VERIFICATION OF COLOR INDICES OBTAINED FROM DIGITAL CAMERAS FOR ESTIMATION OF RICE GROWTH STATUSES UNDER VARIOUS CONDITIONS

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ABSTRACT: Estimation of rice growth statuses, such as leaf area index, total dry weight, and nitrogen concentration are essential for management of rice cultivation. In this study, color indices obtained from different image processing methods and digital cameras were compared to reveal the effectiveness and characteristics of the color indices for estimation rice growth statuses. Three rice varieties were observed periodically from transplanting to heading stage under three nitrogen treatments in at paddy field in Japan. Rice plants were photographed using two digital cameras. On the same day, plants were sampled with 2-week interval for the measurement of total dry weight, leaf area index and nitrogen concentration in leaves. The R-G-B images were corrected using gray patch scale for reduction of weather effect and gamma characteristics. Both of the R-G-B images and the R-G-NIR images were segmented into rice shoot area and non-shoot area, such as soil and water, with a* value of L*a*b* color space. Several color indices were calculated by digital number of R-G-NIR images and R-G-B images for each image processing method. Regression analyses are performed between the color indices and rice growth statuses, and root mean square errors of the relationships were compared for verification of effectiveness of estimation. The color indices showed significant relationships with leaf area index and total dry weight. Root mean square error of the color index of R-G-NIR images were smaller than the others. The color indices showed relationships with nitrogen concentration in leaves, but they reflected changes in date strongly. The results of comparison of image processing methods implied that the segmentation of shoot area and gamma characteristics reduction is unnecessary. The color indices of R-G-B images and R-G-NIR images are useful for estimation of rice growth statuses.

1. INTRODUCTION

The monitoring of crop growth status is important for agriculture because it affects crop yield and management of nutrient fertilization. Nutrient fertilization is essential for plant, but over fertilization causes environmental problems and low fertilization use efficiency. Even in rice cultivation, rice growth status such as biomass and nutrient of leaves is used for prediction of the crop yield and grain quality, and fertilizer management. Several measurement methods have been used to detect the rice growth status, but most of them are destructive, and time-consuming, or low accuracy. For examples, color charts have been used in Japan for management of nitrogen treatment, but it requires skill and the measurement result is uncertainly. The one of other method for management is chlorophyll meter which is high accuracy and not requires skills. However, the chlorophyll meter is expensive generally and requires many sample measurements (Shibayama et al., 2012; Kanbe et al., 2015).

As an alternative method of the rice growth status measurement, remote sensing has attracted attention. The remote sensing method uses spectrum information of objects by digital cameras or the other sensors, and this method is non-destructive, fast, and large measurement area with platforms such as unmanned aerial vehicle and satellite. The spectrum information relates plant activity, biomass, and plant growth. Many studies have researched the remote sensing method for estimation rice growth status. Lee et al. (2013) and Wang et al. (2014) researched rice growth and nitrogen status using color digital camera. Sakamoto et al. (2010) suggested monitoring method of crop community structure using day and night digital images. Shimojima et al. (2017) studied rice growth statuses using unmanned aerial vehicle color image. Hama et al. (2016) researched rice growth statuses using R-G-NIR image camera and R-G-B camera on small unmanned aerial vehicle. Most of researchers reported the color indices from digital camera images showed significant correlation with rice growth statuses and anticipated estimation of the rice growth statuses. Despite many estimation models have been proposed, the color indices and image processing methods are not unified. Digital camera images are affected by different weather and gamma characteristic; hence color and brightness vary among images. Furthermore, the images include non-shoot area such as water, soil, and algae. However, the effect of them and reduction method of them are not considered and compared in many researches. Many color indices have been used for estimation of rice growth statuses by researchers, but characteristics and effectiveness of them are diverse because the color indices are calculated from different bands of sensors. In addition, Lee et al. (2013) and Kanbe et al. (2015) reported estimation models are different in several varieties. Due to these problems, further experiment under various conditions and comparison of the color indices are required to develop high accuracy estimation model.

