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Possibility to use crop models for indirect prediction of glycemic index in rice

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Abstract A process for constructing the prediction equations was developed by using simulated biomass and simulated grain yield to be estimating the glycemic index (GI) of two rice varieties, and reference GI was used as a basis for calculation of predicted GI. The CSM-CERES-Rice model was able to construct the best prediction equations, and the equation developed by using simulated biomass and simulated yield were y = 0.0003x + 59.099 and y = 0.0008x + 59.213, respectively. The equations were also used for prediction of GI values of two rice varieties applied with different methods of nitrogen application. The difference of the equations was 0.0% for both simulated biomass and simulated grain yield. The process for indirect prediction of GI is used available simulated data of biomass and grain yield to improve prediction accuracy.

Keywords: Glycemic index (GI), Simple regression, CSM-CERES-Rice model

Introduction

Diabetes is a non-contagious disease that causes health problem and fatality of people worldwide (Cole *et al*., 2020). The increase in number of people with diabetes is at alarming rate from 108 million in 1980 to 422 million in 2014 (WHO, 2018). According to WHO (2023), the rates of diabetes mortality from 2019 to 2000 increased by 3%.

Carbohydrate is viewed as a main cause of the increase in blood sugar (Unwin *et al*., 2019) as carbohydrate is digested into glucose and transported into blood system (Lal *et al*., 2021). Reduction in blood sugar is an important strategy to reduce diabetes, and people should consume food with low risk for blood sugar increase. Consuming food with low glycemic index is a safest method of avoiding the risk of diabetes.

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The glycemic index, simply put, is a measure of how quickly a food causes our blood sugar levels to rise. The measure ranks food on a scale of zero to 100. Foods with a high glycemic index, or GI, are quickly digested and absorbed, causing a rapid rise in blood sugar (Joshi and Srivastava, 2020). The information on glycemic index is important for consumers to select food that is beneficial to their health. Unfortunately, the information is not available for most foods sold in the market due to obtaining the correct glycemic index is still difficult, costly and time consuming.

Rice sold in the market generally has a high glycemic index of about 69.1% (Rice Department, 2017a). RD43 has a moderate glycemic index of only 57.5%, and Riceberry has a moderate glycemic index of about 62% (Rice Department, 2017b). The glycemic index level in rice may depend on many factors such as growing environment, rice variety (Miller *et al*., 1992), amylose content and amylopectin content (Zhu *et al*., 2011). Variation in glycemic index is also dependent on the properties of rice flour including the shape of the dough grain, the compositions of the flour granules, the size of the dough grain, the rate and extent of digestion of the dough (Bird *et al*., 2009). GI is inversely related to protein content (Jenkins *et al*., 1981). Consumption of rice with low GI is linked to several health benefits (Dhanalakshmi *et al*., 2023).

Environment is an important source of variations in many traits including biomass, grain yield and glycemic index, and variation in fertilizer application has the great effect on the variations in these traits (Kumar *et al*., 2019). According to Han *et al*. (2021), application of nitrogen fertilizer increased protein content in rice, and slightly reduced amylose content. Change in amylose content as affected by nitrogen levels directly affected GI values. Therefore, it might be possible to use the data of biomass and grain yield for indirect estimation of glycemic index in rice through crop simulation model.

In plant breeding, many successes have been reported on using associated traits to indirectly select economically important traits such as grain yield, which is more complex and difficult to select (Jukanti *et al*., 2020). This concept might be applicable for indirect estimation of glycemic index in rice through the use of crop simulation model. To the best of our knowledge so far, there has not been a report on using crop simulation model to indirectly simulate the traits associated with the target traits, and this study might be the pioneering attempt to use crop simulation model to estimate glycemic index in rice.

