Spektrální indexy jako nástroj pro hodnocení růstu chmele

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SPECTRAL INDICES AS A TOOL FOR HOP GROWTH EVALUATION

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ABSTRACT

The use of unmanned aerial vehicles (UAV) to monitor crop growth is nowadays a common non-invasive way how to obtain information on the current state of crops. Spectral indices derived from multispectral images obtained in the right growth stage can then serve as a good data source for agro-technical interventions and yield estimation. Hop belongs among the crops where it is possible to scan the individual growth parameters very exactly. In the year 2021, significant precipitation amounts were recorded during the growing season, when it turned out that UAVs are a very powerful tool for determining the quality of production or quantification of vegetation damage compared to the previous year (2020). It was found that the common spectral indices were possible to use for calculation leaf area, structure, vigor and chlorophyll content of hop gardens.

INTRODUCTION

Monitoring of the growing process, gathering information and collecting data about the plants belongs to one of the main tasks of agronomy (Yang et al., 2015). The variability of plants reflects the characteristics of different varieties and abiotic as well as biotic factors occurring annually, e.g. weather conditions, temperature and relative humidity; or seasonally, e.g. diseases, irrigation systems malfunctions or weather events (Bégue et al., 2008). The ground-based monitoring can collect data with very high accuracy, but it is limited due to high workload and the time requirements (Kumhálová & Matějková, 2017). For this reason, for collecting these data, remote sensing has become a very popular technique (Comba et al., 2018). Among benefits of remote sensing use belongs continuous scanning during the whole vegetation season and time series collection to capture the growth phases (Domínguez et al., 2015), make current images during short time or in one moment. The data could help to analyze the crops growth process and the growth conditions (Yang et al., 2015). The remote sensing became a resource for acquiring agronomical data thanks to its affordability in compare with on-ground platforms of measuring and its sensing efficiency (Andújar et al., 2019). That is why the main aims of this study were to compare the hop gardens in two following years with other meteorological condition in terms of calculating the green area of canopy and structure, vigor and chlorophyll content with the help of selected spectral indices.

MATERIALS AND METHODS

The 1.72 ha study field is located near to Kněževes village (50.1491481N, 13.6205150E), in the Czech Republic, where Premiant hop variety was grown. The monthly precipitation and temperature during the main vegetation season was measured with Agrometeorological station located near to the study site (see Table 1).

Table 1 Monthly precipitation and temperature measured during the main vegetation season 2020 and 2021 at study site

Year	2020				2021			
Months	May	June	July	August	May	June	July	August
Temperature (°C)	11.3	16.8	18.4	19.6	10.8	19.4	18.8	16.6
Precipitations (mm)	43.4	85.0	40.4	68.4	70.0	131.0	68.8	70.6

Premiant is a hybrid semi-late variety with a growing season of 128 to 134 days. This variety is characterized by increased demands on nitrogen fertilization as well as tolerance to lack of water during vegetation. The yield is in the range of 1.8 to 2.5 t/ha.

The hop garden was scanned in two terms – 1st July 2020 and 7th July 2021 using eBeeX fixed wing drone with built-in RTK-PPK functionality (senseFly SA, Cheseaux-Lausanne, Switzerland) equipped with MicaSense Red Edge MX camera (MicaSense, Inc. Seattle, WA, USA) consists of five spectral bands: Blue band (with central wavelength of 475 nm and 20 nm band-width), Green (560 nm, 20 nm), Red (668 nm, 10 nm), Red Edge (717 nm, 10 nm), NIR (840 nm, 40 nm). The flights were performed at 75 m above ground with resulting 0.06 m spatial resolution of images, and 75% longitudinal and lateral overlaps. The obtained images were pre-processed in eMotion SW with the help of postflight tool in order to refine the georeference. Orthophotos and spectral indices were derived in Pix4D SW during the photogrammetric procedure.

Normalised Difference Vegetation Index (NDVI, Rouse et al., 1974), Green Normalised Difference Vegetation Index (GNDVI, Gitelson & Merzlyak, 1996), Chlorophyll Vegetation Index (CVI, Hunt et al., 2011), Triangular Greenness Index (TGI, Hunt et al., 2013) (details in Table 2) were then analysed in ENVI (version 5.6.1), ArcGIS Pro (version 2.9.2) and QGIS (version 3.16.8) SWs. The data extracted from images were then analysed in Statistica (version 13.5.0.17) SW.

