Image-Based (RBG) Technique for Estimating Phosphorus Levels of Crops

M. M. Ali, Ahmed Al-Ani, Derek Eamus, Daniel K. Y. Tan

Abstract**—**In this glasshouse study, we developed a new image-based non-destructive technique for detecting leaf P status of different crops such as cotton, tomato and lettuce. The plants were grown on a nutrient solution containing different P concentrations, e.g. 0%, 50% and 100% of recommended P concentration (P0 = no P, L; P1 = 2.5 mL 10 L^{-1} of P and P2 = 5 mL 10 L^{-1} of P). After 7 weeks of treatment, the plants were harvested and data on leaf P contents were collected using the standard destructive laboratory method and at the same time leaf images were collected by a handheld crop image sensor. We calculated leaf area, leaf perimeter and RGB (red, green and blue) values of these images. These data were further used in linear discriminant analysis (LDA) to estimate leaf P contents, which successfully classified these plants on the basis of leaf P contents. The data indicated that P deficiency in crop plants can be predicted using leaf image and morphological data. Our proposed non-destructive imaging method is precise in estimating P requirements of different crop species.

Keywords**—**Image-based techniques, leaf area, leaf P contents, linear discriminant analysis.

I. Introduction

CROP plants require sufficient phosphorus (P) supply in the soils for their optimum growth and development. Due to its crucial role in cellular division and expansion, P deficiency can inhibit leaf size, light interception and overall carbohydrate assimilation of plants, resulting in stunted growth [1], [2]. On the other hand, higher P concentration in plant tissues can cause toxicity, leading towards growth inhibition, senescence and development of chlorotic or necrotic region on leaves [3]. Thus, yield penalties can be avoided by estimating crop P requirements and timely fertilisation at early reproductive crop growth phases.

The P requirements of crops are generally estimated through soil and tissue sampling and subsequent laboratory analysis (destructive techniques). These techniques are very accurate, but time consuming and expensive [4]. Due to fast data collection, non-destructive techniques can be a good alternative for crop P estimation. However, unlike N, where various non-destructive techniques are available for estimating crop N requirements, there is hardly any information available on the use of non-destructive techniques for estimating crop P requirements. Since P availability in soils and its application rates can significantly influence growth and vegetation index of any crop, estimating these changes by non-destructive techniques [5], may serve a source for classifying crops on the basis of crop P status.

We proposed a new approach that utilises leaf dimension, area, and colour to estimate crop P level. This was motivated by the strong influence of P supply on leaf expansion [6] and pigments [7]. For this purpose, we used linear discriminant analysis (LDA) and the related Fisher's linear discriminant methods, which can separate two or more classes of objects or events. The resulting combinations can be used as a linear classifier.

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II. Materials and Methods

A. Experimental Design

Three crop species; cotton, tomato, and lettuce were grown in plastic pots under the greenhouse at the Faculty of Science, University of Technology Sydney, Australia. The pots were filled with vermiculite and irrigated using a nutrient solution. For the first seven days, P level in the nutrient solution was kept constant for all plants (2.5 mL 10 L^{-1}), and the nutrient solution was renewed every three days. After seven days, three different P treatments in the form of NaH_2PO_4 were applied for seven weeks, (P0 = no P, L; P1 = 2.5 mL 10 L^{-1} of P and P2 = 5 mL 10 L^{-1} of P). The P levels applied to each pot represent three different levels of recommended P application – P0 = 0%, P1 = 50% and P2=100% of the recommended P concentration for crop plants.

B. Data Collection

Data from the leaves of three studied crops were collected after 8 weeks of treatment. The leaf area (LA) and leaf perimeter (LP) of the youngest (uppermost) fully expanded leaves of individual plants of each crop were measured using a portable leaf scanner (Pico Life). The RGB values of leaf images were also collected. The same leaves were used for measuring leaf P contents using an inductively coupled plasma mass spectrometer (ICPMS).

C. Classification of Plants on the Basis of Leaf P Levels

RGB, leaf area and leaf perimeter values of the three studied crops were used for classifying plants on the basis of leaf P levels using a Linear Discriminant Analysis (LDA) classifier. Three distinct groups of leaf P (P0, P1 and P2) concentration were used. The LDA classifier detected the effect of P treatment on leaf colour and dimensions using a cross validation scheme. In this testing scheme, one sample was used for testing at one time, while all other samples, excluding the testing sample, were utilised for training. The error rate was then computed by observing the ability of the classifier to correctly classify all the testing samples.

D. The Proposed Algorithm

We used a genetic algorithm (GA) to identify the weight that needs to be assigned to each one of the variables. GA is a random population–based search methodology inspired by evolution theories that imply the survival of the fittest. Since, its introduction many variants of genetic algorithms have been developed and applied to a wide range of optimisation problems such as graph colouring, pattern recognition, financial market, and multi-objective engineering optimisation.

In this work, we used continuous chromosome representation to search for the optimal weight of each variable.

