MULTISENSORY APPROACH IN HOP GROWTH ASSESSMENT

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Abstract
Nowadays, Unmanned Aerial Vehicles (UAVs) equipped with multispectral and thermal cameras can commonly provide a detailed overview of crop seasonal growth. A suitable combination of selected spectral indices, canopy thermal information and electrical conductivity can serve as an accurate source of data for agrotechnical interventions. Hops belong among the crops where these imaging methods are not commonly used, but at the same time they can be used for very detailed monitoring of the variability in hop varieties. In 2024, the hop gardens were scanned by UAV multispectral and thermal camera during the entire growing season. The results showed that Sládek variety was most sensitive to soil water content in the initial and later growth stages. Soil conductivity at 0.5 m depth explained canopy water stress by up to 56%. Agnus variety was the most resistant, and Sládek variety was the most susceptible to water stress in this 2024 season.

Key words: *unmanned aerial vehicles; multispectral camera; thermal camera; electrical conductivity; crop water stress; vegetation indices.*

INTRODUCTION
Hop *(Humulus lupulus L.)* is a traditional crop grown in the Czech Republic. Hop varieties differ in their qualitative characteristics, as content of alpha acids, and also in terms of phenological development and disease resistance in conventional or organic agrotechnical management *(Řeřicha et al. 2025)*.
The overall vitality of plants and their resistance to stress can be monitored in various ways. The most common method for crop inspection is in-situ monitoring. However, in recent years, unmanned aerial vehicles *(UAVs)* equipped with multispectral or thermal cameras have become a useful tool for assessing various crops *(Pang et al. 2020)*. In general, remote sensing technology offers several advantages over traditional methods *(Guijarro et al. 2011; Zou et al. 2019)*, which are based on the more efficient coverage of larger areas *(Comba et al. 2015)*. Modern sensors on UAVs usually allow, non-invasively, in detail and timely, to assess the vitality, health, stress and overall condition of the entire stand in a very short time, which is not possible with manual inspections *(Velusamy et al. 2021)*.
Spectral indices are often used for crop vigor and structure assessment. One of the oldest and mostly used for agricultural purposes is Normalized Difference Vegetation Index *(NDVI)*. Spectral indices are often used to assess plant vitality and structure. One of the oldest and most widely used for agricultural purposes is the Normalized Difference Vegetation Index *(NDVI)*. Its alternative for estimating stand structure is the Soil-Adjusted Vegetation Index *(SAVI)*. Frequently used indices based on either the green, red edge or NIR bands to determine cellular health and chlorophyll content are the Chlorophyll Red Edge Index *(CIR)*, the Normalized Difference Vegetation Index *(GNDVI)*, the Normalized Red Edge Index *(NDRE) (Meivel et al. 2022]. These indices can contain information on physiological and biochemical properties of plants and thus become useful for accurately estimating the degree of damage or stress in a canopy. With climate change, crop water stress is also increasingly being addressed, and can be derived from thermal images using the Crop Water Stress Index (Idso et al.1981).* CWSI is widely used to derive crop irrigation rates. By early assessment of stress, it can be set up correct and targeted

agrotechnical interventions. The aim of the study is therefore to evaluate the growth development of Czech hop varieties in organic and conventional farming in the 2024 growing season using a multi-sensor approach – UAV scanning with a thermal and multispectral camera and information from electrical conductivity measurements to assess the possibilities of using these sensors for stress detection.

MATERIALS AND METHODS

The study area is located in Stekník *(Czech Republic)* and belongs to production and experimental farm of Hop Research Institute Co., LTD *(HRI)*. The experimental hop garden *(50°19'37.32"N, 13°37'43.05"E)* comprised three varieties – Agnus with the size of 1.5 ha, Premiant *(2.4 ha)* and Sládek *(1.7 ha)*. This experimental hopgarden is conventionally cultivated *(common agrotechnical intervention)* with using drip irrigation system. Monthly precipitations and temperatures for season 2024 and average 5-year's period *(2019-2023)* at the study site are given in Table 1.

Tab. 1 Monthly precipitation and temperature measured during the main vegetation season 2024 and average 5-year's period *(2019-23)* at study site.

