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Investigating the effect of the tractor driving system type on soil compaction using different methods of ANN, ANFIS and step wise regression

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ABSTRACT

Farm tractors have different driving systems, including four-wheel drive and rear-wheel drive which are common systems employed to conduct agricultural operations all over the world. The type of driving system influences tractor wheel slip which is one of the most effective factors in soil compaction. Hence a series of experiments were conducted using Goldoni 240 tractor to investigate the effects of tractor driving systems, including four-wheel drive (4WD), rear-wheel drive (RWD), and front-wheel drive (FWD) at different travel speeds, soil moistures, number of passes (1, 5, and 9), and soil textures (clay loam, loam, and sandy loam) at the depths of 10, 20, 30, and 40 cm. Increasing tractor wheel slip showed a significant effect on increasing soil compaction. The lowest tractor wheel slip was occurred using the 4WD system, and by increasing travel speed in this system, soil compaction decreased. Increasing tractor speed in the FWD system increased tractor wheel slip and soil compaction. In addition, increasing soil moisture content resulted in an increase in soil compaction, and this event was intense in fine soils like clay loam. It was found that adaptive neuro-fuzzy inference system (ANFIS) higher potential to predict the effect of multiple input variables on soil compaction (R^2 =0.99) than regression method. According to the standard coefficients of regression models, depth, type of driving system, number of passes, moisture content, texture, speed, and inflation pressure were the factors significantly influencing soil bulk density, respectively.

1. Introduction

Soil compaction has become a challenging issue for most agricultural scientists and farmers (Moinfar et al., 2021, Błaszkiewicz, 2019). It is due to use of heavy machines to increase productivity has led to subsoil compaction and increment in soil compaction that ultimately has led to crop yield decrement all around the world. Soil compaction affects many physical, chemical, and biological processes in the soil and may cause environmental problems (for example, erosion, flooding, and leaching of nutrients and pesticides into groundwater) and agronomic issues such as decreasing plant growth and yield (Keller and Lamande, 2010; Sprawka et al., 2019; Šimečková et al., 2021). The fact that modern agricultural operations have increased soil compaction and their destructive effects on soil structure and yield necessitates identifying the aggravating factors and creating models based on these factors to predict soil compaction.

Since soil compaction depends on soil water content, bulk density, and texture, it is necessary to achieve a good understanding of the relationships between these factors to define suitable agricultural strategies with respect to climate change. The higher the amount of clay and water content, the greater the sensitivity of soils to the pressure applied and the more intense the soil compaction. In sandy soils, however, compaction is less dependent on water content and more dependent on soil bulk density (Saffih-Hdadi et al., 2009; Seehusen et al., 2021). In modern agriculture, the majority of agricultural practices, including various stages of land preparation, cultivation, and harvesting are

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carried out by heavy machinery and in each pass through the soil surface induces high vertical stress on the soil, thus increasing soil compaction (Williamson and Neilsen, 2000). The load applied by the machine to the soil is affected by axle load, number of tires, dimensions of tires, wheel speed, soil tire interaction, and machine traffic (Sakai et al., 2008).

The majority of studies conducted thus far have investigated artificial and natural factors affecting soil compaction, which can be employed to create a suitable model to predict soil compaction. In recent years, the artificial intelligence (AI) approach has shown its capability to model and predict complex systems; therefore, it can be employed as an alternative method to physical models not responding well when there are numerous input variables (Abbaspour-Gilandeh et al., 2009). Since farming systems and technologies, particularly soil tests, are very complex and uncertain, some researchers have used the AI method for modeling different components of agricultural systems.

In a research, the tractor fuel consumption was predicted using artificial neural network (ANN) and stepwise regression models. The ANN model with six training algorithms was adopted to predict fuel consumption. The highest prediction ability was obtained for a network with two hidden layers, each having 10 neurons, which employed Levenberg–Marquardt training algorithm. The results showed that the ANN model with a determination coefficient of $R^2 = 0.938$ had high potential than the stepwise regression model with a determination coefficient of $R^2 = 0.91$(). To predict soil compaction in a soil bin, researchers have developed a hybrid approach involving ANNs with manifold network functions and have employed a meta-heuristic optimization algorithm to predict the soil compaction index. The network functions employed were the prevailed feed-forward network and the novel cascade-forward network algorithms to adopt the multivariable inputs of wheel load, tire inflation pressure, number of passes, slip, and speed to estimate soil compaction. Each ANN trial was developed by merging with the recently introduced evolutionary optimization technique of imperialist competitive algorithm (ICA). The results showed that the hybrid method provides higher accuracy in predicting soil compaction (Taghavifar et al., 2013). In order to evaluate the potential of the adaptive neuro-fuzzy inference system (ANFIS) in predicting the energy efficiency indices of wheel drive, the experiments were conducted in soil bin. Input parameters included wheel load, speed, and slip at three levels. ANFIS, along with a hybrid method of the gradient descent and the least-squares method, was applied to find the optimal learning parameters using various membership functions (MFs). The results showed high accuracy (MSE= 0.0166 and R^2 =0.98) in prediction (Taghavifar and Mardani, 2013). A model based on the fuzzy logic approach was developed to describe the soil fragmentation for seedbed preparation in the composition of primary and secondary tillage implements of subsoiler, moldboard plow, and disk harrow. An intelligent model based on the Mamdani fuzzy modeling principles was designed to predict soil fragmentation during tillage operations. The model inputs included soil moisture content, tractor speed, and soil sampling depth. The fuzzy model consisted of 50 rules, and three parameters of root mean square error (RMSE), relative error (e), and determination coefficient of R^2 were used to evaluate the fuzzy models. The values of 0.167%, 3.95%, and 0.988% were calculated, respectively. It was found that the fuzzy models can be used as a method for predicting soil fragmentation with high precision during tillage practices (Abbaspour-Gilandeh and Sedghi, 2015). Carman (2008) developed a model based on Mamdani approach fuzzy modeling principles to predict changes in soil compaction due to wheel traffic. Mean relative error of the values measured and predicted was 3.35% for penetration resistance, 7.76% for tire inflation pressure, and 2.98% for bulk density. Furthermore, Marakoglu and Carman (2010) developed a model based on Mamdani approach fuzzy modeling principles for the fuzzy knowledge-based model to predict soil loosening and draft in tillage. Mean relative error of the values measured and predicted was 2.41% for soil loosening and 2.68% for the draft requirement.

