

## Above-ground vegetation indices and yield attributes of rice crop using unmanned aerial vehicle combined with ground truth measurements

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### Abstract

Rice is an important economic and staple crop in several developing countries. Indica rice cultivars, 'KDML105' and 'RD6' are clear favourites, popular throughout world for their cooking quality, aroma, flavour, long grain, and soft texture, thus consequently dominate major plantation area in North-eastern region of Thailand. The objective of present study was to validate UAV (unmanned aerial vehicle)-derived information of rice crop traits with ground truthing non-destructive measurements in these rice varieties throughout whole life span under field environment. Plant height of cv. 'KDML105' was more than cv. 'RD6' for each respective stage. Whereas, number of tillers per clump in 'KDML105' exhibited stability at each developmental stage, which was in contrast to 'RD6' (increased continuously). Moreover, 1,000 grain weight, total grain weight and aboveground biomass were higher in 'KDML105' than in 'RD6' by 1.20, 1.82 and 3.82 folds. Four vegetative indices, ExG, EVI2, NDVI and NDRE derived from UAV platform proved out to be excellent parameters to compare KDML105 and RD6, especially in the late vegetative and reproductive developmental stages. Positive relationships between NDVI and NDRE, NDRE and total yield traits, as well as NDVI and aboveground biomass were demonstrated. In contrast, total chlorophyll pigment in cv. 'RD6' was higher than in cv. 'KDML105' leading to negative correlation with NDVI. 'KDML105' reflected rapid adaptation to Northeastern environments, leading to maintenance of plant height and yield components. Vegetation indices derived from UAV platform and ground truth non-destructive data exhibited high correlation. 'KDML105' was rapidly adapted to NE environments when compared with 'RD6', leading to maintenance of physiological parameters (detecting by UAV), the overall growth performances and yield traits (measuring by ground truth method). This study advocates harnessing and adopting the approach of UAV platform along with ground truthing non-destructive measurements of assessing a species/cultivars performance at broad land-use scale.

**Keywords:** non-destructive measurement; RedEdge; RGB imagery; total chlorophyll; unmanned aerial vehicle; yield attribute

**Abbreviations:** CRD (Completely Randomized Design); CRP (calibrated reflectance); CSSL (chromosome segment substitution lines); DHL (double haploid lines); DN (digital number); EXG (Excess Green Index); EVI2 (Enhanced Vegetation Index 2); GCP (ground control point); GSD (ground sampling

distance); KDML105 (Khao Dawk Mali 105); LAI (Leaf area index); NDRE (Normalized difference Red Edge Index); NDVI (Normalized Difference Vegetation Index); NE (North-eastern region); RD6 (Rice Department 6); RGB (red-green-blue); ROI (region of interest); UAV (unmanned aerial vehicle); VIs (Vegetation Indices)

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## Introduction

Rice is an important economic crop for Thailand, and 'Khao Dawk Mali 105' or 'KDML105' is a premium quality cultivar that is exported around the world (Office of Agricultural Economics, 2018). An ever-increasing world population is a matter of great concern, aggravating the issue of global food security, especially under progressive climatic changes (Khush, 2005). Approximately 41% of total rice plantation area (~3.94 million ha) in Thailand is producing approximately 8.1 million tons of KDML105 (Vanavichit *et al.*, 2018). Rainfed lowland areas in North-eastern (NE) Thailand contribute around 61.5% of its landmass for production of 'KDML105' (Office of Agricultural Economics, 2018). Alternatively, the native farmers in NE Thailand generally practice sticky rice (non-glutinous variety) production as food resource or self-consumption. 'RD6' is another rice cultivar that is second only to 'KDML105' in terms of production and is planted in 22.65% (2.18 million ha) of total rice plantation area in Thailand (Office of Agricultural Economics, 2018). 'RD6' is a mutagenized cultivar derived from 'KDML105' gamma-irradiated mutant. With this basic information, in the present study, 'KDML105' and 'RD6' were selected for further testing in a farmer's field plot in Roi Et province, NE Thailand.