In this study, color indices of R-G-B images and R-G-NIR images were calculated using 6 types of image processing methods. The effectiveness and characteristics of the color indices were verified by comparing relationships with rice growth statuses under various conditions.

2. MATERIALS AND METHODS

2.1 Experimental Field and Field Surveys

The experiment was conducted at experimental paddy filed of Tokyo University of Agriculture and Technology in Fuchu City, Japan (35°39´59´´N, 139°28´15´´E), in 2018. Three rice varieties, Nipponbare (Japonica), IR64 (Indica), and Basmati370 (Indica) were grown under three levels of nitrogen treatments, which were 0g/m², 6g/m², and 21g/m², with three replications. There were totally 27 plots. Sixteen days old seedlings were transplanted on 30 May 2018. After 7 June 2018, 8 rice plants were photographed and sampled six times approximately every two weeks for each plot.
Images of the rice plant were captured using two digital cameras. One digital camera was R-G-B image camera (D5300, Nikon Corporation), and set at aperture of f/5.6, focal length of 18 mm, auto ISO, auto shutter speed, and auto white balance. Another digital camera was R-G-NIR image camera (Yubaflex, BIZWORKS Corp, Inc.), and R-G-NIR images were stored in raw format. The cameras were mounted at nadir position and 8 rice plants were took pictures with gray patch scale (Exposure Profile Target II, SEKONIC Corporation) at local time 9:00–10:00 (Figure 1). On the same day, the above-ground parts of photographed rice plants were sampled. The plant samples were separated into leaves and stems, and dried. The samples were weighted to measure total dry weight (DW) and analyzed for nitrogen concentration in leaves (NcL) and leaf area index (LAI).

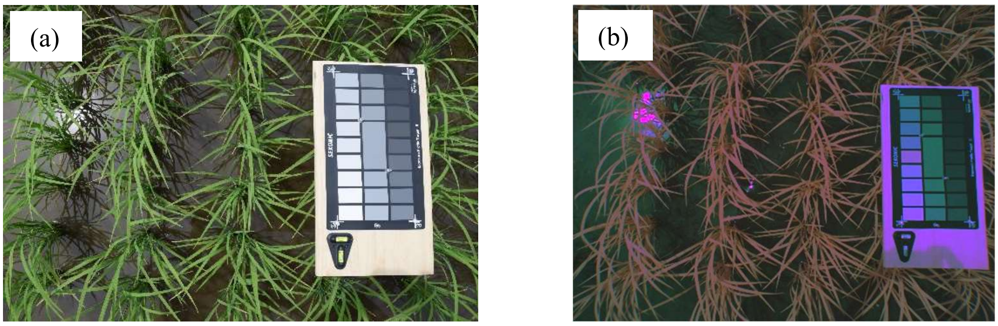

Figure 1. Examples of (a) R-G-B images and (b) R-G-NIR images.
The R-G-NIR image was displayed in the false color image.

2.2 Image processing methods and color indices calculation

The R-G-B images were corrected using gray patch scale for reduction of effect of different weather and gamma characteristic. At first step, color and brightness of the R-G-B images were adjusted to make images under same conditions. The reflectance of 25 gray patches of gray patch scale were measured using spectroradiometer (FieldSpec 4 Hi-Res, ASD Inc.). Digital numbers of two gray patches in each image were measured for each R-G-B. The reflectance of two gray patches were (26.45%, 26.84%, 27.25%) and (4.26%, 4.38%, 4.48%) for R-G-B respectively. The digital numbers of two gray patches used to calculate correction equation using linear conversion, as follows;