In engineering science, ANFIS is a technique applied to solve complex and nonlinear problems such as water, plants, and air (Marakoglu and Carman, 2010; Arkhipov, 2008). ANFIS is able to find non-linear relationships between the inputs and outputs of a problem (Naderloo et al., 2012). Fuzzy systems and ANNs have their own advantages and disadvantages. Fuzzy systems are capable of using human languages and experiences while they are not able to learn them (Buragohain and Mahanta, 2008). In other words, fuzzy systems cannot be trained using observational data. It should be noted that ANFIS does not provide satisfactory results under unanticipated conditions (Dehnavi et al., 2015). However, ANNs have the ability to self-learn using the datasets. ANNs are non-explicit and cannot use human languages. On the other hand, ANNs need a wide range of experimental input and output data for their successful execution (Metin and Murat, 2008). Although ANN is a powerful technique for modeling various problems in the world, it has its own weaknesses. If the input data are ambiguous or uncertain, a fuzzy system like ANFIS might be a better option (Taghavifar and Mardani, 2014).

This paper attempted to focus on the practical aspects of ANFIS modeling of which, in practice, engineers need to be aware to build a more accurate and efficient model. There are five important and effective factors in ANFIS modeling, which are as follows: type of network creation (Grid Partition or Sub Clustering), type of input fuzzy sets, number of input fuzzy sets, type of fuzzy output sets, and optimization methods.

1. In the Grid Partition method, the range of each input is divided into equal intervals, and one rule is created in each multidimensional space resulting from the combination of different inputs. This method of creating a network is suitable when input data are distributed at regular intervals with the same size and there is a low number of inputs; however, by increasing the number of inputs, the combined spaces resulting from these inputs increase and, therefore, the number of rules increases, causing the complexity of the system (Ay and Kisi, 2014).

In the Sub Clustering method, data mining is initially performed on the data sets. For each input, the interval with more data is identified. Instead of the inputs divided into intervals of equal size in areas with more data, additional membership functions are created with a smaller size, while in areas with fewer data, fewer membership functions are created. In this method, the multidimensional spaces resulting from the combination inputs with more data are split into clusters. Fuzzy rules are created for clusters rather than each multi-dimensional space, but they are not created in empty spaces of data. Accordingly, in this method, fewer rules are created and the complexity of the system is reduced. This method will be useful when there are more data distributed in irregular spaces and there is practically a nonlinear relationship between the inputs and the output.

2. Type of input fuzzy sets (membership functions): The fuzzy logic foundation is based on the fuzzy set theory. This theory is a generalization of the classical theory of sets in mathematics. In the classical theory of sets, an element is or is not a member of a set. In point of fact, the membership of the elements follows a zero and one binary pattern. However, the theory of fuzzy sets extends this concept and proposes a gradual membership. Thus one element may be to some extent, not perfectly, a member of a set (Takagi and Sugeno, 1985). In this theory, the membership degree of the elements of the set is determined by the fuzzy function and its value is between zero and one. There is no definite way to select membership functions, but considering the distribution of the input dataset, it may be possible to determine the more efficient membership functions. Moreover, when there is an alternative relationship between an input and its output in the vicinity of the points where the functional alternation alters, the trapezoidal and generalized-bell membership functions can be more appropriate. This is due to the more uniform effect of the elements in the vicinity of the alternating points.

3. The number of membership functions must be determined in such a way that no empty spaces are created. In case of existence such spaces, the number of membership functions should be reduced so that the

domain of the remaining functions increases and it is possible to use the domain of the neighboring elements to study the effects of these elements on the output. The number of these functions should not exceed 3 because the number of rules and the complexity of the system would increase. On the other hand, if the number of these functions is less than three, it will increase the effectiveness of the adjacent elements, possibly leading to system error in prediction.

4. Type of outputs fuzzy sets includes two types of linear and constant functions. ANFIS considers a function for every rule that has built in the spaces of the combination of inputs. This function can be a constant number, which is most commonly used for a set of inputs that produce a constant output in certain intervals due to input changes, or this function can be considered as linear combination of input variables. In most cases, the use of the linear output function produces better results (Dehnavi et al., 2015).

5. Optimization method: The main training method in this system was the error propagation method obtained in combination with the least-squares error and the hybrid combination method. In each training round and when moving forward, the outputs of the nodes were normally calculated up to the fourth layer and then the result parameters are calculated by the least-squares error method. In this research, after calculating the error in return using the descending slope algorithm of error, the error value was distributed to the inputs and the parameters were corrected. Since various field users do not have expertise and capabilities necessary for changing the optimization practices, expertise beyond the users' needs is required. The purpose of this study was to develop comprehensive models for predicting soil compaction based on input variables, including tractor driving system (4WD-FWD-RWD), depth, water content, soil texture, wheel speed, tire inflation pressure and number of passes using ANN, ANFIS, and stepwise regression techniques.

2. Materials and methods

The experiments were conducted in a completely randomized design with three replications. The treatments included different travel speeds of 1.26, 3.96, and 6.78 km/h, tire inflation pressures of 170, 200, and 230 kPa, moisture content of 10%, 15%, and 20% (d.b), slip as an index of the driving system of the tractor (four-wheel drive, rear-wheel drive, and front-wheel drive), number of passes (1, 5, and 9), and two soil textures of clay-loam, loam, and sandy-loam at the depths of 10, 20, 30, and 40 cm. Table 1 presents the properties tested soil. The percentage of clay, silt and sand particles can be used to represent the soil texture in the anfis model, however, this method increases the number of model inputs and consequently will increase the model complexity. Therefore, to solve this problem, a statistical measure called geometric mean diameter(d_g) was used as a representation of soil texture. How to calculate this criterion has been described in detail in several articles (Shirazi and Boersma, and Dashtaki and Homaee, 1984, 2004).

