	0.9100	0.8727	0.1574	0.8797	0.9068	0.9327	0.6904	0.5209	0.3667
Number of understory species : Soil	0.9547	0.6266	0.5175	0.6165	0.4319	0.3549	0.5416	0.1642	0.3688	0.4589	0.2733	0.4916	0.2175	0.3502
Number of main tree species : DTM	0.2178	0.1812	0.9654	0.7851	0.7921	0.6291	0.2984	**0.0065**	0.6573	0.7688	0.5397	0.8662	0.1629	0.2160
Number of understory species : DTM	0.9128	0.8584	0.7823	0.8251	0.7567	0.9627	0.8563	0.0711	0.9451	0.9606	0.8643	0.8205	0.9372	0.5150

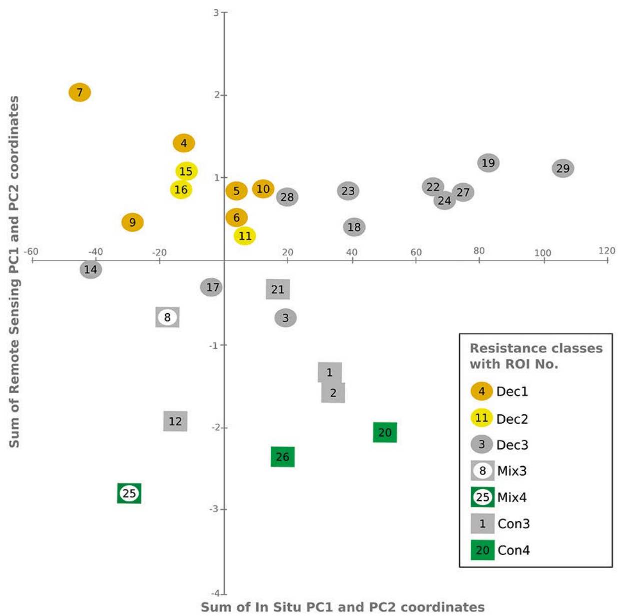

Figure 3. A comparison of the 2 first PCA eignvectors for in situ parameters, with resistance classes from Table 3

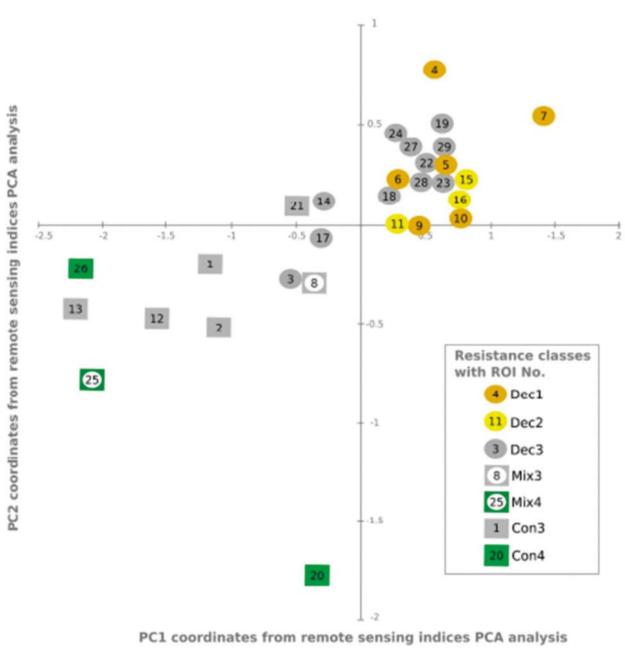

Figure 4. A comparison of the 2 first PCA eignvectors for remote sensing indices, with resistance classes from Table 3

soil type and ground elevation above sea level. The ANOVA analysis was used to check whether there were statistically significant differences between mean changes in a given remote sensing index relative to a given environmental variable or an interaction between two environmental variables. If the analysis of variance demonstrated significant differences between the means in groups, the factors were assessed and a post hoc test (multiple comparisons) was carried out in order to check which of the means were significantly different. Table 7 shows the statistical significance of the differences between the means in groups for many classifying factors at a significance level of 0.05.

