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Research Paper

Predictive zoning of pest and disease infestations in rice field based on UAV aerial imagery

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ABSTRACT

Bacterial leaf blight (BLB), bacterial panicle blight (BPB), and stem borer (SB) are serious infestations to the rice crop. Detection is the first essential step for effective management. The objective of the study is to provide a fast and accurate tool in detecting the infestation damages through Unmanned Aerial Vehicle (UAV) aerial imagery. System of Rice Intensification (SRI) was implemented and a UAV equipped with a digital multispectral camera was used to capture image of 20 rice plots that were treated with two types of fertilizers (organic and inorganic) in two different treatment rates namely; uniform rate and variable rate. Ground truths of infestation were observed and collected. Geospatial interpolation (kriging), linear regression analysis, and Soil Plant Analysis Development (SPAD) value models were carried out to predict the zones and level of infestation damages in the rice field. Maps showing areas with high, medium, and low counts of infestation damages were prepared using spatial analysis. The results of the relationship indicate that there were a strong correlation and high R^2 between SPAD values obtained through the UAV method and infestation counts during the growth stages of 60 Days After Transplanting (DAT), 80 DAT, and 100 DAT. The findings show that the high severity of infestation happened in the plot that used a high amount of fertilizer compared to the plot that supplied with variable rate fertilizer. Infestation maps produced from the UAV aerial image would be an effective tool in detecting the pest and disease in the rice field.

1. Introduction

Plant protection against pests and disease is now playing a vital role to meet the sufficient needs of food quantity and quality in rice cultivation. It is estimated about 24 % to 41 % of rice yield lost to pest & disease infestation (Sarwar et al., 2010). Bacterial leaf blight (BLB), bacterial panicle blight (BPB), and rice stem borer (SB) are one of the serious pests & disease problems to rice cultivation. BLB, BPB, and rice SB have a long history that affected the overall rice productivity around Southeast Asia and other parts of the world that plant the rice. Those infestations could lose the yield up to 70 % when the attack happened at high severity (Sarwar, 2012). Thus, poor quality of rice grains can be affected thus inflict high broken kernels percentage.

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In term of detecting and mitigating the pests & disease problem in rice cultivation still depends on the traditional method. The traditional method to detect rice pest & disease infestation still applied manual inspection according to conspicuous symptoms of the infestation. Hence, to measure accurately the infestations require check-up through the laboratory which demands expert knowledge of the disease and pest. Both of the techniques are time-consuming, labour-intensive, lessen the detection efficiency and delay the timing of controlling measure. Therefore, an efficient and effective detection method is necessary for the early detection of the BLB, BPB, and SB infestation in rice farming.

Rapid development in remote sensing technology and Unmanned aerial system (UAS) has benefited the detecting and monitoring of rice pest & disease infestations. The procedure becomes much easier, faster, and accurate for the field application. Remote sensing data available from the satellite-based and aerial sensors have shown the capability and feasibility of differentiating the damaged plant from the healthy ones (Sabtu et al., 2018). Remote sensing can be useful in detecting plant stresses over a

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large area in a short period by allowing identification, and estimation of different plant stresses through analysis of its unique spectral signatures (Qin and Zhang, 2005). Detection of nutrient deficiencies, damage from pest and disease attacks had been proved to be able to be detected with the reflected light in specific visible, near- and middle-infrared regions of the electromagnetic spectrum (Ballesteros et al., 2014). Physiological stress and damage that happened on the leaves due to pest & disease infestation will directly affect the reflectance properties especially in the visible spectral region rather than in the infrared because of the sensitivity of chlorophyll to physiological disturbances. Thus, changes in the physical characteristics of the plant can be monitored through the image captured by the camera and the image can be very useful to analyse the level of aggravation of the infestation. The imaging technique will be sufficient enough if establish together with the reference data to form meaningful pest and disease detection models (Yang, 2010).

Detection of pest & disease infestation can be applied to a larger geographical area with the help of spatial analysis techniques together with the UAV aerial imagery. Pest and disease zoning can be predetermined to predicted the levels of infestation based on the geospatial interpolation of pest & disease infestations with the classification of the cropped areas (Reji et al., 2013). Areas that are meant to be identified and detected for the infestation can be effectively done through pest and disease zoning map preparations and tagging as a hotspot. Therefore, detection of the pest and disease hotspots may help to avoid or minimize crop loss due to infestation outbreaks. The objective of this present study was to formulate Soil Plant Analysis Development (SPAD), values-based regression models, at specific growth stages of rice plant for the prediction of BLB, BPB, and SB damage in the field. Thus, to investigate the effect of different types of fertilizer (inorganic and organic) at different rates (uniform versus variable rate) on the abundance of BLB, BPB, and SB population in the rice field.

2. Materials and methods

2.1. Experimental site and cultural operations

A field experiment was conducted at Parit 5, Sungai Besar, Selangor, Malaysia (3.683677o N, 101.028650o E) from September 1, 2018, until January 30, 2019. The experiment area size was 0.6 ha and divided into 20 subplots which each of the subplots had an area size of 210 m^2. This area was chosen as the study area based on the occurrence of the BLB, BPB, and SB from the previous season. The System of Rice Intensification (SRI) method was implemented for the field experiment. It included the use of young age of rice seedling from 8 –12 days, wide spacing (25 cm × 25 cm) between planting seeds were performed, and no permanent flooding and only maintained the moist condition of the planting soil throughout the growing period to allow aerobic soil condition.

