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Application of UAV multispectral imaging for determining the characteristics of maize vegetation

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Abstract. Interest in forage maize (*Zea mays L.*) cultivation for livestock feed has grown in northern conditions. In addition, it is important to develop methods and tools to monitor crop development and other characteristics of the crop. For these purposes UAVs are very efficient and versatile tools. UAVs can be equipped with a variety of sensors like lidar or different types of cameras. Several studies have been conducted where data collected by UAVs are used to estimate different crop properties like yield and biomass. In this research, a forage maize field experiment was studied to examine how well the aerial multispectral data correlated with the different properties of the vegetation. The field test site is located in Helsinki, Finland. A multispectral camera (MicaSense Rededge 3) was used to take images from five spectral bands (Red, Green, Blue, Rededge and NIR). All the images were processed with Pix4D software to generate orthomosaic images. Several vegetation indices were calculated from the five spectral bands. During the growing season, crop height, chlorophyll content, leaf area index (LAI), fresh and dry matter biomass were measured from the vegetation. From the five spectral bands, Rededge had the highest correlation with fresh biomass ($R^2 = 0.273$). The highest correlation for a vegetation index was found between NDRE and chlorophyll content ($R^2 = 0.809$). A multiple linear regression (MLR) model using selected spectral bands and vegetation indices as inputs showed high correlations with the field measurements.

Key words: agriculture, maize, multispectral images, UAV, vegetation index.

INTRODUCTION

Unmanned aerial vehicles (UAV) have been very popular devices in research projects. They can be equipped with a variety of different cameras and sensors like red-blue-green (RGB), multispectral, hyperspectral or thermal cameras or lidar (Deng et al., 2018; Shendryk et al., 2020).

Multispectral cameras are versatile tools for field observation. These cameras can take images from multiple spectral bands that can be used for crop monitoring. These spectral bands are also further used in calculating multiple vegetation indices like normalized difference vegetation index (NDVI) (Rouse et al., 1974). Vegetation indices are used to estimate different crop properties or to reduce the errors caused by the external factors on the images (Kaufman et al., 1992; Huete et al., 1994; Näsi et al., 2018). In the recent years, in many studies UAVs have been used to collect data for estimation of crop biomass (Näsi et al., 2018), chlorophyll content (Wu et al., 2008) and crop yield (Nevavuori et al., 2019). Also weed detection with UAVs has been a popular study subject (Mohidem et al., 2021). Many studies have also used methods like neural networks or multiple linear regression that utilize data from multiple spectral bands or vegetation indices to create a model that estimates the crop properties (Maimaitijiang et al., 2020, Wang et al., 2020). These models are usually more accurate than individual spectral bands/vegetation indices.

Forage maize (*Zea mays* L.) is a crop plant with high biomass that can be fed to cattle. Maize production in Nordic conditions and the effect of different management practices on the yield quality has been studied earlier (Liimatainen et al., 2022). The challenges with the Nordic conditions are low average temperature and the short growing season (Pulli et al., 1979). Forage maize can give high dry matter yields in Nordic conditions, but they must be harvested early based on the growing season (Darby & Lauer, 2002). A suitable maize variety and sowing time can influence the yield and its quality (Pulli et al., 1979; Darby & Lauer, 2002).

In addition to studying the crop growth, it is important to develop tools and methods to monitor crop health and its other properties. The aim of this study was to investigate how the data from aerial multispectral images correlates with the measurements done from using field vegetation sensors. The research's test field consisted of multiple plots with different maize varieties, nitrogen (N) fertilization rates, and mulch. This study focuses on the results of one measurement day and one maize variety.

MATERIALS AND METHODS

Experimental site

The field experiment site was in Helsinki, Finland (60°13'22.9"N 25°00'39.8"E). Fig. 1 presents the field experiment area consisting of experimental plots. The plots were sown on 26th May 2020 to 5 cm depth with plastic mulch film (Oxo-Biodegradable 105 Clear Mulch Film, Samco Agricultural Manufacturing, Limerick, Ireland). The experiment included in four replicates four maize varieties, four N fertilization rates (10, 100, 150 and 200 kg N per ha), three harvest times, and mulch treatment. Plots consisted of four rows with 75 cm row spacing, and were sized to 30 m^2 (10 m × 3 m). This research only focuses on one maize variety, cv. P7326 (FAO 180; Pioneer Hi-Bred International, Johnston, IA, USA) and one harvest time (1st of September 2020). Both mulch and no mulch- treatment plots were used in the dataset. The average ear development stage during the harvest time was R^3 (Brown, 2017; Lehtilä, 2023). The topsoil had pH of 6.1 and the soil organic matter content was 9.8%. Phosphorus content was 5.9 mg L^{-1} and potassium content 260 mg L^{-1} (Liimatainen, 2022).

