Estimation of Soil Moisture Profile Using Optimization Methods

S. Farid F. Mojtahedi and Mohsen Sadoughi

Abstract—The goal of this research is investigating variation in the water content due to change in the groundwater level and climate change using the optimization methods in different soil layers. Decrease in the precipitation rate in recent years has resulted in the overuse of groundwater, lowering the groundwater level and change in the soil moisture conditions. The result of these changes is considerable subsidence in the soil layers, where its accurate calculation and estimation requires precise knowledge of the soil conditions especially the water content at the soil surface and in deep layers. In this study, the performance of two optimization methods in estimating of the soil moisture profile is investigated: modeling by the inverse method and the artificial neural network and this problem is solved using the field data presented in the literature for a one-year study period. For this purpose, first, the field data corresponding to an interval of two months was utilized to determine the required parameters for each of these models. Then using the obtained data, the soil moisture profile at different soil layers and for the remained studied interval was estimated and compared to the observed data. Based on the obtained results, in the case of accurate estimation of the model parameters, utilizing the optimization methods would greatly reduce the cost and time associated with investigating the problem and at the same time would provide an acceptable prediction of changes in the soil moisture conditions. Also, the inverse method, considering the soil hydraulic parameters, would provide a better approximation of climate change at different times.

Index Terms—Optimization methods, soil moisture profile, effective hydraulic parameters, unsaturated soil.

I. INTRODUCTION

Excessive groundwater withdrawal in the current climate conditions is not only an effective factor in damage of the mentioned basins and aquifers but also causes serious damages to the surface or buried structures and agricultural products and this issue because of serious subsidence problems associated with change in the soil condition at different. There are numerous factors which impact the amount of soil subsidence at different layers and among the most important of them one could refer to the condition of the surface water and groundwater and also the strength and hydraulic properties of soil. In recent years there have been numerous studies to investigate the subsidence phenomenon and effective factors in this respect, where one could refer to various studies performed by Cui, Dehghani and Fredlund

[1]-[3]. In general, the performed studies on the subsidence phenomenon could be categorized into three groups: the first group investigates the subsidence phenomenon based on the satellite images and in this case changes in the soil parameters and groundwater fluctuations are not investigated [2]. In the second case, this phenomenon is investigated largely with the groundwater management approach and the outcome of the performed studies is generally a linear relationship between depletion of the groundwater level and the subsidence amount at the ground surface [1]. In the third group, the issue is investigated mostly from the geotechnical standpoint and calculation of subsidence is done with respect to the soil properties and changes in the soil parameters in the area.

Based on the presented results, in the majority of the performed studies, the subsidence phenomenon is examined by the first group standpoint and by implementing the radar and satellite images and the effects of hydraulic and mechanical parameters are less under consideration. On the other hand, in the studies in which the subsidence phenomenon is examined with the geotechnical point of view, calculation of the subsidence is performed only by taking into the account of changes in the soil properties at the aquifer layer and the effects due to change in the water content of unsaturated soil layers on Mechanical behavior of soil and also change in the volume due to this are ignored. Based on the recent performed studies, because of change in the water content at different soil layers, the amount of available water between the soil layers is changed and this issue causes change in the inter-particle forces, the state of soil stress and the strength and this problem could significantly impact the behavior associated with change in the soil volume. Therefore, to calculate changes in the water content at different soil layers and at different times of the year and consequently, change in the environmental conditions are among the main parameters in estimation and calculation of the subsidence.

In recent years, different methods and models have been presented for measurement and estimation of the soil moisture profile at different soil layers, including the research performed by Leconte and Walker [4]-[5]. In these studies, calculation of the soil moisture profile is done mainly through the use of a series of empirical and semi-empirical models where the basis is Richards equation [6]. These models although provide a good estimate of soil moisture profile but their application requires knowledge of the weather conditions at the investigated area and the soil hydraulic and mechanical properties at different soil layers, and this issue itself needs performing extensive field and laboratory tests. This issue in recent years has resulted in the development of various relationships and optimization methods for determining the model parameters in which by changing the hydraulic parameters and optimizing the model output, the water content values of the soil layers are obtained. Application of this method greatly reduces the consumed cost

and time needed for measurement of the soil moisture profile with respect to the field and laboratory methods [7].

