Computer Vision Technique for Optimum Nitrogen Application in Rice

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ABSTRACT
Machine-vision-based yield prediction models were developed for Nitrogen (N) management for rice cultivar: Oryza sativa. Field images of rice plants were acquired using a camcorder mounted on an image acquisition unit (IAU) designed for flooded rice fields. The acquired images were digitized and then segmented into plant and background pixels using a segmentation algorithm based on spatially varying mean intensity values and mathematical morphology. Segmented images were used to extract features related to plant health. Several models were developed to predict yield as a function of N application rate and plant measurements; the measurements included features extracted from the rice plant images, manual size measurements and Y-leaf chlorophyll readings. The best models included 20 variables comprised of combinations of machine vision based measurements and leaf-chlorophyll readings. The models were superior to models based on manual measurements alone. The machine vision based N management system may provide an objective method for performing N assessments and making N recommendations that maximize yield or profit. In the experiment it has been approved that the relationship between nitrogen rate (Aman, Boro) to green pixel is strongly significant. The relationship between nitrogen rate (Aman, Boro) to red pixel is moderately significant and the relationship between nitrogen rate (Aman, Boro) to red pixel is not significant.

Key words- *Machine vision technique, Rice, Nitrogen applicaton, Model development, Image analysis.*

1. INTRODUCTION

In Rice growers rely heavily on one or more applications of Nitrogen (N) fertilizer to provide an appropriate supply of N for plants throughout the owing season. N is needed throughout the growing season to sustain growth and to produce healthy vigorous plants that will have a large yield potential. Likewise, N should not be so abundant that vegetative growth is sustained at high levels late into the growing season, which increases the likelihood of disease, lodging, and reduced grain-filling. Wells and Turner [1] showed that split applications of N during the growing season better utilized the total applied N than a single application of N. The practice of applying N incrementally assists in maintaining an appropriate supply of N for plants throughout the growing season while reducing potential N-losses.

Several methods for assessing N availability in rice have been proposed. Chemical soil tests have been used for other crops, but they have not been used successfully to predict rice plant N uptake [6]. However, assessment methods that use a measure of rice plant health or performance at have been effective in predicting the amount of N fertilizer needed to optimize rice yields [8].

Teo et al. (1995) [16] developed models to predict the nutrient (i.e., NH4+, P, and K) uptake in greenhouse and field grown rice crops. No studies have been conducted to develop models to estimate the mid-season N requirements of rice in order to optimize yield. Customized N application rates that optimized yield will also improve runoff water quality; hence, there is a need to develop a model that can provide N recommendation for optimum yield.

The overall goal of this research was to develop a model based on features from images of rice plants at the growth stage referred to as internode elongation to predict yield as a function of N fertilizer rates. Images of rice plants provide a permanent record of many features of the plants. Images that are acquired in a careful and consistent manner provide the basis for a more objective and reliable measure of height and width than manual measurements. Images also provide a means for measuring other features of plants such as projected leaf area and various measures of plant shape, which are difficult to measure manually. The model based on image extracted features provides a tool for selecting optimum N rates based on criteria such as yield or profit.