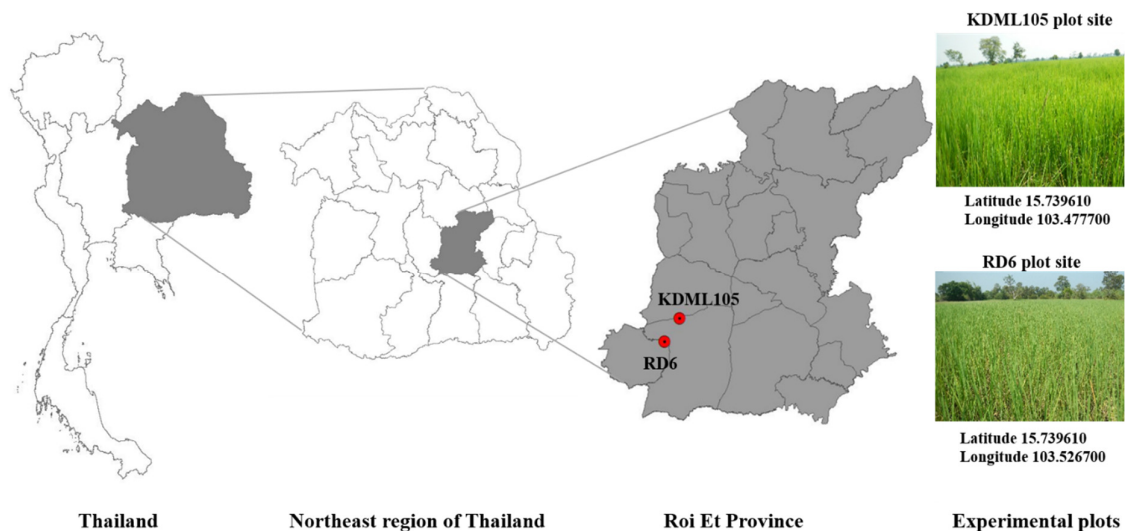
Rainfed mega-environmental climate in NE Thailand experiences colossal challenge, like low nutrient soil solution (due to long-term rice cultivation), water shortage (due to limited precipitation rate), and soil salinity effects, leading to low productivity of rice crop in this area (Jongdee *et al.*, 2006). Overcoming low competitiveness in rice production of this region has been sought through diverse strategies, such as 'KDML105' pyramiding drought and salinity tolerant traits in rice breeding program via chromosome segment substitution lines (CSSL) and double haploid lines (DHL) (Vanavichit *et al.*, 2018; Hungsaprug *et al.*, 2020). Alternatively, management of cultural practices such as sowing date (Sujariya *et al.*, 2019), water productivity in relation to soil clay content (Tsubo *et al.*, 2007), and soil organic matter management (Arunrat *et al.*, 2017) are one of the most common protocols employed for subjugating low productivity concerns. The quest of seeking more non-destructive measures of gaining big data in paddy fields, led to use of novel technologies like remote sensing (Mosleh *et al.*, 2015; Zheng *et al.*, 2016; Barrero and Perdomo, 2018; Kawamura *et al.*, 2020). Sensors together with unmanned aerial vehicle (UAV) are used to collect the reflectance data and calculate the vegetation indices linked to several traits, i.e. plant height, leaf greenness, canopy greenness, leaf area index, aboveground biomass and yield attributes (Maes and Steppe, 2019; Mukherjee *et al.*, 2019; Poley and McDermid, 2020). In addition, the basic data thus obtained from UAV can be exploited through satellite remote sensing on an even larger geographical scale for risk assessment, suggesting management policies, yield prediction (forecasting for price insurance), precision agriculture and income compensation (Kasampalis *et al.*, 2018; Huang *et al.*, 2019; Shiu and Chuang, 2019). Previously, overall growth estimation models of rice crop at different growth stages based on seven vegetation indices (Vis) derived from UAV have been well established (Qiu *et al.*, 2020). Nitrogen fertilizer management in paddy field using VIs of rice canopies in whole life cycle from UAV-based multispectral imagery has been well developed (Zheng *et al.*, 2020). Likewise, estimation of LAI (leaf area index) in rice crop at various growth phases, tillering, stem elongation, panicle initiation and booting stages have been detected by UAV-based digital images (Li *et al.*, 2019), consequently LAI at booting stage is an effective index for grain yield prediction in relation to VIs from UAV-mounted with red edge band (720 nm) and near infrared band (800 nm) (Zhou *et al.*, 2017). Therefore, the suggestion from previous reports in relation to dominant cultivars of paddy environmental fields is mentioned. In Thailand, however, baseline information of VIs in rice crop based on camera imageries during whole life cycle of paddy field environments is still lacking, especially in 'KDML105' and its mutant glutinous rice, 'RD6'. Thus, the aim of this investigation

was to validate UAV-derived information of rice crop traits with non-destructive measurements in 'KDML105' and 'RD6' rice varieties of whole life cycle in two plots (Latitude 15.739610 Longitude 103.477700 and Latitude 15.739610 Longitude 103.526700) under NE region field environments.

## Materials and Methods

### *Plant materials and cultivated conditions*

Seeds of two rice cultivars of indica rice, 'Khao Dawk Mali 105' ('KDML105'; non-glutinous rice) and 'Rice Department 6' ('RD6'; glutinous rice derived from 'KDML105' mutant selection) were provided by Pathum Thani Rice Research Center, Rice Department, Ministry of Agriculture and Cooperative, Thailand (Table S1). Seeds were germinated (sowing date May, 1 2018) at the rate of 156 kg ha<sup>-1</sup> and one month-seedlings-old were then transplanted (May, 31 2018) in 15×15 cm in row and plant spacing in two plot sites of rice field (latitude 15.739610 longitude 103.477700 and latitude 15.739610 longitude 103.526700) at Roi Et province, Northeast region of Thailand (Figure 1). The weather data during the rice cultivation period like air temperature, precipitation and relative humidity were recorded (Figure S1). Weed control and fertilizer schedule in whole life cycle of rice crop in the field trial were practiced following recommendations of Rice Research Institute of Thailand (Rice Research Institute, 2004).



**Figure 1.** Location of rice field experiments at Roi Et in North-eastern region of Thailand

### *Growth performances and yield attributes*

Plant height and number of tillers per clump in each plot site were collected during different developmental stages (vegetative, reproductive and ripening phases) throughout the whole life cycle. Plant height was measured from the shoot base to the longest leaf tip, according to protocol of International Rice Research Institute (IRRI, 2002). Shoot height of four clumps in each plot of 4×4 m<sup>2</sup> (with four plot replications; *n* = 4) were randomly selected and measured. Total chlorophyll content in the leaf tissues of two indica rice cultivars were measured using chlorophyll meter (Minolta SPAD 502, Japan) by blue (400-500 nm) and red (600-700 nm) bands of chlorophyll absorbance peaks, according to Hussain *et al.* (2000). Leaf greenness (SPAD value) in 5 points per leaf of second fully leaf from the shoot tip in each plot of 4×4 m<sup>2</sup> (with four plot replications; *n* = 4) were measured and averaged. At the harvesting stage (November, 5 2018; 185 days after sowing), shoot fresh and dry biomass, number of grains per panicle, one thousand grain mass,

aboveground biomass, and total grain yield were determined by sampling one square meter of the field under study with four replicates each ( $n = 4$ ).

