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Sugarcane canopy detection using high spatial resolution UAS images and digital surface model

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Abstract

The use of an unmanned aerial system (UAS) equipped with multispectral cameras is a potential approach to acquire canopy reflectance to make various correlations with desired crop parameters. However, the acquired reflectance data are mixed with unwanted data, such as reflectance from soil, which significantly affects some commonly used vegetation indices, such as the NDVI. This study compares the performance of three methods for detecting the canopy area of 3-month-old sugarcane crops. These methods extract the canopy areas using 5 NDVI thresholds (0.2, 0.3, 0.4, 0.5, and 0.6), a principal component analysis (PCA) threshold, and a digital surface model (DSM) threshold. The performance assessment will deliberately consider the quality percentage (QP) of each method to correctly detect the canopy area of short sugarcane crops in 10 selected images. The results show that filtration by the PCA threshold method provides the best result with a QP of 65.89-78.72%. The NDVI threshold method at levels of 0.3 and 0.4 follow with QPs of 58.42-68.81% and 40.80-70.81%, respectively, and the lowest accuracy is obtained by the DSM threshold method, which has QPs of 14.80-30.78%.

Keywords: Canopy detection, Unmanned Aerial System (UAS), Digital surface model, Principal component analysis, Normalized vegetation index, Multispectral image

1. Introduction

Collecting agronomic information about crops in the early vegetative stage is crucial for making timely and effective decisions to prevent yield losses. For instance, sugarcane during its early vegetative stage, at 3 months, is when fertilizer is first applied. So the spectral reflectance of canopy at this stage will directly contribute to site management studies such as those on nitrogen assessment, irrigation management, germination rate [1], density of plants in the field, primary yield mapping, and other applications that use correlation regressions from canopy reflectance.

Currently, vegetation indices calculated from multispectral images collected using a UAS platform have become a popular method for calibrating prediction models of these studies. This is because UAS platforms allow use of multispectral cameras to capture of high-resolution images, collect better phenotypic information of crops at the plot-level than satellite imagery, achieve spectral reflectance in range of visible to the Red Edge and NIR band, which are the most sensitive bands in vegetation monitoring, whereas RGB cameras cover only visible band ranges. Furthermore, the acquired data are easier to analyze than data obtained from expensive sensors such as LiDAR, thermal IR, and hyperspectral sensors [2]. However, multispectral cameras still have some limitations. They are frequently inadequate for the analysis of single broadband combinations, such as Normalized Difference Vegetation Index (NDVI), which are remarkably influenced by bare soil reflectance at low LAI values or open-canopies such as sugarcane in early vegetative stage [3]. This effect causes low correlation and results in low prediction accuracy of key parameters.

In [2] the correlation between NDVI values acquired from a multispectral camera with SPAD values for maize in poor growth areas with much uncovered soil, the results clearly showed many soil pixels in images. NDVI plots (average NDVI value of plot which included soil pixels in plot) had lower correlations with SPAD than the average NDVIveg (average of only maize pixels, determined by manual vectorization). These values were 58% for NDVIplot compared to 78% for NDVIveg when considering the number of plots with errors of less than 10%. Additionally, the authors concluded that the NDVI produced by reflectance from both multispectral cameras was seriously influenced by the soil background. It is strongly recommended to reduce soil pixels before performing any further analysis.

To date, various vegetation indices, such as the soil-adjusted vegetation index (SAVI) [4], the transformed SAVI

