

USING MULTISPECTRAL DIGITAL IMAGERY TO EXTRACT BIOPHYSICAL VARIABILITY OF RICE TO REFINE NUTRIENT PRESCRIPTION MODELS.

S L SPACKMAN, G L MCKENZIE, J P LOUIS and D W LAMB

Cooperative Research Centre for Sustainable Rice Production

Charles Sturt University

Locked Bag 588, Wagga Wagga, NSW 2678, Australia

Phone: +61 69 33 4009, Fax: +61 69 33 2737

sspackman@csu.edu.au, gmckenzie@csu.edu.au, jlouis@csu.edu.au,

dlamb@csu.edu.au

Abstract

In this paper we report on two components of research towards incorporating remotely sensed field images with a crop growth and development model to predict spatial variability in yield. Initial regression analysis between crop biomass and normalised difference vegetation index (NDVI) images of a rice crop yield R^2 values of up to 0.73 at the mid-tillering stage of crop development. A rice crop growth and development model specifically modified to accept crop biomass data has predicted crop yield to within an average 0.72 t/ha of the measured values. The potential of combining both the image-derived biomass estimates and the modified crop growth and development model to predict spatial variability of crop yield is also discussed.

Introduction

Crop growth and development models can be useful as a crop management tool. In Australia's temperate rice growing region the model maNage Rice™ is used to advise rice growers on top dressing application rates of nitrogen (N). The model predicts the effect on various rates of mid-season N application rates on the final yield, based on in-field measurements of plant N, water level and shoot density at panicle initiation, and the dates of sowing and of panicle initiation. A meteorological dataset, including average daytime temperature, day-length and solar radiation, is also included in maNage Rice™ which models crop growth and ultimate yield for a range of possible N application rates.

The current best practice using the model involves the use of input data averaged across entire rice fields. Within-field variations in soil characteristics, nutrients and weeds all influence the ability of a crop to develop. However within-field variability is not considered. The ability to update the progression of a crop growth model via the input of timely, spatially referenced data such as biomass and leaf area index (LAI) all derived from remotely sensed imagery, would allow the model to be applied separately to various zones within each field. Here the remotely sensed data itself forms the spatial template for running the model.

Remote sensing data has been used in many instances to quantitatively estimate agronomic variables such as biomass and leaf area index (LAI) (Benedetti & Rossini 1993, Thenkabail *et al.* 1994, Gilabert *et al.* 1996). This paper reports two aspects of

research which aims to combine metre-resolution remotely sensed imagery with a crop growth and development model (maNage RiceTM) in order to predict spatial variabilities in crop yield.

Materials and Methods

Fifty sampling sites were established in a rice field, based on a 100m grid established using a Trimble ProXL differential global positioning system (dGPS). Each site was marked with a fibreglass cane for repeated visits throughout the season. Samples for analysis of biomass were collected four times during the growing season, corresponding to major phenological changes within the rice field; mid-tillering, panicle initiation (PI), flowering and pre-harvest. The corresponding dates for these sampling times were 8th December, 5th January, 3rd March and 30th March. At each sampling point 0.5m² cuts were taken 1m north, south and east of the fibreglass cane, with the final cut centred on the fibreglass cane. Biomass (wet and dry) and final grain yield were measured from each sample location.

The model

The maNage RiceTM model (Williams & Angus 1997) is written in fortran code. The code was modified to incorporate only the basic crop growth and yield prediction routines. The modified model was tested against the original model and successfully replicated the predictions of crop yield under a range of synthetic conditions.

Based on reports of Williams and Angus (1997) that the maNage RiceTM model could predict crop yield with an accuracy of ± 1 t/ha the same was assumed for the modified model. To validate this assumption a random selection from the 50 ground sample locations were tested. From 10 locations, ground biomass measurements were input into the modified model and yield prediction based on the actual mid-season inputs compared with the actual yield (measured by field cuts).