#### *UAV data collection*

Unmanned aerial vehicle (UAV; model DJI Phantom 4 Advanced, DJI Phantom Thailand) installed with two sensors including the digital and multispectral camera was used. Red-Green-Blue (RGB) camera (which came pre-installed with UAV) was capable of taking high resolution (20 megapixels) images with an image size ratio of  $5472 \times 3648$  pixels. In addition, the Multispectral sensor, RedEdge-M by Micasense, was also mounted on the UAV, as five-narrow spectral bands of blue, green, red, red-edge, and near-infrared. UAV imaging data throughout the whole life cycle and developmental stages of rice crop were captured. UAV flight plan was set at altitude of  $\sim 90$  m aboveground with 80 percent front and side image overlap. The image was acquired under clear sky between 10:00 am and 2:00 pm daily with 68 images for 5.10 min. The ground sampling distances (GSD) of digital and multispectral imaging were 2.39 and 6.25 cm per pixel, respectively. Geo-referencing was done using ground control point (GCP). In the initial flight, at least 5 GCPs were required, subsequently performs image-to-image registration in next flights. In addition, MicaSense RedEdge-M calibration using a Calibrated Reflectance Panel (CRP) captured from the panel was immediately practiced before each flight according to calibration manual. In brief, a calibration curve associated with it across the visible and near-infrared spectrum was followed by MicaSense database (MicaSense Inc., USA). An absolute reflectance (a value between 0.0 and 1.0) in the range of 400 nm to 850 nm (in increments of 1 nm) was provided as the calibration data. Five reflectance values, one for each of the 5 bands of the camera imagery, by averaging the reflectance values were practically applied as calibration curve across the bandwidth of each band.

#### *Image processing*

Digital and multispectral imageries were captured from the UAV installed cameras. The images were processed, analysed, georeferenced and ortho-mosaicked, followed by arrangement of the multiple images to the large scene, using Pix4D software (Pix4D Inc., Switzerland). Digital imagery was analysed by the region of interest (ROI) to the ratio of red (R), green (G) and blue (B) colour components using ArcGIS program (version 10.5 for Windows®). Colour index calculation was processed using digital number (DN) values of R, G and B channels extracted from each image using the region of interest (ROI) tool. The DN values of RGB channels in RGB images were reflected the radiance and reflectance performances in visible spectrum of crop canopy. Normalized DN values in term of r, g and b were calculated following by vegetation estimation compared to original RGB DN values (Li *et al.*, 2019). A process of transformation of raw pixel values into reflectance was processed according to ArcGIS software. In brief, convert the raw pixels of the panel image were converted to units of radiance per the process specified in the radiometric calibration model. An average value of radiance for the pixels located inside the actual panel area of the image was calculated. The transfer function of radiance to reflectance was followed by the calibration data of the panel provided by MicaSense.

#### *Computation of the vegetation indices*

Multispectral imagery was also processed and calculated to four vegetation indices, ExG, EVI2, NDVI and NDRE, using Pix4D software. Excess Green Index (ExG) is a vegetation index for greenness identification (Yang *et al.*, 2015). Moreover, the Enhanced Vegetation Index 2 (EVI2) is a vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring through de-coupling of the canopy background signal and reduction of atmospheric influences with two-band EVI (Jiang *et al.*, 2008). The Normalized Difference Vegetation Index (NDVI) is an indicator of vegetation fraction, leaf area index, biomass, and leaf chlorophyll (Tucker, 1979). Especially, the Normalized Difference Red Edge Index (NDRE) is a signal sensitive to chlorophyll content in leaves, leaf area and stress detection (Schuster *et al.*, 2012). The calculation of ExG, EVI2, NDVI and NDRE used the spectral reflectance of red, green, blue, near-infrared and red-edge of the image (Table S2).

*Experimental layout and statistical analysis*

Two indica rice varieties KDML105 and RD6 growing in plot sites were arranged in completely randomized design (CRD) with four replications ( $n = 4$ ). Mean values and significant differences in rice crop morphological characters, total chlorophyll pigment and grain yield attributes randomly sampling in  $4 \times 4$  m<sup>2</sup> plot size were compared using *t*-test at  $p \leq 0.05$  by the SPSS 11.5 software. In addition, the correlations between manual measurements and vegetation indices were analysed through correlation analysis.

**Results***Growth performances, leaf greenness and yield attributes*

Overall growth characteristics from vegetative to ripening phases of 'KDML105' and 'RD6' in the field trials were assessed (Figure 2A). Plant height in two rice cultivars increased in relation to different developmental stages. Interestingly, plant height in 'KDML105' was significantly higher than in 'RD6' at vegetative, reproductive, and ripening stages (Table 1). Number of tillers per clump in 'KDML105' was stable at early vegetative phase and then increased at late vegetative and ripening stages, whereas it was continuously increasing in 'RD6' prior to ripening stage (Table 1). Moreover, number of tillers per clumps in 'RD6' (4-8 tillers per clump) was higher than in 'KDML105' (3-6 tillers per clumps), except at mid-vegetative phase (5 tillers per clumps) (Table 1).

On account of total chlorophyll content in leaf tissues, significant fluctuations, which were dependent on genotype and/or developmental phase, were recorded. At early vegetative stage, total chlorophyll pigment in 'KDML105' was lower than in 'RD6'; however, later it significantly increased over RD, followed by a decline and ultimately becoming stable until reaching the ripening stage (Figure 2B). On the other hand, total chlorophyll content of the cultivar 'RD6' at late vegetative, reproductive, and ripening stages was higher than that in cv. 'KDML105' (Figure 2B). Based on colour index, percentage of green and blue bands in 'KDML105' > 'RD6', especially in vegetative and reproductive stages were evidently observed. In contrast, colour index of red band percentage in 'KDML105' was lower than in 'RD6' (Figure 2C) in relation to leaf greenness or SPAD value.

