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Modeling of Surface Conductance over Sunn Hemp by Artificial Neural Network

Modellazione della conduttanza di superficie su canapa mediante rete neurale artificiale

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Abstract. Performances of an Artificial Neural Network (ANN), a multiple linear regression (MLR) and the Jarvis type model were compared to estimate the surface conductance which is a driving factor affecting evapotranspiration. It was modeled by ANN and MLR using various parameters including global solar radiation, temperature, soil water content, relative humidity, precipitation and irrigation, vapor pressure deficit, wind speed and leaf area index. The measurements were carried out during the growing season of sunn hemp in 2004. The best relationship (r^2=0.73) between the surface conductance and all variables was estimated by the ANN when r^2 was 0.91 in the training period. The average absolute relative error was 26.54% for the ANN (r^2=0.80), 51.07% for the MLR (r^2=0.53) and 58.30% for Jarvis model (r^2=0.26) when vapor pressure deficit, temperature, soil water content, global solar radiation and leaf area index were considered to model. The results showed that the ANN approach had a better modeling potential of the surface conductance compared to the MLR and Jarvis model.

Keywords. Agriculture, Air-water interaction, Evapotranspiration, Neural Networks.

Riassunto. Le prestazioni di una rete neurale artificiale (ANN), una regressione lineare multipla (MLR) e il modello di tipo Jarvis sono state confrontate per stimare la conduttanza di superficie, che è un fattore trainante che influenza l'evapotraspirazione. È stato modellato con ANN e MLR utilizzando vari parametri tra cui radiazione solare globale, temperatura, contenuto di acqua del suolo, umidità relativa, precipitazioni e irrigazione, deficit di pressione di vapore, velocità del vento e LAI. Le misurazioni sono state eseguite durante la stagione di crescita della canapa nel 2004. La migliore relazione (r^2 = 0,73) tra la conduttanza superficiale e tutte le variabili è stata stimata dalla RNA quando r^2 era 0,91 nel periodo di training della rete. L'errore relativo assoluto medio è stato del 26,54% per l'ANN (r2 = 0,80), del 51,07% per l'MLR (r^2 = 0,53) e del 58,30% per il modello Jarvis (r^2 = 0,26) quando il deficit di pressione di vapore, temperatura, contenuto di acqua del suolo, radiazione solare globale e il LAI. I risultati hanno mostrato che l'approccio ANN aveva un potenziale di modellazione migliore della conduttanza superficiale rispetto al modello MLR e Jarvis.

Parole chiave. Agricoltura, interazione aria-acqua, evapotraspirazione, reti neurali.

1. INTRODUCTION

As a dynamic system, the crop growth is influenced by many factors. Surface conductance is one of them and controls evapotranspiration which is strongly related to the stomatal activity and photosynthesis process of vegetation. As a component of hydrological cycle, evapotranspiration plays a crucial role for planning irrigation schedule. It is also affected by many factors such as surface conductance, energy partitioning, water use efficiency and carbon exchange over vegetation surfaces (Woodward and Smith 1994; Sellers *et al*., 1996; Zhang *et al*., 2007). As well known, energy fluxes above canopy such as latent heat flux are mainly controlled by closure of stomata. Unfortunately, surface conductance isn't a routinely and easily measured variable. In general, it is calculated by using some improved equations under consideration of interactions between meteorological and plant factors. Many studies were focused on the estimation of surface conductance by assuming it as a function of driving environmental and biological factors (Şaylan and Bernhofer, 1993). In earlier studies, the surface conductance was modeled by linear and nonlinear techniques. As stated by Huntingford and Cox (1997), the response of surface conductance is highly nonlinear for local environmental conditions. Nonlinearity of surface conductance can also be seen in the Jarvis-Stewart model (Jarvis, 1976; Stewart, 1988).

