Modeling of Soil Water Content for Vegetated Surface by Artificial Neural Network and Adaptive Neuro-Fuzzy Inference System

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Abstract: *Soil water content is one of the critical and dynamic factors for controlling many processes in plant growth and understanding agricultural drought status. It also influences the management of water. Unfortunately, it hasn't been a routinely measured variable in the world, yet. Therefore, this variable is subject to be estimated using related approaches. In this study, an artificial neural network (ANN), a suitable adaptive neuro-fuzzy inference system (ANFIS) and a multiple linear regression (MLR) model were applied and compared for modeling the variation in the measured soil water content for a vegetated surface by meteorological and plant factors such as air temperature, relative humidity, vapor pressure deficit, precipitation and leaf area index. Measurements were carried out over an irrigated field. The results indicated that the best determination coefficient (r^2=0.98) between the measured soil water content and all considered variables was estimated by the ANFIS, whereas weaker relationships were calculated between the same variables by MLR as r^2=0.38 and ANN as r^2=0.56. Comparisons showed that ANFIS approach had a better modeling potential of the soil water content compared to the MLR and ANN model in the trial period, though weaker relationships in the testing period were found by all approaches.*
Keywords: *Soil Water Content, Adaptive Neuro-Fuzzy Inference System, Artificial Neural Network.*

Riassunto: *Il contenuto di acqua del suolo è uno dei fattori critici e dinamici per controllare molti processi nella crescita delle piante e comprendere lo stato di siccità agricolo. Influisce anche sulla gestione dell'acqua. Purtroppo, non è ancora stata una variabile regolarmente misurata nel mondo. Pertanto, questa variabile deve essere stimata utilizzando approcci correlati. In questo studio sono state applicate una rete neurale artificiale (ANN), un adeguato sistema di inferenza adattivo neurofuzzy (ANFIS) e un modello di regressione multipla lineare (MLR) e confrontate per modellare la variazione nel contenuto di acqua misurato nel suolo per una superficie vegetata. Sono stati considerati fattori meteorologici e vegetali come la temperatura dell'aria, l'umidità relativa, il deficit della pressione del vapore, l'indice di precipitazione e l'area fogliare. Le misurazioni sono state eseguite su un campo irrigato. I risultati indicano che il miglior coefficiente di determinazione (r2 = 0,98) tra il contenuto di acqua del suolo misurato e tutte le variabili considerate è stato stimato dall'ANFIS, mentre minori relazioni sono state calcolate tra le stesse variabili con MLR con r2= 0,38 e ANN con r2=0,56. I confronti hanno mostrato che l'approccio ANFIS aveva un migliore potenziale di modellazione del tenore di acqua del suolo rispetto al modello MLR e ANN nel periodo di prova, anche se erano state trovate relazioni deboli nel periodo di prova da parte di tutti gli approcci.*
Parole chiave: *Contenuto di acqua nel suolo, Sistema di Inferenza adattiva Neuro-fuzzy, Rete Neurale Artificiale.*

1. INTRODUCTION

Precipitation amount and distribution are very important for water management, irrigation scheduling and agricultural production in arid and semiarid countries. In this case, precipitation affects the soil water content and can lead to various events such as drought. Some indexes have been developed in order to understand, classify and monitor the drought. Most of the drought indexes estimate the meteorological drought based generally on precipitation amount. Monitoring the agricultural drought, however, depends directly on the soil water content in the root zone of the plants because that amount of water represents the potential available water for the crops. In addition, the surface soil moisture is an important key to define water and energy fluxes between the soil surface and the atmosphere. Unfortunately, in most countries there is no sufficient continuous measurement of soil water content existing in agricultural or forest areas. Unavailability of soil water content data causes problems in monitoring, planning and evaluation of future status of related agricultural, hydrological and meteorological activities. This is because the soil water content is an essential variable for controlling the evapotranspiration and evaporation over canopy surfaces and bare soils, respectively. It is also the major criterion for planning irrigation and managing ground and surface water resources.

