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DETERMINING SUITABLE SPATIAL RESOLUTION TO ESTIMATE NITROGEN STATUS IN MD2 PINEAPPLE CROP CULTIVATED ON MINERAL SOIL

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ABSTRACT

Strengthening of Malaysian food security requires optimum utilisation of agricultural technology to sustainably increase productivity and yield. Digital nutrient monitoring enables more efficient and timely field estimation to complement existing conventional method. However, high UAV acquisition and computational costs can be overwhelming especially when periodical monitoring is involved. This study attempted to improve UAV feasibility by identifying the suitable spatial resolution (SR) to estimate Nitrogen (N) status in MD2 pineapple (*Ananas comosus* var. MD2) crop on mineral soil. Two field plots, respectively representing Alluvial and Red-Yellow Podzolic (RYP) soils, were built in Samarahan Campus Farm of Universiti Teknologi MARA Sarawak, Malaysia. This Randomised Complete Block Design (RCBD) based experiment was comprised of five treatments, ten replicates, and five different combinations of NPK fertiliser and MD2 pineapple leaf biochar application. N status of crop canopy was sampled using non-destructive and destructive methods; respectively involving DJI Phantom 4 Multispectral UAV, SPAD-502 Chlorophyll Meter, and D-leaf extraction. Scores of four vegetation indices (NRI, VARI, GCI and RECI) representing Predicted N, were regressed against Observed N of D-leaf Total N Content. SPAD Chlorophyll Meter provided Predicted Relative N status. This study compared the capability of SR between 0.47 and 4.01 cm to detect crop canopy and support Predicted-Observed N Status regression. Detection capability in this study corresponded with SR, yet not solely with canopy width. The highest resolutions of $SR_{0.75}$ (Alluvial) and $SR_{0.47}$ (RYP) were able to detect all sample crop canopies, and yield the highest Predicted-Observed N correlation based on NRI and VARI estimations. Detectability was largely influenced by canopy width, number of leaves, and crop symmetries. Lower SR estimations were affected by deteriorating pixel purity and biased sample representation. Therefore, SR of below 1.0 cm is recommended for MD2 Pineapple crop N status estimation on mineral soil.

Keywords: *Spatial Resolution, Vegetation Index, N Status, MD2 Pineapple, UAV*

1. INTRODUCTION

Malaysian Agriculture 4.0 agenda recognises agricultural technologies' role in strengthening the nation's food security through improvements of farming efficiency and agricultural output [1]. The combination of prevailing labour shortage and ageing Malaysian farmers [2] calls for larger adoption of technologies such as UAV, IoT, and geospatial to equip farmers with modern skills in practising sustainable agriculture [1]. Sarawak's aspiration to become Malaysian food basket by 2030 [3] is notably depending on technological R&D to promote digital agriculture and related innovations [4] to improve output and subsequently farmers' socioeconomic status and state GDP.

Pineapple cultivation in Malaysia is mainly associated with peat soil [5]. MD2 (*Ananas comosus* var. MD2), a newer variety is also cultivated on mineral soil, where yield produced is of higher quality and sweeter, therefore commanding a higher market value [6]. Its pleasant aroma, lower acidity content, and longer shelf life [7] has enabled MD2 to occupy 80% of global pineapple trade [8]. Significantly lesser nutrient leaching is reported on mineral soil-based cultivation than peat [9]. Therefore, local pineapple farmers should capitalise on digital agriculture on this premium variety.

In an effort to boost local pineapple industry, this study firstly explored the nature and challenges of conventional crop monitoring and primary macronutrients roles in crop growth. An overview of agricultural remote sensing, potential of Unmanned Aircraft System (UAS) for pineapple crop monitoring, and challenges pertaining to Spatial Resolution (SR) effects on crop monitoring are highlighted next. Literature for remote sensing application in pineapple nutrient monitoring are still limited, therefore related studies on various crops are also included.

Malaysian pineapple cultivation industry is dominated by smallholders in terms of number of growers (73%) and planted acreage (67%) [10]. Smallholders largely rely on conventional monitoring that is based on visual ground observations, a time-consuming practice that only captures a portion of field conditions [11] to produce estimations of agricultural acreage and yield [12]. The method lacks accuracy and effectiveness of timely decision-making, for example over fertilisation due to fertiliser application scheduling instead of basing on crop's site and time-specific requirements. Less accurate estimation could affect food security at all levels, with impacts ranging from the lower-income household's ability to meet their dietary needs to the nation's population growth rate [13].

Nitrogen (N) that is comprised of chlorophyll (chl), amino acids, proteins, alkaloids, and protoplasm, is the key nutrient in plant growth, physiology, and carbohydrate content [14]. Chl enables photosynthesis, the process of producing glucose that is essential for plant growth from sunlight, water, and carbon dioxide. The next two very significant nutrients are Phosphorus (P) and Potassium (K), respectively a limiting factor to plant growth [15] due to its energy transfer and storage role, and in maintaining osmotic balance, phloem transport, and photosynthesis [16]. As an indicator of plant growth, N status is an estimation of N requirement at a specific growth stage.