Months	May		June		July		August	
Period	5 years	2024	5 years	2024	5 years	2024	5 years	2024
Temperature *(°C)*	13.5	15.3	20.2	18.6	20.4	21.0	20.1	24.4
Precipitations *(mm)*	44.8	81.2	54.9	54.4	54.6	40.8	64.9	100.8

The experimental hopgardens were scanned by WingtraOne GEN II VTOL *(Wingtra AG, Zurich, Switzerland)* with MicaSense RedEdge-P multispectral *(MS)* camera and by eBeeX fixed wing drone with DuetT thermal camera *(senseFly SA, Cheseaux-Lausanne, Switzerland)* from beginning of growth *(May)* to harvest *(August)* in 2024 vegetation season. The fixed wing drone eBeeX was equipped with a built-in RTK-PPK functionality with accuracy up to 4.8 cm. This service was provided by CZEPOS *(GNSS Permanent Station Network of the Czech Republic services at Czech Office for Surveying, Mapping and Cadastre)* – VRS.MAX-CZEPOS *(master – auxiliary stations)* with correction format of RTCM 3.1. The RINEX PPK post-processing corrections, also from CZEPOS service *(https://czepos.cuzk.cz/)*, were used for images acquired from Wingtra VTOL.
The UAV missions were carried out under the same conditions *(from 11:00 a.m. to 2:00 p.m. CET)* to eliminate the shadows and at low wind speeds to eliminate the crop moving. The flight height over organic hopgarden was 80 m above elevation data and 70 m for conventional hopgarden to reach 5.69 and 5.18 cm. px^{-1} spatial resolution for images of MicaSense Red Edge-P camera, and 11 cm spatial resolution for images from Duet T thermal camera at 84 m flight altitude. The image overlaps were 75% *(lateral, longitudinal)* for MS camera and 80% *(lateral)* - 85% *(longitudinal)* for thermal camera to reach very accurate results. MicaSense Red EdgeP camera consists of 5 spectral bands: Blue with wavelength center of 475 nm and range of 20 nm, Green 560 *(20)* nm, Red 668 *(10)* nm, Red Edge 717 *(10)* nm and Near Infrared *(NIR)* 840 *(40)* nm; Duet T thermal camera 7.5-13.5 µm.
Image analysis comprised data preprocessing in eMotion SW and further data analysis in Pix4D and QGIS SW. Photogrammetric procedure was carried out for orthophoto and spectral indices calculation *(see Table 2)*. Threshold of 0.3 NDVI value was set to separate green part of crop from bare soil. On the base of this procedure the area *(in m^2)* of green part of individual hop-varieties was calculated.
CWSI was derived from thermal images for the individual terms of canopy scanning *(see Table 3)*. The calculation was done in QGIS SW using CWSI plugin *(Ellsäßer, 2024)*.
The data were then statistically processed in Statistica SW *(TIBCO Software Inc. (2018)*. Statistica *(data analysis software system)*, version 13. http://tibco.com.).

Tab. 2 Vegetation indices derived for hop growth evaluation.

Spectral Index	Algorithm	Used for:	References
Normalized Difference Vegetation Index *(NDVI)*	$NDVI = \frac{NIR - R}{NIR + R}$	Biomass, structure, vigor	Rouse et al. *(1974)*

Green Normalized Difference Vegetation Index *(GNDVI)*	$GNDVI = \frac{NIR - G}{NIR + G}$	Chlorophyll	Gitelson et al. *(1996)*
Chlorophyll Red Edge Index *(CIR)*	$CIR = \frac{NIR}{Red\ Edge} - 1$	Chlorophyll	Gitelson et al. *(2005)*
Normalized Difference Red Edge Index *(NDRE)*	$NDRE = \left(\frac{NIR - RedEdge}{NIR + RedEdge}\right)$	Chlorophyl content, health	Barnes et al. *(2024)*
Soil Adjusted Vegetation Index *(SAVI)*	$SAVI = \left(\frac{NIR - R}{NIR + R + L}\right) \times (1 + L)$	Alternative to NDVI that minimizes soil brightness influences	Huete *(1988)*
Crop Water Stress Index *(CWSI)*	$\frac{(\mathrm{Tc} - \mathrm{Ta}) - (\mathrm{Tcl} - \mathrm{Ta})}{(\mathrm{Tcu} - \mathrm{Ta}) - (\mathrm{Tcl} - \mathrm{Ta})}$	Water stress	Idso et al. *(1981)*

R = red; G = green; NIR = near-infrared; Red Edge = red edge reflectance according to the MicaSense RedEdge MX sensor properties; L = constant; Tc (◦C) = measured canopy temperature, Ta (◦C) = air temperature, Tcl (◦C) = canopy temperature of well transpiring or non-stressed crop (i.e., minimum Tc), and Tcu (◦C) = the canopy temperature of a nontranspiring or severely stressed crop (i.e., maximum Tc). Terms (Tcu – Ta) and (Tcl – Ta) are referred to as upper and lower limits.

Tab. 3. Meteorological and thermal information at the time of scanning in 2024 for Crop Water Stress Index *(CWSI)* calculation.

