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RESEARCH PAPER

Monitoring growth and predicting crop yield through UAV-mounted spectral camera analysis of the interplay between soil compaction and vegetation index

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Abstract

This paper aims to introduce a prediction of crop yield based on relationship between soil compaction and vegetation index. The soil compaction increasingly with depth, which was calculated manuallyunevenly distributed in the field. The NDVI/NDRE was conducted by aerial spectral images taken by the UAV. To figure out connection, the Pearson's correlation test was applied to analyze the correlation between factors. These research results show that the NDVI/NDRE in WS and SA crops increased and decreased steadily after reaching the maximum values (0.85 ± 0.02/ 0.38 ± 0.02 and 0.8 ± 0.02/ 0.28 ± 0.02) during the reproductive stage. The NDVI/NDRE had a high relationship with the plant height, tiller number, yield components of rice. WS and SA networks were built and tested according to the training algorithm in the Matlab software for predicting rice yield with high reliability. The developed models showcase promising results in forecasting rice yield, underscoring the potential applicability of this methodology in agricultural yield prediction.

Keywords

soil compaction, UAV, spectral aerial images, Pearson's correlation, NDVI/NDRE, crop yield

Introduction

Unmanned aerial vehicles (UAVs) are increasingly used in agriculture (Sinha et al. 2016). During rice cultivation, UAVs are used to monitor the growth of rice (Norasma et al. 2018) and estimate rice yields (Duan et al. 2019). Phantom 4 Pro V2 UAV which has many smart models is assembled with Sentera Double 4K sensor (Normalized Difference Vegetation Index - NDVI and Normalized Difference Red-Edge - NDRE) can be effectively used for growth monitoring and prediction rice yield (Norasma et al. 2019). The sensor records five spectral bands (blue, green, red, red edge, and near-infrared) to collect visual band imagery as well as vegetation indices. NDVI which ranges from −1 to +1 is calculated from the red and near infrared bands, while NDRE is used to estimate crop health. High NDVI indicates high green cover as well as high crop growth (Huang et al. 2014).

In recent years, research and application on the relationship between NDVI and crop yield has become popular. Huang et al. (2014) built a regression model to estimate crop yields (rice, wheat, maize) in mixed growing areas using time series MODIS- NDVI data. For estimating rice yield, S model ($y = e^{9.308 - 0.143/NDVI}$) was selected among the built models. According to research by Kailou Liu et al. (2015), rice yield could be predicted by regression according to NDVI at field rice stage.if NDVI ranged from 0.28–0.31, rice yield could be high (about 9 tons/ ha). NDVI has a positive relationship with rice yield. The linear regression model between maximum NDVI and rice yield was also determined in the study of Guan et al. (2018) in Thai Binh Province, Vietnam. In 2018, Raza et al. used proportional vegetation index (RVI) and NDVI to estimate rice yield by applying linear regression. The results At heading stage of a study in the Sacramento Valley of California demonstrate that NDVI at the time of field rice was positively correlated with grain yield ($R^2 = 0.58$) (Rehman et al. 2019). The positive relationship between NDRE and rice yield ($R^2 = 0.6414$) was shown in the study of Pipatsitee et al. (2020). NDVI is also applied in the system to monitor the growth and predict the rice yield in smart farms (Cropin and AWS 2021). In general, these rice yield prediction models were built using regression methods with NDVI.

Soil compaction is a physical characteristic of the soil that affects tillering (Guimarães and Moreira 2001) and rice yield (Pinheiro et al. 2016 and Singh et al. 2017).

Early estimation of rice yield is often very important to farmers and managers. Artificial neural network (ANN) has been widely applied in recent years with outstanding advantages. Some studies on the application of ANN to forecast incidents (Tuan 2019; Lanh et al. 2020; Tung et al. 2021), forecast crop yield (Jeong et al. 2022; Son et al. 2022). In this study, a method to predict rice yield was built based on the results of analyzing the relationship between soil compaction, NDVI, NDRE and rice growth and yield measured in the field combined with training ANN.

Materials and methods

Experiment design

The experiments were carried out in the Winter-Spring (WS) crop from 12/2021 to 3/2022 and the Summer-Autumn (SA) crop from 4–7/2022 on the same rice field at Binh Hoa Phu Cooperative belongs to Long Phu commune, Long My town, Hau Giang province (Fig. 1. "Map data 2023(C) Google". It is one of the provinces in the Mekong Delta with a large rice growing area. OM18 rice was manually sown for 2 crops. The number of field data collection in the WS and SA crops were 70 and 80. Groups of 5 experimental plots which were randomly selected in 2 rows were spaced 3 meters apart and marked so that data collection was location-accurate. The soil compaction between these plots changes when the distance between them is 5 meters (Huu et al. 2022).