Plant issue analysis (PTA), involving destructive sampling (permanent removal of a specific part of plant) is a conventional N status estimation method. PTA commonly employ either Dumas Combustion (DC) or Kjeldahl Digestion (KD) method to quantify N status in organic compound. Both methods involve laboratory analysis that is arduous, costly, and time-consuming, On the other hand, DC's N gas analysis is less polluting, unlike KD's ammonia gas analysis that requires usage of toxic reagents [17]

Spectroscopic sensing estimates N status from non-destructively acquired leaf or canopy samples [18]. Measured leaf reflectance and transmittance values represent leaf chl content [19] that is correlated with N status. Spectroscopic values are obtained either proximally or distally (remote sensing), respectively involving high or low proximity between leaf and camera. Proximal sampling utilises handheld spectrometer such as SPAD-502 Chlorophyll Meter and Greenseeker to measure chl reflectance [20],[21] to provide instant N estimation at a lower cost than PTA. For example, [22] identified SPAD value of below 38 as N fertiliser requirement on rice cultivation with

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alternate wetting and drying irrigation. On the other hand, proximal spectroscopy is not feasible for large-scale crop monitoring due to its field data sampling and data interpolation requirements [23],[24],[25]. Proximal sensing is therefore feasible in this study based on the number of sampling points.

Earlier agricultural remote sensing relied on satellite imagery for crop classification applications [26] such as mapping of crop distribution and classification of land use/cover [27],[28]. Subsequent improvements in sensor technology and computational capacity have enabled monitoring at a larger scale, during unfavourable weather conditions, and on rough terrain; and yet restricted by low spatial resolution (SR) data [29],[30]. SR is the measure of the ground area imaged of the instantaneous field of view (IFOV) of the sensor [31]. Current platforms of Unmanned Aircraft System (UAS), manned aircraft, and Light Ranging and Radar (LiDAR) with significantly lower flight height [32] (H in Figure 1) capture imagery with lower Ground Sampling Distance value (GSD: the distance between two ground pixel centroids). A combination of GSD and UAS sensor exposure parameters determine SR [33], [34]. Based on the UAS parameter settings in sub-section 2.3, this study accepted the interchangeability of terms GSD and SR recommended by the photogrammetry software.

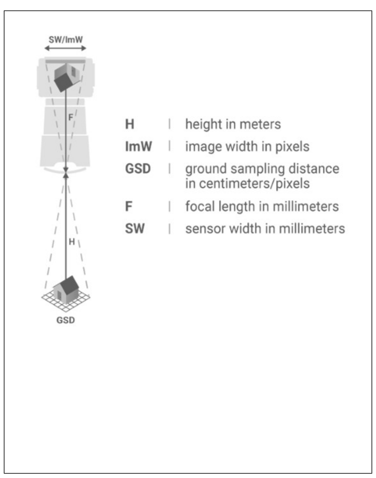

Figure 1: GSD and related parameters
Source: [33]

Higher SR expands agricultural remote sensing applications onto field nutrient estimation, yield and biomass estimation, crop health assessment, weed management, soil monitoring, crop counting, and aerial spraying [35],[36]. According to [37], UAS-based monitoring could improve early detection of gummy stem blight disease in watermelon by 20%. UAS sprayer reduces herbicide dependency in corn field and beet field by up to 90% and 43%, respectively [38], overcomes the problems of terrain faced by ground sprayer [39], and minimise risks of chemical exposure among farmers [40]. In spite of these advantages, most farmers still rely on their own experiences with N management which exacerbated nitrate leaching loss [41]. Larger control over UAS mission planning improves imagery's SR, hence the potential of remote field N nutrient estimation for crops with lesser height such as pineapple.

Higher SR data magnifies object-based crop classification image analysis capability [42] through higher crop pixel discriminating accuracy from the background features. Determining suitable SR requires balancing potential inaccuracy generated in higher and lower resolution imagery. Complex and costlier data acquisition process and feature identification error due to pixel oversampling are associated with higher resolution classification [42],[43], while insufficient pixel purity in crop discriminating may occur in lower resolution [44]. [45] suggested lower SR for identification of major crop classes, and high SR for object-based classification. Spectroscopic N status estimation have been tested on many crops proximally for grapevine [17], paper birch [46], maize [47]; remotely for sugarcane [48] and potato [49], and a combination of proximal and remote sensing for maize [50]. This study is focused on high SR to discriminate pineapple canopy from background features and N status estimation.

