UTILIZING IMAGE PROCESSING METHODS FOR RICE PRECISION FARMING: EXPERIENCES SHARING

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ABSTRACT

The average rice self-sufficiency rate in Malaysia for the year 2019–2022 is 62.5% with an average yield of 3.528 tonnes per hectare. The biggest challenges currently facing local farmers in rice cultivation are water scarcity, the rising costs of fertilisers, herbicides and pesticides and the lack of labour. Therefore, a shift from traditional agriculture to modern agriculture is needed to boost the paddy and rice industry and improve food security. Precision farming (PF) technologies can offer significant potential to increase productivity, profitability, sustainability and environmental protection on farms by using information technology to target the use of inputs. PF is agricultural management that involves the identification and management of variability on the farm. Image processing is generally regarded as one of the most important technologies for interpreting and extracting information from digital images for PF. To date, image processing techniques have been successfully used in a variety of applications for PF in rice farm management. This paper covers the utilization of image processing methods in rice PF technologies for crop density monitoring, fertilizer management and yield prediction.

Keywords: Rice, precision farming, image processing

INTRODUCTION

Precision farming (PF) technologies can significantly increase the productivity, profitability and environmental sustainability of agriculture through the targeted use of inputs (Liaghat and Balasundram 2010). According to Shanwad et al (2004), PF is the application of technologies and principles to manage the spatial and temporal variability associated with all aspects of agricultural production in order to improve production and environmental quality. Successful implementation of PF depends on numerous factors, including the extent to which conditions within a field are known and manage, the adequacy of input recommendation and the degree control of the application.

Image processing is generally regarded as one of the most important technologies for PF. Image processing techniques are widely used to analyse and interpret information from an imaging device to monitor many parameters of crops. The image acquisition platforms can be ground-based, airborne and spaceborne that are important in gathering geospatial data for various PF applications.

Technological progress has led to the development of advanced and affordable platforms, increasing the application of image processing techniques in agricultural and scientific fields. Image processing in agriculture can be categorized into two main groups: one focuses on image understanding techniques, and the other applies these techniques in agricultural settings (Sridhar, et al., 2020).

Recently, the governments of some Asian countries have made special efforts to promote PF. In Malaysia, the Malaysian Agricultural Research and Development Institute (MARDI) conducted research and development (R&D) projects on the production of rice from 2006 to 2020 under the 9th, 10th, and 11th Malaysia Plans. Several image processing techniques have been developed for the rapid integration of geospatial data into rice PF system. This article explores the successful application of image processing techniques in various MARDI rice PF projects, such as crop density monitoring, fertilizer management, and yield prediction.

CROP DENSITY MONITORING

The number of rice tiller is a key indicator in monitoring crop density, providing information on the status of the crop and potential yield. This information can be used to calculate the amount of fertilizer and pesticide to be applied in the field (Abu Bakar, et al., 2018). Ground based sampling methods have been used to count the tillers number for determining plant population in rice field (Oghalo 2011). Sampling is done by randomly selecting different locations within a plot to count the tillers in a 25 cm x 25 cm square frame. However, this method involves manually counting the number of plant tillers in a square frame, making the

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sampling procedure time-consuming, labor-intensive, and costly. To solve this problem, a MARDI research team has introduced a method for automatically counting plant populations in a square frame using an image processing technique (Teoh, et al., 2008).

