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Comparing RGB - based vegetation indices from UAV imageries to estimate hops canopy area

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Abstract. Remote estimation of hops plants in hop gardens is imperative in field of precision agriculture, because of precise imaging of hop garden structure. Monitoring of hop plant volume and area can help to predict the condition and yield of hops. In this study, two unmanned aerial vehicles (UAV) - eBee X senseFly UAV equipped with Red Green Blue (RGB) S.O.D.A. camera and Vertical Take-Off Landing (VTOL) UAV FireFly6 Pro by BirdsEyeView Aerobotics equipped with MicaSense RedEdge MX camera were used to acquire images of hop garden at phenology stage maturity of cones (24 th July) before harvest. Seven commonly used RGB vegetation indices (VI) were derived from these RGB and multispectral (MS) images after photogrammetric pre-processing and orthophoto mosaic extraction using Pix4Dmapper software. Vegetation Indices as the Green Percentage Index (G%), Excess of Green Index (ExGreen), Green Leaf Index (GLI), Visible Atmospherically Resistant Index (VARI), Red Green Blue Vegetation Index (RGBVI), Normalised Green Red Difference Index (NGRDI) and Triangular Greenness Index (TGI) were derived from both data sets. Binary model from each of VI was derived and threshold value for green vegetation was set. The results showed significant differences in hop plant area based on the specifications of cameras, especially wavelengths centres, and design and flight parameters of both UAV types. The comparison of various indices showed, that ExG and TGI indices has the highest congruity of estimated vegetation indices in hop garden canopy area for both used cameras. Further processing by Fuzzy Overlay tool proved high accuracy in green canopy area estimation for ExG and TGI vegetation indices.

Key words: unmanned aerial vehicles, hop garden, vegetation indices, canopy area.

INTRODUCTION

Hops with its growing area belongs to the marginal crops; on the other hand, its cultivation is very effective. In addition, hops have an important position in the world brewing industry, especially the Czech one. For this reason, Czech hops is an important export article (Rybáček, 1991).

The crop growth monitoring is one of the most important tasks in agronomy. The results could help to analyse the crop growth process and the growth conditions (Yang et al., 2015). Remote sensing has become a very popular technique in crop information acquiring due to its ability to collect images in various spectra. There are three commonly used remote sensing methods: satellite, ground based and aerial (e.g. UAV = unmanned aerial vehicles). Satellite methods can help to estimate the crop yield, chlorophyll and nitrogen content (Vincini et al., 2016), leaf area index (Xie et al., 2018), etc., but it is limited to its spatial resolution (Kumhálová et al., 2014). The ground-based platform enables to collect data with high accuracy, but it is limited to high workload, which can require long time of measurement (Kumhálová & Matějková, 2017). The fast development in UAV industry and its ability to hold various cameras and sensors have increased the utilization of UAV in field data collecting (Wan et al., 2018). The UAVs are able to hold various cameras and collect accurate data with strong correlation to the ground based collected data (Santos et al., 2020). The camera-based observation is also important for the determination of canopy area, plant volume and the yield of hops. Regardless of the subject of the analysis, the most important aspect is how to identify the green object. There are more options to identify greenness in a crop image. The usual method to identify the greenness is to use the spectral indices (Guijarro et al., 2011). There are many indices used in the agriculture, most of them have been developed for specific purposes. A quick glance at the results usually shows regions with low and high index values. The output of the index is assigned to a colour from a colour scale and generate a false colour image of the monitored area (McKinnon & Hoff, 2017).