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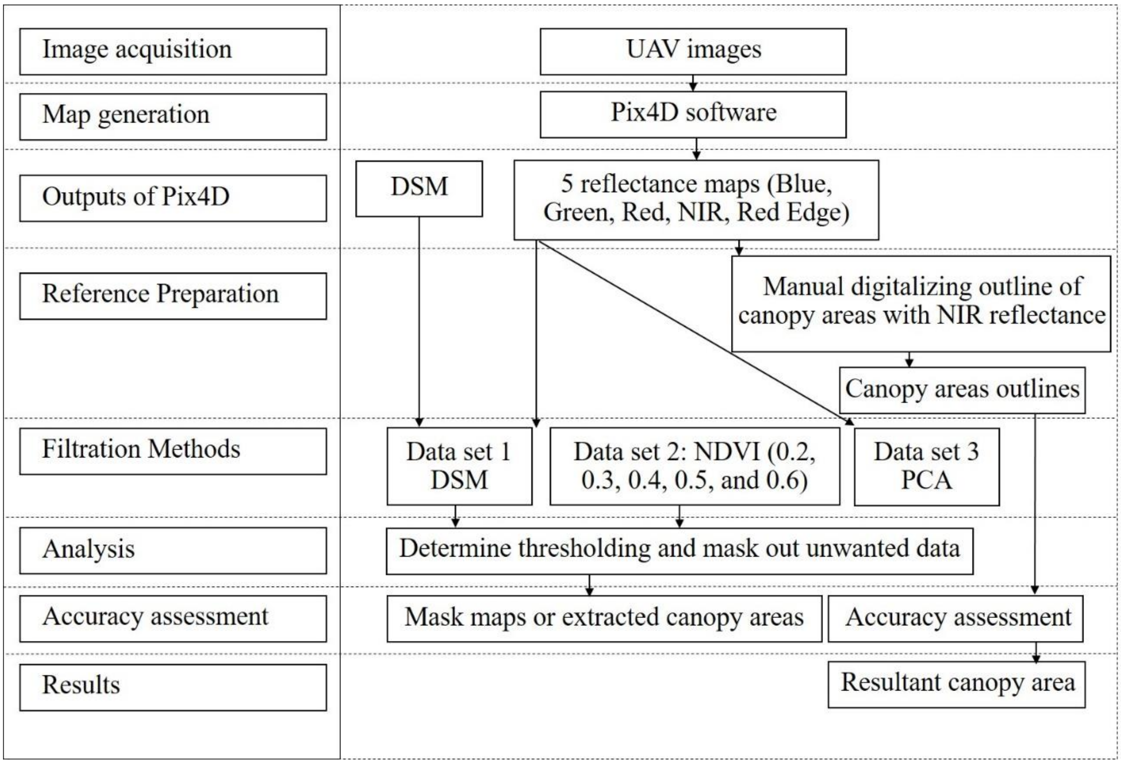

Figure 1 Flowchart of the experiment

(TSAVI) [5], modified SAVI (MSAVI) [6] and optimized SAVI (OSAVI) [7], have been used to compensate for soil background reflectance. In [8] the authors tested the performance of SAVI, TSAVI, MSAVI, and OSAVI to predict the yield of onions. The results showed that those vegetation indices gave similar or lower R^2 values (0.61-0.67) compared to NDVI (R^2 0.66). The comparable accuracies of SAVI, TSAVI, MSAVI, and OSAVI with NDVI's accuracy and low coefficients of these vegetation indices show their limited performance in making reliable prediction models for monitoring phenotypic information of crops with sparse canopy conditions. For example, this condition exists for sugarcane's canopy during first through fifth months of growth.

Alternatively, previous researchers using canopy detection were mainly concerned with trees and aimed to delineate the boundaries of tree crowns [9-12]. Even though such studies achieved good results, these methods only performed well with evergreen trees with a rounded, compact shape [9] and uniform tree size [11-12]. They cannot work with the uncompact and random spread canopy of sugarcane. Alternatively, some authors have tried to use machine learning methods, for instance Maximum Likelihood Classification (MLC), to detect crop canopies. For example, one research group used a maximum likelihood classification method to supervise image classification in attempting to mask out soil pixels from images [13]. However, MLC cannot provide visualization of input parameters that allows for additional observations of some interesting effects on the studied input's trends such as soil color, canopy age, plantation practices, and weather conditions, whereas Principal Component Analysis (PCA) does. So, PCA is more advantageous when observations of input parameter patterns are required for further analysis of factors that cause changes or shifts in trends. This is important information for further study and advances allowing widespread use of such applications.

In addition to the discussed methods above, there are still some potential techniques, such as NDVI and digital surface model (DSM) methods that might work well on canopy detection of short-height and open-canopy crops. First, NDVI has better spectral separability of vegetation and bare soil than other vegetation indices [14]. Sugarcane canopies have NDVI values in the range of 0.2 to 0.6 [15]. Thus, NDVI values might provide a useful and easy thresholding method for extracting sugarcane canopy data if we have precise information about which threshold value of NDVI should be applied. Second, because crop canopies are normally higher than the soil background, a digital surface model (DSM) might also be an effective approach to mask out soil pixels. Canopy data extraction by the DSM method was studied with citrus trees [9, 16-17], and the test results demonstrated that this method provided satisfactory results. Hence, DSM is chosen to study its performance with short-height sugarcane in this paper.