In the study, a total of 113 random image samples of rice plants were taken on October 26, 2004 at the 30-day growth stage using a digital colour camera with an appropriate control height (1 m) from the ground at the MADA Bukit Besar rice field, Kedah. The images were categorised into 19 groups based on the number of tillers and used to develop a model to estimate the rice plant density. To avoid the effect of height (ground to camera), all captured images were calibrated using image processing software. The resolution of each image after calibration was 5.84 mm/pixel. Figure 1 shows one of the random rice plant image samples obtained from MADA. Each recorded colour images that contained a combination of the red (R), green (G) and blue (B) images were classified into plant and non-plant regions by using minimum distance to means classifier in the software as shown in Figure 2. The minimum distance to means algorithm shown in the equation 1 is commonly used for classifying data because it was based on the simple computations to classify an unknown pixel (Jahne 1991; Lo and Yeung 2008).

$$d_c = \sqrt{\left(BV_{ij1} - \mu_{c1}\right)^2 + \left(BV_{ij2} - \mu_{c2}\right)^2 + \cdots \left(BV_{ijk} - \mu_{ck}\right)^2} = \sqrt{\sum_{k=1}^{n}\left(BV_{ijk} - \mu_{ck}\right)^2} \qquad (1)$$

Where,
BV_{ijk} = Brightness value in a row i, column j, of image k
μ_{ck} = Mean vectors for class c measured in images k
c = 1, 2, 3,…, m number of classes
k = 1, 2, 3,…, n number of images

It uses mean vectors for each class in each image μ_{ck}, from the training data to perform classification. A pixel of unknown identity can be classified by computing the Euclidian distance, d between the value of each unknown pixel (BV_{ijk}), and each of the μ_{ck} in their n images, respectively. The unknown pixel was assigned to the class 1, if the calculated d_1 is smallest compared to d_2, $d_3, \ldots, d_m$. The result showed that all unknown pixels in each image sample were assigned to plant or non-plant using this algorithm.

The area of plant region in the frame of each classified image was calculated by the software and used it to correlate with the number of tillers using linear regression analysis. The result indicates a strong correlation between the plant area and the number of tillers, with an r^2 value of 0.8328. The regression model that describes this dependency is as follows:

Tillers Number = 0.1743 (Plant area) - 29.445 (2)

The model was verified using 100 digital images of rice plants obtained from FELCRA, Seberang Perak, Perak on April 14, 2005 at 30-day growth stage for the accuracy assessment of tillers number estimation. The result indicated that the model could estimate the number of tillers with an accuracy ranging from 76.88% to 99.51%, with an average accuracy of 92.17%. Therefore, the image processing technique is practical, feasible and effective in estimating the number of tillers for rice plant density monitoring.

Figure 1. Rice plant image

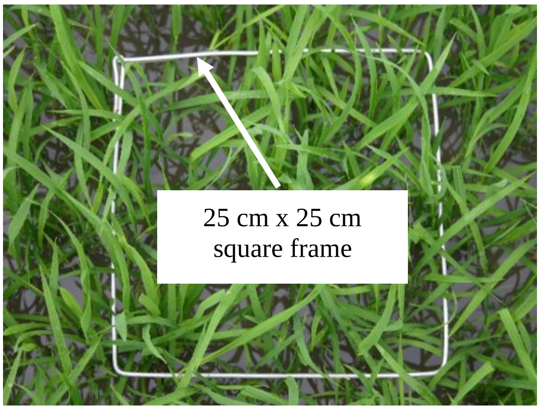
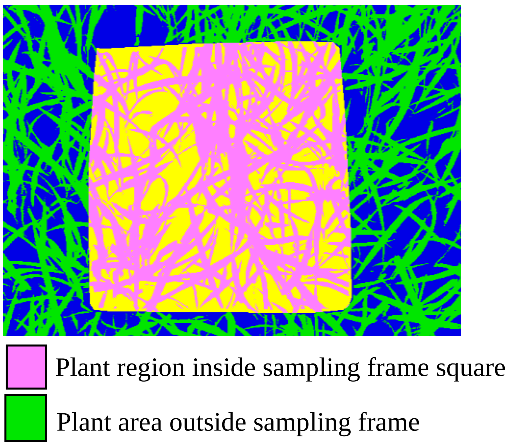


Figure 2. Classified image



Source: Teoh, et al., 2008

FERTILIZER MANAGEMENT

The crop yield is directly related to the amount of nutrients absorbed by the plant. Insufficient fertilization impairs plant growth, while over-fertilization leads to acidification of the soil and water resources. Optimizing fertilizer use is important to minimize production costs, maximize yields and reduce environmental impact. At present, farmers generally follow the blanket or package fertilizer recommendations for large areas, which is not efficient as the indigenous nutrient supply varies greatly in individual rice fields (Dobermann and White 1999, Olk et al., 1999).

