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Estimation of Chlorophyll and Carotenoid Content in Tea Leaves Using UAV Hyperspectral Data with the PROSPECT-D+SAIL Model

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Abstract

The assessment of photosynthetic pigments is a reliable indicator for evaluating plant productivity and environmental stress. Therefore, developing an in-situ method for monitoring photosynthetic pigments is essential for effective tea crop management. Hyperspectral reflectance has been widely applied to assess vegetation properties, including pigment content, using portable spectroradiometers. However, the cost of these devices remains high and inaccessible for general use. This study evaluated the potential of an unmanned aerial vehicle (UAV)-mounted hyperspectral sensor incorporating a cost-effective, fingertip-sized spectrometer (C12880MA-10, Hamamatsu Photonics K.K.) to estimate chlorophyll and carotenoid content in tea leaves using the PROSPECT-D+SAIL model. Based on the ratio of performance to deviation (RPD), the proposed approach demonstrated effective performance in estimating both chlorophyll and carotenoid content, with RPD values exceeding 1.4.

Discipline: Agricultural Engineering
Additional key words: compact spectrometer, radiative transfer model, reflectance

Introduction

Due to growing interest in health, the global demand for green tea has increased in recent years. However, in Japan, production of first-flush green tea (leaf tea) has declined. Conversely, there is a growing demand for high-priced or cost-effective tea for beverages (Chen & Yang 2017). Additionally, the climatic and socio-economic conditions affecting tea production are undergoing significant changes, including the expansion of cultivation areas per tea farm. Consequently, some farmers are cultivating higher-yielding cultivars or those suitable for tencha and black tea production. However, differences in harvesting periods (early or late maturing) and disease resistance indicate that the farming techniques honed for Yabukita, the cultivar with the largest cultivation area, may not directly apply to other cultivars. As a result, multi-cultivar cultivation could complicate tea plantation management, highlighting the need to establish cultivation methods based on objective indicators.

Chlorophyll plays a fundamental role in plants, serving as the primary pigment that captures light energy during photosynthesis. It enables the conversion of light energy into chemical energy, which is essential for the synthesis of carbohydrates from carbon dioxide and water. This process not only supports the plant's growth and development but also serves as the basis for energy transfer in most terrestrial ecosystems. Moreover, chlorophyll content is often used as an indicator of plant health, nitrogen status, and overall physiological activity (Korus 2013). Similarly, carotenoids are pigments that absorb light energy, as do chlorophylls. However, they also play a crucial role in mitigating stress by dissipating excess light energy as heat. Therefore, assessing chlorophyll and carotenoid content across tea plantations is essential for effective management.

Various remote sensing techniques have been used to evaluate vegetation properties and seasonal changes in crops (Gong et al. 2020, Sonobe et al. 2024, Sonobe et al. 2025, Tsuchiya & Sonobe 2025). Hyperspectral remote

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sensing, which utilizes spectral reflectance, is widely used for non-destructive evaluation of plant traits, including the levels of photosynthetic pigments such as chlorophyll and carotenoids. However, commercial spectroradiometers, such as the FieldSpec series (Analytical Spectral Devices, Inc.), are expensive and challenging to maintain in the field due to overseas manufacturing, limiting their adoption in actual production settings. In recent years, highly sensitive and ultra-compact spectrometer heads, such as the C12880MA (Hamamatsu Photonics), have been developed, enabling their integration into a range of compact devices. Their potential for estimating leaf chlorophyll and carotenoid content has been evaluated at the leaf scale using a plant probe comprising a halogen light source and a leaf clip with replaceable white and black background standards (Nofrizal et al. 2022, Sonobe et al. 2022, Sonobe & Hirono 2023a, 2023b). Assessing pigment levels across fields enables precise agriculture techniques, such as site-specific fertilization and irrigation, tailored to the needs of different areas. Furthermore, at the field scale, data on pigment content can refine canopy reflectance models and spectral indices used in remote sensing. This leads to more accurate assessments of crop health and productivity using drones. To evaluate chlorophyll and carotenoid content at the field scale, the hyperspectral image sensor (HIS) manufactured by the Deep Sensing Initiative (DSI) has emerged as a promising solution. This device is based on the Hamamatsu Photonics' micro-spectrometer (C12880MA) (Uto et al. 2016b, 2016a). This study aimed to evaluate the spatial distribution of chlorophyll and carotenoid content in a tea plantation cultivating 38 tea cultivars using spectral reflectance data obtained with the HIS.

