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Analysis of Rice Leaf Area Index Variation under different Irrigation Conditions in Southern Taiwan

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Abstract: ***This study aims to evaluate the relationship between the estimated leaf area index (LAI) and the set of both dependent and independent variables that may have a direct impact on its values, depending on their diversity. Due to its high performance, rice crop (Oryza sativa) variety Tainan 11 was chosen to be planted and monitored in an experimental field. Data analysis highlighted three major variables which had a strong correlation with LAI such as the treatments or the different water depths applied during the growing season, the time interval (R^2 = 0.94, and P≤0.05), the leaf number, and the mineral fertilizers (R^2 = 0.96).LAI variability with 5 different treatments such as 2, 3, 4, and 5cm on soil hairline (SHC) cracks, and 3cm per week the results showed that 3cm SHC gave the high values of LAI. Then, leaf number of 120 hills was used as the main inputs to generatestatistical rice LAI estimating model, while 24 hills leaf number was used for the validation process. Thereby, the research challenge is to develop a model that can be inverted to extract relevant and reliable information from LAI values, providing users useful information about rice plant growth status.***

Keywords: Leaf Area Index (LAI), LAI estimating model, LAI variation

1. Introduction

Rice (*Oryza sativa L.*) is a staple food source for almost half the world's population, and cover over 9% of global arable land[1].Thepractice applied in this study offers the opportunity to reduce world hunger and sustainably manage world water resources; however, it merits a thorough comprehensive research program to unlock its full potential[2]. The need to monitor crop growth and assess the relationships between its yield and hydrological processes is elementary for improving the productivity of water. Leaf Area Index (LAI) monitoring has been investigated as a practice well indicated to rapidly predict crop yield through its both leaves canopy and derivatives of photosynthesis[3]. In current literature, LAI is defined as one half of the total leaf area per unit ground surface area. It is a dimensionless quantity (or m^2/m^2) and measures the amount of leaf material in an ecosystem. Its main purpose in plant productivity is to describe the size of the source of biomass accumulation in relation to the land area that is being cultivated [4]. Obviously, leaves are the plant organs where the least photosynthesis occurs, and where energy, gas, and humidity change required for growth[5].To do this, from field measurements, general linear model (GLM) results indicated that LAI correlated withthe measurement time interval and the difference between water depth applied (R-square = 0.96). Based on these relationships, many research assumes that significant correlation exists between LAI and plant chlorophyll content. In general, LAI values are high in areas where nutrients forplant are enough, and this resulting in a high productivity[6].

In this study, an estimated LAI variation was based on the analysis of its relationship with the independent and dependent variables involved, including external factors using direct measurement. Data of field canopy measurements were obtained at ten (10) growth stages over 20 plots established in a complete randomized block designconsisting of four treatments, i.e. four irrigation water depths, with four replicates as follows: 2, 3, 4, and 5 cm water supplied based on soil hairline cracks and 3 cm per week. Definitively, to generate an efficient statistical SRI model for yield estimating, the measured LAI of 120 hills was used as basic input, while 24 hills were used for validation process through a Stepwise Linear Modeling. The objective was to identify the bestcorrelation between the estimated LAI and both of the dependent, and independent variables involved in its variation, in order to generate a statistical LAI estimating model. The dependent variables consisted of tiller number (TN), leaf number (LN), average leaf length (LL), average leaf width (LW), leaf area (LA), and leaf area index (LAI), while the independent ones consisted of plots, blocks, treatments, nth day after transplanting, and measurements.

2. Material and Methods

2.1 Study Area

2.1.1 Site description

The research was carried out from December 2017 to May 2018 in the irrigation experimental station of National Pingtung University of Science and Technology (NPUST) in Pingtung County, southern Taiwan, (22.39◦ N latitude and 34.95◦ E longitude at 71 m above sea level)(Fig. 1).Experimental soil was classified as loamy. The mean annual precipitation was around 2300 mm and the mean annual air temperature 24.13º C.About fertilization, organic matter was applied for a total of 486g/plot/6m^2, and mineral fertilizer for1944g of 91DAT NPK + 3888g of Nitrogen applied on 12plots, and 1296g of 91DAT BOI + 2592g of Nitrogenon8 plots.During the growing season, the highest and lowest air temperature were observed respectively in 32.1°C and 14.8°C. The maximum relative humidity was around 100% while the lowest was about -15.6%. Data source: NPUST meteorological station.