$$Y_\lambda = (Y_{max\_\lambda}\text{-}Y_{min\_\lambda}/X_{max\_\lambda}\text{-}X_{min\_\lambda})\, X_\lambda \text{ - } (Y_{max\_\lambda}\text{-}Y_{min\_\lambda}/X_{max\_\lambda}\text{-}X_{min\_\lambda})\, X_{min\_\lambda} + Y_{min\_\lambda} \quad (1)$$

where λ was each R-B-G, X and Y were input value and output value respectively, and X_{max} and X_{min} were two gray patch digital number of each image. Y_{max} and Y_{min} were digital number after correction which same value for all images. The digital number of Y_{max} and Y_{min} were 230 and 90 respectively for each R-G-B. After color and brightness correction using eq.1, nonlinear relationship between output value and input value was adjusted. Most commercial cameras used the nonlinear relationship to display images on monitor naturally. The nonlinear relationship was often expressed exponential function formula and called gamma characteristic. For reduction of gamma characteristic, digital numbers of all gray patches, excepted saturated, every two images for each experimental day were measured. The measured digital numbers were compared with reflectance of each patch measured by spectroradiometer, and gamma reduction equation for each R-G-B was derived using least squares method. Both equations of color and brightness correction and gamma reduction were applied to all R-G-B images. Therefore, three types of images, non-correction image (original image), only color and brightness correction image (color correction image), and color and brightness correction and gamma reduction image (gamma reduction image), were prepared to verify color indices.

The R-G-NIR images and the three types of R-G-B images were segmented into rice shoot area and non-shoot area such as water, soil, and algae. The shoot area of R-G-B images were derived from R-G-B original images using threshold. The R-G-B original images were transformed into CIE $L^*a^*b^*$ which were computed from tristimulus values X, Y, and Z. The shoot area was segmented using threshold of a^* value for each original image. The segmented shoot areas of original images were applied to color correction images and gamma reduction images. The shoot area of R-G-NIR images were derived using different threshold. The R-G-NIR images transformed into HSB color space, and the shoot area was segmented using threshold of brightness value for each image.

Four color indices from *R-G-B* values and a color index from *R-G-NIR* values were calculated. After the shoot area segmented, same rectangle areas which included 8 sampled plants were set on the shoot area images and the non-segmented images. *R-G-B* mean values were extracted from the shoot area images and the non-segmented images for original images, color correction images, and gamma reduction images respectively. *gratio* was normalized G values (Shimojima et al., 2017). *GR* was greenness intensity divided by redness intensity (Wang et al., 2013). *VIgreen* was normalized vegetation index (Gitelson et al., 2002). *ΔNGB* was an index that the effect of solar radiation was reduced (Ono et al., 2015). The R-G-B 4 color indices were calculated as follows;

$$gratio = G \,/\, (R+G+B) \tag{2}$$

$$GR = G \,/\, R \tag{3}$$

$$VIgreen = (G-R) \,/\, (G+R) \tag{4}$$

$$\Delta NGB = -\,(G / (R+G+B) / 3 - 1) \,/\, (B / (R+G+B) / 3 - 1). \tag{5}$$

A color index from *R-G-NIR* values was the normalized differential vegetation index (*NDVI*) as follows (Hama et al., 2016);

$$NDVI = (NIR-R) / (NIR+R). \tag{6}$$

NDVI was calculated using Yubaflex (BIZWORKS Corp, Inc.). Mean *NDVI* values were extracted from the shoot area images and the non-segmented images.

Liner regression analysis and non-liner regression analysis were used to detect the relationship between color indices and rice growth statuses, and root mean square error (RMSE) was calculated for each relationship. RMSE were compared with each other to verify effectiveness and characteristics of the color indices.

