AGRICULTURAL ENGINEERING

INTEGRATION OF SPECTRAL MEASUREMENT AND UAV FOR PADDY LEAVES CHLOROPHYLL CONTENT ESTIMATION

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In the agriculture sector, proper crop management can enhance yield production. Determination of the chlorophyll content in crop contributes to this significant topic. In this study, the leaves chlorophyll content of local paddy cultivars Inpari 32 and Inpari 33 was estimated and the difference at various days after planting (DAP) was determined. The procedure involved the combination of spectral reflectance data, aerial photographs taken by unmanned aerial vehicle (UAV), and chlorophyll laboratory analysis data. The chlorophyll content in the cultivars leaves was estimated using the models $\mathrm{MCARI}_{\mathrm{spectroradiometer}}$ and UAV chlorophyll regression (UCR). The results showed a variation in the chlorophyll content not only between the two cultivars on various DAP, but randomly also in the same cultivar of the same DAP. The MCARIspectroradiometer model indicated a lower chlorophyll content for Inpari 32 than for Inpari 33 while the UCR model gave opposite results. The chlorophyll content raises with increasing DAP, but it gradually decreases through the grain filling period until harvest.

leaves spectra, spectral indices, aerial photo, paddy cultivars, Inpari 32, Inpari 33

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INTRODUCTION

Achieving food security is one of the millennium development goals (Stalker, 2008). As an archipelago, the Republic of Indonesia, with more than 75% of its territory covered by the ocean, faces a significant challenge in promoting the food security program (Roza, 2017). For most people of Indonesia rice is their primary food source. Paddy rice is becoming an essential food source here. By establishing a large number of paddy fields by farmers, this sector has become more interesting than others, e.g. fisheries or plantation. This caused the farmers have been responsible for ensuring a high yield of paddy rice over time.

The agriculture support program in Indonesia has been completed in a decade. This program is expected to ensure the highest productivity in rice yield and obtaining food security. Farmers were made responsible for the production intensification, diversification, mechanization and post-harvest procedures important for the yield and crops quality increase. The application of remote sensing technology can also contribute to this program. Some research in paddy rice field has already been done resulting in many suggestions and findings. Fundamental are the problems of soil moisture estimation and evaluation (Arif et al., 2012), variation and changes in soil pH (Mahler, McDole, 1987; Guo et al., 2011; Ghazali et al., 2017, 2019), yield estimation (Nuarsa et al., 2011; Son et al., 2016), and of the relationship between nitrogen content and crop yield estimated based on satellite data (Mosleh et al., 2015; Saberioon, Gholizadeh, 2016). The chlorophyll content is essential for proper plant growth. Its values have been studied in several crop types to estimate crop yield (Schlemmer et al., 2013).

Paddy rice is a plant species from the family Gramineae named *Oryza sativa.* It is a seasonal plant that can be cultivated three to four times a year; its distribution range is from lowlands near the coastline to 1000 m a.s.l. According to Yoshida (1981), paddy rice grows in specific regions and its growth quality is affected by climatic factors like temperature, solar radiation, rainfall and groundwater that differ from place to place.

The physiological process involved in grain production is affected both directly by, and indirectly through plant diseases and insects. Some research has indicated that the variation in temperature affects rice growth (Yuliawan, Handoko, 2016). Temperature rise events accelerate rice growth and possibly decrease the yield; this applies to both the irrigated and rainfed paddy rice. Other studies conducted by Wang et al. (2019) found that the temperature rise breaks paddy rice in the flowering stage so it loses the capability of producing a rare flower which leads to the failure in yields.

Others studies have also described the combined effect caused by temperature and drought. According to Lawas et al. (2018), this situation results in various physiological processes. Each paddy rice cultivar responses in a different way, involves the stress during flowering, grain filling, increased in panicle tissue temperature and followed by yield reduction. Specifically, the brown rice cultivars decrease the yield when exposed to mean temperature exceeding 28°C (Oh-e et al., 2015).

Understanding the yield production in paddy rice through the biochemical characteristics such as the leaf chlorophyll content is exciting. At the leaves level, the chlorophyll content is a critical variable in the photosynthesis process (Kooistra, Clevers, 2016). The chlorophyll content in paddy leaves is measurable by spectral reflectance using a spectroradiometer that provides both the absorbance and reflectance data on invisible material in an object (water, starch, leaves pigment, plant diseases, nitrogen and chlorophyll content, etc.).

The leaves spectral reflectance data can be collected during a field measurement. For example, in the study by Kooistra, Clevers (2016), some vegetation indices (transformed chlorophyll in reflectance index (TCARI), ratio between the triangular chlorophyll index (TCI)) were derived from the spectral reflectance wavelength (Haboudane et al., 2002). Besides, at a leaves level, at an area level, a remote sensing index called normalised area vegetation index (NAVI) is also useful in estimating the chlorophyll content (Carmona et al., 2017).