The Goldoni 240 tractor (4WD) was used for testing. Table 2 presents the technical characteristics of this tractor (Fig. 1). All machines work in three driving system types of four whhel dive, rear wheel drive and front wheel drive. Four-wheel drive, also called 4WD, refers to a two-axled vehicle drivetrain capable of providing torque to all of its wheels simultaneously. Rear-wheel drive (RWD) is a form of engine and transmission layout used in motor vehicles, where the engine drives the rear wheels only. Front-wheel drive (FWD) is a form of engine and transmission layout used in motor vehicles, where the engine drives the front wheels only.

In four-wheel drive tractors unlike two-wheel drive tractors, in order to achieve the best traction performance and the use of traction capacity, the tractor's weight should be distributed equally on both axles. The static weight on the front and rear axle of this tractor is 705 and 360 kg, respectively, which is determined by the manufacturer. While in traction operations, the dynamic weight of the wheel is important. The dynamic weight of the axes is the total of static weight of the axle and the weight transfer due to the application of the traction force. The dynamic load on wheels is calculated by the following equations:

$$W_{dr} = W_{sr} + P(\frac{H}{X}) \tag{1}$$

$$W_{df} = W_{sf} - P(\frac{H}{X}) \tag{2}$$

Where: W_{sr} the static load on rear tires (N), H is the drawbar height(m) and X is the wheel base, (m).w_{df} is the dynamic load on rear tires (N), W_{sf} is the static load on front tires (N), w_{ds} the dynamic load on front tires (N), P is draft (N).

According to the weight transfer carried out during the traction operation, the dynamic weight percentage on the front and rear axle of this tractor is 48% and 52%, which is very close to the recommended values by Barger et al. (1963).

Table 1
Tested Soil properties.

Soil texture	Sand	Silt	Clay	Bulk density ($kg{\cdot}m^{-3}$)	Cone index (kPa)	d_g (mm)
Clay loam	20	30	50	1010	750	0.0154
Loam	46	30	24	1102	820	0.0851
Sandy – loam	73	17	10	1300	950	0.246

Table 2
Tractor characteristics.

Specifications		Unit	value
Engine power		kW	30.8
Static weight on each front tire		kg	705
Static weight on each rear tire		kg	360
Wheelbase		m	1.055
Center-to-center lateral spacing of front tires		m	0.75
Center-to-center lateral spacing of rear tires		m	0.75
front tire		–	7.50R-16″
rear tire		–	7.50R-16″
Tread Depth(mm)	Standard Rim	Section width (mm)	Overall Diameter(mm)
25	5.00 F、6LB	205	810

Fig. 1. Goldoni tractoe moves over the soil surface (left), a scheme of diged soil profile afte the tractor pass(Right top)Placement of strain transducers including endplates inside soil profile in longitudinal, lateral and vertical directions.

The driving system is a category variable, and because fuzzy logic is expressed in terms of linguistic and continuous concepts, the use of the driving system as a variable undermine the modeling process. Research has shown that slippage is strongly influenced by the driving system (Moinfar et al., 2020). Therefore, to solve the problem, slip, which is a continuous variable, was used as an alternative to the driving system. Since the type of driving system is not a numerical property and modeling requires numerical values. The tractor-implement system slip cab be an appropriate index of driving system type. In order to involve the effect of the driving system in the modeling process, the slip value of the tractor in different driving systems was used. With considering all other conditions constant, three values of 14.9%, 22% and 24.8% were computed for four-wheel drive, rear wheel drive and front-wheel drive systems. The lowest value was obtained using 4WD and the highest value was related to FWD system.

To evaluate the effect of driving system type, the front and rear differentials of the tractor were disabled for the related experiments so that the tractor could operate in front- or rear-wheel drive. A fuel tanker was connected to the drawbar connection of the tractor to create 8 kN as a draft force which is usually applied to this type of tractor.

The maximum pulling draft of the Goldoni tractor is 10 kN, hence the draft applied to the tractor was 8 kN in order to be used at different speeds. Therefore, the pull/weight levels applied in this research were in accordance with the manufacturer's recommendations. The recommended inflation pressure for a 7.5R-16 "tire is 200 kN, so the 170 and 230 kN were slightly lower and higher than the recommended value which were selected to investigate and model the effect of inflation pressure on the soil compaction. Since tillage by moldboard plow is the most common field operation in most parts of the world, the travel speed range were within the recommended values for this operation (Al-Suhaibani and. Ghaly, 2010 and Mattetti et al., 2017).

The wheel speed of the tractor was measured by an inductive proximity sensor (pr12–2dn made by autonics) mounted in line with the outer edge of a 34-tooth sprocket which was fixed inside the rear wheel (Fig. 2). The sensor detects passing of each tooth during the wheel rotation such that with each full rotation of the gear or the rear wheel, digital displayer (MP5W-44 made by autonics) of pulses meter which attached to a magnetic sensor displayed the number of gear teeth. This number was divided by 34 to calculate the wheel rotation. The passed distance was calculated by having a perimeter of the rear wheel. The dynamic rolling radius was determined and then considered in computing rear-wheel perimeter. The actual speed of the tractor computed by measuring the time required to pass a determined distance by a stopwatch. The following equation was used to calculate the slip percentage (Damanauskas and Janulevičius, 2015):

$$S(\%) = 1 - \frac{v_a}{v_t} \times 100 \tag{3}$$

Where: v_a = actual velocity, m s^{-1}; v_t = theoretical velocity, m s^{-1}.