The goal of this research is to investigate and make a comparison between the two artificial neural network and inverse optimization methods in determining the soil hydraulic parameters in order to estimate changes in the water content and consequently changes in the ground water level and weather conditions. For this purpose, two software, Rosetta and HYDRUS are presented where one is based on the artificial neural network [8] and the other is based on the inverse optimization method [9]. Also in this study, to achieve our goal first for a time interval of few months using the field data and methods and techniques of optimization, the hydraulic parameters of unsaturated soil are obtained and in the following, using the derived hydraulic parameters, the soil moisture profile is predicted for the coming months and compared with observed data.

II. MATERIALS AND METHODS

In this research, data of Yanco research station located in southeast of Australia is used. The area of the geotechnical stations in this study station is over 3600 square meters which is located in the southern and western parts of Yanco research station. The study stations at different parts including the geotechnical one are administrated by the meteorological organization [10]. It should be noted that this space has a weak plantation and very mild slope and Murrumbidgee River is located in its northern part. The geotechnical study station has 37 sites for soil moisture profile measurement with a different spatial distribution where in this article the Yanco station data are utilized. Yanco station is located at 145.84 degrees longitude and -364.62 degrees latitude. In this station for investigation and monitoring the soil behavior a number of parameters are investigated which are referred to in continuation [11].
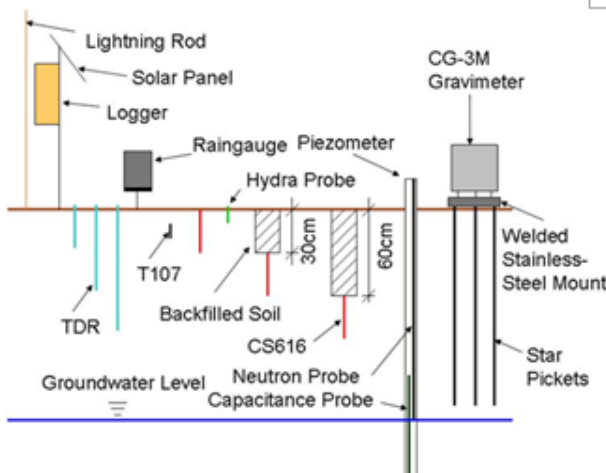

Fig. 1. Setting the instruments and installation of the sensors at Yanco-1 station.

- Precipitation: This parameter is measured using the hydrologic services of TB4 rain gauge with a resolution of 0.2 mm.
- Water content: This parameter is measured using CS-616 soil moisture probes at three different depths of 30cm, 60 cm and 90cm and to measure the surface soil moisture (0-5 cm depth) Stevens Hydra-Probe is utilized.

- Soil temperature: This parameter is monitored at two depths using two different sensors, one at a 3 cm depth using Hydra-Probe thermistor sensor and the other at a 15cm depth using a T-107 thermistor.

In Fig. 1 the corresponding information for setting the instruments is given:

The soil of the study area is the sandy loam type and the general specification for it is given in Table I [12].

TABLE I: SOIL PROPERTIES AT YANCO-1 STATION

Soil Type	Depth (cm)	Clay (%)	Silt (%)	Sand (%)	Density (gr/cm^3)
Sandy Loam	0-100	13.34	32.11	54.55	1.41

III. THEORY AND THE GOVERNING EQUATIONS

Precise estimation of soil moisture profile requires knowledge on the Aquifer layer, soil moisture and temperature conditions at the unsaturated layers, knowledge on the soil properties at different soil layers and finally water flow equations in soil at the saturated and unsaturated conditions. The basis for all the numerical methods for simulation of water flow in the porous media is Richards differential equation [13] which is generally described as equation 1, Where θ denotes volumetric water content, t denotes time, Z denotes depth and k denotes hydraulic coefficient in unsaturated soils (function of suction in the soil).

$$\frac{\partial \theta}{\partial t} = -\frac{\partial}{\partial z}\left(K(\psi)\frac{\partial \psi}{\partial z}\right) + \frac{\partial K(\psi)}{\partial z} \qquad (1)$$

In most cases, the gravimetric head gradient is negligible with respect to the suction gradient. So the basic differential equation without considering the gravimetric portion in unsaturated soils is in the form of equation 2 [14].