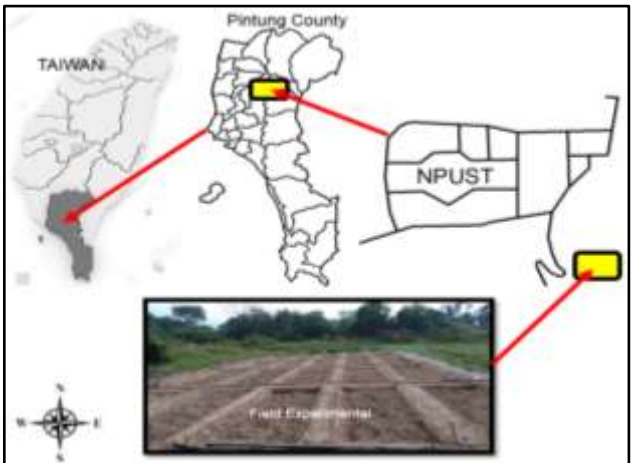

Figure 1: Field Experimental Location

2.1.2 Experimental Design

The total area of the observation site was 241.5 m^2. The rice variety used was by Tainan 11 (TN11) with production cycle of 120-day. Seedlings of 14 days old were transplanted on December 5th, 2017 on rows, and hills spaced on 25 cm (75 hills 6 m^{-2}). As shown in Fig. 2 the experiment was laid out on 20 plots arranged in a complete randomized block design of 2, 3, 4, and 5 cm of irrigation water depth at soil hairline cracks (SHC) corresponding to the treatment codesT2, T3, T4, and T5 respectively, and 3 cm per week corresponding to T3'.Treatment of 5 cm water depth, 4th replication was named T5-4. Irrigation was provided during the growing season based on the observed SHC and time interval. The total water applied during the growing season was16,600, 19,300, 18,000, 19,700, and 16,300m^3ha^{-1}respectively for T2, T3, T4, T5, and T3'.The complementary water of 1,385 m^3ha^{-1} was recorded from rainfall during the same period. Unit plot size was 4 m length and 1.5 m width, and 0.3 m soil bed heights with a spacing of 1 m and 0.5m between blocks and plots, respectively.

2.2 Data collection

Direct measurements without removing leaves were used. This method is the most accurate, unfortunately, it has the disadvantage to be extremely time-consuming and, as a consequence, its large-scale implementation is very unlikely. However, in terms of accuracy, it can be considered important as calibration methods providing the most reliable assessment of LAI and be considered as a standard to validate, for example, results of studies focusing on the indirect or remote sensing methods [7].Notwithstanding that practice interest, LAI was directly determined by taking a statistically significant sample of foliage from a plant canopy, measuring the leaves area (LA) per sample plot and dividing it by the plot land surface area covered by the sample leaves[8]. That involved two techniques applied from 37th DAT to 167th DAT(Table 1). The first step consisted of measuring the length and maximum width of the 3 upper leaves/tiller/sampled hill, counting the tiller and leaves number per plot, and then, computing data to obtain LA and LAI of each leaf based on the length-width method of[9]shown in the formula (1) and (2) below:

Leaf area (LA) = *Kxlxw(GCOS-200)*(1)

$$\text{LAI} = \frac{K\ x\ l\ x\ w\ \text{x number of leaves per hill (sq cm)}}{\text{Spacing (Area of land covered by } n \text{ hills) (sq cm)}} \quad (2)$$

Where K was the "adjustment factor." l was the maximum length, and w was the maximum width. The value of K varies under most conditions (K = 0.75 for all growth stages except the seedling stage and maturity where K = 0.67).