Estimating chlorophyll and carotenoid content from hyperspectral reflectance data employs various techniques, including empirical regressions, machine learning, and radiative transfer models (RTMs). Empirical regressions, while straightforward and easy to implement, often require recalibration because their performance is highly sensitive to variations in the environmental and agronomic conditions surrounding tea production. For example, differences in tea cultivars, sunlight exposure, and seasonal growth stages can affect the relationship between spectral reflectance and pigment concentrations, such as chlorophyll and carotenoids. As a result, a regression model developed in one region or growing season may not be directly applicable to another, necessitating site-specific model adjustments to maintain prediction accuracy. Machine learning techniques such as random forest and neural networks excel in handling complex datasets but demand extensive training data and computational resources. In contrast, the PROSAIL model integrates leaf-level optical properties (via the PROSPECT model) with a canopy structure (via the SAIL model), offering a robust physics-based approach. The PROSAIL model's key advantages include scalability, the ability to utilize the full hyperspectral range, and generalizability across various ecosystems without extensive site-specific calibration. It enables accurate inversion of biophysical parameters such as chlorophyll and carotenoid content from reflectance data, supporting applications in large-scale agriculture and ecosystem monitoring. Additionally, PROSAIL can complement machine learning by integrating physical principles with data-driven methods to improve accuracy. PROSPECT-D, an updated version of the PROSPECT model, estimates chlorophyll, carotenoids, and anthocyanins. Thus, PROSPECT-D is effective for estimating pigment content, including tea leaf chlorophyll and carotenoids, as demonstrated in earlier studies (Sonobe et al. 2018). The PROSPECT-D model, though not the latest version of the PROSPECT family, has demonstrated exemplary performance in estimating the chlorophyll and carotenoid content in tea leaves. Furthermore, it requires fewer parameters, making it more user-friendly than the latest versions. Therefore, the PROSPECT-D model was extended to the canopy scale using the PROSPECT-D+SAIL model based on the PROSAIL model. This hybrid approach combines leaf-scale optical properties with a canopy RTM to estimate chlorophyll and carotenoid content while accounting for canopy-scale variability. This study explored the utility of PROSPECT-D+SAIL for analyzing hyperspectral data acquired with a C12880MA-based hyperspectral imager.

Materials and methods

1. Materials

UAV-based hyperspectral reflectance measurements were conducted on 10 May, 20 June, and 28 June 2022 at the tea plantation (Middle-8 Garden) of the Kanaya Tea Research Station, Tea Research Division, National Agriculture and Food Research Organization (Shimada City, Shizuoka Prefecture, Japan). This tea plantation has produced 38 cultivars of tea plants (*Camellia sinensis*; only Sunrouge has been a hybrid of *Camellia taliensis* × *C. sinensis*) since their planting in 2007.

The target field consisted of 39 hedges: Yabukita was cultivated on two hedges, while each of the other 37 cultivars was grown on a single hedge.

2. Measurement methods

(1) Chlorophyll and carotenoid content determination

A 25 cm square frame was placed on the canopy at 78 points (two per hedge) corresponding to the size of one pixel in the UAV-based hyperspectral image. Within each frame, only the new shoots were harvested, following standard tea harvesting practices, and mature leaves were excluded. These samples were then used to quantify the average chlorophyll and carotenoid content. The third leaf from the top of the new shoot was taken as a sample to determine chlorophyll and carotenoid content, and five leaves were collected from each sampling point. The sampled tea leaves were immersed in N, N-dimethylformamide to extract the leaf components. Next, the chlorophyll and carotenoid contents were quantified using the Wellburn method (Wellburn 1994) based on the absorbance data obtained from a UV spectrophotometer (UV-1800 by the Shimadzu Corporation). To express the pigment content on a per-area basis, the surface area of the tea leaves was measured, and the total pigment amount extracted (in µg) was divided by the corresponding leaf area. This allowed the chlorophyll and carotenoid contents to be represented in units of µg/cm^2.

(2) Hyperspectral reflectance measurements

Tea leaf sampling and spectral reflectance measurements of the target field were conducted simultaneously using a Hyper-Spectral Imager (by Deep Sensing Initiatives Co., Ltd. DSI), which was mounted on a UAV (M600PRO, DJI JAPAN K.K.). The UAV operated at an altitude of 15 meters and a flight speed of 1 m/s, capturing reflectance intensities from 340 to 850 nm with a ground resolution of 25 cm. Before the flight, dark-current calibration and output-value measurements were performed for a standard white panel. These calibrations were used to convert UAV data into reflectance values.

