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A universal estimation model of fractional vegetation cover for different crops based on time series digital photographs

Dongdong Zhang[a,b], Lamin R. Mansaray[a,e], Hongwei Jin[c], Han Sun[d], Zhaomin Kuang[f], Jingfeng Huang[a,*]

[a] Institute of Applied Remote Sensing and Information Technology, Zhejiang University, Hangzhou 310058, China
[b] Institute of Tibetan Plateau Atmospheric and Environmental Science, Lhasa 850000, China
[c] Jiangsu Radio Scientific Institute Co, Ltd, Wuxi 214073, China
[d] Innovation Institute of Disaster Prevention and Reduction at Inner Mongolia, Huhhot 010051, China
[e] Department of Agro-meteorology and Geo-informatics, Magbosi Land, Water and Environment Research Centre (MLWERC), Sierra Leone Agricultural Research Institute (SLARI), Freetown PMB 1313, Sierra Leone
[f] Guangxi Institute of Meteorological and Disaster-Mitigation Research, Nanning 530022, China

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ABSTRACT

The green fractional vegetation cover (FVC) is an important parameter in monitoring crop growth and predicting aboveground biomass. In this study, we monitored crop growth with digital cameras installed at four automatic weather observation stations in different parts of China, from 2010 to 2016. With each station having a particular type of crop, nine color vegetation indices were calculated from the acquired time series digital photographs to arrive at an FVC estimation model applicable to sugarcane, maize, cotton and paddy rice. For individual crop types, our results show that the Excess Green (ExG) is the optimal color vegetation index for the estimation of sugarcane FVC, the Normalized Difference Index (NDI) is the optimal color vegetation index for the estimation of maize FVC, and the Vegetative (VEG) color vegetation index is optimal for the FVC estimation of cotton and paddy rice. However, owing to its higher coefficient of determination (R^2), and lower root mean square error (RMSE) and mean absolute error (MAE) of 0.9504, 0.0721 and 0.0545, respectively, the Color Index of Vegetation Extraction (CIVE) is found more universally applicable for FVC estimation of the four crop types under investigation. The CIVE index has therefore been proposed in this study to be optimal for FVC estimation in sugarcane, maize, cotton and paddy rice mixed cropping agro-systems which are especially common in small and highly fragmented agricultural landscapes such as those in urban and peri-urban areas.

1. Introduction

Vegetation cover is defined as the vertical projection of the crown or shoot area of vegetation canopies from the ground surface, and is expressed as a fraction or percent of the reference area (Purevdorj et al., 2010). Green fractional vegetation cover (FVC) is an important variable for controlling factors in transpiration, photosynthesis and other terrestrial biophysical processes (Jiapaer et al., 1923). FVC can be used as a direct input to crop growth models to predict or estimate crop yield, above-ground biomass, plant nutritional status, and in the estimation of evapotranspiration (Coy et al., 2016; Paton and Boag, 2007, Allen and Pereira, 2009). Based on the above, it is therefore apparent that the development of algorithms for routine investigation of FVC is extremely important in meeting the requirements of ecosystem applications and in modeling crop growth and productivity in the light of environmental management, sustainable development, precision agriculture and food security.

A number of studies have been conducted on the monitoring or estimation of crop green fractional vegetation cover (FVC). Traditional methods of FVC investigation include ground measurements and remotely-sensed data. Several ground measurement techniques for the estimation of percent ground cover of crops have been proposed, and two of the commonly used are described as follows: ① Some agronomists have estimated percent ground cover of vegetation based on visual interpretation (Armbrust, 1990; DUNCAN et al., 1993; Mueller-Dombois and Ellenberg, 2012; Torell and Glimskär, 2009). The major problem of this method is that the results are too subjective, as they are primarily based on the intuition of the observer. Hence, different

* Corresponding author.
E-mail addresses: dongdongzhang@zju.edu.cn (D. Zhang), l.mansaray@slari.gov.sl (L.R. Mansaray), Jin.hongwei@js1959.com (H. Jin), sun_han@163.com (H. Sun), kzhaomin@163.com (Z. Kuang), hjf@zju.edu.cn (J. Huang).

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observers could have different value judgments; ② Another method is based on shaded area measurements taken at-or-near noon (Adams and Arkin, 1977; Thalen, 1979). However, in addition to being time and labor consuming, this ruler or electronic method is also affected by weather conditions and orientation of the instrument during measurement (Zhao et al., 2009). Field measurements, even though relatively simple, are subjected to a variety of uncertainties and can be regarded inefficient especially for operational applications at large scales of FVC inventories (Cui et al., 2011).

With the development of computer technology and digital image analysis, estimating crop FVC using digital photography is becoming increasingly popular. The use of digital photography is providing much information on vegetation cover and growth conditions. Computer-aided vision techniques have been applied on digital photographs to segregate the green vegetation from the soil background (Liu et al., 2012). Using digital image analysis, an accurate color vegetation index is required to properly discriminate crop, soil and residue backgrounds for application in ecological monitoring and assessments, quantitative biophysical modeling, precision crop management, and weed control (Meyer and Neto, 2008).

Previous studies have documented a variety of color vegetation indices for separating crops from their background using digital images. The normalized difference index (NDI), which uses the green and red channels has been frequently used to separate the plant from the soil background in digital color images (Meyer, 1993; Pérez et al., 2000). Meyer et al.(1999), tested the excess green and excess red in segmenting plant pixels from the soil background under varying environmental and lighting conditions. Unsupervised fuzzy excess green and excess red have been developed and employed for identifying green plants from soil and residue backgrounds, but they are however, not suitable for wheat-straw backgrounds (Meyer et al., 2004). A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership (characteristic) function which assigns to each object a grade of membership ranging between zero and one (Zadeh, 1965). The ExG − ExR index has been successfully tested using two commercial color digital cameras to separate plants from their backgrounds under greenhouse field lighting conditions with a fixed zero threshold (Meyer and Neto, 2008). The vegetative index (VEG) has been used to identify plant pixels (Hague et al., 2006). The CIVE index has been mainly used to separate the green plant portion from the soil background (Kataoka et al., 2003). Woebbecke et al. (1995a) selected the R-G, G-B and (G-B)/|R-G|, where the R, G, and B are the red, green, and blue chromatic coefficients for each pixel in the range of 0–1, to find the best optical contrast between plants and their background.

With the availability of inexpensive high-quality digital images, mapping vegetation cover by means of automated image analysis is becoming more common (Bauer and Strauss, 2014). In Zhou and Robson (2001), a method to estimate vegetation cover, density and background brightness parameters in a rangeland environment from low-altitude digital images was presented. In their study, a digital still-frame camera, mounted on a 5.2 m pole was used to acquire images of the ground. The acquired images were then processed using an unsupervised spectral–contextual classifier for the automatic extraction of quantitative measurements. In (Laliberte et al., 2007), ground photographs were acquired from 50 plots using an eight megapixel digital camera. The images were transformed from the RGB (red, green, blue) color space to the IHS (intensity, hue, saturation) color space. An object-based image analysis approach was employed to classify the images into soil, shadow, green vegetation, and senescent vegetation. Shadow and soil were effectively masked out by using the intensity and saturation bands, and a nearest neighbor classification algorithm was used to separate green and senescent vegetation using intensity, hue and saturation, as well as the visible bands. However, classifying leaves under shadows using digital images remains challenging and several classification errors are likely to occur. To address this problem, an automatic shadow-resistant algorithm in the Commission Internationaled'Eclairage L*a*b* color space (SHAR-LABFVC) based on a documented FVC estimation algorithm (LABFVC) has been proposed in (Song et al., 2015). LABFVC is the mean-shift-based color segmentation method and the Commission Internationaled'Eclairage L*a*b* (LAB) color space for the documented FVC estimation algorithm (Liu et al., 2012).