Lussem et al. (2018) conducted a research, where they compared results from different spectral indices based on RGB camera (Sony Alpha 6000) imagery with Yara N-Sensor for dry matter yield prediction in the grassland. They selected for their study such spectral indices as Visible Atmospherically Resistant Index (VARI), Normalised Green Red Difference Index (NGRDI) and Normalised Difference Vegetation Index (NDVI). The results showed a good correlation e.g. the value of determination for NGRDI was obtained 0.62 and for VARI 0.63. Other relevant indices were SR (Simple Ratio Index) (0.63) and NDVI (0.65). The NDVI index is most used index worldwide since its introduction in 1974 (Rouse et al., 1974), therefore, there are many researches based on this index, just like another study comparing UAVs RGB based vegetation indices (VARI & TGI) with NDVI (McKinnon & Hoff, 2017). In general, VARI index is mostly dependent on leaf-area while Triangular Greenness Index (TGI) is mostly dependent on chlorophyll and nitrogen. For this reason, these indices may represent some aspects of the NDVI index; on the other hand, the researchers mentioned almost the same count of failures as successes for VARI & TGI indices in comparison to the NDVI index. The processing of the data for vegetation indices calculation has the limits in the threshold selection for detecting the green object and bare soil. These problems help to eliminate the Otsu´s method, which is based on automatic threshold selection for picture segmentation. The result of this procedure is binary image, which can improve the final results derived from vegetation indices (Otsu, 1979). Pádua et al. (2018) used this method for binary image extraction in vineyards.

However, the use of remote sensing is very challenging in hop gardens or vineyards due to the row structure and plant canopies. Within the vineyard plot or hop garden is bare soil or vegetation cover, which may results in presence of inappropriate information such as: inter-row vegetation cover, shadows produced by the plants etc.; when considering the whole hop garden or vineyard. Rybáček (1991) stated that according to historical documents the Czech hop-growing terminology could be sometimes similar to that used in wine-making. Nevertheless, there are many differences in comparison with vineyard. It is the challenge to use similar methods to vineyard-monitoring for deriving green vegetation of hop gardens and calculate its canopy area. Rybáček (1991) described in his study reproduction (propagation) coefficient of the stand (KRP) which depends on the amount of above-ground biomass and the ration of cones to this biomass. This calculation can be good indicator of hops yield. Spectral indices can serve as simply way how to calculate above-ground biomass. The vegetation indices are usually computed over the entire remote-sensed area. In this case, the unrelated information is present and the separation of sensed plants and inappropriate information is required. Pádua et al. (2018) conduct research on this theme, using UAS (Unmanned Aerial System) equipped by RGB camera with resolution of 12 MPx. There were compared thirteen vegetation indices (VI) and computed crop surface model to estimate which index is the best for vineyard vegetation detection. The best vegetation indices were then: ExG, GBVI, RGBVI, GLI & G%.

The main objective of this study is to calculate RGB indices over the selected hop garden and to find out which index is the best for canopy area calculation with regard to the specific structure of hop garden.

MATERIALS AND METHODS

Study area

The study area is an 5.5 ha experimental field located near to Stekník village

(N 50°19'28.692"N, E 13°37'22.738"), in the Czech Republic. The hop garden comprised 3 hop varieties - Agnus (1.5 ha), Premiant (2.4 ha) and Sládek (1.6 ha) (see Fig. 1). The conventional hop garden technology with irrigation was used for crop cultivation. The mission was arranged in 24 June 2019 when the hop plants are fully growen with cones developing, and plant hight of 7 m (see Fig. 2).

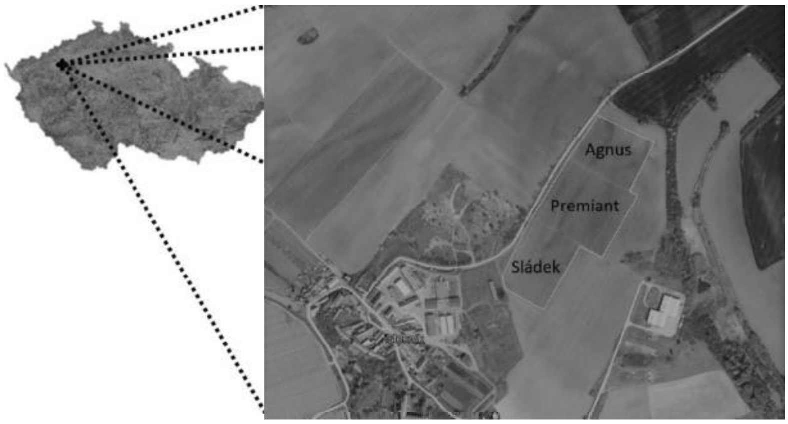

Figure 1. Location of experimental hop garden divided to three parts according to hop variety.

