Asian J Agric & Biol. xxxx(x).
DOI: 10.35495/ajab.2021.09.327

AJAB

Original Article

Establishment of rice yield prediction model using soil compaction

Van Huu Bui, Huu Cuong Nguyen, Quang Hieu Ngo*
Department of Mechanical Engineering, Can Tho University, Vietnam

Received:
October 06, 2021
Accepted:
January 16, 2023
Published Online:
February 26, 2023

**Corresponding author email:*
nqhieu@ctu.edu.vn

Abstract

Soil compaction has a real effect on rice yield in the Mekong Delta. Two field experiments were carried out during 2019 Summer-Autumn and 2020 Summer-Autumn in An Giang Province (Mekong Delta). OM18 rice was cultivated in the plots which were laid out in a randomized complete block design measuring 0.5 × 0.5 m with 5 and 6 m alley between blocks and between plots. The Pearson's correlation test was applied to compare the mean and standard deviation of the soil layers and evaluate the correlation between soil compaction and rice yield in both crops. The present research results showed that the value of soil compaction increased with depth and differed among locations in the rice field. Soil compaction at 10 cm from the surface had a positive correlation with rice yield. Therefore, the prediction model of rice yield is able to build up due to soil compaction at 10 cm from the surface. Moreover, this study provides that the value of 10 cm soil layer compaction ranging between 165 and 190 kPa can be the optimal value of soil tillage for paddy rice cultivation with the highest yield in the Summer-Autumn crop.

Keywords: Soil depth, Soil compaction, OM18 rice, Rice yield, Prediction model

How to cite this:

Bui VH, Nguyen HC, Ngo QH. Establishment of rice yield prediction model using soil compaction. Asian J. Agric. Biol. xxxx(x). 202109327 DOI: https://doi.org/10.35495/ajab.2021.09.327

Introduction

During rice cultivation, heterogeneous soil tillage and the use of agricultural machines locally alter the physical properties of the soil (Phuong et al., 2009), particularly the compaction of the arable soil layer. Some studies have shown that the movement of agricultural machinery wheels created compression pressure, increasing the hardness of the soil surface (Raper, 2005). A tractor-trailer with the slurry application for changing the pressure of wheels on the soil surface was used in the experiment. As a result, the traffic of tractors had serious impacts on some physical characteristics of the 0–70 cm soil layer (Lamand and Schjønning, 2017). One part of another study was conducted in the laboratory to simulate the interaction between wheel and soil by the finite element method. The soil was compacted and changed structure by wheel load (Tenu et al., 2012).

Soil compaction had a great influence on root growth (Correa et al., 2019), shoot growth, and rice yield (Hoque and Kobata, 2000). The compaction of the soil layer was evaluated by the soil bulk density indicator (Hakansson and Lipiec, 2000). Soil compaction had a proportional relationship with soil bulk density, namely, the soil bulk density of the 10–20 cm soil layer was larger than that of the 0–10 cm soil layer (Motschenbacher et al., 2011). This means that the compaction of the 10–20 cm soil layer was also larger than that of the 0–10 cm soil layer.

In recent years, the relationship between the chemical, physical, physicochemical, and biological properties of soil (Noor et al., 2023) and rice yield has been found interesting to researchers. Climate change impacts on rice production in the Lower Mekong River basin. The results pointed out that the CO_2 concentration and rice yield had a positive relationship and the polynomial model was built to verify the impacts of CO_2 concentration on rice yield (Kang et al., 2021). According to the results of Zhang et al. (2018), unitary quadratic polynomial models and unary non-structural fertilizer response models were built to estimate rice yield by fertilizer application rates of nitrogen (N), phosphorus (P), and potassium (K) on rice (Zhang et al., 2018). Another study reported a significant polynomial relationship between changing rice yield and alkalinity and Si ratio of slags. Rice yield increased in case of alkalinity and Si ratio of slags less than 3 (Sandhya and Prakash, 2021). The linear regression equations were built to illustrate that average annual rice yield had a significant correlation with soil microbial biomass C, soil microbial biomass C:N ratio, soil organic C, and soil pH (Li et al., 2016). The study of Pinheiro et al. (2016), demonstrated that the compaction of topsoil of sowing furrow positively affects rice yield by regression analysis method. The quadratic equation of rice yield estimated by the value of soil compaction which was constructed has the maximum value when the soil compaction was in the range of 238.5–280.3 kPa (Pinheiro et al., 2016).