At each experimental area, soil compaction was measured by Field Scout SC 900 soil compaction meter (penetrometer) before sowing rice. The aerial drone images were collected 8 times at 15, 26, 36, 46, 60, 72, 89, 95 and 8, 26, 36, 46, 58, 79, 89, 96 days after sowing of rice (DAS) in the WS and SA crops, respectively. The aerial drone images collection times were separated by an average of 12 days to ensure the tracking of changes NDVI and NDRE. Sentera's 4K precision NDRE and NDRE dual cameras were mounted on the Phantom 4 Pro V2 drone to automatically capture images of rice fields according to flight parameters in the Field Agent software of a tablet. The basic parameters include area (2 ha), height (30 m), speed (4 m/s), side and front overlap (60%) and spatial resolution (0.8 cm/px). Agisoft photo scan software was used to correct geometrical errors of the aerial drone images and merge them into an orthomosaic image with geometrical and positional accuracy (Ngadiman et al. 2018). The process of creating orthomosaic photo was done in 5 main steps: add photos (NDVI or NDRE) from the folder, align photos to position the camera and capture direction for each photo, build dense cloud with relatively even pixel density, build

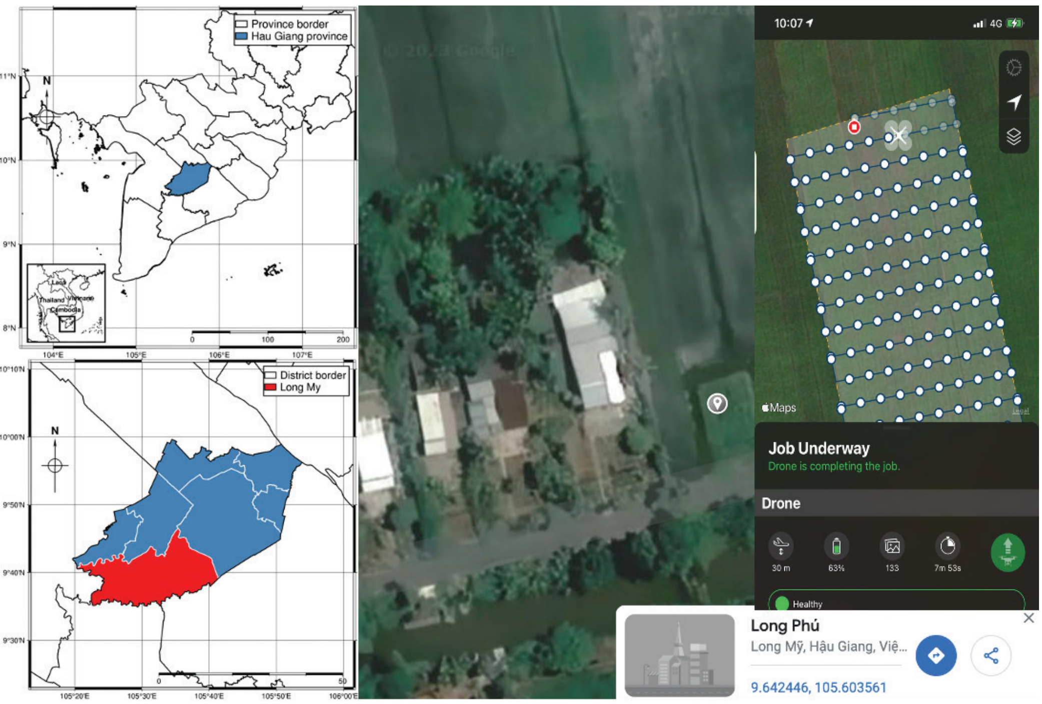


Figure 1. Data acquisition and flight route.

DEM and build orthomosaic photo (Huu et al. 2022b). NDVI and NDRE were determined by Matlab software from blue and red bands on Sentera Double 4K sensor. At each experimental areas of 1 meter square, the value of NDVI and NDRE of 4 sub-areas were calculated according to formulas (3) and (6) as follows. In which, NIR is the near-infrared band, Red is the red band and Red Edge is the Red edge band. The NDVI and NDRE index is calculated by the following equations:

$$RED = -0.966 * ChNir + 1.000 * ChRed \quad (1)$$

$$NIR = 4.35 * ChNir - 0.286 * ChRed \quad (2)$$

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (3)$$

Where:

- ChNir: the nir channel of the spectral ndvi photo
- ChRed: the red channel of the spectral ndvi photo

NDRE index is calculated by using the following formula:

$$REDEDGE = -0.956 * ChNir + 1.000 * ChRed \quad (4)$$

$$NIR = 2.426 * ChNir - 0.341 * ChRed \quad (5)$$

$$NDRE = \frac{NIR - REDEDGE}{NIR + REDEDGE} \quad (6)$$

Where:

- ChNir: the nir channel of the spectral ndre photo
- ChRed: the red channel of the spectral ndre photo

At the marked experimental areas (Fig. 2), agronomic parameters such as the plant height and the number of tillers (branches) of rice in a 25 × 25 cm frame were measured at 26, 36, 46, 60 and 26, 36, 46, 58 DAS. The rice tillers with a minimum of 3 leaves were counted and the plant height was determined from the ground to the top of the highest leaf. At rice harvest, straw biomass, number of panicles, rice yield per m^2 and 1,000-grain weight were also collected. Rice yield and 1,000-grain weight were calculated under standard conditions at 14% humidity (Anh et al. 2012) from rice weight measured by Vibra Shinko Denshi electronic balance and Kett Riceter moisture meter at the time of harvest.

Figure 2. Marked position on paddy field.