To determine the chlorophyll index, Bannari et al. (2008) used the normalised difference pigment index (NDPI). Liang et al. (2016) used the hybrid inversion models (least squares-support vector regression (LS-SVR), random forest regression (RFR), canopy chlorophyll index (CCI), and photochemical reflectance index (PRI)).

Other studies utilised the optical images of Landsat 8 to derive the green chlorophyll index (CI_{green}) and the greenness index (G). These indexes were used to estimate the chlorophyll content in a grassland area (Ying et al., 2016). Gholizadeh et al. (2017) stated that the chlorophyll content positively correlated with the increase in the nitrogen content in paddy leaves.

The chlorophyll content assessment in vegetation leaves based on remote sensing data has become the primary investigation method. In general, the hyperspectral data might be leading in these topics. Besides that, the integration images of RapidEye, Sentinel-2 and EnMAP2 are useful for the leaves chlorophyll content estimating (Cui et al., 2018). The mentioned studies highlighted the significance of optical satellite imagery in supporting a sustainable production of crops through estimating their chlorophyll contents. The chlorophyll content estimation might be the focus for studying both physical and chemical characteristic of the paddy rice plant. Other studies used the parameters like the above-ground canopy (Hirooka et al., 2017), leaves area index (LAI) and nitrogen content (Saberioon, Gholizadeh, 2016) also essential for the paddy rice plant growth quality estimation. These perspectives are critical since the chlorophyll content is affected by the nitrogen intake (Yang et al., 2017), water content both in leaves and soil (Chutia, Borah, 2012), variation of annual rainfall and temperature (Oh-e et al., 2015; Lawas et al., 2018), which are often considered as the yield estimation parameters.

Recently, the unmanned aerial vehicle (UAV) has been used as the cheapest platform in obtaining and collecting aerial photographs. This new method has become essential in supporting the agriculture initiative (Rokhmana, 2015; Muchiri, Kimathi, 2016; Du, Noguchi, 2017). The UAV aerial photography was applied to monitor the paddy rice productivity (Jeong et al., 2018). The method offers the capability of spectral reflectance in assessing plant biochemical characteristics. In the present study, the method was used for the chlorophyll detection in paddy leaves. The procedure involved the integration of both spectral signature and UAV aerial photos. The variation in the plant chlorophyll content was determined based on its distribution in the paddy field, local paddy cultivars Inpari and the days after planting (DAP) difference.

Table 1. Specification of the camera attached to DJI Phantom 4 advanced

Camera specifications	
Sensor	1“ CMOS Effective & Pixels: 20 MP
Lens	FOV: 84° 35 mm, equivalent to 24 mm, aperture: f/2.8-11
ISO range	Auto: 100–3200 and 100–12 800 for manual mode.
Shutter speed	8–1/8000 s
Ratio image size	3: 2: 5472 × 3648
Still photography modes	Auto Exposure Bracketing (AEB): 3/5 bracketed
Photo format	JPEG/DNG (RAW)
Bands	sRGB

MATERIAL AND METHODS

Study site

This study was conducted in Bukateja village, Majasari sub-district, Purbalingga residence, in the Central Java Province (Fig. 1). The paddy field is situated 500 m a.s.l. and is distributed in a hilly region with terraces. Here, two varieties of paddy cultivars (Inpari 32 and Inpari 33) were planted and examined for the chlorophyll content at two different DAP – days 65 and 110. At that time, some parts of the paddy field had already been harvested. The 1 ha study area was monitored by UAV. The climatic condition of this area is classified as Af in the Koppen Climate Classification (Peel et al., 2007), with annual rainfall and average temperature of 3214 mm and 26.4°C, respectively.

UAV aerial images

The aerial images were collected using an UAV type DJI Phantom 4 advanced produced by Shenzhen Dajiang Baiwang Technology Co., Ltd. It is equipped with a 20-megapixel camera that allows capturing the visible light only. Each images taken by the UAV has set up the ground sampling distance (GSD) size of 4 cm from a height of 150 m a.s.l. The UAV took as much as 30 single photos. The collected aerial photos were processed into an orthophoto with true colour in the standard RGB colour space. The details of the camera sensor attached to the UAV DJI Phantom 4 are presented in Table 1.

Empirical estimation of paddy leaves chlorophyll content

The chlorophyll content in leaves of two paddy rice cultivars (Inpari 32 and Inpari 33) was analysed in the laboratory of the School of Life Science and Technology, Bandung Institute of Technology, Indonesia. The chlorophyll content determination followed the standard used by Yoshida et al. (1976). This procedure revealed that the chlorophyll contents in Inpari 33 and Inpari 32 differ. As much as 11.85, 12.85 and 10.27 mg l^{-1} chlorophyll was obtained from Inpari 33 (110 and 65 DAP), and Inpari 32 (65 DAP), respectively. These values were found in a single