Table 2 Vegetation indices derived for hop growth evaluation (R = red reflectance, G = green ref., NIR = near-infrared ref., Red Edge = red edge ref.)

Spectral Index	Algorithm	Used for:
Normalized Difference Vegetation Index	$NDVI = \frac{NIR - R}{NIR + R}$	Biomass, structure, vigor
Green Normalized Difference Vegetation Index	$GNDVI = \frac{NIR - G}{NIR + G}$	Chlorophyll
Chlorophyll Vegetation Index	$CVI = \frac{NIR}{Red\ Edge} - 1$	Chlorophyll
Triangular Greenness Index	$TGI = G - 0.39 \times R - 0.61 \times B$	Chlorophyll, nitrogen, green leaves detection

TGI spectral index was used for deriving binary model with the help of Otsu threshold method (Otsu, 1979). The resulting vector layer exactly delimited the green area of the crop, where a value of 0 meant green crop parts and a value of 1 meant bare soil or another surface. The layer of green vegetation was then smoothed in order to delete errors. The individual selected rows were bounded, and zonal statistics were calculated with the help of raster analysis and geoprocessing tools. The area and vigor of green crops in individual rows were calculated and evaluated.

In 2020 were analysed the first ten rows from the eastern edge of the hop garden. Because in 2021 it was not possible to do in-situ analyses of the same crop rows as in 2020 due to high precipitation totals and the subsequent flooding of part of the hop garden with water, the rows 14, 15, 20 and 21 were selected for a more detailed in-situ analysis in 2021. The UAV campaign covered the entire hop garden, regardless of the flooded parts of the hop garden (Fig.1).