4. Results

Differential Vegetation Indices

Krotoszyn Forest District: In almost all of the deciduous ROIs in the Krotoszyn forest, the condition of stands deteriorated, as indicated by the results of the majority of Differential Vegetation Indices (Table 4). Region 3 demonstrated different response. This fragment of the forest had a high forest diversity index (3.2) among deciduous forests, calculated according to the number of tree species present (Nasiłowska et al. 2016). Here, the largest number of species can be seen in the understory (4); in addition, in the course of a field visit, the understory was determined to be very dense and very high (category 44, Table 2). Moreover, ROI3 was not fully wooded (0.7), with clearances likely influencing the characteristics of the understory. It showed large negative changes, compared with ROI5 and ROI6, which were of a similar age, diameter at breast height, the height or tree density of the stand. This might be caused by the number of species occurring there, as the forest diversity index was more than a half lower (1.5) than in ROI3. Similarly ROI3, the stand situated in ROI9 was characterised by a high value of the forest diversity index (3.45); however, it was mainly determined by the number of main tree species. A field inventory found a much poorer understory in ROI9 compared with ROI3; it was dominated by high but dispersed trees (category 24, Table 2).

Piaski Forest District: The areas designated in the Piaski Forest District (Table 4) showed much less pronounced changes. In 3 regions covered by deciduous forests (ROI11, ROI15 and ROI16), droughts were found to have a substantial impact on the condition of the stand. This was indicated only by some of the selected indices. Importantly, the indices that turned out to be most suitable for the research were the ones based on mid-infrared, that is, those that, in accordance with the literature, should be particularly sensitive to the water content in cellular structures (Hardisky et al. 1983; Hunt, Rock 1989; Key, Benson 2006). Namely, ΔNBR, ΔNDMI and ΔMSI indicated a worse initial condition of the stands within ROI11, 15 and 16. And the stands within ROI14 and 17 were demonstrably more resistant to adverse weather factors. About 70% of region 14 was covered by birch, which responded in a varied manner to water scarcity (Coder 1999). In addition, the field inventory revealed higher soil humidity compared with the surrounding areas (with stagnant water on the road). Moreover, ROI17 was found to have the highest forest diversity index in the Forest District (3.1). It could also contribute to the highest resistance to adverse weather conditions.

Karczma Borowa Forest District: In the forest situated in the Karczma Borowa Forest District, the stand condition was not found to have deteriorated in any of the ROIs. In general, for the majority of the analysed differential vegetation indices,

Table. 7. Mean and standard deviation values for three types of forests in Krotoszyn (Kr), Piaski (Pi) and Karczma Borowa (KB) stands.

Forest district	Forest type	σ	Mean	ΔEVI	ΔMSAVI	ΔNBR	ΔNBR2	**ΔNDMI**	**ΔNDVI**	**ΔSAVI**	**ΔSR**	**ΔGNDVI**	**ΔARVI**	**ΔBNDVI**	**ΔMSI**	**ΔBG**	**ΔGR**
								Mean									
Kr	**Con**	0.48	0.29	-0.26	0.02	0.33	0.49	0.14	0.88	0.34	-0.40	0.98	0.73	1.05	0.03	-0.12	-0.15
	Dec	0.50	0.92	1.09	1.25	1.09	1.23	0.97	1.13	1.22	0.99	1.15	1.12	1.12	0.93	-0.50	0.06
Pi	**Con**	0.48	0.29	-0.26	0.02	0.33	0.49	0.14	0.88	0.34	-0.40	0.98	0.73	1.05	0.03	-0.12	-0.15
	Dec	0.42	0.39	0.37	0.34	0.73	0.38	1.03	0.14	0.17	0.97	-0.09	0.37	-0.17	1.08	-0.01	0.10
KB	**Con**	0.59	-1.18	-1.35	-1.44	-1.43	-1.35	-1.40	-1.28	-1.41	-1.87	-1.18	-1.33	-1.11	-1.49	-0.39	0.56
	Dec	0.16	-0.17	0.00	-0.10	-0.33	-0.31	-0.37	-0.20	-0.10	-0.07	-0.18	-0.25	-0.15	-0.37	0.21	-0.14
								Standard deviation									
Kr	**Con**	0.11	0.15	0.28	0.17	0.28	0.16	0.27	0.06	0.16	0.07	0.08	0.06	0.07	0.34	0.04	0.01
	Dec	0.15	0.37	0.50	0.51	0.38	0.24	0.42	0.41	0.51	0.22	0.44	0.35	0.50	0.49	0.22	0.03
Pi	**Con**	0.10	0.22	0.14	0.15	0.33	0.32	0.39	0.20	0.14	0.23	0.17	0.23	0.16	0.36	0.20	0.05
	Dec	0.14	0.27	0.25	0.16	0.40	0.24	0.43	0.30	0.21	0.22	0.17	0.38	0.15	0.61	0.19	0.07
KB	**Con**	0.30	0.92	0.99	0.73	0.68	0.65	0.73	1.04	0.79	0.68	1.00	1.03	1.09	0.62	1.72	1.18
	Dec	0.06	0.15	0.25	0.21	0.11	0.09	0.17	0.11	0.17	0.18	0.10	0.08	0.16	0.22	0.17	0.02