We used data on LA and RGB to propose three different formulas that estimate leaf P contents of cotton (1), tomato (2) and lettuce (3).

$$R\times(-0.6466) - G\times0.0203 + B\times1.4837 - LA\times0.3758 \quad (1)$$

$$R1\times1.1236 - G1\times0.6644 - B1\times0.5851 + LA1\times0.0249 \quad (2)$$

$$R2\times1.1236 - G2\times0.6644 - B2\times0.5851 + LA2\times0.0249 \quad (3)$$

The leaf P content of all the three studied crops were also estimated using a single equation (4):

$$1.0811\times R - 0.6518\times G - 0.3780\times B + 0.2248\times LA \quad (4)$$

E. Linear Discriminant Model (LDA

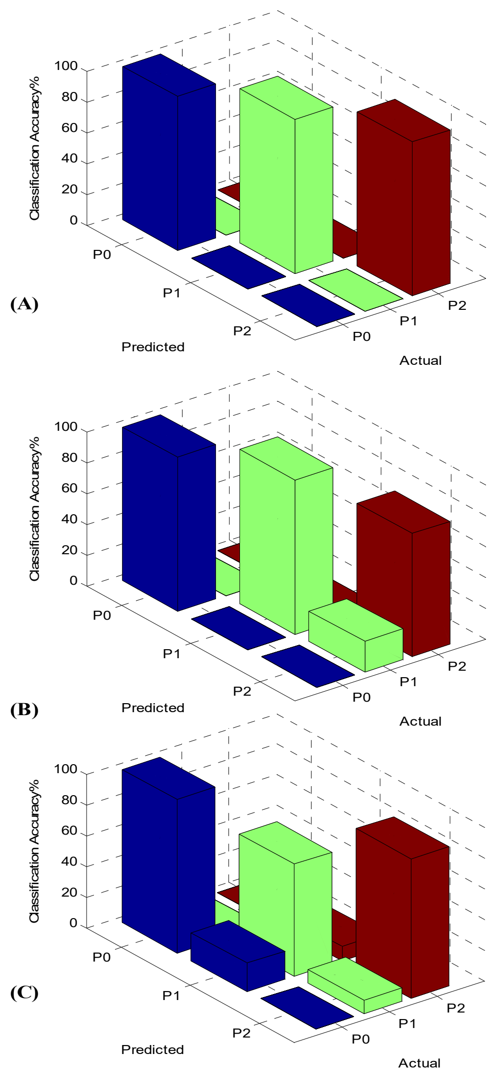
In the present experiment, we have used LDA and related Fisher's linear discriminant method to find the linear combination of features, which best separate two or more classes of objects or events. These combinations were then used as a linear classifier. Considering that we have two classes or categories, which can be related to a certain plant condition (e.g. P sufficient *vs* P deficient), we used LDA to find a projection matrix, when this matrix was multiplied by our original data matrix would increase the distance between the two classes and minimise the distance between samples of the same class.

III. Results and Discussions

LDA-Based Classification of Plants Varying in Leaf P Contents

To classify cotton, tomato and lettuce plants on the basis of leaf P levels, we used an LDA classifier. Using different features such as RGB values, leaf perimeter and leaf area, LDA classifies these plants into 3 distinct classes i.e. P0, P1 and P2. This classifier uses a leave-one-out (LOO) testing scheme that guarantees each testing sample would be used once only. The available data samples were looped in LOO testing scheme by selecting one sample each time for testing, while the remaining samples were used for training. The final error rate was calculated from the number of samples misclassified under the LOO scheme.

The LDA classifier successfully classified the plants into three groups based on the leaf P levels with the error rates of 0%, 20% and 12.12%, respectively, for lettuce, tomato and cotton (Figs. 1 (A)-(C)). The results indicated that leaf growth features in combination with the LDA classifier could be used to estimate crop P efficiently.



	Actual P concentrations in leaf tissues								
	Lettuce			Tomato			Cotton		
Predicted	P0	P0	P2	P1	P2	P1	P2	P1	P2
P0	100	100	0	100	0	0	100	0	0
P1	0	0	0	0	100	0	18	72	9
P2	0	0	100	0	20	80	0	10	90

Fig. 1 Confusion matrix for the classification of (A) lettuce, (B) tomato and (C) cotton plants on the basis of leaf P contents

Since P is required for division and expansion of plant cells, P supply can directly influence leaf size and indirectly its colour [1], [2]. Changes in leaf size and colour are detected by spectral images. LDA used these variables to classify the plants into different group. A high accuracy in grouping the plants on the basis of leaf P contents indicated potential of LDA for estimating crop growth and nutrient (P) status. Zhang and Lei [8] also suggested capacity of LDA for classifying vegetation on the basis of leaf sizes. Similarly, [9] suggested a plant classification model (LDA) that uses leaf characteristics such as shape, contour and colour for separating plants into different groups.

Estimating Leaf P Contents Using Our Proposed Method

The RGB values and leaf area were calculated by the proposed method was used to estimate leaf P contents using different algorithms for each crop (lettuce, tomato and cotton). To validate the efficiency of our proposed method, we compared the estimated P values (computed using RGB-based method) against the original leaf P contents (determined by destructive laboratory technique). Data showed significantly high correlations between the estimated and original P values for lettuce ($R^2 = 0.629$), tomato ($R^2 = 0.7778$), and cotton ($R^2 = 0.807$) (Figs. 2 (A)-(C)).

