RGB Imaging Based Estimation of Leaf Chlorophyll Content

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***Abstract*—Leaf chlorophyll content (LCC) is an important indicator of plant health. It can reveal for instance whether the plant has received too much or too little nutrients (nitrogen in particular). Corrective measures based on early diagnosis of nitrogen deficiency can prevent yield reduction. Optical approaches to estimating LCC are typically based on measuring the reflectance of leaves (close-range sensing) or canopy (remote sensing) with a spectrophotometer or a hyperspectral sensor. Given the cost of such devices, the use of colour cameras for LCC estimation has recently gained interest. However, existing approaches are mostly designed for very close range sensing, i.e. they allow the measurement of LCC for a single plant at a time, which limits their usefulness in practice. Furthermore, they do not exploit the anisotropic reflective properties of leaves and canopies. To investigate the feasibility of RGB imaging for remote sensing-based estimation of canopy LCC, we present a simulation based on a plant canopy reflectance model. An RGB camera model was used to generate RGB images with various reference illuminants and from 10 different viewing angles. We then applied linear and neural network based regression to predict LCC from RGB values without white balance. Results indicate a significant potential to use RGB sensors for remote sensing LCC estimation, particularly with a multi-angle approach.**

***Index Terms*—chlorophyll content, spectral reflectance, ProSail model, RGB sensor**

I. Introduction

Measuring the spectral reflectance of a plant can provide an effective means for fast and non-destructive estimation of plant growing status. To capture the spectral reflectance information, usually a hyperspectral sensor is required. The goal of hyperspectral imaging is the acquisition of a detailed electromagnetic signature of each pixel of the scene or object usually including the visible and the near-infrared ranges. Hyperspectral imaging is useful in many applications and enables a deep analysis of the physical properties of a scene in a non-destructive manner. However, such precision also comes at a high cost, both financial and computational. Those disadvantages have limited the use of hyperspectral imaging to a research-friendly rather than a customer-friendly context. On the other hand, colour imaging systems (Red-Green-Blue: RGB) are low-cost. They can be found in many everyday devices such as single-lens reflex cameras and smartphones. However, as they capture only three broad bands in the visible range, RGB systems are not ideal to identify detailed object properties. Whether it is possible to use an RGB based system to achieve a similar result to hyperspectral imaging in a particular waveband has become an active research topic.

Akhtar and Mian [1] proposed a method to recover spectral details from RGB images of known spectral quantization by modelling natural spectra under Gaussian processes learning. Arad and Shahar [2] presented a sparse recovery of the hyperspectral image from a natural RGB image. Their approach first leverages a hyperspectral prior before creating a sparse dictionary of hyperspectral signatures and their corresponding RGB projections. Describing novel RGB images via the latter then facilitates reconstruction of the hyperspectral image via the former.

In this paper, we present a case study which relates the RGB pixel values from a visible range digital camera to the spectral reflectance change of plant canopy caused by the changing chlorophyll content in plants. The rest of this paper is organised as follows. Section II introduces the background and the material in the case study. The design of the case study is introduced in section III, results and discussion are also covered in this section. Section IV provides the conclusion and future research goals.

II. Background

It is widely known that leaf chlorophyll content (LCC) is an important feature for testing plant status. LCC is virtually essential pigments for the conversion of light energy to stored chemical energy. It can directly determine photosynthetic potential and primary production [3] [4]. Also, it gives an indirect estimation of the nutrient status because much of leaf nitrogen is incorporated in chlorophyll [4] [5]. Furthermore, LCC can be used to analyse plant stress, such as water stress and salt or alkali stress.

Currently, there are two main types of methods to measure the LCC. The first is destructive and laboratory-based. It involves several physical and chemical extraction procedures followed by measurement of red-light transmission through a chlorophyll solution [6]. This approach is time-consuming and labour-intensive [7]. Other methods are based on optical sensors to measure the leaf absorbance and leaf reflectance. The SPAD 502 is a popular device to measure the LCC [8]. It

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measures leaf absorbance in two wavelength regions: red (600-700nm) and near-infrared. There are also many applications based on a higher spectral resolution. Curran [3] pointed out that chlorophyll concentration is related positively to the point of maximum slope in the reflectance spectra of leaves (680-720nm) and this point is termed the *red edge*. However, the *red edge* is typically difficult to measure with an RGB camera due to a limited spectral resolution in that band.