Date of scanning	Temperatures *(°C)*						
Variety		Agnus		Premiant		Sladek	
	Ta	Tc	CWSI	Tc	CWSI	Tc	CWSI
9 May	18.30	14.99	0.32	15.07	0.29	15.82	0.32
20 May	21.40	22.35	0.50	24.24	0.64	24.87	0.67
3 June	17.10	14.37	0.21	14.53	0.21	14.81	0.20
18 June	26.40	27.66	0.45	30.03	0.64	29.43	0.59
8 July	25.90	20.67	0.21	20.74	0.20	21.43	0.23
23 July	26.50	20.84	0.12	20.44	0.11	20.94	0.14
6 August	24.60	15.98	0.24	15.56	0.20	16.44	0.21
20 August	25.80	18.31	0.13	17.69	0.11	17.84	0.11

Tc (°C) = measured canopy temperature of individual hop varieties, Ta (°C) = air temperature.

Soil electrical conductivity *(EC)* is primarily influenced by a combination of the soil's physical and chemical properties. By measuring EC at the scale of entire agricultural fields, it is possible to monitor the spatial variability of the soil profile and assess its overall quality. Variations in EC during different growth stages of cultivated crops can affect their development and ultimately impact yield.

For EC measurements, the EM38-MK2 instrument was used. This device is capable of simultaneously measuring soil conductivity at two different depths, specifically at 0.5 m and 1.0 m. The instrument was mounted on a towed sled.

RESULTS AND DISCUSSION

The results were obtained over the entire vegetation season 2024. Table 4 shows the coefficients of determination between CWSI calculated for all measured terms and varieties and electrical conductivity at depths of 0.5 m and 1 m and spectral indices NDVI, GNDVI, CIR, NDRE and SAVI.

The results showed that the coefficient of determination between CWSI and EC was highest in the Sládek variety *(R^2 =0.56)*, which is probably due to the influence of the local distribution of soil moisture, which affects the hop growth and also the genetic predisposition of this late variety, as confirmed by the results of this study. At the same time, it was shown that CV measured at a depth of 0.5 m had higher determination with CWSI than CV at a depth of 1 m *(see Table 4)*.

In the first scanning term, when the hop was at the beginning of the elongation growth, and in August during the development of the cones in the pre-harvest period, the coefficients of determination between CV *(at a depth of 0.5 m)* and CWSI were the highest. The R^2 values for the Sládek variety were 0.56 on May 9, 0.47 on August 6 and 0.43 on August 20. This meant that during these phenological phases, according to the results, hops could be most sensitive to soil water content depending on the variety.

The opposite trend was evident when comparing spectral indices and CWSI. The initial elongation growth phase as well as the pre-harvest phase of all investigated varieties showed very low determination values. On the contrary, from the end of May, i.e. the advanced elongation growth, until the end of flowering in July, the selected spectral indices were able to explain the water stress of individual hop varieties by up to 40% for the Sládek variety. Each of the indices is generally focused on different characteristics of the crop stand - chlorophyll content and health status *(GNDVI, NDRE, CIR)* or structure *(NDVI, SAVI)*, and therefore they are able to explain and detect water stress to a certain extent. As already mentioned in the case of the CV and CWSI comparison, the meteorological and microclimatic conditions of the site played a significant role in the resulting quality and volume of production. In terms of meteorological conditions, both May and August 2024 were significantly above average in terms of total precipitation and average temperature compared to the five-year average of previous years *(see Table 1)*. June corresponded to average precipitation totals with lower average temperature, and in July there were slightly lower precipitation and higher average temperatures. Significantly higher precipitation totals and higher temperature at the beginning of elongation growth in May significantly supported plant development and growth, which is especially evident in the Agnus variety, where the lowest CWSI value was 0.37 during the elongation growth period *(in May and June)*. In the May term, the CIR index could explain up to 24% water stress. The Premiant and Sládek varieties had identical CWSI values of 0.45 during elongation growth. In the later Sládek variety, this water stress can be explained by the NDVI index *(structural properties)* by up to 30% at the end of elongation growth in the last term in June. In the flowering period, the Sládek variety again had the highest water stress *(CWSI = 0.19)*, which was explained by the GNDVI index *(chlorophyll content)* by up to 40%. The Agnus and Premiant varieties had CWSIs of 0.17 and 0.16. In the pre-harvest period of cones formation in August, the Agnus variety showed the highest stress *(CWSI = 0.19)*. On the other hand, Premiant and Sládek both had 0.16. Spectral indices could not be used in this period to predict water stress. In general, the higher the CWSI value, the greater the stress of plants from water shortage. The results for the entire growing season showed that the Agnus variety was the most resistant to drought *(average CWSI value = 0.27)*. This is a variety that has faster development in the early stages and is thus better able to cope with water shortages. On the other hand, the later Sládek variety was the most susceptible to water shortage stress. This fact is supported by the study of Vandírková et al. *(2024)*. Unfortunately, there is not much knowledge about the use of spectral indices for hop evaluation, so we were inspired by already proven solutions in vineyards, where this group of indices is very often used. The results of the study by Costa et al. *(2023)* in vineyards, where it was found that each cultivar has its own genetic predisposition for vigor level, are also in line with our research. On the other hand, Ferro et al. *(2023)*, who evaluated the suitability of spectral indices for estimating grapevine yield, concluded that each of the used indices was significant at a different growth stage; however, the highest Pearson correlation coefficient was achieved by GNDVI at the last measurement date. In our study, we focused more on the effect of spectral indices on water stress, however, water stress can also affect the resulting yield. Our results suggest that rather than spectral indices from remote sensing, it is appropriate to use proximal sensors, such as electrical conductivity measurements, especially in late stages. The results obtained can be applied in determining the effectiveness of cultivation management and agrotechnical interventions, including hop irrigation. This statement is consistent with the study of Ali et al. *(2021)*. They concluded that IR-based imaging in the thermal part of electromagnetic spectra, could help to identify sensitive plants at the beginning of drought stress or to determine the stress tolerance of different hop varieties. These results can also be supported by measurements using appropriate vegetation indices, as also discussed in the study of Řeřicha et al. *(2025)*.