Evaluation of the relationship between soil compaction, NDVI, NDRE and the growth and yield of rice

The values of soil compaction, NDVI, NDRE and agronomic parameters of rice were rough processed by Microsoft Excel software. The Pearson's correlation coefficient test method was effectively used to compare mean, standard deviation and evaluate the correlation of research subjects by SPSS software (Field 2009). The ANN training method was used to build a model to predict rice yield. With the aid of computers, this method is effective for building forecast models with many variable values. Levenberg - Marquardt was chosen for training and testing data because this algorithm gives fast convergence results (Lanh et al. 2020).

By testing with ANNs with different numbers of hidden layers and neurons, the two hidden layers with 10 and 3 neurons ANN has optimal training and testing results. Two neural networks (named WS network and SA networks for WS and SA crops) with Levenberg - Marquardt training algorithm were set up including 01 input layer with data matrix input layer, 2 hidden layers including 10 and 3 neurons and output layer (Fig. 3). In which, the NDVI and NDRE values which were collected 36, 46, 60 and 36, 46, 58 DAS were 6 inputs for WS network and SA networks, respectively. These input data were chosen because they have a relationship at the 1% significance level with the output data (rice yield), as shown in Tables 1, 2.

The used hidden and output neuron activation functions were tansig and purelin. The chosen error determination function was the function that determines the mean squared error (MSE). The data sets of 280 and 320 in WS and SA were randomly divided into 2 groups of training (90%) and network testing (10%). Initial weight and bias initialization and training of networks WS and SA were performed randomly.

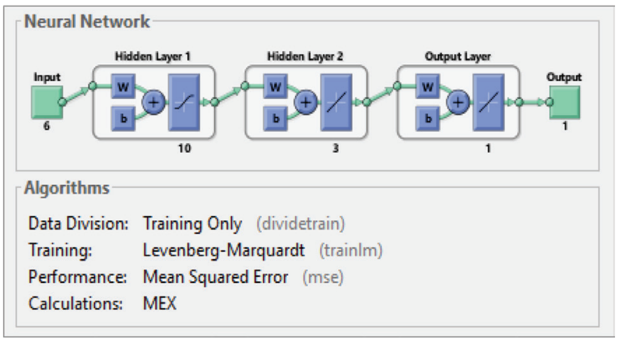
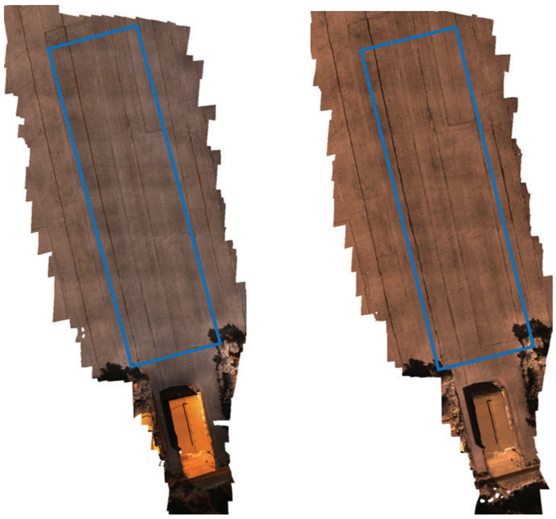


Figure 3. The Structure of Ws and Sa networks.

Results and discussion

Image reconstruction

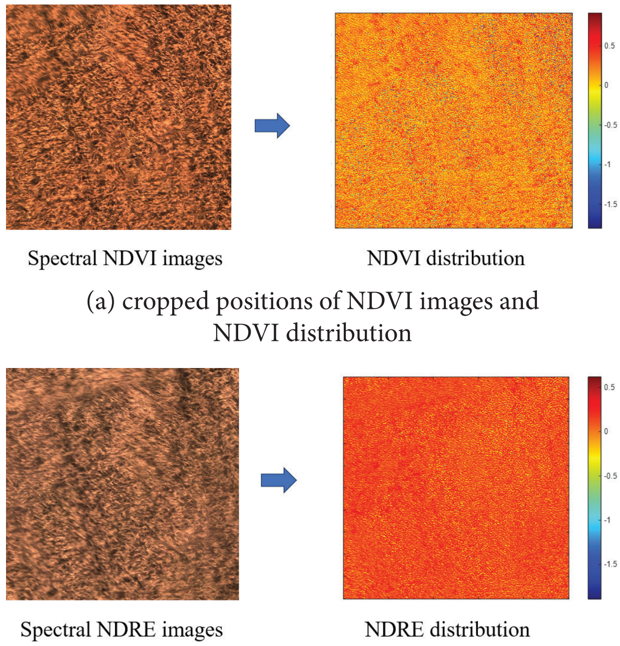
Ortho-image of NDVI and NDRE spectral photos are shown in Fig. 4. Area inside blue rectangle is the experimental field. It is clearly to see that image alignment works well so we can monitor paddy field surface clearly. From these photos, the NDVI and NDRE index can be calculated by using Matlab software supported by image processing toolbox.



(a) Ortho-images of NDVI photos (b) Ortho-images of NDRE photos

Figure 4. Ortho-images of spectral photos.

From the ortho-images, the NDVI distribution and NDRE distribution can be calculated. Parts of observation area with size 100 × 100 pixels (0.8 × 0.8 m^2) are cropped to calculate the distribution value (Fig. 5). These areas can be found by the marker put on the paddy field carefully and the vegetation index distribution of one area shows the average value in the photo.