With the development of machine learning, it has become possible to create a model that predicts LCC from RGB pixel values. Su *et al.* [9] presented a linear RGB model to simulate chlorophyll *a* and lipid content in algae and demonstrated that RGB bands can be extrapolated to estimate the LCC. Yadav [10] also presented an LCC estimation method based on RGB imaging. In their work, pixel values and ratios of primary colours are modelled as linear correlation functions for chlorophyll content. Yadav also pointed out that R and G are negatively correlated with the chlorophyll content, while a positive correlation was observed within the B channel. Tewari *et al.* [11] used image processing to estimate plant nitrogen and chlorophyll content. After testing various features such as R, G, B, normalized 'r' and 'g', the authors provide a regression model with the normalized 'r' for the best accuracy. There are also some applications based on a sensor from a smartphone. Vesali *et al.* [12] developed an android app to estimate chlorophyll content of corn; they use the embedded smartphone RGB camera to measure the absorbance of the leaf via contact imaging. The main limitation of these studies is that they do not account for the anisotropy of leaf and canopy reflectance.

In the following part of this section, the benchmark for this case study is introduced.

A. Research Goal of the Case Study

In this research we make the following assumptions, first an RGB camera sensor is sensitive enough to detect the reflectance change causes by changing the chlorophyll content and the viewing angle. Second, the spectral reflectance of a plant varies with the viewing angle; by measuring the reflectance from multiple viewing angles, it should be possible to have more information about the plants. Third, the extra information provided by measuring multiple viewing angles can provide a better estimation of plant status.

This case study aims to investigate whether an RGB camera sensor can detect the spectral reflectance change caused by the change of chlorophyll content in the plant canopy. Another goal of this case study is to find out how the LCC estimation accuracy can be increased using a multi-angle RGB approach. The relation between the RGB pixel value and the LCC was analysed by regression. To investigate whether it is possible to increase the estimation accuracy by adding viewing angles of the RGB camera, a bidirectional reflectance model named 'ProSail' was used. To get a more general result, different illumination conditions were was tested. The following part of this section introduces the simulated data and the reflectance model used in this study.

B. Reflectance Model

1) Prospect Model: To generate the leaf spectral reflectance data, we used the Prospect model. Prospect (leaf optical properties spectra) model is a leaf optical model based on the principles of radiative transfer, it was first established by Jacquemoud and Baret and became a key model to simulate leaf directional hemispherical reflectance and transmittance over the whole optical domain [13]. In this paper, the Prospect model version 4 is used [14]. It involves six parameters, including the chlorophyll content, carotenoid content, brown pigment content, leaf dry matter, leaf water matter and leaf structure coefficient. Note that this model cannot distinguish chlorophyll type *a* and *b*.

2) Sail Model: The Sail (Scattering by Arbitrary Inclined Leaves) radiative transfer model is based on the 1-D model developed by Suits to simulate bidirectional reflectance of the canopy [15]. The model represents the canopy structure based on leaf reflectance and transmittance, leaf area index and leaf inclination distribution function. To measure the bidirectional reflectance distribution function (BRDF), the viewing geometry is also involved in this model, which include the sun and sensor (observer) zenith angles as well as the relative azimuth angle between the sun and viewer. In this study, we use a constant sun zenith angle and azimuth; and adding viewing angles by changing the sensor zenith angle.

3) ProSail model: This study used a combination of the Prospect and the Sail model named ProSail model to simulate estimating chlorophyll content via RGB cameras at multiple viewing angles [16]. The coupling of these two models was first used to analyse spectral shifts in the red edge spectral region and other studies followed. In the ProSail model, the simulated leaf reflectance and transmittance from Prospect model are fed into the Sail model, along with information about soil optical properties and illumination/observation geometry. The latest version of ProSail calculates the canopy BRDF from 400 to 2500 nm in 1 nm increments as a function of up to 16 input parameters, defining pigment and water content, canopy architecture, soil background, hot spot, solar diffusivity, as well as observation geometry. Fig 1 compares the plant spectral reflectance generated by ProSail model from different viewing angles in the visible range while other parameters are set as default, it is clear the reflectance of a plant varies with the viewing angle.