2.2. Fertilizer treatment

This experiment used two types of foliar fertilizer; organic (4.8:4:3.5) and inorganic (21:21:21) for nitrogen (N), phosphorus (P), potassium (K) compositions. Fertilizer applications were performed at 5 stages that begun from early crop establishment – 15 Days After Transplanting (DAT), mid-tillering (35 DAT), panicle initiation (55 DAT), flowering (65 DAT), and grain ripening (85 DAT). This experiment only took into account N content in the rice leaves for fertilizer calculations while P, K, and other mineral elements ratios were prepared according to the fertilizer supplier recommendation. The experiment consisted of two methods of foliar fertilizer applications; uniform rate and variable rate application (VRA) with two types of fertilizer (organic and inorganic). Each method had five replications arranged in a randomized complete block design (RCBD) and the arrangement can be viewed in Table 1. Both of the methods were sprayed on top of the rice leaves. Uniform rate method of foliar spraying was applied based on the supplier recommendations. While the VRA method of foliar spraying was performed based on precision farming principles with using references of principal component analysis index (IPCA) values to check on the chlorophyll content of the rice leaves which later the chlorophyll content values were transferred into fertilizer formulation to determine precise N amount that needs to be spray on the rice plant.

2.3. UAV and image capture

The 4-rotor UAV equipped with a high-resolution digital camera was used to collect imagery data in the field plot. The UAV is the 3DR Solo (3DR Company Resources, USA) with the advantages of stable 3-axis gimbal, automatic GPS (Global Position System) data recording, and user-friendly flight control. The digital camera offers an image quality of 16 Megapixels with the size of the 4384 × 3288-pixel array for Red (R), Green (G), and Blue (B) bands. Before imagery data were collected, the optimal exposure time for cameras was selected based on lighting conditions and commonly performed from 10:00 am to 2:00 pm. During the flights, the cameras were positioned below the UAV and directly faced the ground surface at 50 m above the ground to cover all field plots. The UAV flight was conducted at 5 stages namely 20 DAT, 40 DAT, 60 DAT, 80 DAT, and 100 DAT.

2.4. Image processing

The captured images with latitude, longitude, and altitude information were mosaicked and processed to produce an IPCA-RGB image. The locations of data taken from the whole plot of every plot treatment were identified by using RTK-GNSS. Average R, G, and B values from the whole plot images were calculated by the ArcGIS 10.3 software based on the IPCA-RGB formula provided to measure the chlorophyll content in the rice leaves thus produce the exact *N*-health condition map of the field plot. Leaf N content from IPCA-RGB calculation that derived through UAV image acquisition was interpolated by using the kriging technique. The purpose of this interpolation was to produce a surface of the predicted value to identify the surface coverage or spatial distribution of the above-mentioned parameters. The adjusted smart quartile method was used to classify the zone and to visualize the variability. Spatial variability of leaf N variable content was divided into different zones for all the variables based on management zones which could be easy to compare.

2.5. Vegetation index calculation

A vegetation index (VI) that is the IPCA-RGB vegetation index was used in the study to determine the chlorophyll content and N composition within the rice leaf. The IPCA-RGB vegetation index was referred to the study performed by Saberioon et al., (2014) that revealed a close association between this vegetation index

Table 1
Treatment table for the experiment.

	Treatment Spraying
T1	Uniform rate Inorganic (R1, R2, R3, R4, R5)
T2	Uniform rate Organic (R1, R2, R3, R4, R5)
T3	VRA IPCA-RGB Inorganic (R1, R2, R3, R4, R5)
T4	VRA IPCA-RGB Organic (R1, R2, R3, R4, R5)

with chlorophyll meter values thus provide another index for determining the chlorophyll and N content in the leaves of rice plant at various growth stages (Saberioon et al., 2014). The IPCA–RGB index equation (1) was used in the experiment.

$$I_{PCA} = 0.994|R - B| + 0.961|G - B| + 0.914|G - R| \quad (1)$$

where: R is red; B is blue and G is green.

IPCA-RGB change maps of different levels of BLB, BPB, and SB severity were generated to illustrate the data collected from UAV aerial imagery and ground truths so that it could help to detect the symptoms and development of the BLB, BPB, and SB at the field scale.

2.6. Collection of ground truth

A ground-based SPAD chlorophyll meter was used throughout the planting period to monitor the rice plant's health condition and measurement of the chlorophyll content to indicate the N content level in the rice plant every 20 days until the harvesting period. Manual observation of the diseases and pest infestations were performed in 1 m^2 of every planting plot every 20 days throughout the planting period. The method of 1 m^2 was performed at 6 points in every sub-plot treatment that give a total of 120 points for the manual observation procedure.

2.7. Data analysis

Data of pest & disease infestations in every treatment plot were measured and recorded every 20 days until the harvesting period. Samples were collected from each plot before the harvesting process and packed accordingly to prevent deterioration. The data measurements and samples were analysed statistically by using an analysis of variances (ANOVA) through Statistical Analysis System Software (SAS 9.1, SAS, USA) package. Mean separation and comparison were performed using Tukey's honest significant difference (HSD) test at probability level $p < 0.05$.