$$\frac{\partial \theta}{\partial t} = -\frac{\partial}{\partial z}\left(K(\psi)\frac{\partial \psi}{\partial z}\right) \qquad (2)$$

With respect to equation 2, which includes two related parameters and implementing a concept named specific water, content which indicates the slope of SWRC curve, one of the two parameters could be removed from equation 2. The corresponding equation for the specific water content is given in equation 3.

$$s(\theta) = -\frac{d\theta}{d\psi} \qquad (3)$$

The reason for using the negative sign in equation 3 is due to the overall concept of SWRC curve and the relation between suction and water content, which by an increase in the water content in the unsaturated soil, the suction is reduced. With respect to the above concepts and equations 2 and 3, in this article, equation 5 is used for modeling the one-dimensional vertical movement of water in a soil layers.

$$K(\psi)\frac{\partial \psi}{\partial z} = K(\theta)\frac{\partial \psi}{\partial \theta}\frac{\partial \theta}{\partial z} = -\frac{K(\theta)}{s(\theta)}\frac{\partial \theta}{\partial z} \qquad (4)$$

$$\frac{\partial \theta}{\partial t} = -\frac{\partial}{\partial z}\left(-\frac{K(\theta)}{s(\theta)}\frac{\partial \theta}{\partial z}\right) \qquad (5)$$

In this article, equation 5 is used in the HYDRUS-1D model for the solution of Richards equation with the initial and boundary conditions specific to the problem [15].

A. Unsaturated Soil Hydraulic Equations

The unsaturated soil hydraulic parameters were parameterized using the Van Genuchten-Moalem model (VGM) [16]. The SWRC equation curve (soil water retention curve) is defined by equation 6 as the effective (dimensionless) saturation degree, where θ_r and θ_s indicate the residual and saturated water contents, respectively. Also α, n and m are the shape parameters of this curve.

$$S(\psi) = \frac{\theta(\psi) - \theta_r}{\theta_s - \theta_r} = (1 + |\alpha\psi|^n)^{-m} \qquad (6)$$

The hydraulic conductivity function is obtained by equation 7, Where, Ks denotes the saturated hydraulic coefficient and L is a shape parameter.

$$K(h) = K_s S(\psi)^L (1 - (1 - S(\psi)^{1/m})^m)^2 \qquad (7)$$

IV. MODELING

In this research, the soil profile with 100 cm depth is discretized using 81 nodes with unequal distances. The nodes are close to each other at the ground surface and by distancing from the ground surface, the distance gradually increases so that at the ground surface the distance between nodes is 0.5 cm and in greater depths, this amounts even to 3.5 cm. The reason for the close distance between the nodes at the ground surface is due to the intense atmospheric changes and consequently, increase in the head pressure gradient in this area. In general, if the distance between nodes exceeds a certain value, the numerical solution of Richards equation would have a large error [17]. In the present research, increase in the number of nodes does not considerably affect the output and therefore this number of nodes are enough for this problem.

A. Initial and Boundary Conditions

The water content measured at the site is input to the model as the initial condition and to attain a stable initial condition, the output of calculations at each stage are utilized as the initial condition for the next stage. Also θ_i is the existing initial water content in the soil.

$$\theta = \theta_i(z) \quad \text{at} \quad -100 \leq z \leq 0, \, t = 0 \qquad (8)$$

The above boundary conditions are selected as the weather and atmospheric conditions which are under the effects of precipitation and evaporation at the soil surface.

$$-K\left(\frac{\partial \psi}{\partial z} + 1\right) = E(t) \quad \text{at} \quad z = 0, \, t > 0 \qquad (9)$$

In this article, the lower boundary condition is selected as the free-drainage as shown in equation 10, Where, θ denotes soil volumetric water content, ψ is denotes existing suction in the soil, K denotes hydraulic coefficient of the unsaturated soil and z denotes depth. E (t) indicates the weather and atmospheric changes for the upper boundary condition which vary with time.

$$\frac{\partial \psi}{\partial z} = 0 \qquad \text{at} \quad z = -100 \quad t > 0 \qquad (10)$$