Previous studies have largely focused on the application of color vegetation indices to segment crops from their background (Hague et al., 2006; Meyer and Neto, 2008; Woebbecke et al., 1995a) and estimate nitrogen status (Jia et al., 2007; Lee and Lee, 2013; Wang et al., 2013). In most previous studies, only one crop type is investigated, posing limitations in FVC estimation under mixed cropping systems. In this study, an approach for FVC estimation is adopted based on the Probabilistic Superpixel Markov Random Field (PFMRF) algorithm presented in Ye et al. (2015), a brief description of which is provided in Section 2.3 of this paper. We utilized raw digital photographs as inputs to derive reference FVC, with which linear relationships are built with color vegetation indices to estimate the FVC of four crops.

To achieve the aforementioned aim, image data of sugarcane, maize, paddy rice and cotton were acquired from four automatic weather observation stations in China from 2010 to 2016. Through correlation analysis between FVC and color vegetation indices derived from the combined (all crops) data, we have proposed an FVC estimation model, capable of universal applicability to these four crop types which are generally characterized by overlapping growth periods and located in mixed agricultural systems most typical in urban and peri-urban areas.

2. Materials and methods

2.1. Study area

The data used in this study were obtained from four automatic weather observation stations in China, each station corresponding to a particular type of the crops under investigation. Fig. 1 shows the location of the four test sites. The agrotype of the respective automatic weather observation stations and details of image acquisition are shown in Table 1.

2.2. Image acquisition

As shown in Fig. 2, the images were captured from automatic observation devices designed by the Jiangsu Province Radio Scientific Institute Co., Ltd. The images were shot daily at hourly intervals throughout the year unless there is a system problem, such as system breakdown or power outage. The automatic observation devices consist of Charge Coupled Device (CCD) cameras, and wireless routers connecting the cameras to computers in each station. Image data of crops captured by the CCD cameras are transmitted through wireless launchers to remote computers using 3G network. Camera parameters differ amongst study areas as shown in Table 2.

All the digital color images were saved to 32 bit or 24 bit true color in the appropriate folder in accordance with the focal lengths and shooting time. In the end, we acquired the time series images of sugarcane, maize, paddy rice, and cotton. As images were acquired at different view angles, we selected the vertically shot images to calculate FVC.

2.3. Measurement of fractional vegetation cover (FVC)

In this study, we consider the FVC calculated by the PFMRF algorithm as the reference FVC of the four crops and the measured FVC of an image is calculated as the ratio of the number of pixels of all vegetation to the total number of pixels in the image (Song et al., 2015). Due to system transmission problems, some images were incomplete, and

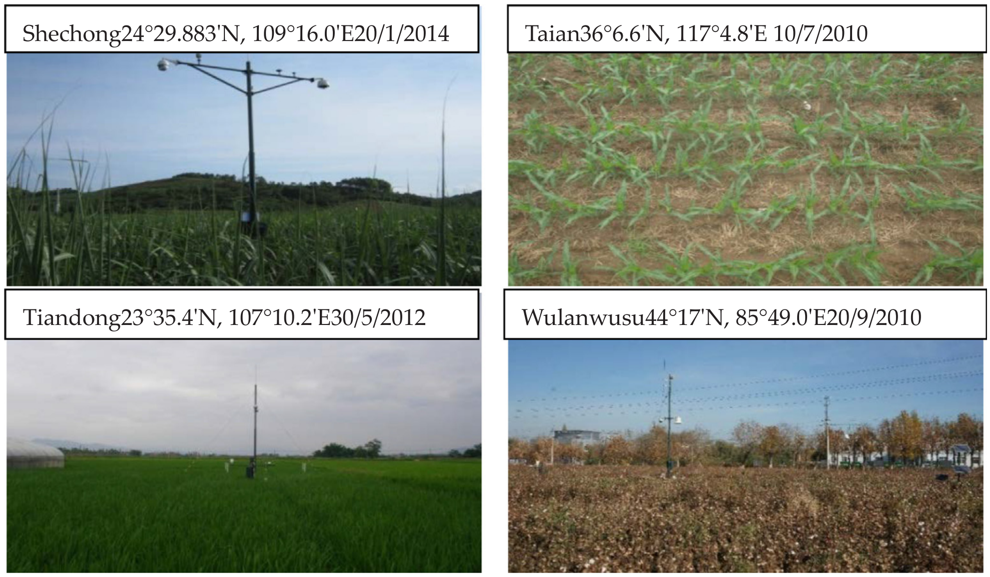

Fig. 1. Location of automatic weather observation stations.

Table 1
Agrotype of automatic weather observation stations and details of image acquisition.

Observation station	Agrotype	Shooting time	Year of image acquisition	Number of images
Shechong	Sugarcane	8:00, 9:00, 11:00 ,15:00	2015, 2016	1011
Taian	Maize	9:00, 10:00, 16:00	2010, 2011, 2012, 2013	927
Tiandong	Paddy rice	8:00, 9:00, 11:00 ,13:00, 14:00, 15:00, 16:00	2012, 2013	1547
Wulanwusu	Cotton	10:00, 11:00, 12:00, 13:00, 14:00, 15:00, 16:00, 17:00, 18:00, 19:00	2012, 2013	2230

Table 2
Camera parameters at different observation stations.

Station	Camera model	Installation height (m)	Image resolution	Bit depth
Shechong	DS-2DF7274-D	6	1280 * 960	36
Taian	OlympusE450	5	3648 * 2736	24
Tiandong	Canon 1000 D	5	4272 * 2848	24
Wulanwusu	OlympusE450	5	3648 * 2736	24

were hence eliminated from the database.

After pre-processing, complete images were used to separate the crops from their backgrounds. There are several methods for the segmentation of digital color images. Given the complex environment and illumination conditions in the areas studied, a robust algorithm is needed to separate crops from their complex backgrounds under varying illumination conditions. Segmentation methods based on PFMRF have been noted robust in limiting the influences of