all the research area yielded results below 0.0. Still, values exceeding -1, meaning significant changes indicating an improved condition of the stand, were obtained only for coniferous and mixed forests. Special consideration should be given to region 21, the results for which indicated a different specificity of the stand (they were close to the threshold value only for the ΔNDMI, ΔSR, and ΔMSI indices). The dominant species was pine (70%) and the forest diversity index was very high (4.6).

Resistance classes

Based on the above conclusions drawn from the analysis of the results given in Table 4, ROIs could be grouped according to their response to the stressors into 5 resistance classes, where Class 1 represented a substantial deterioration of the condition according to a majority of the vegetation indices (6 as a minimum) and so did Class 2 – according to 3 of them as a minimum. Class 3 was assigned to the forests where no changes were recorded, Class 4 represented an improvement of the condition and 5 reflected a substantial improvement of the condition. Moreover, the following categories were recognized according to the types of forests where a given situation occurred: Dec1, Dec2, Dec3, Mix3, Mix4, Con3, and Con5 (Table 4). The classes thus distinguished were used as a reference to the results of the differential analysis in the further stages of the study (PCA).

PCA analysis

The result eigenvectors (PC1 and PC2) are connected to the 'size' of trees (age in PC1 and height: h2 in PC1 and h2 in PC2), biodiversity (the numbers of trees in PC1, the understory in PC2 and the Shannon-Wiener index in PC1), and the general type of the forest stand: coniferous or deciduous (the percentage of coniferous trees in PC1). In the first category, the younger (31–55 years old), thinner and smaller deciduous trees in the ROIs with higher biodiversity (ROIs: 7, 8, 9, 14 and 25) can be distinguished from the ROIs with average coniferous trees (ROIs: 1, 2, 12, 20, 21, 26), and from the ROIs with old, high deciduous trees (121–158 years old). The latter are examples of high biodiversity (with the diversity index varying between 2.5 and 6.3, (Table 2) which can be found in ROIs: 18, 19, 22, 24, 27, 29) (Fig. 3). On the other hand, old trees with a low diversity index (from 1.15 to 3.2) can be found in ROI 3, 5, 6, and 11. In order to compare these results with remote sensing data (Fig 4), each ROI is described as the sum of its PCA coordinates, with values for category 1 below -17.0 and values for category 3 below 66.0.

Coniferous and mixed forests as well as deciduous ones with the greatest resistance to the stress conditions are situated below the 'X' value of '0' along the 'Y' axis. In the upper part of the diagram, the areas covered by deciduous forests where there were no changes can be clearly distinguished from those where their condition was found to have deteriorated. This is related to a decrease in the biodiversity described by the 'X' axis, expressing the sum of the two eigenvectors of the PCA transformation of the field data.

Statistical analysis

According to Table 7, at least half of the analysed cases (changes in the differential indices) demonstrated significant impacts of three factors: forest type, the number of main tree species and soil type, on the changes observed in indices (p-values below 0.05). The impact of the altitude was not demonstrated.

The strongest relationships with the in-situ parameters were found for ΔSR and for indices based on the shortest wavelengths (ΔGR and ΔBG) and mid-infrared that are sensitive to the water content in cellular structures. The variations of all 4 indices sensitive to reflectance in mid-infrared (ΔNBR, ΔNBR2, ΔNDMI, ΔMSI) were significantly related with the in-situ parameters (see: Table 7).

Apart from ΔSR and ΔGR, the interactions among environmental variables were not found to have a significant impact on the changes in indices. The impacts of many of the analysed factors, including certain interactions, were found for SR. In the cases of ΔNDVI, ΔGNDVI and ΔBNDVI, the only factor that significantly differentiated the mean changes in indices was the number of main tree species. However, the post hoc test carried out for them did not show any significant differences between the means in the particular groups.