Weather data was measured at Kumpula, the Helsinki weather station which can be freely downloaded from the Finnish Meteorological Institute website (Finnish Meteorological Institute). The vegetation was harvested 98 days after the sowing. The accumulated rainfall was 262.3 mm and effective temperature sum 1,197.3 °C (Fig. 2).

Figure 1. Orthomosaic map from the research site created from RGB-images. Rectangles indicate the test plots used in this study. The plot number presents the applied nitrogen fertilization (kg N per ha). NM stands for no mulch- treatment.

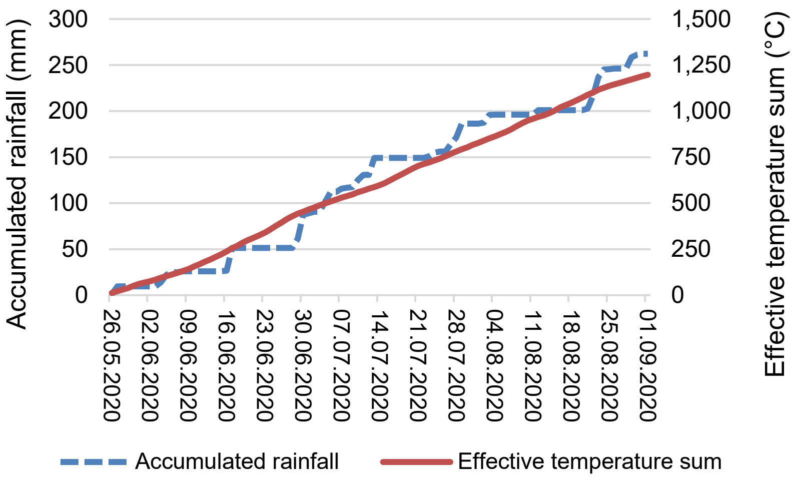

Figure 2. Accumulated rainfall (mm) and effective temperature sum (°C) during the growing season. The effective temperature sum was calculated by measuring the average temperature of each day, subtracting 5 °C from it, and summing the positive differences with each other.

Field measurements

Fresh and dry biomass, chlorophyll content, leaf area index (LAI) and crop height were measured from the vegetation. The chlorophyll content measurements were performed with Apogee MC-100 device (Apogee Instruments, USA). In total, 10 measurements were done from each plot from the top leaves of the randomly chosen plants. As a result, an average value was calculated from the measurements. Chlorophyll content measurements were done on 29th of August.

LAI measurements were performed with AccuPar LP-80 device (Decagon Devices, USA), which consists of light sensors that measure the solar radiation above the vegetation and at the ground level. These radiation measurements were inserted in crop specific equation to calculate the LAI of the crops. The Leaf Distribution Parameter (x) was set to 1.64 on the device. LAI was measured from five different parts of the plot. The LAI measurements were done on 27th of August.

Whole plant samples were collected from each plot before the harvest. Samples were collected from an area that was one meter long and consisted of one crop row (Liimatainen et al., 2022). From these samples, the height of each plant was measured, and an average value was calculated. For the biomass measurements, the whole plot was harvested and weighed. The moisture content was calculated by subtracting the dry biomass from the fresh biomass and divided by the fresh biomass.

UAV measurements

UAV flights were performed with a custom-built hexacopter (Tarot T960) with 18-inch propellers (45.7 cm) and the total weight was around 10 kg (Fig. 3). The UAV was powered with one 14,000 mAh (6 s, 22.2 V) lipo battery. The UAV used a Pixhawk 2 cube (Cubepilot Pty. Ltd, Australia) as flight controller, which made it possible to use Mission Planner software (ArduPilot) to plan the flight missions. Flight missions were performed from 50 m altitude and flight speed was set to 6 m s^{-1}. Side overlap for the images was 80% and the camera was set to take images with 1-second intervals. Flight missions were approximately 7 min long. UAV flights were performed at 28th of August starting at 10:30 a.m.

Figure 3. The UAV and the gimbal for the multispectral cameras light sensor (small figure). The gimbal helps the sensor to point nadir during the UAV flights.