Remotely sensed imagery

The camera system used was the Charles Sturt University Airborne Video System (CSU ABVS), a 2 x 2 array consisting of four monochrome CCD cameras. Each camera has a 740 x 576 pixel array and all are fitted with a 12 mm focal lens. 25 nm band-pass interference filters define the spectral regions imaged, in this case the filters were 440 nm (blue), 550 nm (green) 650 nm (red) and 770 nm (near infrared) (Louis *et al.* 1995).

Imagery was collected between 11 am and 2 pm for each of the four sampling periods. During each flight standard reflectance panels were imaged for calibration purposes. To correct for intrinsic systematic characteristics in the ABVS a series of standard corrections were made. The corrections accounted for shear, vignetting, geometric effects and band to band registration (Spackman *et al.* 2000a). In addition, image digital numbers (DNs) were converted to reflectance using the ground calibration panels.

From the calibrated imagery NDVI, a combination of the red and near infrared bands of the remotely sensed data ($[\text{red} - \text{near infrared}]/[\text{red} + \text{near infrared}]$), was calculated for 5x5 m areas surrounding the 50 sample locations within the field. NDVI was then correlated with the respective ground biomass measurement for individual locations. The correlation analysis is discussed in more detail by Spackman *et al.* (2000b).

Results

Correlation of ground and image data

Correlations were investigated between the NDVI and ground biomass measurements for individual locations. The log relationships for each of the four crop stages of development were established from the data collected and the results are summarised in Table 1 (extracted from Spackman *et al.* 2000b).

Table 1. Regression equations and R^2 and F values for each sampling period (DW = dry weight, biomass)

Crop Stage	Equation	R^2	F value
Mid-tillering	NDVI = 0.239 \ln (DW) - 0.534	0.73	82.8
Panicle initiation	NDVI = 0.210 \ln (DW) - 0.328	0.50	27.7
Flowering	NDVI = 0.078 \ln (DW) - 0.239	0.19	9.2
Pre-harvest	NDVI = 0.147 \ln (DW) - 0.438	0.45	36.7

Spackman *et al.* (2000a) explain the results of the correlation analysis in detail, however in this section it will only be briefly outlined. The prediction of DW at mid-tillering is the most successful as there is greatest contrast between crop vegetation and background water, where as at the flowering period the lowest correlation was achieved as the crop morphology changed. It has been suggested that the flowering canopy obscure the spectral signature of the underlying leaves (Shibayama & Akiyama 1989). A similar process may also compound the lower R^2 at PI as at flowering, as the rice canopy gradually changes. Prior to harvest, water is drained from the field, which will change the background spectra of the plant if it is visible and plants will begin to senesce changing the spectral signature observed for similar biomass at varying rates depending on levels of water and maturity of the plants.

Model manipulation and integration of ground based estimates

The modified model was tested with the field data, from 10 sample locations chosen at random from one field. The accuracy of the comparison between predicted yield, using ground inputs of biomass with the modified model, and actual yield taken from ground measurements are represented in Figure 1 and Table 2.

Figure 1. Predicted versus actual yield, taken from 10 randomly selected sample locations within the target field