An assessment of the environmental factors with respect to the indices for which their statistically significant impacts were demonstrated (Table 7). According to Fig. 6A, as indicated by all the presented mean changes in indices, the condition of deciduous trees showed a deterioration in 2015 relative to 2014, whereas the condition of coniferous trees improved (the indices ΔGR and ΔMSI – inverse interpretation). Post hoc tests demonstrated that the means were significantly different between the groups of coniferous and deciduous trees (con–dec) in the cases of ΔEVI, ΔSAVI, ΔMSAVI, ΔSR, and ΔMSI.

It can be noted that for all the indices except for the ΔGR index the condition in 2015 improved relative to 2014, as the number of tree species increased (Fig. 6B). For most of the mean index changes, the condition noticeably improved in the group consisting of three or four tree species; moreover, the improvement of the condition in the group consisting of four tree species was much greater. Unfortunately, this group ('4') consisted of one observation only; therefore, it was impossible to assess the statistical significance of the differences between the means for this group compared with the others on the basis of a post hoc test. The difference between the means in groups '1' and '2' in the case of ΔGR was statistically significant.

In the case of the number of understory species, there was no distinct tendency for the condition to change as the num-

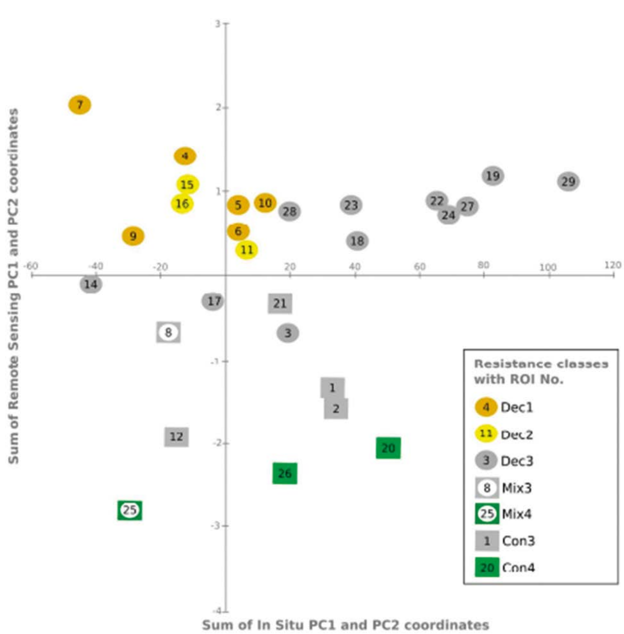

Figure 5. A comparison of the results of in-situ and remote sensing PCA analyses. Resistance classes are marked with sigh colour and shape according to Table 3

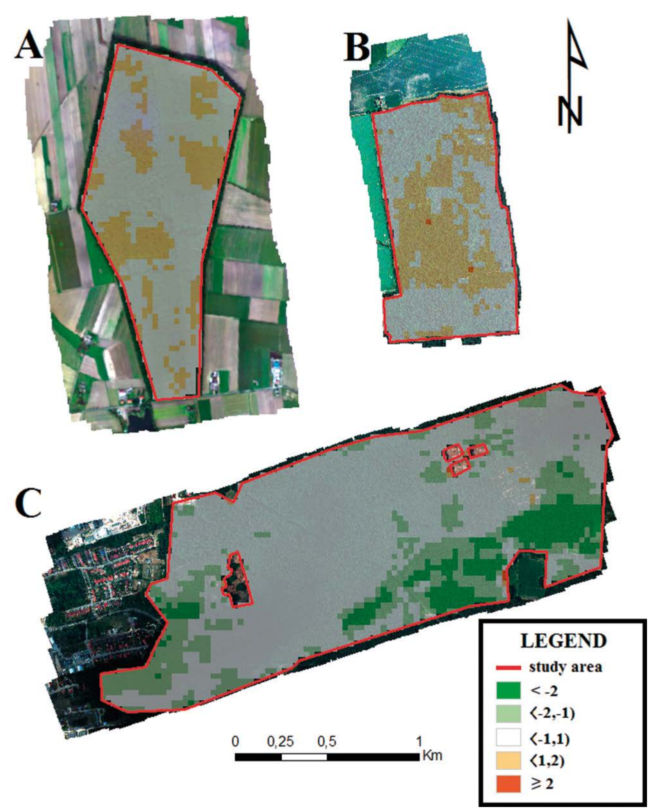

Figure 6. Mean changes in the index value in the particular groups defined, shown for all the indices for which a statistically significant impact of the variable was demonstrated

