The importance of leaf area index in mapping chlorophyll content of corn under different agricultural treatments using UAV images

Anita Simic Milas[1*], Matthew Romanko[2], Patrick Reil[1], Tharindu Abeysinghe[1], Anuruddha Marambe[1]

[1*] Bowling Green State University, School of Earth, Environment and Society, 190 Overman Hall, Bowling Green, Ohio, USA, 43403-0211. Tel 1.419.372.4035, Email: asimic@bgsu.edu.

[2] Satelytics, 1510 N.Westwood Ave. Toledo, Ohio, USA, 43606

Abstract

The impact of structural parameters of agricultural crops on the retrieval of chlorophyll content presents a real challenge for the remote sensing community. Canopy reflectance can differ between crops of different canopy structure even when they have the same canopy chlorophyll content. Thus, structural properties should be incorporated in chlorophyll mapping to reduce modeling errors. The empirical relationships between vegetation indices and chlorophyll content are well established and commonly used in precision agriculture. Recent advances in using unmanned aerial vehicle (UAV/drone) technology offer successful retrieval of crop structural and biochemical parameters. However, transfer of empirical algorithms derived from satellite to UAV based analyses introduces new challenges mainly due to fine spatial resolution and details such as crop rows and between- and within- canopy gaps that are more pronounced in UAV images. There are two components of the analysis in this study. The first part is related to heterogeneity of leaf area index (LAI) and chlorophyll content of corn under four agricultural treatments (conventional ploughed, conventional with no tilling, biological with reduced chemical inputs, and certified organic) at the Kellogg Biological Station Long-Term Ecological Research (KBS LTER) site in Michigan, USA. The second part examines the necessity and importance of LAI in chlorophyll mapping using UAV images collected over the heterogeneous KBS LTER parcels at peak growing season. The UAV-derived Normalized Difference Red Edge Index (NDRE) is found to be highly correlated with canopy chlorophyll, calculated as a product of leaf chlorophyll content and LAI. The coefficient of determination changes from $R^2 = 0.177$ to $R^2 = 0.774$ when LAI is added to the empirical model. NDRE is also found to be highly correlated with LAI ($R^2 = 0.620$). The findings suggest that the conventional corn treatment with

no-tilled soil exhibits the highest crop vigor during the peak growing season. The herbicide management applied earlier in the season may have a strong effect on weeds, reducing the crop-weeds competition for nutrients.

Key words: NDRE, LAI, chlorophyll, Unmanned Aerial Vehicles (UAV)

1. Introduction

The biochemical composition of vegetation canopies is an important indicator of ecosystem health and sustainability (Carter 1994; Lichtenthaler 1998). Leaf chlorophyll and nitrogen contents are principal parameters for quantifying the foliage photosynthesis rate and primary productivity (Ripullone et al. 2003; Gitelson et al. 2006). Retrieval of biochemical information using remote sensing commonly relies on empirical relationships between biochemical contents and spectral reflectance obtained by satellite imagery (Zarco-Tejada et al. 2001; le Maire, Francois, and Dufrene 2004; Gitelson et al. 2005; le Maire et al. 2008). While pigment content controls the spectral signature of leaves and canopy, other factors such as canopy architecture, which encompasses both the angular and spatial distributions of vegetation components, leaf area index (LAI) and background reflectance also contribute to the signal (Chen et al. 2002; Gitelson et al. 2005; Verrelst, Schaepman, and Clevers 2008; Pisek et al. 2010; Simic, Chen, and Noland 2011; Simic et al. 2014).

There are two ways of monitoring chlorophyll content: (1) Leaf chlorophyll (chlorophyll content per unit leaf area) and (2) Canopy chlorophyll (total chlorophyll content per ground area) where leaf chlorophyll is commonly multiplied by LAI to better respond to the radiometric signal of satellite observations (Gitelson et al. 2005; Baret, Houles, and Guerif 2007; Simic et al. 2010; Simic, Chen, and Noland 2011; Peng et al. 2017). The empirical modeling for chlorophyll content retrieval is based on multispectral or hyperspectral vegetation indices (Curran 1989; Elvidge and Chen 1995; Jacquemond et al. 1996; Dawson and Curran 1998; Broge and Leblanc 2001; Zarco-Tejada et al. 2001; Clevers et al. 2002; Smith et al. 2003; le Maire, Francois, and Dufrene 2004; Ustin et al. 2004; Gitelson et al. 2005; le Maire et al. 2008). As summarized by

Liang et al. (2016), fifty hyperspectral vegetation indices used to estimate chlorophyll content are proposed in the literature. While most of them are used separately, to map either leaf or canopy chlorophyll content, some of them are found to be suitable for both leaf and canopy chlorophyll mapping. They include the visible and near-infrared spectral ranges and they are used as simple ratio indices, normalized difference ratios, triangular vegetation indices, modified versions of these three types, derivative spectral indices, and red-edge based indices (Liang et al. 2016). A fine spectral resolution at the red-edge is particularly useful for mapping chlorophyll content (Gitelson and Merlyak 1994; Gitelson and Merlyak 1998) as well as for mapping canopy architecture to a lesser extent.

Structural characteristics influence canopy near-infrared and visible reflectance and, thus, affect the shape of the reflected spectral curve within the red-edge region (Demarez and Gastellu-Etchegorry 2000, Delegido et al. 2008). Canopy reflectance can differ between the plants of different canopy structure even when they have the same canopy chlorophyll content (Gitelson et al. 2005). Thus, proper estimation of structural characteristics is necessary to reduce modeling errors in chlorophyll content retrieval (Simic, Chen, and Noland 2011). Rapid developments in remote sensing technologies over the last two decades inspired scientists to probe into the relationships between structural parameters of a vegetation canopy and multi-angular remote sensing data. In particular, the combination of multi-angular and hyperspectral data is very useful for retrieving canopy structure (Lewis, Barnsley, and Cutter 2001; Urso et al. 2004; Bach et al. 2005; Begiebing et al. 2005; Schlerf and Hill 2005; Rautiainen et al. 2008; Simic and Chen 2008; Vuolo, Dini, and D'Urso 2008; Zhang et al. 2008). The improved multiangle-based LAI was found to have a significant impact on chlorophyll content retrieval in the studies of Simic et al. (2008) and Simic, Chen, and Noland (2011). Similarly, Duan et al. (2014) reported that the Unmanned Aerial Vehicle (UAV/drone)-derived LAI using data from two different angles resulted in increased accuracy of LAI estimates.

Recent developments in remote sensing using the UAV technology represents a true paradigm shift (Salami, Barrado, and Pastor 2014). Having spatial resolution as small as a few centimeters, a sudden expansion of drone-related applications is particularly observed in precision agriculture where farmers and researchers have found a common goal 'to improve crop status and yield'.

Used for monitoring biochemical crops properties as surrogates for crop status, information is generally retrieved based on the existing algorithms that are already widely used for satellite and airborne data (Elarab et al. 2015). However, transfer of empirical algorithms from satellite images to UAV images introduces new challenges mainly due to fine spatial resolution and details, such as crop rows and between- and within-canopy gaps that are more pronounced in UAV images, affecting the importance of structural parameters in chlorophyll content retrieval.

As summarized by Krishna (2016), many studies are conducted where drone is seen as low-cost operation compared to traditional manned aircraft or ground data collections. UAV cameras that operates at visual and NIR bands were found to be useful for monitoring crop status such as detecting crop diseases or crop infestation (Costa et al. 2012; Garcia-Ruiz and Sankaran 2013). UAVs help farmers to monitor low productivity of crops allowing them to correct the amount of fertilizers and pesticides. Different types and amounts of agricultural chemicals applied at different growing stages affect the crop vigor and ultimately crop yield. For instance, early applications of nitrate-based fertilizers and no-tilled soils together with the proper herbicide applications significantly increase corn yield and cause early corn maturity when observed with Landsat (Simic Milas and Vincent 2016). At some crop farms, canopy cover and water usage pattern were also used as indicators for forecasting crop yield (Trout and DeJonge 2017). Constant monitoring of crop vigor through LAI and chlorophyll content retrieval using drones is becoming universal nowadays.