Vegetation index (VI), an indicator of plant vigour, is derived from leaf or canopy reflectance. Reflectance value is correlated to crop nutrient status [24], and different value is generated by respective spectral band. Red and Near Infrared (NIR) are most widely used bands in agricultural remote sensing. Low reflectance in Red imagery is due to high absorption of light by chlorophyll in leaf, and high reflectance of incidence radiation produces high NIR value [51]. For example, Normalized Difference Vegetation Index (NDVI) measures vegetation density, a vital input in plant biomass calculation, drought prediction, and many other applications [52]. In comparing predictive accuracy of nutrient status between Green NDVI (GNDVI) and NDVI of pineapple cultivated on utisol soil [53] found the former a better predictor for P, and the latter, Magnesium. [40] identified Normalized Pigment Chlorophyll Index (NPCI), Plant Senescence Index (PSRI) and Red-Edge Vegetation Index (RVSI) as

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the most suitable VI to monitor K status based on proximal sampling of MD2 pineapple cultivated on peat soil. [41] high spatiotemporal resolution data to monitor in-field variety of crop N status.

Existing digital nutrient mapping mainly rely on either visible or hyperspectral imagery. Visible range (RGB) sensors in digital camera are commonly utilised in agriculture [50] due to its affordability. Hyperspectral has the advantage of high spectral resolution (a measure of number and width of spectral band), at the expense of SR [51] and band redundancy [52]. On the other hand, multispectral imagery possesses lower spectral resolution than remote hyperspectral, yet able to capture is able to capture higher SR imagery [53], hence its potential to monitor N status of pineapple crop. Lower computing costs than hyperspectral due to cheaper sensor price, reduced computation time dan storage requirements from lower spectral resolution; and inclusion of NIR that is lacking in visible imagery highlighted the potential of multispectral UAV pineapple crop nutrient estimation.

SR varies with crop morphology. Both conventional and hyperspectral imagery N status estimations proliferate the costs of computation. Therefore, identifying suitable SR is vital to promote UAV monitoring within Malaysian pineapple industry. This study attempted to identify the suitable SR to for UAV-based, MD2 pineapple N status monitoring of cultivation on mineral soil using visible and multispectral imagery.

2. METHODOLOGY

2.1 Study Area

The field experiment was carried out on Samarahan Campus Farm of Universiti Teknologi MARA, Sarawak Branch at 1.446359122558º N and 110.4519860226º E. The farm is located in in Samarahan division, the second largest pineapple producing region [54] in the state of Sarawak, Malaysia (Figure 2).

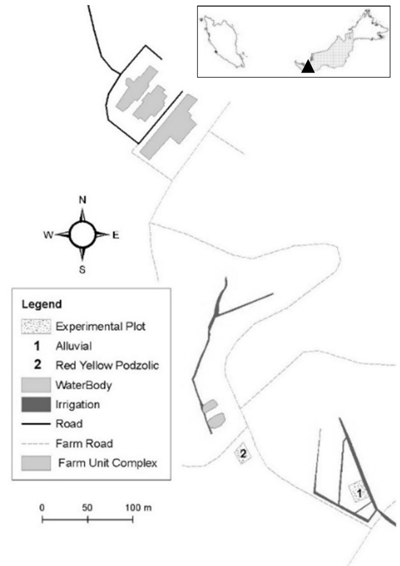
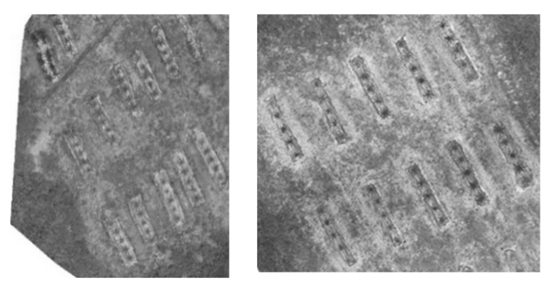


Figure 2: Study Area

2.2 Field Experimental Plot

In Sarawak, Alluvial soil and Red-Yellow Podzolic soil (RYP) of the mineral soil series have been identified as suitable for pineapple cultivation [55]. Samarahan division is mainly comprised of mineral soil and peat soil [55]. This study is focused on cultivation on Alluvial and RYP to boost MD2 pineapple yield especially in Samarahan division as shown in the following Figure 3.



(a) Alluvial soil *(b) Red-Yellow Podzolic soil*
Figure 3: Experimental Plots

Analysis of pre-treatment soil samples from both plots (Table 1) identified typical tropical region's highly weathered soil characteristics of low pH and low nutrient content (except Available P).

Table 1: Pre-Treatment Soil Chemical Properties

Property	Alluvial	Red-Yellow Podzolic
pH	4.10	3.80
CEC ($cmol_+kg^{-1}$)	10.21	3.21
Total N (%)	0.20	0.13
Exchangeable K ($cmol_+kg^{-1}$)	0.13	0.08
Available P (mgL^{-1})	7.50	7.25
Mg ($cmol_+kg^{-1}$)	0.25	0.19
Ca ($cmol_+kg^{-1}$)	0.37	2.16

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This Randomised Complete Block Design (RCBD) based experimental design involved five treatments (Table 2) and ten replicates to avoid data bias [56]. With the exception of Absolute Control Treatment (T1), each remaining treatment was applied with a specific composition of NPK Fertiliser and MD2 pineapple leaf biochar. As shown in Figure 4, each replicate is represented by a 4.3 m x 0.6 m plant bed cultivated with five crops, and separated by mid drains to prevent water logging and minimise nutrient leaching. This study adopted planting distance of 0.9 m, instead of Malaysia Pineapple Industry Board's (MPIB) recommended 0.3 m for commercial cultivation [57] to minimise nutrient leaching.