Explanations: BRk – acid brown soil, Gw – groundwater-dependent gley soil, OGw – rain-dependent gley soil, Pw – lessive ber of understory species changed (Fig. 6C). It can only be noted that in all the cases except for the ΔBG index, the condition improved in the absence of species in the understory (group '0').

Fig. 6D shows the tendency for the vegetation condition to change depending on the soil type. In most cases (except for ΔGR), the condition deteriorated on the OGW soil subtype (rain-dependent gley soil), whereas it improved on the other types. For most indices, the greatest improvement of the condition occurred on the RDbr soil subtype (rusty brown soil). Post hoc tests indicated two pairs of significantly different mean differences between the groups: BRk – OGw and OGw – RDbr (in the cases of all the indices shown in Fig. 6D except for ΔGR).

Vegetation response to rainfall deficits is delayed/lagged due to residual moisture capacity of the soil (Fig. 6D). The values of the differences between remote sensing indices divided according to soil types demonstrate that the greatest extent of the deterioration of the stand condition was found for habitats on sites with rain-dependent gley soils (OGw). The worst condition of these sites is readily observable. The water regime in these soils strictly depends on precipitation. This diagram also clearly shows the finer the mineral components are (the higher soil absorbing capacity is), the less resistance there is to the impact of drought. Lessive soils are built from different formations; most often from loess, dust, clays, or coarser sands. This mineralogical composition causes lesser permeability than that of acid brown soils and rusty brown soils. Moreover, rusty brown soils (RDbr) occur on much lighter formations than acid brown soils (BRk), causing precipitation- to usually seep quickly through to groundwater, with less water being available to vegetation than in the case of the other 4 soil types. Therefore, the water amount supplied by precipitation has a lesser impact on the environment on such soils.

5. Discussion

In the presented study, the highest deterioration of trees' condition was found in Krotoszyn Forest District, where the meteorological data showed the worst situation for plant growth among all the chosen areas. Changes in coniferous and mixed forests show their better resistance on drought stress (classes higher than 3: Mix and Con 3 and 4). The research on the forests in the Karczma Borowa Forest District did not demonstrate a deterioration of the condition of deciduous communities.

The mean values of indices in the particular Forest Districts do not reflect their character, since the species type has to be taken into account. Table 8 shows the results for the particular Forest Districts, for 2 types of forests and excluding mixed forests given the fact that single forests of this type occur (ROI8 and ROI25). The lowest values were found for coniferous forests in all the 3 Forest Districts, which confirmed their highest resistance. Deciduous forests in Krotoszyn suffered most severely from drought. Only 2 indices (ΔBG and ΔGR) showed a different trend. These were based solely on visible light wavelengths and as the only ones among all the indices, these did not include infrared. The standard deviation was the highest for these, indicating substantial diversity within the regions of interest. Different results for these indices can also be seen in the presentation of the differential indices for the particular regions of interest (Table 4). These were calculated using surface reflectance bands. Despite the differences between the trends of the differential indices ΔBG and ΔGR and those of the others, the ANOVA analysis showed their relationship with the environmental characteristics. Moreover, the index based on green and red light is much higher than the one based on blue and green light (Table 7). This shows that despite their different specificity, these indices can be applied to an analysis of natural processes; still, they should not be interpreted in the same way.

The highest values of standard deviation (Table 8) were found for areas dominated by the 'no change' class: coniferous forests in Piaski and Krotoszyn and deciduous ones in Piaski and Karczma Borowa Forest District. The standard deviation was the highest for coniferous forests in the Karczma Borowa (Table 8). At the same time, these areas were the most resistant to stressors. This confirms the conclusion that biodiversity influences the resistance of drought of a study forests area (Anderegg et al. 2018; Grossiord 2018; Kotlarz et al. 2018). The regions of interest consisting of most differentiated pixels, as a result of their spectral reflectance in the particular channels, also had the most diversified land cover. On the other hand, the statistical analysis for the deciduous forests in the Krotoszyn Forest District showed enhanced values of standard deviation. In these areas, the highest deterioration of forest condition over the two years was found. The individual fragments of the stand within one ROI could respond differently to water stress and contribute to its enhanced internal diversity.

