

Nitrate leaching from a potato field using adaptive network-based fuzzy inference system

Hosein Shekofteh, Majid Afyuni, Mohammad Ali Hajabbasi, Bo V. Iversen, Hossein Nezamabadi-pour, Fariborz Abassi and Farid Sheikholeslam

ABSTRACT

The conventional methods of application of nitrogen fertilizers might be responsible for the increased nitrate concentration in groundwater of areas dominated by irrigated agriculture. Appropriate water and nutrient management strategies are required to minimize groundwater pollution and to maximize nutrient use efficiency and production. Design and operation of a drip fertigation system requires understanding of nutrient leaching behavior in cases of shallow rooted crops such as potatoes which cannot extract nutrient from a lower soil depth. This study deals with neuro-fuzzy modeling of nitrate (NO_3^-) leaching from a potato field under a drip fertigation system. In the first part of the study, a two-dimensional solute transport model was used to simulate nitrate leaching from a sandy soil with varying emitter discharge rates and fertilizer doses. The results from the modeling were used to train and validate an adaptive network-based fuzzy inference system (ANFIS) in order to estimate nitrate leaching. Two performance functions, namely mean absolute percentage error (MAPE) and correlation coefficient (R), were used to evaluate the adequacy of the ANFIS. Results showed that ANFIS can accurately simulate HYDRUS-2D behavior regarding nitrate leaching under the circumstances of the present study.

Key words | ANFIS, drip fertigation, modeling, nitrate leaching

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INTRODUCTION

Nitrogen (N) is an essential plant nutrient consumed by crops throughout the growing season. The most common forms of nitrogen found in soils are organic N, ammonium (NH_4^+), nitrate (NO_3^-), and gaseous nitrogen (NH_3 , N_2). Mineralization and nitrification processes convert the organic N and NH_4^+ into NH_4^+ and NO_3^- , respectively. Nitrate is highly mobile and leachable and excessive application of nitrogen fertilizer might therefore lead to nitrate pollution of groundwater and surface water resources (Hayens 1985; Waskom 1994).

As Bar-Yosef (1999) states, the quality of soils, ground, and surface waters is susceptible in areas where irrigation is carried out for agriculture. In such areas, regular and extreme use of nitrogen fertilizers with irrigation water would likely be the reason for the rise in nitrate concentrations of the

groundwater. Hence, substitutive irrigation water and soil management practices are required to increase as far as possible the application efficiency of water and fertilizer; thereby, nitrogen leaching from the root section into the groundwater could be reduced to its least amount.

Another method as a substitution is fertigation where soluble fertilizer is applied through the irrigation water, thus, improving water and nutrient use efficiency and hence increasing the farmer's income and decreasing pollution as far as possible (Bar-Yosef 1999).

Transport processes of water and nutrients in relation to fertigation systems might be complex. Conducting field experiments with varying emitter discharge rates and fertilizer to investigate water and nutrient distribution for evolving appropriate design and management options is

costly and time consuming. A properly calibrated and validated water flow and solute transport model can reduce the time and cost required for studying the water and nutrient dynamics under drip irrigation systems. This will provide an understanding of the relationship between the amount and timing of water and nutrient application, the crop root uptake, crop yield, and risk of groundwater pollution (Antonopoulos 2001). Several models have been developed to simulate water flow, nutrient transport, heat flux, crop water, and nutrient uptake and biological transformation of nutrients in the soil (Bergstrom *et al.* 1991; Hutson & Wagenet 1991; Jarvis 1995; Gabriella & Kenjeni 1996; Breve *et al.* 1997; Lafolie *et al.* 1997). Many researchers have reported that the HYDRUS-2D package (Simunek *et al.* 1999) is a convenient tool for modeling and simulation of nitrogen under drip irrigated conditions (Cote *et al.* 2003; Gardenas *et al.* 2005; Ajdary *et al.* 2007; Dultra & Munoz 2010). According to Vachaud *et al.* (1990) solute transport in the unsaturated zone can be described by mechanistic and functional models. Mechanistic models have been used for several research purposes but are rarely used for management decisions since they require large computational efforts and a high number of input parameters (De Willigen *et al.* 1990). On the other hand, common management codes such as GLEAMS (Leonard *et al.* 1987) or TDNIT (Bogardi & Bardossy 1984) are relatively simple to use. However, those types of models are one dimensional, they have storage routing or piston flow description of water movement, their solute budgeting is lumped and they often have a simplified description of the region between the root zone and the remaining part of the unsaturated zone. Therefore these types of models lack the ability to describe water flow from point sources, such as drip emitters, precisely. In drip fertigation water and solute distribution is three-dimensional. Traditional numerical models (with few exceptions) cannot simulate water and solute movement. Even running those few models themselves requires many input data. It is impossible to fully measure those data in many parts of the world and thus impossible to obtain the required input data.

There is therefore a need to develop physically based but more efficient and practical approaches to the modeling of three-dimensional water flow and solute transport in the unsaturated zone of the soil. One such approach is fuzzy

rule-based modeling. Because fuzzy rule-based modeling is knowledge-based, even in places where few data are available, the fuzzy rule-based models can be used to simulate water and solute movement in soil.