At ripening stage, shoot fresh weight, shoot dry weight and number of grains per panicle in 'KDML105' and 'RD6' varied insignificantly (Table 2). One thousand grains weight, total grain yield and aboveground biomass in 'KDML105' were significantly higher by 1.20, 1.82 and 3.82 folds, respectively, compared to 'RD6' (Table 2). In present study, it was confirmed that yield traits of 'KDML105' (5,478 Kg ha<sup>-1</sup>) growing in rice filed plot were greater than observed for 'RD6' (3,011 Kg ha<sup>-1</sup>) (Table 2).

**Table 1.** Plant height and number of tillers per clump of two indica rice varieties, 'KDML105' and 'RD6' in each developmental stage of whole life cycle in northern region of Thailand

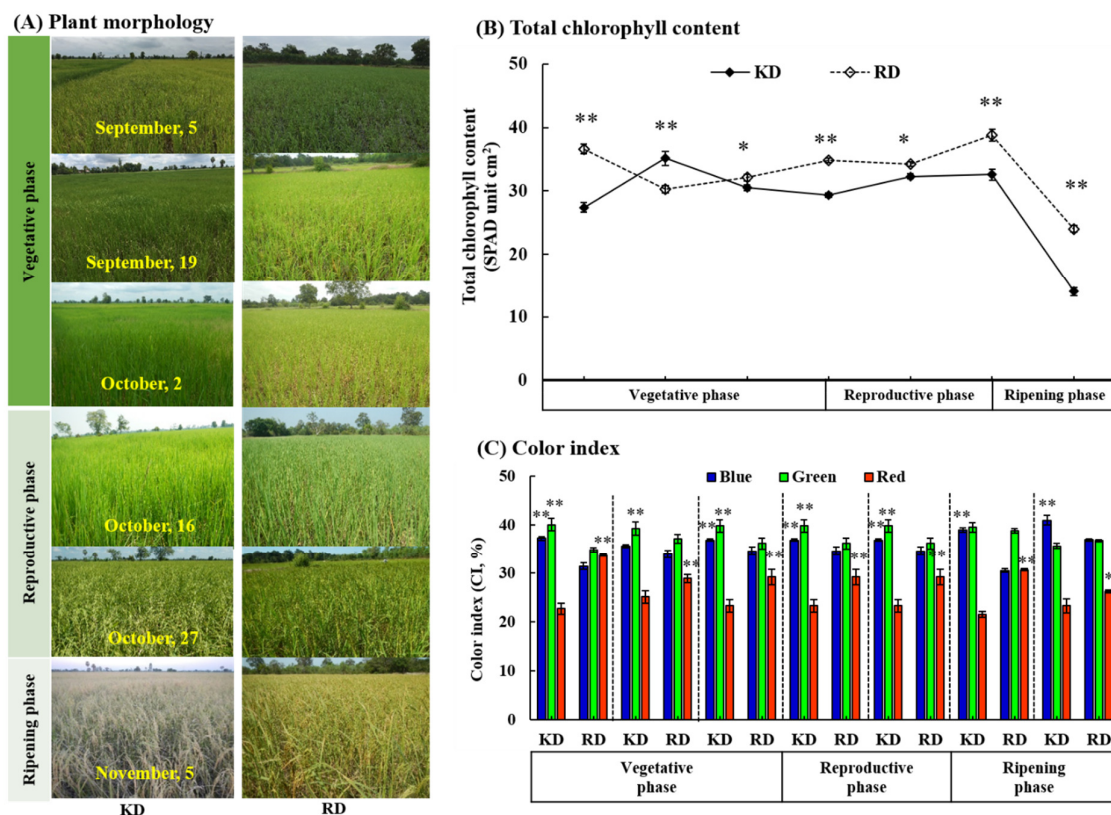
Parameters	Vegetative stage			Reproductive stage			Ripening stage
Plant height (cm)							
'KDML105'	65.2±1.7a	81.6±2.0a	100.0±2.8a	105.4±1.9a	132.7±1.3a	140.4±1.0a	143.1±1.5a
'RD6'	60.7±2.7b	62.8±1.4b	70.3±2.4b	87.5±2.9b	108.3±3.4b	123.2±1.8b	131.7±2.3b
<i>t</i> -test	**	**	**	**	**	**	**
Number of tillers per clump							
'KDML105'	3.0±0.2b	3.0±0.3b	5±0.19	5±0.18b	5±0.18b	5±0.15b	6±0.20b
'RD6'	4.0±0.2a	5.0±0.3a	5±0.31	6±0.31a	6±0.40a	7±0.36a	8±0.40a
<i>t</i> -test	**	**	ns	**	**	**	**

Data presented as the mean of four replications ( $n = 4$ ) with standard error (mean±SE). Different letters in each column represent significant difference at  $p \leq 0.01$  using *t*-test. ns represents not-significant difference.