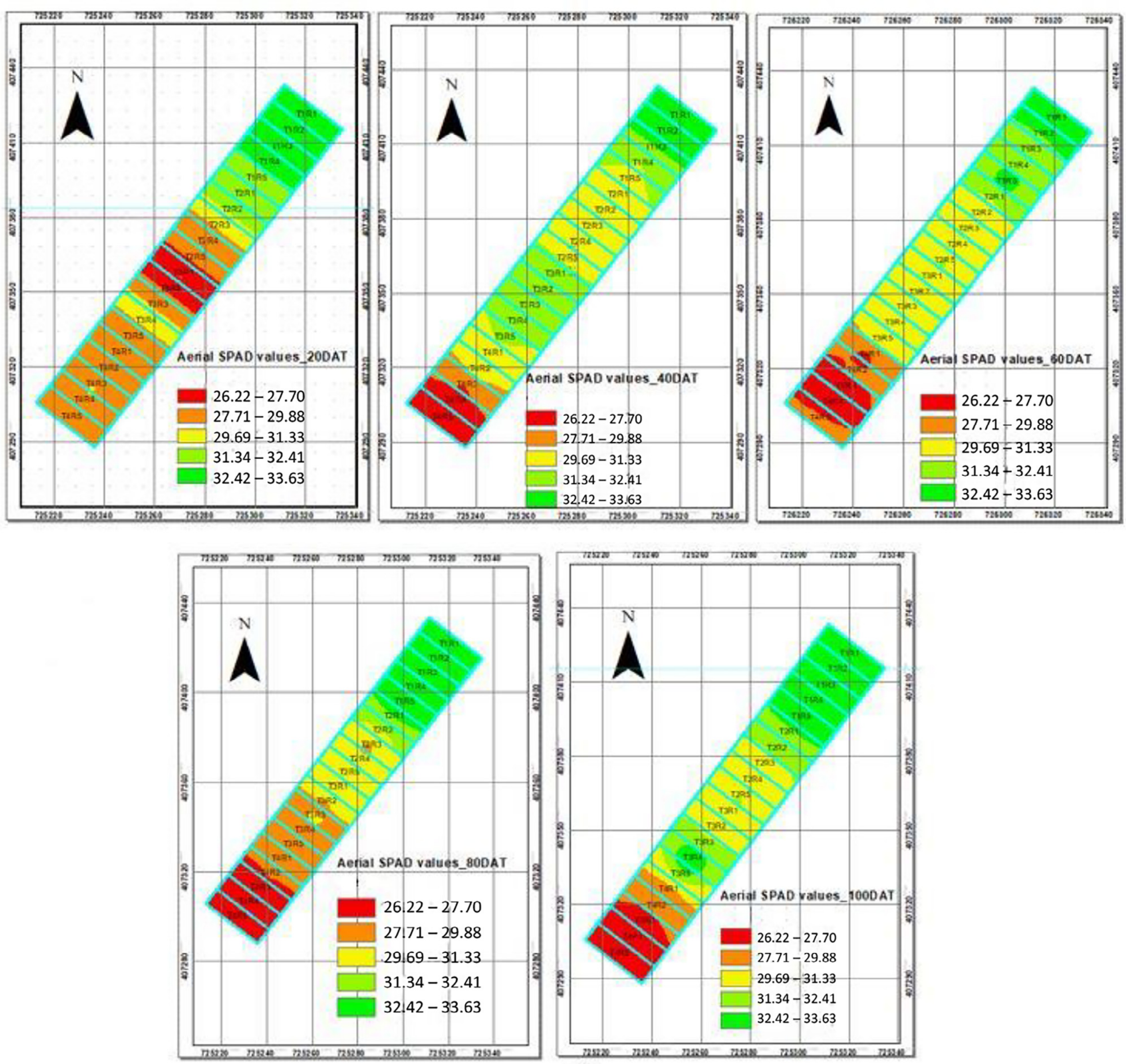

Fig. 1. SPAD spectral reflectance of every treatment plots taken through UAV aerial imagery at every 20 DAT of growing stages.

3. Results and discussion

RGB and multispectral cameras has proven as a reliable tool for field management to detect and diagnose pest & disease infestations thus nutrition problem of crop (Dey et al. 2016). In this study, RGB imaging and spectral reflectance were analysed to detect BLB, BPB and SB infected areas in the rice field plots. Fig. 1 shows the results of the spectral reflectance of every treatment plot that took by UAV aerial imaging and analysed through spatial analysis at every 20 DAT of growth stages.

From Fig. 1, there was SPAD spectral reflectance variability for all the treatments at various growth stages. Treatment T1 shows the highest SPAD values, followed by treatment T2 and T3, whilst T4 shows the lowest SPAD values throughout the growing stages even though there was a fluctuation in SPAD values at different growing stages for all of the treatments. This pattern of variability for SPAD spectral reflectance indicates that treatment plots that received fertilizer at a uniform rate received a higher amount of nutrients compared to treatment that received fertilizer through the variable rate method. Even though there were treatment plots that showed declining in SPAD values from the early growing stage until the harvesting stage, however the values not year reach below than values of 25 since SPAD values below then 25 can cause in poor development of plant physiological and can lead to poor productivity and can reduce the rice yield (Wang et al., 2017).

In this study, a ground truth survey by using 1 m^2 space for each treatment plot was implemented to cross-checked with the UAV aerial imaging detection method to increase the accuracy in detecting pest and disease severity. As can be seen in Fig. 2, SPAD values of rice leave obtained through the ground truth method show a similar trend as the SPAD reflectance obtained through the UAV aerial imagery. The similarities can be observed through the trend of SPAD values perceived from each of the treatment plot fields even though there was a slight difference in the range between both methods. For example, the T1 plot still shows the highest SPAD values compared to other treatment plots and followed by