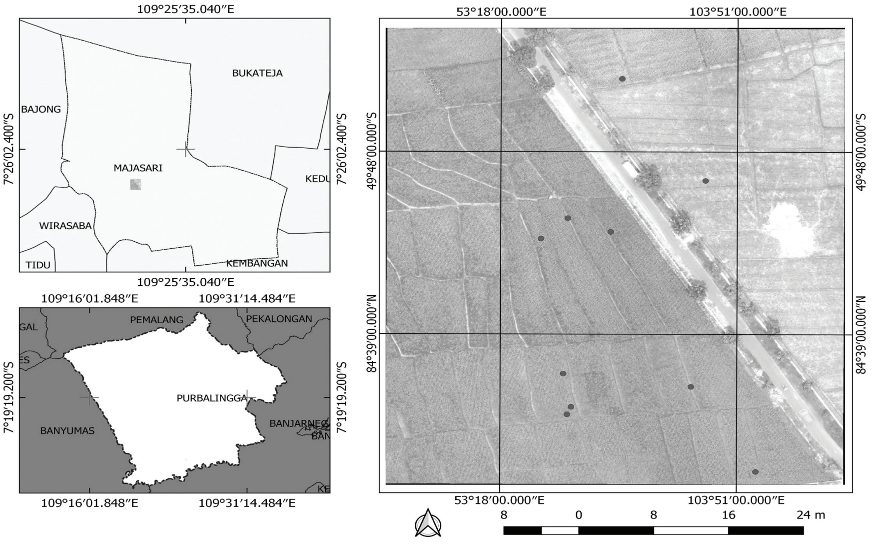

Fig. 1. Study location for chlorophyll estimation and distribution based on aerial photography from unmanned aerial vehicle in Bukateja, Purbalingga residence, Indonesia paddy plant locate on the upper right corner is at 110 days after planting (DAP), in the down left to the right is at 62 DAP, and the black spots = sampling plots for data field acquisition. source: own research.

Table 2. Spectral reflectance of three stages of paddy plant growth (phenology stages) (day 62 after planting, ready to harvest, and harvested). Results were obtained using a spectroradiometer in a range of 520 to 1700 nm. These range are also similar to green, red, near-infrared and shortwave infrared in Landsat 7 satellite images

No.	Wavelength (nm)															Paddy cultivars
	520	560	561	600	601	660	661	662	690	760	810	855	1600	1650	1700	
1	6.35	7.92	6.61	4.78	4.90	6.71	3.46	4.09	9.43	46.33	44.38	53.84	20.00	15.56	21.62	Inpari 32
2	7.42	9.34	7.71	5.42	5.52	7.51	3.88	4.58	11.17	53.25	50.54	60.77	23.15	18.32	22.88	Inpari 32
3	6.87	8.65	7.18	5.13	5.20	7.05	3.63	4.25	10.35	54.57	52.50	63.22	24.95	18.07	14.76	Inpari 32
4	7.01	8.76	7.36	5.28	5.43	7.47	3.88	4.59	10.56	46.33	44.03	53.34	20.67	16.22	19.15	Inpari 32
5	7.41	9.29	7.86	5.81	5.97	8.42	4.36	5.16	11.39	48.22	46.26	56.07	22.31	17.06	17.39	Inpari 33
6	6.74	8.54	7.21	5.28	5.54	7.98	4.15	4.93	10.81	38.00	36.23	44.76	21.76	17.98	18.89	Inpari 33
7	7.35	9.25	7.73	5.60	5.79	8.02	4.14	4.91	11.28	48.59	46.64	56.90	23.18	17.82	17.56	Inpari 33
8	7.37	9.23	7.73	5.58	5.70	7.79	4.03	4.79	11.28	50.09	47.88	57.93	23.13	17.42	15.81	Inpari 33
9	7.23	8.37	7.96	8.10	9.45	16.61	8.91	10.55	12.84	18.97	18.31	23.33	25.88	25.88	10.98	Inpari 33/ harvested
10	7.50	9.36	8.32	7.14	7.82	12.11	6.43	7.72	13.87	35.06	33.49	41.53	22.25	19.34	11.68	Inpari 33/ ready to harvest

paddy leaf, while two sheets of paddy leaves from each cultivar were used.

On the paddy field, four clumps of paddy plants are cultivated per 1 m^2. Each has 20 to 30 paddy leaves. It is thus possible to calculate the total chlorophyll content per 1 m^2 for the two cultivars: Inpari 33 (110 and 65 DAP), and Inpari 32 (65 DAP) can produce approximately 1.422, 1.542, and 1.232 mg l^{-1} chlorophyll per 1 m^2, respectively.

Paddy leaves spectral reflectance

Data on the paddy leaves spectral reflectance were obtained during a field measurement using a portable spectroradiometer. A multispectral radiometer MSR16R (Cropscan Inc., Minnesota-USA) was chosen as it is simple to use and it offers reflectance values similar to those provided by Landsat 7. It allows capturing an object reflectance in a wavelength range from 520 to 1700 nm. The MSR16R has 16 spectral bands classified into four band groups (green, red, near-infrared and shortwave near-infrared).