A current development of DSSAT (Decision Support System for Agrotechnology Transfer) provided a useful tool to estimate crop performance for many agronomically important traits (Jones *et al*., 2003). The crop simulation model can be used as a growth assessment tool for yield and nitrogen content in the grain of rice (Dusserre *et al*., 2020). The rice growth model (CSM-CERES-

Rice) in the DSSAT program can be used to study the responses of rice to management, inputs and growing conditions of different environments (Vilayvong, 2012). The CSM-CERES-Rice model can be used in studies to establish an understanding of nitrogen changes in soils grown under crop rotation systems (Hasegawa *et al*., 2000). The objective was to indirectly estimate glycemic index in rice by using crop simulation model and the data of biomass, grain yield.

Materials and methods

Location and experimental design

Pot experiment was conducted in the open environment at the Department of Plant Production Technology, School of Agricultural Technology, King Mongkut's Institute of Technology Ladkrabang. A 2×4 factorial experiment was set up in a completely randomized design (CRD) with four replications. Two rice varieties consisting of RD43 and Riceberry were assigned as factor A, and four fertilizer treatments including non-fertilized control, urea (46-0-0) (125 kg N ha^{-1}), sunn hemp green manure (*Crotalaria juncea* L.) (2,913.7 kg dry matter ha^{-1}) and urea (46-0-0) (62.5 kg N ha^{-1}) plus sunn hemp green manure (1,456.8 kg dry matter ha^{-1}) were assigned as factor B.

Urea and sunn hemp were not applied for unfertilized control. For sunn hemp alone, sunn hemp at the rate of 2,913.7 kg dry matter ha^{-1} harvested at 50 days after planting (at flowering) was chopped into small pieces and incubated under soil capacity moisture content for 14 days prior to transplanting of rice crop. The rate of 2,913.7 kg dry matter ha^{-1} was equivalent to 125 kg of urea based on nutrient analysis of sunn hemp. The seedlings were planted at the age of 25 days after seeding.

For urea alone, urea at the rate of 125 kg N ha^{-1} was applied to the crop at two splits one at 20 days after transplanting (DAT) and another at 40 DAT. For sunn hemp plus urea, sunn hemp at the rate of 1,456.8 kg dry matter ha^{-1} was incubated for 14 days prior to transplanting of rice crop, and urea at the rate of 62.5 kg N ha^{-1} applied to the crop at two splits one at 20 DAT and another at 40 DAT. The rate of 1,456.8 kg dry matter ha^{-1} was equivalent to 62.5 kg of urea. Irrigation water was monitored regularly and maintained a level of 10 mm above the soil surface.

Data collection data analysis

The crop was harvested at 95 (RD43) and 130 (Riceberry) days after transplanting. Data were recorded for biomass and yield. The samples were ovendried at 65 °C for 72 hours or until dry weights were constant, and the dry weights of the samples were recorded. Data were analyzed statistically according to a 2×4 factorial experiment in a completely randomized design. The differences among or treatment means were compared by Duncan's New Multiple Range Test (DMRT) at 0.05 probability level. All statistical analyses were accomplished using M-STATC program from Michigan State University (Bricker, 1989).

The consistency of the simulated data and the observed data were determined on the root mean square error (RMSE) and normalized root mean square error (RMSEn). Low values of these statistical parameters indicate a close association between the simulated values and the observed values. According to Rinaldi *et al*., (2003), RMSEn values lower than 10% indicate the best prediction of the model, values in the range 10 – 20% indicate good prediction, and values in the range 20 – 30% indicate acceptable prediction, while values greater than 30% indicated poor prediction. RMSE was calculated follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (P_i - O_i)^2}{n}},$$

where P_i is the simulated value for the i^{th} measurement and O_i is the observed value for the i^{th} measurement and n is the number of observations.

RMSEn was calculated follows:

$$\text{RMSEn} = \frac{\text{RMSE} \times 100}{\bar{O}},$$

where $\bar{O}$ is the overall mean of the observed values.

Prediction of glycemic index

The soil, weather, management and plant data at harvest stage were used as input data for crop simulation model. The data were required as input data for calculation of genetic coefficients for phenological traits, growth parameters and grain yield of rice varieties. The CSM-CERES-Rice model was used to simulate biomass and yield similar to simulate crop data under field conditions. This step was carried out in our earlier work of the same project.