The Mekong Delta, likes “Vietnam's Rice Bowl”, has a large land area used for cultivating paddy rice (Clauss et al., 2018). In 2020, Vietnam was the second biggest exporter of the world with 6.25 million tons of rice. The quantity of predicted rice export would rise up to 6.4 million tons by 2021 (USDA, 2021). Farmers relied upon rice cultivation and their incomes come from rice fields. Thus, building up a model to evaluate or predict the rice yield has been a necessary part of the research so that farmers are able to improve their cultivation methods. In present study, the polynomial, exponential, and power functions are created as the prediction models in which soil compaction is used as the input to estimated rice yield.

Material and Methods

OM18 rice, a high-yield rice variety, which had the plant height (90–95 cm) and growth time (90–95 days) was collected from Loc Troi Group Joint-Stock Company, Vietnam (Chuong, 2021). This rice variety was selected for the experiment and being transplanted by a machine with a density of 30 × 15 cm. Rice was carried out for all experimental sets in the same paddy field covered the area of 200 × 24 m in Dinh Thanh Agricultural Research Center (10°18’ 45”N; 105°19’08”E; 1 m), Dinh Thanh Commune, Thoai Son District, An Giang Province. The experiment was conducted in two phases: phase 1 from May–August 2019 (2019 Summer-Autumn crop) with 130 samples and phase 2 from April–July 2020 (2020 Summer-autumn crop) with 98 samples. This research focuses only on the data collection of soil compaction and rice yield. Other factors such as diseases, pests, natural enemies, etc. can affect rice yield will not be considered.

Soil sampling selection and compaction measurements

At the beginning of each rice crop, the soil was improved to reduce compaction and increase porosity before transplanting rice by methods of soaking in water for a few days, ploughing by tiller tractor, leveling the ground, creating drainage ditches. Before transplanting rice, there were 130 and 98 plots in the experimental field in phase 1 and 2. The plots which measured 0.5 × 0.5 m with 6 m inter-block and 5 m inter-plot spacings was laid out in a randomized complete block design (Nawaz et al., 2015) with 2 times. At 1 sample point in each plot, soil compaction values were recorded for layers from 5 cm until the considered depth by using Field Scout SC 900 Soil compaction meter. This data was exported to a computer by a USB port (Pinheiro et al., 2016).

Rice yield measurements

In these experiments, at each plot, rice yield at 14% moisture content (Chuong, 2021) was collected using the standard procedure at the time of rice harvest and converted into tons /hectare unit.

Statistical analysis

Data were pre-processed by Microsoft Excel 2016. Next step, the Pearson correlation coefficient (two-tailed) was used to evaluate the mean, standard deviation, and correlation of the compaction of the soil layers and rice yield by SPSS software (Field, 2009). Linear regression method (Thomas et al., 2020) and non-linear regression method were used to build the prediction model of rice yield by using the Curve

Fitting application in Matlab software. This mathematical model is a function that varies with soil compaction of the following form:

$$Y = f(x) \qquad (1)$$

where Y is the model of rice yield (tons /hectare), x is soil compaction (kPa).