As pointed out by many researchers, earth's climate has been changed and it is changing. Related impacts of the climate change can be observed in past, today and future. One of the possible effects of climate change is the temporal and/or spatial precipitation decrease, namely the drought. Traditionally, in arid

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and semiarid countries, insufficient water for demand is a primary problem. In recent years, corresponding impacts have been observed in many countries as agricultural, hydrological or meteorological droughts. The majority of the drought indexes have been developed for the estimation of the meteorological drought status. Agricultural drought is defined as the lack of soil water in the crop root zone during the crop life or in the growth period. For this reason, there is a clear need to establish the soil water content as a function of other related variables. Results of the modeling approximations for this factor represent also critical inputs for many soil-plant-water models.

Neural networks are widely used in order to find an alternative way to complicated problems. Some researchers such as Kohonen (1984) and Hammerstrom (1993) proved the power of neural networks in modeling complex systems. The technique was successfully applied in fields such as agriculture and engineering (Bolte, 1989; Zhuang and Engel, 1990; İzgi *et al*., 2012). Alavi *et al.* (2010) used ANN (Artificial Neural Network) for the prediction of the soil water content. Similarly, Moreira de Melo and Pedrollo (2015) applied ANN for estimation of the soil water retention. Huntingford and Cox (1997) applied ANN to model the plant surface conductance. Özcep *et al.* (2010) measured the moisture and electrical resistivity of soils and applied an ANN system for soil moisture estimations. Additionally, Van Wijk and Bouten (1999) modeled water and CO_2 fluxes in the forest area using ANN. Neural network models have also been developed in meteorological field to model atmospheric variables such as wind velocity (Öztopal, 2006). Among numerous studies in this context, Lopez *et al*., (2001) modeled global and diffused solar radiation variables and presented important improvements against traditional statistical models. Şen *et al.* (2009) used a fuzzy model for prediction of the ozone surface. Besides, neural networks and fuzzy logic are successful combinations of intelligent techniques and are widely used. For this reason, they are called as neuro-fuzzy systems. These systems have a high success rate when applied in complex applications such as biosphere and atmosphere interactions.

For any agricultural area, soil water content is highly related with the drought conditions by influencing on the quality and quantity of production and hence, a useful practical knowledge for irrigation. Unfortunately, there are very few studies on the application of ANNs and ANFISs (Adaptive Neuro-Fuzzy Inference System) for estimation of the soil water content, in contrast of its importance for irrigation scheduling and management of water resources. In this context, Schaap and Leij (1998) used ANN to predict soil water retention and soil hydraulic conductivity. Jiang and Cotton (2004) applied ANN for the estimation of soil moisture. Zou *et al.* (2010) considered neural networks for soil water content and electricity using data extrapolated from lysimeter measurements. Lazzus (2014) applied neural network technique for representative data prediction of two successive years in the future. Based on soil physical properties; Pachepsky *et al.* (1996) reported that ANNs estimated soil water content better than regression techniques. ANFIS was used by Lee *et al*. (2003) and Mohamed and Hawas (2004) for the prediction of soil water content, where very close relationships were found between the predicted and actual soil water content. Deng *et al.* (2011) compared the results of a least squares support vector machine with a back propagation ANN and an ANFIS.

In addition to these, ANN method was applied by Kumar *et al*. (2002), Lin *et al*. (2007) and Laaboudi *et al.* (2012) for the determination of the evapotranspiration and by Terzi *et al.* (2006) for the estimation of lake evaporation. Patil and Chaturvedi (2012) developed pedotransfer functions using a nearest neighborhood algorithm and made a comparison of the results by artificial neural networks. Successive calibration and validation periods using the soil and water assessment tool (SWAT) and multi-layer perceptron artificial neural network (MLP) on the sediment yield of a watershed in India showed that the MLP model produced better determination coefficients than SWAT (Singh *et al*., 2012). A regularized ANN model, which was developed and proposed by Mukhlisin *et al*. (2012), exposed higher correlations between the saturated soil water content and some major hydraulic features of the soil than the classical ANN approaches. Using in situ and remote sensed environmental data, Jana and Mohanty (2011) applied the Bayesian Neural Network to develop the corresponding pedotransfer functions. Bono and Alvarez (2012) tried to compare the representativeness of polynomial regression and ANN for soil water content estimations. Arsoy *et al.* (2013) used the ANN approach for calculation of the soil water content. Olawoyin *et al.* (2013) applied a self-organizing map-artificial neural network (SOM-ANN) system at four locations in the Niger Delta. Sahoo *et al.* (2005) applied ANFIS approach for the estimation of pesticides in groundwater. Similarly, Doğan (2009) used this technique for modeling the reference evapotranspiration.

