



DEVELOPMENT OF NEW NON-DESTRUCTIVE IMAGING
TECHNIQUES FOR ESTIMATING CROP GROWTH AND NUTRIENT
STATUS

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CERTIFICATE OF AUTHORSHIP/ORGINALITY

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$ChRGB = R + G + B3 - G$	Equation 4-11	78
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List of abbreviations

Active light source (ALS); lab-based analysed leaf N content (Lab_{Chl}); weeks after treatment (WAT); days after sowing (DAS); dark green colour index (DGCI); red, green and blue (RGB); linear discriminant analysis (LDA); phosphorus (P); Nitrogen (N); chlorophyll (Chl); N-use-efficiency (NUE); genetic algorithm (GA); leaf colour chart (LCC); remote sensing (RS); near infrared (NIR); infrared (IR); visible and near infrared (Vis/NIR); Hydro N Tester (HNt); chlorophyll content index (CCI); joint photographers expert group (JPEG); leaf area index (LAI); ratio vegetation index (RVI); difference vegetation index (DVI); green vegetative index (GVI); land perpendicular vegetation index (PVI); inductively coupled plasma (ICP); normalized difference vegetation index (NDVI); leaf chlorophyll content measured by the modified RGB technique (Chl_{RGB})

ABSTRACT

Leaf dimensions and pigments are the important traits in plants that play a key role in estimating light interception, absorption and food production. In predictive research, these parameters are a useful data source for devising crop management techniques such as cultivation, pruning and fertilisation. Destructive and non-destructive techniques are commonly used for estimating crop growth and nutrient status. Although, destructive methods are more accurate, these are expensive, laborious and impracticable for large fields. In contrast, various non-destructive techniques have been developed for predicting crop N requirements that are relatively fast and less expensive. However, lack of consistency in accurately predicting the true N levels of different crop species under variable environments require further exploration of this area. In the present study, a new and relatively more efficient technique has been proposed for measuring leaf dimensions, chlorophyll, and N and phosphorus (P) content.

In the initial study, leaf images from a range of plant species were collected using a handheld portable digital scanner (Pico Life). Edge detection and filtering algorithms were applied to identify the leaf section of the image against the background. Data of forty leaves that vary in shape and size (from grasses to broad leaf plant species) were collected and processed using a new algorithm as well as the Li-Cor 3100. Data indicated high accuracy of the proposed algorithm for estimating leaf area, length, width and perimeter. It was verified by a strong correlation ($R^2=0.999$) between leaf area measured by Li-Cor 3100 and by digital scanner.

After successful application of the digital scanner for estimating leaf size and dimensions, the images collected by this scanner were used for predicting chlorophyll, P and N content of tomato, broccoli and lettuce leaves. The plants were grown under controlled conditions using nutrient solution and at early reproductive growth (after 8 weeks of growth) these were exposed to various N levels for seven weeks. Data on leaf chlorophyll and N content were collected through biochemical assays (Lab_{Chl}). In addition, data were collected by the SPAD-502 and portable scanner. Images collected by the portable scanner were processed by averaging the R (red), G (green) and B (blue) values of all the leaf pixels. Based on the RGB values, a new algorithm was developed that estimates leaf chlorophyll content (Chl_{RGB}). Despite slight variations in response to

applied N levels in the three crops, the leaf chlorophyll and N content significantly increased with increasing N levels in nutrient solution in the studied crop species. Under N deficient conditions (N0), tomato and broccoli plants showed significantly lower leaf N content just 2 weeks after treatment (WAT), compared with N-treated plants (any N level) suggesting a rapid response of these crops to N deficiency. However, response to various N levels in lettuce was slower and the difference in N concentrations in the leaves of N-deficient (0 and 0.2 N) and N-treated plants became significant at 5 WAT. Compared with leaf N, reduction in leaf chlorophyll levels in response to N deficiency was slow, and the difference in leaf chlorophyll content of N-deficient and N-sufficient plants was significant at 5 WAT in all the studied crops. The chlorophyll values calculated by SPAD and by the modified RGB technique were plotted against Lab_{Chl} and N content. The correlation coefficient (R^2) between SPAD values and Lab_{Chl} was 0.90, 0.73 and 0.81 for tomato, lettuce and broccoli, respectively. In contrast, the relationship between Chl_{RGB} and Lab_{Chl} was relatively stronger and more consistent for all three crop species that is 0.97, 0.90 and 0.91 for tomato, lettuce and broccoli, respectively. Similarly, highly significant relationships (R^2 values) were recorded between the leaf N content and Chl_{RGB} such as 0.94, 0.93 and 0.72 for broccoli, tomato and lettuce, respectively.

The high accuracy of the modified RGB technique for measuring the crop N and chlorophyll content was further confirmed by field-based studies. This technique again outperformed the SPAD-502 in estimating leaf chlorophyll content. For example, R^2 values for SPAD readings and Lab_{Chl} were 0.90, 0.92 and 0.84 for broccoli, tomato and lettuce, respectively. The efficiency of this modified RGB technique was also tested against dark green colour index (DGCI), a commonly used algorithm for estimating leaf chlorophyll and N. The result indicated that the modified RGB technique outperformed DGCI in the precision of predicting leaf Chl levels. A separate study was conducted to estimate N requirements of field-grown cotton using the modified RGB technique, where the efficiency of this technique was compared with other non-destructive methods. The crop was grown under various N levels, and leaf N concentrations were measured at different growth stages; late vegetative, peak reproductive and late reproductive growth phase. The data showed that the modified RGB technique was more effective and accurate in estimating cotton leaf N status compared with the SPAD-502 as well as other handheld crop sensor.

In the final experiment, the leaf P and anthocyanin levels of different crops such as cotton, tomato and lettuce was estimated using the modified RGB technique. The plants were grown under on different P concentrations. Leaf chlorophyll anthocyanin and P content were measured using laboratory techniques, while leaf images were collected by the handheld crop sensor. Using RGB values of the collected images, leaf area, leaf perimeter and chlorophyll content were calculated. These data were further used to train a linear discriminant analysis (LDA) classifier for estimating leaf anthocyanin and P content. In addition, a decision tree model was used to classify cotton plants into different groups containing variable P levels. Both LDA and decision tree models successfully classified these plants on the basis of leaf P content, indicating that P deficiency in crop plants can be predicted using morphological data. It also suggested that the modified RGB technique is highly efficient in estimating P requirements in different crop species.