Results

Data analyses of soil compaction

We get the results as shown in Fig-1. In general, the value of soil compaction at 5 cm intervals from 0–40 cm measured in 2019 Summer-Autumn crop increased steadily from 60.49–580.22 kPa. While, the compaction value measured in 2020 Summer-Autumn crop increased rapidly in the upper layer of 30 cm, increased slowly at the layer below 30 cm, and reached the highest value (541.81 kPa) at 40 cm of depth. The standard deviation of soil compaction layers shows that there was a big difference in the compaction of the corresponding soil layers between the selected experimental sites. This result is similar to the results of the study that has been done on compaction and structural degradation of soil layers (Motschenbacher et al., 2011; Phuong et al., 2009).

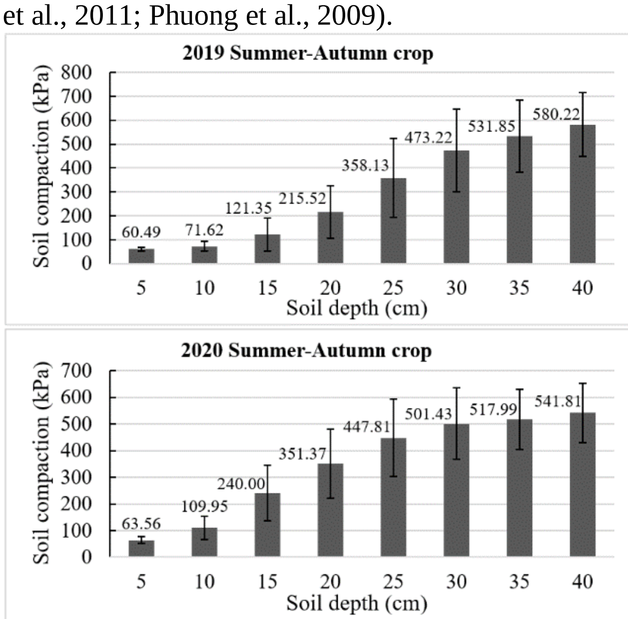

Fig-1. Soil compaction in two seasons of rice crop

The correlation between soil compaction and rice yield factors

The Pearson correlation coefficient test results of the collected data for the 2019 Summer-Autumn and the 2020 Summer-Autumn crop seasons were shown in Table-1 and Table-2. It illustrates that the compaction of soil layers of 10 and 15 cm was positively correlated with rice yield at 1% significance level with the correlation coefficients of 0.275 and 0.266 (Table-1), and the compaction of soil layers of 10 and 15 cm was positively correlated with rice yield at 1 and 5% significance levels with the correlation coefficients of 0.263 and 0.249 (Table-2). However, the compaction of other soil layers was not correlated with the rice yield for both of the data sets. In addition, there were positive correlations between the compaction of soil layers of 10 and 5, 15, or 20 cm with high correlation coefficients at 1 and 5% significance level. They were 0.3, 0.565, 0.274 and 0.256, 0.493, 0.304 for both 2019 and 2020 crops. Thus, compaction of 10 cm was considered as the compaction of topsoil (0-20 cm).

Establishment of prediction models for rice yield

According to the results of Table-1 and Table-2, the compaction of the 10 cm soil layer has a strong correlation with rice yield and the compaction of other topsoil layers (0–20 cm). The compaction of this soil layer is selected as the input parameter for the mathematical models for predicting rice yield. The statistical analyses of rice yield according to soil compaction of 10 cm in the 2019 Summer-Autumn crop are shown in Table-4. The compaction of the 10 cm soil layer which was measured at most experimental sites below 100 kPa was 55 (36.1), 69 (38.4), 83 (10.8), and 97 kPa (7.7 % of samples). The average rice yield of samples with similar soil compaction which was calculated increased gradually from 5.07±1.12 to 7.06 tons / hectare according to the soil compaction of 10 cm soil layer in the range from 55 to 179 kPa.