3. RESULTS AND DISCUSSION

3.1 LAI and DW

There were large variation in LAI (from 0 to10) and DW (from 0 g to 1400 g) depending on the phenology. The color indices of R-G-B images had linear relationships generally with LAI and DW (Figure2). The color indices showed significant correlations with LAI until LAI reached 4. However, after LAI exceed 4, the errors of models became greater as the increased. In relationships between the color indices and DW, there were linear correlation excepted data for the final sampling. DW for the final sampling were larger than prediction of the approximate lines. In the images, only rice canopy cover are appeared. The canopy cover reaches upper limit early, though plants continue to grow under canopy. In addition, DW include rice panicle weight. The relationships of LAI and DW suggest that the color indices of R-G-B images explain LAI and DW until rice canopy covers the whole image.

NDVI had significant exponential relationships with LAI and DW (Figure 3), and *NDVI* could explain LAI and DW after rice canopy covers the whole image. As in Figure 3, the approximate exponential curves of Basmati370 were different from the curves of Nipponbare and IR64. Basmati370 is a traditional variety which leaf color is light, leaves are thin, and plant height is taller than the others. These results show there were clear genotypic difference in the relationship between the color indices and rice growth statuses.

RMSE of regression analysis between the color indices and the rice growth statuses are showed in Table 1. RMSE of the non-segmented images were smaller than RMSE of the shoot area images generally. The color indices of the non-segmented images reflect canopy cover, because proportion of digital number in leaves increases as canopy cover increases. Lee et al. (2013) reported canopy cover showed significant correlation with LAI and shoot dry weight, and correlations of non-segmented datasets were higher than those of the segmented dataset generally. Therefore, the results of this study imply the color indices of the non-segmented images are more effective than the color indices of the shoot area images for estimation of LAI and DW. As in Table 1, RMSE of *NDVI* were smallest in relationships between color indices and rice growth statuses generally. Thus, *NIR* value is most effective for estimation of LAI and DW, because it reflects plant activity. RMSE of *gratio* were smaller than other RMSE of the R-G-B color indices generally. *gratio* reflects intensity of G value, and it suggests that G value is more effective than R and B values. In