3. Analysis methods

After converting the reflectance intensity obtained by the UAV into reflectance values, chlorophyll and carotenoid content maps of the tea plantation were generated using inverse estimation with the PROSPECT-D+SAIL model (Féret et al. 2017, Jacquemoud et al. 2009). The MATLAB code available on the portal site (http://teledetection.ipgp.jussieu.fr/prosail/, accessed on 1 April 2025) was used for the PROSPECT-D+SAIL model. Reflectance from 400 to 780 nm, where the absorption coefficients for chlorophyll and carotenoids are defined, was utilized for the inversion process. The PROSPECT model defines the leaf absorption coefficient, so calibration is recommended for each sample (Féret et al. 2008). In this study, the absorption coefficient for PROSPECT-D was calibrated using results from prior research on tea leaves (Sonobe et al. 2018).

The optimal parameter combination determining the spectral reflectance characteristics was identified using the fminsearch algorithm in MATLAB, which is based on the Nelder-Mead simplex algorithm (Lagarias et al. 1998). The soil type was set to moist, and the solar zenith angle was obtained from Casio's calculation tool (https://keisan.casio.jp/exec/system/1185781259, accessed on 1 April 2025).

The estimation accuracy was evaluated by comparing the predicted values from the PROSPECT-D+SAIL model with the quantified values at 78 sampling points. Evaluation metrics included the coefficient of determination (R^2), RMSE, and RPD, calculated using the following formulas (Williams & Norris 1989):

$$R^2 = 1 - \left(\frac{\sum(O_i - P_i)^2}{\sum(O_i - \bar{O})^2}\right), \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum(P_i - O_i)^2}, \tag{2}$$

$$RPD = {}^{SD}/_{RMSE}, \tag{3}$$

where O_i is the quantified content, and P_i is the estimated content, n is the number of samples, and SD is the standard deviation of the quantified content in the test data. The RPD is used to evaluate the reliability of the predictions. The models were classified into three categories based on their RPD (Ratio of Performance to Deviation) values: category "A" (RPD > 2.0), category "B" (1.4 ≤ RPD ≤ 2.0), and category "C" (RPD < 1.4). These categories correspond to the following levels of predictive performance: A indicates well-predicted, B indicates acceptable, and C indicates poorly predicted.

Results

1. Quantified chlorophyll and carotenoid content determined by UV-spectrophotometer

The distribution of the quantified chlorophyll and carotenoid content is shown in Figures 1 and 2, respectively. The maximum chlorophyll content observed was 74.65 µg/cm^2 in Kanaemaru on 20 June, and the minimum was 18.59 µg/cm^2 in Benihikari on 28 June. On the other hand, the maximum carotenoid content observed was 15.63 μg/cm^2 in Minekaori on 10 May, and the minimum was 6.18 μg/cm^2 in Hokumei on 28 June.

Both chlorophyll and carotenoid content showed a decreasing trend over time in most cultivars. However, Yumekaori recorded the minimum on 10 May. Harumidori, Harumoegi, Harunonagori, and Sakimidori recorded the minimum on 20 June. Cultivars such as Fuushun and Kanaemaru recorded their maximums on 20 June.

2. Inverse estimation results using the PROSPECT-D+SAIL model

The UAV data obtained on 10 May 2022 and processed using the PROSPECT-D+SAIL model to estimate chlorophyll and carotenoid content are presented in Figure 3. In the UAV observation conducted on 10 May, data loss occurred in the lower-left hedge, so it was not possible to obtain estimated values at the two locations where ground measurements were conducted. Figure 4 presents the relationship between the estimated and quantified values of chlorophyll and carotenoid content. The model achieved root mean square errors (RMSEs) of 4.83 μg/cm^2 for chlorophyll and 0.98 μg/cm^2 for carotenoids, with coefficients of determination (R^2) of 0.572 and 0.490, respectively. The ratio of performance to deviation (RPD) exceeded 1.4 for both pigments, indicating a reasonable predictive performance. These evaluation metrics were derived using data collected on 10 May, 20 June, and 28 June 2022. When evaluating the accuracy by observation date, the RMSE for chlorophyll content ranged from 4.53 to 5.39 μg/cm^2, and for carotenoid content, it ranged from 0.94 to 1.03 μg/cm^2, maintaining stability. On 10 May, the chlorophyll estimation model exhibited a relatively low coefficient of determination ($R^2 = -0.04$), suggesting that the estimated values did not explain the variability of the quantified values effectively. In contrast, on 20 and 28 June, chlorophyll estimation showed moderate predictive ability, with R^2 values of 0.45 and 0.47, respectively, and RMSE values around 4.5-5.4 μg/cm^2. The estimation