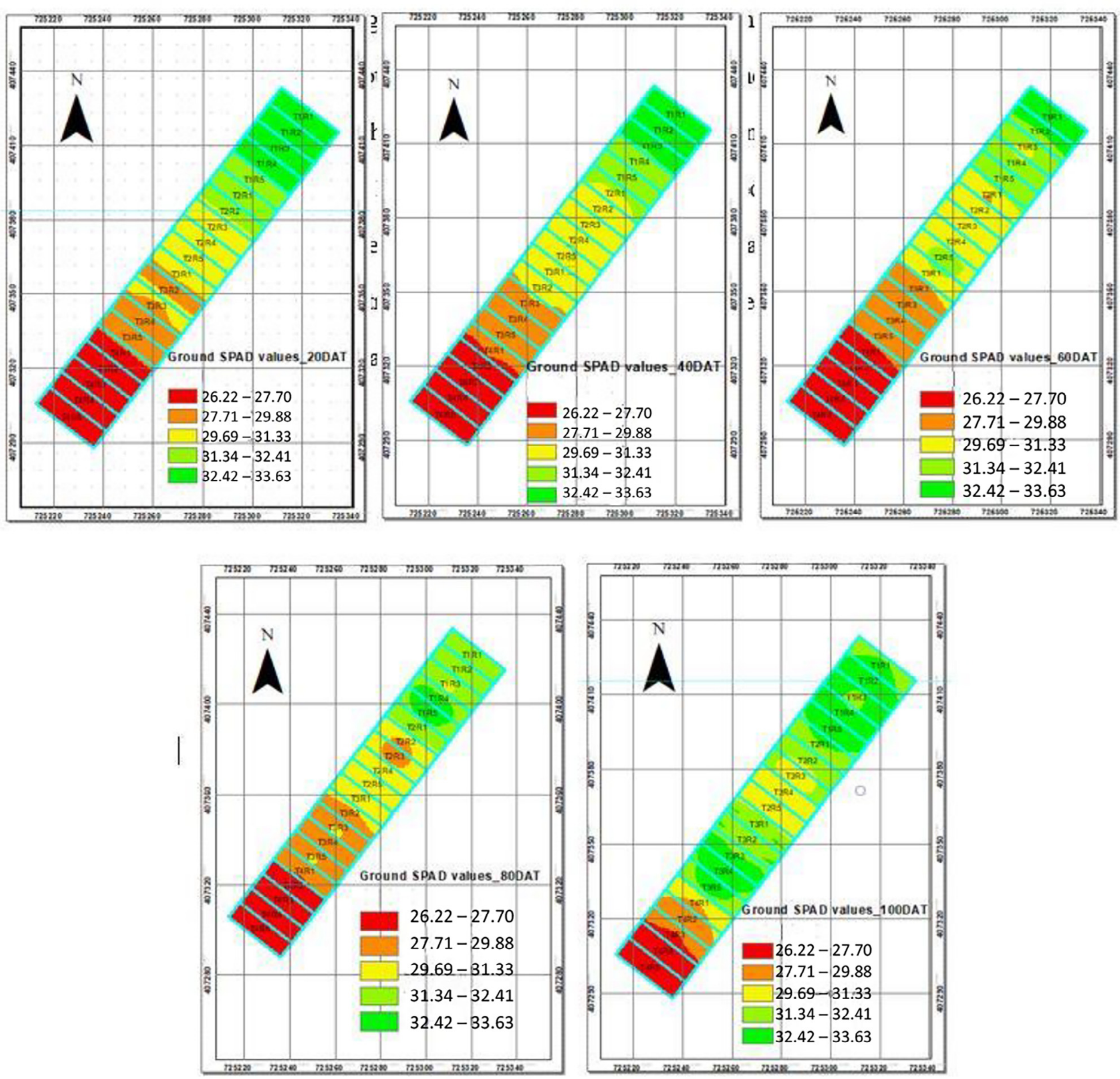

Fig. 2. SPAD spectral reflectance of every treatment plots taken through ground truth survey at every 20 DAT of growing stages.

the treatment plot of T2 and T3 respectively. Meanwhile, the plot of treatment T4 still exhibits the lowest SPAD reflectance throughout the growing stages. The similarities indicate that both methods are reliable in detecting the spectral reflectance of the rice leaf in the field. However, acquisition of spectral reflectance by using UAV aerial imagery is much preferred due to its field operational friendly and cost-effective for larger scale compared to the ground truth survey method which is more tedious, high energy, and less cost-effective for pest and disease severity detection.

Predictive pest and disease zoning involve the spatial interpolation of the probable levels of pest and disease severity in the treatment plot was performed with help of a VI model. The predictive zoning maps of the rice field indicate the areas having severe, high, moderate, and low levels of pest and disease damages. Figs. 3, 4, and 5 show the results of the BLB, BPB, and SB infestation counts for every treatment plot at every 20 DAT of growing stages that obtained through the ground-truth survey process. The infested rice plant would exhibit low SPAD values due to physiological damage caused by the pest & disease infestations (Bhutto et al., 2015). However, in our present study, the results show differently where the rice plot had higher SPAD values showing high severity of pest & disease infestation compared to the rice plot that exhibits average or lower SPAD values. For example, treatment T1 had higher BLB, BPB, and SB infestation counts compared to other treatments due to higher SPAD values perceived. This shows that a high amount of fertilizer applied to the crop would attract pests & disease thus increase the rate of infestation compared to the crop that received an average or low amount of fertilizer.

RGB imaging spectral reflectance plays important role in the incidence of crop pest and disease hence the models based on the spectral reflectance were useful for forewarning the pest & disease infestations in the field. In the present study, the analyses indicated that SPAD values of rice leaves during the 60 DAT, 80 DAT, and 100 DAT exhibiting a better correlation with the intensity of the pest & disease infestations. As can be seen from Table 2, the UAV aerial method had a higher correlation between spectral

