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Relationship of Foliar Colour Parameters to Paddy Leaf Area Index and Green Red Vegetation Index

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ABSTRACT

Foliar colour is the resultant of physical interaction of light on structureswithin and on surface of leaves. Quantitative representation of foliar colour provides a means to express the condition of crop.The Red, Green Blue (RGB) values from raw digital photographs of rice crops were transformed to CIE L a b colour space in Matlab®. Authors present results that convey strong relation between colour dimension 'a' of *Commission Internationale de l'Eclairage* (CIE) L a b colour model and Green Red Vegetation Index (GRVI). More than 90% variability of Green Red Vegetation Index (GRVI) of rice crop was explained by 'a'. This provides an affordable means for ground based remote observation to monitor crop condition in real-time.

Key Words: Foliar colour, Paddy, CIE L a b, LAI, GRVI

INTRODUCTION

Space based remote sensing is the best available means to monitor temporal dynamics of spatial entities on the surface of the Earth. Periodic updates on crop husbandry (Nain *et al.* 2012) forest health (Dutta *et al.* 2016)ocean (Nagami *et al.* 2015)atmospheric condition (Das *et al.* 2014)etc., derived from remote sensed data, translate as invaluable insights for prudent planning, resource administration and rescue and relief operations. Whilst optical remote sensing has matured with operational systems (Ray *et al.* 2014) they are constrained by their inability to identify *'needles'* in spatial *'haystacks'*. With the advent of big data and analytics realm, computational technology has acquired the capability to identify *'needles'*. Proponents of big data and analytics, rely on data from diverse sources, use multiple analytical techniques and generate various metrics to provide a more comprehensive output. Backed by incisive and colossal computational capabilities of new techniques that can concurrently filter spatial processes/entities with each other, at scales, fine enough to make individual recommendations; the focus lies shifted from macro to micro and even entity level advisories.

A thrust on ground based remote sensing to complement its space counterpart, is a non-negotiable requisite to harness benefits of increased computational capabilities to deliver tailored recommendations. Crowd sourcing and participatory citizen science (See. 2016) approach are two ways to acquire spatio-temporal data that may be screened for useful information. With rapid increase in smart phone density, participatory approach, is today more pragmatic. Trained farmers and fishermen relaying real-time data about crops in field and sea-surface temperatures, are two of the many possible '*ground complements*' that will add to the efforts to findthe *'needles'*. Here, we present a method to assess real-time crop health by measuring leaf color using digital photographs. The technique was demonstrated on potted paddy crop and corroborated withrelationship of colour metric to Leaf Area Index (LAI), estimated using hemispherical imagery and Green Red Vegetation Index (GRVI).

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Colour vision in humans is a perception and not a physical reality. It is generated by opponent mechanism, wherein visual system contrasts different wavelengths of light to produce the perception. Human colour perception results from superposition of neural signals from three kinds of photo receptors (cones), in the human eye. With maximum sensitivities in the Red (peak absorption at 565 nanometre), Green (peak absorption at 535 nanometre), and Blue (peak absorption at 445 nanometre) regions of the electromagnetic spectrum; cones bestow us trichromatic vision (Tabakov, 2013).

Contemporary colour technologies are built on the theory of trichromacy (Horiguchia *et al.* 2013) Digital photographs record colour as trichromatic raster: Red, Green, Blue (RGB).Qualitative representation of color as red, green, blue, etc., infuse subjectivity and masks its potential to be used as 'ground complement'. Whereas, quantitative representation of colour from digital photographs providea means toextract latent information. Quantitative relation between colours and perceived human colours were defined by the *Commission Internationale del' Eclairage* (CIE). The CIE colour space is based on the tristimulus model and addresses limitations of RGB model. In 1976, the CIE adopted *CIE (L ab)* colour model, which is based on the opponent colour system. It is a device-independent, non-linear transformation of the RGB colour space, modeled on human perception. *CIE (Lab)* has linear measures of lightness (L) and two colour dimensions; *a* and *b*that represent spectrum from green (negative) to red (positive) and blue (negative) to yellow (positive) respectively (Kendal *et al.* 2013)

MATERIALS AND METHODS

20gramseach, pre-soakedpaddy seeds were sown in twelve earthen pots of identical size, Fig. 1(a1).All pots were filled with equal volume of cow dung enriched pulverized soil. They were uniformly irrigated dailyat 16.00 Hrs. Digital photographs of the pots were taken daily using Canon EOS 1000Dcamera at 11.00 Hrsfor30consecutive days (from 20April 2017). Camera settings were carefully selected to obtain highest quality and uniform resolution of images. Whilst selection of highest pixel count ensured capture of maximum colour information, lowest sensitivity (ISO) settings, maximized signal to noise ratio.