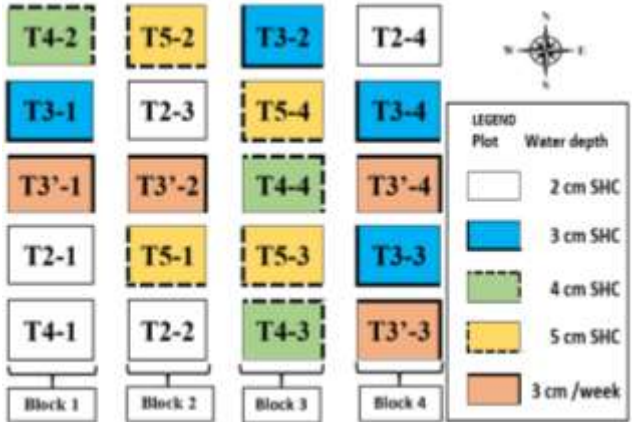

Figure 2: Field Experimental Design

Table 1: Measurements dates, corresponding DAT and rice growth stages

Date	DAT	Growth Stage	Stage	Short Name
Jan. 11, 2018	37	3rd trifoliolate leaf unfolded	VS	V1a
Jan. 22, 2018	48	38% tillering (1-3 tillers)		V1b
Feb. 02, 2018	59	72% tillering (2 -3 tillers)		V2a
Feb. 12, 2018	69	83% tillering (3 - 5 tillers)		V2b
Mar. 02, 2018	87	98% tillering (4-10 tillers)		V3a
Mar. 13, 2018	98	100% tillering (6-16 tillers)		V3b
Mar. 27, 2018	112	82% Bulging	RS	R1a
Apr. 10, 2018	126	15% Heading		R1b
Apr. 21, 2018	137	59% Heading		R2
May. 15, 2018	155	92% Grain filling	MS	M1a
May. 21, 2018	167	100% Maturation ; 80% Maturity		M1b

NB: VS: vegetative stage; RS: reproductive stage; MS: maturity stage

2.3 Data Analysis

The goal of these analyses was modeling LAI based on its variability in correlation with the dependent and independent variables. The approach was, first to analyze the correlation between the different variables for each treatment, and then identify the variables which correlate more with LAI and can be used to generate the final model for LAI estimation.The general linear model (GLM) using SAS Deployment Manager 9.4 wasapplied to perform the analysis of variance. It is a multiple linear regression model used in case of more than one dependent variables. It incorporates a number of different statistical models, such as ANOVA, ANCOVA, etc., ordinary linear regression, t-test, and F-test[10].Thus, for checking trends and correlation in all data, an exploratory analysis was performed by plotting the mean values for each measurement in the variables and their covariance matrix through a Stepwise Linear Modeling and Linear Fitting.

3. Results and Discussions

3.1 Trends and correlation analysis

From the correlation analysis based on the general linear model (GLM) process, results showed that dependents variables strongly correlated with each independent variables for R-square of about 0.94. Concerning the independent variable variance for LAI, there is a significant difference between them ($p \leq 0.05$). Thus, after an exploratory analysis, it was indicated that the variables globally tend to increase through the growing stages and between the treatments, according to Duncan's Grouping test. In particular, LAI interacted significantly with the time interval of data measurements (i.e. the nth DAT), and treatments, with the highest sum of squares (SS) equal 248.766 and 23.725 respectively, and $p < 0.0001$ for both. In the other words, there was a linear increase in total biomass as growth duration increased[11].

3.2 Leaf Area Index variationover time interval

LAI evolution was significantly linked to the time interval progress. The test for slight variations of Duncan's Multiple Range Test indicated a significant difference between the mean values of LN, LA, and LAI for all vegetative stages.Table 2 below indicated LAI variation along the different growing stages. Its mean values increased suddenly from 0.72 to 2.76 between 98th and 126th DAT (in 28 days). This increasing is the response to mineral fertilizers used the 91st DAT which favored the increase of the leaf mass as well in number, in length as in width. [12]assume that the fertilizer application times and rates play a key role in influencing plant growth and nutrient uptake. In addition, after reaching their peak at 126th DAT, these values experienced a downward trend. This could be explained by the progressive decrease of the crop biomass at maturity stage beginning. For [13],that happens about 100 days after showing.