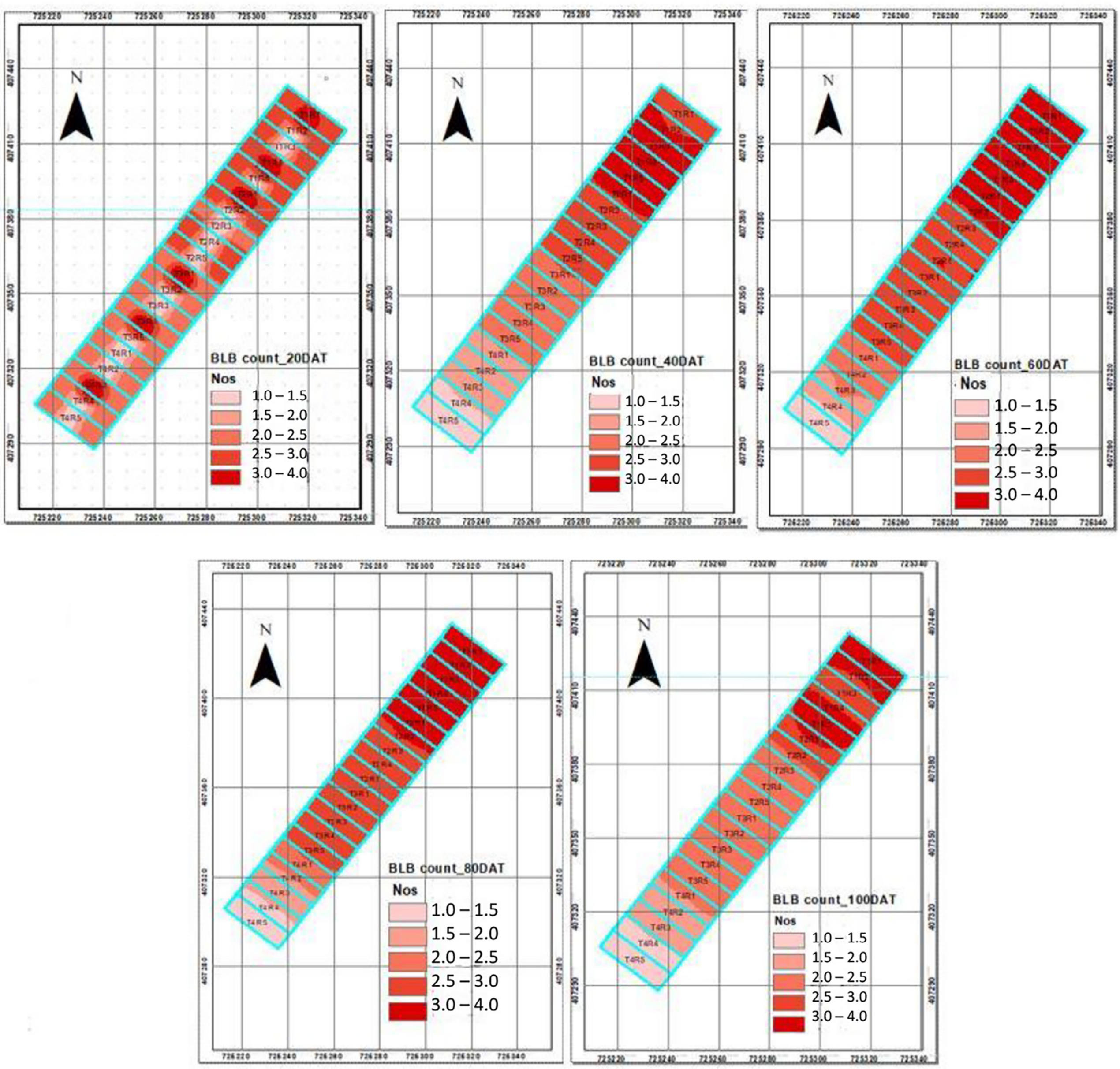

Fig. 3. Bacterial leaf blight (BLB) infestation counts in every treatment plot at every 20 DAT of growing stages.

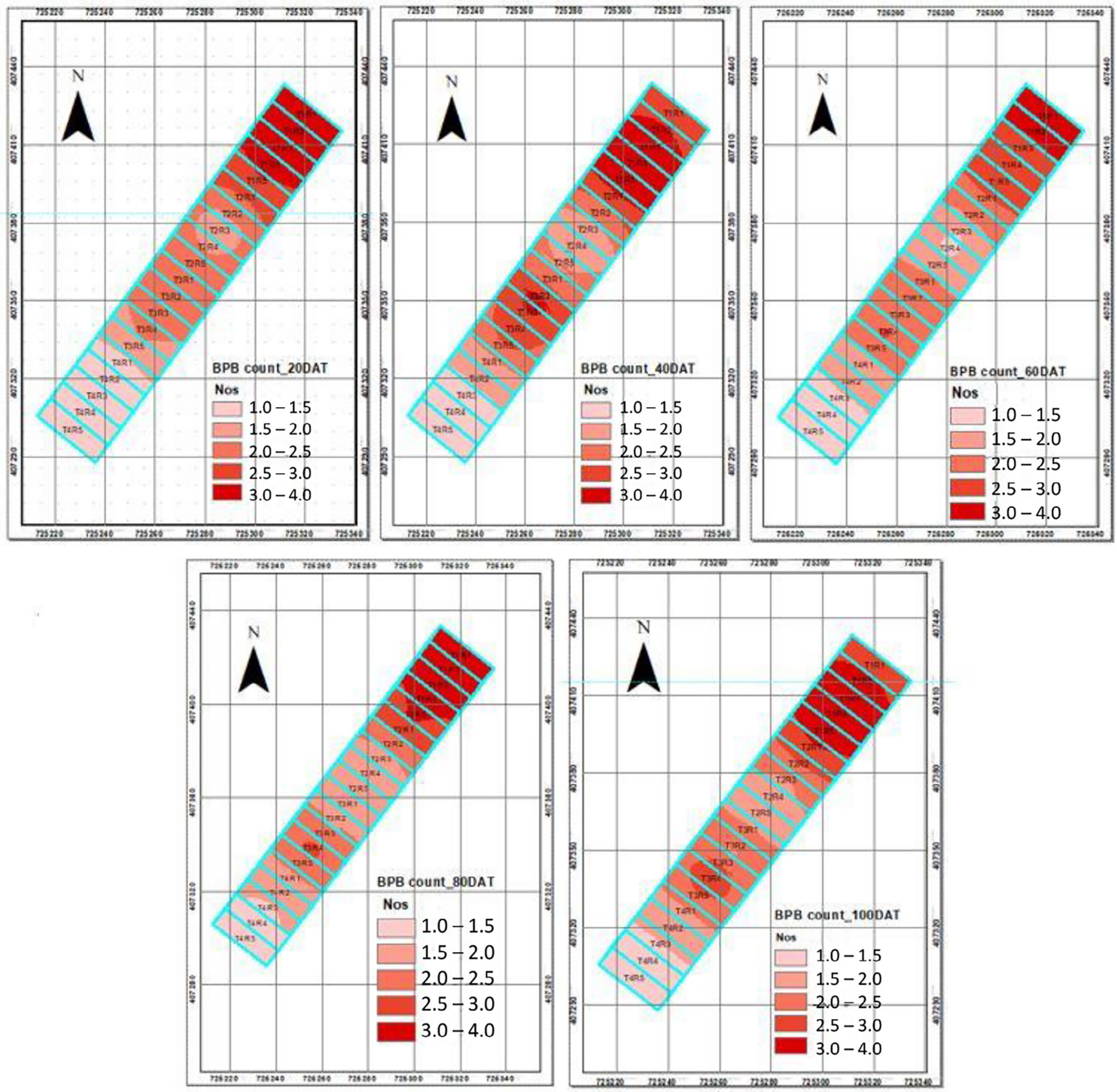

Fig. 4. Bacterial panicle blight (BPB) infestation counts in every treatment plot at every 20 DAT of growing stages.