Having knowledge on drought status related to soil water content in the root zone can be used to analyze the influences of different factors on crop. Yet, there is still a great need for a better understanding of the relationship between soil water content and environmental variables. However, evaluation of the variation of soil water content during the growth period is rather sophisticated. Thus, ANFIS, ANN and MLR techniques were used to analyze this complex problem and improve models between the dependent and independent variables.

Main objective of this study was to determine the soil water content of sunn hemp (*Crotalaria juncea* L.) as a function of five variables using nonlinear ANFIS, ANN and linear MLR approaches on highly infiltrated sandy soils of the experiment field at the Arid Land Research Center of Tottori University in Tottori City, Japan. In this study, the soil water content was assumed to be affected by air temperature (T), relative humidity (RH), vapor pressure deficit (VPD), leaf area index (LAI); precipitation and irrigation (P+I).

2. MATERIALS AND METHODS

2.1. Site Description

The research was carried out on a field located at the Arid Land Research Center, University of Tottori Japan (35°32'N, 134°13'E, 15 m above sea level). The study area is characterized by humid temperate climate and under the influence of maritime air currents. Long term annual average temperature is 14.6 °C and total precipitation amount is 1900 mm. The size of the research field was about 1 hectar. During the measurement period, the experiment field was tilled on July 29 and the sunn hemp was harvested on October 18, 2004 (Takagi, 2005; Takagi *et al*. 2009). Sand, silt and clay contents of the soil were 96.1, 0.4 and 3.5 %, respectively. Besides, saturated soil water content, field capacity and permanent wilting point of the soil were measured as 0.413, 0.074 and 0.022 m^3m^{-3}, respectively (Dehghanisanij *et al*. 2004). In order to avoid water shortage due to high infiltration of the sandy soil, the site was continuously irrigated using sprinkler during the growth period.

2.2. Artificial Neural Networks (ANN)

The ANN approach is based on learning the relationship between input and output variables by studying previously recorded data as stated by Lopez *et al*. (2001). For the application of any ANN model; input, hidden and output layers are required. The input and output layers contain nodes that correspond to input and output variables. Every layer consists of a number of neurons, which are interconnected according to their corresponding weights. In the hidden layer, every neuron receives its input from the related input layers. Detailed theoretical description of the neural networks can be found in Haykin (1994). In this study, backpropagation neural network was used where the total sum of the squared errors between measured and modeled soil water content values was minimized by tuning the ANN parameters; as used by Van Wijk and Bouten (1999). Transfer function used for the hidden layer was the sigmoidal function as introduced by Kaul *et al*. (2005). Every neuron in the hidden layer gives an associated output O_j through an activation function. The considered O_j was the sigmoidal function given as follows:

$$O_j = f(y_j) = \frac{1}{1+e^{\frac{-(y_j+b_j)}{\theta}}} \qquad (1)$$

where; y_j is the input value of the j_{th} neuron in the hidden layer, $f(y_j)$ is the output of the neuron, θ is the bias and b_j is the initial value (Hamidi and Kayaalp, 2008). Fig. 1 presents a typical neuron and a one layer backward network.

2.3. Adaptive-network-based fuzzy inference system (ANFIS)

ANFIS is a learning network algorithm, which was proposed originally by Jang (1993). The approach uses neural network learning and fuzzy theories by representing a fuzzy inference system (FIS). Typical structure of the ANFIS is based on a network consisting of a number of nodes. Each node in this network has a node function with adjustable and fixed parameters. In order to fit the training data, best parameter values are obtained within the training and learning processes. The ANFIS is a fuzzy Sugeno model and it can be used as an adaptive system for learning and adaptation (Jang, 1993; Güler and Übeyli, 2005; Kişi *et al*. 2009; Yıldız *et al*. 2009). There are principally 5 components in an ANFIS model, which are represented as the input and output databases, a