Machine vision is based on digital images and tries to mimic human perception to provide information or input to systems that need it for application of site specific crop production. The most common application of machine vision is based on silicon sensors (CCD or CMOS arrays) that are sensitive to the range of 400-1000 nm. Within this group, color machine vision is most common, because of its low price and multitude of information contained in the color images. Color machine vision includes three wide spectral channels (approximately 150 nm FWHM), centered at the three basic colors, red (~ 600 nm), green (~550 nm) and blue (~450 nm). Nevertheless, multispectral cameras employing specific bands have been used to enhance segmentation [4]. The main areas that color machine vision has been developed for precision farming include weed detection for site specific herbicides spraying, row detection for autonomous navigation and fruit detection for yield estimation or robotic harvesting. Maybe the most acute problem with machine vision is the problem of color changes caused by variation in natural illumination, both in intensity and spectral content. Common practice when dealing with intensity changes is the use of color ratios, whereas changes in spectral content present more of a problem. Various methods have been proposed for image binarization when the intensity of the illumination varies ([3],[11],[12]). These methods are based on ratios between color channels, or indices like Excessive Green (EG) and Red minus Blue (RB), or the angular position of a pixel in a plane normal to the illumination vector in the R, G, and B coordinate space. Spectral changes in the illumination can also be compensated when assumptions about the functional form of the illumination's spectral characteristics are made. Most of the activities in precision agriculture are performed outdoors under natural daylight. When natural sunlight is considered as the illumination source, it can be represented in a form whereby it is possible to derive a monochrome image that is invariant to illumination spectral changes, from a 3-band color image. Precision agriculture in orchards considers the tree as an individual production unit. In such an approach, sensing technologies are required in order to provide information about the status of each tree, regarding the nutrients, water status, fruit load and yield. The technology for nutrients and water status detection is similar for field crops. Nevertheless, yield estimation, as well as site specific (tree specific) handling often depends on the fruit load of the tree. Therefore, much effort has been invested in automatic fruit detection and yield estimation of fruits. Some of the fruits have distinct color differences from the foliage and make them more distinguishable (for example mature oranges, red apples) and others have colors similar to that of the tree canopy, making them more difficult to detect (for example immature oranges and green apples). Color machine vision has been found useful for detection of Fuji apples (red in color) in the tree canopy when the color contrast is high [5]. Multispectral imaging showed the potential for detecting immature green oranges [7]. Hyperspectral imaging, along with morphological image processing was also shown to have good potential for detecting green apples in the tree canopy [10]. Occlusion is an obstacle to two-dimensional machine vision recognition of fruits and plants in natural outdoor scenes. The watershed algorithm was proved to be suitable to improve the recognition of occluded fruits in a tree canopy, as well as plant leaves ([10],[14]).

The objectives of this research were to:

1. To develop a model using machine vision technique to predict Nitrogen requirements for rice.
2. To determine the relationship between image pixels to fertilizer rate.

2. MATERIALS AND METHODS

The experiment was conducted at the period from August to December 2010 at the Agronomy Field Laboratory of Bangladesh Agricultural University, Mymensingh to evaluate the effect of N fertilizer.

2.1Description of the Experimental Site

2.1.1 Location

The experimental site was located 24075' latitude and 90050' E longitude at an elevation of 18 m above the sea level under the Old Brahmaputra flood plain (Agrological zone-9) [13] in Bangladesh Agricultural University (BAU), Mymensingh. The region occupies a large area of Brahmaputra sediments which are laid down before the river shifted into its present Jamuna channel about 200 years ago [13].

2.1.2 Soil

The soil of the experimental field belongs to the sonatola soil series of no calcareous cark grey flood plain soil under the Ole Brahmaputra Alluvial Tract which is more or less neutral in reaction with 1.86% organic matter content and ph value 6.8. The experimental field was a medium high land and well drained condition. The physical, chemical and morphological properties of the soil are given in Table 2.1

Table 2.1 Taxonomic, Morphological, Physical and Chemical Characteristics of Soil

A. Taxonomic Soil Classification		
Order	:	Inceptisol
Suborder	:	Aquepts
Subgroup	:	Aeric Haplaquepts
Soil series	:	Sonatala
B. Morphological Characteristics		
Location	:	Agronomy field Laboratory, BAU, Mymensingh
AEZ	:	Old Brahmaputra Floodplain (AEZ 9)
General soil type	:	Non-calcareous Dark Grey Floodplain soil
Parent material	:	Old Brahmaputra river borne deposits
Drainage	:	Moderate
Topography	:	Medium highland, fairly level
Flood level	:	Above flood level
Cropping pattern	:	Rice crop grown year round (rice-rice)
C. Textural Class		
% Sand	:	10.64
% Slit	:	78.00
% Clay	:	11.36
Textural class	:	Silt loam
D. Chemical Characteristics		
pH (Soil:water =1:2.5)	:	6.69
Organic matter (%)	:	1.86

Total N (%)	:	0.07
Available P (ppm)	:	9.11
Available S (mg kg^{-1})	:	7.14
Exchangeable K ($cmol\ kg^{-1}$ soil)	:	0.17
Cation exchange capacity ($cmol\ kg^{-1}$ soil)	:	12.06