Fuzzy logic, first introduced by Zadeh (1965), has mostly been applied to decision-making processes and control theory. Fuzzy logic in general and fuzzy rule-based modeling in particular has been successfully applied to water resources and environmental engineering. For example, fuzzy logic was used for rainfall-runoff process and soil erosion (Mitra *et al.* 1998; Nisar Ahmamed *et al.* 2000; Yu & Yang 2000; Ozelkan & Duckstein 2001; Tran *et al.* 2002; Mahabir *et al.* 2003; Metternicht & Gonzalez 2005). Also, fuzzy rule-based approaches have found applications in the following areas related to water resources and environmental engineering: infiltration process (Bardossy & Disse 1993; Bardossy *et al.* 1995), reservoir operations (Russell & Campbell 1996; Shrestha 1996; Muzzammil & Alam 2011; Zanganeh *et al.* 2011; Rankovic *et al.* 2012), prediction of regional drought (Pongracz *et al.* 1999), modeling of nitrogen and nitrate leaching on watershed scale (Haberlandt *et al.* 2002; Bardossy *et al.* 2003; Shrestha *et al.* 2007), water quality problems (Lu & Lo 2002; Chaves & Kojiri 2007; Alavi *et al.* 2010), and water flow and solute transport processes in soil (Dou *et al.* 1999).

Dou *et al.* (1999) used a fuzzy rule-based approach to describe solute transport in the unsaturated zone through a soil column using the Mamdani fuzzy inference system (Mamdani & Assilian 1975). They used simulation results of the SWMS-2D model to obtain a data set for derivation and verification of fuzzy rules. In their study, fuzzy rules operated between two adjacent cells at each time step. Also, they used solute concentration of the upper cell, and solute concentration difference between two adjacent cells as premises. For a given time step, the solute flux between the two cells was taken as the response, which was combined with the conservation of mass to update the new solute concentration for the new time step. The methodology was applied to solve the breakthrough curve of bromide movement in a soil column. Moreover, they generalized the fuzzy rule-based model to the same problem under different soil and boundary conditions. According to their findings, the fuzzy solution was similar to the measured bromide concentration and the SWMS_2D model results.

ANFIS (adaptive network-based fuzzy inference system) is a fuzzy rule-based system that uses artificial neural networks (ANNs) theory in order to determine the parameters of the fuzzy membership functions. In ANFIS, both the learning capabilities of a neural network and the reasoning capabilities of fuzzy logic were combined in order to give enhanced prediction capabilities, compared with the use of a single methodology. ANFIS has shown potential in modeling nonlinear functions. It learns features of the data set and adjusts the system characteristics according to a given error criterion (Jang 1993).

Traditional numerical models developed for water and solute transport need a large number of input parameters and their calibration is often difficult. For instance, to run HYDRUS-2D, soil hydraulic parameters, like saturated and saturated-hydraulic conductivity, as well as climatic parameters are required. In some parts of the world, e.g. most regions in Iran, it is impossible to measure and collect these parameters. Despite the increase in processor speed of computers, running these models for a long time span such as the entire growing season can be time consuming (e.g. at least 5 h is required to run HYDRUS-2D during the entire growing season of potato). On the other hand, running fuzzy models comparatively takes less time. In this study, HYDRUS-2D was used to obtain training and test sets for ANFIS. According to our knowledge, no attempt has yet been made to use fuzzy rule-based modeling in the prediction of solute transport on a field scale. The present study aims to present an ANFIS to describe nitrate leaching on a field scale in a sandy soil grown with potatoes.

MATERIALS AND METHODS

Experimental details and measurements

The experiment was conducted at an agricultural experimental station in the city of Jiroft in Kerman Province, located in the southern part of Iran (26°N to 29°N and 56°E to 59°E) during 2009–2010. The soil textural class was a sandy soil according to the USDA (United States Department of Agriculture) classification system. The climate is categorized as semi-arid with a mean annual temperature of 27.8 °C and a mean annual rainfall of

175 mm. Before planting the potatoes, the field was heavily irrigated twice to leach excess salts out of the root zone. Irrigation water was applied at a rate of 1 L h⁻¹ through drip emitters placed at the soil surface parallel to and within the crop row. The distance between each emitter was 20 cm and distance between each potato row was 60 cm. Potassium nitrate (KNO₃) was used as fertilizer in the fertigation system and was applied through the irrigation water. Fertigation was started immediately after the germination of the potato plants. A total of 600 mm irrigation water and 200 kg of N was applied through the fertigation system during the entire growing season in 1 ha. Application of N fertilizer was performed five times during the growing season in equal amounts. We used an irrigation and fertigation schedule typically practiced by the farmers in the region cultivating potato under drip fertigation.

Soil samples were collected from different depths (0–0.2, 0.2–0.4, 0.4–0.6, 0.6–0.8, 0.8–1.0 m) at a horizontal distance of 0, 0.15 and 0.30 m from the emitter using a tube auger to determine spatial and temporal distribution of water and nitrate during the growing season. The samples were collected before the fertigation events. In addition, samples were also taken after selected irrigation events. In the laboratory, soil samples were analyzed to determine the gravimetric moisture content. The nitrate concentration was measured using the spectrophotometer method (Page *et al.* 1982).

HYDRUS-2D

To model nitrate leaching from the potato field under drip fertigation, the computer simulation model, HYDRUS-2D (Simunek *et al.* 1999) was used. HYDRUS-2D simulates water and solute transport, which is either two-dimensional or axi-symmetrical three-dimensional, in soils. The model can be used under a wide variety of boundary conditions, inconsistent boundaries, and soil homogeneities or heterogeneities.