Fig. 2. Wheel speed transducer for measuring the tire rotation.

In order to compare the compaction caused by different treatments, changes in bulk density were used as benchmark comparisons. In order to obtain soil bulk density, samples from different depths were taken using a standard sampling cylinder and after they were dried in an oven, soil bulk density was determined. Three soil samples were taken from each target depth. To evaluate the accuracy of the values obtained through the cores, three displacement sensors were placed in horizontal, lateral, and vertical directions under tire path on one side of the tractor at the soil depth of 30 cm (Fig. 1). Tractor used in this research is a garden tractor with a spacing of 80 cm between wheels, which is less than the distance between the trailer wheels (240 cm), resulting in a minimum distance of 80 cm between the sampling point and the trailer wheels and the trailer wheels were not crossed on the surface of the soil and their effect were not significant**.** To reach to required soil moisture by weighting water spray in different times of mixing operation the required water sprayed on the soil during mixing and then was filled into the pit again (Fig. 1).

To prevent moisture evaporation, all tests were related to a determined value of moisture were conducted consecutively at definite time period in a day. Also temperature was 17–20 °C and the soil surface kept covered with a plastic sheet to minimize soil moisture loss when we were not working on that particular part of the soil, hence no significant evaporation was observed.

In order to measure soil displacement, a differential transducer with linear variation (model DHL-A-50), the sensitivity of 3.64 mv/v, and the maximum displacement of 50 mm was employed. Two plates were installed at the endpoints of the transducer to transfer soil compression or tension pressure to the transducer for measuring soil displacement accurately. All data were logged to a laptop via a data logger (Data Taker 800).

Bulk density of the loose soil was initially 1102 kg·m^{-3}. To determine the changes in soil density using the displacement transducers, the mass of soil located inside an imaginary cube which dimensions consist of the three transducers was calculated from Eq. (4).

$$m = \rho_1 V = \rho_1 l_{x1} l_{y1} l_{z1} \tag{4}$$

Where.

m = soil mass, kg·

ρ_1 = initial soil density, kg·m^{-3}·

l_{x1} = initial length of longitudinal transducer, m·

l_{y1} = initial length of lateral transducer, m·

l_{z1} = initial length of vertical transducer, m·

Assuming a constant mass of soil between the end plates installed on the displacement gauges, final soil density was computed from Eq. (5).

$$\rho_2 = \frac{m}{V} = \frac{m}{l_{2x} \quad l_{2y} \quad l_{z2}} \tag{5}$$

Where:

ρ_2 = final soil density, kg·m^{-3}·

l_{x2} = final length of longitudinal transducer, m·

l_{y2} = final length of lateral transducer, m·

l_{z2} = final length of vertical transducer, m·

All of the tests were performed in a canal with dimensions of 3 m long, 1 m wide, and 0.6 m deep. To create uniformity in testing and prevent errors caused by variations in soil texture, after that each test soil was removed from the soil bin and was sieved to eliminate compaction caused by previous tests, then it was refilled into the canal. The soil inside the pit was compacted in layers of 10 cm using a hand roller to a mass of 500 kg to eliminate the looseness of the soil and reach the desired compaction. Soil compaction in each layer was measured using a conical index. The cone index of plowed soil was considered as a criterion for soil compaction.

The basis of the network developed using input parameters was default curve fitting of MATLAB 2016 which is the most optimal method for building the network. Feed-forward backpropagation algorithm was employed to construct an ANN-based model. The training function used in the network was a trailm which was selected by trial and error method from the existing functions to achieve the best performance. The adaption learning function was of the learngdm type. There were 2 hidden layers and 10 neurons were used in the first layer to run the network. Moreover, three types of transfer functions, including tangent hyperbolic conversion, sigmoid (tan sig), and linear motion (pure line) function among layers were used for ANN models.

ANFIS creates a fuzzy inference system using a set of input and output data. The membership function parameters of this system were adjusted through the post-propagation algorithm or its combination with the least-squares method. This operation allows the fuzzy system to learn its structure from the data set. The adaptive neuro-fuzzy inference system consists of two neural and fuzzy networks and has the benefits of both techniques (Kaveh et al., 2020).

In this research, a model was developed based on seven input factors, including soil texture, depth, slip (as an index of driving system type), water content, inflation pressure, number of passes, and speed in ANFIS to predict bulk density. The Grid Partition structure was chosen to create the network. Four types of triangular, trapezoidal, Gaussian, and generalized-bell membership functions were considered as membership functions to represent the inputs. Due to the large number of inputs, the number of membership functions for each input was considered the minimum possible value of 2 to prevent the creation of more rules and the complexity of the system. The output membership function in this network was linear.

The hybrid optimization method was used for network training. The number of rules created by the network was 128 which would increase up to 2197 when using 3 membership functions for each input. The key to the success of the fuzzy theory is that to predict an object, two membership functions overlapping in the set of the input space can be used simultaneously. Therefore, in order to improve the system accuracy and reduce the prediction error, it is not necessary to increase the number of membership functions and create more rules; rather, the membership functions should overlap more so that each object can be supported at least by two rules. Since there was a high number of rules created, Table 3 presents only a few of them for a better understanding of how the model was developed by ANFIS. These rules were made based on the fuzzy type of Takagi-Sugeno-Kang or TSK. In this system, the priori part (if-then) was fuzzy rules, but the resultant part was non-fuzzy and was a linear combination of input variables. The range of all inputs was divided into two parts: the low region with the membership function of L and the greater area with the membership function of H. Regression models use only one particular equation to predict the output, but the ANFIS model uses different equations to predict output in different intervals. The purpose of Table 3 is to provide different regression equations for different intervals, so that the reader can understand clearly the better ability of the ANFIS model in predicting output in comparison to the regression model.

When implementing the network, the rules were activated, each predicting a value (Fig. 3).