The schematic diagram of the study is presented in Figure 1. The process for prediction of glycemic index consisted of five steps including model evaluation, regression of simulated data with observed glycemic index, prediction of reference GI, prediction of GI of two rice varieties and prediction of GI of two rice varieties treated with different methods of nitrogen application.

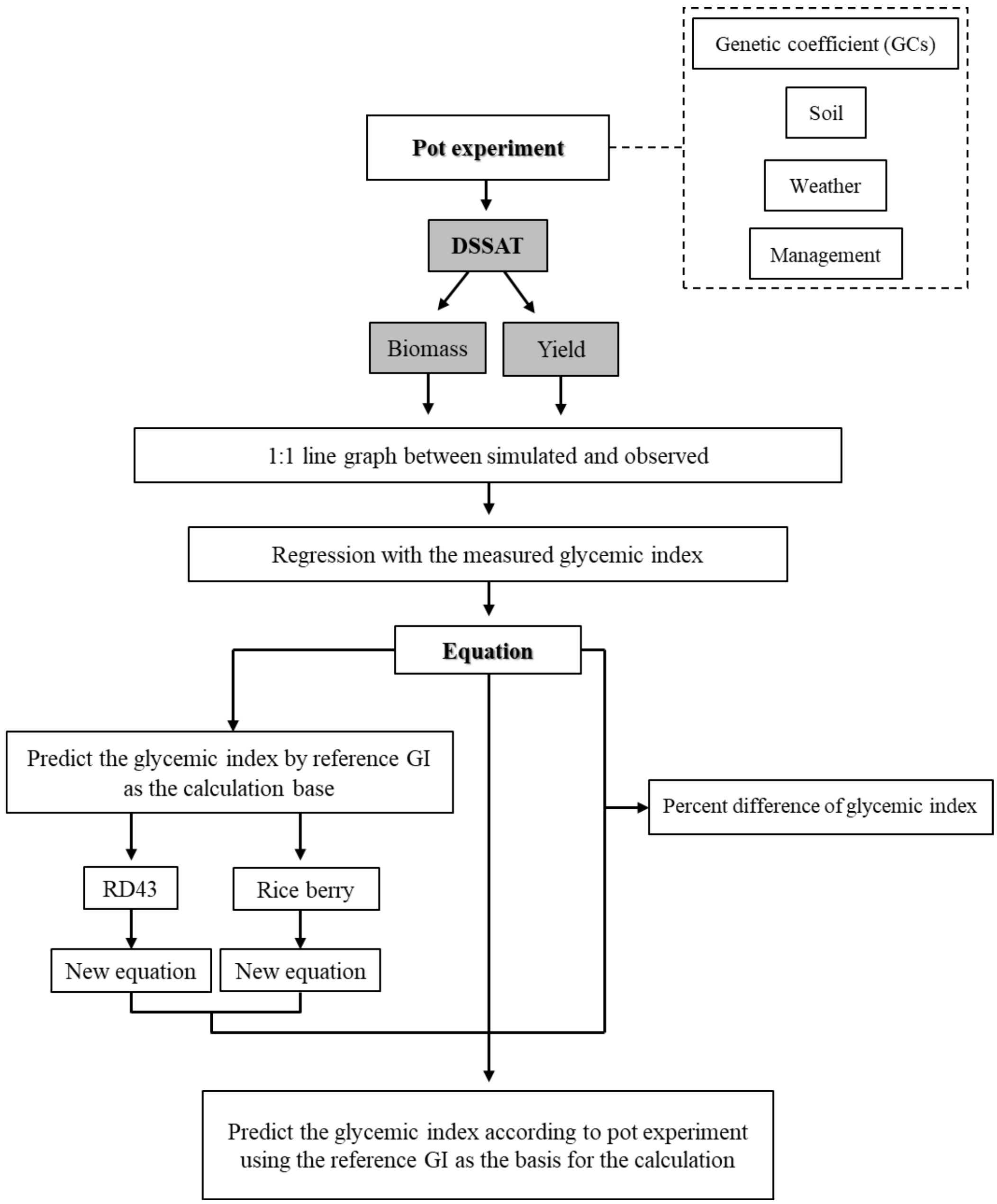


Figure 1. Schematic diagram of the study

Evaluation of the model was carried out by comparing the simulated values with their corresponding observed data using coefficient of determination (R^2) and normalized root-mean-square error (RMSEn) (Figure 2). The evaluation was done under the assumption that variable Y increased proportionally with X variable at the ratio of 1:1. At first step, the regression analysis was based on plot data, but the result was not significant. The model was then evaluated treatment means.

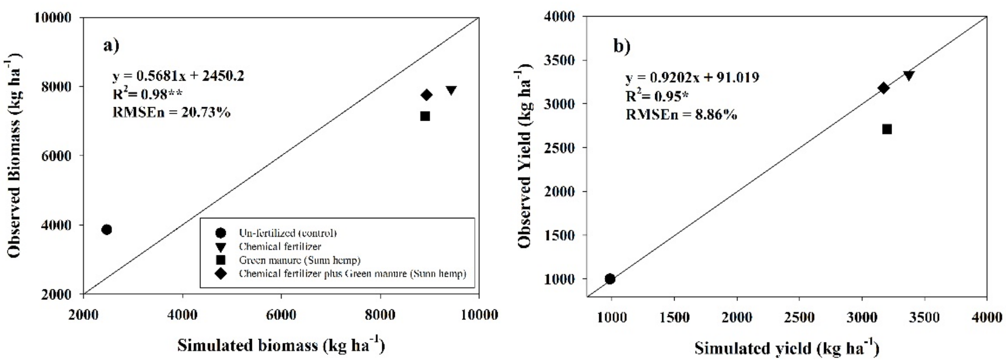


Figure 2. Model comparison between simulated and observed values (a) biomass (b) yield for two rice varieties

Simulated data were regressed with observed glycemic index. The indexes were based on treatment means, which were averaged from two replicates because of the limited samples of rice grain from pot experiment. The assumption underlying the regression was referenced for glycemic indexes which increased proportionally with simulated data at the certain ratio. The model was run until the correct ratios of 1:0.0003 and 1:0.0008 for biomass and grain yield, respectively, were obtained (Figure 3).