The equation for two-dimensional soil water flow in HYDRUS-2D is:

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial r} \left(K_r \frac{\partial h}{\partial r} \right) + \frac{\partial}{\partial z} \left(K_z \frac{\partial h}{\partial z} \right) - \frac{\partial K}{\partial z} - WU(h, r, z) \quad (1)$$

where θ is the volumetric soil moisture content ($L^3 L^{-3}$), K functions as the unsaturated hydraulic conductivity ($L T^{-1}$), h is the soil water pressure head (L), r is the lateral coordinate, z is the vertical coordinate, t is time (T), and WU (h, r, z) conveys root water absorption (T^{-1}). K and WU are functions of θ and/or h . With subscripts r and z it is possible to include soil anisotropy to simulate water flow with the unsaturated hydraulic conductivity. Referring to the mass conservative iterative scheme suggested by Celia et al. (1990), the numerical Galerkin finite element scheme was applied to solve Equation (1).

The solute transport equation in HYDRUS-2D, (Simunek et al. 1999), is depicted as:

$$\frac{\partial \theta c}{\partial t} = \frac{\partial}{\partial x_i} \left(\theta D_{ij} \frac{\partial c}{\partial x_j} \right) - \frac{\partial q_i c}{\partial x_i} - NU(c, r, z, t) \quad (2)$$

where θ is the volumetric soil moisture content ($L^3 L^{-3}$), q is volumetric flux intensity ($L T^{-1}$), t is time (T), the subscripts i and j convey either r or z , and c is the nitrate concentration in soil solution ($M L^{-3}$), D_{ij} is the dispersion coefficient ($L^2 T^{-1}$), and NU as a function of time and space expresses the local passive nitrate absorption ($M L^{-3} T^{-1}$) by plant roots. The first part of the equation shows the solute flux due to dispersion, the second represents the solute flux as a result of convection with flowing water, and the last term indicates root nutrient absorption. Initial condition for water was given as the initial water content in different soil layers within the flow domain as already observed. A $60 \times 60 \text{ cm}^2$ domain was used in the modeling with a no flux boundary condition at the sides. For the lower boundary condition, free drainage was used since the water table was situated far below the domain of interest. Figure 1 shows the conceptual diagram of the simulated domain. To take into account the emitter discharge during irrigation, a flux type boundary condition was used. Nitrate fertilizer was applied along with irrigation water and a third-type Cauchy boundary condition was used to describe the concentration flux along the flux variable at the top boundary. Cumulative nitrate leaching below the root zone, i.e. the lower boundary of the flow domain, was controlled by the nitrate concentration at depth and the corresponding water flux.

The model was calibrated with respect to the hydraulic conductivity and dispersivity values of water and nitrate at various sampling points. The model was run by giving the

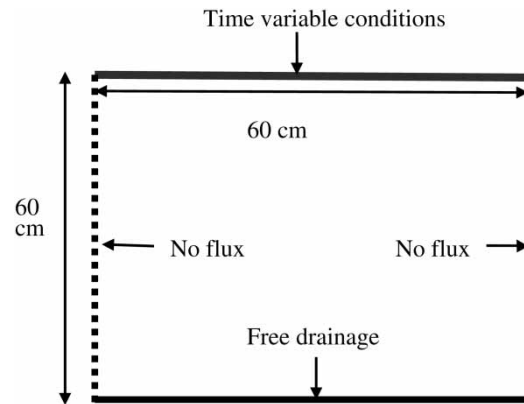


Figure 1 | Conceptual diagram of simulated area.

required input parameters. Calibrated parameters were selected when the mean correlation coefficient (R) between predicted and observed values was higher than 0.95. After calibration, the model was validated with the seasonal data to examine its predictability. During calibration runs, the simulation period was kept to 267 h, which included two fertigation and six irrigation events. For the validation, the simulation period was kept to 3,000 h equal to the growing period of potato. For the various hydraulic input parameters required in HYDRUS-2D, saturated water content (θ_s), residual water content (θ_r), empirical factors (α, n) and saturated hydraulic conductivity (K_s) were obtained from the neural network option available in HYDRUS-2D to parameterize the van Genuchten-Mualem (van Genuchten 1980) analytical model without hysteresis. The l parameter in the van Genuchten-Mualem model was set to 0.5. Values of longitudinal and transverse dispersivity confirmed through calibration were 8 and 0.8 cm, respectively. After calibration and validation, the model was used to predict the nitrate leaching below the root zone. Here, emitter discharge rates were varied from 0.5 to 8 L h^{-1} with increments of 0.5 L h^{-1} and the amounts of potassium nitrate were varied from 950 to $2,550 \text{ kg ha}^{-1}$ with increments of 50 kg ha^{-1} yielding a total of 528 scenarios simulating and evaluating the nitrate leaching out of the root zone of the soil. In the simulation and validation, we focused on one emitter only and the reported nitrate leaching was obtained from the same emitter. In a 1 ha potato field there were 45,000 emitters. We used the results of model simulations (528 scenarios) for the construction of ANFIS.

Fuzzy inference system (FIS)

Figure 2 depicts the structure of a FIS generally. Basically, a FIS consists of four blocks: a knowledge-base, a fuzzifier, an inference system (engine), and a defuzzifier. In the first block, the expert gives the information as linguistic fuzzy rules, the next converts the crisp inputs into degrees in accordance with linguistic values. The third block applies linguistic values as well as the knowledge-base to make inference applying a reasoning method, and the last, relying on a defuzzification method, converts the fuzzy results of the inference into a crisp output (Herrera & Lozano 2003).