UAV equipment and flight configuration

Aerial survey were conducted using eBee X and FireFly6 Pro (FF6P) drones. The eBee is the fixed-wing drone (senseFly SA, Cheseaux-Lausanne, Switzerland), equipped with a built-in RTK-PPK functionality, and S.O.D.A. camera (Sensor Optimised for Drone Applications; senseFly SA, Cheseaux-Lausanne, Switzerland) with 20 Mpx RGB sensor and 28 mm focal lens. The FF6P is fixed-wing UAV (BirdsEyeView Aerobotics), equipped with multispectral MicaSense RedEdge-MX camera (MicaSense, Inc. Seattle,

Figure 2. Current status of Premiant hop variety in 24 July 2019.

WA, USA) containing five spectral bands and 1.2 Mpx per EO (Earth Observation) band sensor resolution. Spectral properties of cameras used in this study is given in Table 1.

Table 1. Spectral properties of cameras used in this study

Band (nm center)	S.O.D.A. eBee X	MicaSense Red Edge-MX FF6P
BLUE	450 nm (center, 100 nm bandwitdth)	475 nm (center, 20 nm bandwitdth)
RED	520 nm (center, 250 nm bandwitdth)	560 nm (center, 20 nm bandwitdth)
GREEN	660 nm(center, 130 nm bandwitdth)	668 nm (center, 10 nm bandwitdth)
RED EDGE	-	717 nm (center, 10 nm bandwitdth)
NEAR-IR	-	840 nm (center, 40 nm bandwitdth)

This study flight took place in 24 June 2019 between 11:30 a.m. and 1:00 p.m CET for both UAV technology. The eBee X flight was performed at 119 m above take-off height, with speed 15 m s^{-1} in average, and with resulting 2.77 cm spatial resolution of images. The images overlap was 80% longitudinal and 65% lateral. SW eMotion by SenseFly (see https://www.sensefly.com/software/emotion/) was used for setting the flight mission parameters. The FF6P flight was performed at 90 m above take-off height, with speed 16 m s^{-1} in average, and with resulting 7.43 cm spatial resolution of images. The images overlap was 80% longitudinal and 65% lateral.

UAV images processing

Acquired data were processed using Pix4Dmapper (Pix4D SA, Cheseaux - Lausanne, Switzerland), where image calibration, point cloud densification and orthophotomosaics (in WGS 84 UTM Zone 33 coordinate system) were calculated from each of datasets. Orthophotomosaics were then processed in ENVI, ArcGIS SW (ESRI, Redlands, CA, USA) and QGIS SW (Free Software Foundation, Inc., Boston, MA, USA). Selected RGB indices (see Table 2) were calculated for each of varieties and data sets. Green Percentage Index (G%), Excess of Green Index (ExGreen), Green Leaf Index (GLI), Visible Atmospherically Resistant Index (VARI), Red Green Blue Vegetation Index (RGBVI), Normalised Green Red Difference Index (NGRDI) and Triangular Greenness Index (TGI) were chosen to estimate the area of hop plants.

Table 2. RGB vegetation indices used in this study for UAV systems comparison

RGB Spectral Index	Algorithm	References
Green Percentage Index	$G\% = \frac{G}{R + G + B}$	(Richardson et al., 2007)
Excess Green	$ExG = 2 \times g - r - b$	(Woebbecke et al., 1995)
Excess Green- Excess Red	$ExG - ExR$	(Meyer & Neto, 2008)
Green Leaf Index	$GLI = \frac{(G - R) + (G - B)}{2G + R + B}$	(Gobron et al., 2000; Hunt et al., 2013)
Red Green Blue Vegetation Index	$RGBVI = \frac{G2 - (B \times R)}{G2 + (B \times R)}$	(Bendig et al., 2015)
Visible Atmospherically Resistant Index	$VARI = \frac{G - R}{G + R - B}$	(Gitelson et al., 2002)
Normalised Green Red Difference Index	$NGRDI = \frac{G - R}{G + R}$	(Falkowski et al., 2005; Gitelson et al., 2002; Kawashima & Nakatani 1998; Tucker, 1979)
Triangular Greenness Index	$TGI = G - 0.39 \times R - 0.61 \times B$	(Hunt et al., 2013)

Where g = G/(R+G+B); b = B/(R+G+B); *r* = R/(R+G+B); and green (G), red (R) and blue (B) are the reflectance values of each band.