Table 2: Composition of Treatment

Treatment	**NPK Fertiliser: MD2 Pineapple Leaf Biochar (%)**
T1 (Absolute Control)	0
T2 (Control)	100:0
T3	75:25
T4	50:50
T5	25:75

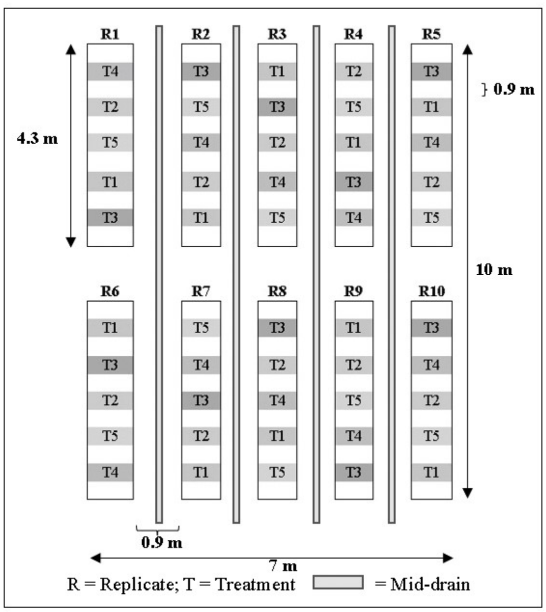

Figure 4: Field Experimental Layout

2.3 Data Collection

Estimations of N status in this study were derived at vegetative stage that recorded the highest nutrient uptake for most crops [58] to maximise leaf chlorophyll content, and therefore higher discrimination of crop canopy from background features. All data for each soil type were acquired on the same day to ensure comparability. Firstly, relative chl content per D-leaf was measured using SPAD-502 Chlorophyll Meter (Konica-Minolta, Japan) (Figure 5a). D-leaf as the most physiologically active and identifiable leaf [59], provides reliable nutrient status for pineapple [60]. Once calibrated, three measurements of N status were taken per leaf, and mean N status was subsequently derived. D-leaf was also measured for its width to provide reference measurement for subsequent geospatial analysis.

(a) SPAD-502 Chlorophyll Meter

(b) DJI Phantom 4 Multispectral

(c) D-leaf samples

Figure 5: Data Sampling Tools

The first non-destructive sampling dataset was acquired using DJI Phantom 4 Multispectral (DJI P4M) (DJI Technology, Guangdong, China) UAS (Figure 5b). DJI P4M is equipped with six global shutter cameras with 1/2.9 CMOS sensors, mounted on a three-axis stabilised gimbal, and comprising of one RGB camera and five multispectral cameras: Blue (B, 450 ± 16 nm), Green (G, 560 ± 16 nm), Red (R, 650 ± 16 nm), Red Edge (RE, 730 ± 16 nm) and Near-Infrared (NIR, 840 ± 16 nm). A comparison of potatoes N status values acquired using PTA tissue analysis, SPAD Chlorophyll Meter, and Quickbird satellite's multispectral imagery by [61] ranked remote

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multispectral data as the least significant. Low SR of between 0.6 to 2.4 m had likely influenced the rank. This study focuses on visible and multispectral imageries to estimate N status in crop canopy using the following vegetation indices (Table 3).

Table 3: Vegetation Indices of Interest

No	Vegetation Index	Spectral Band
1	Nitrogen Reflectance Index (NRI) $[(R_G - R_R) / (R_G + R_R)]$	Visible (*Red, Green, Blue)*
2	Visible Atmospherically Resistant Index (VARI) $[(R_G - R_R) / (R_G + R_R + R_B)]$	
3	Green Chlorophyll Index (GCI) $[(R_{NIR} - 1) / (R_G - 1)]$	Multispectral *(Red, Red Edge, Near Infrared, Green, Blue)*
4	Red Edge Chlorophyll Index (RECI) $[R_{NIR} / (R_{RE} - 1)]$	

DJI P4M aircraft operated on intelligent, positioning-mode (P-mode) that depend on Global Navigation Satellite Service (GNSS) and Vision System for stable data capture and is also equipped with spectral sunlight sensor to detect solar irradiance [62]. Data was captured at 2.0 second shutter interval, the lowest interval value supporting more than two monochrome cameras. While minimum Front Overlap Ratio and Side Overlap Ratio for flat agriculture fields are recommended at 85% and 70%, respectively [63], 70:80 is the maximum ratio combination that can optimise flight speed at the lowest flight height undertaken by this study. This study utilised Pix4DMapper photogrammetry software (PIX4F, Lausanne, Switzerland) that auto calibrates the remaining UAS parameters in order to generate imageries at three different SR.