The multispectral camera used in this study was MicaSense Rededge 3 (MicaSense Inc., USA). It takes images from five spectral bands (Red, Green Blue, Rededge and Near-infrared, (NIR)). The center wavelengths (nm) and band widths (nm) of the spectral bands were as follows: Red (668,10), Green (560,20), Blue (475, 20), Rededge (717,10) and NIR (840, 40). The camera was attached to a gimbal to keep the camera horizontally aligned. The multispectral camera's light sensor had a separate gimbal to keep it steady. This would reduce errors caused by shadows forming on the sensor when the UAV is tilting away from the sun. All the multispectral images were processed with Pix4D Mapper software (Pix4D, Switzerland) to create orthomosaic maps from the research site. In the multispectral image processing, the Ag multispectral- template (generates index, reflectance, classification, and application maps) was used on Pix4D. Inverse-distance weighting method was used in creating the DSM (Digital surface model). In DSM creation the sharp setting was used on the surface smoothing. The resolution for the orthomosaic images were 3.3 cm pixel^{-1}. The image calibration was also performed with Pix4D. In the calibration the camera manufacturer's reflectance panel was used with known reflectance values for each spectral band.

Vegetation indices

Several vegetation indices were calculated based on spectral bands (Table 1). Some of the indices were modified from the original equation (M-MTCI) to suit the spectral bands of the multispectral camera.

Table 1. Vegetation indices, their equations and corresponding literature reference

Vegetation index	Equation	Source
DVI (Differenced Vegetation Index)	$\mathrm{NIR} - \mathrm{RED}$	Richardson & Wiegand, 1977
ExG (Excess Green Index)	$2 * \mathrm{Green} - \mathrm{Red} - \mathrm{Blue}$	Woebbecke et al., 1995
GEMI (Global Environment Monitoring Index)	$\eta(1 - 0.25\eta) - \frac{\mathrm{Red} - 0.125}{1 - \mathrm{Red}}$ where $\eta = \frac{(2(\mathrm{NIR}^2 - \mathrm{Red}^2) + 1.5\mathrm{NIR} + 0.5\mathrm{Red}}{(\mathrm{NIR} + \mathrm{Red} + 0.5)}$	Pinty & Verstraete, 1992
GNDVI (Green normalized difference) vegetation index	$\frac{\mathrm{NIR} - \mathrm{Green}}{\mathrm{NIR} + \mathrm{Green}}$	Gitelson & Merzlyak, 1994
GRVI (Green Red Vegetation Index)	$\frac{\mathrm{Green} - \mathrm{Red}}{\mathrm{Green} + \mathrm{Red}}$	Tucker, 1979
M-MTCI (Modified MERIS terrestrial chlorophyll index)	$\frac{\mathrm{NIR} - \mathrm{Rededge}}{\mathrm{Rededge} - \mathrm{Red}}$	Dash & Curran, 2010
MSAVI2 (Modified Soil Adjusted Vegetation Index)	$\frac{2 * \mathrm{NIR} + 1 - \sqrt{(2 * NIR + 1)^2 - 8(NIR - Red)}}{2}$	Qi et al., 1994
NDRE (Normalized difference red edge index)	$\frac{\mathrm{NIR} - \mathrm{Rededge}}{\mathrm{NIR} + \mathrm{Rededge}}$	Fitzgerald et al., 2010
NDVI (Normalized Difference Vegetation Index)	$\frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}}$	Rouse et al., 1974
OSAVI (Optimized Soil-Adjusted Vegetation Index)	$1.16 * \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red} + 0.16}$	Rondeaux et al., 1996
RGBVI (Red Green Blue Vegetation Index)	$\frac{\mathrm{Green}^2 - (\mathrm{Blue} * \mathrm{Red})}{\mathrm{Green}^2 + (\mathrm{Blue} * \mathrm{Red})}$	Bendig et al., 2015
RI (Redness Index)	$\frac{\mathrm{Red} - \mathrm{Green}}{\mathrm{Red} + \mathrm{Green}}$	Escadafal & Huete, 1991
Normalized R (Normalized Red)	$\frac{\mathrm{Red}}{\mathrm{Red} + \mathrm{Green} + \mathrm{Blue}}$	Putra & Soni, 2018
Normalized G (Normalized Green)	$\frac{\mathrm{Green}}{\mathrm{Red} + \mathrm{Green} + \mathrm{Blue}}$	Putra & Soni, 2018
Normalized B (Normalized Blue)	$\frac{\mathrm{Blue}}{\mathrm{Red} + \mathrm{Green} + \mathrm{Blue}}$	Putra & Soni, 2018