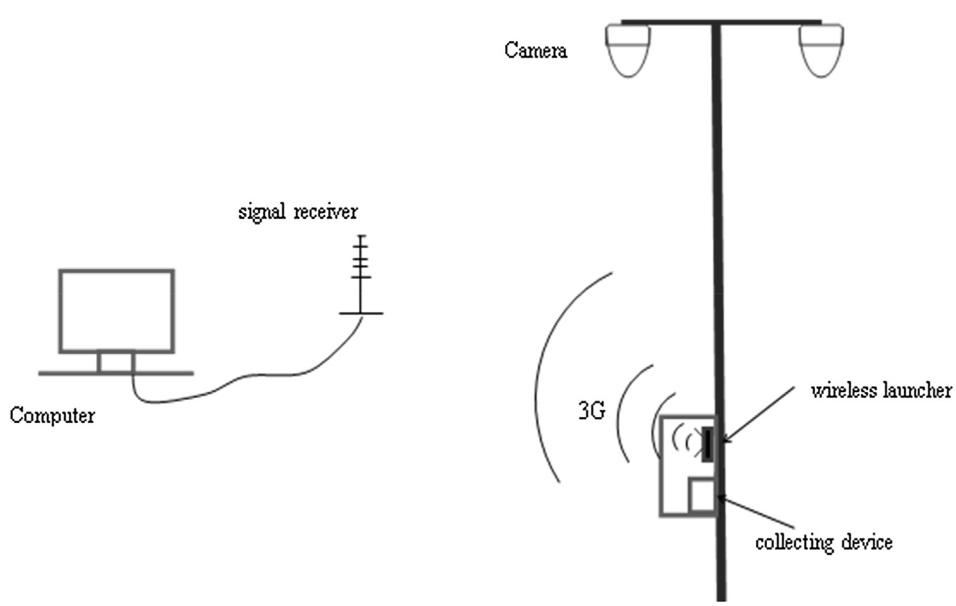

Fig. 2. The automatic observation device.

illumination conditions (cloudy, sunny and over-sunny weather) and soil background on crop segmentation accuracy (Hamuda et al., 2016), and hence, PFMRF is employed in the current study.

The PFMRF algorithm proposed by Ye et al. (2015) is based on the assumption that, color changes gradually between highlight areas which represent image regions under high illumination conditions and the neighboring non-highlight areas which represent image regions of low illumination conditions, and this holds true for other regions. This priori knowledge is embedded into the MRF–MAP framework by modeling the local and mutual evidences of nodes. The Markov random field (MRF) is a stochastic process that specifies the local characteristics of an image and is combined with the given data to reconstruct the true image. The MRF–MAP framework is a graphical model based on MRF. The superpixel and Fisher linear discriminant analyses have also been utilized to construct the probabilistic superpixel patches. The Loopy belief propagation algorithm is then adopted in the optimization step, and the label for the crop segmentation is provided in the final iteration result. The belief propagation (BP) algorithm is a tool with which one can calculate beliefs, marginal probabilities, of probabilistic networks without loops (e.g., Bayesian networks) in a time proportional to the number of nodes (Taga, 2006). This method is efficient under strong illumination and can be applied to generic species. The PFMRF algorithm is also capable of extracting the crop from shadow regions.

In this study, the segmented images were transformed into binary images and the connected components were labeled, then the noise was removed by an area threshold value (Sun et al., 2006). Images whose connected regions are less than 60 were considered noise and were thus deleted to derive the final segmentation images. Finally, reference FVC for sugarcane, maize, paddy rice and cotton were calculated from the final segmentation images using the PFMRF algorithm. The temporal segmentation results of the four crops are presented in Fig. 3.

In Fig. 3, the temporal growth of the four crop types is illustrated, and it can be observed that the PFMRF algorithm performs well in segregating these crops from their backgrounds.

2.4. Calculation of color vegetation indices

Several color vegetation indices have been developed for separating the green plant from the background. Table 3 shows nine color vegetation indices (Zhang et al., 2016) which have been more commonly used in recent years.

The color vegetation indices and FVC that were calculated using the above method were divided into single time point and combined time point datasets for each crop. Single time point data are those at each image shooting time, whereas the combined time point data are those derived from a combination of all image shooting times.

2.5. Research process

Fig. 4 below illustrates the work flow or methodological approach employed in this study. Firstly, we used the PFMRF algorithm to segment the complete images and calculate reference FVC. Secondly, we calculated the color vegetation indices of the utilized images. Thirdly, optimal estimation models of individual crop FVC and the universal crop FVC estimation model are established based on the calculated color vegetation indices.

2.6. Assessment of FVC estimation accuracy

The performance of an estimation model is usually evaluated by comparing the coefficients of determination (R^2), the root mean square error (RMSE) and the mean absolute error (MAE) (Chen et al., 2007; Yang et al., 2007). In this study, R^2 is the square of Pearson's correlation coefficient between measured FVC and model-predicted FVC. The root mean square error (RMSE) and the mean absolute error (MAE) can be calculated using Eqs. (1) and (2):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

where y_i is the measured value, $\hat{y}_i$ is the predicted value of crop parameters, and n is the number of verified data points. We have used these three indicators to compare and select the optimal models for FVC estimation. Generally, good prediction models would have large values of R^2, and small values of RMSE and MAE, though they are not necessarily monotonically related (Li et al., 2015).

3. Results

3.1. Analysis of crop samples

The measured FVC described in Section 2.3 and the color vegetation indices (Table 3) at different shooting time were calculated based on the approach illustrated in the flow chart (Fig. 4). The results of Pearson's correlation analysis of the FVC and color vegetation indices of sugarcane, maize, paddy rice and cotton at different shooting time are shown in Tables 4–7, respectively. With the exception of (G-B)/|R-G|, all other correlation coefficients (r) between FVC and color vegetation indices at different shooting time are greater than 0.5 and significant at the 0.01 confidence level for the four crops. This indicates that the (G-B)/|R-G| index is not sensitive to changes in FVC of the four crops. In addition, FVC is positively correlated with G-B, ExG-ExR, ExG, NDI and VEG, while it shows a negative correlation with ExR, R-G and CIVE. The correlation coefficients (r) between color vegetation indices and FVC are different with respect to agrotype, image shooting time and color vegetation index.

We selected the color vegetation indices obtained from the combined datasets (all shooting time) for each crop whose correlation coefficients (r) with FVC are greater than 0.8 and are significant at the 0.01 confidence level, to evaluate the individual crop FVC estimation models (Tables 4–7). In order to make the FVC estimation models more reliable, we divided the data into two groups. One group was categorized as training samples to train the model, and another group as testing samples for the validation of model accuracy, where the training and testing samples are 3/4 and 1/4, respectively of their individual total sample sizes. To compare the performance of the color vegetation indices in estimating crop FVC, we used the R^2, RMSE and MAE derived from linear and nonlinear regression models.

3.1.1. Sugarcane FVC estimation model

In this study, we have selected the CIVE, ExG-ExR, and ExG color vegetation indices for building the estimation models. Our experimental results indicated that FVC has an obvious nonlinear relationship with CIVE, ExG-ExR and ExG. Therefore the second-order polynomial regression was chosen as an equation to estimate sugarcane FVC from the values of CIVE, ExG-ExR and ExG. The testing samples were used to evaluate the accuracy of the sugarcane FVC estimation model, and the assessment parameters include R^2, RMSE and MAE as shown in Table 8.

From the results in Table 8, it can be seen that all the models for estimating sugarcane FVC based on the variables of CIVE, ExG-ExR and ExG show R^2 values ranging from 0.825 to 0.906, RMSE values varying between 0.0561 and 0.0762, and MAE ranging from 0.0446 to 0.0608. It is observed that the second-order polynomial regression using ExG is the best model for estimating sugarcane FVC as it recorded the highest R^2 and lowest RMSE and MAE of 0.906, 0.0561 and 0.0446, respectively. The optimal model for estimating sugarcane FVC is $FVC = -0.0002 * ExG^2 + 0.0248 * ExG - 0.0105$.