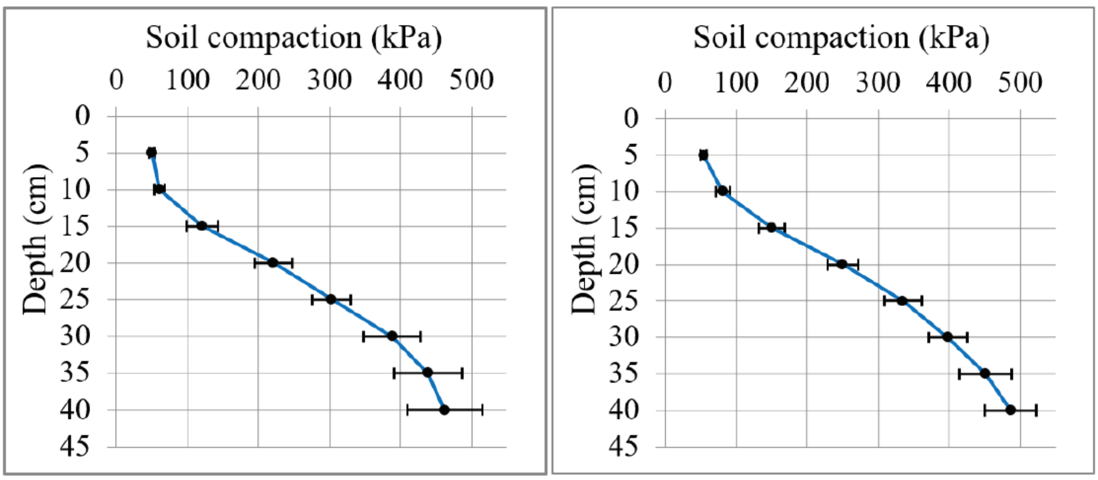
(a) cropped positions of NDVI images and NDVI distribution

(b) cropped positions of NDRE images and NDRE distribution

Figure 5. The spectral images and vegetation distribution.

Statistical analyses of soil compaction

The average value of soil compaction recorded at the experimental areas by depths of 5, 10, 15, 20, 25, 30, 35 and 40 cm (named SC_5cm, SC_10cm, SC_15cm, SC_20cm, SC_25cm, SC_20cm, SC_35cm and SC_40cm) were calculated and graphically illustrated in Fig. 6. In general, the average of soil compaction increased rapidly at the layer of 10–20 cm and increased slowly at the layer below 20 cm and the soil compaction varied within 20% of the mean value. The change of soil compaction with depth in this study was similar to the results of Huu et al. (2022). This result could be explained and was consistent with the research that has been done on compaction and structural degradation of soil layers (Phuong et al. 2009).



(a) WS crop (b) SA crop

Figure 6. The compaction of soil layers in WS and SA crops.

Statistical analyses of the growth and yield of rice

The results of field data analysis at the experimental areas were shown in Fig. 7. It can be seen that the plant height and the number of rice tillers per m^2 in WS crop were higher than in SA crop. The number of rice tillers increased rapidly during the tillering stage (about 46 DAS) to the maximum value of the number of tillers about 527 ± 40 and 420 ± 33 per m^2 before decreasing slightly to 517 ± 40 and 394 ± 32 per m^2. The number of effective tillers positively affects the number of panicles and grain yield. The plant height increased steadily since sowing and reached the high value between about 96.6 ± 3.5 and 89 ± 2.5 cm at flowering panicle stage in the WS and SA crops, respectively.

The number of panicles per m^2, 1,000-grain weight , actual rice yield, rice biomass in the WS and SA crops were 393 ± 41, 27.9 ± 0.3, 6 ± 0.6, 468 ± 53.9 and 301 ± 31, 19 ± 0.7, 4.2 ± 0.5, 391.5 ± 48.5, respectively. The rice component yield, actual rice yield, rice biomass in WS crop were higher than in the SA crop. Better nutritional and weather conditions in the WS crop could be responsible for this result.

The statistical analyses of NDVI and NDRE

The results of analysis of NDVI and NDRE values were presented in Fig. 8. We can see that the change trend of NDVI and NDRE values in 2 crops were similar. The NDVI and NDRE values gradually increased and decreased after reaching the maximum values of about 0.85 ± 0.02 and 0.38 ± 0.02 at the time when the rice reached 46 DAS in the WS crop and 0.8 ± 0.02 and 0.28 ± 0.02 at the time of 58 DAS in the SA crop, respectively. The results of this study was similar to those of Minh et al. (2015). The NDRE value was always lower than and has a positive relationship with the NDVI value at all times of data recording as the research results of (Murata et al. 2016; Pipatsitee et al. 2020). The peak values of NDVI and NDRE values of rice in the WS crop were slightly higher than these values in the SA crop.