This study compares the performance of masking out soil pixels from images and the capability to precisely extract sugarcane canopy pixels. It also determines the suitable soil pixel thresholding methods and appropriate canopy conditions for applying these methods to achieve best spectral reflectance of crop canopies. This can lead to accurate enhancements for sugarcane yield and quality prediction at an early stage.

2. Materials and methods

The sugarcane field used in this study is located in an experimental field of the Agriculture Faculty, Khon Kaen University, Thailand. This field was a breeding field on which 3-month-old sugarcane was grown (from seeds). The height of the sugarcane varied from 20 to 30 cm. Ten spots were randomly selected in this field. A flowchart for this experiment is shown in Figure 1.

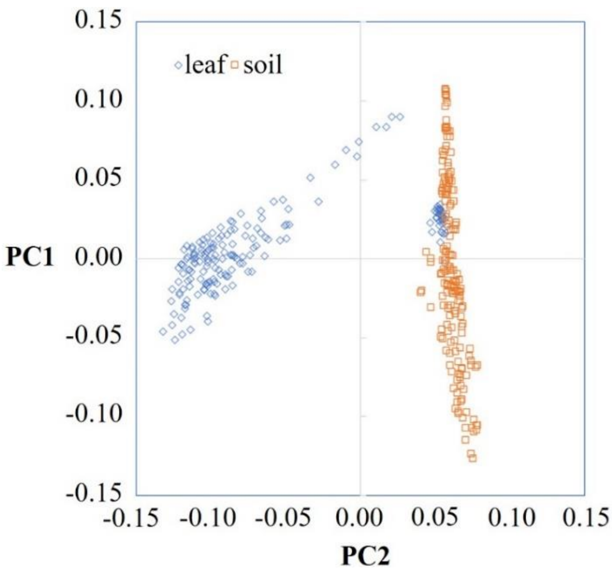

Figure 2 Plot of PC1 vs PC2 in trained sample

2.1 Flight mission

Images were captured by a MicaSense RedEdge 3 camera (MicaSense, RedEdge, USA), which was mounted on a six-rotor VESPA HEX 650 UAV (HG Robotic Company, Thailand). The flight mission was conducted at approximately 13:00 according to recommendations from the MicaSense RedEdge 3 user manual (2017). A ground sampling distance of 3 cm and an approximate height of 44 m were used, so that the structure of sugarcane canopy could be clearly seen in acquired reflectance maps, resulting in the production of high quality manually outlined references.

2.2 Map generation

After the flight mission, all acquired images were processed using Pix4D Mapper Version 4.0 software (Pix4D, Switzerland). The final products were a reflectance map in five bands (blue, green, red, near-infrared, and red-edge) and a DSM file. After choosing 10 spots in the field and identifying their pixel locations in Adobe Photoshop CS6, Version 13.0 (Adobe, United State), all 5-band reflectance maps and DSM files were cropped separately in the MATLAB program, Version 2017 (The MathWorks, Inc., United States).

2.3 Thresholding by NDVI

As discussed in the introduction, sugarcane canopies have NDVI values in the range of 0.2 to 0.6 [15]. So, NDVI values have a potential to be a useful and simple thresholding method for extracting sugarcane canopy measurements if we have precise information about which age of sugarcane canopy that each level of the NDVI threshold can provide the best performance. Hence, this experiment was conducted to find a NDVI threshold level that gives the best performance with 3 month old sugarcane. This is the stage when fertilizer is first applied.

First, the NDVI maps were calculated for each spot, and then five threshold levels (0.2, 0.3, 0.4, 0.5, and 0.6) were individually applied to those NDVI maps. Pixels with NDVI values lower than the given threshold level were masked out by assigning the value "Not a Number" or "NaN", whereas the remaining pixels with higher NDVI values were assigned an input value of "1". Finally, a masked map for each spot was produced. All steps were run in MATLAB with written codes.

2.4 Thresholding by Principal Component Analysis

Principal component analysis or PCA is a variable compression method that reduces a large data set of a X (K × N) matrix to a simple one that consists of smaller A variables called the principal components (PCs) to more accurately interpret data [18]. Thus, correlated variables in the original large data set will form into new groups called "principal components or PCs". PCA can be expressed as a mathematical model that follows [18]:

$$X=TP^{T}+E \tag{1}$$

where T (N× A) is a score matrix containing the A scores for the PCs. The scores are intensities of the new A variables for the samples. P (K×A) is a loading matrix containing the A loadings for the PCs, and E (K× N) is a matrix of model residuals.