B. Inverse Modeling

For precise estimation of the soil moisture profile, we could utilize the one-dimensional HYDRUS-1D model which numerically solves Richards equation. HYDRUS-1D is a Windows-based model used for one-dimensional water flow analysis and is able to estimate the soil hydraulic parameters by the inverse method. In this model for the numerical solution of the governing equations the linear Galerkin finite element method and for optimization of the parameters, the Levenberg-Marquardt method is utilized [9]. This method has been utilized in many fields and laboratory studies to optimize and estimate the unsaturated soils features by the inverse method and the corresponding results have been desirable [18]. The inputs for this model include the soil hydraulic parameters and as the soil hydraulic parameters are not available in this research, so first the effective hydraulic parameters should be determined by the inverse method for a time interval and in continuation using the estimated hydraulic parameters, the soil moisture profile is predicted for the future time intervals. Prediction of the parameters in this method is performed by minimizing the target function [19] as shown in equation 11, Where, m is the number of observations, θ_{obs} and θ_{sim} are the observed and simulated water contents, respectively. B is the vector of unknown parameters and c is the vector of known parameters.

$$\phi(\theta; b \,|\, c) = \sum_{i=1}^{m} [\theta_{obs}(t_i) - \theta_{sim}(t_i, b \,|\, c)]^2 \qquad (11)$$

Uniqueness and stability of the of HYDRUS-1D model responses is confirmed by repeated solution of the problem using different combinations of random values for the unknown parameters. These random values are determined based on the interval assigned to each parameter. The output of each calculation is stored and at the end of each stage the error values between the model output and the intended output (actual data) are measured and finally after a number of repeated solutions those parameters which generate the minimum error are considered as the effective hydraulic parameters.

C. Artificial Neural Network Modeling

In this research in addition to estimating the effective hydraulic parameters by the inverse method, the Rosetta software is utilized for estimating some of the soil hydraulic parameters. Rosetta software is able to estimate the corresponding parameters of Van Genuchten-Moalem model. Rosetta software is able to estimate the unsaturated soil

hydraulic parameters through using some basic soil properties as the input data including the textural classes, the percentage of the soil particles and soil density [8]. In this article using the soil particles percentage at the station where measurement of the soil water content data is performed, the soil hydraulic parameters are predicted. Rosetta software implements the artificial neural network models for estimation and prediction of the parameters and for calibration utilizes a huge data bank information [20].

Type of the implemented method	θ_r	θ_s	α	n	m	K_s
Unit	cm^3cm^{-3}	cm^3cm^{-3}	cm^{-1}	-	-	cm/day
Artificial Neural Network	0.079	0.44	0.020	1.33	0.25	24.03
Inverse Method	0.07	0.55	0.075	1.89	0.47	106.1

V. RESULTS AND DISCUSSION

With respect to the lack of access to soil hydraulic parameters at the area, the first goal of this research is to derive the effective hydraulic parameters and the second goal in this article is accurate prediction with a minimum possible error in the soil moisture profile. In the following, the results obtained from each of the above-mentioned sections are given.

A. Required Parameters for Analysis and Estimation of Soil Moisture Profile

In this study to determine the soil hydraulic parameters two optimization methods are implemented: A) Use of the neural network model (Rosetta software) and the basic information on the soil in the area and B) Use of the HYDRUS-1D model and the inverse method alongside the corresponding observed data of the soil moisture profile for a specified time interval of the year. In both methods, a total number of 5 effective hydraulic parameters are derived for the unsaturated soils and list of the parameters is given in Table II. These parameters were determined using the obtained data from the study area for a period of 2 months and their values are summarized in Table III. It should be mentioned that at first, based on the assigned interval for the parameters, the error value was high in the best-optimized case but by making the intervals smaller, the error value was reduced and became acceptable. Table II shows the intervals in which the model searches for the most optimal values. The obtained values were then utilized in HYDRUS-1D software for predicting and comparing water content variation with depth.