The spectral reflectance was measured using a canopy level as the measurement unit. The MSR16R can capture the maximal area of 6.5 m^2, the distance from the radiometer sensor to the canopy is 2 m in height (Fig. 2). The reflectance measurement took place in the same area the laboratorily analysed paddy leaves were taken from. Ten spectral reflectance measurements were carried out for two cultivars, at three different rice phenological development stages based on day after planting (DAP). The leaves reflectance values were distributed in 16 single bands (Table 2), and were expressed as the spectral signature of paddy rice leaves at the canopy level (Fig. 3).

The reflectance values measured the actual condition of the paddy plants. Results of ten spectral reflectance measurements for two cultivars were recorded: four for Inpari 32 and six for Inpari 33 (Table 2). In the green and red region from 520 to 561 nm, the reflectance values for healthy vegetation are lower. According to these values, both Inpari 32 and 33 were in healthy condition. At the near-infrared region, the reflectance values must be 3–4× higher than the values in the green and red region. But, in some cases a 3× lower value indicates an unhealthy vegetation. After this, all the reflectance values decrease gradually in the short wave infrared region.

Based on the combination of these reflectance values (from the green to the short-wave infrared region) we

Fig. 2. Acquisition of spectral reflectance data in a paddy field at Bukateja village, Indonesia using a multispectral radiometer (MSR16R) left to right: sampling site, system spectroradiometer MSR16R, data logger controller (DLC), nivo, CT100 controller and head radiometer source: own research

drew the spectral curves. A typically shaped spectral curve obtained from the vegetation is depicted in Fig. 3. Although all the spectral curves show a similar pattern, a variation is observable in each single sample. For instance, it occurs not only in the context of healthy and unhealthy vegetation, but also with respect to the day after planting (DAP).

The spectral curves have an essential role in explaining the vegetation characteristics, including the biophysical aspect such as the plant structure (erectophile and planophile), plant composition (nitrogen, lignin, chlorophyll a and b), and quantitative characteristics (biomass per unit area, LAI, and plant height) (Thenkabail et al., 2002, 2012; Papes et al., 2010). Furthermore, the chemical characteristics can be determined at 300–900 nm for carotenoids, xanthophylls, and chlorophyll contents. Water content is determinable at 1000, 1200, 1500, 1900 and 2500 nm, while sugar, starch protein, and cellulose lignin at the spectral range 1700–2500 nm (Numata, 2012). These parameters, influencing plant health status during the growing season, were also examined in the paddy plants.

Spectral curves of the paddy plants at 62 DAP show a typical pattern that is lower at 520–690 nm, suddenly higher at 760–855 nm and finally decreasing in reflectance value at 1600–1700 nm due to water absorbance. This holds for samples No. 1–9 (Fig. 3a, b), an exception is sample No. 10 (Fig. 3c).

In general, both Inpari 32 and 33 plants were divided into two groups – healthy and fairly healthy. The paddy plants in samples No. 1–3, 5 and 7–8 were healthier than those in samples No. 4, 6 and 9 of the same DAP. For Inpari 32 (Fig. 3a), spectral curves No. 2 and 3 are for healthier plants than No. 1 and 4, showing the lowest reflectance values in the near-infrared region. In Inpari 33, the situation is similar (Fig. 3b). A difference is noticeable when observing the shape of the spectral pattern of harvested paddy rice and of that ready to be harvested (Fig. 3c). In the harvested paddy rice, the reflectance values in the near-infrared region tend to be lower than in the unharvested. Like in samples No. 4 and 6, these spectral have lower reflectance values, especially in wavelength 760–855 nm.. This situation is similar with sample No. 9, when it compares with sample No. 10 as ready to harvest of paddy. However, in wavelength 660 nm, the reflectance value is 5% higher.

With increasing DAP, the paddy rice leaves colour turned from green to golden brown, following the chlorophyll reduction. The plant used the energy obtained from photosynthesis dominantly for creating both rice flower and rice grain. This situation is the reason for decreasing the reflectance values at 62 and 110 DAP. In this case, the reduction of chlorophyll content does not indicate a plant disease, but is characteristic for paddy grains filling. But there might exist a difference in the condition between sample No. 4 and sample No. 6. Sample No. 9 has a different shape if compared with the other samples. During the harvest, farmers cut the rice straw. It means that the process of photosynthesis suddenly stops. This situation is reflected in a decrease in the near-infrared region.

Integrating paddy leaves spectral reflectance with UAV aerial images digital number

Both spectral reflectances obtained from spectroradiometer and aerial photos of UAV are different. The difference is in the data format, which is in the form of images and numbers. The pixel values stored as a digital number in aerial photos of UAV are express as a grey level that range between 0-255, while the reflectance values show in percent (%).