**Table 2.** Shoot fresh weight and shoot dry weight, grain numbers, 1,000 grains weight, grain yield and aboveground biomass between two *indica* rice varieties, ‘KDML105’ and ‘RD6’ at ripening stage

Varieties	Shoot fresh weight (g)	Shoot dry weight (g)	Number of grains per panicle	1,000 Grains weight (g)	Grain yield (kg ha <sup>-1</sup> )	Aboveground biomass (kg ha <sup>-1</sup> )
‘KDML105’	7.21±0.95	2.31±0.35	181.25±35.47	28.54±0.39a	5478.77±693.46a	8680.22±799.04a
‘RD6’	10.46±1.96	3.02±0.53	214.75±13.29	23.73±1.00b	3011.00±359.86b	2274.83±449.69b
<i>t</i> -test	ns	ns	ns	**	**	**

Data presented as the mean of four replications (*n* = 4) with standard error (mean±SE). Different letters in each column represent significant difference at *p* ≤ 0.01 using *t*-test. ns represents not significant difference.



**Figure 2.** Plant morphological characteristics (A) total chlorophyll content (B), and color index (red:green:blue) (C) in whole life cycle of two indica rice genotypes, KD (‘KDML105’) and RD (‘RD6’) in the field trial

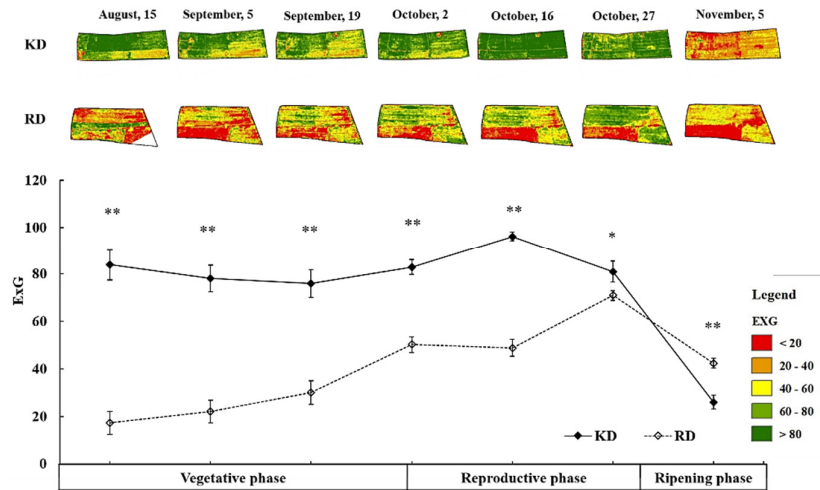
Data presented as the mean of four replications (*n* = 4) with standard error (mean±SE). \*, and \*\* represent as significant difference at *p* ≤ 0.05 and *p* ≤ 0.01, respectively using *t*-test.

*Vegetation Indices (VIs) and correlation between data measurements and VIs*

Four vegetation indices, including ExG, EVI2, NDVI and NDRE derived from RGB imageries were calculated. ExG value in vegetative and reproductive developmental stages of ‘KDML105’ was significantly greater than in ‘RD6’ in relation to dark green colour (top panel), whereas it was significantly declined at ripening phase (yellow to red colour) (Figure 3). Similarly, EVI2 index in ‘KDML105’ was also greater than observed in ‘RD6’ (identified by green colour) (Figure 4). NDVI in ‘KDML105’ also maintained higher value prior to early reproductive stage, but it was not significantly different from ‘RD6’ at late reproductive phase and exhibited a sharp declining at ripening stage (Figure 5). Moreover, NDRE at early vegetative phase of two rice cultivars was unchanged and stable, followed by sustained high levels in ‘RD6’ until late reproductive stage.

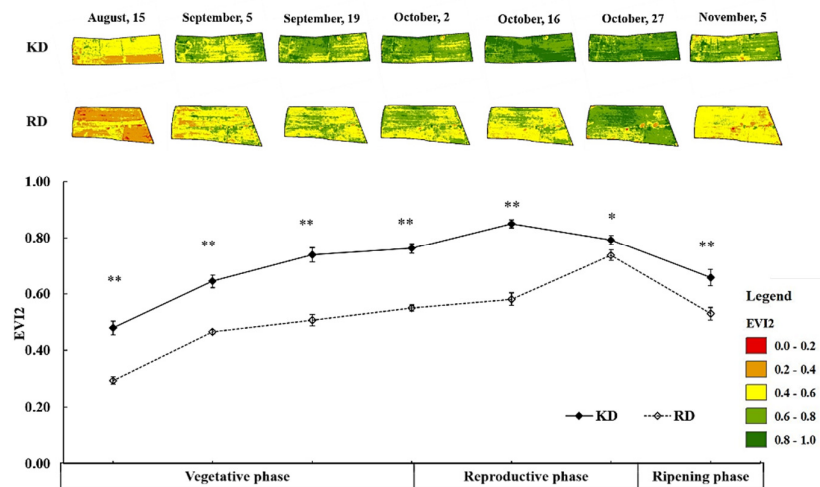
In addition, at ripening phase, level of NDRE in ‘KDML105’ showed more decrease than ‘RD6’ as indicated by yellow colour (Figure 6).

Negative relationship between total chlorophyll content and NDVI throughout the whole life cycle of two rice genotypes in field trial plots was evidently demonstrated (Figure 7A) with high correlation coefficient ( $R^2 = 0.4397$ ). At early reproductive phase, a positive relationship between NDVI and NDRE was found ( $R^2 = 0.7363$ ; Figure 7B). Moreover, positive relations between NDRE and total grain yield ( $R^2 = 0.6414$ ; Figure 7C), as well as NDVI and aboveground biomass ( $R^2 = 0.6504$ ; Figure 7D) in two indica rice at early reproductive stage were validated. Based on the data of the present study, a good correlation of non-destructive measurements and vegetation indices from UAV platform in relation to final yield performances of rice crop was verified.