This study aims to explore the importance of LAI in chlorophyll mapping of heterogeneous corn fields using UAV images. There are two components of the analysis in this study. The first part is related to heterogeneity of vigor status and LAI of corn grown under four agricultural treatments (conventional ploughed, conventional with no tilling, biological with reduced chemical inputs, and certified organic) based on field and UAV measurements of the Normalized Difference Red Edge Index (NDRE), LAI, and chlorophyll content collected at the Kellogg Biological Station in Michigan, Ohio, USA. The second part examines the necessity and importance of LAI in chlorophyll mapping using UAV images over the parcels at peak growing season by incorporating LAI in the chlorophyll retrieval algorithm. The relationships between NDRE and leaf and canopy chlorophyll content are investigated and validated. NDRE is widely used by farmers and it consists of the red edge band, which is important in chlorophyll mapping. Both drone and field-derived NDRE using a field spectroradiometer are explored in the empirical relationships to predicting LAI and chlorophyll content. Spatial heterogeneity of vegetation cover introduces major uncertainties in large-scale analyses when sensors with fairly coarse spatial resolution are used (Ehleringer and Field 1993, Simic et al. 2004). The fine resolution analyses (e.g. UAV) closely represent reality and the relationship between field and remote sensing data (e.g. leaf and canopy chlorophyll) is believed to be differently impacted by structural parameters such as LAI.

2. Data and Method

2.1. Study Site and Field Data Collection

The study site is located within the Kellogg Biological Station (KBS) in Michigan, USA (42°24'N, 85°22′W) (Figure 1(*a*)). The KBS is a research area that includes different experimental treatments related to ecological interactions and agronomic performance. The KBS farmland is managed under a national network of the Long-Term Ecological Research (LTER) sites established by the National Science Foundation (Robertson et al. 2012; Robertson and Hamilton 2015). The 1-ha plots that undergo different treatments are mixed and randomly spread over the study area (Robertson et al. 2012). The annual cropping systems are corn–soybean–winter wheat rotations ranging in management intensity from conventional to biologically based (Robertson et al. 2012; Gage, Doll, and Safir 2014; Simic Milas and Vincent 2016).

[Figure 1]

In this study, 24 parcels of corn were considered (Figure 1(*b*)). Six parcels (replicates) with the same management were assigned to each treatment (Michigan State University (MSU) 2017). There were four agricultural practices: (1) genetically modified (GM) corn treated in three different ways: (*a*) T1 – conventional ploughed; (*b*) T2 – conventional with no tilling; and (*c*) T3 – biological with reduced chemical inputs, and (2) T4 – certified organic, non-genetically modified (non-GM) corn with no chemical treatments. Information about different type and quantity of fertilizers and herbicides were provided by Michigan State University (MSU 2017) (Table 1).

[Table 1]

A field campaign over 24 corn parcels were conducted concurrently with the UAV flight on 11 August 2017. Field measurements of leaf chlorophyll content (Chl_{Leaf}) and hyperspectral reflectance were collected at two or three randomly chosen locations at each parcel. In addition, digital hemispherical photographs (DHPs) were taken at each location and used to derive LAI. The sampling locations were approximately 10-15 m apart and positioned as a triangle around the center of each parcel. This allowed us to avoid any negative impact from the edge effect and mini-plots placed at the corners of parcels, and to compare the results with our previous Landsat-based study by Simic Milas and Vincent (2016). At each location, three measurements were collected within a radius of 3-5 m. Chl_{Leaf} measurements for validation were collected from an additional location at each parcel. The field measurements were compared between the treatments (T1-T4) to explore the heterogeneity of LAI and chlorophyll content / corn vigor during the peak growing season and possible impact of different treatments, including different types and application timing of fertilizers and herbicides, on crop status (Table 1).

Plant chlorophyll was measured using the Konica Minolta Chlorophyll Meter SPAD-502Plus. SPAD units are linearly related to chlorophyll content. The meter has an accuracy of +/- 1 SPAD unit (Spectrum Technologies 2017). The measurements were taken from top and middle part of plant as expected to be seen on the UAV image.

DHPs were taken using a Canon EOS Rebel T5 digital SLR 18.7-megapixel camera with a Sigma 8 mm F3.5 EX DG Circular Fisheye lens at each location. The photographs were taken vertically pointing up through the canopy (upward look), and pointing down through the canopy (downward look) for T4 parcels where open soil was observed (INRA 2017). The photographs were processed using the Can-Eye software package (INRA 2017), which classifies images using a binary classification technique and measures gap fraction from which LAI was calculated.

Hyperspectral reflectance measurements of corn leaves were collected in situ using the Spectral Evolution RS-3500 portable spectroradiometer. The meter collects 1024 discrete measurements of reflected ER from 346.2 nm to 2505.4 nm (~2 nm average spectral resolution). Calibration accuracy is +/- 5% at 400 nm, +/- 4% at 700 nm, and +/- 7% at 2200 nm (Spectral Evolution 2017). Pre-processing of the in situ hyperspectral reflectance data was automatically done using the DARWin SP data acquisition software installed in the hand-held data logger.

The field hyperspectral reflectance measurements were spectrally aggregated to form NDRE ($NDRE_{Field}$) to simulate the Sequoia camera for easier comparison of field and UAV derived parameters. Using ANOVA–Tukey-Kramer approach at the 0.05 level of significance, the mean values for $NDRE_{Field}$, Chl_{Leaf} and LAI were compared for each treatment to explore the impact of each treatment on corn status.

2.2. UAV Data Collection

To collect UAV spectral information over KBS we used eBee AG Sensefly UAV and the Sequoia camera. The eBee is a fixed-wing drone with a very light weight of just 700 g. eBee AG is easy to use as it allows for pre-launching flight preparation and simulations, and the flight plan can be altered during the flights. The planning and control computer system eMotion was used to plan and fly the system (Sensefly 2017). The flight area ceiling was set up for 400 m /ATO and the working radius was 2700 m. Lateral and longitudinal overlap was set up to 75% and spatial resolution was ~13 cm $pixel^{-1}$. Data were collected in a single flight. During the flight, the wind was low and the weather was clear. The UAV data were processed with Pix4Dmapper Pro, a drone mapping software (Pix4D 2017). The images were mosaicked and reflectance images were created for each green (530-570 nm), red (640-680 nm), red edge (RE) (730-740 nm) and near-infrared (NIR) (770-810 nm) band (Figure 2(*a*)). The image was registered to a corrected UAV image acquired the same day over the study area with the red-green-NIR Cannon camera that had a spatial resolution of 3.2 cm $pixel^{-1}$ where corn plants, marked sampling locations, and fixed poles with known coordinates located in the field were clearly visible on the image. In addition, Digital Terrain Model (DTM) and Digital Surface Model (DSM) images were generated (Figure 2(*b*) and 2(*c*), respectively).

[Figure 2]

NDRE calculated from UAV data ($NDRE_{UAV}$) was used in the empirical approach to explore the capability of this index to map crop status, chlorophyll content and LAI. The presence of NIR and RE bands, in particular, enables chlorophyll content retrieval. NDRE (Barnes et al. 2000) is calculated as

$$\mathrm{NDRE} = \frac{\mathrm{NIR} - \mathrm{RE}}{\mathrm{NIR} + \mathrm{RE}} \tag{1}$$

Simple linear regression models were generated and $NDRE_{UAV}$ was compared to: (1) structural corn properties, LAI; (2) leaf chlorophyll measurements, Chl_{Leaf}; and (3) canopy chlorophyll estimates (Chl_{Canopy}) (expressed as Chl_{Leaf} x LAI) for each parcel. Using the prediction algorithm, LAI and chlorophyll maps were generated. Validation of the estimated leaf chlorophyll values ($Chl_{Leaf\text{-}estimated}$) were conducted using Chl_{Leaf} measurements collected over the validation locations. Region-of-interest areas of approximately 5 x 5 m were chosen on the image around each field sample location to compare the results. The timing of the agricultural chemical applications as well as the possible impact of DTM on the results are also considered in the analysis to better understand the results.