In this study, we used five soil matrices (S1, S2, S3, S4, S5) and five canopy matrices (C1, C2, C3, C4, C5) to form a "trained sample". Each matrix has a size of 36×5, where 36 rows represent the reflectance value of each pixel of the trained sample image. Each column is reflectance data in blue, green, red, near-infrared, and red-edge bands. These ten matrices are combined into one large 360×5 matrix called the "trained sample", whose first 180 rows are canopy data, and the last 180 rows are soil data. After applying the PCA method, plots of PC1 and PC2 (Figure 2) were visualized, in which the canopy scores are marked in blue, and the soil scores are in orange. The locations of the soil scores were identified, and the conditions required to recognize the soil scores were determined. Consequently, the mean value of each factor, loading matrix and the condition of the soil scores, PC2> 0, were obtained and applied to the data from all flight missions.

The 5-band reflectance data from each test sample were transformed into a 5-column matrix, and then the 5-factor

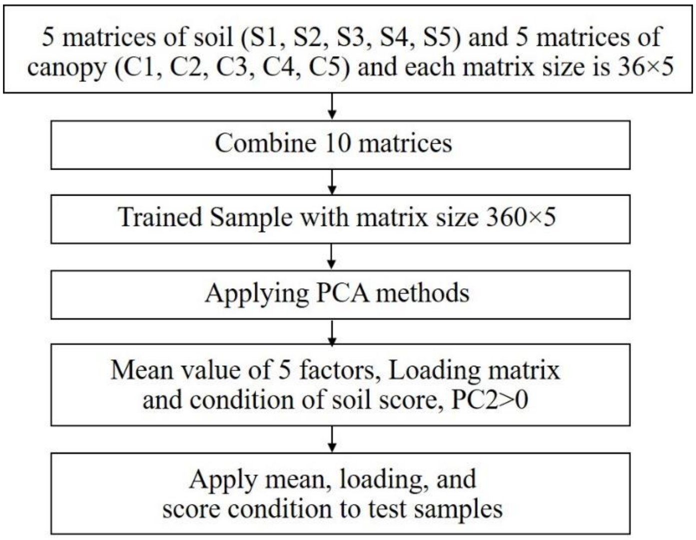

Figure 3 Flowchart of PCA

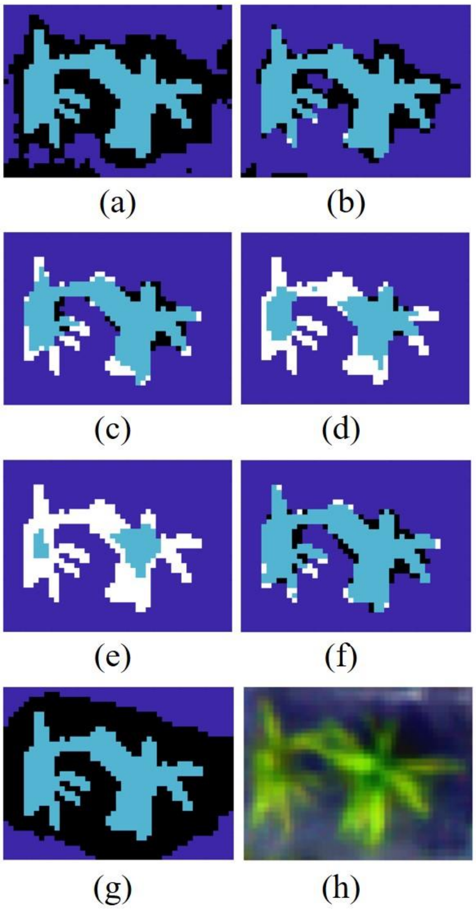

Figure 4 The extracted canopies of sample number 8 overlaid on a reference canopy using a thresholding method by NDVI levels of 0.2, 0.3, 0.4, 0.5, and 0.6 (a, b, c, d, and e), thresholding by PCA (f), thresholding by DSM (g), and image in RGB (h). Dark blue = soil pixels, light blue (TP) = correct canopy detection, white (FP) = missed canopy detection, black (FN) = over-canopy detection

matrix was substituted with the mean value of each factor from the trained sample. The data were then multiplied by the loading of the trained sample to achieve the scores. Finally, the locations of the soil score whose PC2>0 were identified. Pixels with score values in the range of the soil score were masked out by assigning a "Not a Number" or "NaN" value, whereas the remaining pixels were assigned an input value of "1". Finally, a masked map for each spot was produced. A flowchart of the PCA process is shown in Figure 3.