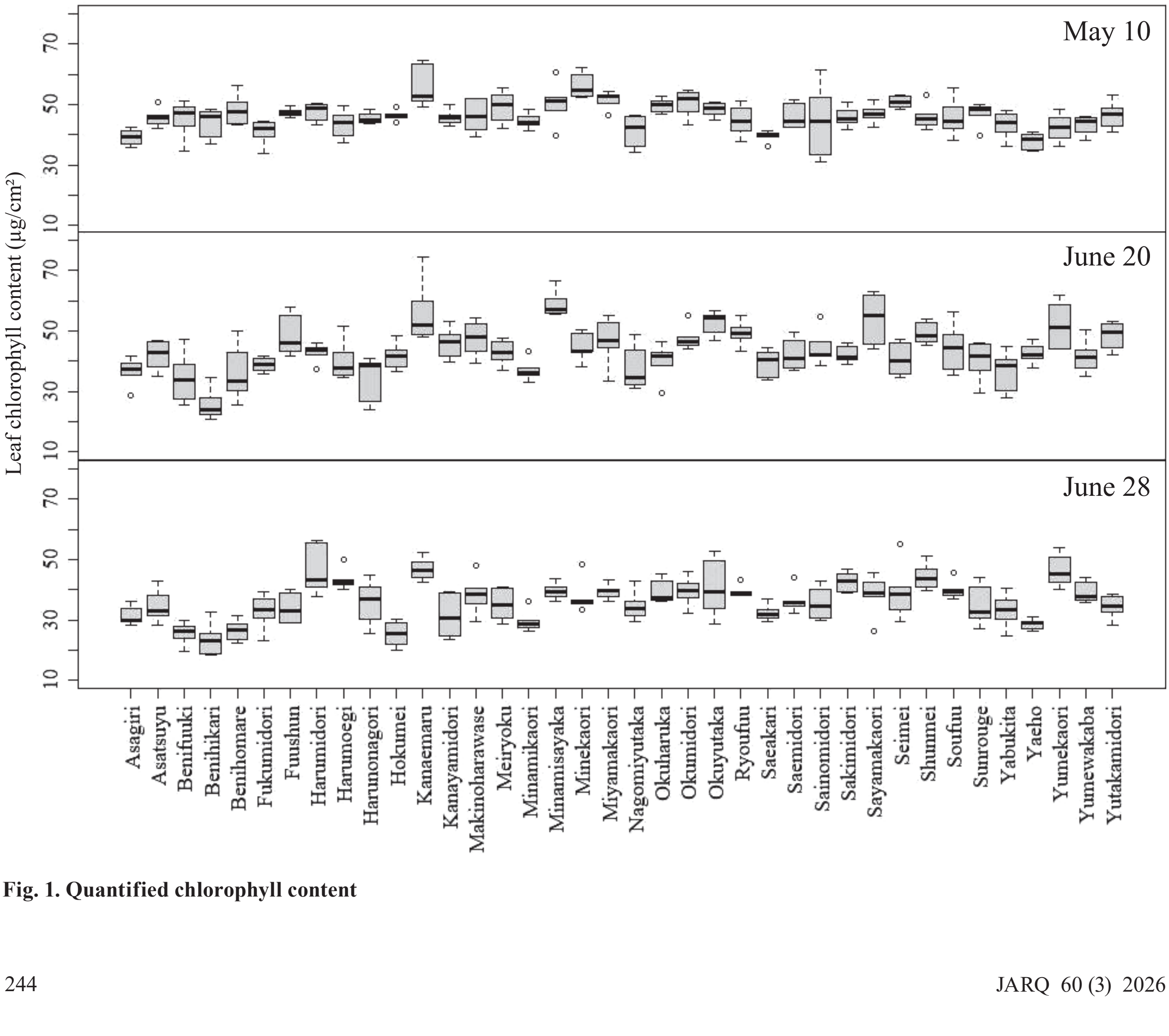

Fig. 1. Quantified chlorophyll content

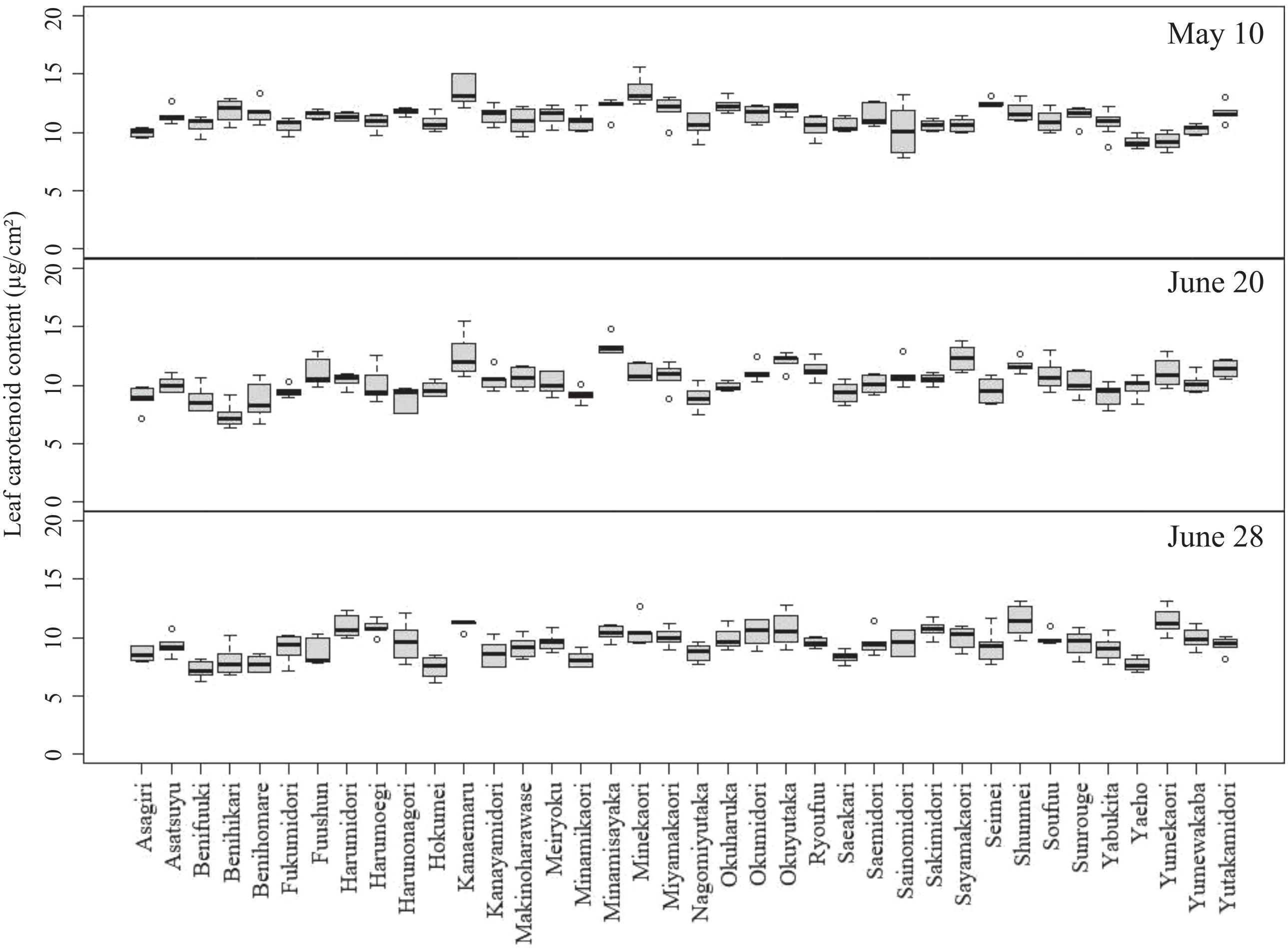

Fig. 2. Quantified carotenoid content

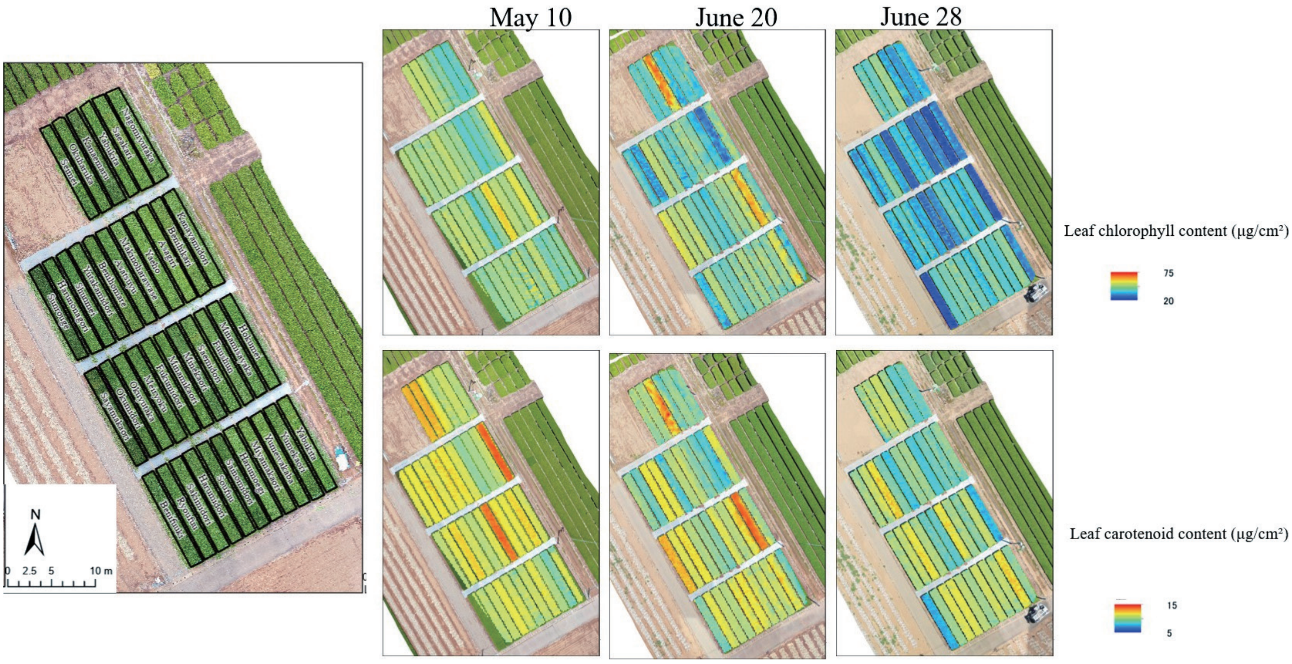

Fig. 3. Hedge layout, cultivated tea cultivars, and distribution of chlorophyll and carotenoid contents estimated by the PROSPECT-D+SAIL model

accuracy of carotenoid content varied across the three measurement dates: 10 May, 20 June, and 28 June 2022. On 20 June, the model showed the highest goodness-of-fit, with an R^2 of 0.435 and an RMSE of 0.96 μg/cm^2. In contrast, 10 May and 28 June yielded lower R^2 values of 0.135 and 0.238, respectively, with RMSE values of 0.94 and 1.03 μg/cm^2.

Table 1 presents the estimation accuracy of chlorophyll and carotenoid contents across tea cultivars using RMSE and RPD metrics. Chlorophyll estimation showed high accuracy (RPD > 3.0) in such cultivars as Ryoufuu (6.60), Saeakari (5.39), Yaeho (4.35), and Okuharuka (3.23). In contrast, low RPD values