3. Results

During data collection, the corn was at the peak of productive growth stage and kernel development. While the canopies for T1-T3 treatments looked relatively closed and similar in their appearance, T4 organic parcels had shorter corn plants, open canopies and more exposed soil than any other treatments (Figures 2(*c*) and 3).

[Figure 3]

Summary statistics show the highest mean values for T2 treatment for all three corn parameters: $NDRE_{Field}$, Chl_{Leaf} and LAI. The values are closely followed by T3 treatment with the exception of T4 treatment having slightly higher chlorophyll content than T3 treatment. T1 treatment has lower values than T2 and T3 conventional treatments, while T4 treatment has considerably lower values for $NDRE_{Field}$ and LAI than any other treatment (Table 2).

[Table 2]

The ANOVA–Tukey-Kramer analysis in Table 3 shows that parcels with T4 treatment have significantly lower $NDRE_{Field}$ and LAI than other treatments; however, Chl_{Leaf} is not significantly different from T3 treatment. Parcels with T2 treatment have the highest values for all three parameters although the parameters are not significantly different from T3 treatment for $NDRE_{Field}$ and LAI.

[Table 3]

The field and UAV measured NDRE ($NDRE_{Field}$ and $NDRE_{UAV}$, respectively) are moderately associated (R^2 = 0.614) suggesting that more than 61% of $NDRE_{UAV}$ can be explained by $NDRE_{Field}$ (Figure 4(*a*)). The $NDRE_{Field}$ measurements multiplied by LAI explains almost 80% of the $NDRE_{UAV}$ (R^2 = 0.793) (Figure 4(*b*)). This difference of almost 20% suggests that LAI is a critical parameter for the information retrieval using $NDRE_{UAV}$ measurements.

High variability of LAI between and within different treatments (T1-T4) is shown in Figure 4(*c*). The within-treatment variability is more pronounced for T1 and T3 treatments on the graph. However, much higher variability of LAI than the graph suggests was observed for T4 treatment in the field suggesting some possible bias in choosing the sample locations at T4 parcels. This can also be confirmed by negative values of NDRE on the UAV image where the red edge values become higher than the NIR values in some areas of T4 parcels where the terrain elevation/DTM is higher. Generally, higher LAI values are observed for lower DTM values where most likely soil moisture and/or higher concentration of nutrients accumulated from surrounding areas increased corn productivity (Figure 2(*b*)). The within-parcel variability of LAI most likely affects the relationship between $NDRE_{UAV}$ and LAI, which is moderately strong in this study (R^2 = 0.620).

[Figure 4]

$NDRE_{Field}$ and Chl_{Leaf} are not highly correlated (R^2 = 0.363). Although we attempted to measure leaf chlorophyll content at the same location of a leaf from which we measured the reflectance using the hand-held spectroradiometer, either high within-leaf variability of chlorophyll content, or some minor effects of the outside light during the reflectance measurements caused uncertainties. We surmise that high variability of chlorophyll content observed within T4 parcels is the reason for the results (Figure 5(*a*)). However, the difference in the regression relationship between $NDRE_{UAV}$ and chlorophyll is considerably improved when Chl_{Leaf} is multiplied by LAI. The coefficient of determination changes from R^2 = 0.177 to R^2 = 0.774.

The canopy chlorophyll map, Chl_{Canopy} (expressed as Chl_{Leaf} x LAI) is then derived by using empirical algorithm:

$$NDRE_{UAV} = a\,(Chl_{Leaf} \times LAI) - b \qquad (2)$$

where a = 0.002 and b = 0.062 in this study;

$NDRE_{UAV}$, LAI and Chl_{Canopy} and Chl_{Leaf} maps using the proposed algorithm (eq. 2) are demonstrated in Figures 6(*a-d*), respectively. The validation process shows reasonably high correlation between the measured Chl_{Leaf} and $Chl_{Leaf\text{-}estimated}$ with the Pearson correlation coefficient r = 0.712 (Figure 5(*d*)).

[Figure 5]

[Figure 6]

4. Discussion

The results related to vigor status of the four treatments in this study are very similar to those of Simic Milas and Vincent (2016) where Landsat data were used to monitor corn crop status at the same site and under similar conditions in 2014. In summary, the results suggest that T2 treatment shows the highest crop vigor among all treatments. Closely followed by T3, there is no significant difference between T2 and T3 treatments for $NDRE_{Field}$ and LAI. T1 treatment exhibits the lowest crop vigor when compared with other conventional treatments. T4 treatment has significantly lower $NDRE_{Field}$ and LAI than other treatments; however, its chlorophyll content is not significantly different from T3 treatment. We state that the intense early herbicide applications of Roundup and ammonium sulfate in combination with no-till soil management produce the highest crop vigor for T2 treatment during the peak growing season. There are several possible explanations for this trend. The herbicide management used for treatment T2 (Table 1) may have an earlier and a stronger effect on weeds, reducing the crop-weeds competition for nutrients (Green 2014). It is also possible that nutrients and water are leached less in no-till soils having better interactions with the roots at initial contact, which further may increase green leaf productivity (Bender and van der Heijden 2015; Yu, Hui et al. 2016). For opposite reasons, the soil tillage management as well as later and less intense herbicide application (Roundup, in particular) most likely inhibit the early nitrogen uptake for treatment T1 (Simic Milas and Vincent 2016). The insignificant difference between LAI and $NDRE_{Field}$ values for T2 and T3 treatments in this study occurs most likely due to the additional early herbicide application to T3 treatments in 2016, which was not done in 2014. However, that early herbicide application invested in LAI at the expense of chlorophyll content for T3 treatment (Table 1).

When compared with the study of Simic Milas and Vincent (2016), the UAV image demonstrates more variability within- the treatments than Landsat images. Also, T4 treatment has somewhat lower vegetation index values relative to other treatments. Although, this difference for T4 treatments could be due to a slightly different soil status and/or differences in the weather between 2014 and 2016, the difference is most likely the result of different spatial resolutions between UAV and Landsat data. Drone pixels are considerably finer and have higher purity than Landsat pixels, serving more as the ground truth. Open canopies are more pronounced and better captured by UAV. While drone images are more valuable for farmers in precision agriculture, and while they capture within-treatments variability accurately, it is likely that coarser pixel size of satellite imagery such as Landsat data better capture the between-treatment variability and differences between parcels at the ecosystem level.

While physically-based canopy reflectance models, based on radiative transfer principles, show a real potential in employing structural canopy characteristics in the retrieval of leaf chlorophyll content (Simic, Chen, and Noland 2011; Liang et al. 2016), the main limitations of the empirical models are the use of site- and sensor- specific relationships that do not fully account for the influence of the complexity of canopy structure. The empirical models lack robustness and portability from one study area to another (Demarez and Gastellu-Etchegorry 2000). It should be noted that this study incorporates corn grown under different agricultural treatments, which results in high heterogeneity of canopy coverage between the treatments. Most likely, this high heterogeneity causes somewhat lower R^2 values ($R^2 = 0.774$) between NDRE and chlorophyll content than in some other studies where red-edge based indices were also used but over more homogenous areas. Back in 1994, Gitelson and Merzlyak found a strong correlation between the RE band at 700 nm and chlorophyll concentration in higher plant leaves (Gitelson and Merzlyak 1994; Gitelson and Merzlyak 1998). In 2008, Delegido et al. claimed that the combination of the 674 nm and 712 nm wavebands, that corresponded to the maximum chlorophyll absorption and the RE position, respectively, was more sensitive to LAI than NDVI, reaching $R^2 = 0.820$ over several agroecosystems. In the study of Peng et al. (2017), Sentinel-2 data were used to explore the advantages of RE in chlorophyll mapping of corn. While the RE-based chlorophyll index showed a high correlation in their study ($R^2 = 0.890$), the maximum coefficient of determination ($R^2 = 0.920$) was reached using the Normalized Difference Vegetation Index (NDVI), which consists of Red and NIR bands. Although the goal of this study has not been to explore the performance of different vegetation indices, the RE position is praised as a critical spectral region for both LAI and chlorophyll content.