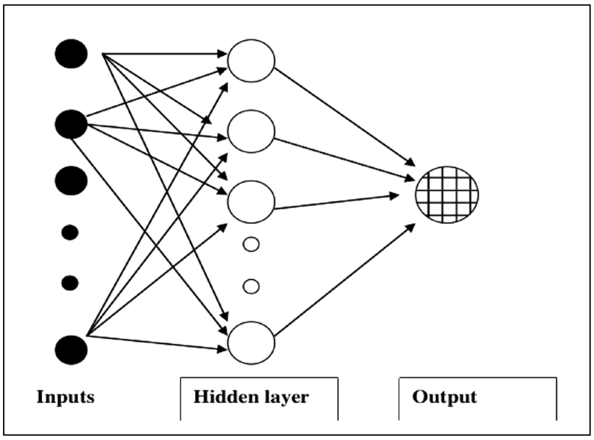

Fig.1 - Scheme of a typical neuron and a one-layer backward network.
Fig. 1 - Schema di un tipico neurone e di una rete one-layer backward.

fuzzy system generator, an adaptive neural network and a fuzzy inference system (FIS), consecutively. In this study, the Sugeno-type FIS was used for modeling the soil water content. To achieve this, following two fuzzy "if–then" rules based on a first order Sugeno Model were considered to represent the ANFIS architecture (Yıldız *et al*. 2009; Sugeno, 1985):

Rule 1: IF f(x is A_1) and (y is B_1)
THEN ($f_1 = p_1x + q_1y + r_1$)

Rule 2: IF f(x is A_2) and (y is B_2)
THEN ($f_2 = p_2x + q_2y + r_2$)

where A_i and B_i are the fuzzy sets, x and y are the inputs, f_i are the outputs within the fuzzy region specified by the fuzzy rule, r_i, p_i and q_i are the design parameters.
General Structure of an ANFIS is given in Fig. 2. Detailed knowledge about ANFIS specifications can be found in Jang (1993).

2.4. Multiple linear regression (MLR) procedure

As a widely used statistical approach, the MLR presents the relationship between one dependent variable and at least two independent variables:

$$\hat{y} = a + b_1X_1 + b_2X_2 + \ldots + b_mX_m \quad (2)$$

where; $\hat{y}$ is predicted value of the dependent variable, X_1 through X_m are *m* distinct independent variables; *a* is the intercept and b_1 through b_m are slope parameters (or regression coefficients) (Bayazıt and Oğuz, 1998).

2.5. Measurements

Measured soil water content at 0-30 cm depth was selected for modeling because most of the soil water variation can often occur in the topsoil. Moreover; crops also recompense the major portion of their water needs from the same region. In order to obtain the actual soil water content at that interspace, soil water content reflectometers (CS615, Campbell Sci.) were

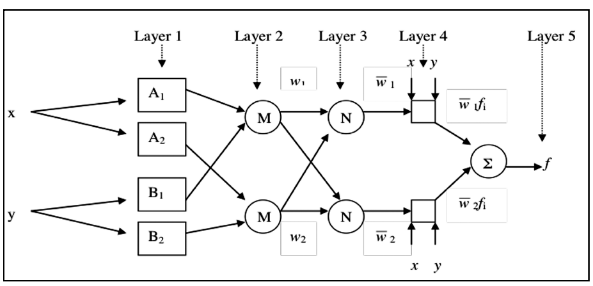

Fig. 2 - The architecture of an ANFIS equivalent to a first-order Sugeno fuzzy model.
Fig. 2 - L'architettura di un ANFIS equivalente a un primo modello Sugeno fuzzy.

used. It measured the volumetric water content using time-domain measurement methods in an interval of 2 s. Before the data collection period, all reflectometers were calibrated according to the simultaneous in situ measurements using gravimetric method. Additionally, relative humidity and air temperature were measured at fixed heights of 2 m above the ground surface. Precipitation amount was recorded by a tipping bucket rain gauge (34-T, Ota Keiki). All meteorological data were measured in an interval of 1 s. Finally, data collection was done at 30-min intervals using a data logger (CR23x, Campbell Sci.). Leaf area index of the crop was measured by using a plant canopy analyzer (LI-COR 2000) biweekly. Detailed information on the instrumentation and measurements are given in Takagi (2005) and Takagi *et al*. (2009).