This study required these two data to develop a model for chlorophyll estimation. But in fact, the difference exists since the paddy leaves spectral has the reflectance values range between 0 -100%, which is divided into 16 bands and classified to green, red, near-infrared, and short-wave infrared. When it compared to an aerial photograph of a UAV that only has three portions of bands, includes red, green, and blue, there are only two bands that similar these are red and green bands. To accommodate this similarity, both

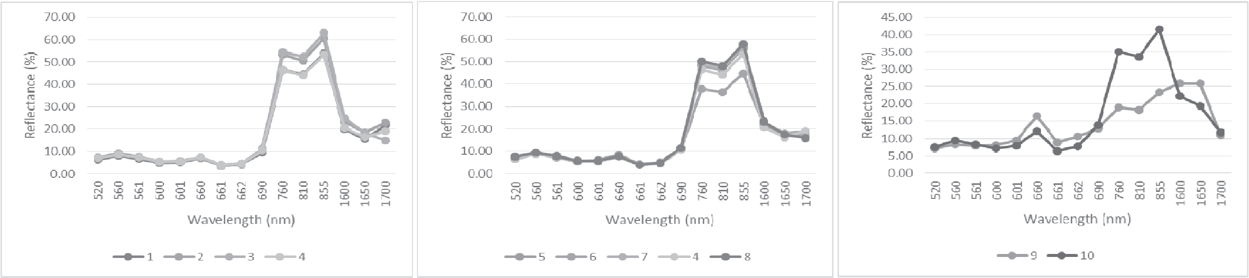

Fig. 3. The spectral reflectance comparison for Inpari 32 (left) and Inpari 33 cultivars at 62 days after planting (center) and comparison between harvested paddy plants and those ready for harvest (right)
source: own research

data need to combine through finding the relationship between reflectance values to the digital number of aerial photographs and converting the digital number (DN) into reflectance values. The value conversion is needed to equalize the range of digital values for aerial photographs to the value of the spectral reflectance of paddy leaves. In advance, the study used the spectral reflectance as reference data for doing image classification using Linear Spectral Unmixing (LSU) (Gandharum et al., 2015).

Corrected satellite images also own the spectral reflectance at the stage of surface reflectance or bottom of atmosphere (BoA) (Lin et al., 2015). It was applied to satellite images (such as Landsat 8). All the pixels are influenced by scattering in the atmosphere layer, causing an error in the digital numbers and necessary to apply a correction procedure named the atmospheric and radiometric correction (U.S. Geological Survey, 2016). In an aerial photograph, which is made by UAVs in the lower atmospheric layer below 1 km above the Earth's surface. The atmospherical effect received by aerial photos is lower than the satellite images.

The equation formula (Eq.1) was developed based on the relationship of reflectance values and DN of UAV and shown in scatterplots (Fig. 4). This relationship is expressed by a model used for converting the UAV's DN into the surface reflectance in %. This equation is a rescale method that transforms the lowest raw UAVs to 0 and the highest to 100%. These two linear regressions between those values indicate the relationship between the field measurement (paddy field) and the DN of UAVs. The scatterplot said that both data are linear, with a moderate negative correlation. In other words, a change in the reflectance value will change the DN values. Where the decrease in the reflectance value of paddy leaves will cause an increase in the digital value of the band in aerial photographs. The converted values of aerial photographs show in Table 3.

In general, the values range from 0 to 100%. The green bands have lower values than the red ones, while the blue bands have the lowest values.

$$\text{Reflectance (\%)} = [(\text{DN} - 0) / (225 - 0)] \times 100 \qquad \text{Eq.(1)}$$

Paddy leaves chlorophyll content estimation

This study used two different models to estimate the paddy leaves chlorophyll content. The first one aimed to evaluate the chlorophyll content in the single clump of paddy leaves, while the second model proposed to determine the chlorophyll content in the paddy field. The model proposed by Daughtry et al. (2000) known as the modified chlorophyll absorption ratio index (MCARI) was used to estimate the chlorophyll content in single paddy leaves. This model utilised the spectral reflectance from hyperspectral bands at 550, 670 and 700 nm (Eq. 2). These spectral bands are different in specific wavelength from those of MSR16R but are still located in the same region. According to Sheffield (2009), in Liang (2004) both equations utilised the bands in the visible light region, including 550–760 nm, and were considered as the chlorophyll absorption bands. This approach is the real reason why the spectral reflectance value in leaves is lower in that range. The chlorophyll cell absorbs much green and red reflectance.

However, it is required to match the original bands (MCARI) with those of the MSR16R. In the modification series of MCARI, they are designated as $\text{MCARI}_{\text{spectroradiometer}}$ (Eq. 3). This model replaces the spectral band at 550 nm by 560 nm, at 670 nm by 660 nm, and at 700 nm by 760 nm. The chlorophyll content at the paddy field level was estimated using the model UAV chlorophyll regression (UCR). This model was derived from a multiple linear regression between the expected chlorophyll content obtained from MCARI spectroradiometer (Eq. 3) with the corrected digital numbers of UAV (Table 3). This model (Eq. 4) used the RGB image from the UAV orthophoto.