Statistical processing

IBM SPSS software (IBM, USA) was used to calculate correlations and to perform multiple linear regression (MLR) modelling on the data. Multiple linear regression uses multiple independent variables (spectral bands/vegetation indices) to estimate the value of dependent variables (fresh and dry biomass, moisture content, chlorophyll content, LAI, height). All the spectral bands and vegetation indices were input to the SPSS. The software included the following spectral bands/vegetation indices to the MLR model: BLUE, DVI, EXG, MSAVI2, M-MTCI, NDRE, NDVI, OSAVI, RED, RGBVI, Blue normalized and Red normalized. The rest of the spectral bands/vegetation indices were excluded from the model. Coefficient of determination (R^2) values were calculated between individual spectral bands/vegetation indices and the vegetation measurements (fresh biomass etc.)

RESULTS AND DISCUSSION

Table 2 presents the mean, standard deviation (STD), minimum and maximum values for each spectral band/vegetation index from the dataset. Overall, the STD as percentage was higher for the spectral bands than for the vegetation indices. Among the vegetation indices, NDVI and GNDVI had the lowest deviation as well as the normalized spectral bands.

Percentage values for maize measurements were similar exception to moisture content (Table 3). Same kind of results could be seen in the four spectral bands (Green, Nir, Red and Rededge) (Table 2). All the vegetation indices cannot directly be compared with each other because their equations differ from each other, and they can get different minimum and maximum values. The dry matter yield in this study corresponded to the same levels as in research conducted in Sweden where the dry matter yield was at lowest 5.5 t ha^{-1} and at highest 19.3 t ha^{-1} (Mussadiq et al., 2012). Budakli et al. (2010) research in Turkey achieved dry matter yields varying from 14.0–23.9 t ha^{-1} depending on the used fertilization rate and plant density. Nitrogen fertilization level was at highest 400 N kg ha^{-1} while in this research the maximum level was 200 N kg ha^{-1}.

Table 2. Mean, Standard deviation (STD), Coefficient of Variation (CV, STD/Mean), minimum and maximum values for each spectral band/vegetation index from the dataset

	Mean	STD (P)	CV (%)	Min	Max
BLUE	0.028	0.002	7.6	0.024	0.031
GREEN	0.062	0.007	11.2	0.051	0.078
NIR	0.497	0.055	11.0	0.432	0.623
RED	0.036	0.004	10.1	0.030	0.042
REDEDGE	0.118	0.013	11.5	0.096	0.151
DVI	0.461	0.052	11.2	0.402	0.582
EXG	0.060	0.009	14.4	0.048	0.085
GEMI	0.915	0.038	4.1	0.862	0.996
GNDVI	0.789	0.017	2.2	0.736	0.811
GRVI	0.270	0.020	7.3	0.243	0.336
MSAVI2	0.706	0.041	5.8	0.655	0.796
M-MTCI	5.327	0.754	14.2	3.261	6.331
NDRE	0.633	0.030	4.7	0.541	0.668
NDVI	0.872	0.007	0.8	0.857	0.886
OSAVI	0.765	0.022	2.9	0.740	0.815
RGBVI	0.585	0.025	4.3	0.555	0.669
RI	-0.270	0.020	-7.3	-0.336	-0.243
Normalized B	0.222	0.006	2.7	0.208	0.230
Normalized G	0.494	0.010	2.0	0.483	0.529
Normalized R	0.284	0.007	2.5	0.263	0.296

Table 3. Mean, Standard deviation (STD), Coefficient of Variation (CV, STD/Mean), minimum and maximum values for each crop measurement from the dataset. Fresh and dry biomass (kg ha^{-1}), moisutre content (%), Chlorophyll content (µmol m^{-2}), LAI (m^2 m^{-2}) and height (cm)

	Mean	STD (P)	CV (%)	Min	Max
Fresh biomass	73764.16	7688.36	10.4 %	52873.33	85395.03
Dry biomass	14249.95	1742.48	12.2 %	9348.01	16862.65
Moisture content	80.69	1.27	1.6 %	78.76	83.23
Chlorophyll content	525.75	61.75	11.7 %	339.80	605.60
LAI	5.24	0.67	12.9 %	4.10	6.55
Plant height	346.23	10.99	3.2 %	324.00	368.71

Among the spectral bands, Rededge had the highest correlation with chlorophyll content, crop height, fresh and dry biomass (Table 4). However, green bands seemed to have the best fit for moisture estimation, and NIR for LAI estimation. The highest correlation for a vegetation index and crop property was observed between NDRE and chlorophyll content (0.809).