2.2 Layout of the Experiment

The experiment was laid out in Split-Plot Design with three replications. The entire experimental area was divided into four blocks; block was divided into fourteen unit plots. Thus the total number of unit plots was 56. The size of each unit plot was 5 m x 2 m and plots were separated from each other by drains (100 cm). Unit bock was separated from one another by 25 cm. The treatments were randomly distributed to the plots in each block. The layout of the experiment is shown in Fig.2.1

<table>
<tr><td rowspan="3">F_1</td><td>S_1</td><td>F_3</td><td>S_1</td><td rowspan="2">F_3</td><td>S_2</td><td rowspan="2">F_4</td><td>S_2</td></tr>
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<tr><td rowspan="2">F_4</td><td>S_1</td><td>S_1</td><td>S_2</td><td>S_2</td></tr>
<tr><td>S_2</td><td>F_4</td><td>S_3</td><td>S_3</td><td>S_1</td></tr>
</table>

Fig.2.1 Layout of the plot

R_1	Replication 1	F_2	fertilizer N_{100}kg ha^{-1}
R_2	Replication 2	F3	fertilizer N150kg ha-1
R_3	Replication 3	F4	fertilizer N200kg ha-1
R_4	Replication 4	S_1	Treatment 1
F_0	fertilizer N_0 kg ha^{-1}	S_2	Treatment 2
F_1	fertilizer N_{50}kg ha^{-1}	S3	Treatment 3

2.3 Experiment

A field experiment was conducted in 7-8 August 2010 at the Agronomy Field. The experiment was designed to induce various levels of N stress in 36 plots of rice of the long-grain cultivars *Oryza sativa*. The experimental design was randomized block, with three replications and a two-factor factorial arrangement of treatments. The two factors were preflood N rate (0, 50, 100, 150, and 200 kg/ha) and Nitrogen rate (0, 38, 76, and 100 kg/ha).

On 7-8 August 2010, samples and field measurements were acquired from a 17.8 cm x 28 cm area of each plot. Conventional procedures were used to measure plant area, leaf color, leaf N content, and biomass. At the time the standard tests were performed carefully staged color images of the plant canopy in each plot were recorded by digital camera.

The features extracted from the images and the measurements obtained using conventional methods were then used to develop models for yield. Plant height and width measurements using the manual plant area method were compared with the image analysis method. A model based on the features extracted from the images as well as chlorophyll meter readings was developed to predict mid-season N requirements.

2.4 Image Acquisition and Processing Equipment

An image acquisition unit (IAU) was designed and constructed for acquiring the field images. The IAU consisted of a camera, web cam etc. A laptop is used for further processing. The system is governed as two methods:

1. Real time or Online: In online system the webcam is used for uploading images. The downward view of the rice leaf is taken.
2. Offline: In offline system the picture is taken by a digital camera. Then it is taken to laptop for further acquisition.

2.5 Processing and Feature Extraction

While image quality from the naturally illuminated field scenes was sufficient for human visual inspection, ordinary image segmentation algorithms were not sufficient to differentiate many of the plant pixels from the background pixels. An algorithm incorporating spatial segmentation and mathematical morphology was developed to compensate for non uniform intensity levels and to eliminate artifacts occurring in the image due to the motion of the leaves. The algorithm provided an effective means of automating the classification process for pixels.

The segmentation algorithm produced binary images that contained only the necessary information for extracting the plant border and other plant features. Various image-based features related to plant shape and size, thought to be related to plant health, was developed. The procedures for extracting these features are included as:

1. Total projected plant area (PAt.)
2. Five measures of plant height (PH) denoted as plant features PH1-PH5 and based on horizontal leaf densities of 10, 15, 20, 25, and 30 pixels, respectively.
3. Five measures of plant width (PW) denoted as plant features PWI-PW5 and based on vertical leaf densities of 10, 15, 20, 25, and 30 pixels, respectively.
4. Maximum horizontal deviation of any leaf from the vertical axis extending from the base of the plant, termed "leaf spread" (LS).
5. Maximum plant height (PHmax).
6. Maximum plant width (PWma).
7. The height corresponding to PWmax (Hpw).
8. Ratio of vertical position of maximum width to plant height 'maximum width position' (MWP).
9. A measure of shape or slope of the top of the canopy cross-section using the ratio of a characteristic vertical dimension to a characteristic horizontal dimension, where the vertical dimension was the vertical distance to the top of the plant from the height of the maximum width of the plant, and the horizontal dimension was one half of the maximum width - "maximum width slope" (MWS).