The obtained prediction equations were used for prediction of glycemic index of two rice varieties (Figure 3, 4, 5), and comparison of the equations was reported in Table 1. The difference of the model was 0.0%. The last step used the equations for prediction of glycemic index of two rice varieties treated with different methods of nitrogen application (Table 2).

Results

The process for prediction of glycemic index is started by constructing a 1:1 line plot for each parameter. As the observed values and the simulated values for biomass and grain yield which were well associated, and the biomass and grain yield were used for prediction of glycemic index (Figure 2). Regression coefficient (R^2) and RMSEn were used for determination of the relationship between observed values and simulated values. R^2 value indicated the close association between observed values and simulated values, whereas RMSEn indicated the deviation of these values from 1:1 line. By using these criteria, biomass was more closely associated than grain yield as it showed higher R^2 value (0.98**) and but the values had higher deviation lower RMSEn value (20.73%), whereas grain yield had R^2 value of 0.95* and RMSEn value of 8.86%.

The second step for prediction of glycemic index was simulated biomass and grain yield against observed GI. Grian yield was better associated with observed GI than biomass as indicated by higher R^2 value of 1.00** as compared 0.91* of biomass (Figure 3). The regression equation for biomass was y = 0.0003x + 59.099, indicating that increase in 1 kg of biomass resulted to increase 0.0003 g of GI (Figure 3a). The regression equation for grain yield was y =0.0008x + 59.213, indicating that increased in 1 kg of biomass resulted to increase 0.0008 g of GI (Figure 3a).