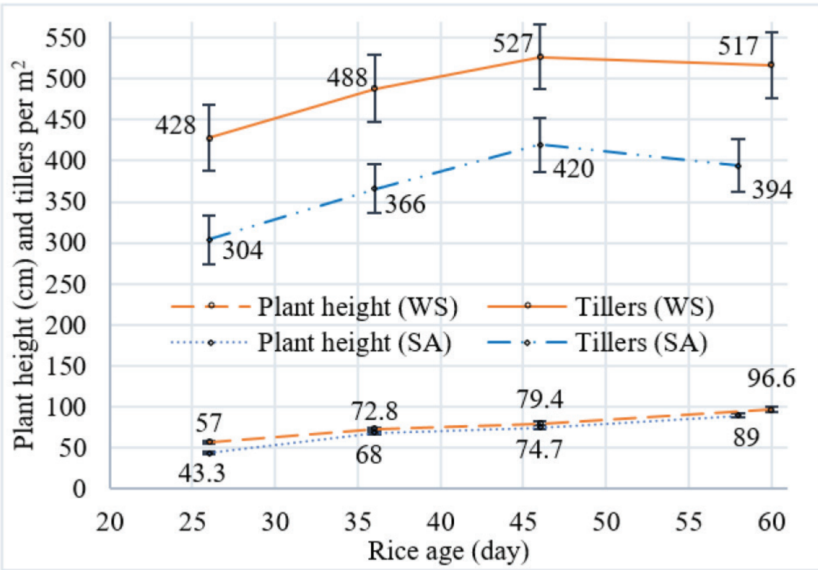


Figure 7. The agronomic parameters of rice.

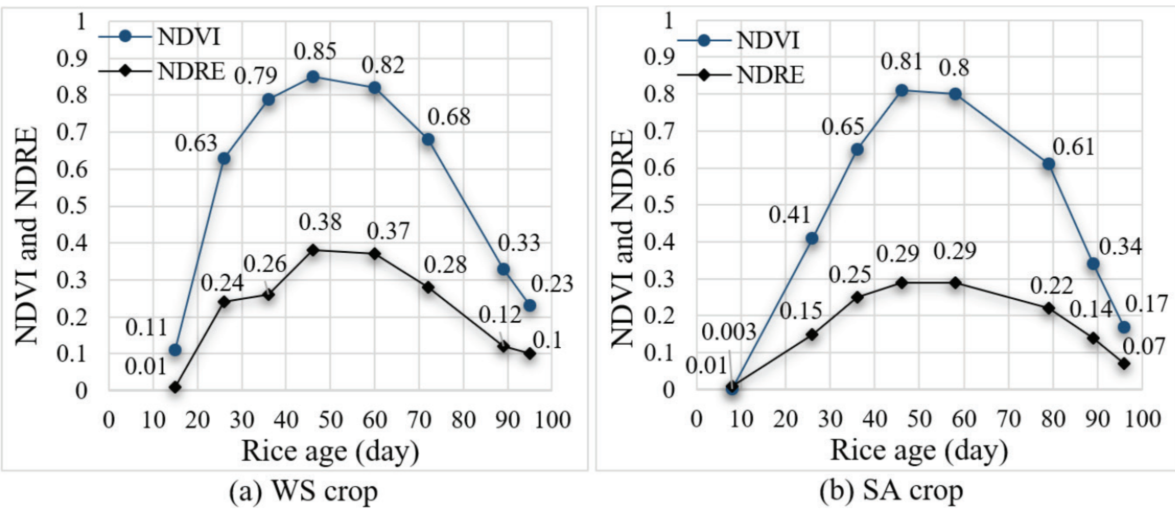


Figure 8. NDVI and NDRE values in WS and SA crops.

The effect of NDVI, NDRE and soil compaction on the growth and yield of rice

The correlation coefficients between NDVI, NDRE, soil compaction and plant height, the number of rice tillers and rice component yield, actual rice yield, rice biomass in WS and SA crops are present in Tables 1, 2. The relationship between NDVI/ NDRE and agronomic parameters which were recorded at the previous time point was not considered in this research. In both WS and SA crops, NDVI at heading stage showed a positive correlation with rice yield with coefficients of 0.452 and 0.363 at the 1% significance level respectively. When NDVI was high, rice yield also tended to be high. There is a similarity in the relationship between NDVI and rice yield in this study compared to the study of Kailou et al. (2015). The rice yield increased from 6–9 tons/ha as NDVI increased from 0.25–0.28.

Table 1 shows that NDVI/NDRE had a negative correlation with the plant height and a positive correlation with the tiller number at 26, 36, and 46 DAS, however this correlation was positive with the plant height and the tiller number at 60 DAS. Another highlight that can be seen is that NDVI at 36 and 46 DAS of rice had a correlation coefficient with the plant height/ the tiller number (0.275/ 0.173 and 0.213) at the 1% significance level. NDVI/NDRE recorded at various times during the rice period from 26 DAS to harvest had a positive correlation with the tiller number; rice straw biomass and yield with correlation coefficients from 0.211–0.448/ 0.127–0.344; 0.28–0.504/ 0.217–0.379 and 0.155–0.455/ 0.165–0.368, respectively at the 1% significance level in the WS crop. However, NDVI at 72 DAS had a negative correlation (0.303) with 1,000-grain weight at the 1% significance level. Similarly, NDRE at 46 and 60 DAS had a negative correlation (0.192 and 0.182) with 1,000-grain weight at a highly significant level. Another result can be seen in that soil compaction at depths of 5, 10, 15 and 20 cm had inverse relationship with plant height at 36 DAS with a correlation coefficient of 0.21–0.268 at the 1% significance level. Soil compaction in these soil layers also had a positive relationship with the tiller number at 36; 46 and 60 DAS with correlation coefficients from 0.133–0.208; 0.162–0.261 and 0.141–0.254, respectively. With the component yield indices of rice, most soil compaction at recorded depths had a positive correlation with the panicle number; straw biomass; yield and 1,000-grain weight with correlation coefficients from 0.128–0.86; 0.155–0.365; 0.123–0.311 and 0.158–0.289 at high significance level. In particular, soil compaction at depths of 10 cm had the most relationship with productivity compared to the soil compaction at other depths.