Although the idea of incorporating LAI in the empirical algorithm is not new, this study explores the impact of the fine spatial resolution of UAV images on chlorophyll mapping challenging the hypothesis that LAI may have a less critical role in the canopy chlorophyll mapping using UAV than using satellite imagery. While structural and biochemical vegetation characteristics, such as clumping and chlorophyll content, may vary considerably even within the same species under the same conditions (Houborg and Boegh 2008), in precision agriculture, the coupling between structural and biochemical parameters is essential in spatio-temporal modeling of crop status and yield using UAVs due to rapid phenological changes and high spatial heterogeneity intensified by different treatments and sporadic chemical applications.

Conclusion

This study considered the impact of LAI on the retrieval of chlorophyll content for corn grown under four agricultural treatments: full conventional, full conventional with no-tilled soil, biological with reduced quantities of chemicals and organic treatment. A field campaign was conducted at the Kellogg Biological Station (Michigan, USA) concurrently with the UAV/drone data acquisitions on 11 August 2017. The field campaign included measurements of hyperspectral reflectance using the field spectroradiometer, LAI using the Digital Hemispherical Photography and leaf chlorophyll content acquired with SPAD chlorophyll meter. The empirical model showed that NDRE was a sensitive vegetation index for both chlorophyll and LAI mapping. NDRE was found to be moderately correlated with LAI (R^2 = 0.620). Chlorophyll mapping was significantly improved when LAI was incorporated as an input parameter in the predictive algorithm for canopy chlorophyll content retrieval. The coefficient of determination changed from R^2 = 0.177 to R^2 = 0.774 when LAI was added to the empirical model. While predictive algorithms based on the linear relationship between chlorophyll content and indices may be more reliable for closed canopies, our study showed that LAI considerably enhanced the retrieval of chlorophyll content using UAV for agricultural fields where variability of canopy coverage was high. The conventional corn treatment T2, with no-tilled soil and early herbicide applications exhibited the highest crop vigor during the peak growing season. Organic treatment had the lowest NDRE and LAI but its chlorophyll content was not significantly different from T3 treatment. The herbicide management applied earlier in the season may have a strong effect on weeds, reducing the crop-weeds competition for nutrients.

Acknowledgements

Support for this research was provided by the NSF Long Term Ecological Research Program (DEB 1027253) at the Kellogg Biological Station and by Michigan State University AgBioResearch.

Disclosure Statement

No potential conflict of interest was reported by the authors.

References

Bach, H., S. Begiebing, D. Waldmann, and B. Rowotzki. 2005. "Analysis of hyperspectral and directional data for agricultural monitoring using the canopy reflectance model SLC; Progress in the Upper Rhine valley and Baasdorf test-sites." In *Proceedings of the 3rd CHRIS/Proba Workshop*, ESRIN, Frascati, Italy. ESA SP-593 (21-23 March 2005).

Baret, F., V. Houles, and M. Guerif. 2007. "Quantification of plant stress using remote sensing observations and crop models: the case of nitrogen management." *Journal of Experimental Botany* 58: 869-880.

Barnes, E. M., T. R. Clarke, S. E. Richards, P. D. Colaizzi, J. Haberland, M. Kostrzewski, P. Waller, C. Choi, E. Riley, T. Thompson, R. J. Lascano, H. Li, and M.S Moran. 2000. "Coincident detection of crop water stress, nitrogen status and canopy density using ground based multispectral data." In *Proceedings of the Fifth International Conference on Precision Agriculture*, Bloomington, MN, USA (16 – 19 July 2000).

Begiebing, S., H. Bach, D. Waldmann, and W. Mauser. 2005. “Analysis of spaceborne hyperspectral and directional CHRIS data to deliver crop status for precision agriculture.” In *Proceedings of the 5th European Conference on Precision Agriculture*, J. Stafford, A. Werner (Ed.), Wageningen Academic Publishers, The Netherlands (9-12 June 2005).

Bender, S. F., and M. G. A. van der Heijden. 2015. "Soil biota enhance agricultural sustainability by improving crop yield, nutrient uptake and reducing nitrogen leaching losses." *Journal of Applied Ecology* 52 (1): 228-239.

Broge, N. M., and E. Leblanc. 2001. “Comparing predictive power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf, area index, and canopy chlorophyll density.” *Remote Sensing of Environment* 76: 165-172.

Carter, G.A. 1994. “Ratios of leaf reflectances in narrow wavebands as indicators of plant stress.” *International Journal of Remote Sensing* 15 (3): 697-703.

Chen, J. M., G. Pavlic, L. Brown, J. Cihlar, S. G. Leblanc, H. P. White, R. J. Hall, D. R. Peddle, D. J. King, J. A. Trofymow, E. Swift, J. Van der Sanden, P. K. E. Pellikka. 2002. “Derivation and validation of Canada-wide coarse-resolution leaf area index maps using high resolution satellite imagery and ground measurements.”*Remote Sensing of Environment* 80: 165-184.

Clevers, J. G. P. W., S. M. De Jong, G. F. Epema, F. D. Van Der Meer, W. H. Bakker, A. K. Skidmore, and K. H. Scholte. 2002. “Derivation of the red edge index using the MERIS standard band setting.” *International Journal of Remote Sensing* 23: 3169-3184.

Costa, F. G., J. Ueyama, T, Braun, G. Pessin, F. S. Osorio, P. A. Vargas. 2012. “The use of unmanned aerial vehicles and wireless sensor network in agricultural applications.” In: *Geoscience and Remote Sensing Symposium (IGARSS)*, 2012 IEEE International, Munich, Germany (22-27 July 2012). http://dx.doi.org/10.1109/ IGARSS.2012.6352477.

Curran, P.J. 1989. “Remote sensing of foliar chemistry.” *Remote Sensing of Environment* 30: pp. 271-278.

Dawson, T.P., and P. J. Curran. 1998. “A new technique for interpolating the reflectance red edge position.” *International Journal of Remote Sensing* 19: 2133-2139.

Delegido, J., G. Fernandez, S. Gandia, and J. Modeno. 2008. “Retrieval of chlorophyll content and LAI of crops using hyperspectraql techniques: application to PROBA/CHRIS data.” *International Journal of Remote Sensing* 29 (24): 7107-7127.

Demarez, V., and J. P. Gastellu-Etchegorry. 2000. “A modeling approach for studying forest chlorophyll content.” *Remote Sensing of Environment* 71: 226-238.

Duan, S.-B., Z.-L. Li, H. Wu, B.-H. Tang, L. Ma, E. Zhao, and C. Li. 2014. “Inversion of the PROSAIL model to estimate leaf area index of maize, potato, and sunflower fields from unmanned aerial vehicle hyperspectral data.” *International Journal of Applied Earth Observation and Geoinformation* 26(0): 12 – 20.

Ehleringer, J. R., and C. B. Field. 1993. “Scaling physiological processes: Leaf to globe.” In *Physiological Ecology*, edited by Roy J. Academic Press, Boston.

Elarab, M., A. M. Ticlavilca, A. F. Torres-Rua, I. Maslova, M. McKee. 2015. “Estimating chlorophyll with thermal and broadband multispectral high resolution imagery from an unmanned aerial system using relevance vector machines for precision agriculture.” *International Journal of Applied Earth Observation and Geoinformation* 43: 32-42.

Elvidge, C.D., and Z. Chen. 1995. “Comparison of broad-band and narrow-band red and near-infrared vegetation indices.” *Remote Sensing of Environment* 54: 38-48.

Gage, S. H., J. E. Doll, and G. R. Safir. 2014. "A crop stress index to predict climatic effects on row-crop agriculture in the U.S. North Central Region," In *The ecology of* *agricultural ecosystems: long-term research on the path to sustainability,* edited by Hamilton, S. K., J. E. Doll, and G. P. Robertson, 235-248. Oxford University Press, New York.