Table-1. The correlation between soil compaction and rice yield in the 2019 Summer-Autumn crop

	5 cm	10 cm	15 cm	20 cm	25 cm	30 cm	35 cm	40 cm
5 cm	1							
10 cm	.300**	1						
15 cm	-.007	.565**	1					
20 cm	-.262**	.274**	.688**	1				
25 cm	-.307**	.149	.430**	.790**	1			
30 cm	-.249**	.146	.334**	.650**	.882**	1		
35 cm	-.272**	.082	.261**	.511**	.739**	.891**	1	
40 cm	-.269**	.064	.217*	.400**	.608**	.742**	.872**	1
Rice yield	-.013	.275**	.266**	.112	.079	.108	.081	-.024

,. Correlation is significant at the 0.05, 0.01 level (2-tailed)*

Table-2. The correlation between soil compaction and rice yield in the 2020 Summer-Autumn crop

	5 cm	10 cm	15 cm	20 cm	25 cm	30 cm	35 cm	40 cm
5 cm	1							
10 cm	.256*	1						
15 cm	.048	.493**	1					
20 cm	.137	.304**	.749**	1				
25 cm	.031	.174	.503**	.704**	1			
30 cm	.008	.166	.389**	.559**	.860**	1		
35 cm	.027	.182	.365**	.484**	.737**	.857**	1	
40 cm	.070	.144	.252*	.342**	.529**	.561**	.794**	1
Rice yield	-.004	.263**	.249*	.114	-.014	-.068	.080	.021

,. Correlation is significant at the 0.05, 0.01 level (2-tailed)*

The traditional mathematical models, as shown in Table-3, were able to utilize to evaluate the suitability of the establishment of rice yield prediction models as Eq. (1). To establish an empirical model to determine rice yield, linear and non-linear regression methods were used (Ostertagová, 2012; Zhang and Ordóñez, 2012) with the application of Curve Fitting Tool in Matlab software (Zielesny, 2011). The coefficients of the model were determined by the Levenberg-Marquardt optimization algorithm (Table-5). Data collected in the 2019 Summer-Autumn crop season, shown in Table-4, has been used to test for the traditional mathematical models. The results of establishing rice yield prediction models are shown in Fig-2 by using polynomial, exponential, and power regressions as model names. In the present study for five models developed, the predicted values of the models were approximate to the actual rice yield values in the range of 10 cm soil layer compaction from 55–179 kPa. However, the values of Y Polynomial 1, Y Exponential, and Y Power models tended to increase more strongly than the other two models in the case of the soil layer compaction over 179 kPa. The coefficients of the rice yield prediction models are presented in Table-5. The correlation coefficient (R^2) values of the five established models were very reliable in the range from 0.658 to 0.8079. The RMSE of the models was a slight chance in the range from 0.2954 to 0.3649. There was the highlight that Y Exponential model had the highest R^2 value and the smallest RMSE value, whereas Y Polynomial 3 model has the opposite value.

Table-4. Statistical analyses of average rice yield according to soil compaction of 10 cm depth in the 2019 Summer-Autumn crop

Compaction of 10 cm soil layer (kPa)	Sample number (percentage (%))	Mean ± SD of rice yield (tons / hectare)
55	47 (36.1)	5.07±1.12
69	50 (38.4)	5.43±1.06
83	14 (10.8)	5.99±1.03
97	10 (7.7)	5.67±0.98
110	4 (3.1)	5.56±2.1
124	3 (2.3)	6.29±1.35
152	1 (0.8)	6.28
179	1 (0.8)	7.06

Table-5. Coefficients of rice yield prediction models

Model	a	b	c	d	R^2	RMSE
Y Polynomial 1	0.01605	4.187	-	-	0.8047	0.2979
Y Polynomial 2	-7.107e-05	0.0269	3.91	-	0.7219	0.3291
Y Polynomial 3	3.325e-07	-0.0002471	0.05429	2.726	0.658	0.3649
Y Exponential	4.378	0.00267	-	-	0.8079	0.2954
Y Power	1.751	0.2652	-	-	0.7822	0.3146