The results of analyzing the relationship between factors in the SA crop presented in Table 2 show that NDVI/NDRE had a positive correlation with plant height at 36; 46 and 58 DAS with correlation coefficient 0.47/ 0.269; 0.328/ 0.313 and 0.255 at the 1% significance level. NDVI/ NDRE had a positive correlation with the tiller number with a correlation coefficient of 0.308/ 0.208; 0.312/ 0.303; 0.318/ 0.313 and /0.176 at the 1% significance level with measurement data at 26; 36; 46 and 58 DAS. There was another positive correlation between NDVI/ NDRE and the the rice panicle number; rice yield and 1,000-grain weight with correlation coefficients from 0.19–0.362/ 0.117–0.33; 0.139–0.372/ 0.113–0.35 and 0.119–0.23/0.129–0.269, respectively at the 1% significance level. With agronomic indices of rice plants, soil compaction at depths of 5 and 10 cm had a significant positive relationship with plant height at 46 DAS with coefficients of 0.214 and 0.226 at the 1% significance level. Another analysis result can be seen that soil compaction at

Table 1. The correlation between NDVI, NDRE, soil compaction and rice growth, yield, biomass of rice in the WS crop.

	Plant height (26)	Tillers (26)	Plant height (36)	Tillers (36)	Plant height (46)	Tillers (46)	Plant height (60)	Tillers (60)	Panicles	Rice biomass	Actual rice yield	1,000-grain weight
NDVI (26)	-0.112	0.043	-0.047	0.076	0.101	0.063	0.046	0.054	0.114	0.150*	0.155**	0.111
NDRE (26)	-0.173**	-0.076	-0.045	-0.052	-0.048	0.004	0.056	0.003	0.127*	0.217**	0.165**	0.061
NDVI (36)			-0.275**	0.173**	-0.161**	0.234**	0.114	0.234**	0.309**	0.386**	0.427**	0.050
NDRE (36)			-0.127*	0.059	-0.174**	0.098	0.150*	0.108	0.187**	0.364**	0.368**	-0.102
NDVI (46)					-0.213**	0.117	-0.007	0.117	0.211**	0.280**	0.258**	0.025
NDRE (46)					-0.139*	0.099	0.215**	0.119*	0.247**	0.379**	0.339**	-0.192**
NDVI (60)							0.128*	0.135*	0.267**	0.336**	0.332**	-0.133*
NDRE (60)							0.131*	0.115	0.190**	0.291**	0.354**	-0.182**
NDVI (72)									0.366**	0.407**	0.414**	-0.303**
NDRE (72)									0.330**	0.376**	0.351**	0.067
NDVI (89)									0.458**	0.462**	0.452**	-0.097
NDRE (89)									0.344**	0.353**	0.296**	-0.128*
NDVI (95)									0.456**	0.504**	0.455**	-0.097
NDRE (95)									0.242**	0.314**	0.361**	0.010
SC_5cm	-0.341**	0.108	-0.210**	0.157**	0.106	0.261**	-0.115	0.254**	0.355**	0.313**	0.257**	0.175**
SC_10cm	-0.391**	0.083	-0.268**	0.133*	0.039	0.242**	-0.063	0.234**	0.386**	0.365**	0.311**	0.069
SC_15cm	-0.078	0.146*	-0.260**	0.186**	-0.043	0.184**	0.007	0.175**	0.128*	0.155**	0.099	0.288**
SC_20cm	0.029	0.192**	-0.242**	0.208**	-0.051	0.162**	-0.128*	0.141*	0.154**	0.108	0.123*	0.289**
SC_25cm	-0.039	0.111	-0.123*	0.111	-0.167**	0.115	-0.088	0.101	0.201**	0.242**	0.257**	0.158**
SC_30cm	0.003	0.185**	-0.030	0.180**	-0.082	0.163**	-0.014	0.160**	0.256**	0.277**	0.310**	0.164**

Note: *, **- Correlation is significant at the 0.05, 0.01 level and (number)- number is DAS.

Table 2. The correlation between NDVI, NDRE, soil compaction and rice growth, yield, biomass of rice in the SA crop.