The ProSail model has been used to generate the spectral reflectance data in many applications, i.e., simulation of canopy reflectance for diverse vegetation types [17] [18]; simulation of biophysical and biochemical variables on spectral reflectance (or vegetation indices) [19] [20]; design, test and adaptation of vegetation indices [21] [22]; assimilation of simulation reflectance/vegetation indices into crop growth/vegetation dynamic models [23] [24]; emulation of canopy reflectance [25]. We conclude that the ProSail model is sufficient to generate spectral reflectance data for multiple purposes.

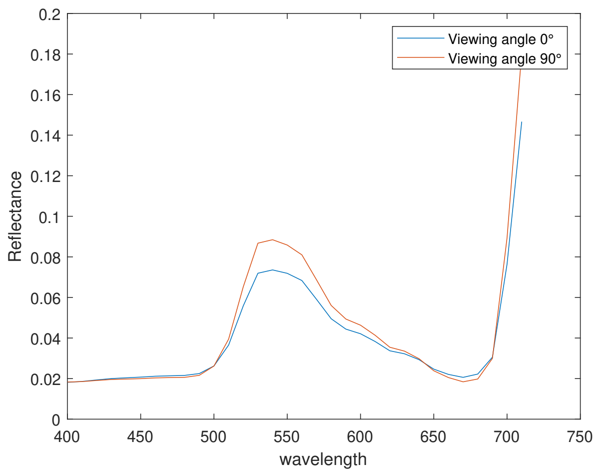

Fig. 1: Plant spectral reflectance generated by ProSail model in the visible range from different viewing angle.

C. Illumination and Camera Spectral Responses

A total of 28 camera spectral response models were considered in this study to test the sensitivity of RGB devices when detecting changes in leaf spectral reflectance caused by changing the leaf chlorophyll content. The cameras data was obtained from Rochester Institute, which includes professional, point-and-shoot and industrial cameras. Then we selected the camera model that is the most sensitive to change in LCC. The resolution of the camera spectral sensitivity is 10 nm. Ten different spectral power distributions of daylight with different colour temperatures were used in this study. All the illumination data have a spectral resolution of 10 nm.

III. Design of the Case Study

Based on the models provided in the last section, a simulation has been designed. This simulation can be separated into five parts. Part one analysed the sensitivity of an RGB camera to the spectral reflectance change caused by changing the LCC. Part two estimated the chlorophyll content based on known light condition. Part three estimated the chlorophyll content using a neural network with more realistic data. Part four analysed the influence of the viewing angle on the estimation result. The last part examines whether the estimation accuracy can be improved with a multi-angle approach.

A. Using an RGB Camera to Detect Changes in Chlorophyll Content

In this part of the case study, the sensitivity of RGB devices to changes in leaf spectral reflectance caused by changing the leaf chlorophyll is tested. The Prospect model 4 was used to generate the leaf spectral reflectance for different levels of chlorophyll; in this part of the case study, the only variable is the chlorophyll content, the other 5 parameters of the model are set as default. Although the Prospect model can measure leaf spectral reflectance from visible to near-infrared, we focused on the change within the visible range. After

TABLE I: Parameters of the Prospect model and how they were randomised to make our simulation more realistic.

Parameters	Default value	Randomisation
Carotenoid content	8 $\mu g/cm^2$	$\pm$ 2 $\mu g/cm^2$
Brown pigment content	0	0
Dry matter content	0.009 g/cm^2	$\pm$ 0.002 g/cm^2
Equivalent water thickness	0.01 cm	$\pm$ 0.004 cm
Leaf structure index	2.0 Text follows	$\pm$ 0.2

testing 28 different camera spectral responses, the average sensitivity is 0.33$\mu g/cm^2$ per pixel value from the R channel and 0.3$\mu g/cm^2$ per pixel value from the G channel, the B channel has a sensitivity of 3.2$\mu g/cm^2$ per pixel value. The red and green channels are more sensitive to changes in LCC. In the rest of this study, a camera which is most sensitive to change in LCC has been selected to generate the RGB values.