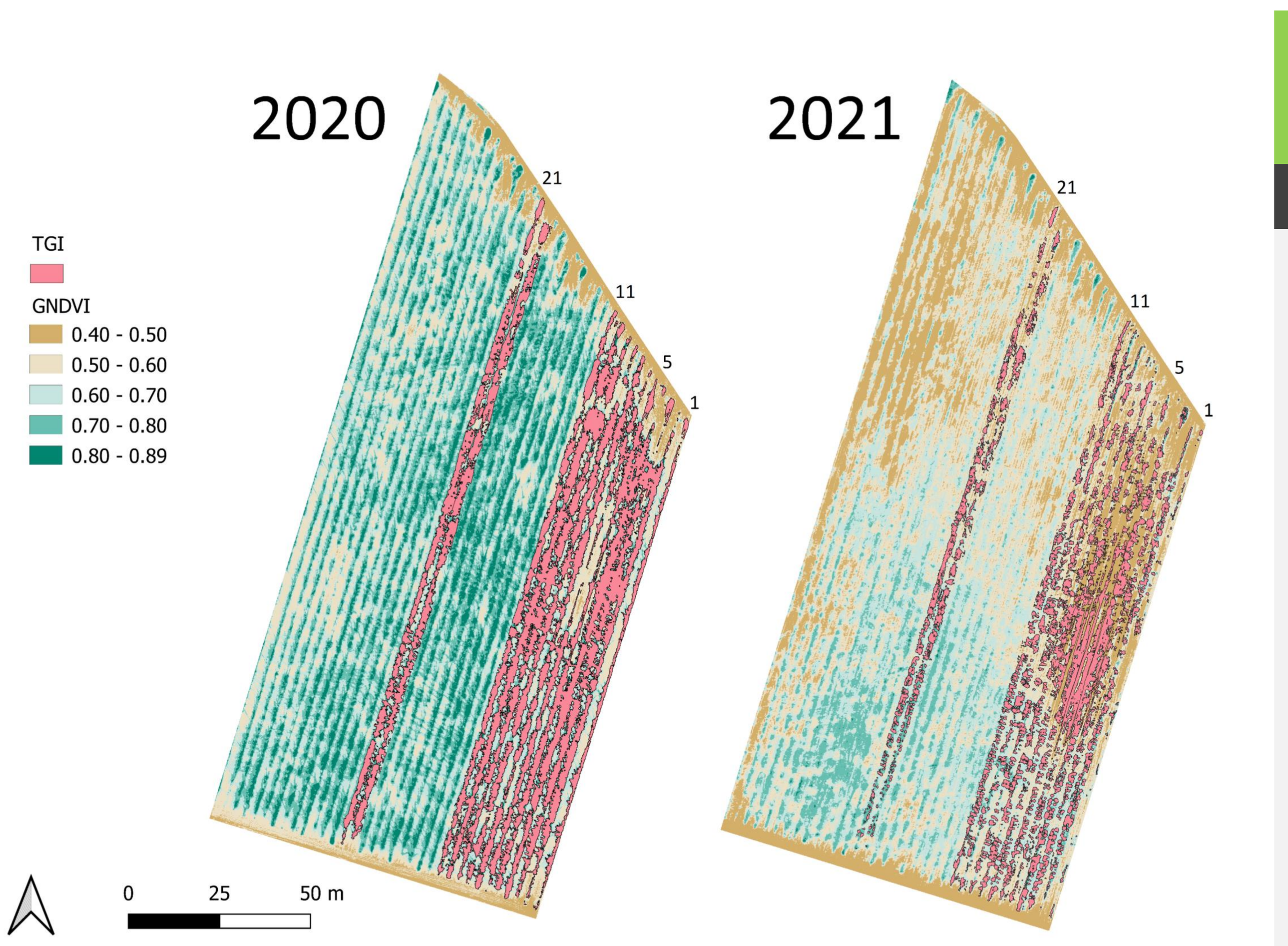

Figure 1 The difference between of the hop garden for 2020 and 2021 (GNDVI = Green Normalized Difference Vegetation Index and TGI = Triangular Greenness Index)

RESULTS AND DISCUSSION

Calculated area of green crops and selected variables (mean, standard deviation (StDev) and range) of zonal statistics for NDVI, GNDVI and CVI vegetation indices in individual rows are given in Table 3 for 2020 and in Table 4 for 2021.

The results showed that the area of the selected rows in 2021 was in average 55.8% (from 16% to 84%) smaller than in the previous year 2020 due to higher precipitation totals in 2021, which caused the subsequent flooding of the hop garden with water (details in Table 4). The green area extraction method used proved to be useful in terms of the possibility of calculating for a larger area and in case it is not possible to evaluate the vegetation in-situ. For example, Andújar et al. (2019) found that the use of aerial imagery techniques resulted in positive net returns, whereas the on-ground technologies needed a faster time of acquisition in order of them to be profitable.

NDVI as an indicator of vigor and structure of the canopy showed lower values in the year 2021 when the crop hops were damaged. On the other hand, the standard deviation was lower, and the range was higher in 2021 than in 2020. The results of GNDVI and CVI values were contradictory in standard deviation and data range, although both indices are often used as indicators of chlorophyll content in leaves. This could be probably caused due to the use of other spectral bands in the calculation. While GNDVI worked with reflectance values of GREEN and NIR bands, the CVI index used the NIR and RED EDGE spectral bands. This agrees with the findings of Segarra et al. (2022) that Greenness sensitive indices such as CVI had different results in contrast with the biomass sensitive indices (GNDVI). Mean GNDVI value was much higher in 2020 with lower standard deviation and data range than in the year 2021. A very high difference between the mean CVI values in 2020 and 2021 confirmed the lack of chlorophyll in leaves and poorer crop vigor in 2021. On the other hand, the canopy had higher variability in 2020, when the crops were in better condition.

Table 3 Calculated area and spectral indices values (NDVI = Normalized Difference Vegetation Index, GNDVI = Green NDVI and CVI = Chlorophyll Vegetation Index) for selected hop rows and in average (Avg) in 2020