3. RESULTS AND DISCUSSION

3.1. Observations

Meteorological measurements were conducted between 1st August (Day Of Year, DOY 214) and 8th October 2004 (DOY 282) using an agro-meteorological weather station installed in the experiment field (Fig. 3). Average air temperature at 2 m high (T_{2m}) was measured as 24.4°C and ranged from about 17.8 to 30.1°C within that period. Air temperature was maximum while the total precipitation was minimum

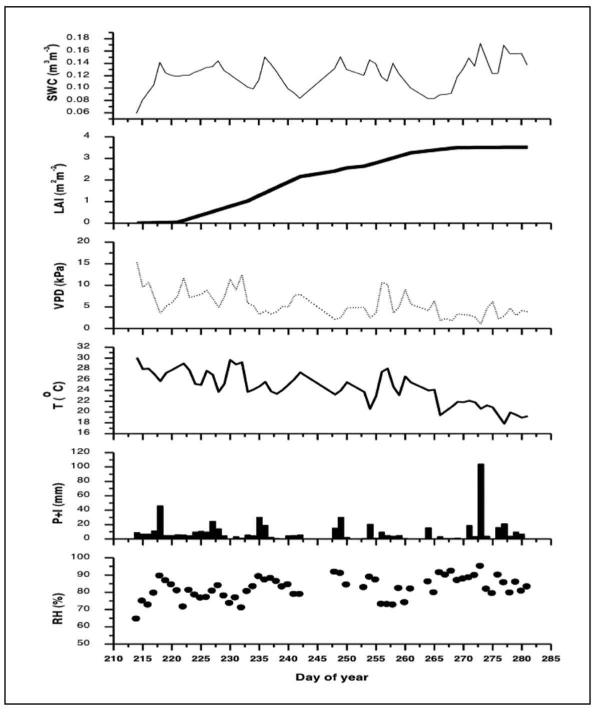

Fig. 3 - Time series of LAI and meteorological variables during the measurement period of vegetation of sunn hemp.
Fig. 3 - Serie temporale di LAI e variabili meteorologiche durante il periodo di misurazione della vegetazione della canapa

during August, as expected. Though, the minimum air temperature was observed in the last week of the measurement interval; owing to the above mentioned typhoon season. Mean air temperature decreased gradually toward the end of the measurement period. The relative humidity (RH) was ranged from 64.4 to 95.0%. As a result of heavy rains, RH tended to increase in September and October according to the air temperature decrease during that time. Meanwhile, total irrigation and precipitation amounts were recorded as 172 and 408 mm, respectively (Fig. 3). The gap occurred in meteorological data was filled using data of a near meteorological station located around 300 m away from the experiment area in the Arid Land Research Center territory. The Leaf Area Index (LAI) was measured periodically during the growing period, for which the maximum value was recorded as 3.52 during the last period of monitored crop cycle. Due to irrigation and precipitation, the soil water content (SWC_{act}) tended to increase just after beginning of the measurements. Daily averaged soil water content (SWC_{act}) was 0.12 m^3 m^{-3} and had an increasing trend so it reached up to 0.14 m^3 m^{-3} at the end of the period (Fig. 3). The amount and distribution of rainfall together with irrigation were accounted for temporary increases in SWC_{act} during the growing period. Lastly, the Vapor Pressure Deficit (VPD) ranged from 1.0 to 15.3 hPa with an average value of 5.7 hPa.

Time series of daily averaged meteorological factors, which were calculated for 30-min averaged data during the measurement period, are presented in Tab. 1 and Fig. 3. As seen in Fig. 3, VPD was high at the beginning of the measurements in August, but later it had a decreasing trend until the end of the period. All these can be attributed to heavy rain and high soil water content on the related days in September and October.