Tab. 4. Coefficients of determination between Crop Water Stress Index *(CWSI)* and spectral indices *(NDVI, GNDVI, CIR, NDRE and SAVI)* measured at individual date of hop scanning; and CWSI and electrical conductivity *(CV)* measured in 1m and 0.5m of deep of soil. Significant at $p \leq 0.05$.

		Elongation growth				**Flowering**		**Cones development**	
Date		**9 May**	**20 May**	**3 June**	**18 June**	**8 July**	**23 July**	**6 August**	**20 August**
Variety	Variables				**Crop Water Stress Index**				

Agnus	**CV 1m**	0.07	0.02	0.04	0.01	0.03	0.02	0.05	0.12
	CV 0.5m	0.15	0.03	0.10	0.01	0.05	0.04	0.11	0.21
	NDVI	0.01	0.23	0.13	0.22	0.14	0.11	0.02	0.04
	GNDVI	0.00	0.23	0.12	0.20	0.11	0.13	0.02	0.05
	NDRE	0.03	0.24	0.13	0.17	0.12	0.14	0.03	0.06
	CIR	0.02	0.24	0.12	0.16	0.09	0.11	0.03	0.05
	SAVI	0.00	0.10	0.09	0.12	0.01	0.01	0.01	0.00
Premi-ant	**CV 1m**	0.09	0.01	0.03	0.00	0.03	0.05	0.07	0.09
	CV 0.5m	0.29	0.02	0.19	0.01	0.11	0.12	0.27	0.30
	NDVI	0.01	0.23	0.17	0.26	0.21	0.17	0.04	0.11
	GNDVI	0.00	0.22	0.14	0.24	0.19	0.21	0.05	0.13
	NDRE	0.02	0.24	0.17	0.22	0.18	0.21	0.06	0.15
	CIR	0.02	0.24	0.15	0.22	0.15	0.17	0.06	0.14
	SAVI	0.00	0.09	0.15	0.21	0.04	0.02	0.00	0.02
Sladek	**CV 1m**	0.34	0.05	0.16	0.00	0.00	0.00	0.29	0.26
	CV 0.5m	0.56	0.08	0.33	0.00	0.01	0.01	0.47	0.43
	NDVI	0.01	0.17	0.09	0.30	0.34	0.37	0.01	0.03
	GNDVI	0.00	0.15	0.05	0.28	0.34	0.40	0.02	0.05
	NDRE	0.01	0.18	0.03	0.25	0.31	0.39	0.02	0.08
	CIR	0.01	0.18	0.04	0.24	0.24	0.28	0.03	0.08
	SAVI	0.01	0.06	0.12	0.24	0.07	0.06	0.01	0.00

CONCLUSIONS

The results showed that a multisensory approach using multispectral and thermal data obtained by UAV scanning hops in combination with electrical conductivity information can play a major role in the correct setting of agrotechnical practices, e.g. irrigation of hopgardens. The results also showed that the Sládek variety is most sensitive to soil water content in the initial stages of growth, where CV at a depth of 0.5 m can explain water stress by up to 56%. Later pre-harvest dates are equally important. From the point of view of spectral index and CWSI analysis, it follows that the Agnus variety was the most resistant to drought. On the contrary, the later Sládek variety was the most susceptible to water stress in this 2024 season.

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