The knowledge-base has two sections: a data-base and a rule-base. The first part defines the membership functions of the fuzzy sets employed in the fuzzy rules. In the second component, specific operators combine linguistic rules in the form of a collection.

A fuzzy rule has two components: an 'IF' part as antecedent and a 'THEN' part as consequent. Equation (3) exhibits the fuzzy rule structure:

$$\text{IF } \langle \text{antecedent} \rangle \text{ THEN } \langle \text{consequent} \rangle \quad (3)$$

Employing AND, OR and NOT logical operators, the antecedent of a fuzzy rule may mix multiple simple conditions into a complex string. Commonly, based on differences in the consequent part of the rules, FIS has two types. The first type makes use of the Mamdani inference method in which the rule consequent is fuzzy sets; the method has the following structure (Mamdani & Assilian 1975):

$$\text{IF } x \text{ is } A \text{ and } y \text{ is } B \text{ THEN } f \text{ is } C \quad (4)$$

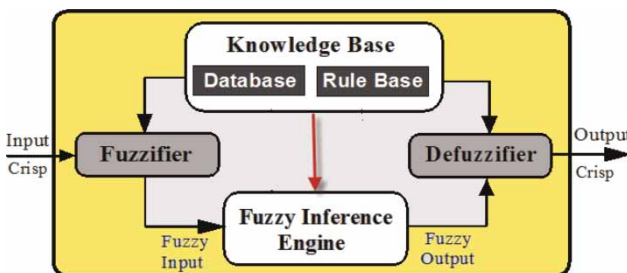


Figure 2 | A flow diagram of a fuzzy inference system (FIS).

where A , B and C are fuzzy membership functions, x and y are inputs, f is the output of the FIS. The second FIS, suggested by Takagi, Sugeno and Kang (TSK), has an inference engine in which a weighted linear combination of the crisp inputs instead of a fuzzy set constitutes the conclusion of a fuzzy rule. Its structure is as follows:

$$\text{IF } x \text{ is } A \text{ and } y \text{ is } B \text{ THEN } f = px + qy + r \quad (5)$$

where p , q and r are constant parameters (Takagi & Sugeno 1985; Sugeno & Kang 1988).

Adaptive network-based fuzzy inference system (ANFIS)

As Jang (1993) states, ANFIS, as a multilayer feed-forward network, applies each node to both specifically direct the incoming signals and to work on a set of parameters connected with the relevant node. Similar to ANN, ANFIS is capable of mapping unseen inputs to their outputs by learning the rules from the previously seen data. A simple structure of this type of network having just two inputs of x and y and one output of f is shown in Figure 3.

According to the figure, ANFIS contains five layers in its architecture including, the fuzzify layer, product layer, normalize layer, defuzzify layer, and total output layer. Assuming just two membership functions for each of the input data x and y , the general form of a first-order TSK type of if-then fuzzy rule has been given by Equation (6). Here, we rewrite the rule i of the ANFIS as:

$$\begin{aligned} \text{Rule } i: \text{ IF } x \text{ is } A_i \text{ and } y \text{ is } B_i \text{ THEN} \\ f_i = p_i x + q_i y + r_i, \quad i = 1, 2, \dots, n \end{aligned} \quad (6)$$

where n is the number of rules and p_i , q_i and r_i are the parameters determined during the training process. At the first stage of the learning process, the membership function (μ) of each of the linguistic labels A_i and B_i are calculated as follows:

$$O_i^1 = \mu_{A_i}(x), \quad i = 1, 2, \dots, n \quad (7)$$

$$O_i^1 = \mu_{B_i}(y), \quad i = 1, 2, \dots, n \quad (8)$$

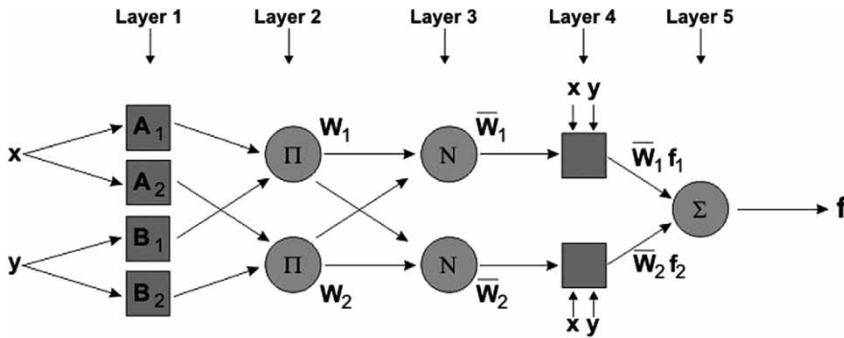


Figure 3 | ANFIS architecture.

At the second layer which is the product layer, the previously calculated membership degrees of linguistic variables are multiplied as shown in Equation (9):

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \quad i = 1, 2, \dots, n \quad (9)$$

The third layer is the normalize layer, where the ratio of each weight to the total weight is calculated:

$$O_i^3 = \bar{w} = \frac{w_i}{\sum_{i=1}^n w} \quad i = 1, 2, \dots, n \quad (10)$$

The fourth layer is the defuzzification layer with adaptive nodes, where their outputs depend on the parameter(s) pertaining to these nodes and the learning rule specifies how these parameters are altered to minimize the measured prescribed error. The relationship for these nodes is as follows:

$$O_i^4 = w_i f_i = w_i(p_i x + q_i y + r_i) \quad i = 1, 2, \dots, n \quad (11)$$

Finally, in the fifth layer, the summation of all the incoming signals is performed where the output of the system is the final result:

$$O_i^5 = \sum_{i=1}^n \bar{w}_i f_i \quad i = 1, 2, \dots, n \quad (12)$$

where O_i^5 is the output of Layer 5 and the output of the system (Jang 1993).