2.6 Model Development

Several multiple linear regression models were developed to represent the relationship between leaf pixels to Nitrogen Application Rate (NAR). The models were based on the conventional measurements (i.e., plant area and chlorophyll meter) and/or image extracted features. The four models studied were:

1. yield = f(NAR, PFN, GP), where PFN was the pre-flood N rate, and Green Pixel (GP)
2. yield = f(NAR, PFN, PH_m, $PW_{m.}$), where PHt. and PWrnan were the manual measurements of plant height and width using the plant board method developed by Wells and Norman [2] as described in Casady et al. [15].
3. yield = f(NAR, PFN, image extracted features), where image extracted features included all of the features that were extracted from the image.
4. yield = f(NAR, PFN, image extracted features, GP).

Models I and 2 were based only on conventional measurements while model 3 was based only on machine vision measurements and model 4 was a hybrid model based on both conventional and image extracted measurements. In developing each model, the interactions between NAR and NAR^2 with all other measurements were considered. Interactions between some of the features and squared terms that had physical meaning were also included in models 3 and 4.

Because models 3 and 4 became quite large, they were arbitrarily limited to an evaluation of the best 20-variable models.

2.7 Flow chart of the program

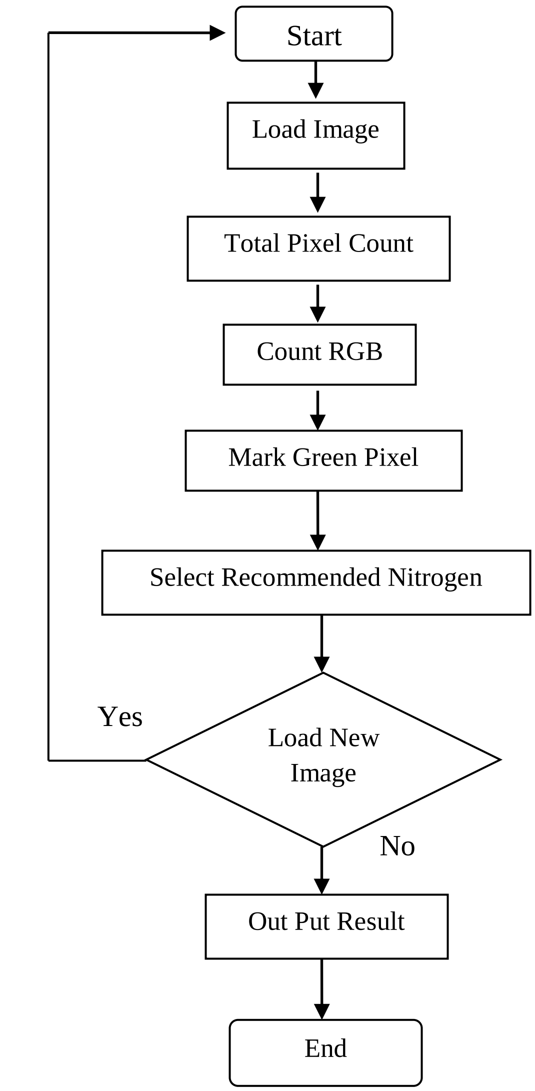

Fig.2.2 Flow chart of the program

3. RESULTS AND DISCUSSION

The images were collected by a digital camera and then converted into digital, true color (24 bit) bitmaps (1024 x 768 pixels in BMP format) by a scanner. The converted digital photos were then saved for analysis. Fourteen images were kept for analysis. Binary classes of rice leaf pixels were created for each rice leaf photo by splitting the 24 bit color images into individual RGB planes. Nitrogen was applied by knowing the value of green pixels at the right amount which was based on the recommendation of Leaf Color Chart (LCC). The images then were analyzed by the program that was modeled.

3.1 Plant Height

The rice differed significantly in terms of plant height. Plant height of 200 kg fertilizers was significantly higher for the variety. The application of different levels of N progressively increased the plant height of rice.