Binary models (0;1) were then derived from resulting indices with the help of threshold based on Otsu´s method (Otsu, 1979). This nonparametric and unsupervised method is based on automatic threshold selection for picture segmentation. In our study the value 0 equals to bare soil and value 1 represent vegetation. Resulted binary rasters were then converted to vector model (polygon shapefiles) for calculating area possibilities for each of varieties and UAV data sets. Excess Green (ExG) and TGI index were used for next image analysis because these indices showed the most accuracy estimation of vegetation cover in hop garden area in comparison with RGB orthophotomosaics. Using Map algebra tool in ArcGIS SW the ExG and TGI indices for each data sets (eBee and FF6P) were deducted from each other with the aim to find out the accuracy of vegetation area calculation. The tool Fuzzy Overlay (Spatial Analyst tool - Overlay; ArcGIS SW) were then used for two model deriving ExG and TGI, which combines the raster of both binary model based on selected index (Fuzzy Overlay of ExG from eBee and ExG from FF6P; and Fuzzy Overlay TGI from eBee and TGI from FF6P). Fuzzy Overlay tool allows the analysis of the possibility of a phenomenon belonging to multiple sets in a multicriteria overlay analysis. Fuzzy Overlay not only determines what sets the phenomenon is possibly a member of, but also analyses the relationships between memberships among multiple sets. The Fuzzy 'Or' Overlay type, which was set for our purposes, will return the maximum value of the sets the cell location belongs to. This technique is useful when you want to identify the highest membership values for any of the input criteria (ArcGIS 10.4, ESRI, 2019). These resulting models derived on the base of Fuzzy Overlay algorithm were compared with each other to determine the accuracy of these models.

RESULTS AND DISCUSSION

Table 3 shows leaf area for each hop variety. The leaf area is derived from both UAV systems: eBee X and FF6P. The results show differences between both sensing which could be caused for various reasons. The eBee X had higher spatial resolution than FF6P and with the Otsu´s binary model for automatic threshold detection the differences between both sensing occurred. The differences between the sensing vary for each indices differently. Similar studies realized in vineyards proved, that UAVs with various cameras spatial resolution could provide accurate data. To provide accurate data, the sensor-related radiometric and spectral calibration are important (Brook et al., 2020). As was confirmed by Pádua et al. (2018) higher accuracy or the least difference is between the ExG and NDVI indices. The ExG as well as TGI indices were used for further processing and in the Table 3 the values are highlighted. The TGI (McKinnon & Hoff, 2017) and ExG indices are mostly dependant on the chlorophyll and nitrogen content, this mean that these indices should be very similar, but even there are differences. These differences are characterized by higher values of TGI index in all variants. These differences, between these two indices, could have occurred due to colour shade change by shadows of the hop canopy, which occurs at any circumstances, due to the technology of hop growing in hop gardens. Another possibility of these differences could be the different colour of leaves (mostly yellow) in the lower layer of hop canopy which is mainly dependant on the hop growth stage and its variety. As proved in the study of Fuentes-Peailillo et al. (2018) the TGI index has best results in canopy cover determination also by different sparse crops in comparison with NDVI. On the other hand the results show that the accuracy of the canopy cover determination depends on the spatial resolution of image. Hunt et al. (2013) proved that the utilization of TGI index has best results in later phenology stages, when it is only affected by leaf chlorophyll content, therefore TGI is the best to detect crop nitrogen requirements. In our study this statement was confirmed, when ExG and TGI were used for further analysis.