To calculate the final output, the weight of each rule was determined. The weight was calculated in such way that, in each rule, the membership degree of the input signal in the membership functions of each variable was determined and their minimum value was considered as the weight of the rule. Fig. 4 schematically illustrates this for a network with two inputs. Finally, the final output of the model was calculated by Eq. (6).

$$f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \tag{6}$$

Where f_1 and f_2 are linear functions related to rules 1 and 2, respectively and w_1 and w_2 are the weights corresponding to each rule.

Two statistical parameter were selected to analyze the performance and efficiency of statistical models: the coefficient of determination (R^2) and Mean absolute percentage error (MAPE), which are commonly used by various researchers (Arkhipov et al., 2008). MAPE as a measure of accuracy in a fitted series value in statistics was also used for comparing the prediction performances of the models. The coefficient of determination (R^2) of the linear regression line between the predicted values of the model and the desired output was computed by Eq. (7):

$$R^2 = \frac{\sum_{i=1}^{N} (Y_{measured} - Y_{predicted})^2}{\sum_{i=1}^{N} (Y_{measured} - Y_{predicted})^2} \tag{7}$$

3. Results and discussions

A number of models were developed based on ANN, ANFIS, and stepwise regression techniques to predict the bulk density caused by natural and artificial factors. Among the developed models, Table 4 presents the models with a high determination coefficient of R^2 to compare their performance. ANFIS models showed the least mean absolute percentage error (MAPE) and a high determination coefficient of $R^2 = 0.99$. Stepwise regression model showed a high MAPE and the lowest determination coefficient of $R^2 = 0.87$. The neural network model revealed slightly weaker performance in comparison with the ANFIS models.

It is clear that the ANFIS and ANN models have a high capability of $R^2 \geq 0.99$ to predict bulk density due to the large number of input data (2187). However, due to the large number of input parameters (7 inputs), the regression model showed a low capability of $R^2 = 0.87$ to predict the soil bulk density.

Comparison of the performance of the models showed that the ANFIS model, compared to the ANN and regression models, had high ability and accuracy in estimating the bulk density value. Therefore, the ANFIS model provided much closer data to the data measured compared to the ANN and regression models (Table 5). In addition, the deviation between the values measured and those predicted was calculated and plotted. the standard deviation of the values predicted by the ANFIS

Table 3
A part of the rules in the model.

Rules	Input variables							Linear output function (%BD)
	dg	depth	slip	wc,%	IP	pass	speed	
Rule 1	L	L	L	L	L	L	L	BD= 0.03376dg − 0.003703d − 0.01321 s − 0.00796w + 0.003245i − 0.02092p + 0.04623sp − 0.2575
Rule 10	L	L	L	H	L	L	H	BD= −0.3556dg+ 0.009901d- 0.2217 s + 0.02417w − 0.01627i+ 0.01764p − 0.007478sp − 0.02756
Rule 22	L	L	H	L	H	L	H	BD= −0.108dg+ 0.2193d − 0.9922 s − 0.06009w+ 0.1347i − 0.3192p − 0.2048sp − 0.04611
Rule 72	H	L	L	L	H	H	H	BD= 0.04812dg − 0.02813d − 0.6039 s − 0.09089w+ 0.03411i − 0.02871p − 0.01609sp − 0.001764
Rule 101	H	H	L	L	H	L	L	BD= 0.04521dg+ 0.001689d − 0.01066 s − 0.005427w+ 0.002055i − 0.01029p − 0.005584sp − 0.124
Rule128	H	H	H	H	H	H	H	BD= 0.1642dg+ 0.0813d+ 0.2045 s + 0.1777w − 0.06094i+ 0.0377p+ 0.05008sp+ 0.01024

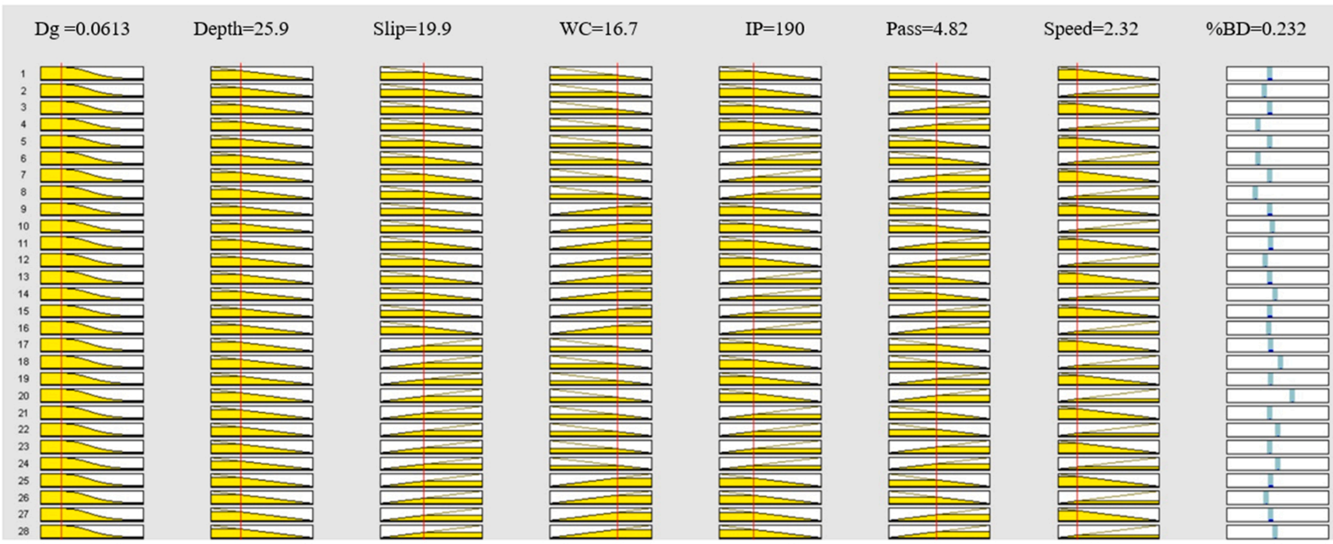

Fig. 3. ANFIS rule viewer and rules of the soil compaction models.