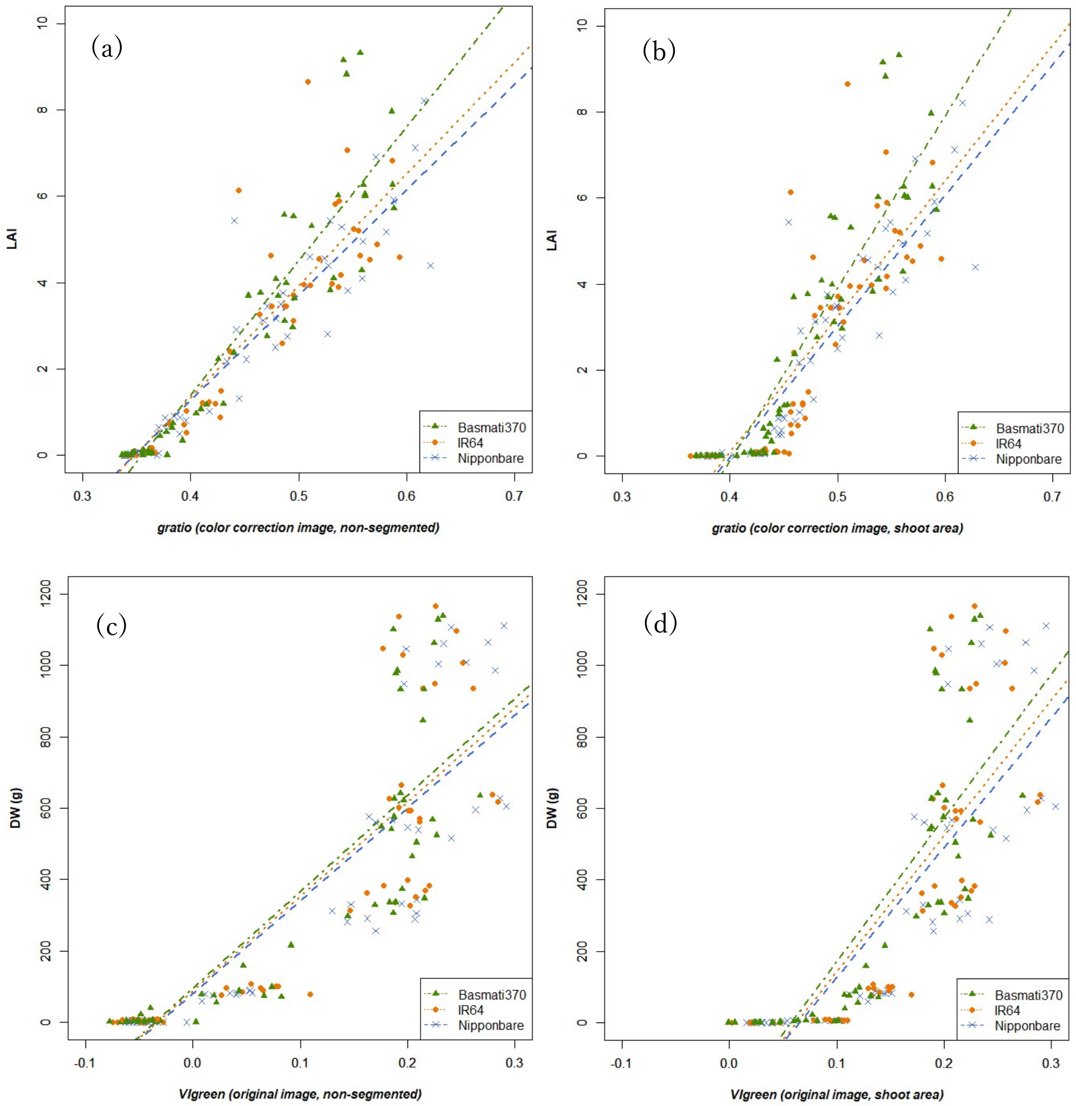

Figure 2. Examples of relationships between the color indices and rice growth statuses: (a) *gratio* of the non-segmented color correction image and LAI, (b) *gratio* of the shoot area color correction image and LAI, (c) *VIgreen* of the non-segmented original image and DW, and (d) *VIgreen* of the shoot area original image and DW.

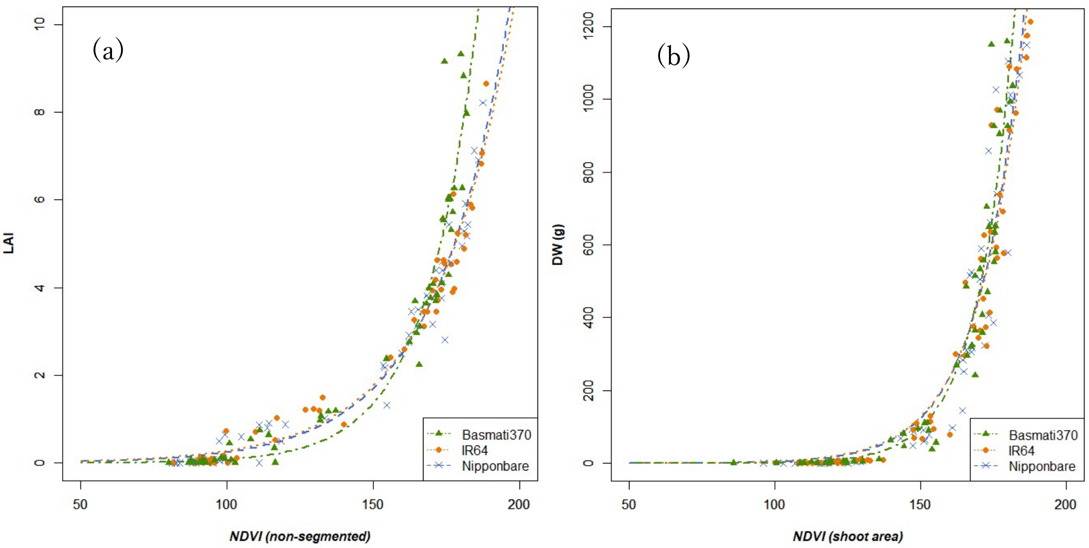

Figure 3. Examples of relationships between *NDVI* and rice growth statuses: (a) *NDVI* of the non-segmented image and LAI, and (b) *NDVI* of the shoot area image and DW. *NDVI* was scaled in 0-255.