were observed in Kanaemaru (0.67), Saemidori (0.78), Minamikaori (0.80), Yumewakaba (0.87), Minamisayaka (0.88), Hokumei (0.94), Harumoegi (0.98), and Harumidori (1.09), indicating poor model performance. Carotenoid estimation generally yielded lower RPDs. Best-performing cultivars included Okuharuka (4.09), Benihomare (3.54), Benifuuki (3.25), and Seimei (3.19), while cultivars such as Minamisayaka (0.63), Sakimidori (0.65), Saemidori (0.66), Hokumei (0.67), Yumewakaba (0.71), Minamikaori (0.83), Minekaori (0.83), Shunmei (0.88), Kanayamidori (0.88), and Kanaemaru (0.95) performed poorly.

Discussion

The relatively poor estimation accuracy observed on 10 May is attributed, at least in part, to the strong winds during the UAV flight, which affected the UAV's attitude control stability. As a result, the hyperspectral measurements did not precisely align with the intended canopy locations, leading to spatial misregistration between the spectral data and the ground-truth sampling points. Furthermore, the hyperspectral imager used in this study employs a CMOS sensor, which is sensitive to high temperatures and may experience degraded performance under such conditions. As the temperature increases, thermal noise (also known as dark current) in the sensor also increases, reducing image quality, particularly in low-light environments. High temperatures can also lead to increased power consumption, reduced dynamic range, and pixel defects, such as hot pixels and fixed-pattern noise. This positional discrepancy contributed to the reduction in model performance observed on that date. In addition to UAV instability, another factor that may have contributed to the reduced accuracy was a GPS positioning error, which caused an eastward shift approximately one meter in the geolocation of the hyperspectral data. This spatial offset further exacerbated the misalignment between imagery and ground-truth data, ultimately compounding the decline in model performance observed on 10 May.