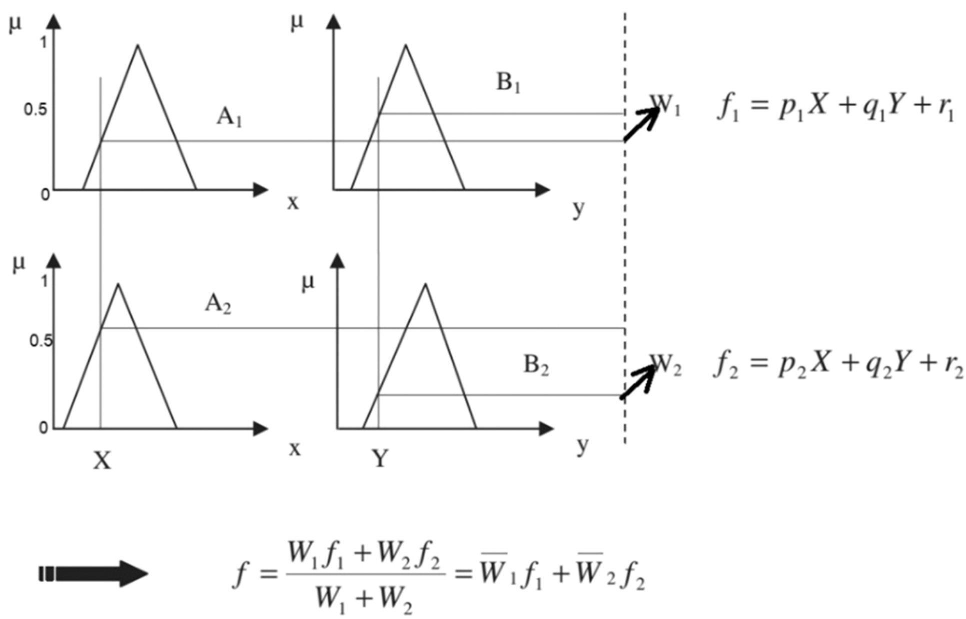

Fig. 4. The Takagi–Sugeno fuzzy inference system.

Table 4
The characteristics of the best structure of developed ANFIS, ANN and regression architectures; the boldfaced values show the outperforming models.

Model	Network type	Training function	Adaption learning function		Transfer function	MAPE (%)	R^2
ANN	feed-forward backprop	trailm	learngdm		logsig	7.3	0.9913
ANFIS	Type of MF		Number of MF		Optimization method	MAPE	R^2
	Input	Output	Input	Epo			
	Trimf	Linear	2 2 2 2 2 2 2	20	Hybrid	5	0.9957
	Gaussmf	Linear	2 2 2 2 2 2 2	20	Hybrid	4.6	0.9962
	Tramf	Linear	2 2 2 2 2 2 2	20	Hybrid	5.2	0.9938
	Gbellmf	Linear	2 2 2 2 2 2 2 2	20	Hybrid	4.7	0.9961
Regression	C= 0.1 − 0.267 ×ST − 0.00616 ×D + 0.00788 ×S + 0.00906 ×M+ 0.000395 ×IP + 0.0127 ×P − 0.00512 ×V					21	0.8768

model (ranging from 0.027 to −0.015) was much lower than that of the values predicted by the ANN model (ranging from 0.029 to −0.03) and the regression model (ranging from 0.11 to −0.09).

Table 6 presents the statistical characteristics of the step-by-step regression model for predicting bulk density. The regression model, in comparison with the ANFIS and ANN models, has weaker performance in prediction (R^2 =0.88). However, the regression model presented valuable advantages in comparison to the ANFIS and ANN models. The ANFIS and ANN models do not provide a specific relationship for modeling the output variable and an indicator for comparing the effect

Table 5
The standard deviation of predicted values by ANFIS, ANN and regression model in different working conditions.

Soil texture		The average of standard deviation			The max of standard deviation			The min of standard deviation		
		Depth								
		20 cm	30 cm	40 cm	20 cm	30 cm	40 cm	20 cm	30 cm	40 cm
Clay – loam	Regression	0.0364	0.022	0.0251	0.111	0.0506	0.0831	-0.0899	-0.1344	-0.0819
	ANN	0.0076	0.006	0.0063	0.028	0.0340	0.0307	-0.0300	-0.0875	-0.0234
	ANFIS	0.0044	0.005	0.0042	0.027	0.0248	0.0219	-0.0154	-0.0543	-0.0191
Loam	Regression	0.0323	0.019	0.0258	0.078	0.0372	0.1006	-0.0976	-0.1252	-0.0795
	ANN	0.0077	0.006	0.0065	0.068	0.0236	0.0356	-0.0217	-0.0831	-0.0248
	ANFIS	0.0041	0.005	0.0044	0.024	0.0221	0.0315	-0.0164	-0.0606	-0.0236
Sandy – loam	Regression	0.0303	0.021	0.0311	0.067	0.08216	0.1439	-0.1056	-0.0647	-0.0642
	ANN	0.0074	0.005	0.0063	0.025	0.0202	0.0261	-0.0336	-0.0217	-0.0250
	ANFIS	0.0042	0.005	0.0033	0.017	0.0221	0.0164	-0.0170	-0.0290	-0.0156

Table 6
Statistical characteristics of stepwise regression model for %BD based on slip, pass, texture, speed, water content, depth and pressure.