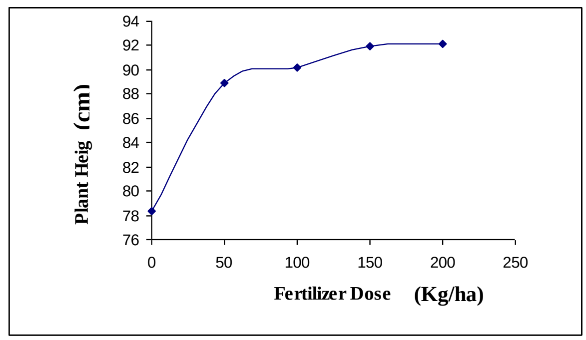

Fig.3.1 Effect of fertilizer dose on plant height

Plant height varies from 78.3 cm to 92.1 cm at control plot and 200 kg ha-1 urea used, respectively shown in Fig.3.1. The treatment ranked in order of $N_{200}>N_{150}>N_{100}>N_{50}>N_0$ with respect of plant height. Similar response of plant height to N dose also observed by Haque et al. [9].

3.2 Grain Yield

Grain yield was the most important parameter of this study. It was found that the mean grain yield due to application of different levels of N fertilizer ranged from 3.1 to 5.1 t ha-1.

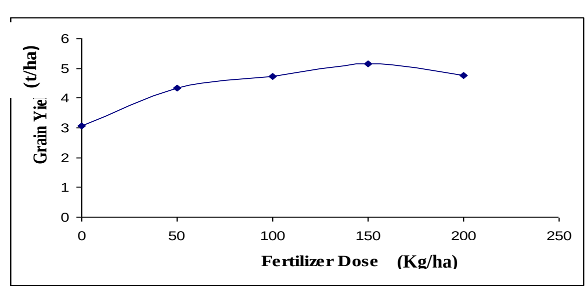

Fig.3.2 Effect of fertilizer dose on grain yield

The highest mean grain yield (5.1 t ha^{-1}) was recorder in N_{150} (150 kg ha^{-1}) and the lowest yield (3.1 t ha^{-1}) was recorded in N_0 shown in Fig.3.2. The effect of variety in N application with response to grain yield was statistically significant. The grain yield for was the highest because all its yield components perform the best.

3.3 Leaf Area Index

The different levels of N application had significant effect on leaf area index of rice. The leaf area index in different levels of N application varied from 2.7 in control treatment to 4.6 in N_{200} (200kg urea per ha) treatment.

Leaf area index (%) = (Total area of the leaf/Projected area) x 100

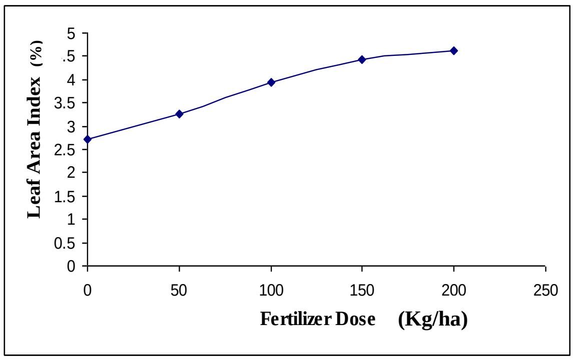

Fig.3.3 Effect of Fertilizers Dose on Leaf Area Index

The highest LAI (4.6) was recorded in N_{200} (200 kg urea per ha) and the lowest (2.7) was recorded in N_0 (0 kg urea per ha) shown in Fig. 3.3.

3.4 Findings from the image analysis

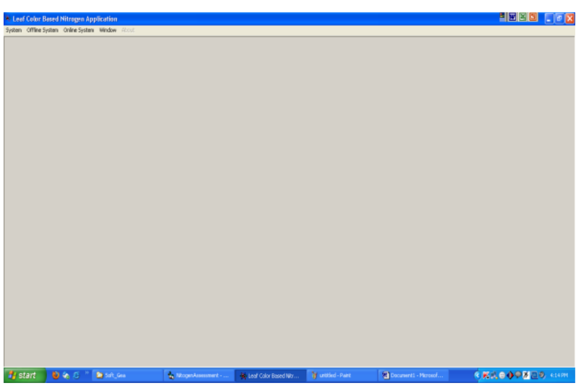

Fig.3.4 Opening page of the Software

The procedure of image analysis step by step which was done from the stored images that we kept and the appearance of the screen of the modeled program can be described as Fig. 3.4