According to Jang (1993), the learning in ANFIS is carried out by a hybrid algorithm. It consists of the gradient descent and the least-squares methods. Particularly, node

outputs move forward up to Layer 4 in the forward direction of this algorithm and the least-squares method determines the consequent parameters. In the backward direction using back propagation algorithm, the error signals propagate backwards and using the gradient descent the premise parameters are updated.

Development of a fuzzy system for the prediction of nitrate leaching

In this study, we had two sets of input data: emitter discharge rate and fertilizer amount, and one set of output data: nitrate leaching. The emitter discharge rates and various amounts of fertilizer (KNO_3) were used as inputs and nitrate leached from an emitter was used as the output of ANFIS. The data set had a total of 528 data points. It was randomly divided into two smaller sets: a training data set (352 data points) and a testing data set (176 data points). The aim of the training process was to minimize the error between the actual target and ANFIS output. This allows ANFIS to learn features observed from the training data and then to implement them in the system rules. In the performance phase, the test data were introduced into the learned system for evaluation. A test error having an adequately small value indicated the system's good generalization capability. The model was implemented in MATLAB. The selection of rules in ANFIS is automatic and based on the before-mentioned data. Output surface of the fuzzy rule-based model used in ANFIS is displayed in Figure 4. This figure shows the relationships between the input and output variables. The number of rules in this study was 40. In ANFIS, three types of methods:

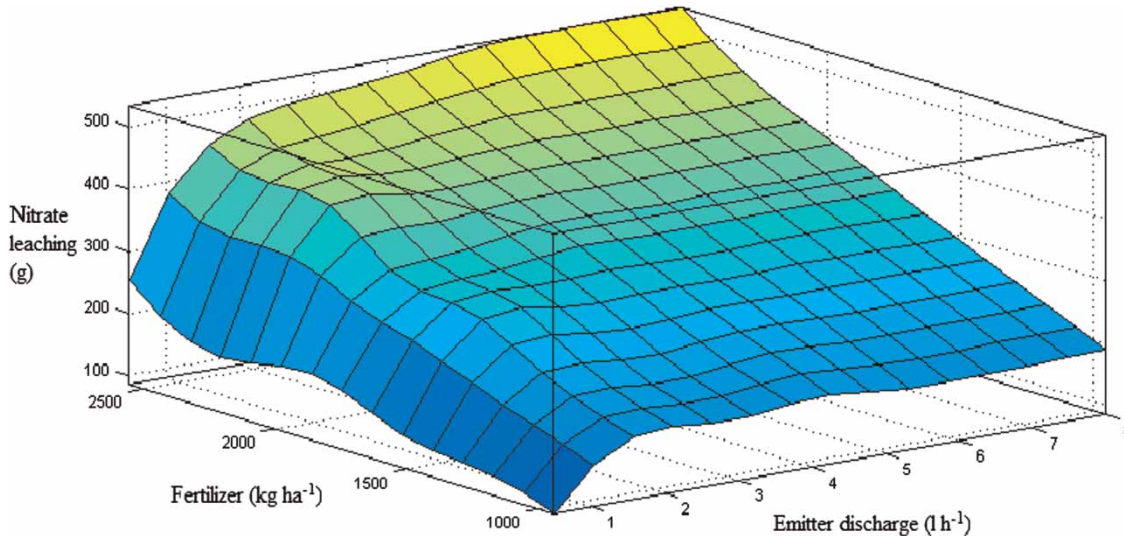


Figure 4 | Output surface of the fuzzy rule-based model: fertilizer amount and emitter discharge versus nitrate leaching.

grid partitioning, subtractive clustering, and fuzzy c-means clustering are generally utilized to generate the membership functions. Next, in ANFIS, the TSK system is framed into a network and learning is carried out based on the input-output data. In the learning phase, fuzzy rules coefficients are adjusted through a RLS (Recursive Least Square) algorithm and the membership function parameters are adjusted by the back propagation algorithm. In this study, three methods for generating membership functions were tried and finally we found with selection of the subtractive clustering method the error between observed and simulated data was least. In the subtractive clustering method, we put to test many radii clusters and finally with choosing radius 0.2 we reached the least possible error. The back propagation algorithm is used for tuning membership function parameters in ANFIS. This algorithm works on the basis of the gradient descent algorithm. Therefore, in ANFIS, differentiable membership functions must be used. So, there are limitations in the choice of membership function shape. The choice is limited to Gaussian and bell-shaped membership functions. The use of Gaussian membership function shape is more common, and is that on which we have relied.

Figure 5 displays the shape of membership. In addition, for the logical operator AND, fuzzy operator product was used. Implication was performed with the product function, and aggregation with the maximization operation.

RESULTS AND DISCUSSION

Table 1 displays maximum, minimum, median, mean, variance, and standard deviation (SD) of variables.