reflectance in form of SPAD values with the number of BLB, BPB, and SB damages compared to the ground truth method especially during growth stages of 60 DAT until 100 DAT. However, during the growth stages of 20 DAT, the ground truth method exhibits better correlation compared to the UAV aerial method in detecting early infestations of BLB, BPB, and SB in the field plot. While during 40 DAT, only BPB shows a positive correlation with the SPAD values of rice leaves for both method in acquiring an exact amount of chlorophyll content of rice leaves.

The relationship between the level of infestation damage and SPAD values of rice leaves in every treatment plot was found vary at different planting growth stages. This indicates that the infestation damage with the SPAD values models was site and temporal specific. Among the regression models formulated as stated in Table 3, only 60 DAT until 100 DAT were reliable in the predictive values with significant differences at p-value < 0.05, and the aerial method shows better R^2 compared to the ground truth method. However, during 60 DAT, only the predictive regression model of BLB infestation was not reliable with no significance different to p-value < 0.05 and had low R^2 values for both methods in acquiring the chlorophyll content.

The differences in the amount of fertilizer application to the crop are much likely to influence the abundance of the pest & disease infestations in the treatment plot where the ground truth survey of pest & disease infestations in the 1 m^2 space at different growth stages led to varied numbers in the population count. Fig. 6,7, and 8 show the number of BLB, BPB, and SB infestations counted in every treatment plot at every growth stage. As can be seen in Figs. Fig. 6, Fig. 7, and Fig. 8., T1 shows the highest number of BLB, BPB, and SB infestation counts and shows significance different compared to other treatment while T4 shows significantly the lowest counts followed by T3 and T2 respectively throughout the growth stages. As noted, the number of BLB, BPB, and SB infestations show an increment in numbers from the beginning of early

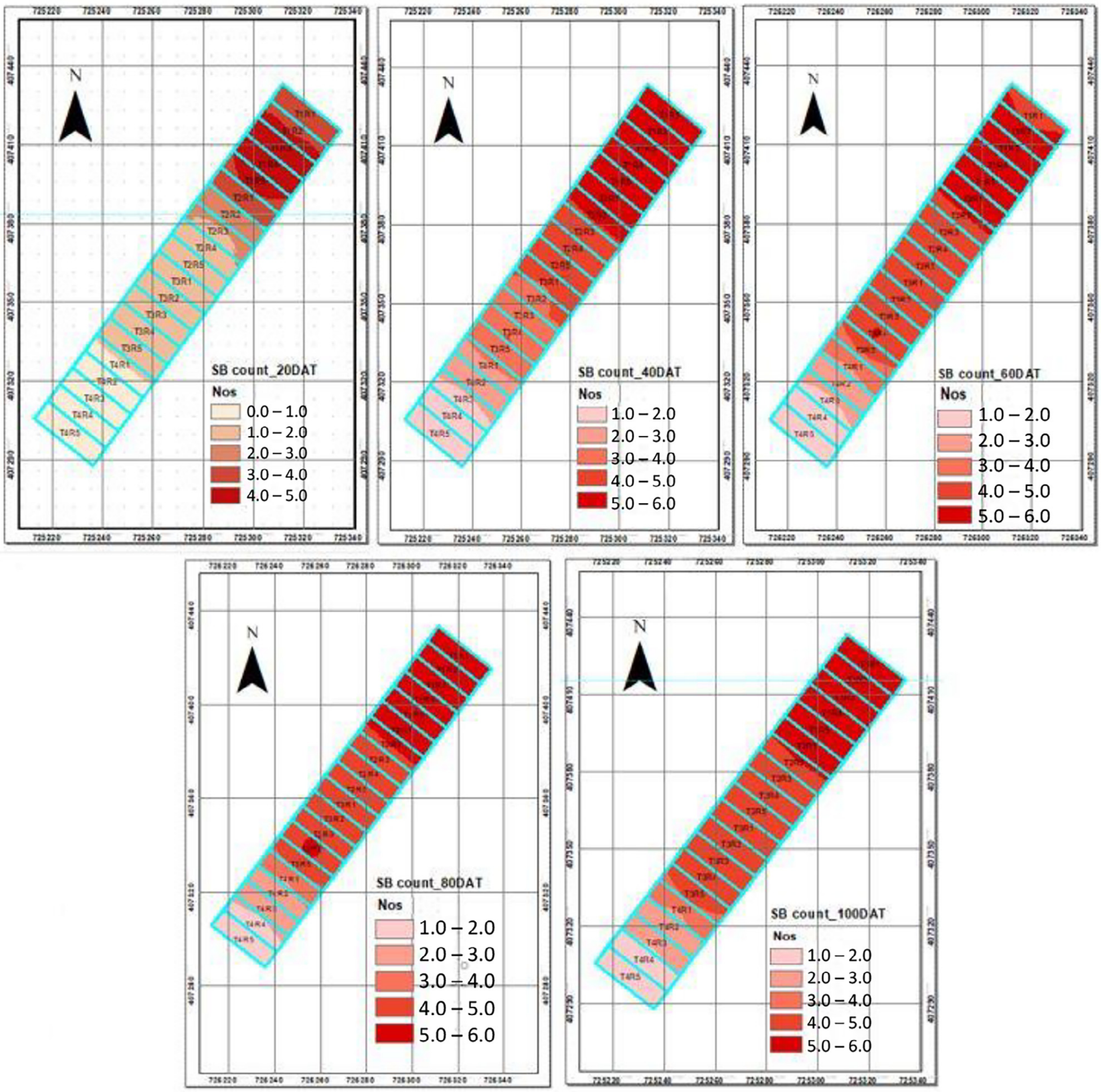

Fig. 5. Rice stem borer (SB) infestation counts in every treatment plot at every 20 DAT of growing stages.