TABLE II: REQUIRED PARAMETERS FOR PREDICTING THE SOIL MOISTURE PROFILE TOGETHER WITH ESTIMATION INTERVALS FOR EACH OF THE PARAMETERS

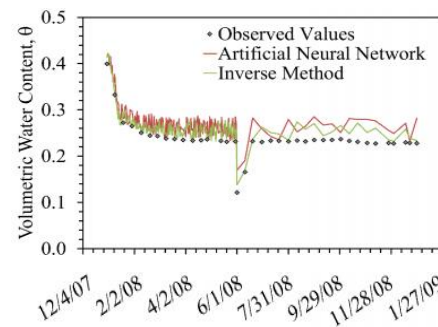| parameter	unit	Lower limit	Upper limit
θ_r	cm^3cm^{-3}	0.001	0.10
θ_s	cm^3cm^{-3}	0.40	0.70
α	cm^{-1}	0.002	0.50
n	-	1.1	4
$m = 1 - \dfrac{1}{n}$	-	0.90	0.75
K_s	cm/day	0.10	100000

TABLE III: ESTIMATED VALUES FOR EACH OF THE EFFECTIVE HYDRAULIC PARAMETERS BY THE TWO ARTIFICIAL NEURAL NETWORK AND THE INVERSE METHODS
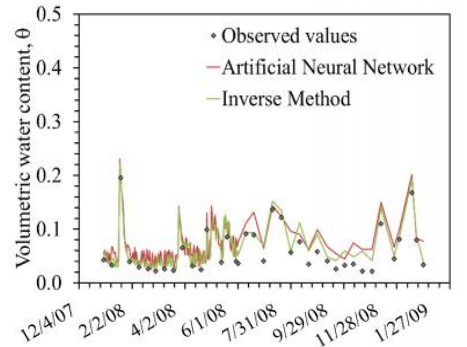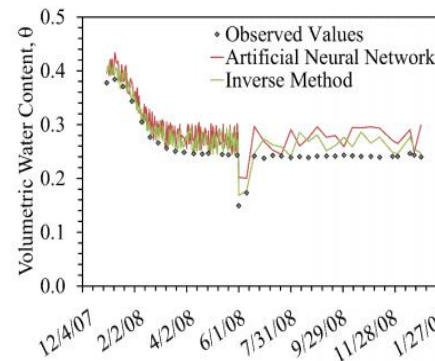

(A)
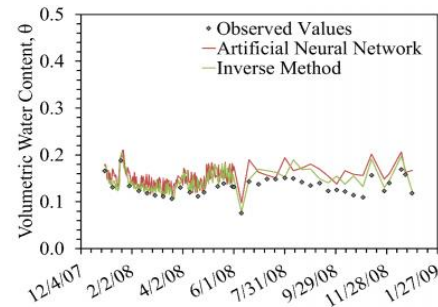
(B)

(C)

(D)

Fig. 2. Water content values predicted by the two artificial neural network and inverse methods at depths of (A) 5, (B) 30, (C) 60 and (D) 90cm.