The images were purposefully underexposed by at least 0.3 to avoid RGB channel saturation that can resultinloss of colour information. RAW file capture option of the camera was used to save the images to avoid information loss through JPEG conversion (Kendal *et al.* 2013). Non-destructiveestimation of leaf area index (LAI) within each pot was concurrently carried out by analysing hemispherical images in Gap Light Analyzer (Frazee *et al.* 1999). Hemispherical images of paddy crops were taken using a detachable hemispherical lens mounted on a smart phone (Fig. 1 a2-e2).

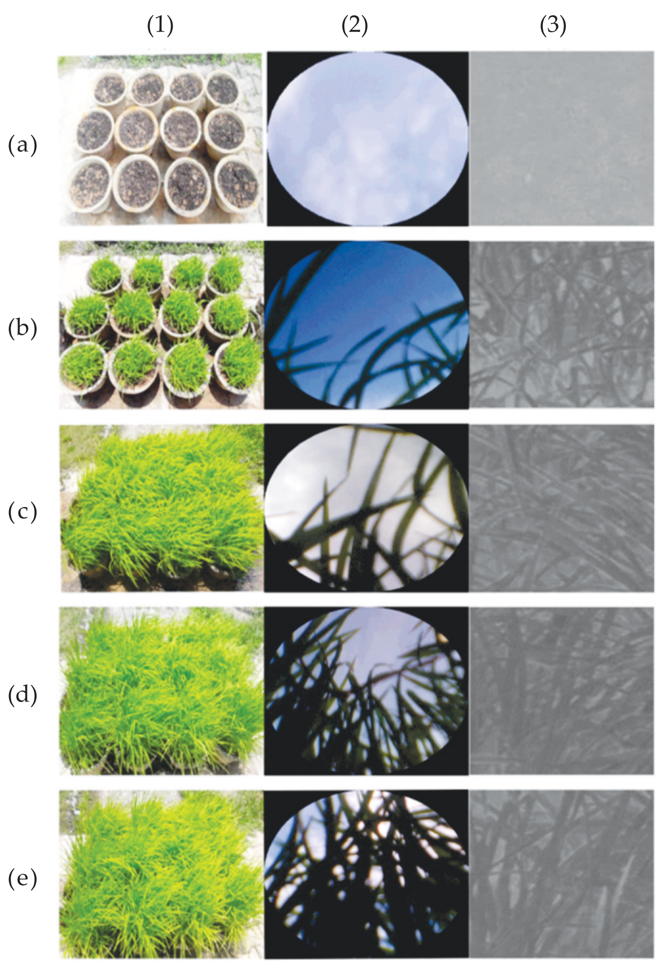

Fig.1:Representative images of (1) paddy crop in pots, (2) Hemispherical image of corresponding day and (3) *'a'* value image of corresponding day. Immediately after sowing (0 Day After Sowing (DAS)); (b) 07th DAS; (c) 15th DAS; (d) 21st DAS and (e) 30th DAS.

The mean R,G,B value of digital photographs within a fixed window (400x400) was recorded as corresponding daily RGB value for each pot. The average R,G,B of the twelve replicates was considered as R,G,B value of paddy crop for a given day. Daily GRVI of paddy was computed from mean RGB values for the day as the ratio of difference of Red from Green, to their sum (Ide *et al.* 2011). Daily mean R,G,B were transformed to *CIE (L a b)*values using standard transformation equations (Hunt and Pointer, 2011)in Matlab® environment (Fig. 1a3-e3). Similarly the average LAI of twelve replicates was taken as the mean LAI of paddy crop for the corresponding day.

Temporal dynamics of *'a'*,and *'L'* values of paddy crop during the study period are depicted in Fig. 2a and Fig. 2b respectively. *CIE (L a b)* values on 1st Day After Sowing (DAS) (82.54, 4.94, 30.23) and 30 DAS (63.08, -40.48, 42.15) correspond to the colours - 'blanched almond' and 'mantis', respectively. As days advanced (with increasing greenness) Fig. 1 (a1-e1); *'a'* value assumed progressively lower negative values (Fig. 2a). The *'L'* value remained more or less stable during the study period (Fig. 2b). Increasing vegetation cover had little effect on blue-yellow axis.