The PCA analysis confirmed the ΔVI results described above, namely that coniferous trees were more resistant to drought than deciduous ones. Higher resistance to drought was found in ROIs with high biodiversity of trees and understory. Even deciduous trees in ROI25 with the related high Shannon-Wiener index were resistant to drought (they had the best condition among all the deciduous ROIs).

The results presented in Table 6 highlight the differences between ΔNDMI, ΔMSI, and ΔAVRI indices. ΔNDMI and ΔMSI are vegetation indices that are sensitive to plant water content (Xu 2006) and useful for water stress measurements (Cohen 1991). These results confirm the significant impact of drought on the forests in ROIs.

As a result, two categories with extreme changes can be found (Fig. 4): the positive one (ROIs: 1, 2, 12, 20, 25, 26) with the diversity index between 1.3 to 4.1, and the negative one (ROIs: 4, 7) with the diversity index between 1.75 and 1.8 (Table 2). The mean vegetation index change in the positive category is +0.65 (±0.50) σ with the greatest impact on ΔEVI (+1.01 σ), ΔMSAVI (+1.04 σ), and ΔSR (+1.22 σ) indices. The change in ΔMSI in this category is negative (-0.86 σ), confirming water stress in these ROIs and very good response to this stress.

Table 8. Characteristics of categories. Column titles according to Table 1.

Category	In-situ							Remote sensing							
	cnf	SW	age	h	nsp	nun	dtm	ΔEVI	ΔMSAVI	ΔNBR	ΔNDMI	**ΔNDVI**	**ΔSAVI**	**ΔARVI**	**AverageΔ**
”Old”	0.00	0.00	136.30	30.58	1.00	3.60	126.48	0.47	0.46	0.26	0.21	0.36	0.44	0.37	0.29
	±0.00	±0.00	±10.78	±1.47	±0.00	±2.07	±3.26	±0.10	±0.12	±0.07	±0.16	±0.13	±0.13	±0.07	±0.12
„Young. uniform”	0.00	0.00	31.00	11.69	1.00	2.00	154.39	1.28	1.08	0.71	0.71	0.66	1.01	0.68	0.61
„Young non - uniform”	3.00	0.39	44.27	16.72	3.00	2.00	140.20	-0.30	-0.38	-0.29	-0.25	-0.51	-0.45	-0.45	-0.29
	±3.00	±0.15	±9.49	±5.44	±1.00	±1.00	±24.50	±0.80	±0.95	±0.59	±0.55	±0.79	±0.88	±0.74	±0.70
Coniferous	9.17	0.18	84.23	25.20	2.00	3.00	145.07	-0.87	-0.83	-0.63	-0.69	-0.46	-0.68	-0.55	-0.49
	±0.75	±0.11	±11.24	±3.47	±0.63	±1.55	±21.06	±0.66	±0.48	±0.47	±0.51	±0.71	±0.51	±0.69	±0.61

The mean vegetation index change in the negative category is -0.48 (±0.34) σ with the greatest impact on ΔEVI (-0.92 σ), ΔMSAVI (-0.96 σ) and ΔSAVI (-0.862 σ) indices. This confirms a significant negative change in the biomass condition in these ROIs.

We can postulate three dependencies between ROI characteristics and response to drought in 2015: based on forest age, type, and biodiversity. Older, larger trees are more sensitive to drought than younger, smaller ones (Schuster, Oberhuber 2013; Bennett et al. 2015; Zhang et al. 2017). Nevertheless, the sensitivity of young forest stands depends on other factors, such as biodiversity. This result requires further work and confirmation using more precisely selected test sites (ROIs). Unfortunately, all of the ROIs with older trees are very uniform. Further work should include ROIs with diverse deciduous trees.

The results of the ANOVA analysis demonstrated a statistically significant impact of three factors (forest type, the number of main tree species and soil type) on the variability of the indices considered. Deciduous forests turned out to be more vulnerable to drought than coniferous and mixed forests. The number of tree species in the ROIs analysed was found to have a significant impact. As the number of tree species increased, the forest condition in a given area improved. However, as a result of too small a size of the groups analysed, it was impossible to carry out a more detailed analysis – a post hoc test – and to confirm statistically significant differences among most groups of these indices. The impact of the two factors describing the forest type and biodiversity coincided with the results obtained using the PCA method (Kotlarz et al. 2016).