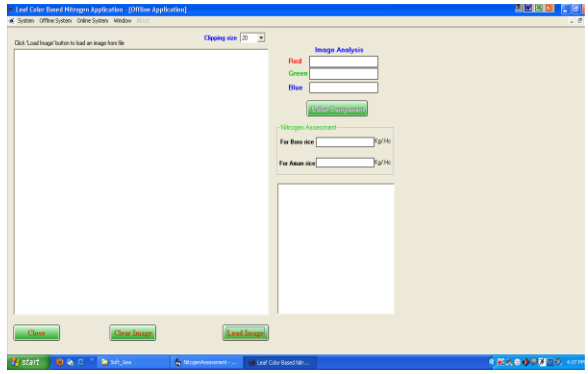

Fig.3.5 The main Graphical User interface of developed program.

The first page of this software is the blank page which waits for command for next attempt as offline or online system. The page is titled as Leaf Color based Nitrogen Application. The offline system page was found shown in Fig.3.5. It was seen that the screen had a title bar named Leaf Color based Nitrogen Application and the screen contained many other thing, namely there had many command buttons namely Load Image, Clear Image, Start Processing and there also some text box named Red, Green, Blue under the topic Image analysis and the information that we got from the Nitrogen Assessment for Boro and Aman rice in kg/hac. Some information about command buttons and the appearance of text shown below:

1. Load Image: This command button load the image that was stored for analysis and that was in the screen.
2. Clear Image: This command button clear the unnecessary image or to analyze the other image.
3. Start Processing: This button at a time process the image into binary classes of rice leaf pixels were created for each rice leaf photo by splitting the 24 bit color images into individual RGB planes. Then depending on the value of green pixels the nitrogen assessment text declare amount of nitrogen required for Boro and Aman rice in kg/hac

respectively. The flow chart of the program (Fig.2.2) represents the stored images that contained a file named modinew.

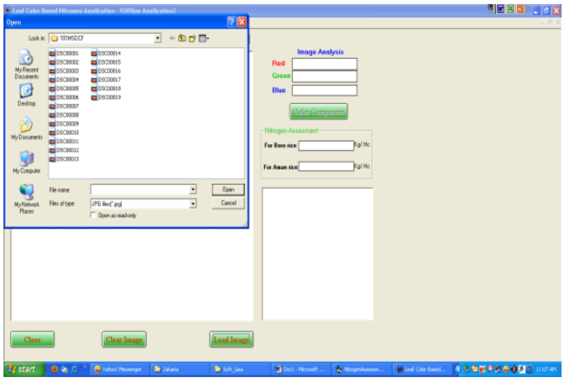

Fig.3.6 Image loading system

From that screen it is observed that when we click the Load Image command button then this screen is appeared. Then we select the image File name and also select the Files of type i.e. All Files (*.*) and then after clicking the open button and finally the image was ready for analysis shown in Fig.3.6

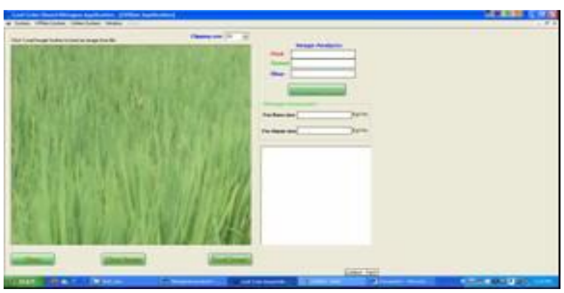

Fig.3.4. Graphical User Interface at loading

The screen that appeared when the image was loaded. When the image is completely loaded then the screen seems alike the Fig.3.4

Fig.3.5. Example of image acquisition

From the screen show in Fig.3.5 it is observed that the value of Red, Green and Blue pixels were 130, 171 and 98 respectively and for the value of green pixels we got the amount of nitrogen for Boro and Aman 17.5 & 14.9 kg/ha respectively according to the recommendation of LCC.