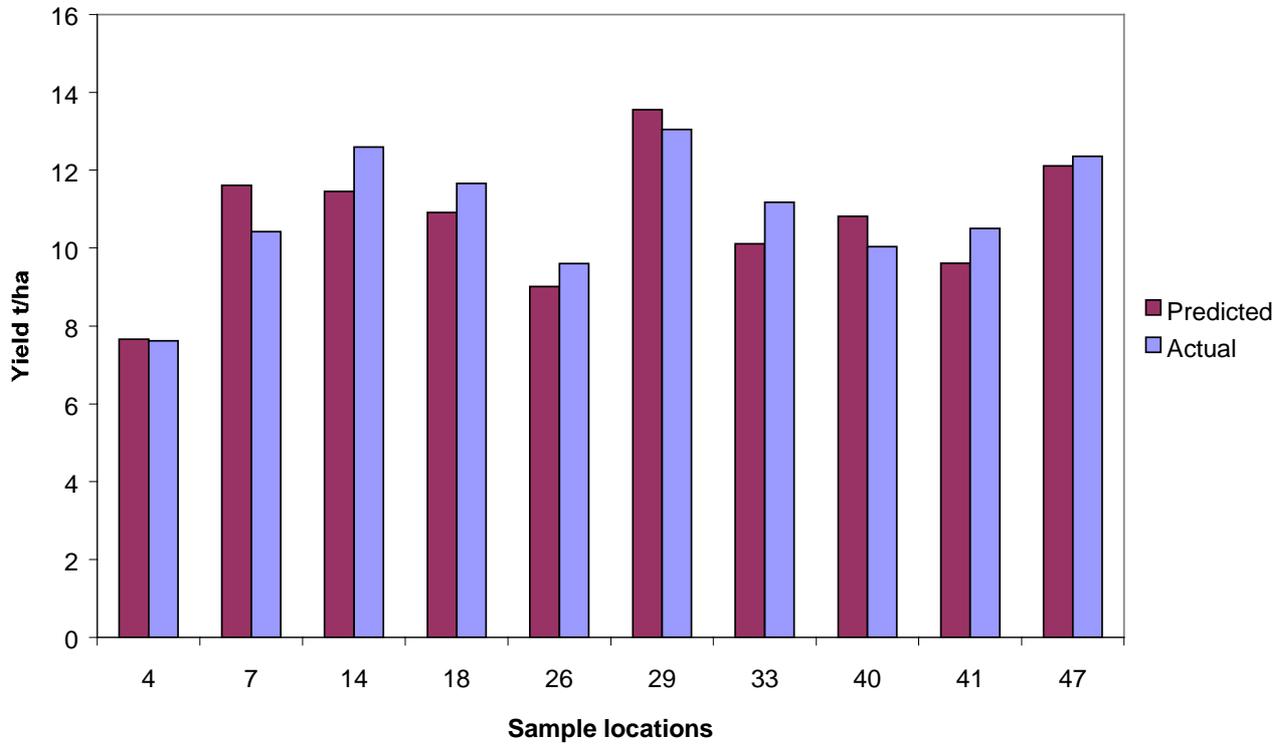


Table 2. The differences in yield estimation for 10 randomly selected sample locations within the target field

Sample Locations	Predicted Yield (t/ha)	Actual Yield (t/ha)	Difference (t/ha)
4	7.66	7.62	0.04
7	11.61	10.42	1.19
14	11.46	12.60	1.14
18	10.91	11.66	0.75
26	9.01	9.60	0.59
29	13.55	13.04	0.51
33	10.11	11.18	1.07
40	10.81	10.04	0.77
41	9.61	10.50	0.89
47	12.11	12.36	0.25
Average			0.72

From this sample data set, the estimated yields were on average 0.72 t/ha different from the hand yield measurements.

Conclusions

The main focus of this paper was to outline research aimed at incorporating remotely sensed biomass estimates into a crop growth model. One component required quantitative estimation of biomass from the remotely sensed multispectral airborne imagery, and the other research goal was to modify an existing crop model to accept the remotely sensed data at an unspecified time throughout the season.

Based on these preliminary results, the accuracy of the estimation for remotely sensed biomass in the first two major phenological stages of rice is 20% at mid-tillering and 26% at PI. These relationships need to be refined by further considering the image pre-processing techniques and re-establishing new correlations. The initial results are promising, as mid-tillering, which has the highest correlation, is around the time farmers are thinking about N application requirements.

The modification of the maNage Rice™ model were successfully tested against the original model. The initial model yield estimates, using the ground-measured biomass, are encouraging with a prediction accuracy of better than one tonne per hectare.

The paper has established working relationships between remotely sensed NDVI and ground biomass measurements providing a spatial map of biomass variability within rice fields. In conjunction with the modified maNage Rice™ model this spatial biomass map can be used by farmers to estimate mid-season N rates on a sub paddock basis.

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