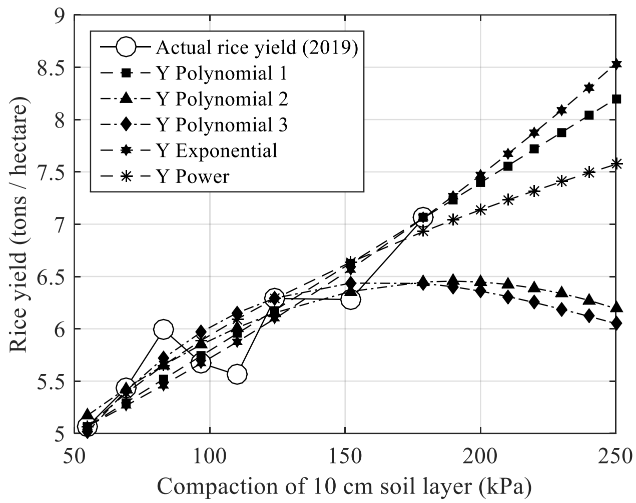

Fig-2. The graphs of established rice yield prediction models

Verification of prediction models for rice yield

The statistical data of 98 collected samples in the 2020 Summer-Autumn crop (Table-6) was used to verify the effectiveness of the above-established models. This data was slightly similar to the collected data in 2019. Samples with soil compaction values below 110 kPa accounted for a high percentage. These were 97 (21.5), 69 (20.5), and 110 kPa (11.2% of samples). Collected actual rice yield which increased steadily in the soil compaction range of 55–165 kPa, reached a peak of 7.07±2.41 tons / hectare at 165 kPa, fluctuated greatly in the soil compaction range of 165–234 kPa and tended to decrease slightly to 6.48±0.17 tons / hectare at 234 kPa. The result of verifying the rice yield prediction models showed that the actual rice yield of the tested samples and the calculated rice yield from five models were roughly equal in 10 cm soil layer compaction range from 55–165 kPa, but there was a high difference in case of 10 cm soil layer compaction over 165 kPa for Y Polynomial 1, Y Exponential, and Y Power models (Fig-3).

Table-6. Statistics of average rice yield according to soil compaction of 10 cm depth in the 2020 Summer-Autumn crop

Compaction of 10 cm soil layer (kPa)	Sample number (percentage (%))	Mean ± SD of rice yield (tons / hectare)
55	8 (8.2)	5.05±1.12
69	20 (20.5)	5.1±1.69
83	6 (6.1)	4.8±2.45
97	21 (21.5)	6.36±1.95
110	11 (11.2)	5.64±1.97
124	7 (7.1)	6.26±1.98
152	9 (9.2)	6.27±1.15
165	7 (7.1)	7.07±2.41
179	2 (2)	5.52±1.7
193	3 (3.1)	6.84±2.02
207	2 (2)	5.82±0.25
234	2 (2)	6.48±0.17

Table-7. MSE and MAE of rice yield prediction models

Model	RMSE	MAE	MAE / actual rice yield average (%)
Y Polynomial 1	0.8556	0.6394	12.5
Y Polynomial 2	0.5091	0.4273	4.59
Y Polynomial 3	0.5132	0.4302	4.7
Y Exponential	0.9072	0.668	13.91
Y Power	0.7259	0.5614	9.25