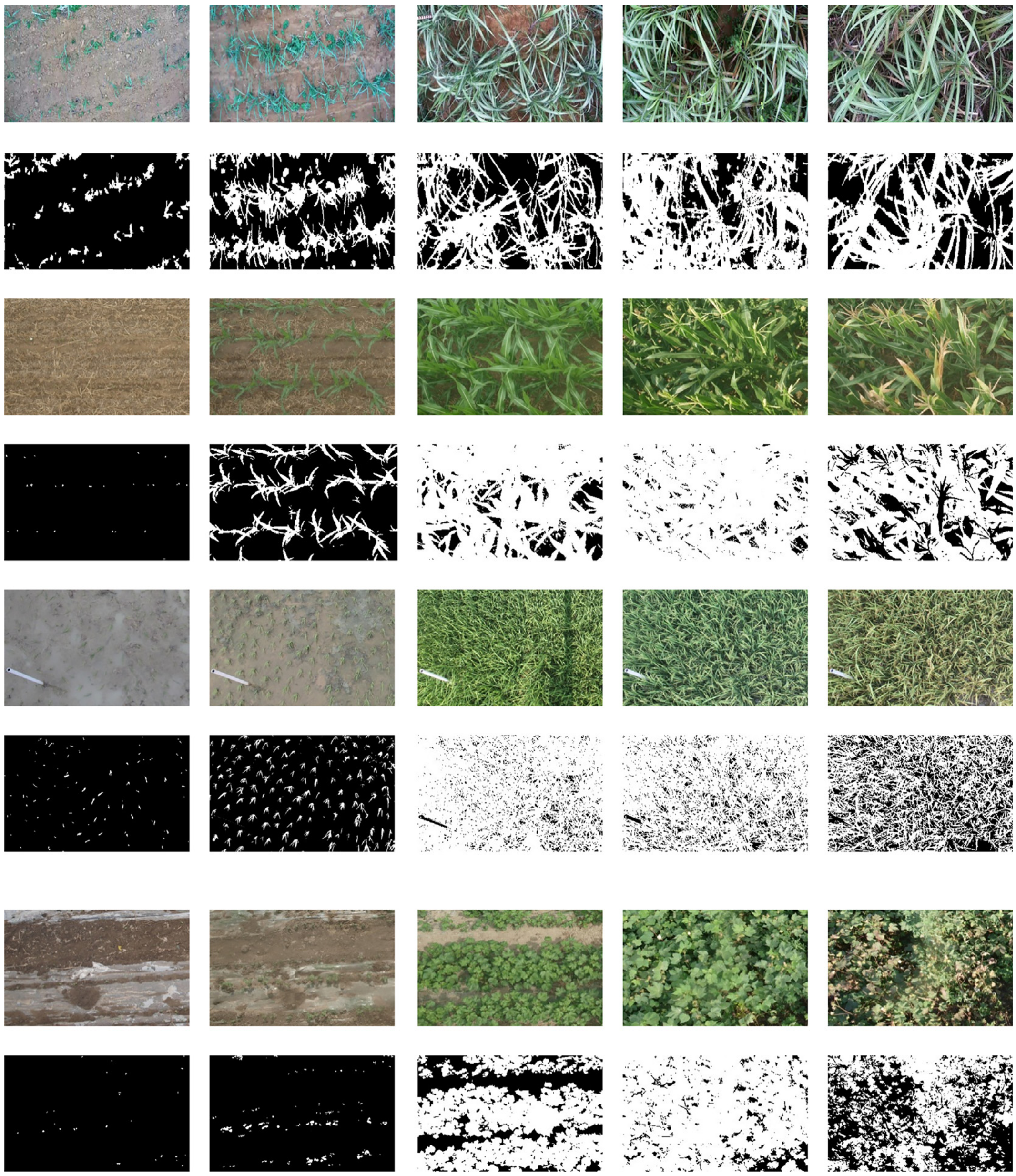

Fig. 3. The segmentation results of four crops, from top to bottom are sugarcane, maize, paddy rice and cotton, respectively. We selected five main crop development stages from each crop. From left to right are the five main crop development stages captured by the imaging devices.

Table 3
Color vegetation indices used in this study.

Abbreviation	Index name	Formula	Reference
G-B	Subtracting Blue from Green	$G - B$	Woebbecke et al. (1995a, 1995b)
ExG-ExR	Excess Green minutes Excess Red	$2 \times G - R - B - (1.4 \times R - G)$	Meyer and Neto (2008), Shanmugam and Asokan (2015) and Soontranon et al. (2014)
ExG	Excess Green	$2 \times G - R - B$	Meyer et al. (1999) and Soontranon et al. (2014)
ExR	Excess Red	$1.4 \times R - G$	Meyer and Neto (2008) and Meyer et al. (2004)
R-G	Subtracting Green from Red	$R - G$	Woebbecke et al. (1995a, 1995b)
NDI	Normalized Difference Index	$(G - R)/(G + R)$	Pérez et al. (2000)
(G-B)/|R-G|		$(G - B)/R - G\|$	Woebbecke et al. (1995a, 1995b)
CIVE	Color Index of Vegetation Extraction	$0.441 \times R - 0.811 \times G + 0.385B + 18.78745$	Kataoka et al. (2003)
VEG	Vegetative	$G/(R^{0.667} \times B^{0.333})$	Hague et al. (2006)

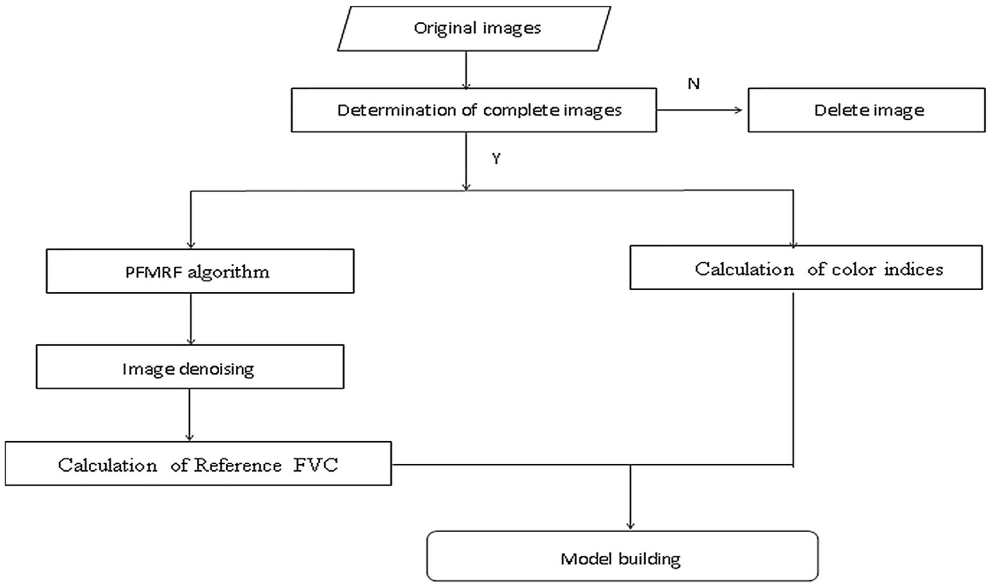

Fig. 4. Schematic of the FVC estimation methodological approach.