Garcia-Ruiz F., S. Sankaran, J. M. Maja, W. S. Lee, J. Rasmussen, R. Ehsani. 2013. "Comparison of two aerial imaging platforms for identification of Huanglongbing-infected citrus trees." *Computers and Electronics in Agric*ulture 91, 106–115. 10.1016/j.compag.2012.12.002

Gitelson A., and M. N. Merzlyak. 1994. "Quantitative estimation of chlorophyll-a using reflectance spectra: experiments with autumn chestnut and maple leaves." *Journal of Photochemistry and Photobiology B: Biology* 22: 247-252.

Gitelson A. A., and M. N. Merzlyak. 1998. "Remote sensing of chlorophyll concentration in higher plant leaves." *Advances In Space Research* 22(5): 689-692.

Gitelson, A. A., A. Vina, V. Ciganda, D. C. Rundquist, and T. J. Arkebauer. 2005. "Remote estimation of canopy chlorophyll in crops." *Geophysical Research Letters* 32: L08403, doi: 10.1029/2005GL022688.

Gitelson, A. A., A. Vina, S. B. Verma, D. C. Rundquist, T. J. Arkebauer, G. Keydan, B. Leavitt, V. Ciganda, G. G. Burba, and A. E. Suyker. 2006. "Relation between gross primary production and chlorophyll content in crops: implications for the synoptic monitoring of vegetation productivity." *Journal of Geophysical Research, Atmospheres* 111(8), [DO8S11], doi: 10.1029/2005JD006017

Green, J. M. 2014. "Current state of herbicides in herbicide-resistant crops. Review." Wiley Online Library. http://onlinelibrary.wiley.com/doi/10.1002/ps.3727/abstract. Accessed July 27 2016. doi: 10.1002/ps.3727.

Houborg, R., and E. Boegh. 2008. "Mapping leaf chlorophyll and leaf area index using inverse and forward canopy reflectance modeling and SPOT reflectance data." *Remote Sensing of Environment* 112: 186-202.

INRA, CAN-EYE software. Url: https://www6.paca.inra.fr/can-eye/. Accessed 20 Nov 2017.

Jacquemoud, S., S. L. Ustin, J. Verdebout, G. Scmuck, G. Andreoli, and B. Hosgood. 1996. "Estimating leaf biochemistry using the PROSPECT leaf optical properties model." *Remote Sensing of Environment* 56: 194-202.

Krishna Kowligi, R. 2016. "Push Button Agriculture: Robotics, Drones, Satellite-Guided Soil and Crop Management," by Apple Academic Press, Inc. Oakville, ON Canada and Waretown, NJ, USA. , ISBN 978-1-77188-304-7.

Lewis P., M. J. Barnsley, and M. Cutter. 2001. "CHRIS-PROBA: Mission status and prospects for mapping surface biophysical parameters." In *Proceedings of the International Geoscience and Remote Sensing Symposium (IGARSS),* Sydney, Australia (9-13 July 2001).

Liang, L., Z. Qin, S. Zhao, L. Di, C. Zhang, M. Deng, H. Lin, L. Zhang, L. Wang, and Z. Liu. 2016. "Estimating crop chlorophyll content with hyperspectral vegetation Indices and the hybrid inversion method." *International Journal of Remote Sensing* 37(13): 2923-2949.

Lichtenthaler, H. K. 1998. "The stress concept in plans: As introduction." *Annals of the New York Academy of Science* 851: 187-198.

Le Maire, G., C. Francois, and E. Dufrene. 2004. "Towards universal broad leaf chlorophyll indices using PROSPECT simulated database and hyperspectral reflectance measurements." *Remote Sensing of Environment* 89: 1-28.

Le Maire, G., C. Francois, K. Soudani, D. Berveiller, J.-Y. Pontailler, N. Breda, H. Genet, H. Davi, and E. Dufrene. 2008. "Calibration and validation of hyperspectral indices for the estimation of broadleaved forest leaf chlorophyll content, leaf mass per area, leaf area index and leaf canopy biomass." *Remote Sensing of Environment* 112: 3846-3864.

Michigan State University, Kellog Biological Station, Long-Term Ecological Research (LTER). 2016. http://lter.kbs.msu.edu/. Accessed 20 November 2017.

Peng Y., A. Nguy-Robertson, T. Arkebauer, and A. A. Gitelson. 2017. "Assessment of canopy chlorophyll content retrieval in maize and soybean: Implications of Hysteresis on the Development of Generic Algorithms." *Remote Sensing*, 9 (226), doi: 10.3390/rs9030226.

Pisek, J., J. M. Chen, J. R., Miller, J. R. Freemantle, J. I. Peltoniemi, and A. Simic. 2010. "Mapping forest background reflectance in a boreal region using multi-angle Compact Airborne Spectrographic Imager (CASI) data." *IEEE Transactions on Geosciences and Remote Sensing*, 48 (1, 2): 499-510.

Pix4D. Url: https://pix4d.com/. Accessed 20 November 2017.

Rautiainen, M., M. Lang, M. Mottus, A. Kuusk, T. Nilson, J. Kuusk, and T. Lukk. 2008. "Multi-angular reflectance properties of a hemiboreal forest: An analysis using CHRIS PROBA data." *Remote Sensing of Environment* 112: 2627-2642.

Ripullone, F., G. Grassi, M. Lauteri, and M. Borghetti. 2003. "Photosynthesis – nitrogen relationships: interpretation of different patterns between *Pseudotsuga menziesii* and *Populus* x *euroamericana* in mini-stand experiment." *Three Physiology* 23: 137-144.

Robertson, G. P., S. L. Collins, D. R. Foster, N. Brokaw, H. W. Ducklow, T. L. Gragson, C. Gries, S. K. Hamilton, A. D. McGuire, J. C. Moore, E. H. Stanley, R. B. Waide, and M. W. Williams. 2012. "Long-term ecological research in a human-dominated world." *BioScience* 62: 342-353.

Robertson, G. P., and S. K. Hamilton. 2015. "Long-term ecological research at the Kellogg Biological Station LTER Site: Conceptual and experimental framework," In *The ecology of agricultural landscapes: long-term research on the path to sustainability,* edited by Hamilton, S. K., J. E. Doll, and G. P. Robertson, 134-152. Oxford University Press, New York.

Salami E., C. Barrado, and E. Pastor. 2014. "UAV flight experiments applied to the remote sensing of vegetated areas." *Remote Sensing* 6: 11051-11081.

Schlerf, M., and J. Hill. 2005. "Estimation of forest biophysical characteristics through coupled atmosphere-reflectance model inversion using hyperspectral multi-directional remote sensing data – A contribution to future forest inventory strategies." In *Proceedings of the 3rd CHRIS/Proba Workshop*, ESRIN, Frascati, Italy. ESA SP-593 (21-23 March 2005).

Sensefly 2017. https://www.sensefly.com/drones/ebee.html. Accessed 20 October 2017.

Simic, A., J. M. Chen, J. Liu, and F. Csillag. 2004. "Spatial scaling of net primary productivity using subpixel information." *Remote Sensing of Environment* 93:246-258.

Simic, A., and J. M. Chen. 2008. "Refining a hyperspectral and multi-angle measurement concept for vegetation structure assessment." *Canadian Journal of Remote Sensing* 34 (3): 174-191.

Simic A., J. M. Chen, J. Freemantle, J. R. Miller, and J. Pisek. 2010. "Improving clumping and LAI algorithms based on multi-angle airborne and ground measurements." *IEEE Transactions on Geosciences and Remote Sensing*, 48 (4, 1):1742-1759.

Simic, A., J. M. Chen, and T. L. Noland. 2011. "Retrieval of forest chlorophyll content using canopy structure parameters derived from multi-angle data: The measurement concept of combining nadir hyperspectral and off-nadir multispectral data." *International Journal of Remote Sensing* 32 (20): 5621-5644.

Simic, A., J. M. Chen, S. G. Leblanc, A. Dyk, H. Croft, and T. Han. 2014. "Testing the top-down model inversion method of estimating leaf reflectance used to retrieve vegetation biochemical content within empirical approaches." *IEEE JSTARS* 7 (1): 92-104.

Simic Milas A., R. K. Vincent 2016. "Monitoring Landsat vegetation indices for different crop treatments and soil chemistry." *International Journal of Remote Sensing* 38(1): 141-160. doi: 10.1080/01431161.2016.1259680.