Table 4. Coefficient of determination (R^2) values between the spectral bands/vegetation indices and the crop measurements

	Fresh biomass	Dry biomass	Moisture content	Chlorophyll content	LAI	Plant height
BLUE	0.143	0.042	0.049	0.046	0.011	0.131
GREEN	0.197	0.062	0.067	0.100	0.039	0.188
NIR	0.000	0.012	0.051	0.137	0.138	0.090
RED	0.029	0.001	0.049	0.000	0.013	0.081
REDEDGE	0.273	0.109	0.050	0.161	0.083	0.227
DVI	0.000	0.013	0.065	0.153	0.148	0.089
EXG	0.299	0.111	0.072	0.210	0.113	0.237
GEMI	0.001	0.008	0.052	0.152	0.167	0.061
GNDVI	0.332	0.034	0.365	0.744	0.503	0.032
GRVI	0.502	0.239	0.053	0.712	0.619	0.211
MSAVI2	0.004	0.009	0.088	0.197	0.199	0.058
M-MTCI	0.426	0.083	0.267	0.798	0.677	0.038
NDRE	0.402	0.073	0.280	0.809	0.591	0.052
NDVI	0.113	0.011	0.599	0.464	0.259	0.008
OSAVI	0.010	0.009	0.124	0.238	0.224	0.057
RGBVI	0.442	0.170	0.099	0.495	0.388	0.273
RI	0.502	0.239	0.053	0.712	0.619	0.211
Normalized B	0.127	0.023	0.105	0.066	0.022	0.176
Normalized G	0.469	0.190	0.091	0.569	0.443	0.265
Normalized R	0.437	0.237	0.022	0.712	0.661	0.135

Qiao et al. (2022) achieved 0.617 correlation (R^2) between NDVI and maize LAI. For the NDRE the correlation was 0.754 and for OSAVI 0.696. The lower correlation in this study can be caused of the smaller data set. Qiao et al. (2022) used data from 5 to 6 growth stages whereas the data in this research was based only on one growth stage. Also, the weather conditions can influence the vegetation indices and therefore affect the correlations (Änäkkälä et al., 2022).

The green spectral band had higher correlation value with crop height than red (Table 4). This supports Martínez-Casasnovas et al. (2015) conclusion on that the vegetation indices that used green spectral band correlated better with maize height than vegetation idices with red spectral values (e.g. NDVI).

Multiple linear regression (MLR) had the highest correlation with LAI (0.902) (Table 5). Many studies support that combining data from multiple spectral bands/vegetation indices produced the highest correlation with the crop properties (Bendig et al., 2015; Näsi et al., 2018). Bendig et al. (2015) MLR model performed better than individual vegetation indices when estimating barley biomass. Maimaitijiang et al. (2020) combined data from multiple cameras (thermal, RGB and multispectral camera) to estimate soybean yield. The results showed that combining data from multiple camera improved the models accuracy.

Table 5. Coefficient of determination (R^2) values between the crop measurements and the estimataed values made with the MLR model

	Fresh biomass	Dry biomass	Moisture content	Chlorophyll content	LAI	Plant height
MLR	0.869	0.823	0.889	0.899	0.902	0.874

CONCLUSIONS

The presented research show how data from aerial multispectral images correlated with different crop properties of the maize. Data was collected from a single growth stage and from one maize variety. Multiple vegetation indices were calculated from the multispectral images to be compared with the field measurements.

From the spectral bands, Rededge was the most versatile for estimating the different crop properties. When comparing the vegetation indices, there was no clear index that would have correlated with all the crop properties. Overall, the vegetation index NDRE and chlorophyll content had the highest correlation. The multiple linear regression model indicated the strongest correlation with all the crop properties and is best suited for estimating the crop properties in this study.

The models used in this study do not necessarily work as well in other vegetations and are tied to this measurement session and data. Also, other external factors like weather conditions and crop varieties have an effect on the correlations and the models accuracy. Using vegetation indices that are less affected by the external factors could improve the accuracy of these models. With a larger data set and using other calculation methods, such as neural networks, more general models could be generated that would perform on a wider data set. There is still a need to study and develop methods to remotely observe crop properties and their health.

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