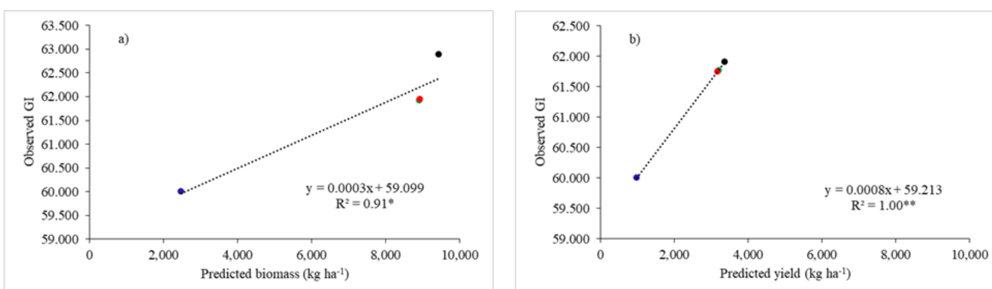
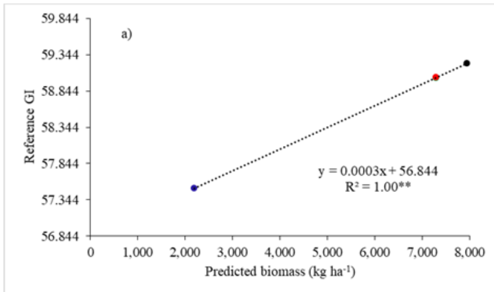


Figure 3. Relationship between observed GI and predicted biomass (a) yield (b) using mean values of two rice varieties

The third step for prediction of glycemic index was to plot the simulated biomass and simulated grain yield against reference GI, and the data were separately evaluated for each rice variety. In RD43, the simulated biomass and grain yield provided similar information, and the R^2 value for simulated biomass and grain yield were 1.00** (Figure 4). However, simulated biomass and grain yield were differed in prediction equations. The prediction equation for biomass was y = 0.0003x + 56.844, whereas the prediction equation for biomass was y =0.0008x + 56.899. The results indicated that changes in biomass and grain yield of 1 kg resulted to change in GI of 0.0003 and 0.0008, respectively.



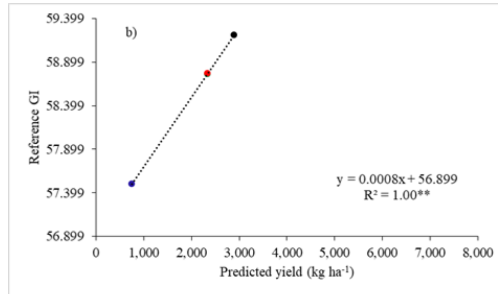
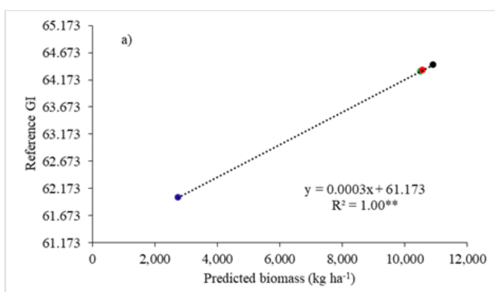


Figure 4. Relationship between observed GI and predicted biomass (a) yield (b) using mean values of the glycemic index of RD43

In Riceberry, regression coefficient for simulated biomass (1.00**) was higher than regression coefficient for simulated grain yield (1.00*) (Figure 5). The relationship between simulated biomass and GI was slightly better than the relationship between simulated grain yield and GI. The prediction equation for biomass was y = 0.0003x + 61.173. The equation implied that the lowest GI index was 61.173, and GI indexes increased with simmulated biomass at the rate of 0.0003 of every 1 kg of simulated biomass. Similarly, the prediction equation for grain yield was y = 0.0008x + 61.026. The equation suggested that the lowest GI index was 61.026, and GI indexes increased with grain yield at the rate of 0.008 for every 1 kg of grain yield.