Smith, M. L., M. E. Martin, L. Plourde, and S. V. Ollinger. 2003. "Analysis of hyperspectral data for estimation of temperate forest canopy nitrogen concentration: Comparison between and airborne (AVIRIS) and a Spaceborne (Hyperion) Sensor." *IEEE Transactions on Geoscience and Remote Sensing*, 41 (6), pp. 1332 – 1337.

Spectral Evolution. Url: http://www.spectralevolution.com/. Accessed 20 November 2017.

Spectrum Technology. Url: https://www.specmeters.com/. Accessed 20 November 2017.

Trout T. J., and K. C. DeJonge. 2017. "Water productivity of maize in the US high plains." *Irrigation Science*, doi: 10.1007/s00271-017-0540-1.

Urso, G. D., L. Dini, F. Vuolo, L. Alonso, and L. Guanter. 2004. "Retrieval of leaf area index by inverting hyperspectral multi-angular CHRIS/PROBA data from SPARC 2003." In *Proceedings of the 2rd CHRIS/Proba Workshop*, ESRIN, Frascati, Italy. ESA SP-578 (28-30 April 2004).

Ustin, S. L., D. A. Roberts, J. A. Gamon, G. P. Asner, and R. O. Green. 2004. "Using imaging spectrometry to study ecosystem processes and properties." *BioScience* 54 (6): 523-534.

Verrelst, J., M. E. Schaepman, and J. G. P. W. Clevers. 2008. "A modeling approach for studying forest chlorophyll content in relation to canopy composition." *The International*

Archives of the Photogrammetry, Remote Sensing, and Spatial Information sciences XXXVII (B7), Beijing, 2008.

Vuolo, F., L. Dini, and G. D'Urso. 2008. "Retrieval of leaf area index from CHRIS/PROBA data: an analysis of the directional and spectral information content." *International Journal of Remote Sensing* 29 (17-18): 5063-5072.

Yu, C-L., D. Hui, Q. Deng, J. Wang, K. Chandra Reddy, and S. Dennis. 2016. "Response of corn physiology and yield to six agricultural practices over six agricultural practices over three years in middle Tennessee." *Scientific Reports*. Url: https://www.openaire.eu/search/publication?articleId=dedup_wf_001::695285092da699d0f0de4c4f68fde614

Zarco-Tejada, P. J., J. R. Miller, G. H. Mohammed, T. L. Noland, and P. H. Sampson. 2001. "Scaling-up and model inversion methods with narrow-band optical indices for chlorophyll content estimation in closed forest canopies with hyperspectral data." *IEEE Transactions on Geoscience and Remote Sensing*, 39 (7): 1491-1507.

Zhang, Y., J. M. Chen, J. R. Miller, and T. L. Noland. 2008. "Leaf chlorophyll content retrieval from airborne hyperspectral remote imagery." *Remote Sensing of Environment* 112: 3234-3247.

Tables:

Table 1. A summary of the four treatments. Note: 0-0-60 potash at 0.0087 kg m^{-2} (70 lbs acre^{-1}) equals 0.0047 kg m^{-2} (42 lbs acre^{-1}) K2O; 19-17-0 liquid fertilizer at 0.01 l m^{-2} (14 gallons acre^{-1}) equals 0.003 kg N m^{-2} (29.22 lbs N acre^{-1}) and 0.003 kg P2O5 m^{-2} (26.14 lbs P2O5 acre^{-1}); 28-0-0 liquid fertilizer (Urea-Ammonium-Nitrate) at 0.041 l m^{-2} (41gallons acre^{-1}) equals 0.0133 kg N m^{-2} (122 lbs N acre^{-1}).

	Corn and treatment type	Fertilizer application	Pesticide application	Tilling
T1	Conventional (CT) Dekalb DKC52-59 Corn Hybrid-GM *(planted 16 May 2017, harvested 18 October 2017)*	8 May 2017: 0-0-60 potash at 0.009 kg m^{-2} (80 lbs acre^{-1}) 16 May 2017: 19-17-0 liquid fertilizer at 0.01 l m^{-2} (14 gallons acre^{-1}) 21 June 2017: 28-0-0 liquid fertilizer (Urea-Ammonium-Nitrate) at 0.041 l m^{-2} (41 gallons acre^{-1})	9 June 2017: Lexar at 0.0007 l m^{-2} (3 quart acre^{-1}) & Roundup Power Max at 0.00016 kg m^{-2} (22 oz acre^{-1}) & ammonium sulfate at 0.00034 kg m^{-2} (3.4 lbs acre^{-1}) [T1r4 Roundup Power Max at 0.0002 kg m^{-2} (32 oz acre^{-1})]	Conventional tillage: spring chisel ploughing followed by secondary tillage
T2	Conventional (CT) Dekalb DKC52-59 Corn Hybrid-GM *(planted 15 May 2017, harvested 18 October 2017)*	8 May 2017: 0-0-60 potash at 0.009 kg m^{-2} (80 lbs acre^{-1}) 15 May 2017: 19-17-0 liquid fertilizer at 0.01 l m^{-2} (14 gallons acre^{-1}) 21 June 2017: 28-0-0 liquid fertilizer (Urea-Ammonium-Nitrate) at 0.041 l m^{-2} (41 gallons acre^{-1})	24 April 2017: Roundup PowerMax at 0.00023 l m^{-2} (1 quart acre^{-1}) & ammonium sulfate at 20.37 kg m^{-2} (17 lbs per 100 gal) & 2,4-D Ester at 0.0009 l m^{-2} (1 pint acre^{-1}) & anti-foaming agent at 1.273 kg m^{-3} (1 oz per 100 gal) 9 June 2017: Lexar at 0.0007 l m^{-2} (3 quart acre^{-1}) & Roundup Power Max at 0.00016 kg m^{-2} (22 oz acre^{-1}) & ammonium sulfate at 0.00034 kg m^{-2} (3.4 lbs acre^{-1})	No till
T3	Biological with reduced input of chemicals (BT) Dekalb DKC52-59 Corn Hybrid-GM *(planted 24 May 2017, harvested 18 October 2017)*	8 May 2017: 0-0-60 potash at 0.009 kg m^{-2} (80 lbs acre^{-1}) 24 May 2017: 19-17-0 liquid fertilizer at 0.01 l m^{-2} (14 gallons acre^{-1})	8 June 2017: Roundup Power Max at 0.00016 kg m^{-2} (22 oz acre^{-1}) & ammonium sulfate at 0.00034 kg m^{-2} (3.4 lbs acre^{-1}) & Dual II Magnum at a rate of 0.00012 l m^{-2} (1.33 pint acre^{-1})	Weed control provided by tillage and by rotary hoeing and cultivation after planting

T4	Biological organic treatment (BT) Blue River Hybrids Corn Hybrid 25M75 Organic Corn-non-GM *(planted 3 June 2017, harvested 18 October 2017)*	None (no manure and no compost added)	None	Weed control provided by tillage and by rotary hoeing and cultivation after planting

Table 2. Summary statistics of field measurement for T1-T4 treatments: field NDRE ($NDRE_{Field}$), leaf chlorophyll content (Chl_{Leaf}) in SPAD units and leaf area index (LAI).

Mean (standard deviation)			
Treatments	$NDRE_{Field}$	Chl_{Leaf} (SPAD)	LAI
T1	0.101 (0.040)	35.705 (8.890)	1.360 (0.429)
T2	0.154 (0.030)	46.727 (3.576)	1.623 (0.219)
T3	0.144 (0.035)	38.828 (8.063)	1.558 (0.456)
T4	0.086 (0.021)	39.672(6.547)	0.752 (0.338)

Table 3. A summary of testing differences between treatment means for field NDRE ($NDRE_{Field}$), leaf chlorophyll content (Chl_{Leaf}) and leaf area index (LAI) collected on 11 August 2017 using ANOVA–Tukey-Kramer approach at the 0.05 level of significance. The *p* values show upper limits of all significant results for a given parameter (SD: Significant Difference; n-SD: non-Significant Difference).