2.5 Thresholding by Digital Surface Model

For DSM thresholding, the μ-σ value of the DSM of samples was determined and applied as a threshold [11]. Hence, pixels with DSM values lower than the threshold were assigned a "Not a Number" or "NaN" value, whereas the remaining pixels were given the input value of "1". Subsequently, a masked map for each sample was created.

2.6 Validation

The reference canopy area of each sample was manually outlined in Adobe Photoshop CS6 using a reflectance map in the near-infrared band. The canopy area calculated using the above methods was compared with the reference canopy area, and qualitative accuracy assessment was performed using the following parameters [9]:

Branching factor (BF): $BF = FP \div TP$ (2)

Miss factor (MF): $MF = FN \div TP$ (3)

Tree detection percentage (TDP):
$TDP = 100 \times TP \div (TP + FN)$ (4)

Quality percentage (QP):
$QP = 100 \times TP \div (TP + FN + FP)$ (5)

where TP = true positive (correct canopy detection), FN = false negative (missed canopy detection), and FP = false positive (over-canopy detection).

3. Results and discussion

Figure 4 illustrates that the detected canopies of sample number 8 were overlaid on its reference canopy. The light

Table 1 The accuracy assessment results of extraction approach by NDVI threshold level 0.2, 0.3, 0.4, 0.5, 0.6, PCA threshold, and DSM threshold

Parameter	**Sample/ methods**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
BF	NDVI level 0.2	1.47	1.64	2.32	1.51	2.08	1.12	2.48	1.65	2.35	1.16
MF		0	0	0	0.01	0	0.01	0.01	0	0	0.02
TDP		100	100	100	98.95	100	98.98	99.25	100	100	97.70
QP		40.54	37.81	30.09	39.64	32.45	46.88	28.63	37.72	29.81	45.70
BF	NDVI level 0.3*	0.41	0.52	0.70	0.61	0.43	0.28	0.58	0.55	0.69	0.36
MF		0.06	0.03	0.01	0.04	0.03	0.30	0.02	0.01	0.02	0.13
TDP		94.73	97.56	98.67	96.59	97.27	77.16	98.12	99.19	97.73	88.51
QP		68.41	64.81	58.49	60.93	68.81	63.60	62.59	64.16	58.42	67.25
BF	NDVI level 0.4*	0.13	0.14	0.17	0.16	0.03	0.05	0.17	0.16	0.11	0.06
MF		0.38	0.41	0.32	0.29	0.69	1.40	0.25	0.25	0.46	0.81
TDP		72.46	70.73	75.86	77.43	59.09	41.62	80.08	80.00	68.64	55.17
QP		66.37	64.44	66.98	68.76	58.04	40.80	70.53	70.81	63.71	53.33
BF	NDVI level 0.5	0.01	0	0.04	0.03	0	0	0.02	0.05	0.02	0
MF		1.34	1.99	1.45	1.19	4.64	10.59	1.16	1.13	2.61	5.21
TDP		42.77	33.45	40.85	45.67	17.73	8.63	46.24	47.03	27.73	16.09
QP		42.52	33.45	40.21	45.08	17.73	8.63	45.72	46.03	27.60	16.09
BF	NDVI level 0.6	0	0	0	0	NaN	NaN	0	0	0	0
MF		5.17	12.67	6.25	5.35	NaN	NaN	5.05	4.00	13.67	57.00
TDP		16.21	7.32	13.79	15.75	0	0	16.54	20.00	6.82	1.72
QP		16.21	7.32	13.79	15.75	0	0	16.54	20.00	6.82	1.72
BF	PCA*	0.18	0.12	0.12	0.30	0.10	0.12	0.19	0.19	0.18	0.15
MF		0.16	0.19	0.30	0.09	0.19	0.40	0.15	0.08	0.13	0.33
TDP		85.94	84.32	77.19	91.34	84.09	71.57	87.22	92.97	88.18	75.29
QP		74.70	76.34	70.80	71.60	77.73	65.89	74.60	78.72	76.08	67.88
BF	DSM	3.21	3.13	2.42	2.54	4.98	4.68	3.65	2.25	5.75	4.51
MF		0	0	0	0	0	0	0.02	0	0	0
TDP		100	100	100	100	100	100	98.50	100	100	100
QP		23.74	24.24	29.22	28.29	16.73	17.61	21.42	30.78	14.80	18.14