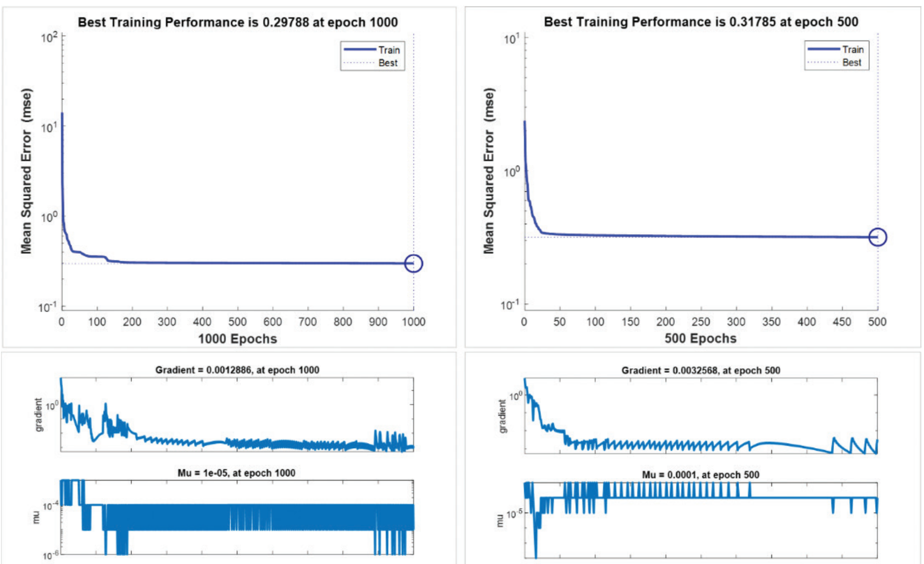
	Plant height (26)	Tillers (26)	Plant height (36)	Tillers (36)	Plant height (46)	Tillers (46)	Plant height (58)	Tillers (58)	Pani-cles	Rice bio-mass	Actual rice yield	1,000-grain weight
NDVI (26)	0.008	0.308**	0.516**	0.285**	0.199**	0.311**	-0.406**	0.250**	0.069	0.275**	0.139*	0.155**
NDRE (26)	0.040	0.208**	0.291**	0.156**	0.109	0.166**	-0.191**	0.131*	0.069	0.163**	0.127*	0.100
NDVI (36)			0.470**	0.312**	0.345**	0.331**	-0.138*	0.301**	0.242**	0.142*	0.250**	0.230**
NDRE (36)			0.269**	0.303**	0.177**	0.367**	-0.065	0.341**	0.225**	0.000	0.310**	0.269**
NDVI (46)					0.328**	0.318**	-0.049	0.229**	0.210**	0.085	0.365**	0.128*
NDRE (46)					0.313**	0.313**	0.044	0.280**	0.330**	-0.011	0.350**	0.129*
NDVI (58)							0.255**	0.003	0.119*	-0.083	0.329**	0.119*
NDRE (58)							0.106	0.176**	0.231**	0.134*	0.280**	-0.027
NDVI (79)									0.219**	0.004	0.261**	0.004
NDRE (79)									0.198**	0.066	0.169**	-0.007
NDVI (89)									0.362**	-0.165**	0.363**	0.071
NDRE (89)									0.098	-0.015	0.113*	0.201**
NDVI (96)									0.286**	-0.136*	0.372**	0.023
NDRE (96)									0.117*	0.044	0.241**	0.027
SC_5cm	0.016	-0.075	-0.010	-0.082	0.214**	-0.100	-0.022	-0.013	0.084	0.097	-0.040	-0.016
SC_10cm	0.142*	-0.016	-0.049	0.049	0.226**	0.019	0.085	0.065	0.188**	0.054	0.308**	0.059
SC_15cm	0.090	-0.011	-0.021	0.090	0.104	0.082	0.102	0.174**	0.278**	-0.071	0.233**	-0.007
SC_20cm	-0.026	-0.071	0.005	0.016	0.010	-0.030	-0.008	0.041	0.252**	-0.043	0.293**	-0.207**
SC_25cm	-0.060	0.021	0.101	0.056	0.102	0.060	-0.156**	0.093	0.113*	0.102	0.101	-0.101
SC_30cm	-0.125*	0.041	0.146**	0.034	0.134*	0.020	-0.011	0.032	0.131*	-0.079	0.222**	-0.124*

Note: *, **- Correlation is significant at the 0.05, 0.01 level and (number)- number is DAS.

depths of 10, 15, 20 and 30 cm had a positive correlation at the 1% significance level with rice panicle number and rice yield with a correlation coefficient range from 0.113–0.278 and 0.222–0.308, respectively. In particular, the correlation with the highest coefficient (0.308) between soil compaction at a depth of 10 cm and rice yield was determined.

Establishment of prediction models for rice yield

The training value with 90% of the collected data of the WS and SA networks is shown in Fig. 9. The gradient value of the WS and SA networks decreased rapidly to low values (approximately 0.0013 and 0.0033) at epochs 250 and 75 and fluctuated slightly around this value until epochs 1,000 and 500, respectively. Similarly, the MSE values of the WS and SA networks also decreased rapidly to low values (approximately 0.298 and 0.332). The MSE values of two models were approximately the same as the MSE value (0.257) of the regression model predicting rice yield of late rice in the study of Kailou et al. (2015). However, these values were slightly lower than the MSE value (0.187) of the deep learning model predicting rice yield of Jeong et al. (2022). The adaptation value (mu) of the WS and SA networks is 1.00*e-5 and 0.0001, which were many times smaller than the set value (0.001).



(a) WS network (b) SA network

Figure 9. MSE, gradient and adaptation value of two networks.