B. Estimating LCC with Known Illumination Type

To investigate the relationship between the LCC and the RGB pixel value, the plant canopy reflectance with different chlorophyll content was generated using the ProSail model. To make the simulation more realistic, the parameters of the Prospect model were randomised (see Table I) and white Gaussian noise (with standard deviation of 2 out of 256 values per colour channel) was added to the RGB pixel values.

The estimation was first tested with known illumination types, the spectral reflectance was generated by the ProSail model with LCC varied from 10 to 80 $\mu g/cm^2$ in steps of 1 $\mu g/cm^2$. The RGB pixel value was provided by the chosen camera model with the most sensitivity to the LCC change. Under each illumination type, both the plant chlorophyll content and the RGB pixel values were collected. Then the data was analysed by the Matlab linear regression learner. Regression models were developed between R, G and B pixel values and the plant chlorophyll content. Table II shows the error in estimation result using different combinations of RGB values. For linear regression, the most successful model is the combination of the R and G value with a second-order polynomial linear relation. The root mean square error (RMSE) between the estimated LCC and the given value is less than 5 $\mu g/cm^2$. Fig 2 shows the given chlorophyll content (blue dots) and the estimated value (red stars) from a linear regression model, the RMSE of this estimation is 3.6 $\mu g/cm^2$. However, when building and testing the linear regression model, the same type of illumination was used. From this simulation, the RGB device can provide a reasonable estimation result under known daylight conditions.

C. Estimating LCC with Neural Network

To investigate whether an RGB device can achieve a similar estimation accuracy as the hyperspectral based method, another simulation was designed. We made the simulation environment as realistic as possible. When collecting the data, we used 10 different types of daylight to model an unknown light condition, 10 viewing angles from 0° to 90°, and 20 sets of parameters of the Prospect model. The chlorophyll content

TABLE II: Comparison of the estimation error $\mu g/cm^2$ of different combinations of RGB with linear regression under certain illumination type.

Viewing angle	0	10	20	30	40	50	60	70	80	90
RGB	5.98	5.85	5.17	5.45	5.60	5.25	5.53	5.44	5.72	4.59
RG	6.2	6.01	5.16	5.45	5.59	5.19	5.43	5.44	5.15	4.83
RR^2 & GG^2	2.89	2.36	2.56	2.67	3.25	2.48	3.05	2.48	2.64	2.33

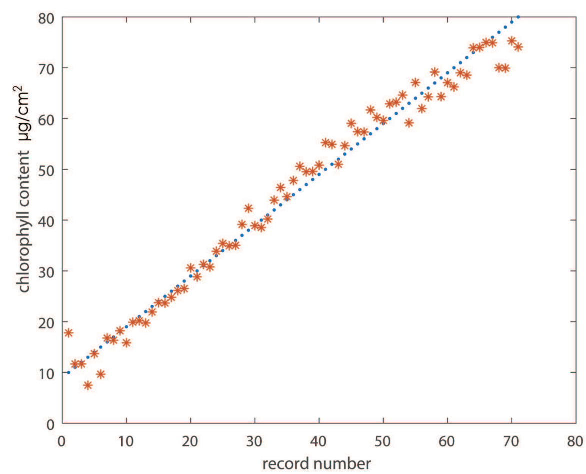

Fig. 2: Given (blue dots) and estimated LCC (red stars).

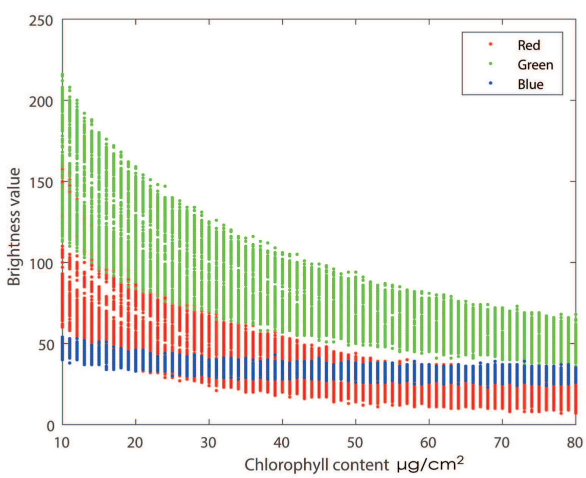

Fig. 3: Pixel value against LCC for simulated data when the observer zenith angle is 0°.

varied from 10 $\mu g/cm^2$ to 80 $\mu g/cm^2$, giving a total of 14200 different data points of each RGB channel. Fig 3 shows the variation in RGB pixel values with the LCC change when the observer zenith angle is 0° (nadir). Each point corresponds to a set of randomised parameters. As can be seen for a certain chlorophyll content value, the red and green values change in a wide range. On the other hand, for a certain colour channel value, the corresponding chlorophyll content value also varies in a wide range. The simulated data have sufficient variance to represent the real data.