PF is a solution for minimizing fertilizer use and maximizing yields. According to Patil (2009), PF is a management strategy that uses detailed site-specific information to precisely manage production inputs. Nitrogen (N) is needed in large quantities, and its application often dramatically increases crop yields, but N requirements vary spatially across fields and landscapes (Scharf et al., 2002). Managing N at variable rates is one of the most important activities in PF to apply the precise amount of fertilizer needed to maximize crop yields. In the study by Gholizadeh et al (2011), it was shown that the Soil Plant Analysis Development (SPAD) chlorophyll meter can be used to predict the total amount of N in the leaves and the future N requirements of the plants. Adaptation of the SPAD meter is required in PF for Malaysian double-cropped rice fields to assess the N status of the plants and determine plant's needs. However, manually measuring the N content of plants in the field with the SPAD meter is time-consuming and laborious. A method for predicting SPAD values was developed by the MARDI research team using an unmanned aerial vehicle (UAV) and image processing technique (Teoh, et al., 2012).

In the study, an experiment on plant growth was conducted in the rice field of FELCRA Seberang Perak on April 13, 2009. For the trial, seeds of the variety MR 219 were planted in four plots with six fertilizer treatment, and each plot was divided into six subdivided treatment plot (STP). A certain amount of N fertilizer was applied to each STP as follows: STP1 = 0 kg, STP2 = 1 kg, STP3 = 2 kg, STP4 = 3 kg, STP 5 = 3.5 kg and STP6 = 4 kg. The field-based SPAD data were collected on 3 June 2009 using SPAD meter. Data were collected by SPAD measurements at the four corners and the centre of a 25 cm^2 square frame in the middle of each STP.

A total of 100 RGB images of the study area were taken on 3 June 2009 by a RGB digital camera mounted on a UAV (Figure 3) at an altitude of 280 m. All the captured images containing of the latitude, longitude, and altitude information were mosaicked by image processing software. After processing, the spatial resolution of the image was 6.25 cm. A 4 x 4 pixel mask equal size with a 25 cm^2 square frame was marked at the centre of each STP on the mosaicked image (location SPAD measurements) for extraction of the R, G and B digital values.

Figure 3. CropCam UAV for RGB images acquisition

The relationships between the SPAD values and the values of R, G, B, R/(R+G+B), G/(R+G+B) and B/(R+G+B) were analysed. The R/(R+G+B) value displays the highest correlation with the SPAD values, with an r^2 value of -0.9695. The equation for the SPAD value prediction model is

$$\text{SPAD value} = -277.05\,[R/(R+G+B)\text{ value}] + 127.05 \qquad (3)$$

The SPAD value prediction model is able to predict SPAD values with an average accuracy of 89% after being validated by 8 random SPAD values obtained outside the experimental plots.

A SPAD measurement map (Figure 4) was generated by converting the digital values of images into SPAD measurement values using the SPAD value prediction model. The SPAD value map was classified into low, medium and high clusters (Figure 5) using the Iterative Self Organizing Data Analysis (ISODATA) image classification technique. ISODATA is an unsupervised classification method that uses an iterative approach incorporating a number of heuristic procedures to compute clusters. This clustering method uses minimum spectral distance formula, which is based on Euclidean distance equation to form clusters (Swain and Davis 1978). The equation is given below:

$$SD_{xyc} = \sqrt{\sum_{i=1}^{n}(\mu_{ci} - X_{xyi})^2} \qquad (4)$$

where
n = The number of images
i = The image number
c = A particular class
X_{xyi} = The data file value of pixel x, y in image i
μ_{ci}= The mean of data file values (digital numbers) in image i for the sample for class c
SD_{xyc} = The spectral distance from pixel x, y to mean of class c