contrast, the color index which RMSE is high was *ΔNGB*. *ΔNGB* reflects ratio of *G* and *B* values, and reduced effect of solar radiation. Error of *ΔNGB* in same replications of this experiment were smallest than the other color indices; hence the weather effect of *ΔNGB* were reduced compared to the other color indices. However, it did not reflect difference of rice growth statuses. In relationships of Nipponbare and IR64, RMSE of gamma reduction images were larger than the others generally, and in relationship of Basmati370, RMSE of original images were larger than the others and RMSE of the color correction images were smaller. The range of *R-G-B* values of gamma reduction images narrowed by equation of gamma reduction, and gamma reduction method affected the accuracy. This result suggests that gamma reduction is not necessary.

Table 1. RMSE of regression analysis between the color indices and rice growth statuses.

Rice growth status	Variety	Segment	Original image				Color correction image				Gamma reduction image				*NDVI*
			gratio	*GR*	*VIgreen*	*ΔNGB*	*gratio*	*GR*	*VIgreen*	*ΔNGB*	*gratio*	*GR*	*VIgreen*	*ΔNGB*	
LAI	Nipponbare	shoot area	0.786	0.978	1.042	1.791	0.976	1.015	1.013	1.254	1.166	1.222	1.247	1.579	0.807
		non-segmented	0.661	0.731	0.817	1.383	0.778	0.833	0.828	0.963	0.900	0.948	0.896	1.200	0.423
	IR64	shoot area	1.194	1.176	1.224	1.720	1.327	1.195	1.196	1.324	1.423	1.381	1.435	1.679	1.013
		non-segmented	0.944	0.917	0.954	1.335	1.014	0.933	0.915	0.971	1.053	0.958	0.947	1.213	0.419
	Basmati370	shoot area	1.550	1.562	1.604	2.095	1.209	1.087	1.133	1.453	1.428	1.355	1.455	1.905	0.828
		non-segmented	1.361	1.325	1.380	1.754	1.020	0.923	1.017	1.270	1.139	1.006	1.097	1.596	0.760
DW	Nipponbare	shoot area	149.6	208.4	214.1	322.4	154.1	172.3	175.1	225.7	165.8	197.3	205.8	276.5	114.6
		non-segmented	135.1	176.5	184.2	264.7	132.4	152.8	157.0	190.5	135.4	161.9	161.0	226.1	97.8
	IR64	shoot area	196.4	228.0	234.0	315.0	213.4	212.7	215.4	249.1	218.6	241.5	249.9	299.9	103.1
		non-segmented	172.8	199.7	204.3	264.1	176.1	182.3	184.2	206.8	175.0	189.5	190.8	241.1	96.2
	Basmati370	shoot area	199.2	216.5	221.4	291.2	143.1	146.6	154.4	207.4	173.9	187.5	200.4	266.1	106.3
		non-segmented	181.3	190.0	196.0	246.5	127.1	131.4	145.3	184.8	143.8	147.6	159.4	226.2	106.8