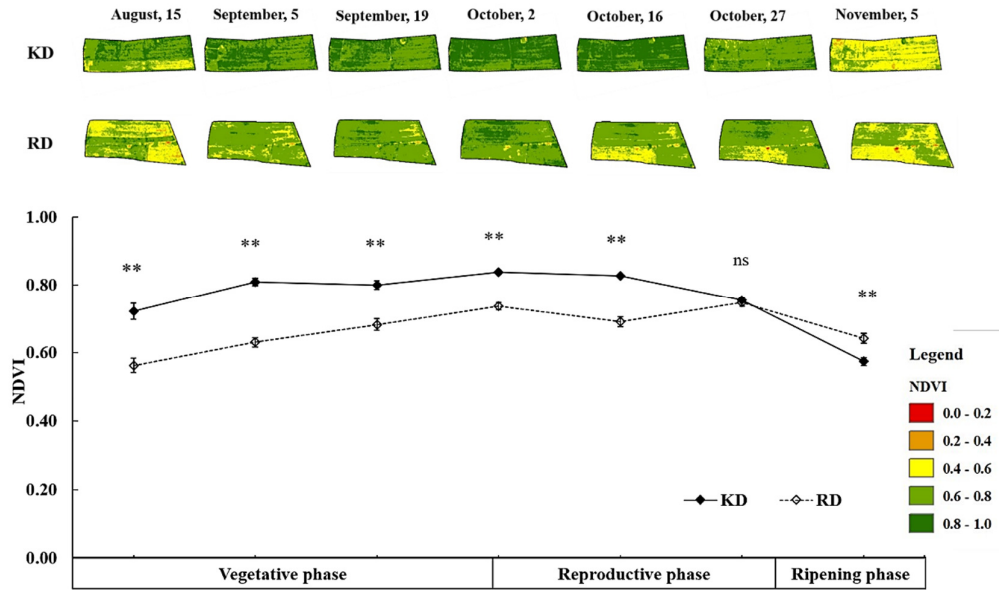
**Figure 3.** EXG vegetation index in whole life cycle of two indica rice genotypes, KD (‘KDML105’) and RD (‘RD6’) in the field trial

Data presented as the mean of four replications ( $n = 4$ ) with standard error (mean  $\pm$  SE). \*, and \*\* represent as significant difference at  $p \leq 0.05$  and  $p \leq 0.01$ , respectively using  $t$ -test.

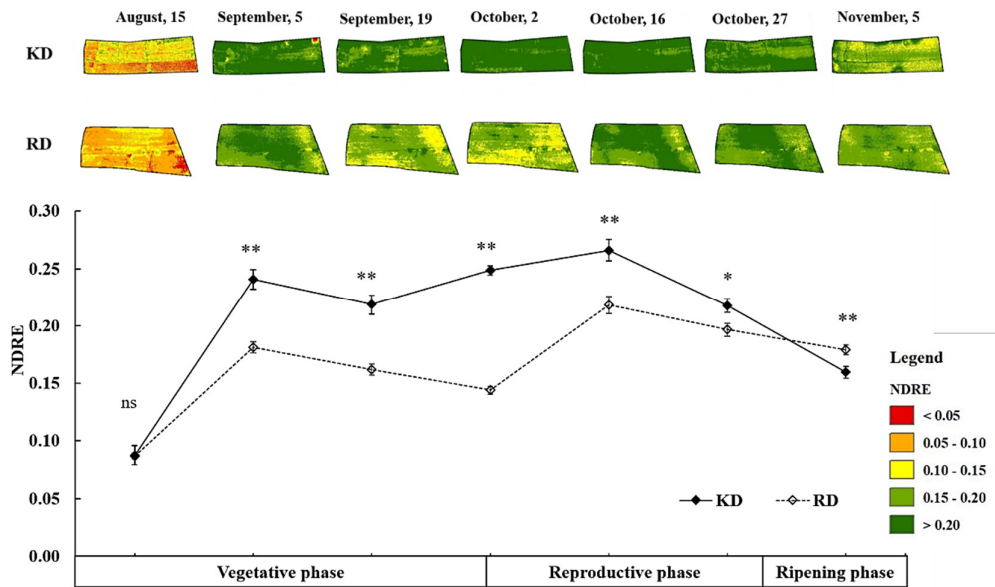


**Figure 4.** EVI2 vegetation index in whole life cycle of two indica rice genotypes, KD (‘KDML105’) and RD (‘RD6’) in the field trial