$$\text{MCARI} = (700 - 670) - 0.2 \times (700 - 550) \times (700/670) \qquad \text{Eq.(2)}$$

$$\text{MCARI}_{\text{spectroradiometer}} = (760 - 660) - 0.2 \times (690 - 560) \times (760/660) \qquad \text{Eq. (3)}$$

$$\text{UCR} = 1.954 - 0.963 \times \text{Red} + 1.589 \times \text{Green} - 0.217 \times \text{Blue} \qquad \text{Eq. (4)}$$

RESULTS

The chlorophyll content estimation based on the $\text{MCARI}_{\text{spectroradiometer}}$ (Eq. 3) gave specific chlorophyll content values in the paddy plant at the canopy level. On an area of 6.5 m^2, it generally showed a 2–3× higher amount of chlorophyll than was the actual content measured in a laboratory. Inpari 33 (110 DAP) displayed a lower chlorophyll content, the laboratory

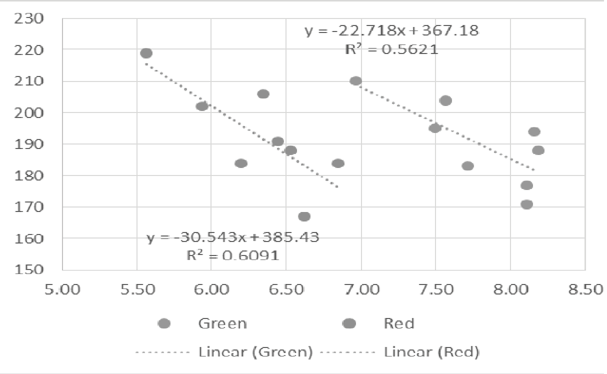

Fig. 4. Relationship between paddy plant reflectance and unmanned aerial vehicle's digital numbers described in a linear regression; Green - left, Red - right;
source: own research

Table 3. Relationship between the paddy leaves reflectance, the digital number of aerial photos and the converted UAV reflectance (in nm)

.No	Spectroradiometer		DN–UAV			Reflectance–UAV (%)		
	green average	red average	red	green	blue	red	green	blue
1	6.96	5.56	219	210	128	85.88	82.35	50.2
2	8.16	6.35	206	194	126	80.78	76.08	49.41
3	7.57	5.94	202	204	111	79.22	80	43.53
4	7.71	6.2	184	183	98	72.16	71.76	38.43
5	8.19	6.85	184	188	97	72.16	73.73	38.04
6	7.5	6.45	191	195	109	74.9	76.47	42.75
7	8.11	6.62	167	177	104	65.49	69.41	40.78
8	8.11	6.53	188	171	108	73.73	67.06	42.35
9	7.85	11.08	205	162	130	80.39	63.53	50.98
10	8.39	9.18	217	186	122	85.1	72.94	47.84

UAV = unmanned aerial vehicle, DN = digital number

and MCARI$_{spectroradiometer}$ values (Eq. 3) were 10.27 mg l^{-1} and 23.24 ml per 6.5 m^2, respectively. Inpari 33 seedlings of 62 DAP were younger than those of 110 DAP, therefore the chlorophyll content of Inpari 33 at 62 DAP was higher than at 110 DAP (12.85 mg l^{-1} and 44.43 ml per 6.5 m^2, respectively). Moreover, the difference in DAP was influenced by the characteristics of the plant leaves biochemical content.. Even in the case of the same paddy plant cultivar, the variation in DAP plays a major role in the current chlorophyll content value.

Within this study we were not able to compare Inpari 32 in different stages of phenology, in the paddy fields only Inpari 33 occurs in two different stages of DAP. This situation enabled us only a general comparison in the chlorophyll content of the cultivars. These varieties showed 11.85 mg l^{-1} and 38.83 ml per 6.5 m^2 for laboratory and MCARI$_{spectroradiometer}$ (Eq. 3) measurements, respectively. At this point, the earlier conclusion is that Inpari 33 is better than Inpari 32 in producing the chlorophyll. For details see Table 4. Like the estimation result of MCARI$_{spectroradiometer}$ (Eq. 3) given above, the spatial distribution of estimated chlorophyll over the whole study area is also following the variation in the days of planting, including paddy rice at 62 and 110 days after planting (DAP), and a harvested field with a burned spot (Fig. 5).

In the area of 62 DAP, the chlorophyll content was estimated in the range from 34.19 to 45.78 ml per 6.5 m^2. This value is higher than for the paddy in the field of 110 DAP. At this place, the chlorophyll was estimated in the range from 21.2 to 38.6 ml per 6.5 m^2. The anomaly has existed in the harvested area, and the chlorophyll content was determined in a range of 15.6 to 42.4 ml per 6.5 m^2. The model used for predicting the chlorophyll content showed a negative trend of the chlorophyll content change during planting. It was successful in proving that the DAP increase is followed by a drop in the chlorophyll content. Outside these phenomena, the burned paddy straw showed the highest chlorophyll content. In other plants, e.g. in grasses, a lower chlorophyll content was detected if compared with the paddy at 62 DAP, but a higher one at 110 DAP (34.19 and 21.2 ml per 6.5 m^2, respectively).