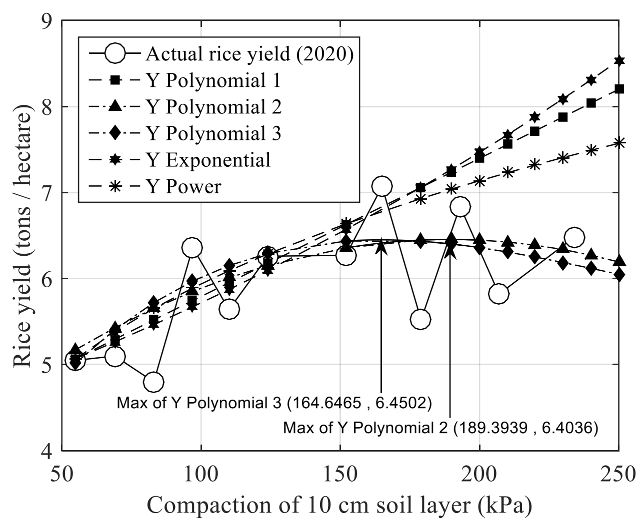

Fig-3. The graphs of verified rice yield prediction models

Discussion

In present study, the 10 cm soil layer compaction was positively correlated with rice yield for both crops. This layer of soil which was the growing range of rice roots (Gangwar et al., 2004), was selected to evaluate relations between soil tillage, crop rotations, soil fertility regime and soil compaction by Motschenbacher et al. (2011). According to the statistical results in Table-4, we observed that the average rice yield of 130 experimental samples in 2019 was approximately 5.42 tons/hectare. This value was roughly equal to the average rice yield of 50 samples at the soil compaction of 69 kPa as well as the average soil compaction of all samples. If the compaction increased or decreased by about 20%, the average rice yield increased by about 25% or decreased by about 7%. Applying this calculation to the data of 98 samples collected in 2020 (Table-6), the estimated average rice yield, which was approximately 6.36 or 5.64 tons/hectare at the soil compaction of 97 or 110 kPa was about 6% higher or lower than the actual average rice yield (approximate 6 tons/hectare). Therefore, the average soil compaction (71.62 and 109.95 kPa in two seasons of rice crop) can be used for estimating the rice yield by crossing the established prediction model. Considering the average value, the rice yield recorded in our study was about 1 ton/hectare lower than that in the study of Chuong (2021). Differences in crop season and cultivation method can be explained for this yield disparity.

The RMSE and MAE values calculated from the model data and collected data were presented in Table-7. The RMSE/MAE value of Y Exponential, Y Polynomial 1, Y Power, Y Polynomial 3, and Y Polynomial 2 model values were 0.9072/0.668, 0.8556/0.6394, 0.7259/0.5614, 0.5132/0.4302, and 0.5091/0.4273, respectively. The RMSE/MAE values were low for Y Polynomial 2 and Y Polynomial 3 models. In addition, values of R^2 of these models in Table-5 were between 0.65 and 0.75. It illustrates that the value of regression models well fitted measured rice yield data (Ostertagová, 2012). The ratio of the models' MAE to actual rice yield average was an insignificant difference in the range of 4.59–13.91%.

The graphs of the models established in Fig-3 show that Y Polynomial 1, Y Exponential, and Y Power models had a rapid increase compared to the average value of actual rice yield in case 10 cm soil layer compaction was over 165 kPa. Besides, the RMSE/MAE values of three models were higher than that of the Y Polynomial 2 and Y Polynomial 3 models (Table-7). Therefore, these models were not selected. The deviations between the predicted and collected values for the Y Polynomial 2 and Y Polynomial 3 models were low, which indicated that established models had high reliability and could be applied to predict rice yield.

The estimated value of the Y Polynomial 2 and Y Polynomial 3 models were slightly similar to the previous study. The rice yield increased quadratically with increasing soil compaction pressure on the sowing furrow, and the highest upland rice yield obtained at the compaction on the sowing furrow ranging from 238.5 to 280.3 kPa (Pinheiro et al., 2016). The grain yield of upland rice increased when the compaction pressures in both no-tillage and conventional tillage systems were range from 25 to 126 kPa (Pinheiro et al., 2016). However, the opposite trend was found in study of Mohanty et al. (2007), namely, the rice yield decreased to an approximately half with three times increase of soil penetration resistance. Considering the shape on the graph, the trend of changing rice yield values according to the Y Polynomial 2 or Y Polynomial 3 models was the same as that of soybean in the study of Beutler et al. (2008) or Sivarajan et al. (2018) with an increase in soil compaction, although plants in these studies were different.