NaN = Not a Number, because there are no TP (correct canopy detection) in sample 5 and 6 by NDVI threshold level 0.6 method.
*** =** refer to methods that provides good performance

blue color (TP) represents correct canopy detection, whereas the white color (FN) indicates missing canopy detection. This means that canopy exists in the reference image, but the approach failed to identify it. Conversely, the black color (FP) indicates over-canopy detection, which implies that this is soil area, but the approach distinguished it as canopy area.

For ten samples using each extraction method, the calculated BF, MF, TDP, and QP values are demonstrated in Table 1. The TDP values using an NDVI threshold of 0.2 are almost 100% while the QP values are still low at 28.63-45.70% because the detected areas contain large over-detected areas. For NDVI thresholds of 0.5 and 0.6, their TDPs are 8.63-47.03% and 0-20%, and the QPs are 8.63-46.03% and 0-20%, which are the lowest percentages due to the considerable misdetected areas. The best results are at NDVI thresholds of 0.3 and 0.4, which have TDP values of 77.16-99.19% and 41.62-80.08% and QP values of 58.42-68.81% and 40.80-70.81%, respectively. This better performance likely occurred because the sugarcane crops used in this experiment were only two months old. They had sparse and light green canopies, which were similar to the canopies of grasslands or shrubs with NDVI values ranging from 0.3 to 0.4 [19]. Thus, the canopy conditions in this study result in good performance at these two specific levels.

The filtration approach of PCA has TDPs in the range of 71.57-92.97 with the highest QPs of 65.89-78.72%. This result indicates that the reflectance values of the five bands acquired from a narrow-band multispectral camera can be effectively used to train a classifier to separate the soil and green canopy using the principal component analysis technique. Since the application of the classifiers produced by PCA relies on the input data, there is a possibility to develop artificial intelligence, such as machine learning, for detecting canopy areas using the reflectance of these five bands and PCA methods.

Detection methods by DSM can determine canopy areas with TDPs of 100%, but the QP values will be low at only 14.80-30.78% due to over-detection. This result is contrary to the results other published results [9], which obtained good accuracy using DSM data to detect citrus tree crowns. The first reason for this disparity might be that these experiments examined tall citrus trees with have average heights of 4.5 m, whereas this study tested with short-height sugarcane, which was only 0.2-0.3 m tall. Thus, even a slight slope or uneven soil surfaces in a field will significantly affect canopy extraction by the DSM method. Second, this field represents the conditions of sugarcane fields in the northeast region of Thailand. Here, sugarcane farming is characterized as rain-fed farming [20]. Therefore, a smooth and well-balanced field is not essential because there is no requirement to keep water in the field for long periods. Third, sugarcane is planted in rows, so it is inevitable to have raised soil around the rows. For these three reasons, there is low performance of canopy detection by the DSM method, even though the test samples were only small blocks in the field that contained 2-3 stalks.

4. Conclusions

This study presents the performance of three simple but essential extraction methods for canopy area detection. According to the experimental results, extraction by the PCA approach provides the best detection, but it requires a complicated process. However, if more wide-range data are used as inputs, machine learning for identifying canopy areas can possibly be developed. Alternatively, filtration using an NDVI threshold is easy and generally applicable, However, users must pay more attention to the conditions of the canopy in the test plot because a sugarcane canopy has an NDVI in the range of 0.2 to 0.6 [15]. Therefore, users should utilize the appropriate NDVI threshold level. Alternatively, the canopy extracted by the DSM method did not provide good results when applied to short sugarcane with heights of 0.2-0.3 m grown in fields with rugged surfaces. Thus, the user should consider the current crop heights and the conditions of the field including the slope and unevenness of the field surface before using the DSM method for canopy filtration. With the good results of the PCA method, the authors will study and input additional data to develop a machine learning method for extracting canopy data using the PCA method.

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