In the area of 62 DAP, there were two paddy rice cultivars planted. For Inpari 32, the distribution of samples used at this location is following this setup: the first three samples (No. 1–3) are located in the northern part of the area, while sample No. 4 is located

Table 4. Comparison between laboratory determined and estimated chlorophyll content and its spectral reflectance for Inpari 32 and Inpari 33 cultivars

Cultivars/DAP	Spectroradiometer (nm)				Chlorophyll content	
	560	662	690	760	Lab (mg l^{-1})	MCARI$_{spectro}$ (ml per 6.5 m^2)
Inpari 33/110	9.36	7.72	13.87	35.06	10.27	23.24
Inpari 33/65	9.34	4.58	11.17	53.25	12.85	44.43
Inpari 32/65	5.81	2.65	6.7	42.8	11.85	38.83

DAP = days after planting, Lab = laboratory result, MCARI$_{spectro}$ = spectroradiometer in the south. Inpari 33 is represented by samples No. 5–8 situated in the middle part of the paddy field between samples No. 1–3 and 4. Sample No. 9 is located upper right near sample No. 10 which is in the south (Fig. 5).

The paddy cultivar Inpari 32 planted in these locations has a higher chlorophyll content compared to Inpari 33. This condition is based on the results given by UCR (Eq. 4) (Table 5). The chlorophyll content for this cultivar ranges from 38.12 to 45.93 ml per 6.5 m^2. For the paddy cultivar Inpari 33, the range of values for 62 DAP, 110 DAP and the harvested area is 29.56–41.03 ml per 6.5 m^2, 23.24 ml per 6.5 m^2 and 6.81 ml per 6.5 m^2, respectively. Near the location of samples No. 5–8, the lowest chlorophyll content was detected (29.56 ml per 6.5 m^2). In the paddy field, the lowest chlorophyll content corresponds with this paddy plant that planted in the same location (Fig. 6).

Table 5. Overview of the chlorophyll contents estimation in 10 samples of paddy rice plant

No.	Paddy cultivars	Stages of phenology	Estimated chlorophyll (ml per 6.5 m^2)
1	Inpari 32	62 DAP	38.83
2	Inpari 32	62 DAP	44.43
3	Inpari 32	62 DAP	45.95
4	Inpari 32	62 DAP	38.12
5	Inpari 33	62 DAP	39.14
6	Inpari 33	62 DAP	29.56
7	Inpari 33	62 DAP	39.65
8	Inpari 33	62 DAP	41.03
9	Inpari 33	harvested	6.81
10	Inpari 33	110 DAP	23.24

DAP = days after planting

DISCUSSION

The estimation of chlorophyll content based on the integration model covering both spectral reflectance and UAV aerial imagery gave a view of the variation in the chlorophyll content in paddy leaves. Theoretically, the variation in the paddy leaves chlorophyll contents may be influenced by water as reported by Chutia, Borah (2012). In this case, deficiency in the plant water intake is contributing to a significant decrease in the total chlorophyll content. In vineyards, the situation is opposite. The water status has no relationship with the chlorophyll content (Hailemichael et al., 2016).

As the paddy plants are easily observable through their phenology, a possible factor influencing the chlorophyll content is the day of the year (DOY). Ishikawa et al. (2015) observed that three different growing stages of paddy rice (tillering, heading, and mature grain stage) correspond with the change in the chlorophyll absorption spectrum in blue and red bands. Zhang et al. (2014) extended the spectral band of 640 nm to 680 nm. This is in line with the estimation result obtained from $MCARI_{spectroradiometer}$ (Eq. 3), although a new band in the near-infrared at 760 nm was added.

The growing stages correspond with the changes in paddy rice phenology. This study has dealt with the vari-