planting stages until the harvesting stages of every treatment. However, the number of the SB show dramatically increased with an increase in the number of tillers during the 40 DAT as more SB larvae were found during the vegetative growth compared to other growth stages. The main reason why the population of SB dramatically increased during the vegetative growth was due to large stem diameter was develops during the vegetative stage to flowering stage. Thus, during those periods, a high amount and better quality of nutrients inside the stem were formed to build up the SB population.

BLB and BPB infestation show dramatically increase in counts when the rice reach planting stages of reproductive stages (60 DAT) and ripening stages (80 DAT). Both of the diseases begin to spread and the symptom appeared at the panicle part and turns the grain into blank while the leaves begin to wilt, dry up and die without prior warning. As the rice plant reaches the harvesting stages (100 DAT), all the treatments show accumulation of the BLB, BPB, and SB infestations. Treatment T4 had the lowest infestation counts and show distinct significance different compared to the other treatment. While T1 shows no significant differences to T2 and T3 however show significantly different to T4 for BLB, BPB, and SB infestations. Overall, T1 and T3 which applied a uniform rate of fertilizer had the highest counts of the BLB, BPB, and SB infestations compared to T2 and T4 which performing the variable rate of fertilizer. This can be assured that high application of N can cause high severity of BLB, BPB, and SB infestations to the rice plant due to weak silica forming within the rice plant that allowed high susceptibility of the disease to attack (Xin-Gen Zhou, 2019). Hence, in the study rice plots that are treated with the variable rate of fertilizer can help to regulate N amount at a balanced rate for suffi-

Table 2
Correlation between the SPAD values of rice leaves infected with both methods in acquiring the chlorophyll content and number of BLB, BPB and SB damages in every treatment plot.

Plant growth stages (DAT)	Infestation	UAV aerial method	Ground truth method
20	BLB	0.2141	0.3244
	BPB	0.4341	0.6539
	SB	0.3039	0.4324
40	BLB	−0.1041	0.0610
	BPB	0.4531	0.4947
	SB	0.1368	0.1187
60	BLB	0.4594	0.4185
	BPB	0.7899	0.6798
	SB	0.7754	0.5929
80	BLB	0.8068	0.8313
	BPB	0.7853	0.6699
	SB	0.8031	0.8291
100	BLB	0.8324	0.8426
	BPB	0.8715	0.8430
	SB	0.9386	0.9294

Table 3
Linear regression models between the SPAD values of rice leaves infected for both methods in acquiring the chlorophyll content and number of BLB, BPB and SB damages in every treatment plot.

Plant growth stages (DAT)	Infestation	UAV aerial method			Ground truth method		
		Equation	R^2	*P-value*	Equation	R^2	*P-value*
20	BLB	Y = −2.00 + 0.0727x	0.0458	0.3647	Y = −3.48 + 0.1179x	0.1053	0.1628
	BPB	Y = −4.50 + 0.1533x	0.1884	0.0558	Y = −7.59 + 0.2474x	0.4276	0.0018*
	SB	Y = −4.03 + 0.1526x	0.0923	0.1927	Y = −6.67 + 0.2327x	0.1870	0.0569
40	BLB	Y = 2.09 – 0.0378x	0.0108	0.6622	Y = −0.22 + 0.0292x	0.0037	0.7985
	BPB	Y = −7.18 + 0.2385x	0.2053	0.0448*	Y = −9.41 + 0.2957x	0.1811	0.0614
	SB	Y = −0.69 + 0.0849x	0.0187	0.5652	Y = −1.20 + 0.0972x	0.0141	0.6182
60	BLB	Y = −5.79 + 0.2152x	0.2111	0.0415*	Y = −4.61 + 0.1748x	0.1527	0.0885
	BPB	Y = −14.37 + 0.4735x	0.6240	0.0000*	Y = −12.49 + 0.4049x	0.5005	0.0004*
	SB	Y = −23.19 + 0.7836x	0.6012	0.0000*	Y = −19.98 + 0.6645x	0.4740	0.0008*
80	BLB	Y = −7.88 + 0.3235x	0.6509	0.0000*	Y = −8.25 + 0.3244x	0.6138	0.0000*
	BPB	Y = −8.3 + 0.3458x	0.6311	0.0000*	Y = −7.36 + 0.3080x	0.4198	0.0020*
	SB	Y = −13.13 + 0.5715x	0.6649	0.0000*	Y = −11.38 + 0.5009x	0.4648	0.0009*
100	BLB	Y = −5.50 + 0.2653x	0.6929	0.0000*	Y = −6.11 + 0.2741x	0.7099	0.0000*
	BPB	Y = −5.41 + 0.2703x	0.7651	0.0000*	Y = −5.62 + 0.2666x	0.7143	0.0000*
	SB	Y = −8.99 + 0.4668x	0.8810	0.0000*	Y = −9.72 + 0.4717x	0.8637	0.0000*
	Note:	Y = BLB, BPB, and SB derived from UAV image (unit: Nos) X = SPAD values			Y = BLB, BPB, and SB derived from ground observation data (unit: Nos) X = SPAD values		

*Show significant at the p = 0.05 levels of probability.