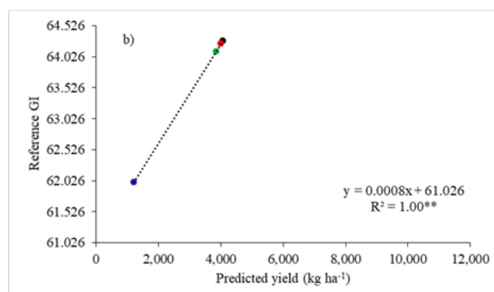


Figure 5. Relationship between observed GI and predicted biomass (a) yield (b) using mean values of the glycemic index of Riceberry

Prediction equations from the model were compared with prediction equations of RD43 and Riceberry which used for prediction of reference GI values (Figures 3,4,5, Table 1). The equation using simulated biomass obtained from averaged values of two rice varieties was y = 0.0003x + 59.099. This equation was used for constructing new equations for RD43 and Riceberry. The new equation for RD43 was y = 0.0003x + 56.844, and the equation for Riceberry was y = 0.0003x + 61.173. The difference between the equation was 0.0%, indicating that simulated biomass could be used for prediction of GI of RD43 and Riceberry with aceptable acuracy.

Table 1. Percentage difference in the equation for predicting the glycemic index of rice, using the value of the glycemic index from the reference glycemic index as the basis for calculation

Glycemic index (GI)	*Biomass (kg ha^{-1})*	*Difference (%)*	*Yield (kg ha^{-1})*	*Difference (%)*
Equation from model	y = 0.0003x + 59.099		y = 0.0008x + 59.213	
RD43 57.5[1/]	y = 0.0003x + 56.844	0.0	y = 0.0008x + 56.899	0.0
Riceberry 62.0[1/]	y = 0.0003x + 61.173	0.0	y = 0.0008x + 61.026	0.0

[1/] = Predict the glycemic index using the values reference GI of the characteristic (Rice Department, 2017a,b) as default.

The equation using simulated grain yield obtained from averaged values of two rice varieties was y = 0.0008x + 59.213 (Figure 3). This equation was used for constructing new equations for RD43 and Riceberry. The new equation for RD43 was y = 0.0008x + 56.899, and the equation for Riceberry was y = 0.0008x + 61.026. The difference between the equation was 0.0%, indicating that simulated biomass could be used for prediction of GI of RD43 and Riceberry with acceptable accuracy.

The simulated biomass and grain yield were used for prediction of GI of two rice varieties treated with four methods of nitrogen fertilizer application. In RD43, simulated biomass values ranged between 2,188 and 7,949 kg ha^{-1}, and urea at the rate of 125 kg ha^{-1} was highest (7,949 kg ha^{-1}), whereas unfertilized control was lowest (2,188 kg ha^{-1}) (Table 2). The predicted GI values were in a range between 57.500 for unfertilized control and 59.228 for urea at the rate of 125 kg ha^{-1}.

The simulated grain yield values ranged between 751 and 2,891 kg ha^{-1}, and urea at the rate of 125 kg ha^{-1} was highest (2,891 kg ha^{-1}), whereas unfertilized control was lowest (751 kg ha^{-1}). GI values were ranged between 57.500 for unfertilized control and 59.212 for urea at the rate of 125 kg ha^{-1}.

Riceberry showed simulated biomass values ranged between 2,755 and 10,921 kg ha^{-1}, and urea at the rate of 125 kg ha^{-1} was highest (10,921 kg ha^{-1}), whereas unfertilized control was lowest (2,755 kg ha^{-1}). The predicted GI values were in a range between 62.000 for unfertilized control and 64.450 for urea at the rate of 125 kg ha^{-1}. The simulated grain yield values ranged between 1,218 and 4,066 kg ha^{-1}, and urea at the rate of 125 kg ha^{-1} was highest (3,858 kg ha^{-1}), whereas unfertilized control was lowest (1,218 kg ha^{-1}). GI values were in a range between 62.000 for unfertilized control and 64.112 for urea at the rate of 125 kg ha^{-1}