The correlation coefficient (R) and mean absolute percentage error (MAPE) between the estimated nitrate leaching values from HYDRUS-2D and the estimated nitrate leaching values from the ANFIS model were used to evaluate the performance of the ANFIS. The MAPE and R are denoted as below:

$$\text{MAPE} = \left(\frac{1}{n} \sum_{i=1}^n \frac{|Y(p_i) - Y(o_i)|}{Y(o_i)} \right) \times 100 \quad (13)$$

$$R = \frac{\sum_{i=1}^n (Y(p_i) - \bar{Yp})(Y(o_i) - \bar{Yo})}{\sqrt{\sum_{i=1}^n (Y(p_i) - \bar{Yp})^2 (Y(o_i) - \bar{Yo})^2}} \quad (14)$$

where $Y(p_i)$ and $Y(o_i)$ are the leached nitrate values from ANFIS and HYDRUS-2D outputs respectively, \bar{Yp} and \bar{Yo} are the means of ANFIS and HYDRUS outputs respectively, and n is the number of data points. A plot of the estimated leached nitrate predicted by the ANFIS model from training data versus simulated nitrate leached by HYDRUS-2D (Figure 6) shows that the model captured the relationship between the input parameters and nitrate leaching. The correlation R was 1. This value shows that ANFIS can simulate the behavior of HYDRUS-2D with

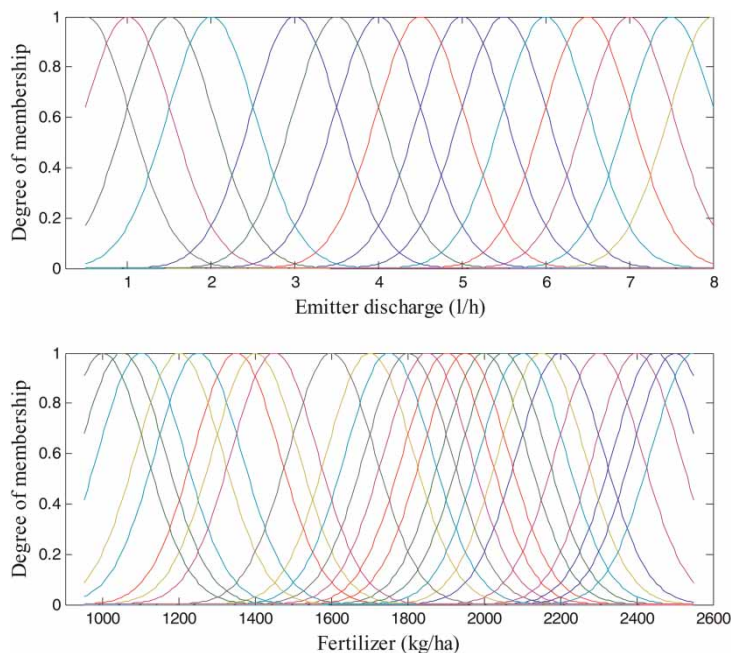


Figure 5 | Membership functions for inputs of ANFIS.

a high accuracy. The R and MAPE values for the ANFIS models for training data are presented in Table 2. The results of Table 2 and Figure 6 indicate that the ANFIS model is a useful tool for modeling solute transport in the soil. The ANFIS test results (predicted data) are compared with the results obtained from HYDRUS-2D data in Figure 7. This figure shows the scatter plot and line of best fit between the outputs of the two models. Here, R was 0.99. The R and MAPE values for the ANFIS model for test data are presented in Table 2 as well. The results show that ANFIS can accurately model and predict nitrate transport and nitrate leaching, which are both

Table 1 | Statistical characteristics of variables

	Emitter discharge (l h ⁻¹)	Fertilizer (kg ha ⁻¹)	Nitrate leaching (mg)
Maximum	8	2,550	762
Minimum	0.5	950	85.1
Mean	4.25	1,750	324.94
Median	4.25	1,750	324
Variance	5.322	227,096.8	10,583
Standard deviation	2.307	476.54	102.87

taken from HYDRUS-2D simulation in the soil. The relationship between input variables and their contribution to the output of ANFIS and HYDRUS-2D for training and test data is displayed in Figures 8 and 9 respectively. It is clear that the results obtained by ANFIS are in almost complete agreement with the results from HYDRUS-2D.

Inputs and output variables as well as training and test data which were used in ANFIS are also used in linear regression (LR). The correlation coefficient (R) between HYDRUS-2D and LR data for training and test data was 0.90 and 0.92 respectively (Figures 10 and 11). The performance criteria values for the LR model for training and test data are presented in Table 3. Comparing the obtained results from the proposed ANFIS with those from LR models indicated that the ANFIS technique was more accurate in predicting the nitrate leaching (taken from the simulation of HYDRUS-2D) from a potato field in a sandy soil than the LR model. Furthermore, the proposed ANFIS model in the current study was more effective in predicting the nitrate leaching (of which the source is HYDRUS-2D simulation) than the LR model when the performance criteria were compared. The MAPE and R values for the ANFIS model for test data were 0.99 and 0.49 respectively,