	$NDRE_{Field}$	Chl_{Leaf} (SPAD)	LAI
p for SDs	<0.001	<0.002	<0.000
T1 to T2	SD	SD	SD
T1 to T3	SD	SD	SD
T1 to T4	SD	SD	SD
T2 to T3	n-SD	SD	n-SD
T2 to T4	SD	SD	SD
T3 to T4	SD	n-SD	SD

Figures:

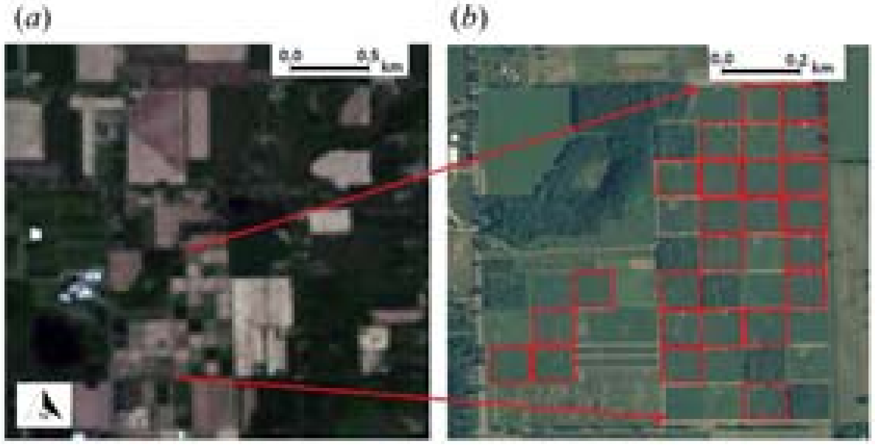

Figure 1. (*a*) Landsat image of the study area: W. K. Kellogg Biological Station, Michigan (42°24′N, 85°22′W); (*b*) distribution of 24 parcels used in the study. Source: USGS and Google Earth (Simic Milas and Vincent 2016).

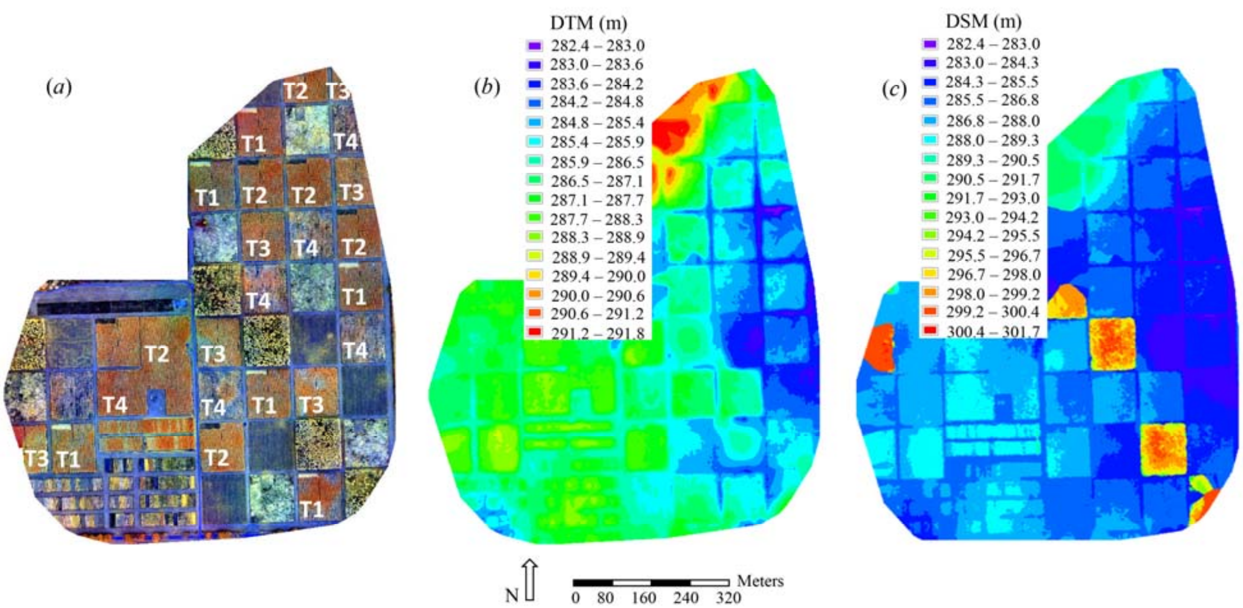

Figure 2. (*a*) UAV composite image (NIR band in red color; RE band in green color; red band in blue color); (*b*) Digital Terrain Model (DTM); (*c*) Digital Surface Model (DSM) generated over KBS on 11 August 2017.

Figure 3. Representative Digital Hemispherical Photographs used in Can-Eye to generate gap fraction and LAI for each treatment (T1-T4).

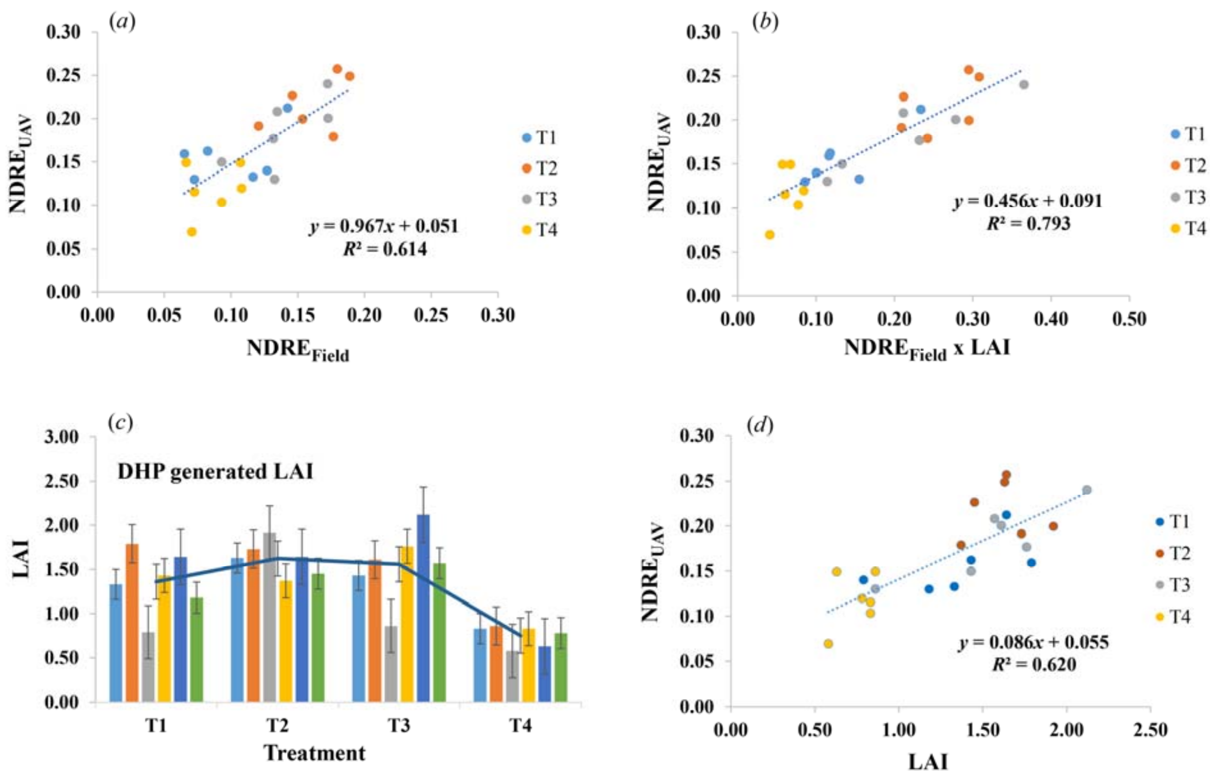

Figure 4. (*a*) Relationships between NDRE calculated from the spectroradiometer measurements ($NDRE_{Field}$) and UAV ($NDRE_{UAV}$); (*b*) Relationships between $NDRE_{Field}$ multiplied by Leaf Area Index (LAI) and $NDRE_{UAV}$; (*c*) LAI calculated using Digital Hemispherical Photography (DHP) averaged for each parcel (error bars represent +/- 1 standard deviation of uncertainty); (*d*) Relationship between $NDRE_{UAV}$ and LAI generated using DHP.