This study firstly compared crop canopy detection capability among imageries captured at flight heights (H) of 10 m, 50 m and 70 m. 10 m is the lowest height supported by DJI P4M's automatic mode data capture. Height of 50 m was identified from existing literature on UAV-based rice and winter wheat N monitoring, respectively by [64] and [65], based on their height similarity with pineapple at approximately 1.2 m. [66] adopted 70 m to identify individual plant species on arid and semi-arid land vegetation in South-eastern Arizona, USA. While imagery with the highest SR is expected to produce the most reliable N estimation, this study also assessed the lower SR's detection capability.

All data collection missions were executed at around 2 pm when the optimal course angle of perpendicular to current azimuth can be identified by the aircraft. All plant beds were installed with plastic mulching sheet to, among others, eliminate weeds that can affect nutrient uptake in crops [67]. Manual weeding is carried out prior to data collection day to maximise pixel purity by eliminating potential background reflectance from weed leaves.

Each experimental plot occupied a portion of previously cultivated sector of the farm. Significant land features have been either removed or altered prior to this study, hence the lack of ground control point candidates on both flat field plots. The study constricts area of interest to the immediate adjacent areas to field plot perimeter to reduce imagery data size and processing time.

Once all missions were completed, all sample D-leaves were manually extracted from the plant (Figure 5c). All samples were oven-dried at 70°C for up to 72 hours until constant weight is achieved. Then samples were grounded, and sifted through 40-mesh prior to being stored in airtight container [68]. N status was quantified using Dumas Combustion method of PTA. Sample preparation works were carried out in the laboratory of Faculty of Plantation and Agrotechnology. UiTM Sarawak, prior to N analysis at Agriculture Research Centre of Department of Agriculture, Sarawak.

3. RESULTS AND DISCUSSION

[43] proposed a two-pronged technique of spatial measurement similarity and goodness-of-fit assessment to identify suitable SR for geospatial analysis. Detectability of crop canopies with various leaf widths were found to be largely corresponding with SR. This study also identified association between highest SR of below 1.0 cm and more reliable N status estimation for both Alluvial and RYP plots.

3.1 UAV Imagery (Predicted N)

A study by [69] identified the period between 0 and 10 Week After Treatment (WAT) of NPK and SRI fertilisers as the optimum period to monitor MD2 pineapple growth performance. In this study, all field data and D-leaf samples were collected on 7 WAT and 5 WAT of NPK fertiliser from alluvial and RYP plots respectively (Table 4). The non-uniform data collection timeline was attributed to the current monsoon transition phase effects [71].

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Table 4: Crop Timeline

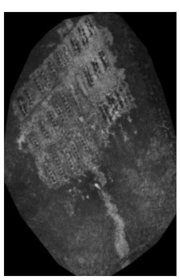
Plot	Planting	Fertiliser Application	Data Collection
Alluvial	18 May 2020	25 August 2020	7 Oct 2020
Red-Yellow Podzolic	5 June 2020	3 September 2020	8 Oct 2020

Three datasets were captured consecutively from each field plot (Table 5) to ensure uniformed atmospheric conditions during data collection missions.

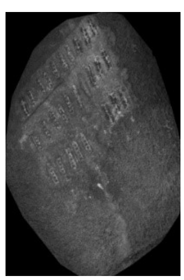
Table 5: Imagery Datasets

Plot	Flight Height (m)	Spatial Resolution (cm)
Alluvial	10	0.75
	50	2.91
	70	4.01
Red-Yellow Podzolic	10	0.47
	50	2.66
	70	3.40

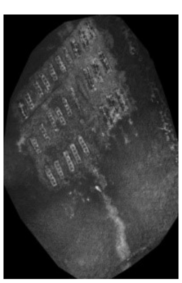
In total, 24 reflectance maps were derived from five single-band imageries shown in Figure 6 to represent a VI per SR per plot. VI pixel values were computed using Pix4DMapper software (PIX4F S.A., Lausanne, Switzerland) based on the formula listed in Table 3. Each reflectance map was next resampled at SR 1.0 cm, the highest resolution supported by the software, in order to be compatible with ArcGIS 10.3 (ESRI Inc., USA) software for further analysis.



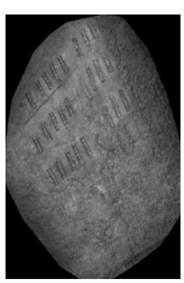
Red



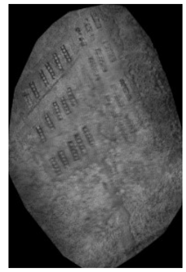
Green



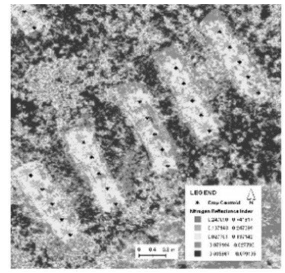
Blue



Red Edge



Near Infrared



NRI Reflectance Map

Figure 6: Imageries and Example of Reflectance Map from Alluvial plot at Spatial Resolution 0.75 cm