Table 4
Correlation coefficients between FVC and color vegetation indices of sugarcane at different shooting time.

Index	Shooting time				
	8:00 (n = 231)	9:00 (n = 266)	11:00 (n = 271)	15:00 (n = 243)	All the time (n = 1011)
G-B	0.608**	0.730**	0.618**	0.608**	0.655**
ExG-ExR	0.824**	0.841**	0.841**	0.879**	0.851**
ExG	0.898**	0.918**	0.920**	0.930**	0.916**
ExR	−0.724**	−0.731**	−0.756**	−0.805**	−0.755**
R-G	−0.747**	−0.753**	−0.777**	−0.786**	−0.769**
NDI	0.683**	0.707**	0.730**	0.758**	0.722**
(G-B)/|R-G|	−0.320**	−0.169**	−0.374**	−0.212**	−0.245**
VEG	0.743**	0.779**	0.792**	0.825**	0.786**
CIVE	−0.889**	−0.908**	−0.913**	−0.924**	−0.908**

* and ** indicate significance at 0.05 and 0.01, respectively. Where n is the number of samples.

Table 5
Correlation coefficients between FVC and color vegetation indices of maize at different shooting time.

Index	Shooting time			
	9:00 (n = 290)	10:00 (n = 326)	16:00 (n = 311)	All the time (n = 927)
G-B	0.669**	0.695**	0.656**	0.672**
ExG-ExR	0.942**	0.949**	0.947**	0.946**
ExG	0.900**	0.911**	0.899**	0.903**
ExR	−0.957**	−0.962**	−0.955**	−0.956**
R-G	−0.964**	−0.966**	−0.965**	−0.964**
NDI	0.952**	0.956**	0.951**	0.952**
(G-B)/|R-G|	−0.113	−0.136*	−0.130*	−0.098**
VEG	0.877**	0.893**	0.886**	0.885**
CIVE	−0.909**	−0.920**	−0.910**	−0.913**

* and ** indicate significance at 0.05 and 0.01, respectively. Where n is the number of samples.

3.1.2. Maize FVC estimation model

As shown in Table 5, all correlation coefficients (r) between maize FVC and color vegetation indices at different shooting time are greater than 0.8, except for the (G-B)/|R-G| and G-B indices. The relationship between maize FVC and color vegetation indices including CIVE, ExG-ExR, ExG, ExR, NDI, R-G and VEG were fitted based on the second-order polynomial regression. The accuracy of the maize FVC estimation model is shown in Table 8.

From Table 8, it can be seen that the performance of the maize FVC estimation model based on the ExG index is poorer compared to other color vegetation indices. The RMSE is greater than 0.1, at 0.1022. The performance of the models for estimating maize FVC based on the other six color vegetation indices are good, with R^2 values ranging from 0.9084 to 0.9545, RMSE ranging from 0.0624 to 0.0885, and MAE between 0.0483 and 0.0676. The accuracy of the second-order polynomial model based on the NDI index is the highest with R^2, RMSE and MAE of 0.9545, 0.0624 and 0.0483, respectively. The optimal model for estimating maize FVC is $FVC = -11.585*NDI^2 + 4.9598*NDI + 0.4684$.

3.1.3. Paddy rice FVC estimation model

Table6 indicates that, with exception of the G-B and (G-B)/|R-G| indices, the correlation coefficient (r) between the other color vegetation indices and paddy rice FVC at different shooting time are greater than 0.8. Our experimental results indicated that the performance of the second-order polynomial regression is better than the monadic linear regression in estimating paddy rice FVC. The accuracy of the second-order polynomial regression for paddy rice FVC estimation is shown in Table 8.

From Table 8, it can be seen that the RMSE and MAE of paddy rice FVC estimation models based on ExG, ExR, NDI and R-G indices are larger than those based on CIVE, ExG-ExR and VEG. The performance of the models for estimating paddy rice FVC based on the variables of CIVE, ExG-ExR and VEG are good, with R^2 between the predicted values and measured values varying from 0.954 to 0.973, RMSE between 0.0513 and 0.067, and MAE ranging from 0.0383 to 0.0449. As with the maize FVC estimation model, the accuracy of the second-order polynomial model based on the VEG index is the highest, with the highest R^2 and lowest RMSE and MAE of 0.973, 0.0513 and 0.0383, respectively. The optimal model for estimating paddy rice FVC is $FVC = -6.0185*VEG^2 + 16.717*VEG - 10.66$.

3.1.4. 3.1.4. Cotton FVC estimation model

Table 7 indicates that, with the exception of (G-B)/|R-G|, the correlation coefficient (r) between cotton FVC and the other color vegetation indices at different shooting time are greater than 0.9. The performance of the second-order polynomial regression is better than the monadic linear regression in estimating cotton FVC. The accuracy

Table 6
Correlation coefficients between FVC and color vegetation indices of paddy rice at different shooting time.

Index	Shooting time								
	8:00 (n = 189)	9:00 (n = 192)	10:00 (n = 191)	11:00 (n = 229)	13:00 (n = 186)	14:00 (n = 188)	15:00 (n = 185)	16:00 (n = 187)	All the time (n = 1547)
G-B	0.628**	0.594**	0.697**	0.744**	0.755**	0.691**	0.595**	0.557**	0.602**
ExG-ExR	0.969**	0.969**	0.961**	0.948**	0.950**	0.948**	0.963**	0.970**	0.956**
ExG	0.957**	0.958**	0.951**	0.951**	0.964**	0.959**	0.951**	0.947**	0.944**
ExR	−0.935**	−0.931**	−0.916**	−0.871**	−0.864**	−0.876**	−0.917**	−0.934**	−0.883**
R-G	−0.927**	−0.917**	−0.905**	−0.876**	−0.882**	−0.884**	−0.901**	−0.915**	−0.887**
NDI	0.921**	0.911**	0.899**	0.865**	0.852**	0.858**	0.889**	0.911**	0.868**
(G-B)/|R-G|	−0.294**	−0.187**	−0.018	−0.094	−0.019	−0.006	−0.040	−0.073	−0.013
VEG	0.940**	0.946**	0.936**	0.939**	0.938**	0.932**	0.949**	0.945**	0.932**
CIVE	−0.962**	−0.963**	−0.956**	−0.954**	−0.965**	−0.961**	−0.957**	−0.955**	−0.952**

* and ** indicate significance at 0.05 and 0.01, respectively. Where n is the number of samples.

report of the cotton FVC estimation model is shown in Table 8.

As shown in Table 8, the performance of the model for estimating cotton FVC based on the G-B index is poorer compared to other color vegetation indices, with the RMSE and MAE of 0.1355 and 0.1097, respectively. Therefore, the color vegetation index G-B could not be used in this study to estimate cotton FVC. The performance of the models for estimating maize FVC based on the other seven color vegetation indices are good, with R^2 between the predicted values and measured values, ranging from 0.9391 to 0.9743, RMSE varying from 0.0575 to 0.0891 and MAE between 0.0447 and 0.0677. The accuracy of the second-order polynomial model based on the VEG index is the highest as it showed the highest R^2 and lowest RMSE and MAE of 0.9743, 0.0575 and 0.0447, respectively. The optimal model for estimating cotton FVC is $FVC = -3.9644*VEG^2 + 11.667*VEG - 7.6487$.