Atzberger [26] presented an inversion of the ProSail canopy reflectance model using neural nets. In their work, the data was captured by a multispectral camera with 13 bands, and then PCA (principal component analysis) is used to reduce the dimensionality of the data into 6 components. We compared the estimation result from the RGB based method with their method.

The data was trained with a neural network with two hidden neurons in Matlab toolbox, the training algorithm is Levenberg-Marquardt. 70% of samples were used to train the network, with 15% for validation and 15% for testing. Different combinations of R, G and B data was tested, compared with only taking the red and green channels into account adding the blue channel to the neural network can improve the estimation accuracy. For the spectral data-based method, we use the leaf spectral reflectance multiplied by illumination to simulate the spectral data captured by a hyperspectral camera; white Gaussian noise was added to the spectral reflectance. Then PCA was applied to the data, testing both 3 and 6 components to estimate the LCC. For the RGB based method, different combinations of RGB values have been tested to train the neural network. After the simulation, using spectral data after PCA with the neural network can reduce the error to 2.5 $\mu g/cm^2$, while the RGB based neural network has an average error over 7 $\mu g/cm^2$. Table III compares the RMSE in the estimation for using spectral data with PCA and using RGB data at different viewing angles. The high accuracy achieved by the hyperspectral data based neural network is because the input of this network is spectral reflectance times illumination data, without taking the spectral responses of a hyperspectral camera into account. Using 6 components can achieve a slightly better result than only using 3 components.

D. Best viewing angle for Estimating the Plant Chlorophyll Content

The ProSail model also allowed us to test the influence of the viewing angle to the estimated chlorophyll content. In Table III the viewing angle changes from 0 to 90 degree in steps of 10 degrees. The solar zenith angle of New Zealand varies from about 30° to 45° with season [27]. In this research, the solar zenith angle is set to be 40°. After comparing the estimation result, when the observer zenith angle changes from 0° to 70°, there are just some small changes among the estimation result. However, when the observer zenith angle is close to 90° a better estimation result can be achieved by both spectra based and RGB based methods. Fig 4 shows how the error in estimation changes with the viewing angle for an RGB based estimation. Therefore, we make the following suggestion, when estimating chlorophyll content using an

TABLE III: Comparison of the LCC estimation error $\mu g/cm^2$ with an artificial neural network (2 hidden neurons) and a 10-fold cross validation.

Viewing angle	0	10	20	30	40	50	60	70	80	90
PCA 6	2.54	2.60	2.57	2.51	2.5	2.62	2.50	2.40	2.08	1.75
PCA 3	2.54	2.61	2.59	2.51	2.65	2.62	2.59	2.50	2.15	1.75
RGB	7.62	7.64	7.63	7.70	7.60	7.77	7.42	7.40	7.07	6.46
RG	9.52	9.51	9.52	9.51	9.47	9.45	9.38	9.26	9.01	8.65

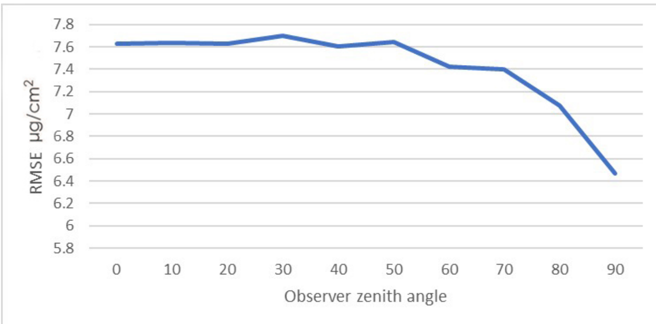

Fig. 4: Observer zenith angle and the error in estimation.

