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.

Key words: *unmanned aerial vehicles; geoinformatics; crop stress; vegetation parameters.*

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 analyse 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).

Hop belongs to marginal crops with regards to its growing area, but its cultivation is efficient, in addition, hops play a very important role in the world and especially in the Czech brewing industry. For this reason, Czech hop is an important export crop (Rybáček, 1991). Plants observation and counts in early stages of growth are very valuable for the hop growers because they still have time to replant the plants. The camera-based observation is also important for the determination of the plant volume and the yield of hops. The important aspect is how to identify the green object, the usual method is to use the spectral indices (Guijarro et al., 2011).

One of them spectral indices Normalised Difference Vegetation Index (NDVI; Rouse et al., 1974) is often stated as reliable estimator of crop health and structure. This spectral index belongs among according to the scientific literature the most used for crop condition estimation as well (Khan et al., 2018). For example, Pádua et al. (2019) created a vitality map based on NDVI values with the aim to analyse vineyards vegetation during the whole growing season.

Another is Green Normalized Difference Vegetation Index (GNDVI; Gitelson & Merzlyak, 1996). This spectral index is an indicator of the photosynthetic activity of the vegetation and is most used for multispectral data which do not have an extreme red channel. Compared to the NDVI, GNDVI is more sensitive to chlorophyll concentration, it is used in assessing depressed and aged vegetation (Candiago et al., 2015).

Next index of them Chlorophyll Vegetation Index (CVI; Hunt et al., 2011) has an increased sensitivity to the content of chlorophyll in the deciduous cover. CVI is used from early to mid of the crop growth cycle for a wide range of soils and sowing conditions by analysing a large synthetic data set obtained using a leaf surface reflectance model. This index uses to the concentration of chlorophyll in the leaf an effective normalization of various values obtained with the introduction of red and green colours (Vincini et al., 2014).

Pádua et al. (2019) used only RGB images to calculate area of vegetation (in this case vineyards) for crop growth estimation. RGB images works only with the visible part of electromagnetic spectrum, there are several RGB spectral indices for estimating the area.

One of these, Triangular Greenness Index (TGI; Hunt et al., 2013), appears to be sensitive to the chlorophyll concentration in the green parts of plants and is able to extract green parts well from other vegetation (Hunt et al., 2013). This procedure seems to be effective in case of typical hop garden row structure.

The data processing for the calculation of vegetation indices has limits in the choice of threshold for the detection of green object and bare soil. These problems help to eliminate the Otsu´s method, which is based on automatic threshold selection for picture segmentation. This procedure results in a binary image that can improve the final results obtained from vegetation indices (Otsu, 1979). Pádua et al. 2018 used this method for binary image extraction in vineyards, but the use of remote sensing data is challenging in hop gardens due to the row structure and plant canopies. It is the challenge to use similar methods to vineyard monitoring to derive the green vegetation of hop gardens and calculate its volume.

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).

Tab. 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 bandwidth), 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 georeferenced. Orthophotos and spectral indices were derived in Pix4D SW during the photogrammetric procedure. Normalised Difference Vegetation Index (NDVI), Green Normalised difference Vegetation Index (GNDVI), Chlorophyll Vegetation Index (CVI), Triangular Greenness Index (TGI) (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.

Tab. 2 Vegetation indices derived for hop growth evaluation.

Spectral Index	Algorithm	Used for:	References
Normalized Difference Vegetation Index	$NDVI = \frac{NIR - R}{NIR + R}$	Biomass, structure, vigor	Rouse et al. (1974)
Green Normalized Difference Vegetation Index	$GNDVI = \frac{NIR - G}{NIR + G}$	Chlorophyll	Gitelson et al. (1996)
Chlorophyll Vegetation Index	$CVI = \frac{NIR}{Red\ Edge} - 1$	Chlorophyll	Gitelson et al. (2005)
Triangular Greenness Index	$TGI = G - 0.39 \times R - 0.61 \times B$	Chlorophyll, nitrogen, green leaves detection	Hunt et al. (2013)

R = red reflectance, G = green reflectance, NIR = near-infrared reflectance, Red Edge = red edge reflectance.

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 analyzed the first ten rows from the eastern edge of the hop garden. Because in 2021 it was not possible to do in-situ analyzes 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).

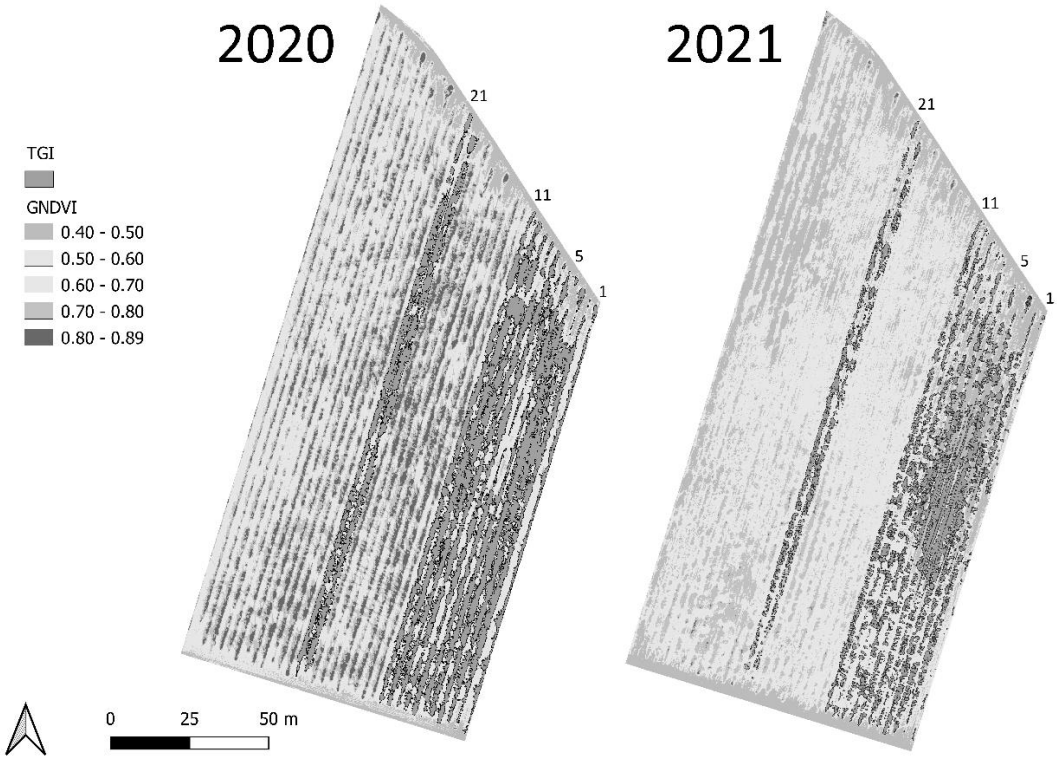

Fig.1 The difference between of the hop garden for 2020 and 2021 (GNDVI = Green Normalized Difference Vegetation Index and TGI = Triangular Greenness Index).

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.

Tab. 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

Tab. 4 Calculated area (absolute values in m^2 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

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 (Rouse et al., 1974) 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 (Meng et al., 2015). This could be probably caused due to the use of other spectral bands in the calculation (Lorencs et al., 2014). 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.

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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