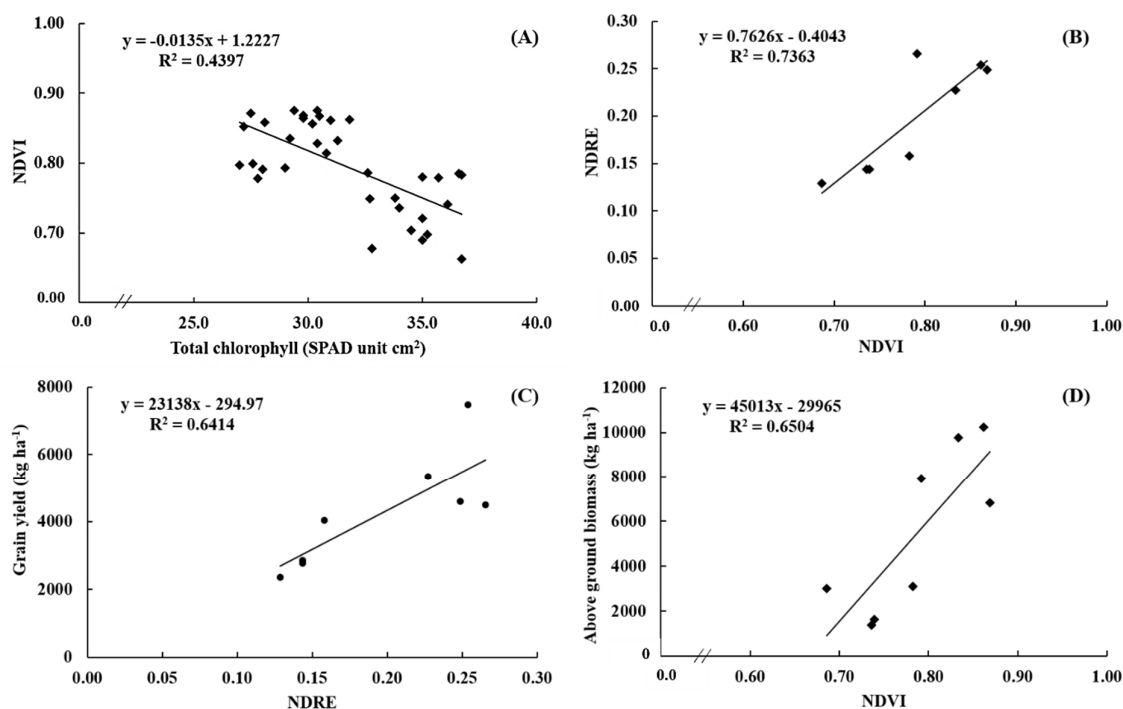
Data presented as the mean of four replications ( $n = 4$ ) with standard error (mean  $\pm$  SE). \*, and \*\* represent as significant difference at  $p \leq 0.05$  and  $p \leq 0.01$ , respectively using  $t$ -test.



**Figure 5.** NDVI vegetation index in whole life cycle of two indica rice genotypes, KD ('KDML105') and RD ('RD6') in the field trial  
Data presented as the mean of four replications ( $n = 4$ ) with standard error (mean+SE). ns and \*\* represents as non-significant difference and significant difference at  $p \leq 0.01$ , respectively using  $t$ -test.



**Figure 6.** NDRE vegetation index in whole life cycle of two indica rice genotypes, KD ('KDML105') and RD ('RD6') in the field trial  
Data presented as the mean of four replications ( $n = 4$ ) with standard error (mean+SE). \*, and \*\* represent as significant difference at  $p \leq 0.05$  and  $p \leq 0.01$ , respectively using  $t$ -test.



**Figure 7.** Relationship between total chlorophyll and NDVI in whole life cycle (A), NDVI and NDRE (B), NDRE and grain yield (C) NDVI and aboveground biomass (D) at ripening phase of two indica rice genotypes in the field trial

## Discussion

Overall growth performances including plant height and number of tillers per clump of two indica rice cultivars, 'KDML105' and 'RD6', in the field trial at Roi Et province were determined according to respective plant developmental stages: vegetative, reproductive, and ripening phases. According to our results, number of tillers per clump in 'RD6' was greater, whereas plant height was shorter compared with 'KDML105'. Previously, number of tillers and plant height of 'RD6' growing in Khon Khan University station and Khon Khan Rice Research Center (Northeast region of Thailand) were recorded as 9.0 tillers per clump and 204.9 cm, respectively (Aung Nan *et al.*, 2019). In addition, 'KDML105' showed better performance in terms of total grain yield (1.9-ton ha<sup>-1</sup>) of irrigated field trials in northeast Thailand compared to yield of 'RD6' in rainfed regions (0.9-ton ha<sup>-1</sup>), which declined sharply from 1.7-ton ha<sup>-1</sup> to 0.2-ton ha<sup>-1</sup> establishing its sensitivity to drought stress (Jongdee *et al.*, 2006). In contrast, total yield of 'RD6' in irrigated lowland was maximized at 3.193-ton ha<sup>-1</sup>, which was greater than that of KDML105 (2.853-ton ha<sup>-1</sup>) by 1.12-fold (Sujariya *et al.*, 2019). Earlier, 'RD6' has been established by Nishimura *et al.* (2011) as a drought and salt sensitive cultivar in comparison to 'KDML105', which resulted in reduced yield components in the field trials in NE Thailand (Tsubo *et al.*, 2007; Arunrat *et al.*, 2017). In the present study, low productivity in 'RD6' was evidently observed, depending on basic physical and chemical properties of soil including sandy soil type (low water productivity), low N-P-K nutrition and low organic matter when compared with 'KDML105' plot site. Interestingly, water holding capacity in relation to clay content (Tsubo *et al.*, 2007) and organic matter (Arunrat *et al.*, 2017) is an important factor to keep high productivity of rice crop in rainfed areas of NE Thailand. Severity rate of 'RD6' coping with extreme environments, i.e. water shortage (depending on precipitation rate per year) and soil salinity (underground rock salts) in NE region of Thailand is one of the most critical factors indicating towards low yield attributes (Cooper *et al.*, 1999; Jongdee *et al.*, 2006). In the

future, the rice lodging derived from strong wind (storm) and long period of water shortage in paddy field, especially in the booting stage using UAV platform might further be investigated to yield loss prediction in on-farm studies.