Besides positional factors, cultivar-specific pigment characteristics significantly determined model performance. In all cultivars, a strong positive relationship between chlorophyll and carotenoid contents was observed (r^2 = 0.91). This indicates that the variation in these two pigments across all cultivars occurs together and should be considered equally when assessing prediction accuracy. From the RPD-based ranking (A–C for estimation accuracies of both chlorophyll and carotenoid), most cultivars agglomerated into either

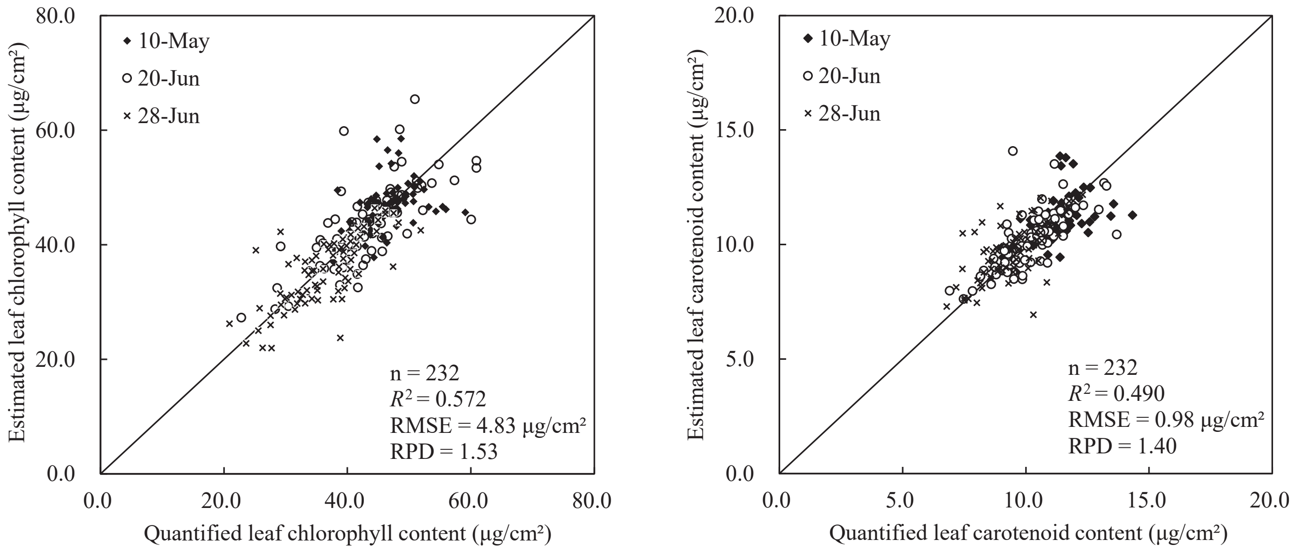

Fig. 4. Relationship between the estimated and quantified chlorophyll and carotenoid content

high-performance (AA, AB; n = 14) or low-performance (CC; n = 14) groups. The high-performance group showed relatively low levels of both chlorophyll and carotenoid, while the low-performance group tended toward higher levels. This trend suggests a relationship to the model's calibration baseline. The PROSPECT-D+SAIL model used here was calibrated initially with Yabukita, which has moderate pigment levels (chlorophyll = 37.86 μg/cm^2, carotenoids = 9.67 μg/cm^2). Cultivars with pigment attributes closer to Yabukita—low chlorophyll, low carotenoid—realized higher RPD values. Those with high chlorophyll and high carotenoid content tended to be less accurate. For example, Kanaemaru and Harumidori had high chlorophyll content (52.81 and 45.62 μg/cm^2, respectively) and high chlorophyll-to-carotenoid ratios (4.3 and 4.2). They reduced RPDs (0.67 and 1.09, respectively). The deviations are likely to have shifted spectral absorption features in the visible range, which cannot be explained by a calibration set developed initially for another purpose. In addition, Harumidori maintains a low chlorophyll a/b ratio of about 2.73—lower than the 3:1 assumption reportedly used in building PROSPECT models (Katayama & Shida 1970, Féret et al. 2008)—and may further alter absorption characteristics, reducing estimation accuracy. Similarly, cultivars like Minamisayaka, which presented low carotenoid content (11.98 μg/cm^2), also registered poor RPD values (0.63)—probably because field conditions do not actually support such a strong carotenoid spectral signal as assumed by models developed under more controlled laboratory conditions. Interestingly, within the low-performance group (CC), chlorophyll and carotenoid contents correlated even more strongly (r^2 = 0.95) than across the full dataset; this suggests that, in pigment-rich cultivars, the two pigment levels are not independent and may interact to reduce model discrimination power under its current calibration.

These findings point to two pathways for improvement: (1) expand the calibration dataset to include high-chlorophyll, high-carotenoid cultivars to better capture spectral variability, and (2) explore alternative modeling approaches such as Cubist or 1D-CNN, which have shown robustness to spectral noise (Haghi et al. 2021, Li et al. 2024). Incorporating pigment-diverse cultivars during calibration could improve generalization across the full range of pigment content observed in Japanese tea cultivars.