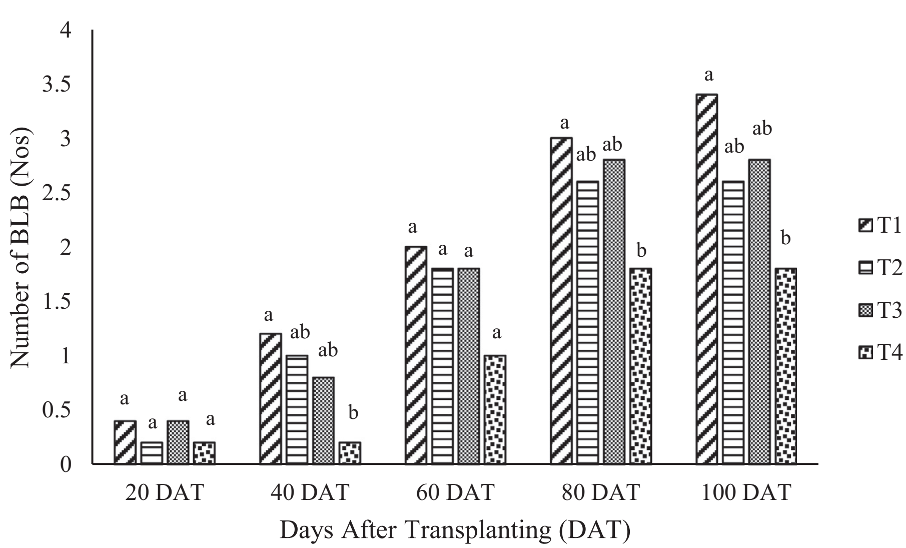

Fig. 6. BLB infestation counts recorded from 20 DAT until 100 DAT at every treatment plot. Bars with the same letter are not significant at P < 0.05.

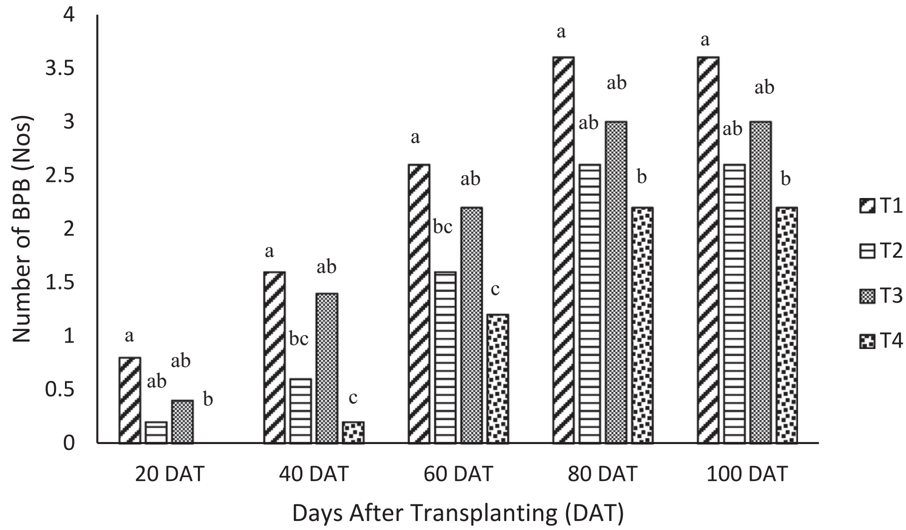

Fig. 7. BPB infestation counts recorded from 20 DAT until 100 DAT at every treatment plot. Bars with the same letter are not significant at P < 0.05.

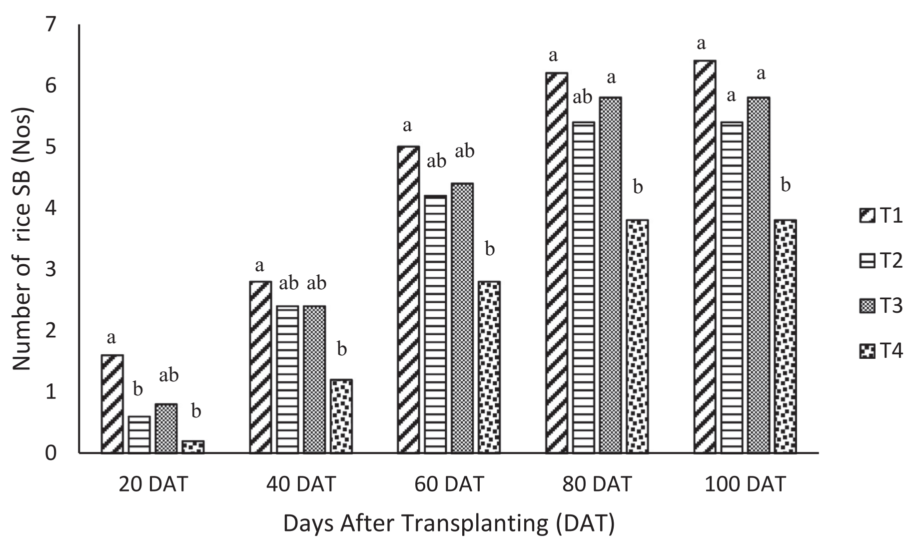

Fig. 8. Rice SB infestation counts recorded from 20 DAT until 100 DAT at every treatment plot. Bars with the same letter are not significant at P < 0.05.

cient consumption of rice plant without attracting further infestation from the pest and disease due to overconsumption of the fertilizer.

4. Conclusions

The study can conclude that by using UAV aerial imagery combines with IPCA-RGB vegetative index to acquire the spectral reflectance of rice leaf at canopy level and performing the specific spatial analysis has strong potential to detect the BLB, BPB, and SB infestation within the rice field. These combinations would be useful in developing a decision support system for rice pest and disease management. Hence, higher application of fertilizer at a uniform rate to the rice plant can lead to high severity of pest & disease infestations in the field compared to the method that applies fertilizer in form of the variable rate.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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