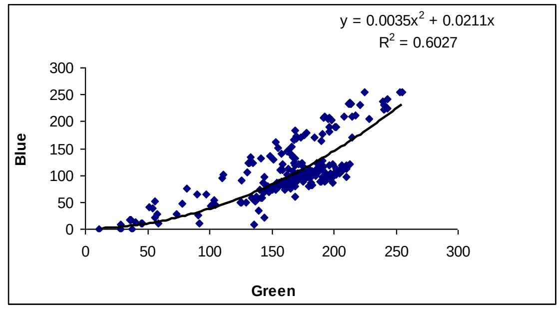

Fig.3.6. Relationship between Green pixels to Blue pixel

The relationship between pixels to its yield for Aman and Boro is given in Fig.3.6. A curve is found. The relationship between blue pixels to green pixel is not significant.

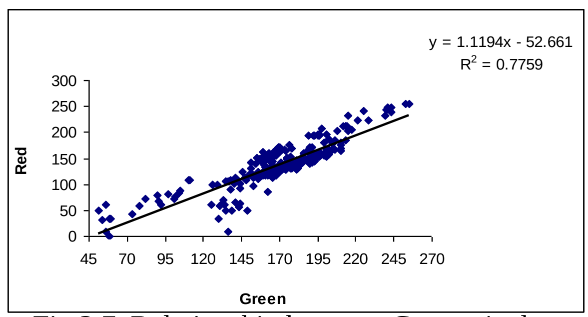

Fig.3.7. Relationship between Green pixel to Red pixel

The relationship between green pixel to red pixel shown in Fig.3.7. A straight line is found. The relationship between blue pixel to green pixel is moderately significant.

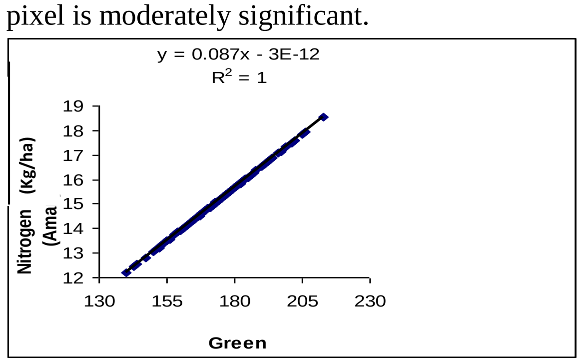

Fig.3.8. Relationship between Green pixel to Nitrogen Rate (Aman)

The relationship between nitrogen rate (Aman) to green pixel shown in Fig.3.8. A straight line is found. The relationship between nitrogen rate (Aman) to green pixel is strongly significant.

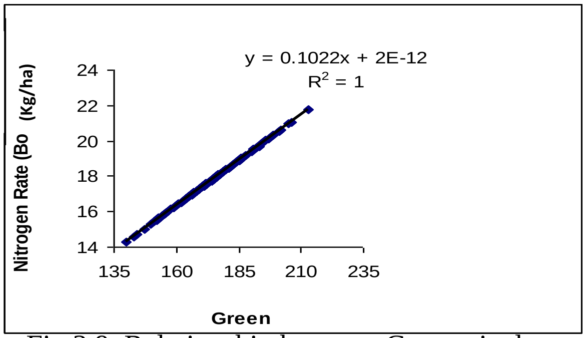

Fig.3.9. Relationship between Green pixel to Nitrogen Rate (Boro)

The relationship between nitrogen rate (Boro) to green pixel shown in Fig.3.9. A straight line is found. The relationship between nitrogen rate (Boro) to green pixel is strongly significant.

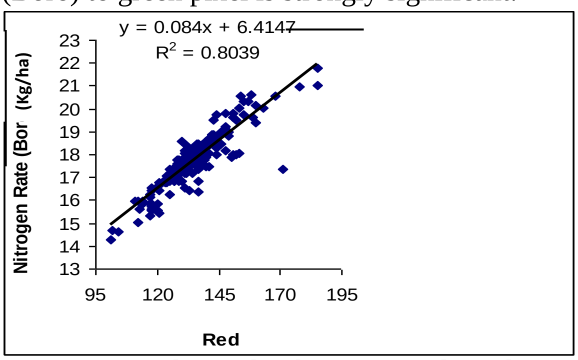

Fig.3.10 Relationship between Red pixel to Nitrogen Rate (Boro)

The relationship between nitrogen rate (Boro) to red pixel shown in Fig.3.10. A straight line is found. The relationship between nitrogen rate (Boro) to red pixel is moderately significant.