Oak reacts differently, since its leaves only shoot in the early part of the growing season. Pine and other coniferous species have different tissue properties; therefore, their response to a lack of water is different (Coder 1999; Sass-Klaassen et al. 2006; McDowell et al. 2008). For this reason, the different results for coniferous and deciduous forests can be explained with the physiological properties of these tree types (Chara-Vaskou et al. 2012; Brodribb et al. 2014; Zhang et al. 2017).

Soil type was a third factor that demonstrated a significant impact on the variability of indices. The results show that forests growing on permeable soil turned out to be more resistant to drought than forests on hardly permeable soil. However, further research is required to confirm this conclusion, given the small size of the ROIs analysed and the fact that this conclusion was not confirmed by the PCA method.

It is important to analyse the situation of each Forest District separately. The weather conditions are variable locally. The distance between Karczma Borowa and Krotoszyn forests is about 100 km (Piaski is in the middle). In addition, the time distribution of precipitation deficits and the occurrence of high temperatures are diversified during the growing season in the particular regions. This had a significant effect on the course of the processes unfolding in vegetation. The research was done with use of data for three forests exposed to the impacts of three weather situations: typical conditions, the occurrence of drought and a moderate precipitation deficit. Table 1 presents measurements only from one location, east side of the analysed region.

The indices using the mid-infrared range are clearly more sensitive to water stress (Kim et al. 2015; Xue, Su 2017). Indices constituting products of two channels or those using the shortest electromagnetic wavelengths also demonstrated different behaviour. The use of many indices for the purposes of the present research and their analysis indicate their diversified potential. It also makes it possible to present the data in such a way as to highlight the individual aspects of a given area and the factors that affect them. It is important to note the constraints related to the use of medium-resolution data in the research on forest communities. The diameters of the individual treetops are much smaller than the size of a pixel and, as a matter of fact, diseases affect single trees; therefore, the response to stress is individual in nature. However, medium-resolution data give a general insight and are a result of the response of the vegetation in a given habitat. The calculated standard deviation values for the particular stand types show that in spite of a 30 m pixel, certain dependences are visible. However, their correct interpretation requires detailed knowledge of the habitat characteristics.

6. Conclusions

Remote sensing techniques can be used successfully in assessing forest stands. The conducted study made possible a remote confirmation of the following:

- Biodiversity has a positive effect on habitat resistance to stressful water conditions.
- Conifer/deciduous forest type determined the resistance of forest stand to drought stress.
- Water limitation in both form (precipitation and groundwater) have different effects on the condition of the forest stands depending on soil type.

The study confirmed the usefulness and effectiveness of the use of remote sensing methods in monitoring the occurrence of natural phenomena (on the example of drought) taking into account the additional parameters for environmental components. Individual remote sensing indices have been shown to have different applications and to be sensitive to different aspects of observed changes. The appropriate remote sensing methods should be carefully selected according to the defined specific requirements for the operational use of the algorithm.

The methods used for detailed mapping of drought extent are usually generated on the basis of multisource data, as meteorological and atmospheric models are needed, and they are highly dependent on field samplings. However, in order to simultaneously acquire basic, general information for an entire geographic region, only satellite-based models can be applied. Satellite remote sensing methods in drought monitoring may be used effectively even in areas where field data from the monitoring of groundwater, soil, evaporation or other such parameters are not available.

The presented analysis, provides a short-term prognosis for the forest condition related to the forest response to drought stress. The differential method proposed in this article is simple and, importantly, it can work without detailed field data; still, the correct understanding of results requires minimum field information (e.g., type of forests, soil properties). The presented method is based on easily accessible, popular Landsat-8 OLI Images. The method is easy for implementation, so operational use for large-scale monitoring would not cause any serious technical problems.

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Authors' contribution

S.A.N. was responsible for vegetation indices (VI) changes analysis; J.K. was responsible for PCA analysis; A.R. was responsible for statistical analysis; M.K. was responsible for the introduction and drought description and analysis; K.R. was responsible for preparation of aerial data; J.K., A.R. and S.A.N. analysed the data. S.A.N., M.K., J.K., and A.R. wrote the paper.