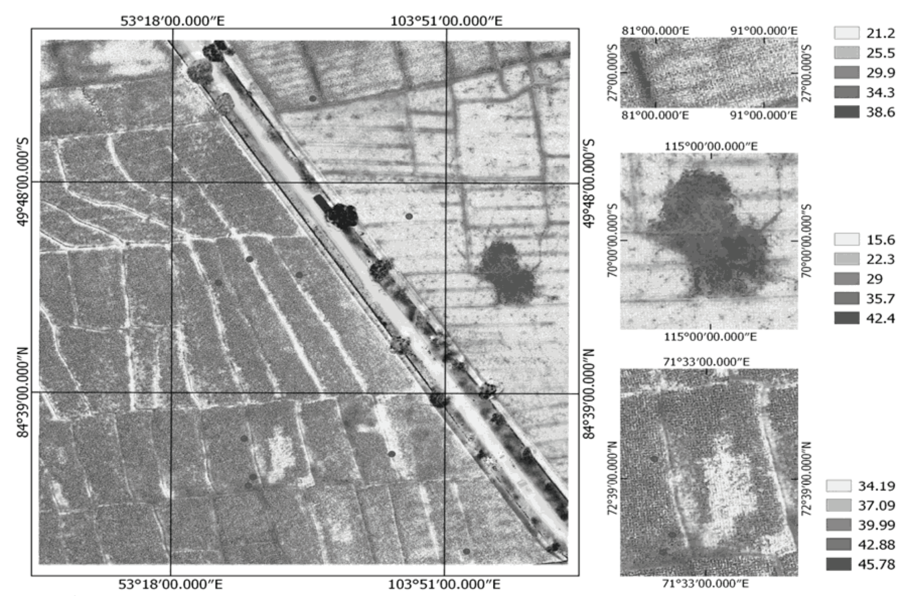

Fig. 5. Spatial distribution of estimated chlorophyll content in three different types of paddy field (left image). Chlorophyll content in paddy plant at harvest period (top image), post-harvest (mid image) and 62 days after planting (bottom image)
source: own research

ation of DAP, instead of using the DOY (Ishikawa et al., 2015). The result given by $\mathrm{MCARI}_{\mathrm{spectroradiometer}}$ (Eq. 3) has explained more explicitly related to this variation. The cultivars Inpari 33 at 62 DAP and 110 DAP has grown in two different stages (maturity and grain filling) and show different chlorophyll contents. Changes in the chlorophyll contents occur dynamically during all paddy rice growing stages. Young plants of paddy rice begin at lower levels of chlorophyll, then its content increases as the plants develop, and finally decreases with their ageing (Yang, Lee, 2001).

The chlorophyll absorption bands range from the blue to the green region was previously described implicitly by Thenkabail et al. (2002), Gitelson (2011) and Numata (2012). The studies said that these spectral bands are capable of detecting and estimating the chlorophyll content in plant leaves. It likely supports the decision to change the configuration of bands used in MCARI (Eq. 2) for the new one in $\mathrm{MCARI}_{\mathrm{spectroradiometer}}$ (Eq. 3). It is possible to change all the configuration bands as long as it is the same range in the blue to green region.

Since the chlorophyll content varied in individual paddy leaves, this variation may occur on the field scale as well. The results given by UCR (Eq. 4) have proved it thoroughly. The variety of paddy rice cultivars planted in Bukateja village situated 500 m a.s.l. do not show the same chlorophyll content. It was not influenced by the elevation. This situation is applicable both to paddy rice and woody plants (Covington, 1975; Li et al., 2013). The elevation factor was genuinely influenced by the plant physiological performance rather than by the biophysical one (Kofidis et al., 2003; Cleavitt, 2016). In paddy rice, it influenced the yield gap (Kitilu et al., 2019). The information relates to the biophysical characteristic and its change occurs based on the difference of time planting or day after planting (DAP) of paddy rice in chlorophyll content. Both the laboratory analysis and the estimated values from both models proposed gave the same results. With increasing DAP the chlorophyll content decreases as physically the paddy rice leaves colour turns into golden yellow.

Fig. 6. Condition of paddy rice cover in a paddy field with sparse distribution
source: own research

As stated above, the chlorophyll content variation occurs not only based on the DAP variety but it is also affected by several natural factors such as water content and its caused drought stressed. An obvious explanation also corresponding with our results presented Yang, Lee (2001): when the paddy rice plant is entering the age of 62 and 110 days, the chlorophyll content decreases. The level of chlorophyll observed in this study might be lower than its level on another day before entering this age. The area of 1 ha was minimal. However, we could observe both the spatial distribution and variation in the chlorophyll content over the paddy field.

CONCLUSION

This study has focused on the chlorophyll content estimation and detection both in individual paddy rice leaves and on the field scale. The combination of the spectral data measurement and the UAV aerial imagery was chosen as a potential approach to detect the chlorophyll content of selected cultivars, while the results were compared with those from laboratory analyses.

The laboratory analysis revealed that the chlorophyll content of Inpari 32 cultivar is lower than that of Inpari 33. This fact was confirmed by the modified MCARI model. The UCR model gave an opposite result, i.e. that Inpari 32 contains more chlorophyll than Inpari 33 at the same DAP. Then the UAV technology was applied to predict the chlorophyll content spatially on the field scale. Two conclusions were inferred:

(1) The chlorophyll content variation occurs not only with respect to the variety of cultivars planted and DAP, but it is also distributed randomly within the same DAP and cultivars. This situation means that at the same DAP, the chlorophyll content of any cultivar (Inpari 32 or 33) can be at the minimum or maximum level.

(2) DAP is corresponding with the growth stages or phenology. A rising DAP is accompanied by the rising amount of chlorophyll in plant that, however, gradually decreases during the grain filling period until the plant is ready to harvest.

Our approach and results will hopefully enhance further studies of biochemical and biogeography factors based on the spectral reflectance and UAV images. This study dealt only with the plant chlorophyll content; however nitrogen, water content, soil minerals etc. can also be determined based on the UAV method. The contribution of remote sensing technology through the information provided by UAV is valuable for fulfilling the food security program, especially for the countries where paddy rice represents a primary carbohydrate resource.

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