Fig. 5 shows an obvious non-linear relationship between FVC and CIVE employed in this study. Using a second-order polynomial regression model, samples from the four crop types were well fitted with the CIVE. The relationships between the FVC of these four crops and other color vegetation indices are also characterized with non-linearity (Not shown).

3.2. Analysis based on combined crop samples

It can be observed from the previous analysis that the CIVE and ExG-ExR indices could estimate the FVC of the four crop categories, though with different accuracies due to different crop types. Therefore, we have proposed a universal FVC estimation model for the crops studied herein based on the different color vegetation indices, which could have a universal applicability regardless of crop type, image shooting time and spatial distribution of crops. In this study, we divided the data into nine groups according to the nine color vegetation indices. We combined the values of the color vegetation indices and their corresponding reference FVC at all image shooting time for all crop types and for each color vegetation index. Finally, we obtained the combined data samples of sugarcane, maize, paddy rice and cotton.

3.2.1. Correlation between color vegetation indices and FVC of combined samples

Based on the time series images acquired in this study, crop FVC and color vegetation indices were calculated using the approach presented in Sections 2.3 and 2.4. The results of Pearson's correlation analysis between FVC and color vegetation indices of combined samples are shown in Table 9. With the exception of (G-B)/|R-G|, all other correlation coefficients (r) between FVC and color vegetation indices at different shooting time are larger than 0.5 and are significant at the 0.01 confidence level for the four crops. This indicates that a change of crop type or shooting time could not affect the performance of the (G-B)/|R-G| index. In addition, FVC is positively correlated with G-B, ExG-ExR, ExG, NDI and VEG, in contrast to a negative correlation with ExR, R-G and CIVE.

3.2.2. Universal crop FVC estimation model

Intercropping and mixed cropping are common agronomic practices in many agricultural landscapes, especially those in which the most efficient use of land is sought. This system is most often practiced to optimize the utility of limited agricultural land, as common in urban and peri-urban areas. Assuming the four crop types studied herein coexist in a given agricultural landscape, it would be worthwhile to generate robust models capable of automatic extraction of combined crop FVC, data which could support both agricultural mapping and initiatives aimed at integrated crops management. We have therefore, proposed in this study, an optimal FVC estimation model capable of universal applicability to sugarcane, maize, cotton and paddy rice. We obtained 4287 training samples and 1428 testing samples in accordance

Table 7
Correlation coefficients between FVC and color vegetation indices of cotton at different shooting time.

Index	Shooting time										
	10:00 (n = 234)	11:00 (n = 222)	12:00 (n = 240)	13:00 (n = 210)	14:00 (n = 229)	15:00 (n = 223)	16:00 (n = 199)	17:00 (n = 230)	18:00 (n = 218)	19:00 (n = 225)	All the time (n = 2230)
G-B	0.904**	0.902**	0.920**	0.936**	0.941**	0.941**	0.944**	0.938**	0.932**	0.918**	0.910**
ExG-ExR	0.981**	0.981**	0.984**	0.983**	0.985**	0.981**	0.982**	0.985**	0.982**	0.980**	0.981**
ExG	0.972**	0.971**	0.973**	0.975**	0.976**	0.973**	0.973**	0.975**	0.973**	0.971**	0.970**
ExR	−0.962**	−0.969**	−0.974**	−0.976**	−0.981**	−0.976**	−0.977**	−0.980**	−0.976**	−0.970**	−0.968**
R-G	−0.983**	−0.986**	−0.985**	−0.984**	−0.984**	−0.980**	−0.979**	−0.981**	−0.976**	−0.975**	−0.980**
NDI	0.972**	0.976**	0.978**	0.978**	0.979*	0.975**	0.975**	0.978**	0.974**	0.972**	0.973**
(G-B)/|R-G|	−0.083	−0.205**	−0.145*	−0.178**	−0.085	−0.193**	−0.119	−0.158*	−0.161*	−0.174**	−0.076**
VEG	0.956**	0.954**	0.965**	0.964**	0.969**	0.964**	0.965**	0.970**	0.967**	0.966**	0.963**
CIVE	−0.965**	−0.974**	−0.976**	−0.977**	−0.979**	−0.976**	−0.975**	−0.978**	−0.975**	−0.974**	−0.973**

* and ** indicate significance at 0.05 and 0.01, respectively. Where n is the number of samples.

Table 8
Accuracy assessment report of the sugarcane, maize, paddy rice and cotton FVC estimation model which is based on testing samples at all shooting times.

		Color vegetation indices							
		G-B	ExG-ExR	ExG	ExR	R-G	NDI	CIVE	VEG
Agrotype									
Sugarcane	R^2		0.825	0.906				0.8974	
	RMSE		0.0762	0.0561				0.059	
	MAE		0.0608	0.0446				0.0476	
Maize	R^2		0.9388	0.8963	0.9438	0.9527	0.9545	0.9084	0.9237
	RMSE		0.0734	0.1022	0.0704	0.0658	0.0624	0.0885	0.0808
	MAE		0.057	0.0766	0.0538	0.0527	0.0483	0.0676	0.062
Paddy rice	R^2		0.9662	0.9322	0.8346	0.8473	0.8588	0.954	0.973
	RMSE		0.0574	0.1319	0.1428	0.1247	0.1171	0.067	0.0513
	MAE		0.0415	0.1143	0.0961	0.0942	0.0824	0.0449	0.0383
Cotton	R^2	0.8714	0.9728	0.9674	0.9391	0.9684	0.963	0.9705	0.9743
	RMSE	0.1355	0.0591	0.0648	0.0891	0.0638	0.069	0.062	0.0575
	MAE	0.1097	0.0457	0.0513	0.0677	0.0475	0.0495	0.0494	0.0447

with the method used in section 3.1. Table10 indicates that, with the exception of (G-B)/|R-G| and G-B, the correlation coefficient (r) between FVC and all other color vegetation indices are greater than 0.8. Here, we used the second-order polynomial regression for estimating combined crop FVC. The accuracy of this universal crop FVC estimation model is shown in Table 10.

One could observe in Table 10 below that the accuracies of the universal crop FVC estimation model based on the CIVE, ExG-ExR, ExG and VEG are higher than those based on the other color vegetation indices. The R^2 between the predicted values and measured values varies from 0.9385 to 0.9504, RMSE varies from 0.0721 to 0.1003, and MAE varies from 0.0545 to 0.0810. Scatter plots of measured values and predicted values of the universal crop FVC estimation model are shown in Fig. 6.