B. Comparison between the two Inverse and Artificial Neural Network Methods
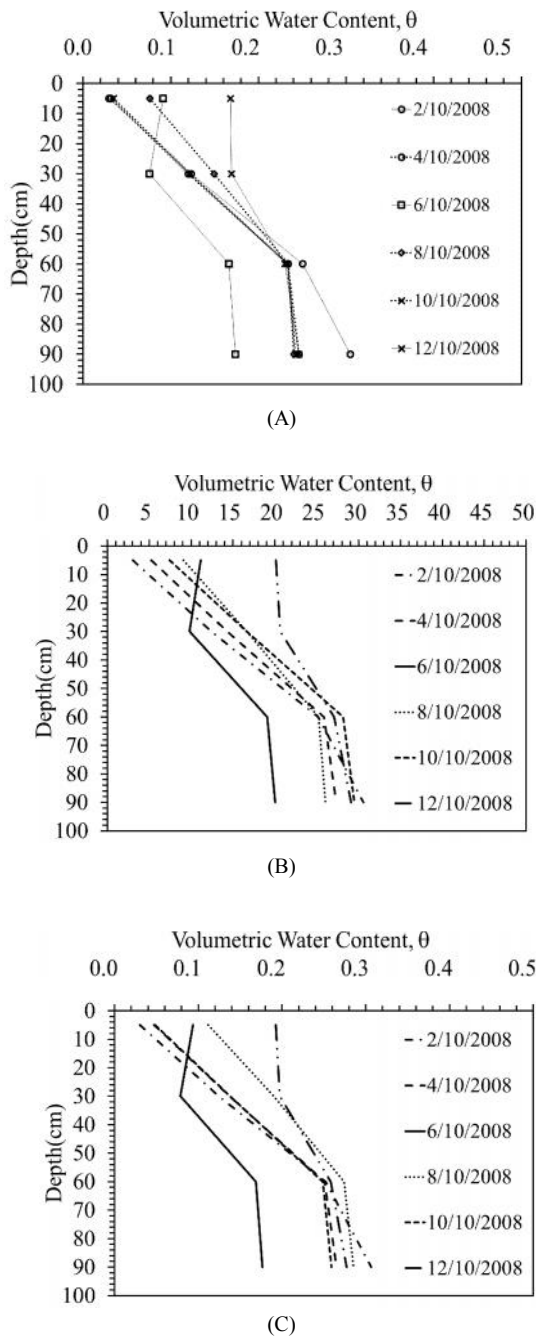

(A)

(B)

(C)

Fig. 3. Comparison between changes in the soil moisture profiles at different depths and at different season of the year 2008, soil moisture profile for A) Observed data, B) Artificial neural network method, C) Inverse method

Fig. 2 shows the water content values at different soil depths for the year 2008, estimated by HYDRUS software and their comparison with observed data. As seen in Fig.2, the inverse method better predicts the moisture values than the Artificial Neural Network method. Based on the obtained results the RMSE values in the first two months of the year 2008 (Used interval for prediction of the hydraulic parameters) for the inverse method at depths of 5, 30, 60 and 90cm are 0.86, 1.14, 1.43 and 1.71, respectively, but the error values for the rest of months of the year 2008 (validation interval) are increased with values of 2.04, 2.31, 2.36 and 2.63. When predicting the moisture values using the neural network method, the calibration interval is meaningless and the error values at depths of 5, 30, 60 and 90cm are 2.42, 2.72, 3.02 and 3.32, respectively.

C. Changes in the Moisture Content of the different Layers at different Seasons of the Year

The main goal of this article is a precise estimation of the moisture profiles at different seasons of the year. In this section the soil moisture profiles at the middle of six different months of the year are compared to each other. In Fig.3 the soil moisture profiles corresponding to the observed data are compared with the modeled soil moisture profiles utilizing the two Artificial Neural Network and inverse methods. The estimated profiles corresponding to both methods have appropriate precision. It is observed that with an increase in depth, the corresponding water contents for different seasons of the year have a greater difference with respect to the layers located at the surface or near the surface. This difference is also present in the modeled soil moisture profiles. Although good estimates of the soil moisture profile were obtained using the aforementioned methods in HYDRUS-1D software it seems that there is a need for further studies for investigating the precision of these methods in multi-layer soils and greater depths and this in itself requires performing field tests and recording more water content data at different soil depths.

VI. CONCLUSION

In this article the goal was prediction of the moisture profile for future time intervals and based on the obtained results, the HYDRUS-1D model has the capability of modeling water flow in the soil with respect to atmospheric fluctuations such as the evaporation, precipitation etc. alongside fluctuations in the groundwater levels. In addition to these advantages, this model has this feature that performs both the spatial and temporal simulations i.e. describe permanent changes. The HYDRUS-1D model exhibits a better performance in modeling the soil moisture profile at the soil surface and in greater soil depths the ability of modeling with this model is reduced. Use of the inverse method for estimating the hydraulic parameters are appropriate but its application requires experimental and computational knowledge to achieve convergence in solution. The inverse method is a type of optimization algorithm and such an algorithm yields best outputs when it uses less than 5 parameters for estimation. Also, application of the inverse method when the number of data is large and the number of intended parameters for estimation is small, results are much less error, and where the number of data is small and the number of intended parameters for estimation is high, unacceptable answers are obtained.

In parameter estimation by the inverse method using the HYDRUS-1D model, appropriate determination of the intervals for each of the hydraulic parameters has a basic role in the output of the optimization algorithm. To estimate the hydraulic parameters, in addition to implementing the inverse method as one of the optimization algorithms, one could also use the artificial neural network method with a huge data bank alongside other soil basic information in the study area.

Finally, one other conclusion in this research is that first the soil effective hydraulic parameters are estimated by the two artificial neural network and inverse methods and for the first 2-month interval in the year 2008 the corresponding precisions of both methods were assessed and it was observed that the inverse method yielded a better precision in estimating the parameters and predicting the soil moisture profile.

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