3.2. Model Comparison

In order to estimate daily average soil water content at 0-30 cm depth by ANN, ANFIS and MLR, daily average air temperature, relative humidity, vapor pressure deficit, precipitation, irrigation and LAI data were used as input. To test the ANFIS, ANN and MLR models, a training process was applied to randomly selected data that corresponded to about 70% of the whole. Thus, the remaining 30% were used to test the models. After the data normalization step, the variables were trained and tested by considered approaches. Back-propagation algorithm was used for training the neural networks on the estimation of daily average SWC. Concordantly, the best network consisted of five inputs, five neurons in two hidden layers and one neuron in the output layer. In the ANN model; the number of epochs, learning rate and hidden layers used in the optimization were calculated as 100, 0.80 and 2, respectively. For modeling by ANFIS, the squash factor, accept ratio and reject ratio were considered as 1.25, 0.5 and 0.15, respectively. Data were optimized by using the hybrid method. Error tolerance and epochs were chosen as 0 and 3, respectively.

As usual, the training procedure was repeated until the error function approached a minimum value in ANN, ANFIS and MLR. The training process was followed by the testing procedure, during which the calculated SWC values by ANFIS (SWC_{ANFIS}), ANN (SWC_{ANN}) and MLR (SWC_{MLR}) were evaluated under consideration of the measured SWC at 0-30 cm (SWC_{act}) depth. Following this testing period, performance of the developed model by ANFIS (SWC_{ANFIS}) was also compared with these of the SWC_{ANN}, SWC_{MLR} and SWC_{act}. Performance test of these three models was done according to the calculation and comparison of the corresponding average absolute relative errors (AARE), root mean square errors (RMSE) and determination coefficients (r^2) as follows (Eq. 3-5):

$$RE = \frac{(SWC_{act} - SWC_{model})100}{SWC_{act}} \quad (3)$$

$$AARE = \frac{1}{n}\sum_{i=1}^{n}|RE| \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(SWC_{act} - SWC_{model})^2} \quad (5)$$

The significance level was considered as 95 % for all calculations of determination coefficients. Tab. 2 presents the comparison of the MLR, ANN and ANFIS approaches for the whole data set. Using this measured data for SWC, the determination coefficient (r^2=0.21) was simulated by MLR, when VPD was considered as the only input variable. In the training period, the MLR method fitted a slightly higher r^2 (0.32) with a lower RMSE for the VPD, T and P+I combination.

	T	VPD	RH	P+I	SWC	LAI
	(°C)	(hPa)	(%)	(mm)	(m^3m^{-3})	(m^2m^{-2})
Average	24.4	5.7	82.2	9.4	0.12	2.0
Maximum	30.1	15.3	95.0	104	0.17	3.5
Minimum	17.8	1.0	64.4	0	0.06	0

Tab. 1 - Daily average, maximum and minimum values of measured variables.
Tab. 1 - Valori giornalieri medi, valori massimi e minimi delle variabili misurate.

	MLR r^2	RMSE	ANN r^2	RMSE	ANFIS r^2	RMSE
SWC-VPD, T	0.22	0.02	0.21	0.02	0.37	0.02
SWC-VPD, T, P+I	0.32	0.02	0.38	0.02	0.58	0.02
SWC-VPD,T, P+I, RH	0.37	0.02	0.48	0.02	0.71	0.01
SWC-VPD,T, P+I, RH, LAI	0.38	0.02	0.56	0.02	0.98	0.01

Tab. 2 - Performance indicators of the MLR, ANN and ANFIS models.
Tab. 2 - Indicatori di performance dei modelli MLR, ANN e ANFIS.