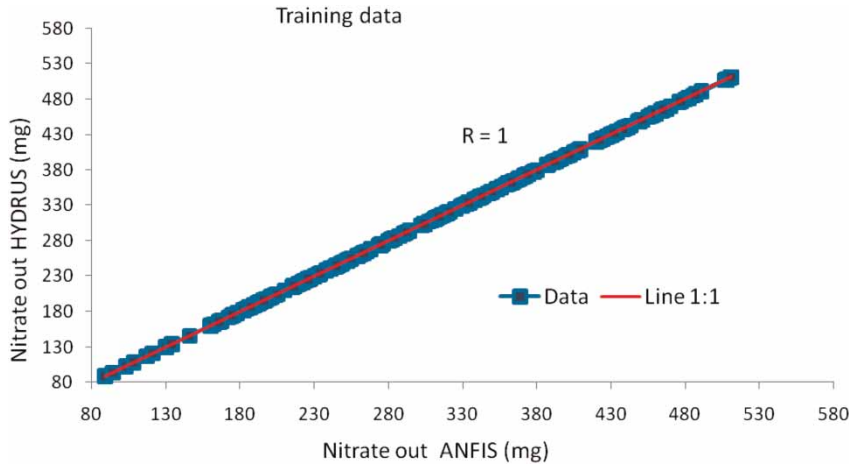


Figure 6 | Estimates of nitrate concentration by the ANFIS model using training data versus outputs from HYDRUS-2D.

Table 2 | Values of performance criteria in ANFIS

	Training data	Test data
Correlation coefficient (R)	1	0.99
Mean absolute percentage error (MAPE)	0	0.49

while these values were 0.92 and 11.14 for the LR model (Tables 2 and 3). Higher performances of the ANFIS model were due to its greater degree of robustness, nonlinearity handling ability, and fault tolerance than those of the traditional statistical models such as LR.

With regard to Figure 4, perhaps if we use the two-line LR model (one for low values of emitter discharge, and

the second for the rest), we can improve the performance criteria values.

To the best of our knowledge no other study has investigated solute transport through the FIS on a field scale. Dou *et al.* (1999) used the Mamdani fuzzy inference system (Mamdani & Assilian 1975) to investigate solute transport through a soil column. They used the fuzzy rule-based model to predict the breakthrough curve of bromide on a soil column. Their reports showed that the largest difference in bromide concentration output between the fuzzy rule-based model, the SWMS_2D model and the experimental measurements occurred at the beginning of the breakthrough curve. Based on their study, the reason

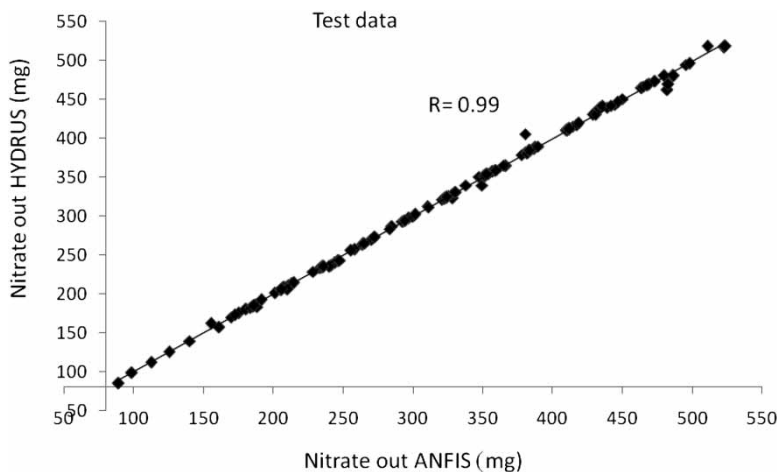


Figure 7 | Estimates of nitrate concentration by the ANFIS model using test data versus outputs from HYDRUS-2D.

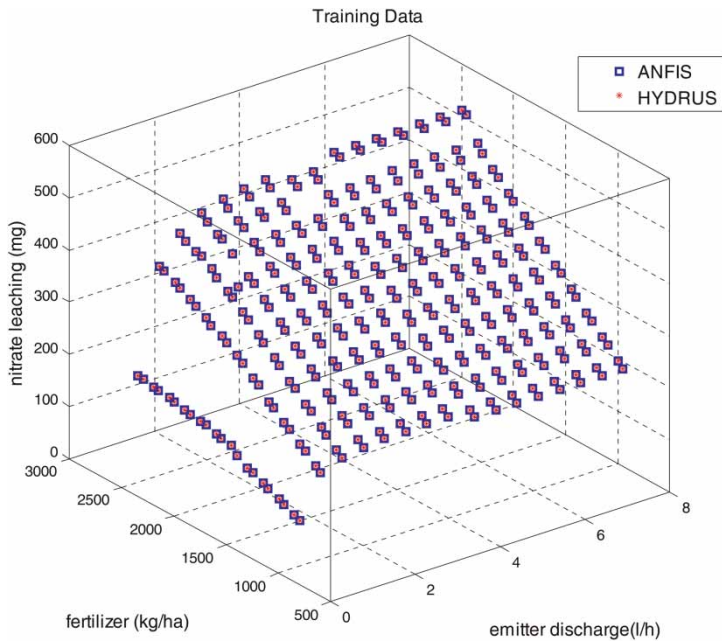


Figure 8 | Three-dimensional scatter plot of input variables versus nitrate leaching obtained by the ANFIS and HYDRUS models using training data.