The readings were further validated using a single formula for all three species. We obtained reasonably good between estimated and actual P levels for all crop species studied. The R^2 values were 0.77 and 0.76 for lettuce and cotton, respectively; although R^2 value for tomato crop was only 0.53 (Table I). These data indicate that customising the formula for individual species can produce more effective estimation of leaf P contents for some crops but may not be useful for a range of crop species. Hence, developing individual algorithms may be preferred for this purpose. Further studies with a wider range of plant species can further confirm this hypothesis. Data obtained with the proposed algorithms together with the LDA and decision tree models suggest that crop P contents can be estimated using non-destructive methods. In addition, our method is simple and straightforward, which not only can estimate P contents of different crops but also can classify the plants on the basis of P application rates. Thus, it can assist in scheduling P application rates and time for crops.

IV. Conclusion

The present study showed that crop P requirements may be estimated on the basis of simple morphological characteristics, such as leaf colour and dimensions. Due to ease of collecting data on leaf colour and dimension using a simple scanner, we suggested that non-destructive methods can be applied for estimating crop P requirements. Using different features and RGB data to train linear discriminant and decision tree models, we successfully classified cotton, lettuce and tomato plants on the basis of leaf P levels. In addition, our proposed algorithms for estimating leaf P showed good relationships with the true leaf P contents indicating that this non-destructive method can efficiently estimate the P contents of crops growing under variable P levels.

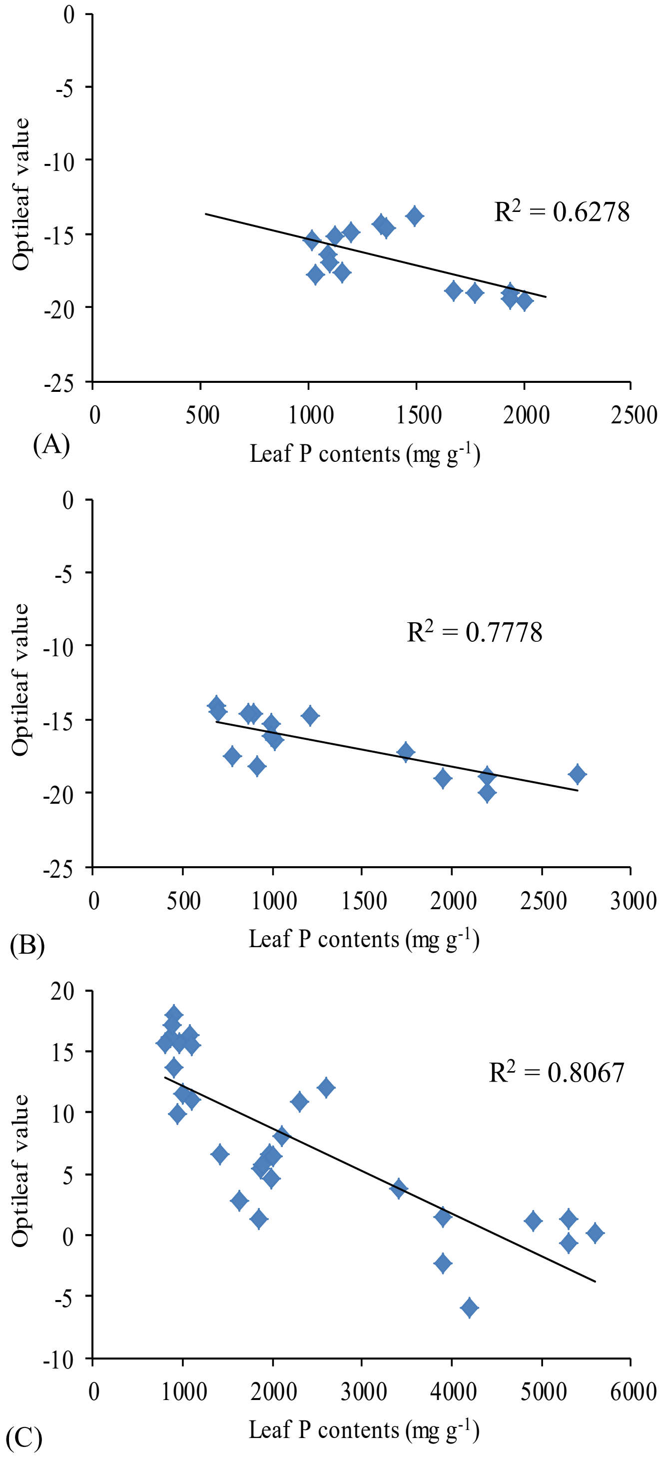


Fig. 2 Correlation between leaf P contents (laboratory based analysis) and values estimated by our proposed method in (A) lettuce, (B) tomato and (C) cotton

TABLE I
CORRELATION COEFFICIENT (R^2) VALUES BETWEEN ESTIMATED (SINGLE EQUATION) AND ORIGINAL P CONCENTRATIONS IN LEAVES

Crop	R^2 value
Lettuce	0.77
Tomato	0.53
Cotton	0.76

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