Total chlorophyll pigments in cv. 'RD6' were significantly higher than those in cv. 'KDML105', especially at late vegetative and ripening phases. Previously, total chlorophyll content in the leaf tissues of 'RD6' seedlings (28-day-old) were observed to be greater than in cv. 'KDML105' by 1.24 folds, whereas net photosynthetic rate ( $P_n$ ) in 'KDML105' was greater than in 'RD6' by 1.04 folds (Jiang *et al.*, 2008). SPAD value is assessed to estimate only the green colour of leaf as preliminary data. Low level of SPAD unit in rice seedlings cv. 'KDML105' at 100% field capacity (well-irrigated condition) was evidently observed, compared with CSSL and double haploid population (Hungsaprug *et al.*, 2020). At heading stage, SPAD value in KDML105 growing in NE Thailand is lowest when compared with IR57514-PMI-5-B-1-2 and HY71, leading to reduction in shoot dry weight and grain yield (Hayashi *et al.*, 2010). Based on the greenness of canopy of rice crop, staying green is an efficient strategy to identify the healthy plants in relation to prediction of high yield attributes (Yoo *et al.*, 2007; Zhao *et al.*, 2019). A basic information forming link between ground truth data of SPAD value and reflectance sensors of UAV sensing technology has been well established as non-destructive measurement, especially in rice crop in response to optimize nitrogen application rate (Zhang *et al.*, 2016; Duan *et al.*, 2019a). Red band reflectance profile in cv. 'RD6' was larger than in cv. 'KDML105' during whole life cycle. Interestingly, the red band intensity (observed reflectance by orange, red, purple, and violet colours; 440-550), indicating total chlorophyll content or leaf greenness has been validated in several plant species (Gitelson *et al.*, 2003). Moreover, chlorophyll pigment, which is a major component of light harvesting complexes in photosynthetic abilities in plant canopy, has been used to generate the vegetation indices through remote sensing technology (Gitelson and Merzlyak, 1996; Cortazar *et al.*, 2015). Therefore, CO<sub>2</sub> assimilation in the paddy field trial using Eddy covariance flux tower was recommended to analyse in term of stomatal function in relation to carbohydrate sink-source regulation, especially in the grain filling stage.

Four vegetation indices, ExG, EVI2, NDVI and NDRE in whole life cycle of cv. 'KDML105' were greater than those in cv. 'RD6', except for ripening phase where decline was witnessed. Based on the colour vegetation indices, ExG is one of the most sensitive parameters linking to canopy greenness (Lee *et al.*, 2020). It retains high values in both vegetative and reproductive stages but show decrease in ripening stage (turn to yellow). In ripening phase, the colours of canopy mixing by green and yellow of rice crop are identified as the major limitation to validate by UAV robotic system (Devia *et al.*, 2019a). EVI2 is very low in the seedling stage (3-4 week after planting) in paddy field (-0.03-0.15; very low greenness), increasing to maximum capacity (0.35-1.0; contrast greenness) in 8-13 weeks after planting (Sugianto *et al.*, 2020) and later declining in harvesting stage (Qiu *et al.*, 2015). In present study, EVI2 was low in early vegetative stage (seedling 0.30) and then increased (>0.40) to identify dark greenness canopy. NDVI establish link with green colour in a rank of 0.2-0.3 as orange (seedling or stressed plants), 0.3-0.6 as light green (healthy vegetation) and 0.6-1.0 as dark green (dense vegetation) (Cárdenas *et al.*, 2018). In general, NDVI has already been monitored and categorized as (i) very low at the germination and early vegetative stages; (ii) continuously increase over the vegetative-to-reproductive stage; and (iii) gradually decrease with maturation of the ripening stage (Mosleh *et al.*, 2015). In whole life cycle of japonica rice (cv. 'Shendao-47'), leaf NDVI and canopy NDVI demonstrated similar pattern of low values in seedling stage, an increase to maximum in reproductive and a decline in ripening phase (Yu *et al.*, 2016). In present study, negative relationship between SPAD unit and NDVI was demonstrated with high correlation coefficient ( $R^2 = 0.4397$ ), whereas NDVI was >0.6 at vegetative to reproductive stages. Previously, a positive relationship between SPAD and NDVI value in rice cvs. 'Wu Youdao 3' and 'Yang Guang 4' ( $R^2 = 0.7655$ ) was reported by Zhang *et al.* (2016). Consequently, aboveground biomass of rice crop is also predicted by NDVI, corroborated by previous reports demonstrating high regression coefficient ( $R^2 > 0.50$ ), especially in the pre-heading developmental stage (Devia *et al.*, 2019b; Wang *et al.*, 2019; Zheng *et al.*, 2019). In addition, NDVI derived from UAV and Greenseeker was closely related, ranging from  $R^2 = 0.38$  to 0.90 in wheat crop (Hassan *et al.*, 2019). Ultimately, NDRE in present study was only <0.30, representing the green canopy in

relation to canopy chlorophyll content index (Barnes *et al.*, 2000) and leaf area index ( $R^2 = 0.5476$ ) (Duan *et al.*, 2019b). Moreover, NDRE in heading stage is closely related to total grain yield of rice crop ( $R^2 = 0.4858$ ) (Duan *et al.*, 2019a). Based on the results, vegetation indices derived from UAV sensors should further be validated from multi-location paddy fields and applied for different rice cultivars for an effective modelling approach.

## Conclusions

'KDML105' was identified to possess as rapid adaptation strategies when compared with 'RD6', leading to maintenance of the overall growth performances and yield traits. Vegetation indices derived from UAV information and ground truth non-destructive data were validated, moreover NDRE exhibited positively interaction with total grain yield of rice crop. This study advocates harnessing and adopting the approach of UAV platform along with ground truthing non-destructive measurements of assessing a species/cultivars performance at broad land-use scale.

## Authors' Contributions

Conceived, design and performed the experiment: PP, AE and SC. Analyzed the data: RT, KT, SK and KS. Contributed measurements, data analysis and related analysis: RT, KT, SK and KS. All authors wrote and approved the final manuscript. All authors read and approved the final manuscript.

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## Conflict of Interests

The authors declare that there are no conflicts of interest related to this article.

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