Figure 4. SPAD reading map

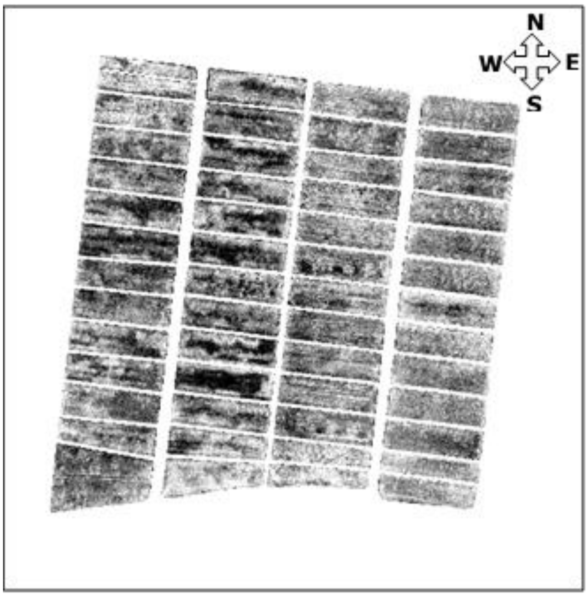
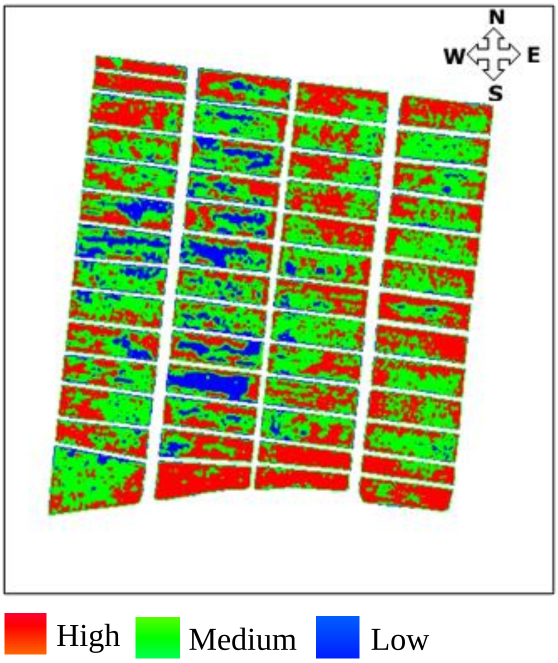


Figure 5. Classified SPAD value map



Source: Teoh, et al., 2012

This SPAD value map is useful for easily identifying the N stress level of crops in the field. If combined with information on soil fertility and yield, it can provide the opportunity to develop a variable rate N application system for site-specific farming practises.

YIELD PREDICTION

The ability to predict crop yield before harvest is an important factor because it allows farm managers to change farming practises throughout the growing season to maximise profit and yield while minimising costs. Recently, various indices derived from remote sensing imagery have been used to assess the condition of crops, and the normalised difference vegetation index (NDVI) has been found to be directly related to crop yield. The NDVI value is calculated by

$$NDVI = \frac{NIR-R}{NIR+R} \qquad (5)$$

where, NIR is radiance value for near-infrared band and R is radiance value for red band (Rouse et al., 1973).

Several crop yield prediction methods have been developed, such as creating regression models to develop direct empirical relationships between NDVI measurements and crop yield. These methods are used because many of the conditions that influence the growth, development and ultimately the yield of plants can be measured using the NDVI (Huang et al., 2013). Recently, the NDVI derived from satellite image data has often been used to predict crop yields. However, the use of satellite images is limited to a low spatial and temporal resolution. As mentioned in the study by Lamb and Brown (2001), the low spatial resolution satellite images are only valuable for large-scale studies and are not suitable for the smallholder farms prevalent in many areas of Asia. They also pointed out that some satellites that provide higher spatial resolution imagery have long revisit times (low temporal resolution), which will limit the utility for applications that require frequent imagery for crop monitoring in PF. Hence, a method using UAV and image processing technique was developed by MARDI research team to predict rice yield in the fields (Teoh, et al., 2016).