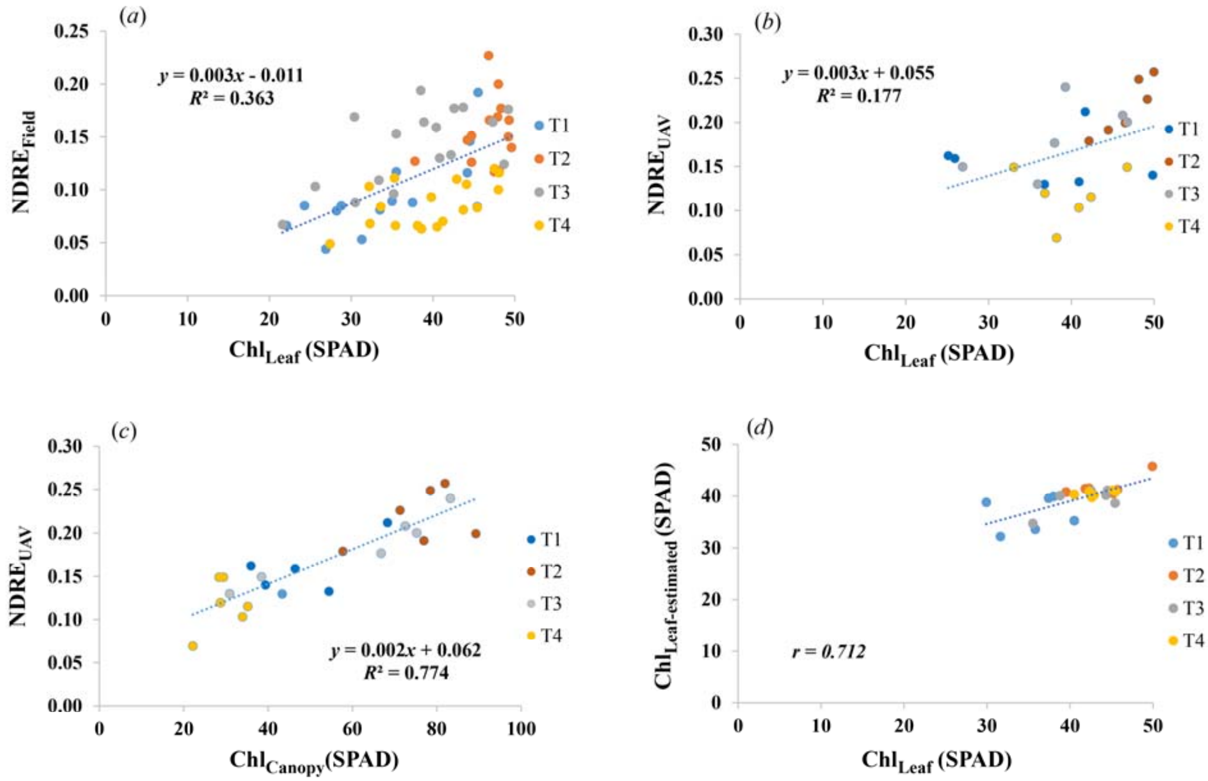

Figure 5. Relationship between (*a*) $NDRE_{Field}$ and leaf chlorophyll content measurements (Chl_{Leaf}); (*b*) $NDRE_{UAV}$ and Chl_{Leaf}; (*c*) $NDRE_{UAV}$ and Chl_{Canopy}; and (*d*) validation of estimated leaf chlorophyll content ($Chl_{Leaf-estimated}$) with Chl_{Leaf}.

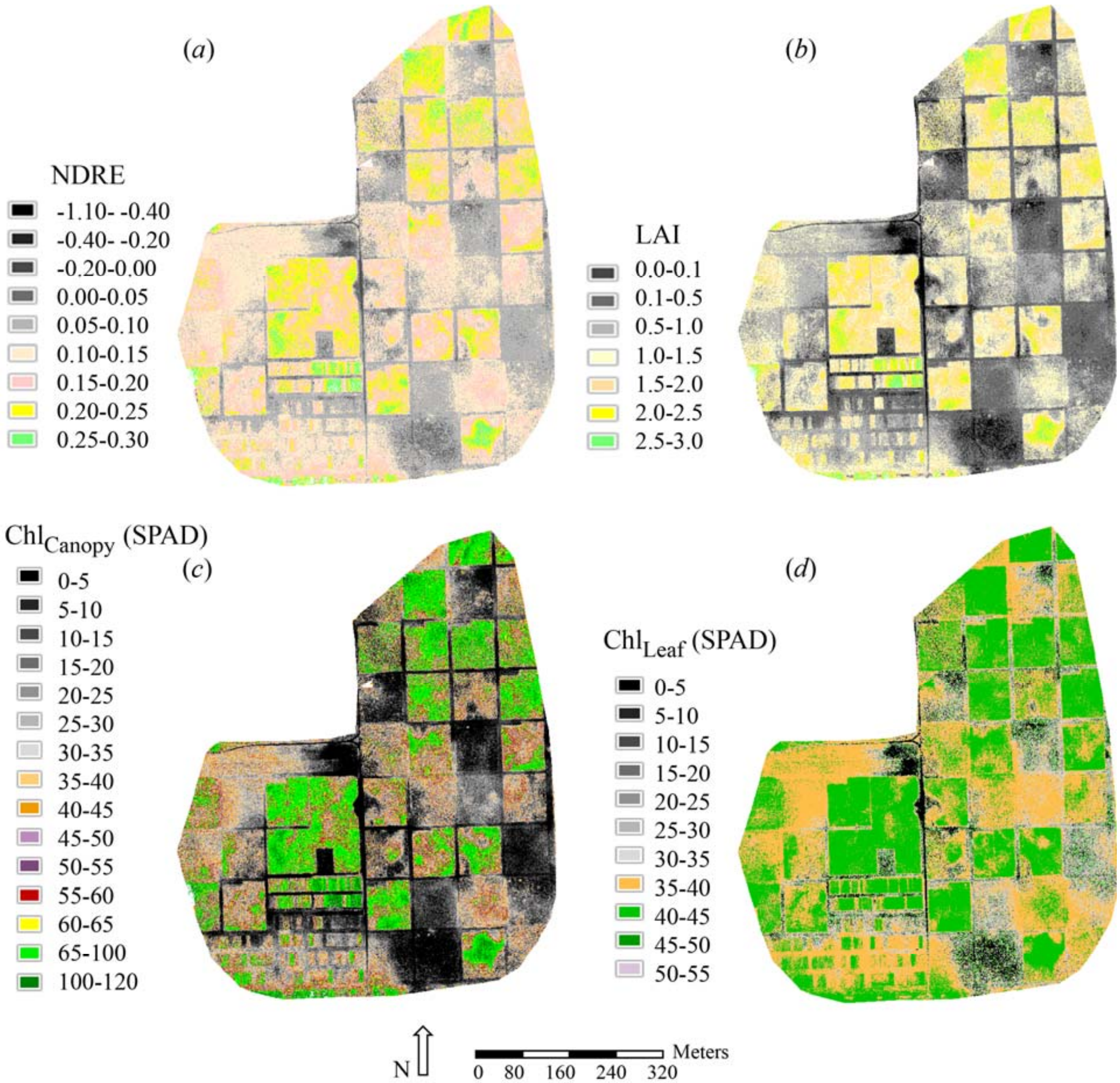

Figure 6. Maps for the KBS site (*a*) $NDRE_{UAV}$; (*b*) LAI based on the $NDRE_{UAV}$ and LAI algorithm (see Figure 4(*d*)); (*c*) Canopy chlorophyll map Chl_{Canopy} (see eq. 2) (*d*) Leaf chlorophyll map Chl_{Leaf} generated from the Chl_{Canopy} and LAI maps.