Table 2. Prediction of a glycemic index from biomass and yield obtained from models based on different fertilization methods using reference values GI

	Biomass (kg ha^{-1})	***Predicted GI***	***Yield (kg ha^{-1})***	***Predicted GI***
		RD43		
GI initial value	57.5 (reference)[1/]		57.5 (reference)[1/]	
prediction equation	y = 0.0003x + 59.099		y = 0.0008x + 59.213	
Un-fertilized	2,188	57.500	751	57.500
Urea (125 kg ha^{-1})	7,949	59.228	2,891	59.212
Sunn hemp (2,913.1 kg ha^{-1})	7,290	59.031	2,330	58.763
Urea (62.5 kg ha^{-1}) plus Sunn hemp (1,456.8 kg ha^{-1})	7,296	59.032	2,336	58.768
		Riceberry		
GI initial value	62.0 (reference)[1/]		62.0 (reference)[1/]	
prediction equation	y = 0.0003x + 59.099		y = 0.0008x + 59.213	
Un-fertilized	2,755	62.000	1,218	62.000
Urea (125 kg ha^{-1})	10,921	64.450	3,858	64.112
Sunn hemp (2,913.1 kg ha^{-1})	10,524	64.331	4,066	64.278
Urea (62.5 kg ha^{-1}) plus Sunn hemp (1,456.8 kg ha^{-1})	10,584	64.349	4,009	64.233

[1/] = Predict the glycemic index using the values reference GI of the characteristic (Rice Department, 2017a,b) as default.

Discussion

Nitrogen is an important fertilizer for crop production as it is used by the crop to produce biomass, and a part of biomass produced by plant is translocated to harvestable yield. In cereals, biomass and grain yield is closely associated (Bogale and Tesfaye, 2016; Ghassemi and Tajbakhsh, 2012), and they rely heavily on nitrogen input (Sarker *et al*., 2023). Nitrogen is important for growth and yield of crops, and it is also important for crop quality (Yousaf *et al*., 2021). According to Han *et al*. (2021), amylose content was closely related nitrogen application, and, GI value was indirectly correlated with grain yield and biomass.

The explanation of these relationships is beyond the scope of this study. However, nitrogen input might be related to the ratios of amylose and amylopectin in rice grain and starch structure. Panlasigui *et al*. (1991) reported that amylose content and starch structure determined the differences in GI values in rice. GI values in rice were also dependent on growing environments and rice varieties (Boers *et al*., 2015).

The above-mentioned relationships arouse our attention to use simulated biomass and simulated grain yield to predict GI values in rice. The concept of using associated traits and genetic markers as a criterion to select target traits has been widely used in crop breeding (Sukumaran *et al*., 2022). The authors are hopeful to use this concept in crop modeling. We worked some trials and errors and ended with the process reported herein.

The increased concern with health problem of the consumers changes consumer behavior to select more health food products. Some countries have legal enforcement to label health information on food products including GI values (Marinangeli *et al*., 2020). However, GI values are not legally enforced for rice products in Thailand although Thailand is a leading rice exporter. According to Fiona *et al*. (2008), GI values are divided into three levels including low range (≤ 55, 2) medium range (56 – 69) and high range (≥ 70). The labelling of GI values in rice products in Thailand would be at the rough values of the ranges by using only varietal information. If the information on fertilizer application, biomass production and grain yield is available, the use of crop simulation models to predict GI values can provide more useful information to rice consumers. The discussion in this study is focussed on the process of developing the prediction equations to predict GI values of rice and how to improve the process and the data from the experiments to obtain more accuracy of the prediction.