Table 2: Leaves number (LN), Leaf Area (LA) and Leaf Area Index (LAI) mean value on time interval (DAT) according Duncan Grouping

Duncan Grouping			Mean			N	Vegetative Stages	DAT
LN	LAI & LAI		LN	LA	LAI			
A		A	373.75	10352.2	2.76	20	R2a	126
A		A	366.25	10308.6	2.75	20	R2b	137
A		B	360.95	9222.5	2.46	20	M1a	155
B		C	261.75	6064.8	1.62	20	R1b	112
C		D	163.45	2693.5	0.72	20	R1a	98
D		E	115.95	1504.5	0.40	20	V2d	87
E	F	E	70.00	514.6	0.14	20	V2c	69
E	F		56.05	365.4	0.10	20	V2b	59
F	F		32.15	172.9	0.05	20	V2a	48
F	F		17.90	70.4	0.02	20	V1	37

NB: Means with the same letter are not significantly different

3.3 Leaf Area Index variation over treatments

From the analysis, the results showed that the main variable LAI had a strong relationship with all independent variables with a correlation coefficient of about 0.91. However, it mostly depended on the treatment with significance level Alpha of 0.05, while the Error Mean Square (EMS) very low was 0.19, giving LAI consequently higher precision when estimating it over the treatment. Furthermore, a Generalized Linear Analysis and Duncan's grouping shown that treatment T3 presented the best relationship among variables(Table 3). Thus, the results indicated that the LAI values varied from a minimum 0.459 to a maximum 2.314. In Boreal Mixed-wood Forest of Ontario (Canada)[14]found 0.37 as minimum and 5.01 as maximum values of LAI, using Light Detection and Ranging (LiDAR), and WorldView-2 Imagery.

Table 3: LAI mean value and the best treatment highlighted according to Duncan Grouping

Duncan Grouping					Mean	N	Treatment
			A		2.314	10	T3-1
			B		1.906	10	T3-3
	C		B		1.604	10	T4-4
	C		D		1.229	10	T3-4
			D		1.198	10	T3'-1
	E		D		1.141	10	T5-4
	E		D		1.141	10	T4-2
	E		D	F	1.129	10	T3'-2
	E	G	D	F	1.108	10	T4-3
	E	G	D	F	1.102	10	T2-4
	E	G	D	F	1.049	10	T5-3
H	E	G	D	F	1.023	10	T3'-3
H	E	G	D	F	0.996	10	T5-2
H	E	G	D	F	0.985	10	T3'-4
H	E	G	D	F	0.981	10	T2-3
H	E	G	I	F	0.719	10	T2-1
H		G	I	F	0.675	10	T2-2
H		G	I		0.664	10	T3-2
H			I		0.588	10	T4-1
			I		0.459	10	T5-1

NB: Means with the same letter are not significantly different.

3.4 Leaf Area Index Modeling

From the analysis, the results showed that the dependent variables highly interacted with each other for all the treatments with a correlation coefficient of about 0.90. Especially, this coefficient was about 0.99 for T3. Taking into account this strong correlation for T3, data from this later were used for LAI modeling. In addition, Figure 3illustrates again the correlation analysis which showed that it was possible to get LAI estimation based only on the TN and LN with respective correlation of 0.96 and 0.99 with LAI. [15]estimated the correlation coefficient at 0.98 in the linear variation of LAI and the amount of rice foliage. From the model characteristics used in the Stepwise Linear Fitting above, the underlying equation that can be used for estimating LAI can be written as follow:

$$\mathbf{LAI = 0.009 * LeafNumber - 0.4703} \quad (3)$$

Performing an Exploratory Data Analysis to check assumptions and verify the model characteristics, variables were scatterplotted except the Leaf Area against the LAI. The result of the Predictor Scatter plot in Figure 4indicated that a linear relationship can be only expected between the

TN, LN and LAI (R-square = 0.96 for TN, and 0.99 for LN) which corroborate the obtained model.