Table 3. Leaf area (m^2) derived from eBee X and FF6P UAV systems for individual hop varieties

Index/ Variety	eBee X			FF6P		
	Agnus	Premiant	Sládek	Agnus	Premiant	Sládek
ExGExr	3,374.8	5,223.5	7,711.3	8,227.2	13,478.5	12,081.2
ExG	**5,251.6**	**8,802.0**	**8,089.2**	**3,702.6**	**4,851.4**	**6,117.6**
GLI	709.6	1231.8	478.9	10,579.7	17,166.9	13,947.1
GPI	-	-	-	7,769.1	13,036.3	11,999.7
NGRDI	1,919.2	1,886.7	438.5	8,130.0	13,333.7	11,992.2
RGBVI	-	-	-	9,166.5	15,351.4	13,172.2
TGI	**5,520.0**	**9,240.4**	**8,260.4**	**4,452.3**	**6,278.1**	**6,998.8**
VARI	1,959.3	1,920.3	464.6	8,279.1	13,490.1	12,050.3

The comparison of ExG and TGI from eBee X and FF6P in Table 4 shows, that the green vegetation was mostly identified in both layers. The majority of the vegetation was identified by both UAVs, but the eBee has more unique identification of green vegetation than it is in FF6P layer. This is caused by the difference of both cameras their different spectral properties and by various spatial resolution too. Additional small differences should be caused by the different length and/or position of the shadows of hop canopy caused by impossibility to fly over monitored area at the same time with both UAVs due to law restriction and safety of persons and property.

Table 4. Changes of area of hop garden (m^2) derived from models eBee and FF6P UAVs systems deducted from each other for individual hop varieties. The value 0 = no changes; -1 = green vegetation' was only 'FF6P' layer, 1 = green vegetation' was only in 'eBee' layer

Index/ Variety	Changes	Agnus	Premiant	Sládek
ExGeBee-	-1	283.9	466.0	196.7
ExG FF6P	0	12,792.3	19,835.6	14,122.6
	1	17,77.9	4,355.8	2,040.2
TGIeBee-	-1	381.9	799.8	499.8
TGI FF6P	0	13,065.5	19,328.9	14,184.8
	1	1,406.7	3,706.9	1,674.9

From the previous results (Table 3 & 4) is obvious that it is possible to use standard RGB cameras with high resolution to estimate these indices and leaf area at least in hop gardens and probably in vineyards. This agrees with Lussem et al. (2018) who confirmed the usage of RGB camera in grasslands, but in this case were used different indices namely NGRDI and SR. Pádua et al. (2018) found out similar results with RGB camera utilization. They stated that low-cost RGB camera proved to have enough accuracy for vineyard monitoring. Barbosa et al. (2019) concluded in their study that all of the evaluated vegetation indices, derived for grass monitoring, were affected by lighting condition of the scanned location. We solved similar problems with hop crops.

Thanks to the spatial analyst tool Fuzzy Overlay, the leaf area is presented in Table 5. The leaf area is derived from the multicriterial overlay analysis. This tool utilizes layers ExG from eBee X and FF6P and area from TGI from eBee X and FF6P for the leaf area determination with the highest possible accuracy.

Table 5. Leaf area (m^2) calculated for ExG and TGI model with the help of Fuzzy Overlay tool (combination of layers ExG eBee and ExG FF6P; TGI eBee and TGI FF6P)

Index/Variety	Agnus	Premiant	Sládek
FuzzyExG	5,575.7	10,119.9	8,820.2
FuzzyTGI	5,953.6	13,681.8	7608.7

For selected hops varieties there are also presented comparisons of Fuzzy models. In the Table 6 the changes of hop garden area for models FuzzyExG and FuzzyTGI are presented. The table proves that both models are very accurate, because the differences between the layers are less than 4% in comparison with the common (both layers) area. These changes are also shown in Fig. 3. This figure demonstrate the differences between ExG and TGI fuzzy

Table 6. Changes of area of hop garden (m^2) derived from Fuzzy models (FuzzExG minus FuzzyTGI) for selected hop varieties. The value 0 = no changes; -1 = 'green vegetation' was only TGI layer, 1 = 'green vegetation' was only in ExG layer

Index/ Variety	Changes	Agnus	Premiant	Sládek
FuzzyExG-	-1	385.3	781.6	424.2
TGI	0	14,160.1	22,863.6	15,968.3
	1	93.9	150.8	33.3

models. Differences can be caused by the actual status of individual plants. The results of individual flights can be affected by movement of main stem (bine) and its lateral branches (shoots) which are wrapped around wires. The stem reaches a height of 7 m (upper limit of construction) and grows at an angle, which can caused different lighting condition inside of the hop garden (shadows) (Rybáček, 1991). Other reasons may be different flight altitudes and other camera and drone specifications. However Caruso et al. (2017) in their study reported that the RGB consumer camera mounted on UAV can be sufficient tool for canopy modelling.