Centroid of each sample crop canopy was determined manually based on field observations and imagery characteristics (Figure 7). According to Castro, as cited in [59], D-leaf PTA is less performed due to its high N mobility in plants. D-leaf location varies among canopy, and is semi-visible from above since it is still not fully developed. Therefore, a buffer zone around canopy centroid is proposed as an impartial sector representation crop's estimated N status. Buffer zone size is determined by D-leaf width value (Table 6) to ensure the inclusion of leaf's reflectance in the estimation. Variation in width sizes was attributed to treatment's NPK fertiliser-pineapple leaf biochar composition (Table 2). A combination of zero fertiliser and low soil nutrient content (Table 1) in T1 has resulted in the smallest buffer zone for both plots.

Predicted or estimated N per VI and per SR represented the mean of multiple leaves' N at various stages of growth. D-leaf contains the highest N status value due to its most physiologically active nature [59], therefore predicted N should not exceed the corresponding observed N.

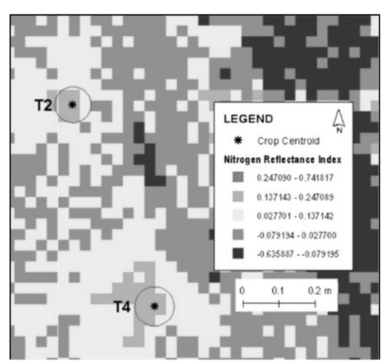


Figure 7: Crop Centroid and Buffer Zone

Table 6: Treatment Properties

Plot	*Alluvial*			*Red-Yellow Podzolic*		
Treat-ment	*SPAD*	*D-Leaf Width (cm)*	*Num of Leaf*	*SPAD*	*D-Leaf Width (cm)*	*Num of Leaf*
T1	65.24	4.27	32	70.48	3.34	29
T2	92.40	5.06	34	79.25	4.18	31
T3	78.23	5.52	32	84.50	3.71	32
T4	102.09	5.52	34	100.52	4.57	29
T5	79.26	5.38	33	78.98	3.92	29

3.2 Plant Tissue Analysis (Observed N)

D-leaf samples were measured for their width and Total N content, and the latter value recognised as observed N status. For each treatment, D-leaf width represented mean width of all samples (Table 6). Observed N status for each treatment is presented in Table 7 below.

Table 7: D-Leaf Total N Content

Treatment	Alluvial (%)	Red-Yellow Podzolic (%)
T1	0.91	0.81
T2	1.63	1.10
T3	1.31	0.93
T4	1.90	0.98
T5	1.08	0.91

3.3 Crop Canopy Detection Capability

Theoretically, detection capability corresponds to the degree of SR, where higher SR (lower SR value) is able to detect more crop canopy. This study was also interested in the feasibility of lower SR capability due to its lesser monitoring costs. Detection capability per SR at both field plots for each VI are summarised as follows:

Table 8: Canopy detection per plot per VI

Treatment	Spatial Resolution 0.75	2.91	4.01	%	Ave
1a	√	√		67	89
1b	√	√	√	100	
1c	√	√	√	100	
2a	√			33	44
2b	√		√	67	
2c	√			33	
3a	√	√		67	44
3b	√			33	
3c	√			33	
4a	√	√		67	56
4b	√			33	
4c	√	√		67	
5a	√	√		67	78
5b	√	√		67	
5c	√	√	√	100	
%	100	60	27		

(a) Alluvial Soil (GCI)

Treatment	Spatial Resolution 0.75	2.91	4.01	%	Ave
1a	√	√		67	89
1b	√	√	√	100	
1c	√	√	√	100	
2a	√	√		33	67
2b	√	√	√	67	
2c	√			33	
3a	√	√		67	44
3b	√			33	
3c	√			33	
4a	√	√		67	56
4b	√			33	
4c	√	√		67	
5a	√	√		67	78
5b	√	√		67	
5c	√	√	√	100	
%	100	73	27		

(b) Alluvial Soil (NRI, VARI and RECI)

Treatment	Spatial Resolution 0.75	2.91	4.01	%	Ave
1a	√			33	33
1b	√			33	
1c	√			33	
2a	√			33	44
2b	√	√		33	
2c	√	√		67	
3a	√			67	44
3b	√			33	
3c	√			33	
4a	√			33	44
4b	√	√		67	
4c	√			33	
5a	√		√	67	44
5b	√			33	
5c	√			33	
%	100	20	7		

(c) Red-Yellow Podzolic Soil (All VIs)

As shown in Table 8, canopy detection capability improved with SR across all plots and VI. Pixel purity decreases with SR because lower SR pixels may contain both canopy and background reflectance, where the latter is comprised of either soil or plastic mulching sheet reflectance, or both. Mis-discrimination occurs when pixel represents more background than canopy reflectance.