Row	Area	NDVI			GNDVI			CVI		
(-)	(m^2)	Mean	StDev	Range	Mean	StDev	Range	Mean	StDev	Range
1	113.2	0.75	0.11	0.51	0.73	0.06	0.31	1.30	0.37	2.44
2	202.8	0.79	0.10	0.52	0.76	0.05	0.32	1.57	0.40	2.55
3	238.0	0.77	0.11	0.56	0.75	0.06	0.40	1.49	0.44	2.61
4	282.6	0.79	0.11	0.52	0.77	0.06	0.32	1.63	0.47	2.63
5	208.0	0.78	0.11	0.55	0.76	0.06	0.34	1.56	0.45	2.82
6	156.4	0.76	0.12	0.52	0.75	0.06	0.33	1.51	0.46	2.43
7	220.5	0.78	0.11	0.51	0.76	0.06	0.34	1.56	0.43	2.83
8	223.9	0.78	0.11	0.51	0.76	0.06	0.33	1.59	0.45	2.55
9	249.3	0.78	0.11	0.56	0.76	0.06	0.35	1.59	0.46	3.00
10	310.4	0.80	0.11	0.53	0.77	0.06	0.35	1.69	0.48	3.15
11	243.8	0.79	0.11	0.57	0.77	0.06	0.36	1.65	0.48	3.05
20	304.9	0.79	0.10	0.55	0.76	0.06	0.36	1.61	0.46	3.18
21	293.7	0.78	0.11	0.54	0.76	0.06	0.38	1.58	0.48	3.17
Avg	435.4	0.78	0.11	0.53	0.76	0.06	0.35	1.56	0.45	2.80

Table 4 Calculated area (absolute values in m2 and comparison to 2021 in %) and spectral indices values (NDVI = Normalized Difference Vegetation Index, GNDVI = Green NDVI and CVI = Chlorophyll Vegetation Index) for selected hop rows and in average (Avg) in 2021

Row	Area	Area to 2021	NDVI			GNDVI			CVI		
(-)	(m^2)	(%)	Mean	StDev	Range	Mean	StDev	Range	Mean	StDev	Range
1	18.5	16.3	0.76	0.12	0.51	0.63	0.10	0.46	1.05	0.47	2.32
2	113.8	56.1	0.80	0.07	0.55	0.65	0.06	0.51	1.00	0.30	2.26
3	119.1	50.0	0.76	0.10	0.59	0.60	0.09	0.57	0.82	0.36	3.35
4	198.6	70.3	0.73	0.13	0.67	0.58	0.11	0.55	0.73	0.37	2.66
5	146.6	70.5	0.65	0.15	0.68	0.49	0.12	0.54	0.47	0.35	2.19
6	131.4	84.0	0.69	0.14	0.62	0.52	0.12	0.56	0.56	0.34	1.99
7	153.1	69.4	0.74	0.11	0.61	0.58	0.10	0.56	0.73	0.32	2.27
8	137.3	61.3	0.76	0.09	0.56	0.60	0.08	0.51	0.77	0.25	2.05
9	118.5	47.5	0.77	0.08	0.54	0.62	0.06	0.45	0.83	0.26	2.28
10	125.0	40.3	0.80	0.07	0.49	0.65	0.05	0.41	0.97	0.30	2.46
11	147.3	60.4	0.78	0.08	0.57	0.63	0.05	0.42	0.86	0.25	1.99
20	140.1	45.9	0.78	0.10	0.54	0.65	0.07	0.45	1.00	0.37	2.68
21	157.2	53.5	0.79	0.09	0.51	0.66	0.07	0.48	1.04	0.38	2.56
Avg	131.3	55.8	0.75	0.10	0.57	0.60	0.08	0.50	0.83	0.33	2.39

CONCLUSIONS

This study addressed the hop gardens in two following years with other meteorological condition. The results showed that the area of the selected rows in 2021 was in average 55.8% smaller than in the previous year 2020 due to higher precipitation totals in 2021. NDVI as an indicator of vigor and structure of the canopy showed lower values in the year 2021 when the crop hops were damaged. On the other hand, the standard deviation was lower, and the range was higher in 2021 than in 2020. The results of GNDVI and CVI values were contradictory in standard deviation and data range. Mean GNDVI value was much higher in 2020 with lower standard deviation and data range than in the year 2021. A very high difference between the mean CVI values in 2020 and 2021 confirmed the lack of chlorophyll in leaves and poorer crop vigor in 2021. On the other hand, the canopy had higher variability in 2020, when the crops were in better condition. The selected common spectral indices were possible to use for calculation leaf area, structure, vigor and chlorophyll content of hop gardens.

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