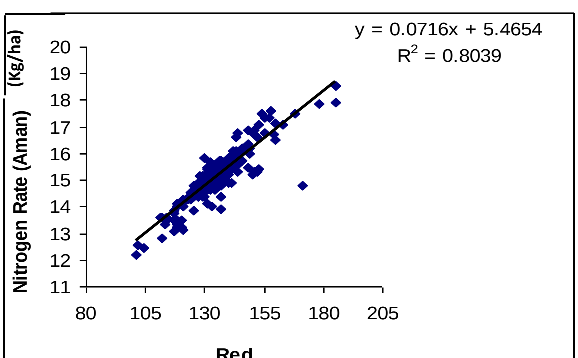

Fig.3.11 Relationship between Red pixel to Nitrogen Rate (Aman)

The relationship between nitrogen rate (Aman) to red pixel shown in Fig.3.11. A straight line is found. The relationship between nitrogen rate (Aman) to red pixel is moderately significant.

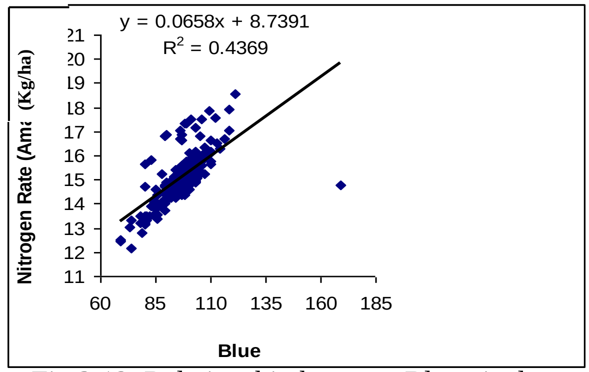

Fig.3.12. Relationship between Blue pixel to Nitrogen Rate (Aman)

The relationship between nitrogen rate (Aman) to blue pixel shown in Fig.3.12. A straight line is found. The relationship between nitrogen rate (Aman) to red pixel is not significant

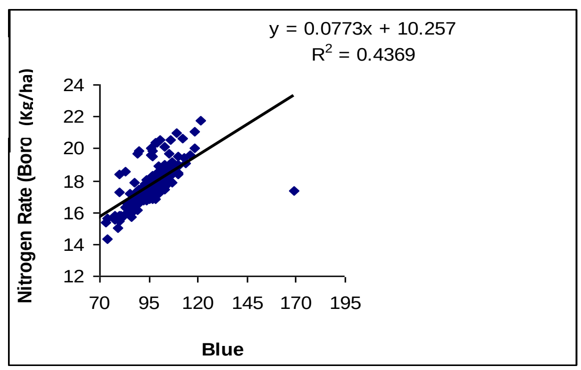

Fig.3.13 Relationship between Blue pixel to Nitrogen Rate (Boro)

The relationship between nitrogen rate (Boro) to blue pixel shown in Fig.3.13. A straight line is found. The relationship between nitrogen rate (Boro) to blue pixel is not significant.

4. SUMMARY AND CONCLUSION

As nitrogen is a component of essential crop compounds required in numerous biological processes, including genetic transmission, crop growth (proteins, enzymes) and photosynthesis (chlorophyll) and nitrogen is also the nutrient that is most likely to be lost to the environment. Excess nitrogen in the environment can adversely affect humans, animals and the biology of the environment. So it should need to improve its using efficiency, by improving its efficiency and proper management will produce the optimum yield of a crop. Therefore for good management of nitrogen fertilizer and to increase its use efficiency and is to apply the nitrogen fertilizer at an optimum level the use of a computer programming(Using visual basic computer programming language) which is based on color images of rice leaf is the best. Therefore development of this computer program and its use is very much essential; because of increasing the nitrogen use efficiency will give the optimum yield and reduces the nitrogen loss at an optimum level.

5. REFERENCES

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