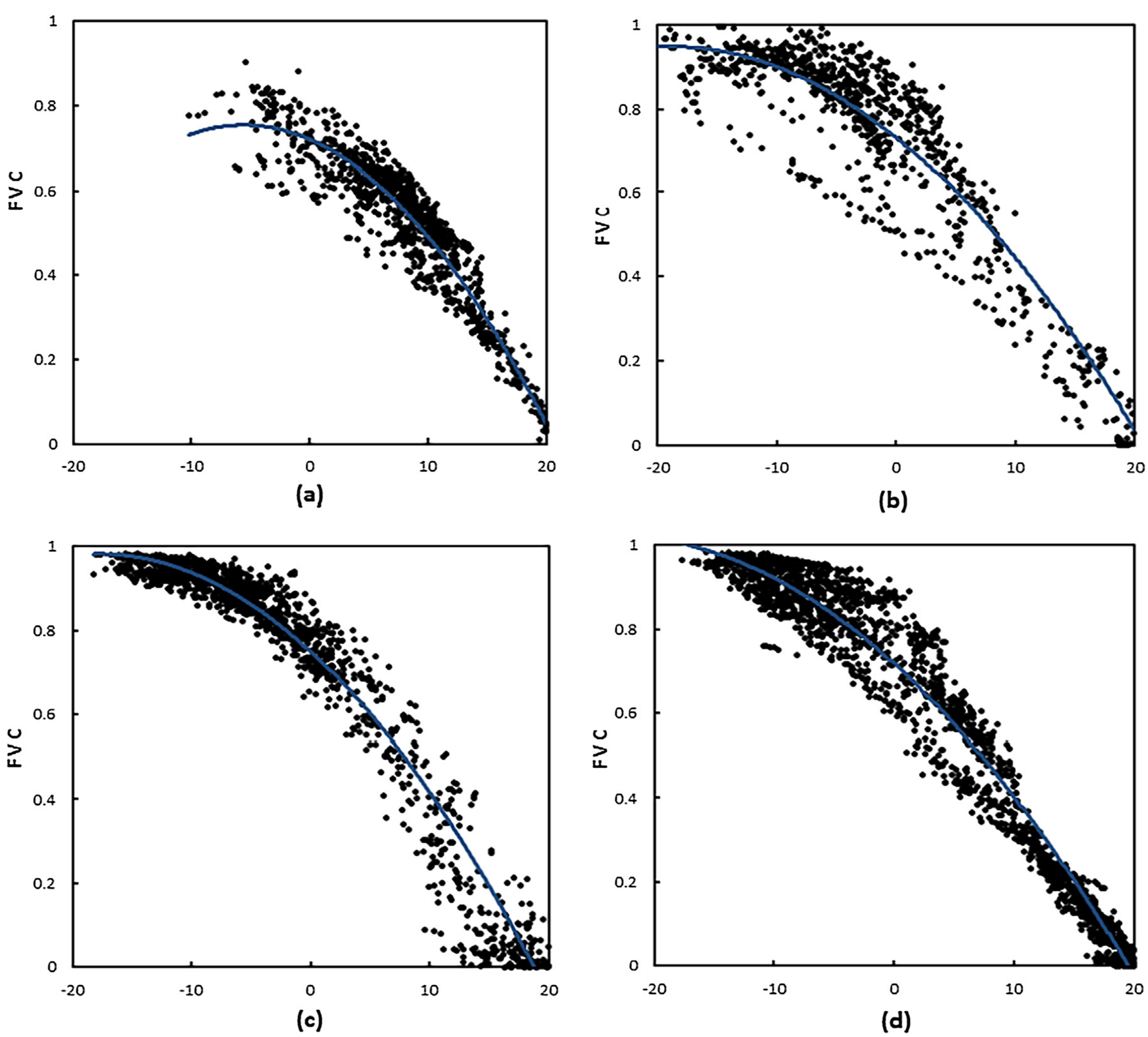

Fig. 5. The relationships between the CIVE and FVC of the four crop categories: (a) Sugarcane; (b) Maize; (c) Paddy rice; (d) Cotton;

Table 9
Correlation coefficients between FVC and color vegetation indices in the combined sample data.

Index	G-B	ExG-ExR	ExG	ExR	R-G	NDI	(G-B)/|R-G|	VEG	CIVE
	0.690**	0.957**	0.942**	−0.879**	−0.888**	0.876**	−0.023	0.924**	−0.950**

* and ** indicate significance at 0.05 and 0.01, respectively. And the number of samples is 5715.

Table10
Accuracy assessment report of the universal FVC estimation model of the four crop types based on testing samples.

Index	ExG-ExR	ExG	ExR	R-G	NDI	VEG	CIVE
R^2	0.9385	0.9386	0.7901	0.8149	0.8239	0.9454	0.9504
RMSE	0.0805	0.1003	0.1483	0.1394	0.1357	0.0756	0.0721
MAE	0.0619	0.0810	0.1152	0.1133	0.1066	0.0581	0.0545

It can be seen in Fig. 6 that the accuracy of the universal crop FVC estimation model based on the CIVE index is higher than the other three universal models, with R^2, RMSE and MAE values of 0.9504, 0.0721 and 0.0545, respectively. Thus, the FVC estimation model based on the CIVE index is proposed in this study, to be optimal for automatic and integrated FVC estimation in agricultural systems of mixed cropping patterns involving sugarcane, maize, paddy rice and cotton.

4. Discussion

A comparison of these four crops shows that the correlation coefficients (r) between FVC and the color vegetation indices for maize, paddy rice and cotton are higher than that of sugarcane, as shown in Tables 4–7. This is due to two possible reasons. Firstly, the images of sugarcane were obtained by a video camera which is of a lower resolution than the CCD camera, thereby leading to relatively poorer image segmentation results. Secondly, the data from 12 May 2015 to 22 June 2015 were missing because of system failure or power outage, and thus, the discontinuous image acquisition at this period is a major source of uncertainty in the estimation results. Another possible reason is the interference of weeds during the segmentation of sugarcane, which can cause large deviations in FVC calculated by the PFMRF algorithm. The correlation coefficients (r) between FVC and the same color vegetation indices, whether for sugarcane, maize, paddy rice or