Table 1. Summary of quantified and estimated chlorophyll and carotenoid content for each tea cultivar. The table presents the mean values of quantified chlorophyll and carotenoid content, the root mean square error (RMSE) between quantified and estimated values, and the residual predictive deviation (RPD), which indicates the model's goodness of fit for each cultivar

Cultivar	Chlorophyll content			Carotenoid content			Cultivar	Chlorophyll content			Carotenoid content		
	Mean (μg/cm^2)	RMSE (μg/cm^2)	RPD	Mean (μg/cm^2)	RMSE (μg/cm^2)	RPD		Mean (μg/cm^2)	RMSE (μg/cm^2)	RPD	Mean (μg/cm^2)	RMSE (μg/cm^2)	RPD
Asagiri	35.70	1.74	2.26	9.17	0.31	2.33	Nagomiyutaka	37.81	2.27	1.72	9.43	0.36	2.66
Asatsuyu	40.76	2.52	2.36	10.27	0.54	2.03	Okuharuka	43.01	1.66	3.23	10.69	0.32	4.09
Benifuuki	30.08	4.15	1.31	8.00	0.30	3.25	Okumidori	45.93	2.18	2.41	11.05	0.40	1.57
Benihikari	31.11	3.93	2.72	9.10	1.16	1.96	Okuyutaka	47.25	4.88	1.45	11.63	0.71	1.33
Benihomare	36.90	5.22	2.02	9.39	0.57	3.54	Ryoufuu	44.45	0.69	6.60	10.47	0.35	2.42
Fukumidori	37.59	3.57	1.25	9.73	0.62	1.27	Saeakari	37.12	0.68	5.39	9.44	0.36	2.91
Fuushun	43.21	6.29	1.17	10.43	1.46	1.00	Saemidori	41.55	6.75	0.78	10.35	1.53	0.66
Harumidori	45.62	4.00	1.09	10.91	0.59	1.04	Sainomidori	41.38	5.81	1.17	10.22	1.09	1.09
Harumoegi	42.31	2.94	0.98	10.56	0.65	0.98	Sakimidori	43.57	1.44	1.78	10.62	0.52	0.65
Harunonagori	38.62	3.17	1.95	10.11	0.85	1.72	Sayamakaori	46.53	4.73	1.78	11.01	0.59	2.13
Hokumei	37.85	10.68	0.94	9.32	2.28	0.67	Seimei	43.60	2.73	2.14	10.45	0.50	3.19
Kanaemaru	52.81	8.42	0.67	12.38	1.25	0.95	Shunmei	46.52	2.30	1.35	11.62	0.69	0.88
Kanayamidori	41.07	5.59	1.35	10.22	1.48	0.88	Soufuu	43.40	2.87	1.35	10.58	0.48	1.46
Makinoharawase	44.12	4.87	1.17	10.28	0.71	1.46	Sunrouge	40.70	4.74	1.54	10.39	0.86	1.38
Meiryoku	42.44	2.75	2.41	10.41	0.67	1.46	Yabukita	37.86	4.34	2.34	9.67	0.98	2.09
Minamikaori	37.08	8.34	0.80	9.42	1.57	0.83	Yaeho	36.39	1.47	4.35	8.92	0.61	1.77
Minamisayaka	49.58	10.22	0.88	11.98	2.17	0.63	Yumekaori	46.84	3.80	1.38	10.58	0.61	1.91
Minekaori	46.14	7.79	1.13	11.70	1.90	0.83	Yumewakaba	41.32	2.33	0.87	10.15	0.30	0.71
Miyamakaori	45.89	3.58	1.66	10.94	0.65	1.52	Yutakamidori	43.14	3.55	2.05	10.82	0.43	2.81

Conclusion

This study demonstrated the potential of a UAV-mounted hyperspectral sensor using a low-cost, fingertip-sized spectrometer to estimate chlorophyll and carotenoid content in tea leaves. By applying the PROSPECT-D+SAIL radiative transfer model, we successfully generated pigment distribution maps across multiple cultivars and confirmed reasonable predictive performance, with RPD values exceeding 1.4 for both chlorophyll and carotenoids. The results highlight the system's utility for non-destructive, in-situ monitoring of photosynthetic pigments in tea crops. However, estimation accuracy varied across cultivars and dates, partly due to differences in pigment composition, limitations in spectral resolution, and environmental factors during data acquisition. Cultivars with extreme pigment levels or atypical chlorophyll-to-carotenoid ratios exhibited lower model performance, suggesting the need for improved model calibration and potential refinement of parameter assumptions. Future efforts incorporating machine learning techniques and expanded calibration datasets are expected to further enhance the system's robustness and accuracy. Overall, this approach offers a practical and scalable solution for precision tea cultivation and crop monitoring.

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