For the VPD, T, P+I and RH integration, MLR gave slightly better relationships (r^2=0.37) for estimating the soil water content at the depth of 30 cm in the test period. Again, the MLR model showed the highest r^2 value (0.38) under consideration of all meteorological factors (VPD, RH, T, LAI, P+I) together as model inputs (Tab. 2).
The determination coefficient for SWC was estimated by ANN (r^2=0.21) approach using only meteorological variables (VPD and T) as input. It showed that these variables were not enough to simulate actual SWC. After P+I was considered as a combination of VPD and T variables, the correlation increased significantly (approximately 2 times). This is because the precipitation and irrigation components are the main resources of water budget in the soil that can eventually increase the soil water content. Similarly, including RH as a meteorological variable into the input list of VPD, T and P+I caused increases in the model fitting performance because also RH is related to the temperature, evaporation and transpiration. Afterwards, integrating LAI as a crop factor into the meteorological (VPD, T, RH, P+I) inputs allowed to ANN approach to better model the measured SWC values. It could be attributed to the LAI parameter, which is one of the important indicators of plant growth and water consumption at the same time. For this latter combination, the determination coefficient was 0.56 with RMSE of 0.02 and AARE equal to 1.27%. In general, ANN modeling showed higher relationships compared to MLR approach (Tab. 2).
The comparison of the three approaches given in Tab. 2 shows that the ANFIS approach estimated the best fitting with r^2 of 0.98 and RMSE=0.01 for SWC by considering VPD, T, RH, P+I and LAI as the inputs for SWC modeling. Integrating LAI into the input data caused to a significant increase in the determination coefficient. This aspect indicates the importance of integrating also the crop growth indicators into the modeling process of soil water content during crop growing period. As expected, using of multiple regressions between independent meteorological and crop variables showed that the SWC was found to be in decrease when the total amount of precipitation and irrigation (P+I) decreased as VPD, RH, T and LAI increased. In fact, an increase of LAI means to uptake more water for crop transpiration. Scatter plots in Fig.4 indicate a good linear relationship between SWC_{ANFIS} and SWC_{act}. The linear MLR model slightly underestimated the SWC_{act} whereas ANN overestimated it. Consequently, ANFIS approach on SWC gave a closer relationship with the SWC_{act} when compared to the performances of the artificial neural network (SWC_{ANN}) and multiple regressions (SWC_{MLR}) (Fig. 4).

4. CONCLUSIONS

In this study: ANFIS, ANN and MLR techniques were applied to model and estimate the soil water content for sandy soil conditions during a measurement period within the sunn hemp growing season. For modeling of the soil water content, five independent

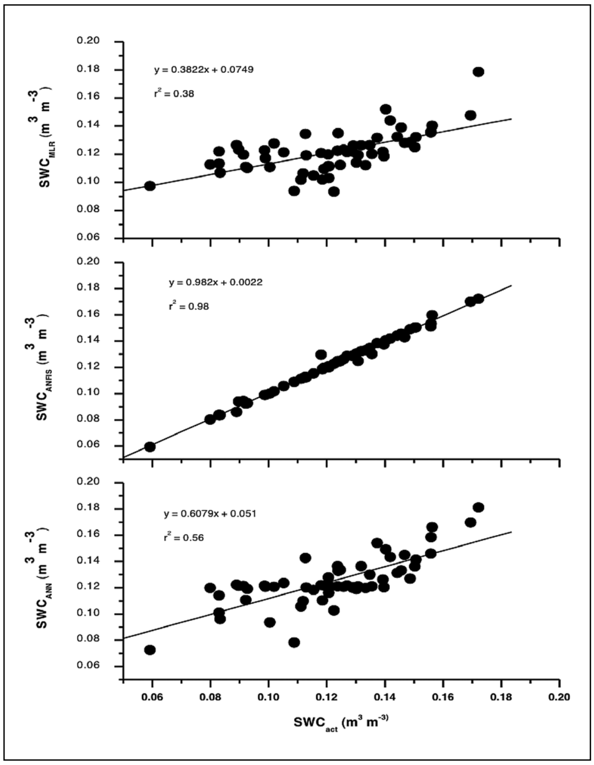

Fig. 4 - Comparison of SWC_{ANN}, SWC_{ANFIS}, SWC_{MLR} with SWC_{act} data.
Fig. 4 - Confronto dei dati di SWC_{ANN}, SWC_{ANFIS}, SWC_{MLR} con SWC_{act}.

variables (meteorological and plant) were included in the training process. As a result, the ANFIS method, in which the modeled SWC_{ANFIS} was very close to SWC_{ACT}, produced more accurate predictions of soil water content than ANN and MLR. Generally, the performance for the usefulness of the fuzzy-neural approach on prediction and analysis of soil water content was successful. However, ANN overestimated the SWC while a slight underestimation by the MLR technique was obtained. Overall prediction ability of the nonlinear ANFIS approach was very high when compared to ANN and MLR in the training period of SWC data. However, weak relationships were found in the test period by all models. It could be resulted from the impacts of unconsidered factors for modeling or limitations of used approaches.

Acquisition and usage of real time data for soil water content could allow quite satisfactory applications of various modeling approaches for this variable worldwide together with the opportunity of managing with the drought phenomenon.

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