Construction of a 1:1 line plot

1:1 line plot was constructed in order to test the association between observed data and simulated data for biomass and grain yield. At initiation of the step, the data all plots were used, but the data were not well associated. Later, the data of treatment means were used, and the data were well associated. The lack of association between observed data and simulated data from plot values was possibly due to too small experimental size in plot experiment and the treatments associated with Sunn hemp may confound the results as application of Sunn hemp increased acidity (Yuliana *et al*., 2015) although nitrogen rates from calculation were the same. Larger experiments have better and more accurate results because larger experiments reduce error and standards of deviation. According to Tshering (2019), the authors suggested to increase more treatment number, more replications and more runs of the model to increase efficiency of model prediction of KDML 105 rice yield. It is highly recommended to use field experiment data from larger plots as input data of the model.

Plotting the simulated biomass and simulated grain yield against observed GI

The observed GI values were obtained from a laboratory, and were averaged from two replicates for each plot because of limited seed samples from pot experiment. The results were similar to the results of a 1:1 line plot in which the data of all plots were not well associated, and the data of treatment means were well associated. More number of replicates for each plot might increase the accuracy of GI measurement. This step generated prediction equations which explained the relationship between the variable X and the variable Y. The model was run for many rounds until the equations were best fit with the data sets for both biomass and grain yield. The equations are applicable under assumption that the relationship is linear and positive. Research is focused on rice yield, agronomic traits and phenological traits. As this research is rather novel, direct comparison among different studies is difficult. To the best of our knowledge, the authors have not found similar work in the literature. However, the concept of using related traits to predict target traits is not new. Toda *et al.* (2020) used growth related traits to predict biomass of rice in two steps, and they used genomic prediction to predict growth related traits at the first step. By principle, GI is associated with nutrient compositions (Ngo *et al*., 2023; Pereira *et al*., 2024; Rytz *et al*., 2019), and rice biomass and rice yield are also associated with fertilizers applied to the crop especially for nitrogen (Sun *et al*., 2023). Therefore, the authors used biomass and grain yield to evaluate GI.

Prediction of glycemic index

The equations obtained were used to predict glycemic index of two rice varieties. In this step, the reference GI was used as a starting point for calculation of GI of rice varieties. The selection of suitable reference GI is important for the model to predict the accurate GI. The suitable reference GI would be lowest to conform with the treatment without nitrogen application, which had the lowest biomass and the lowest grain yield. The reference GI values were obtained from the varietal characteristics of RD43 (Nilkamheang, 2021) and Riceberry (Muangchan *et al*., 2022) reported by the department of rice affairs, Thailand. The concept of using reference value is generally used in agricultural research such as reference plant for drought resistance (Rosa *et al*., 2019) and reference plant for nitrogen fixation (Cox *et al*., 2022). The reference plant should be of the same plant type of evaluated plant. In peanut, a non-modulating line has been used to evaluate nitrogen fixation of peanut (Khan and Yoshida, 1995). Because the relationships of the values in the line constructed by the equation is systematic, the ideal reference value should be identical to the lowest GI of the rice variety.

Using the equations for prediction of glycemic index of two rice varieties treated with different methods of nitrogen application

In this study, we used the predicted biomass and the predicted grain yield to evaluated GI values of two rice varieties treated with different methods of nitrogen application. The predicted values and observed values of GI were in a similar range of the corresponding data sets for both biomass and grain yield. The results indicated that the equations obtained in this study could be used to predict glycemic index of RD43 and Riceberry, and the accuracy of prediction was acceptable. The authors were not able to compared our results with other studies because this might be the first report on using this method to evaluated GI in rice. However, the method proposed in this study will be used for evaluation of IG in rice with different varieties and grain types. The differences if any would be based on the reference GI values used as a starting point and differential responses of rice genotypes to different environments and agronomic practices.

Indirect evaluation of glycemic index in rice is a means to reduce cost of evaluation from direct method. This study proposed an indirect method by using crop simulation model and the data of grain yield and biomass to simulate glycemic index. Suggestions have been made to improve the accuracy of the model prediction. The data from larger experiments are required for the model as the good data generate the good results. Selection of reference Gi is very important for accuracy of model prediction.

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