Model	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Level of Significance (Sig)
(Constant)	1.00	0.354		13.312	0.00
Depth	-0.006	0.000	-0.507	-67.483	0.00
Slip	0.008	0.000	0.406	44.627	0.00
Pass	0.013	0.000	0.418	55.523	0.00
Water content	0.009	0.000	0.373	49.598	0.00
Texture	-0.267	0.008	-0.266	-35.404	0.00
Speed	0.005	0.000	-0.116	-13.370	0.00
Pressure	0.0035	0.000	0.098	10.469	0.00

B- linear regression equation constants coefficient.

of each input variable on the output variable. The regression model directly deals with the effect of each of the factors and tries to present a model in which the importance and impact of each of the factors is clearly evident. According to the standard coefficients listed in Table 6, the depth, slip (driving system type), number of passes, water content, texture, speed, and inflation pressure indicated the greatest effect on the soil bulk density, respectively.

Based on the results of Table 6, the slip has a positive effect on the soil bulk density, as shown in Fig. 5. According to this figure, the bulk density increased significantly by increasing slip in all depths. The trend of these changes was very intense and clear at the depth of 10 cm, but by increasing depth, the effect of slip was reduced and increment trend in bulk density was slow. The maximum bulk density occurred at the depth of 20 cm and the slip of 33%. The higher slip is related to the FWD system and the low slip is associated with the 4WD system. Many researchers have reported that an increase in slip leads to an increase in surface soil compaction. This could be due to the increasing time of wheel travel on the soil and the blows of wheel tread (Botta et al., 1999). As shown in Fig. 5(b), a higher density can be prevented by increasing the speed. However, when the slip rises, which is related to the FWD mode, the increasing speed cannot prevent soil compaction. Because travel speed cannot increase without slip increment, thus increasing the speed leads to higher slip and soil compaction. Reducing soil compaction by increasing speed has clearly been observed in many studies using 4WD of RWD systems (Carman, 2008; Shahgholi and Abuali, 2015).

Fig. 6(a) shows that the finer soil texture of clay loam soil results in high compressibility, particularly in higher moisture content. Fine-textured soils are very compressible and by applying force to the surface of these soils, there is a greater displacement in them. As a result, the increment in BD is higher than that of the coarse textures. The reason for this behavior can be attributed to the fact that fine-textured soils have higher adhesion properties and their particles tend to stick together under the influence of moisture (Jain et al., 2010). Therefore, when the pressure is removed from fine-textured soils, their reversibility is lower than other soils and they become denser. Saffih-Hdadi (2009) stated that the reason for this behavior is the cohesion among the particles of the soil, which is aggravated by increasing moisture. The pressure applied causes the soil particles to compress into each other and moisture preserves this position. They reported that compaction in the cohesion and heavy soils rises by increasing moisture. Other researchers have reported such a process (Grecenko, 2016; Gupta et al., 1989; Horn et al., 1995).

The interaction between inflation pressure and depth in Fig. 7(a) shows that high inflation pressure destroys the soil and increases soil

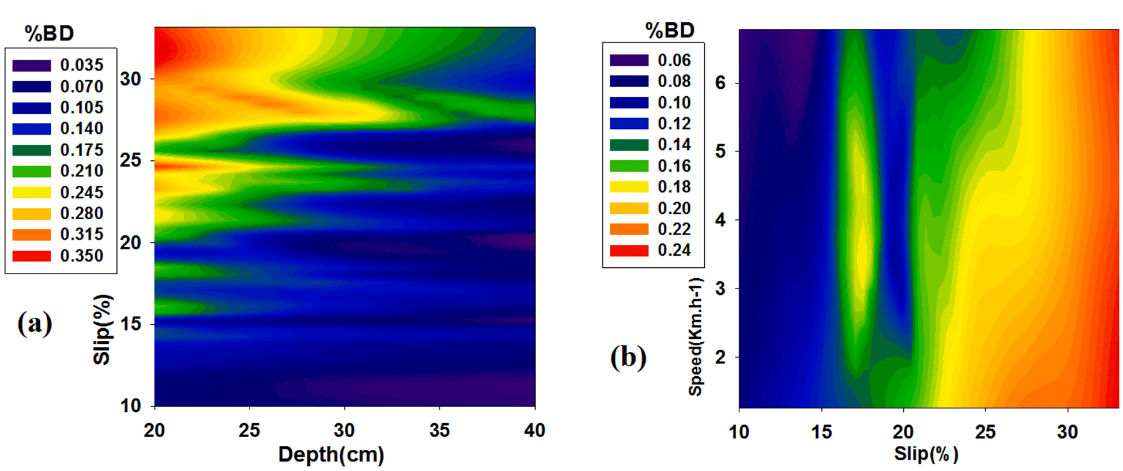

Fig. 5. Interaction: a) Slip × depth b) Slip × Speed on the bulk density.

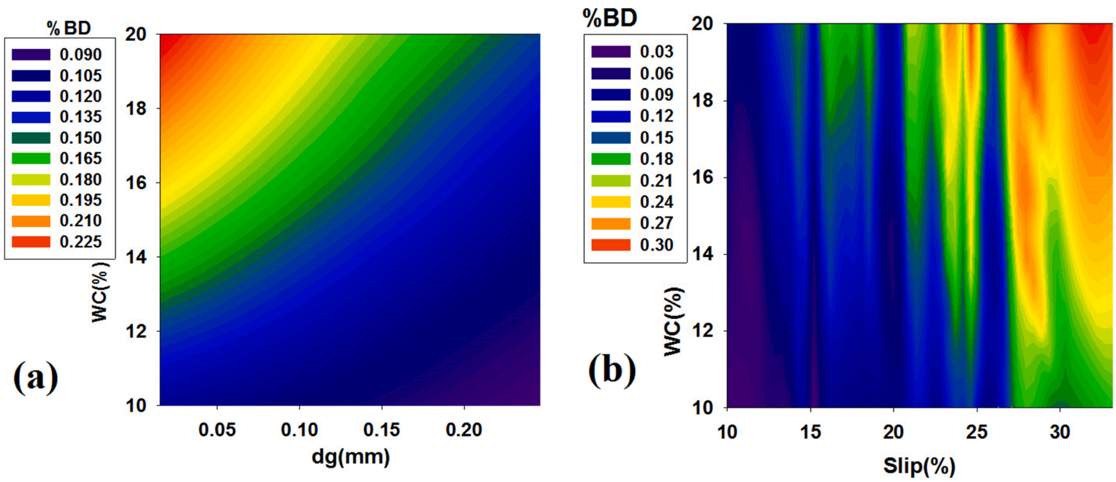

Fig. 6. Interaction: a) moisture content × soil texture b) Slip × moisture content on the bulk density.