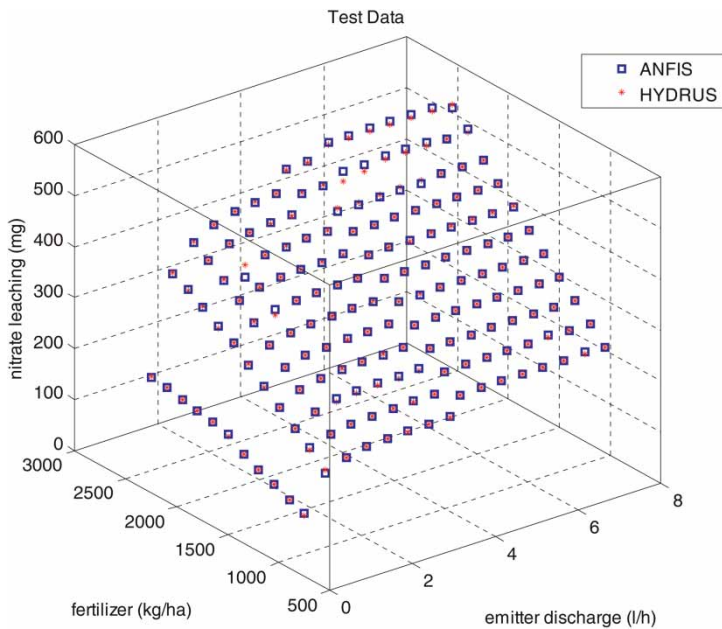


Figure 9 | Three-dimensional scatter plot of input variables versus nitrate leaching obtained by ANFIS and HYDRUS-2D models using test data.

for this fact is that fewer rules were needed at the end of the breakthrough curve since the concentration was almost constant. Therefore, by optimizing the rules, the accuracy of the fuzzy model could be improved. One of the ways for

optimizing the rules is using artificial neural nets to improve the assessment of the membership functions in the fuzzy rules (Muster *et al.* 1994). ANFIS as a matter of fact uses ANN properties to tune the membership functions.

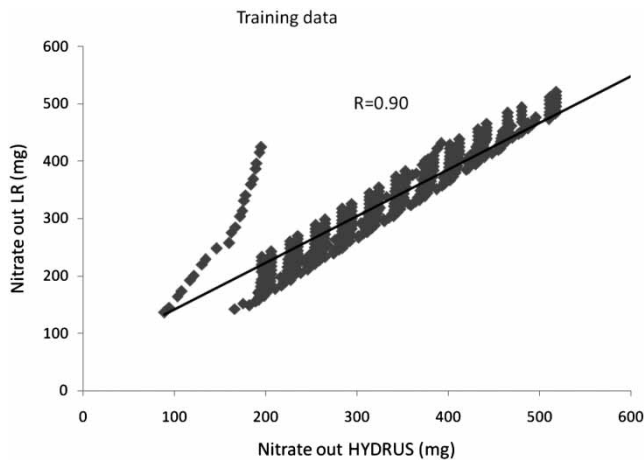


Figure 10 | Estimates of nitrate concentration by the linear regression (LR) using training data versus outputs from HYDRUS-2D.

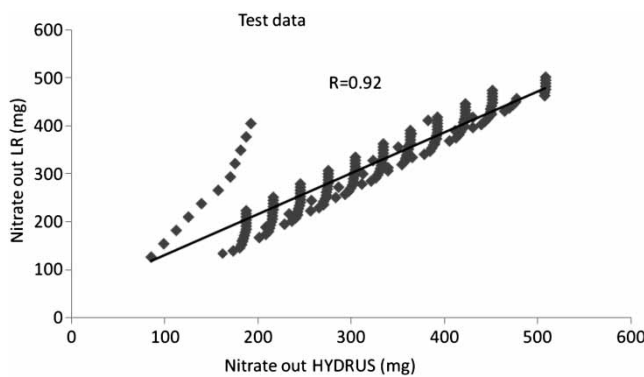


Figure 11 | Estimates of nitrate concentration by the linear regression (LR) using test data versus outputs from HYDRUS-2D.

Table 3 | Values of performance criteria in linear regression (LR)

	Training data	Test data
Correlation coefficient (R)	0.90	0.92
Mean absolute percentage error (MAPE)	0.30	11.14

In their system, they selected only a triangular membership function. In this study, regarding the existence of different methods (grid partitioning and clustering methods), for the construction of the membership functions and the adjustment of their parameters, it seems that the membership functions can be both opted and adjusted more accurately in ANFIS.

Furthermore, the rule structure is predetermined by an expert person for the fuzzy rule-based models. In practice,

these models may not perform satisfactorily due to limited knowledge of the experts and improper selection of membership parameters (Jang *et al.* 1997). In the proposed ANFIS methodology, the parameters are tuned automatically during the learning stage. This means that the membership functions can properly represent the nonlinear behavior of the system being studied with an optimal performance.

Compared with HYDRUS-2D, ANFIS significantly decreases the calculation time. For example, to run HYDRUS-2D for a 3,000 h period, it might take several hours; whereas, the system proposed here decreases the calculation time to several minutes. HYDRUS-2D needs a high amount of input parameters, some of which it is not possible to measure accurately. Also, the input parameters have a higher or lower degree of uncertainty. For example, in HYDRUS-2D, the input parameter evapotranspiration must be divided into evaporation and transpiration using other models. HYDRUS-2D needs input of the hydraulic properties of the soil such as the saturated and the unsaturated hydraulic conductivity, measurement of which is difficult and time consuming.

CONCLUSION

Relying on the data from the HYDRUS-2D simulation, a new application of the ANFIS to predict nitrate leaching from a potato field under drip fertigation was presented. Performance criteria values (between the outputs of ANFIS and HYDRUS-2D models) showed that the overall accuracy of the ANFIS model is high and that ANFIS can accurately simulate HYDRUS-2D behavior, related to nitrate leaching under the circumstances of the present study.

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