(a) 0° R=46, G=96, B=33 (b) 90° R=53, G=110, B=33

Fig. 5: RGB images from different viewing angles.

optical method, it is better to have the device placed with a large observer zenith angle.

E. Multi-angle Approach

Roosjen *et al.* [28] demonstrated that by adding a viewing angle to a multispectral camera, the estimation accuracy of the chlorophyll can be improved slightly. This case study also tested whether it is possible to increase the estimation accuracy by measuring multiple angles when using an RGB device. Fig 5 shows two RGB images with a certain chlorophyll content captured from different viewing angles; as can be seen, there is a difference in colour. This difference is from the plant canopy anisotropy, which means the spectral reflectance of plant canopy varies with viewing angle. This variation can be detected by an RGB device, and furthermore provides more information to estimate the plant parameters including chlorophyll content. Table IV shows the error in LCC estimation when using RGB values from two viewing angles with neural network-based regression. Compared to using only one viewing angle, it can provide better estimation results. Looking for instance at 0° (nadir), adding the 10° angle to the measurement reduces the LCC estimation error by 0.5 $\mu g/cm^2$. When one of the observer zenith angles is 90° the error can be reduced to less than 6 $\mu g/cm^2$ which is a significant improvement compared to a single-angle model. Compared with measuring the same viewing angle twice (diagonal of the table), using two angles can provide a better estimation accuracy. Note that when measuring the same viewing angle twice the data is different because of the noise added to the ProSail parameters and the RGB pixel values. Therefore we can make the following conclusion, that the increase in the estimation accuracy is caused by the additional information from using multiple angles RGB. It is possible to increase the estimation accuracy by considering multiple viewing angles.

TABLE IV: RMSE for LCC estimation using two viewing angles and a neural network for regression (10-fold cross validation). Note how using the same angle twice (even with noise in the ProSail parameters and RGB values) gives worse results than using two different angles.

Θ_1 & Θ_2	0	10	20	30	40	50	60	70	80	90
0	7.63	7.16	7.09	7.13	7.12	7.04	7.02	6.89	6.48	**5.67**
10		7.60	7.15	7.10	7.06	7.06	7.02	6.90	6.46	**5.64**
20			7.65	7.19	7.33	7.16	6.83	7.08	6.51	**5.60**
30				7.66	7.10	7.09	6.97	6.90	6.43	**5.66**
40					7.65	7.11	7.05	6.98	6.56	**5.76**
50						7.63	7.01	6.88	6.57	**5.79**
60							7.52	6.87	6.54	**5.75**
70								7.39	6.62	**5.85**
80									7.70	**5.95**
90										**6.40**

Another possible method to provide more information for an RGB based estimation is using multiple cameras. Table V compares the estimation error from using two viewing angles and using two cameras. The LCC is estimated from the RGB values using a neural network. The two angle method combines the listed viewing angle with 90°. For the two camera method, two different camera models were used for each viewing angle. We conclude that using one camera at two viewing angles can provide a better estimation result than using two cameras at one viewing angle. Furthermore, measuring the plant's spectral reflectance from multiple angles can provide more information than using multiple sensors at a single viewing angle.

IV. Conclusion and Future Work

This study suggests that RGB cameras hold promise for the assessment of leaf chlorophyll content. After regression learning, the most successful model is a neural network model with two hidden neurons which uses the pixel values of the R,

TABLE V: Comparison of the LCC estimation error $\mu g/cm^2$ from two viewing angles (one at 90°) and two cameras (both at listed angle).

Viewing angle	0	10	20	30	40	50	60	70	80	90
Two viewing angles	5.67	5.64	5.60	5.66	5.76	5.79	5.75	5.85	5.95	6.40
Two cameras	7.22	7.33	7.25	7.21	7.15	7.20	7.08	7.06	6.73	6.07

G and B channel as input. To achieve the best estimation, the camera needs to be placed at an observer zenith angle near 90° when the solar zenith angle is 40°. One of the key findings of this research is that the estimation accuracy can be increased by considering two viewing angles instead of one.

This paper only uses simulation data, further investigation needs to be conducted to evaluate the model of chlorophyll content estimation with real data. Another target in future research is to investigate whether it is possible to recover spectral reflectance from RGB pixel values.

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