In our study, the estimated rice yield of the Y Polynomial 2 or Y Polynomial 3 models increased gradually with an increase in soil compaction, and started to decline after reaching an optimum soil compaction for the best rice yield (6.4 or 6.45 tons/hectare at 189.39 or 164.65 kPa of soil compaction), decreased with an increase in soil compaction. In other words, farmers need to improve the paddy soil with the compaction in the range of 165–190 kPa to achieve the highest yield of the Summer–Autumn crops.

Conclusions

The research had determined that the compaction of soil layers increases with depth and there are differences among locations in the field. The 10 cm soil layer compaction was positively and closely correlated with rice yield with a high correlation coefficient. The rice yield prediction models were established by nonlinear regression methods and verified from the results of data collected in both experiments in the Summer-Autumn crop seasons of 2019 and 2020, namely, Y Polynomial 2 and Y Polynomial 3 were the more reliable models, and suitable for predicting rice yield through soil layer compaction at 10 cm from the surface. Rice yield in Summer–Autumn crop would be highest (approximate 6.4 tons/hectare) in case of the value of soil compaction at 10 cm depth ranging between 165 and 190 kPa after soil tillage.

Acknowledgements

The authors acknowledge the partly financial support by the Can Tho University Improvement Project VN14-P6, supported by a Japanese ODA loan.

Disclaimer: None
Conflict of Interest: None
Source of Funding: This study was funded by the Can Tho University Improvement Project VN14-P6, supported by a Japanese ODA loan.

References

Beutler AN, Centurion JF, Silva AP da, Centurion MAP da C, Leonel CL and Freddi O da S, 2008. Soil compaction by machine traffic and least limiting water range related to soybean yield. Pesqui. Agropecuária Bras. 43: 1591–1600. https://doi.org/10.1590/s0100-204x2008001100019.

Chuong NV, 2021. Effects of alternate wetting and drying irrigation and different ratios of lime on the Arsenic uptake and yield of rice OM18. Ann. R.S.C.B. 25: 20396–20405.

Clauss K, Ottinger M, Leinenkugel P and Kuenzer C, 2018. Estimating rice production in the Mekong Delta, Vietnam, utilizing time series of Sentinel-1 SAR data. Int. J. Appl. Earth Obs. Geoinf. 73: 574–585.

Correa J, Postma JA, Watt M and Wojciechowski T, 2019. Soil compaction and the architectural plasticity of root systems. J. Exp. Bot. 70: 6019–6034.

Field A, 2009. Discovering Statistics Using SPSS. SAGE Publications, London, UK.

Gangwar KS, Singh KK and Sharma SK, 2004. Effect of tillage on growth, yield and nutrient uptake in wheat after rice in the Indo-Gangetic Plains of India. J. Agric. Sci. 142: 453–459.

Hakansson I and Lipiec J, 2000. A review of the usefulness of relative bulk density values in studies of soil structure and compaction. Soil Tillage Res. 53: 71–85.

Hoque MM and Kobata T, 2000. Effect of soil compaction on the grain yield of rice *(Oryza sativa L.)* under water-deficit stress during the reproductive stage. Plant Prod. Sci. 3: 316–322.

Kang H, Sridhar V, Mainuddin M and Trung LD, 2021. Future rice farming threatened by drought in the Lower Mekong Basin. Sci. Rep. 11: 1–15.

Lamand M and Schjønning P, 2017. Soil mechanical stresses in high wheel load agricultural field traffic: a case study. Soil Res. 56:129–135.

Li Y, Wu J, Shen J, Liu S, Wang C, Chen D, Huang T and Zhang J, 2016. Soil microbial C:N ratio is a robust indicator of soil productivity for paddy fields. Sci. Rep. 6: 1–8.