In the study, an experiment on plant growth was conducted with an application of six different fertilizer treatments in the paddy field at Kampung Setia Jaya, Yan, Kedah. For the trial, seeds of the variety MR 219 were planted in eighteen 12 m x 12 m plots and arranged in a randomised block design for three replicates with six N treatments (i.e. 0, 50, 100, 130, 150 and 170 kg/ha) to obtain a potentially wide range of yields. The matured rice plants were harvested from all the sample areas of 5 m^2 at the centre of each treatment plot on 9 January 2013.

The relationship between rice yields and N fertilizer treatments indicates a close correlation. Rice yield increased linearly from 0.83 kg/m^2 to 1.01 kg/m^2 when the amount of N applied was increased from 0 kg/ha to 150 kg/ha. This is because the plants absorb enough available nutrients to develop a healthy crop. However, the rice yield eventually fell to 0.93 kg/m^2 despite the increase in N with 170 kg/ha application rate. Excessive N fertilization reduces rice yields and promotes excessive vegetative growth, which makes the plant susceptible to insects, pests and diseases. Therefore, optimal utilization of N fertilization is essential for the growth and development of rice plants for a better yield. Therefore, an optimum usage rate of N fertilization is essential in growth and development of rice plants for better yield (Islam et al., 2008).

A Tetracam digital camera was mounted on a UAV to capture red (R), green (G) and near-infrared (NIR) images of rice plants at 300 m above the ground on 9 January 2013. All the captured images with latitude, longitude and altitude information were mosaicked and processed to produce an NDVI image using image processing software. After processing the image spatial resolution was 12 cm. The locations of the yield data taken at each centre of the treatment plot were identified in image. A 42 x 42 pixel mask corresponding to an area of 5 m^2 square was marked at the centre of each treatment area on the image for each treatment plots. The average R, G, NIR and NDVI values under the mask were calculated by the software. Seven treatment plots were selected, with rice yields ranging from 0.8 kg/m^2 to 1.1 kg/m^2. These values approximated the average rice yield at different N fertilizer rates for three replicates to develop a yield prediction model.

The relationships between yield and R, G, NIR and NDVI values were analysed to develop a model for estimating rice yield. The best r^2 value of the linear model was selected to estimate the yield. The results showed that the highest correlation value was found in NDVI ($r^2 = 0.75$) followed by R ($r^2 = 0.73$), G ($r^2 = 0.39$) and NIR ($r^2 = 0.01$). Therefore, the NDVI value was chosen to estimate the rice yield. The regression model describing the relationship between rice yield and the NDVI value is shown in the following equation

$$\text{Rice yield (kg/m}^2\text{)} = 3.744 \text{ (NDVI value)} - 1.508 \quad (6)$$

The regression model for yield prediction was verified using twenty-two randomly selected famer plots outside the treatment plots. The rice plants at mature stage were harvested with a combine harvester and the data on rice yields were recorded after weighing yield in the rice mill. The comparative results indicated that the NDVI value is able to estimate rice yield with an accuracy of 62.3% to 98.9%, with an average accuracy of 80.3%.

CONCLUSION

In this paper, the potential applications of image processing methods for crop density monitoring, fertilizer management, and yield prediction in rice PF have been highlighted. Image processing technique has developed rapidly in recent years and offers potential applications in PF, enabling farmers to optimize yields from inputs while protecting the environment. The processing and analysis of image data collected by ground-based and UAV can be used to make decisions and take necessary corrective actions in PF to increase production and minimize costs. However, there are still many challenges to overcome before the techniques can possibly be used in large-scale precision agriculture for rice.

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