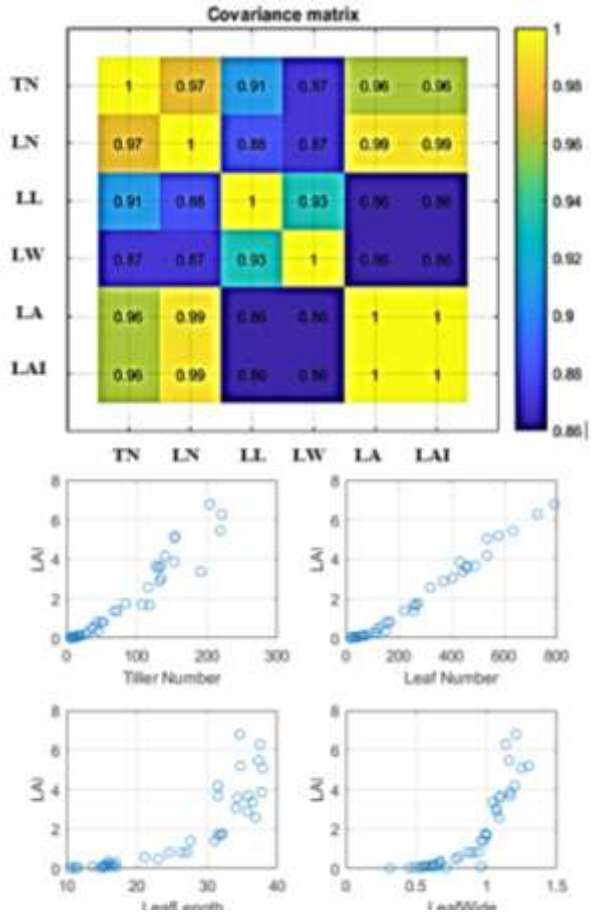

Figure 3: Correlation analysis from T3Figure 4- Scatter plot of Predictors vs Response Variable

3.5 Test and model validation

The model test and its validation were performed using a new data from treatment T5 to check how well the model can estimate LAI from new measurements. Figure 6presents the normal fitting to the errors from this validation process. From this graph, we can globally conclude that the model is accurate for LAI estimation because the errors produced during the test and validation are normally distributed by being located under the normal distribution curve.

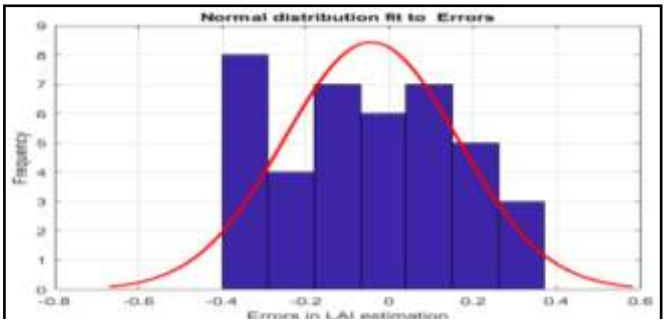

Figure 6: Normal fit to the errors in LAI estimation during the test and validation of the model

4. Conclusion

The current study used ground measurements of rice plant foliar organs in the experimental field of NPUST to monitor LAI variation over variables involved including external factors. This practice was suitable and contributed to the better prediction of crop yield in ricecultivation under five different water applications. Duncan Grouping results identified water treatment T3 (with a mean value of 2.59) as the suitable water depth which strongly correlated with LAI, followed by T2 which recorded 2.14. Consequently, T3 was used to generate LAI prediction model using the Stepwise Linear Fitting. Ultimately, the generated model for LAI estimating to highlight crop healthy map, can better predict its yields and be helpful for decision makers.

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