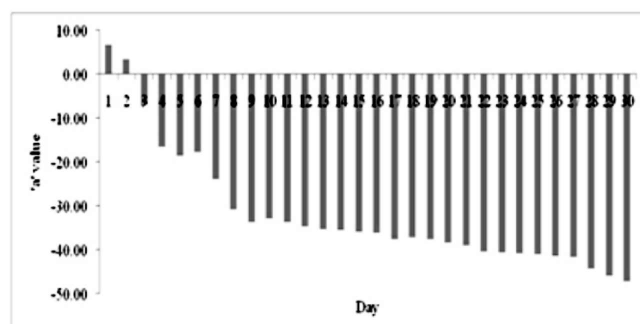

Fig. 2: Progressively decreasing 'a' value of paddy images indicate the shift towards green in CIE L a b colour space

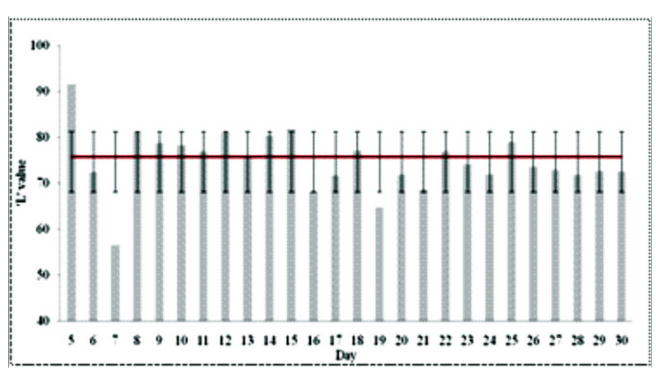

Fig. 2b: Daily 'L' value of the paddy crop during the study period (April 20- May 20, 2017). Error bars indicate Standard Deviation (SD). All 'L' values lie within ±3 SD. horizontal bold line indicates mean 'L' value

Temporal profile of paddy LAI during the study period is shown in Fig. 2c. An almost perfect and significant negative correlation ($r = -0.97$; $p < 0.0001$)observed between GRVI and *'a'* value (Fig. 2d) and strong negative and significant correlation ($r = -0.68$; $p < 0.0001$) between *'a'* value and paddy LAI, underscores the utility of *'a'* value extracted from digital photographs, as a metric of crop condition. The decline of paddy LAI after its peak value of 2.4,could be attributed to severe competition for nutrients within the pots. Whilst satellite derived GRVI has been reported as useful crop phonological indicator (Ide *et al.* 2011) to the best of our knowledge, our methodology and results pioneer the realm of quantitative representation of colour as metric of crop health using *affordable* ground based remote sensing.

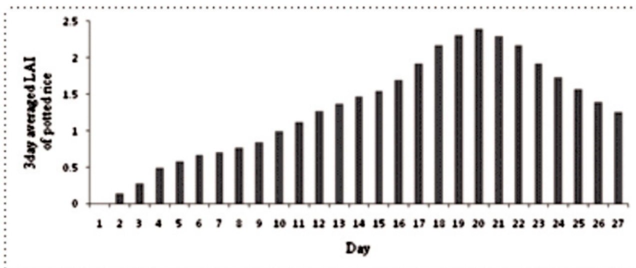

Fig. 2c: Three-day averaged temporal profile of LAI of potted paddy crop

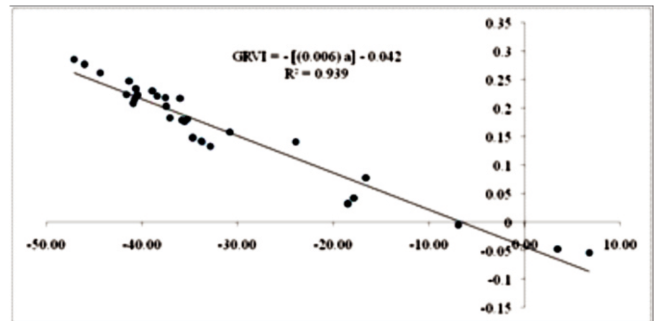

Fig. 2d: Very strong negative correlation observed between GRVI and 'a' value of paddy crop

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