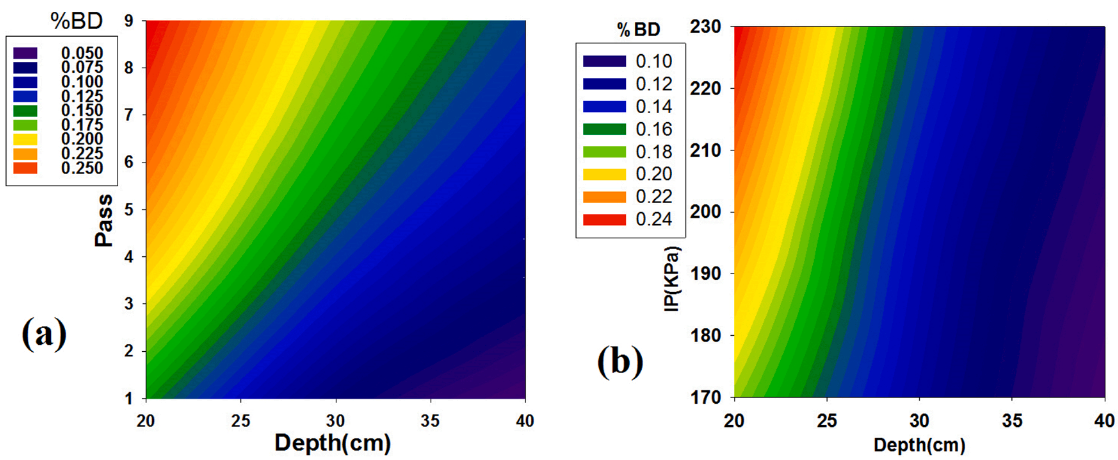

Fig. 7. Interaction: a) Depth × inflation pressure b) Depth× pass content on the bulk density.

compaction, but it influences topsoil layers more significantly, and by increasing depth, the adverse effects of inflation pressure disappear. At the depth of 40 cm, bulk density is almost the same in all inflation pressures, while at the depth of 10 cm, there is a significant difference in bulk density between the different tire inflation pressures. The reason for this difference could be the stress that wheels apply to the topsoil, but the rate of stress transmission to the subsoil is negligible.

As Arvidsson et al. (2011) reported that the difference between the stress exerted on the soil at the depth of 40 cm as a result of moving a single wheel, double wheel tractors, and tracks is almost small. However, the stress is altered by increasing the load applied to the wheel drive, reflecting the fact that the force applied to the soil has the greatest impact on compaction in the subsoil. It was found that the compaction of the topsoil depends, to a large extent, on the ground pressure, but the compaction of the subsoil is related to the load applied to the drive wheel (Botta, 1999). Moreover, according to Fig. 7(b), it was indicated that the first pass has a significant effect only on the topsoil, but when the number of passes increases, the pressure applied to the topsoil is slowly transferred to the subsoil and compresses it. This reflects the fact that subsoil compaction, unlike topsoil compaction, occurs over time. A similar trend was reported in other researches (Shahgholi and Abuali, 2015; Ghadernejad et al., 2015).

Numerous studies have shown that with increasing depth, the most important factor affecting soil compaction were the weight of the tractor, tire's slip, type of drive system and tire inflation pressure (Wong, 1989, 2022). Also it was found that that at low forward speeds, the soil compaction was more affected by the weight of the tractor for a longer period of time. In fact, low speed has a similar effect to weight increment and causes pressure to be transferred to subsoil layers and subsoil compaction occurs (Pulido-Moncada, and Graves et al., 2019, 2015). The study of the effect of number of passes on soil density showed that increasing the passage has a strong effect on the compaction of subsoil, while it does not affect the surface layers(Han et al., 2009; Gerasimov and Katarov, 2010; Shaheb et al., 2021). Fine-textured like clay soils are more sensitive to machine passage, and that increasing machine weight at high humidity causes compaction in deeper layers(Hamza and Anderson, 2005 and Batey, 2009; Hamza et al., 2011). Finally, according to the results of previous research and matching them with the results of the present research it was concluded that to reduce surface soil density, inflation pressure, slip and type of drive system should be considered, and to reduce deep soil density, the weight, speed and number of passes should be managed.

4. Conclusions

1. In the study range, depth and slip had the greatest impact on the bulk density, and depth had a negative effect and slip had a positive effect on increasing bulk density. The 4WD driving system showed a low slip, and soil compaction decreased by increasing speed, while the FWD driving system indicated high slip and soil compaction increased by increasing speed. It was found the 4WD system is the optimum system for agricultural operations because it reduces the effect of agricultural

machinery on soil compaction.

2. Inflation pressure indicated a significant effect on the increment in soil compaction in the topsoil. However, in the subsoil, the effect of inflation pressure almost disappeared by increasing depth up to more than 40 cm.

3. Increasing moisture content showed a significant effect on increasing soil compaction in fine soils like clay loam. At high moistures, the maximum compaction occurred on top layers of soil, and by decreasing moisture, compaction was transferred to subsoil layers.

4. Since the effect of multiple inputs was investigated on soil bulk density, the ANFIS model showed better performance compared to the ANN and stepwise regression models due to the determination coefficient of 0.99 in predicting the soil bulk density.

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The authors declare that the research complied with all ethical standards.

Consent to Participate

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data sharing is not applicable to this article.

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