Mohanty M, Painuli DK, Misra AK and Ghosh PK, 2007. Soil quality effects of tillage and residue under rice-wheat cropping on a Vertisol in India. Soil Tillage Res. 92: 243–250. https://doi.org/10.1016/j.still.2006.03.005.

Motschenbacher J, Brye KR and Anders MM, 2011. Long-term rice-based cropping system effects on near-surface soil compaction. Agric. Sci. 02: 117–124.

Nawaz M, Wahla AJ, Kashif MS, Waqar MQ and Ali MA, 2015. Effect of split application of nitrogenon the yield of rice crop. Asian J Agric Biol. 3: 99–104.

Noor H, Shahbaz K, Shah SA, Anwar S, Min S and Zhiqiang G, 2023. The combined effect of sowing methods and nitrogen rates on wheat yield and regulation of soil water consumption in Loess Plateau. Int. J. Appl. Exp. Biol. 2(1):15-26.

Ostertagová E, 2012. Modelling using polynomial regression. Procedia Eng. 48: 500–506. https://doi.org/10.1016/j.proeng.2012.09.545.

Phuong NM, Hubert V, Khoa LV and Guong VT, 2009. Physical soil degradation on intensive rice cultivation areas in the Mekong Delta and the effects of crop rotation on aggregate stability of paddy soils. J Sci Can Tho Univ. 11: 194–199.

Pinheiro V, Nascente AS, Stone LF and Lacerda MC, 2016. Seed treatment, soil compaction and nitrogen management affect upland rice. Pesqui. Agropecuária Trop. 46: 72–79. https://doi.org/10.1590/1983-40632016v4638428.

Pinheiro V, Stone LF and Barrigossi JAF, 2016. Rice grain yield as affected by subsoiling, compaction on sowing furrow and seed treatment. Rev Bras Eng Agric e Ambient. 20: 395–400.

Raper RL, 2005. Agricultural traffic impacts on soil. J Terramechanics. 42: 259–280.

Sandhya TS and Prakash NB, 2021. Alkalinity–silicon ratio as an assessment factor for the efficiency of silicate slags in wetland rice. Sci Rep. 11: 1–8.

Sivarajan S, Maharlooei M, Bajwa SG and Nowatzki J, 2018. Impact of soil compaction due to wheel traffic on corn and soybean growth, development and yield. Soil Tillage Res. 175: 234–243. https://doi.org/10.1016/j.still.2017.09.001.

Tenu I, Carlescu P, Cojocariu P and Rosc R, 2012. Resource management for sustainable agriculture: Impact of agricultural traffic and tillage technologies on the properties of soil. pp. 263–296. IntechOpen Ltd, London, UK.

Thomas P, Mondal S, Roy D, Meena M, Aggarwal B, Sharma A, Behera UK, Das T, Jatav R and Chakraborty D, 2020. Exploring the relationships between penetration resistance, bulk density and water content in cultivated soils. J Agric Phys. 20: 22–29.

USDA, 2021. Grain and feed annual. 1–25. https://apps.fas.usda.gov/newgainapi/api/Report/DownloadReportByFileName?fileName=Grain%20and%20Feed%20Annual_Mexico%20City_Mexico_03-15-2021 (Accessed 30 August, 2021).

Zhang C and Ordóñez R, 2012. Extremum-seeking control and applications: A numerical optimization-based approach. pp. 31–45. Springer-Verlag, New York, USA.

Zhang M, Li J, Chen F and Kong Q, 2018. Unary non-structural fertilizer response model for rice crops and its field experimental verification. Sci Rep. 8: 1–10.

Zielesny A, 2011. From curve fitting to machine learning. Scientific Publishing Services Pvt. Ltd, Chennai, India.

Contribution of Authors

Ngo QH: Conceived idea, designed research methodology, data interpretation, manuscript final reading and approval.
Bui VH: Literature review, data collection and manuscript write up.
Nguyen HC: Literature review and data interpretation.