Canopy detection capability also do not solely correspond with D-leaf width. Overall, higher detection recorded by alluvial plot is likely attributed by its wider canopy and also higher or equivalent number of leaf than corresponding RYP treatment (Table 6). On the other hand, Treatment 1 of alluvial plot has the narrowest D-leaf, and yet obtained the highest detection capability rate for all VIs across all SR, surpassing T3 and T4 with the widest D-leaf (5.52 cm). As canopy reflectance were captured in nadir imagery, T1 crop symmetry pattern and

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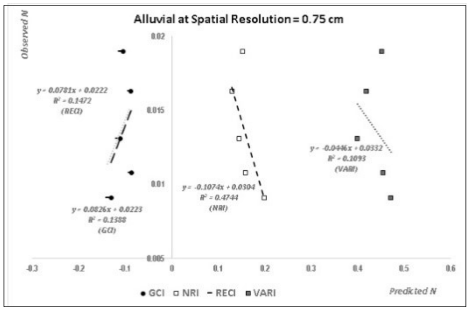
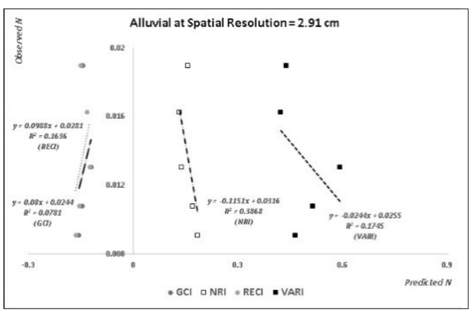
atmospheric effects might have influenced their rate of detection. This study found crop canopy detection capability largely corresponding with SR.

3.4 Regression of Predicted-Observed N Status

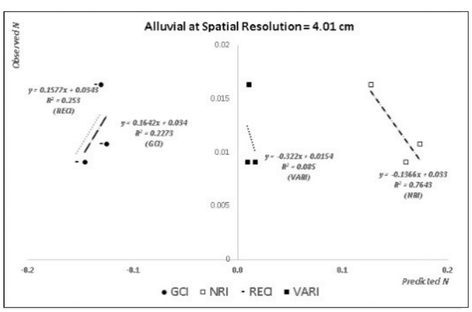
The goodness-of-fit assessment of predicted-reference N status complements the reliability of previous canopy detection assessment. This study compared visible and multispectral ranges VIs capability to estimate predicted N status in MD2 crop canopy, and not attempting to identify the most suitable VI for N status estimation. Predicted-observed N status regressions per SR per VI are presented in the following Figure 8.



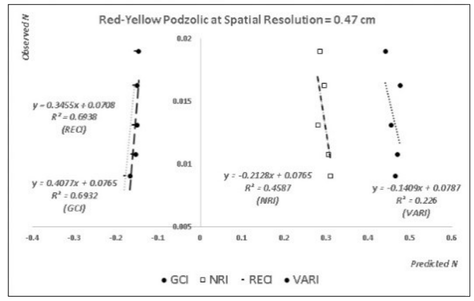
(a) Alluvial (H = 10 m)



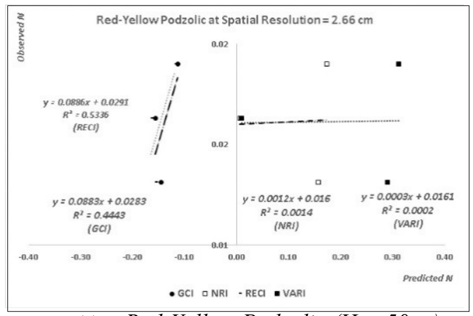
(b) Alluvial (H = 50 m)



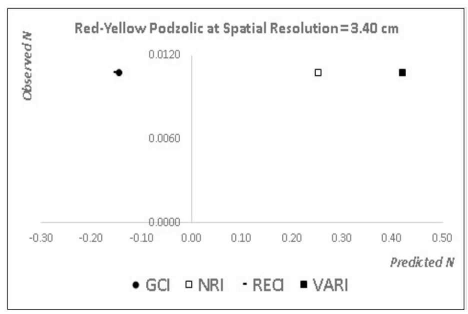
(c) Alluvial (H = 70 m)



(d) Red-Yellow Podzolic (H = 10 m)



(e) *Red-Yellow Podzolic (H = 50 m)*



(f) *Red-Yellow Podzolic (H = 70 m)*

Figure 8: Regression of Predicted and Observed N Status

A summary of R^2 scores from Figure 8 above are shown in the following Table 9:

Table 9: R^2 Score per Vegetation Index and per Spatial Resolution

Plot	Alluvial			Red-Yellow Podzolic		
SR	0.75	2.91	4.01	0.47	2.66	3.40
NRI[a]	0.4744	0.3868	0.7643	0.4587	0.0014	-
VARI[a]	0.1093	0.1745	0.0850	0.2260	0.0002	-
GCI[b]	0.1388	0.0781	0.2273	0.6932	0.4443	-
RECI[b]	0.1472	0.1636	0.2530	0.6938	0.5336	-