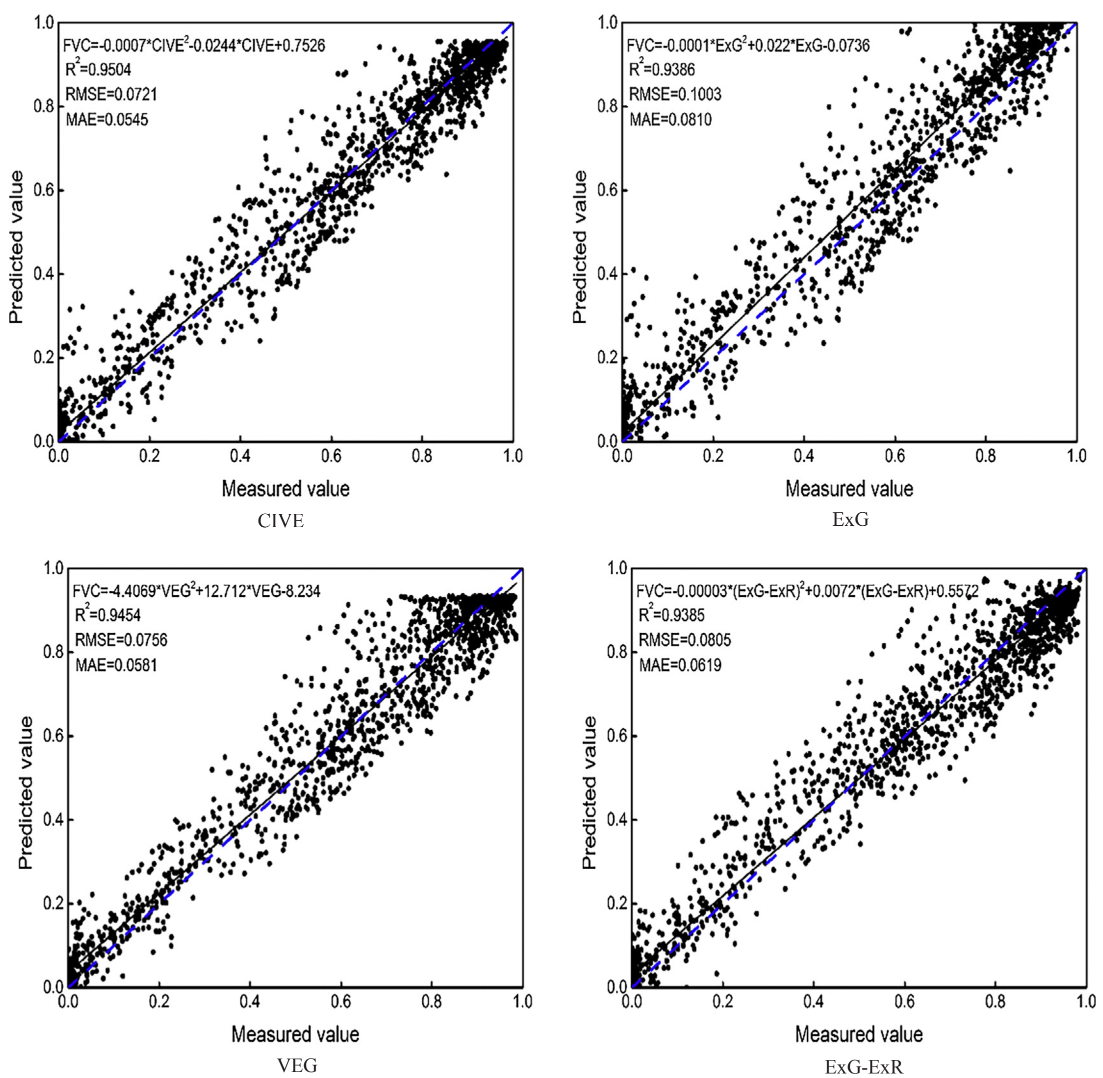

Fig. 6. Comparison between measured FVC and estimated FVC based on different color vegetation indices. The black solid line is the regression line and the blue dash line is the 1:1 line.

cotton, are different at different image shooting time as shown from Table 4–7. This has mainly been caused by the different values of the same color vegetation index calculated in a day. This phenomenon is attributable to either the combined effects of constant changes in sunlight intensity and solar zenith angles (Zhang et al., 2016) or the differences in image color caused by variations in incident light or plant age (Woebbecke et al., 1995a). The accuracies of FVC estimation models are different with respect to the four crop types. This is attributable to the differences in crop types, planting area and sensor parameters of the fields under investigation as shown in Tables 1 and 2. Although the accuracy of crop FVC estimation models and the optimal color vegetation indices in the estimation of FVC are largely different (except for the optimal color vegetation index for paddy rice and cotton), we have proposed a single optimal color vegetation index for FVC estimation of the four crop types, due to its higher accuracy relative to that obtained by the other color vegetation indices in estimating the FVC of all crop types.

The approach used in this study could be regarded as relatively time and cost effective in the FVC estimation of sugarcane, maize, paddy rice and cotton. Compared with LABFVC (Liu et al., 2012), SHAR-LABFVC (Song et al., 2015), and ACE (Coy et al., 2016), the universal FVC estimation model proposed in this study can avoid the influence of manual interference to a certain extent. LABFVC, SHAR-LABFVC and ACE require manual steps in segmenting images. Our method only calculates the color vegetation index of digital photographs to estimate crops FVC.

In our study, a universal estimation model of the FVC of different crop types in different areas is proposed and validated, as opposed to (Lukina et al., 1999) in which binary pseudo-color images were used to estimate wheat FVC only. In Lee and Lee (2013) and Tian et al. (2004), digital camera and satellite images were respectively, used to model individually, the FVC of paddy rice and maize. In the current study, the FVC of sugarcane, maize, paddy rice and cotton are estimated at the same time without modifying model parameters for each crop.

Our proposed algorithm for the automatic retrieval of crop FVC can be integrated with automatic weather observation stations to realize real-time monitoring of crop growth, information which is relevant not only in precision agricultural applications but could also be useful in validating the relatively lower temporal resolution air-borne and space-borne remote sensing products. We have only studied four crops due to limitations in installation and observation devices. Our future work would involve the validation of this proposed universal FVC estimation model for other ephemeral and annual crops such as winter wheat and oilseed rape at national scales. Furthermore, we only used the regression method for modeling the training samples. Therefore, future studies should exploit the use of machine learning methods such as support vector machine (SVM), neural network (NN) and random forest (RF) for modeling training samples. Such methods would improve the FVC estimation accuracy.

The scope of the current study is limited to the use of vegetation indices derived from the visible bands of the electromagnetic spectrum (with digital cameras) for integrated FVC estimation of sugarcane, maize, paddy rice and cotton. As several other vegetation indices are obtainable from near infrared bands, perhaps capable of providing more robust crop FVC estimation, future studies are advised to explore the use of customized cameras with such spectral information. Near infrared bands have been found to be very effective in segmenting crops from their host environment (background) as presented by Woebbecke et al. (1995a). Using near infrared and visible band combinations in customized cameras would not only bring about better FVC estimation results but would also allow for the use of such high resolution results for validation of corresponding estimates obtained from airborne or spaceborne sensors which are generally of lower spatial, spectral and temporal resolutions.

5. Conclusions

In our study, a method for estimating the fractional vegetation cover (FVC) of sugarcane, maize, paddy rice and cotton using time series digital photographs is developed and validated in four study sites in China, each with a specific type of crop. Nine color vegetation indices were tested for estimating FVC of the four crop types. The results suggest that with exception of the (G-B)/|R-G| index, the other indices are very sensitive to temporal changes in the FVC of sugarcane, maize, paddy rice and cotton, and hence, the FVC of these crops can be estimated from digital photographs with high accuracy using non-linear equations. However, the accuracy of models and the optimal color vegetation indices vary according to crop type. The optimal color vegetation index for estimating the FVC of paddy rice and cotton is VEG, whereas those of sugarcane and maize are ExG and NDI, respectively.

This study has also demonstrated that with exception of the (G-B)/|R-G| index, the correlations between FVC and the other indices in the combined data (under the assumption of intercropping or mixed cropping) are very good. Therefore, crop FVC estimation models based on the different color vegetation indices are obtainable, and could have universal applicability regardless of differences in image shooting time and spatial distribution of the crops under investigation. The crop FVC estimation models based on the CIVE, ExG-ExR, ExG and VEG indices were validated with the testing data, and the simulation results show that they have a much better performance than models based on the other color vegetation indices. However, based on its relatively higher R^2, and lower RMSE and MAE with reference data, the CIVE index is regarded optimal for use in the construction of an FVC estimation model capable of universal applicability to sugarcane, maize, paddy rice and cotton agro-ecologies, the estimation model being $FVC = -0.0007*CIVE^2 - 0.0244*CIVE + 0.7526$. This proposed universal crop FVC estimation model based on the CIVE index is hereby recommended for application in the automatic and integrated extraction of green FVC in agricultural landscapes characterized by mixed cropping patterns involving sugarcane, maize, paddy rice and cotton.

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