3.2 NcL

The color indices of R-G-B images and R-G-NIR images had negative linear relationships with NcL (Figure 4). The data for the first sampling were different from the other date. The images of the first observation date were strongly affected by soil and water because rice plant was small. In addition, some segments of shoot area included aquatic plants on the first observation day. Therefore, the data for the first sampling were low accuracy and removed from the color indices data for linear regression analysis. As in Figure4, the color indices of R-G-B non-segmented images were gathered for each observation date. In particular, error of the color indices of tillering stage were large. Wang et al. (2014) researched leaf nitrogen concentration for each rice growth stage, and suggested that the relationships between color index and leaf nitrogen concentration were affected by the rice developmental stage. Since the data were few to compare the relationships for each growth stage, further experiment was required to reveal the relationships between the color indices and NcL. The approximate lines of the all relationships are different for each variety. This suggested that spectrum characteristics depends on variety.
RMSE of linear regression analysis between the color indices and NcL are shown in Table 2. RMSE of the non-segmented images were smaller than RMSE of the shoot area images. The non-segmented images reflected the canopy cover and the color indices of the non-segmented images were gathered for each observation date. Thus, the relationships between the color indices of the non-segmented images and NcL suggest that the color indices reflect changes in the canopy cover over time. In the R-G-B images, RMSE of the original images were smaller than the other images excepted *ΔNGB*. The color indices of the R-G-B images were normalized by equation. Thus, this result implies that color and brightness correction and gamma reduction are not necessary for estimation of the NcL. RMSE of *gratio* and *NDVI* were smaller than the other color indices generally, and this suggested that *G* values reflect changes in NcL.

4. CONCLUSSION

In this study, the color indices were derived from different digital cameras and image processing methods, and compered with LAI, DW, and NcL. In the relationships with LAI and DW, the color indices showed significant correlation, and RMSE of *NDVI* and *gratio* were smaller than the others in all images and R-G-B images respectively. RMSE of the relationships between the color indices and NcL are large because they reflected changes in phenology strongly. The segmentation of shoot area and gamma redaction are not necessary for estimation rice growth statuses. The estimation models of regression analysis varied depending on rice varieties. In particular, traditional rice variety Basmati370 was different from the other varieties in the relationships with LAI and DW.
The results which the color indices of non-segmented images were small RMSE implies that spectrum information of unmanned aerial vehicle and satellite are valid for estimation rice growth statuses. *NDVI* which used *NIR* value is

the most effective color indices for estimation plant growth indices. However, R-G-NIR image camera are more expensive than R-G-B image camera generally, and estimation models of NcL are low accuracy. Therefore, further analysis and validation are required using data of more experiments to improve the color indices of the R-G-B images.