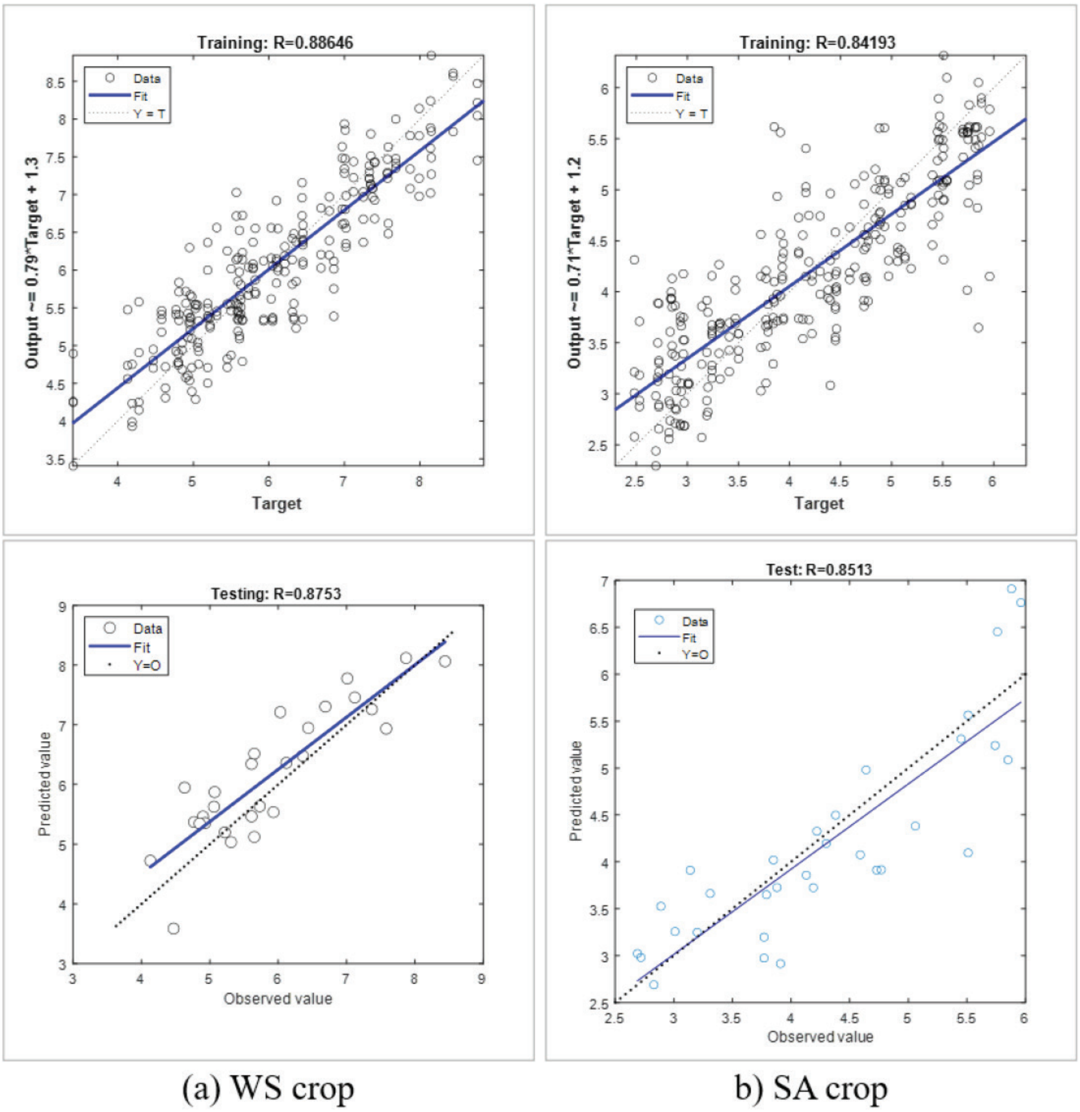


Figure 10. The correlation between predicted and observed values in two crops.

Fig. 10 shows the results of training and testing the WS and SA networks at epochs 1,000 and 500, respectively. The regression coefficient of the training data and the output data of the WS network was R = 0.8865. We can see that the training results of WS network are better than SA network with regression coefficient R = 0.8419. Using 10% of the collected data to test the WS and SA networks shows that the level of deviation between the observed rice yield and the predicted value through the WS and SA models were low, the regression coefficient is R = 0.8753 and R = 0.8513, respectively. The results of a high regression coefficient and a low difference between the predicted value and the observed value show that the WS and SA networks were successfully trained in both WS and SA crops.

Conclusions

The NDVI and NDRE in the WS and SA crops increased during the reproductive stage of rice and decreased until the time of rice harvest. NDVI and NDRE had the relationship with plant height, tiller number, panicle number, rice straw biomass, rice yield and 1,000-grain weight at a highly significant level.

Using NDVI, NDRE and rice yield measured in WS and SA crops with training and testing through WS and SA networks (including 1 input layer, 2 hidden layers and 1 output layer) according to the Levenberg - Marquardt training algorithm and applying the tansig and purelin activation functions gives results in predicting rice yield with high reliability. In the future, the early prediction of rice yields could be transferrable to WS or SA crops by applying the advanced models by training ANN.

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