[a] visible range vegetation index
[b] multispectral range vegetation index
SR = spatial resolution

In spite of their high R^2 scores, GCI and RECI recorded negative predicted N status across all SR (Figure 8), therefore both multispectral band VIs are excluded from further evaluation. Imageries with SR of up to approximately 4.0 cm and 0.5 cm were

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able to estimate N status at alluvial and RYP plots respectively using NRI and VARI. Extremely low R^2 scores at $SR_{2.66}$ on RYP plot was attributed to its biased data, based on 20% representation of sample canopy and 60% experimental treatment. Visible band VIs did not produce any regression trend: Predicted N fitted the regression line better with SR on RYP, and fluctuated on alluvial. While $SR_{2.91}$ represented an average of 67% of canopy samples on alluvial, deteriorating pixel purity have attributed to crop-background discriminant accuracy, more so on VARI with prediction improvement by 0.0652 from the highest SR. The lowest resolution of $SR_{4.01}$ is a biased prediction due to its 27% canopy sample representation. No R^2 score was recorded at RYP $SR_{3.40}$ due to single canopy detection from the entire field plot. Therefore, imagery with the highest SR produced the more reliable estimation of MD2 crop canopy N status on both alluvial and RYP plots based on visible range VI assessments.

According to Figure 9 below, regression of predicted relative N (SPAD value) and observed N (PTA) provided a more reliable estimation based. The comparison was made at single leaf level, therefore reiterating SPAD Chlorophyll Meter's capability to produce proximal estimation of N status.

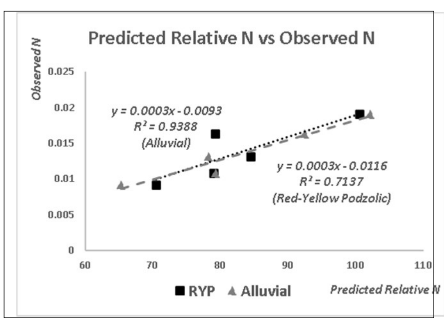

Figure 9: Regression of Predicted Relative and Observed N Status

4. CONCLUSION

Imagery with SR of below 1.0 cm was able to detect all sample crop canopies, and therefore enabled complete MD2 pineapple crop monitoring on mineral soil under field condition. The same resolution also supported more reliable UAS-based N status estimation in MD2 crop canopy of all tested resolutions. NRI is deemed a feasible visible band VI to estimate N status in MD2 crop canopy. Further exploration is needed on multispectral imagery acquisition techniques to improve its potential in monitoring MD2 crop N status.

Periodical monitoring proliferates the costs of data processing and storage requirement. Thus, identification of suitable SR value will support a more cost-effective N monitoring especially at medium and larger scale cultivation. Public agencies including MPIB can play more active role in providing technical assistance with UAS-based crop monitoring among smallholders through initiatives such as AgriCOP programme [70]. Smallholders can subsequently capitalise on e-satellite farm allocation to Farmers' Organisation Authority in the national budget [10] to acquire the technology.

Further investigation is needed to identify suitable VI to monitor N and other nutrient status of MD2 pineapple crop to promote cultivation of this premium food crop. While UAS is yet to emulate the accuracy of conventional monitoring method, the platform is able to assist with sufficient timely estimation of field parameters (such as nutrient status), an essential component of sustainable agriculture.

Larger scale MD2 crop nutrient monitoring should also consider incorporation of deep learning techniques into high resolution imagery processing to assist with crop canopy and crop centroid detection at larger scale cultivation, as demonstrated by [11] in flowering pineapple crop counting.

In future, higher SR from lower UAV flight height (less than 10 m) may be able to complement SR from proximal sensing, and covering a larger area of interest. Estimation of N status for crops with similar morphology with pineapple can be more correlated with Observed N, and therefore produce more reliable N status estimation.

Future study can also explore the feasibility of remote monitoring K status, the primary macronutrient that is more significant at the later growth stage (reproductive) [7] as sufficient K is essential to produce optimum yield. To the best of our knowledge, only proximal sensing techniques has been tested for K on marginal soil [9].

For a more conclusive monitoring of MD2 macronutrient status, future study should also be expanded to monitoring throughout the crop cycle. Therefore, nutrient status, and subsequent nutrient requirement can be identified at any stage of pineapple growth.

Local pineapple varities (Moris, Sarawak, Gandul, Maspinee, Josapine, Yankee, Moris Gajah,N36, MD2, View of Sunset, Madu Kaca, Keningau Diamond, Cobek) possess similar agronomic traits that include plant morphology, fertilisation technique, fertiliser requirement and crop cycle. The combination of trait similarity and uniformed Malaysian tropical climate is suggesting applicability of SR recommendation from this study in N status monitoring of local pineapple varieties. SR of below 1.0 cm is also applicable to hilly slope cultivation as UAV can be calibrated to fly on non-flat land area of interest.

The recommended SR of below 1.0 cm is also applicable to hilly slope cultivation as UAV can be calibrated to fly on non-flat land area of interest

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