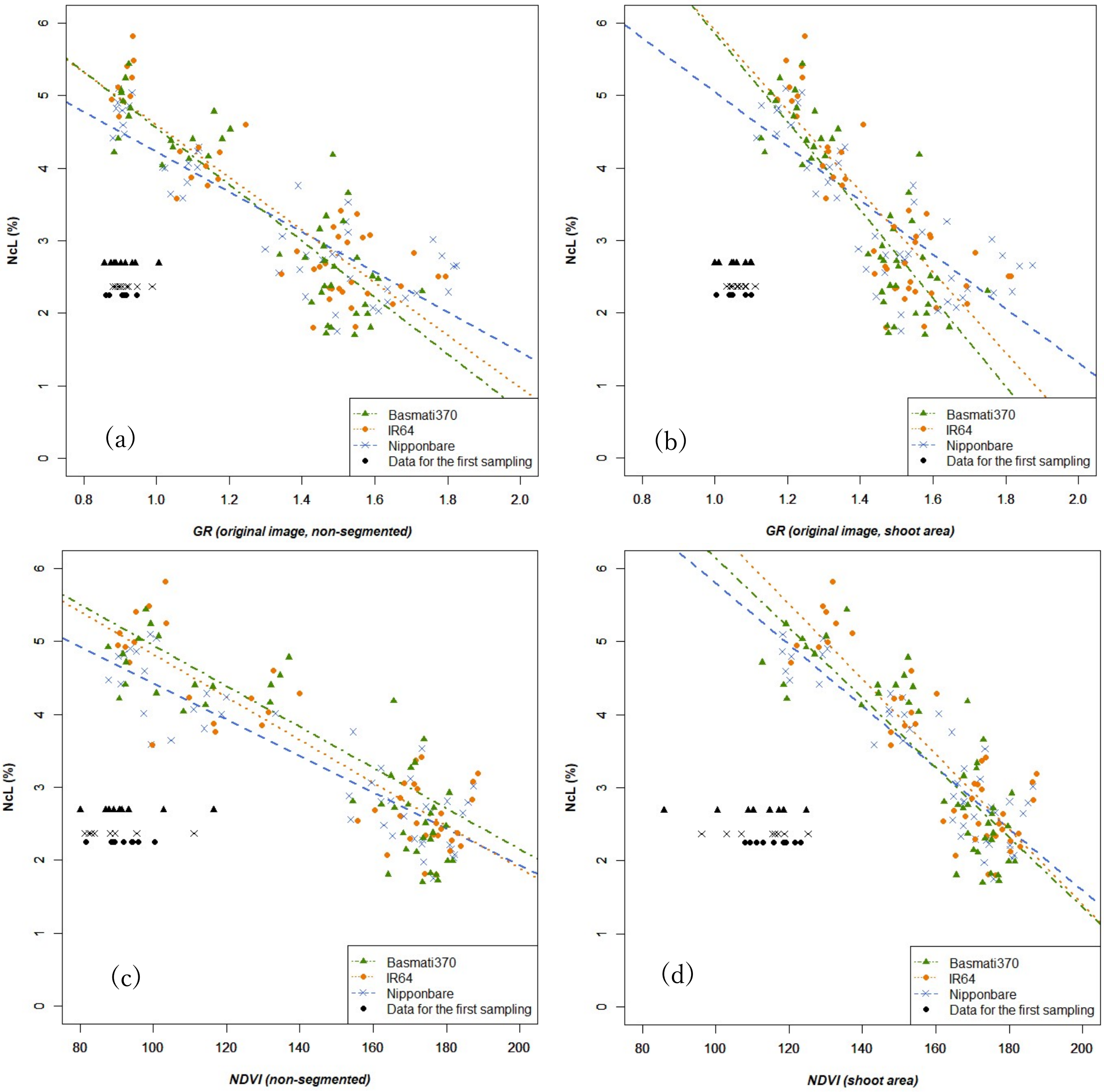

Figure 4. Examples of relationships between the color indices and NcL: (a) *GR* of the non-segmented original image, (b) *GR* of the shoot area original image, (c) *NDVI* of the non-segmented image, (d) *NDVI* of the shoot area image. The black markers show data for the first sampling. The approximate lines are calculated excepted data for the first sampling. *NDVI* was scaled in 0-255.

Table 2. RMSE of linear regression analysis between the color indices and NcL.

Variety	Segment	Original image				Color correction image				Gamma reduction image				*NDVI*
		gratio	*GR*	*VIgreen*	*ΔNGB*	*gratio*	*GR*	*VIgreen*	*ΔNGB*	*gratio*	*GR*	*VIgreen*	*ΔNGB*	
Nipponbare	shoot area	0.455	0.584	0.551	0.865	0.576	0.674	0.626	0.652	0.649	0.706	0.665	0.725	0.436
	non-segmented	0.418	0.482	0.440	0.554	0.503	0.575	0.503	0.457	0.542	0.608	0.532	0.486	0.427
IR64	shoot area	0.488	0.633	0.592	0.977	0.718	0.775	0.734	0.761	0.810	0.850	0.821	0.904	0.533
	non-segmented	0.444	0.530	0.493	0.644	0.578	0.630	0.573	0.540	0.630	0.669	0.606	0.574	0.511
Basmati370	shoot area	0.453	0.628	0.620	1.005	0.566	0.685	0.654	0.750	0.685	0.781	0.764	0.944	0.611
	non-segmented	0.447	0.550	0.557	0.766	0.481	0.586	0.566	0.605	0.540	0.646	0.621	0.718	0.552

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