The results of Fuzzy Overlay are with agreement with Baidya et al. (2014). They concluded that fuzzy overlay analysis is computationally more expensive but it gives more accurate and consistent results.

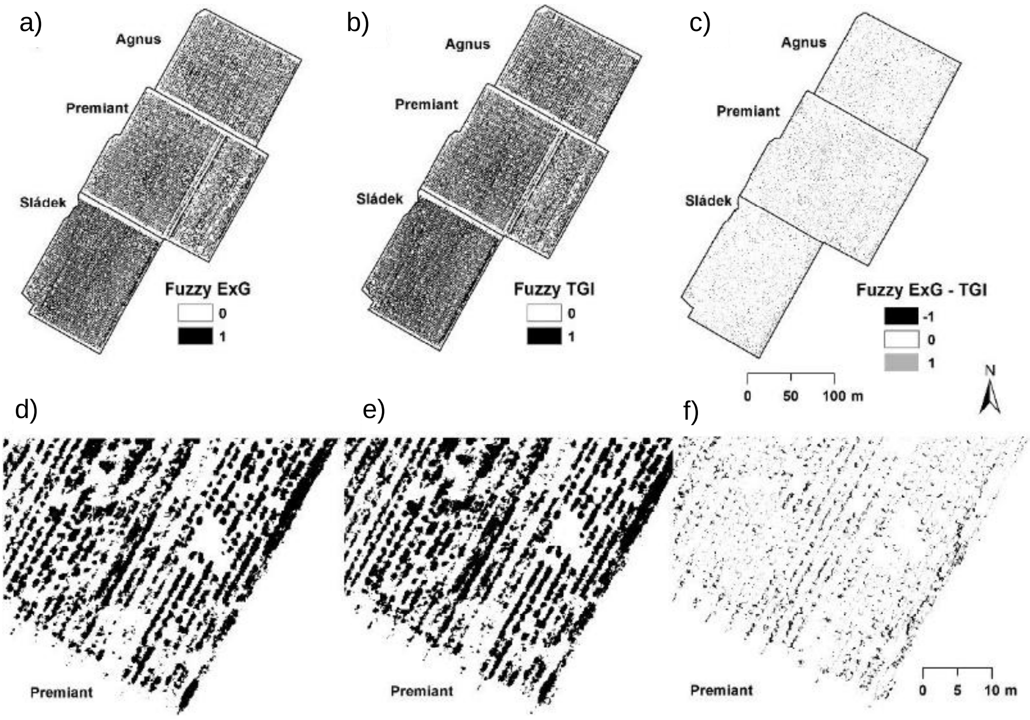

Figure 3. Fuzzy models ExG (a) and TGI (b) and changes of area of hop garden (m^2) derived from Fuzzy models (FuzzExG minus FuzzyTGI) (c) for selected hop varieties. Premiant hop variety Fuzzy models and its changes are shown in detail below - Fuzzy ExG detail (d), Fuzzy TGI detail (e), and changes (Fuzzy ExG - TGI) detail (f).

CONCLUSIONS

The results showed that vegetation indices could be used for the hop plants area monitoring. Hop belongs to the least researched crops, because hop monitoring has its specifics, which must be taken into account.

The comparison of various indices showed, that ExG and TGI indices has the highest congruity of estimated vegetation indices in hop garden area for both used cameras (S.O.D.A. and MicaSense). On the other hand, indices such as: ExGExr, GLI, GPI, NGRDI, RGBVI and VARI did not show significant accordance.

Further processing by Fuzzy Overlay tool proved high accuracy in leaf area estimation for ExG and TGI vegetation indices. Both of these indices had very similar results in crop area detection, because the calculated mutual deviation in detection of hop garden area is smaller than 4%.

Also was confirmed that for the estimation of crop area is possible to use RGB camera and it is not necessary to use more expensive multispectral cameras.

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