Neural networks are widely used nonlinear approaches in order to find an alternative way to solve complex problems. From past to present, many studies such as Kohonen (1984) and Hammerstrom (1993) showed the power of neural networks in modeling complicated systems. Bolte (1989), Zhuang and Engel (1990), Thai and Shewfelt (1991), and Kaul *et al.* (2005) successfully applied the neural networks in the agriculture and engineering field. Huntingford and Cox (1997) applied ANN for modeling the surface conductance of plants. Additionally, van Wijk and Bouten (1999) modeled water and CO_2 fluxes in the forest by ANN. Pachepsky *et al.* (1996) indicated that ANN gave better results for the soil water content according to soil physical properties than other regression techniques. Sahoo *et al.* (2005) also applied this approach for the estimation of pesticides in groundwater. Additionally, the same technique was applied by Terzi and Keskin (2005) for modeling evaporation; by Kumar *et al.* (2002), Lin *et al.* (2007) and Kişi (2007) for the determination of evapotranspiration; by Mohandes *et al.* (1998) for the modeling of global solar radiation. Öztopal (2006) used ANN to model wind data. Doğan (2008) modeled reference evapotranspiration by adaptive neuro-fuzzy inference system. Alves and Pereira (2000) applied the Jarvis model to obtain the surface resistance by using Penman-Monteith equation. Şen *et al.* (2009) used a fuzzy logic model for the prediction of surface ozone. Şaylan *et al.* (2017) applied ANN and ANFIS approaches to model the soil water content. Ribeiro *et al.* (2018) used MLR and ANN techniques to build cross validation in estimating the yield response to drought. Yang *et al.* (2018) used a back-propagation ANN to model above-ground biomass which is an important factor for agricultural management. Niedbala (2019) built an ANN to predict winter rapeseed yield in Poland. Benali *et al.* (2019) used ANN to model solar radiation in three components: beam, diffuse and global. Another recent study on the projection of harvestable water from air humidity data using the ANN approach was conducted by Khaledi (2019).

ANN techniques are capable to show high rates of success when applied in complex applications. Especially in meteorological applications, neural network models can be used to model radiation variables indicating crucial improvements against traditional models used in statistics (Lopez *et al*., 2001).

Estimation of surface conductance is useful for agriculture and highly related with evapotranspiration. Knowledge about the characteristics of surface conductance of sunn hemp related to evapotranspiration status can be used to investigate the effects of particular factors on crop. It is also important for the planning of irrigation and therefore for the management of water. Yet, surface conductance modeling over the growing period is a complex problem.

The characteristics of sunn hemp were investigated by Takagi *et al.* (2009). There is however still a clear need to better understand the relationship between surface conductance and environmental factors. There are only few studies on the application of ANNs for the estimation of surface conductance such as Shen *et al.* (2002).

The main objective of this study was to model and compare the surface conductance of sunn hemp as a function of plant and meteorological variables by using nonlinear ANN, linear MLR and Jarvis type approaches. Related conductance data were collected from the high infiltrated sandy soil in the experiment field at the Arid Land Research Center of Tottori University located in Tottori, Japan. It was assumed that the surface conductance is affected by air temperature (T), global solar radiation (R_g), vapor pressure deficit (VPD), soil water content (SWC), relative humidity (RH), precipitation and irrigation (P+I), wind speed (u) and leaf area index (LAI).

2. MATERIALS AND METHODS

2.1. Site description

This study was conducted on a research area (Fig. 1) located at the Arid Land Research Center (ALRC), Tottori University, city of Tottori, Japan (35° 32' N, 134° 13' E, 15 m above sea level). From climatological point of view, this field is characterized by humid temperate climate. The long term annual mean temperature and total precipitation are 14.6 °C and 1900 mm, respectively. The field was about 1 ha. In addition, the experiment field was tilled on July 29 and harvested on October 18, 2004 (Takagi 2005; Takagi *et al*., 2009). The contents of sand, silt and clay in the soil were 96.1%, 0.4% and 3.5% respectively. The field capacity and permanent wilting point of the soil were 0.074 m^3 m^{-3} and 0.022 m^3 m^{-3}, respectively (Dehghanisanij *et al*., 2004). Although, the study area is one of the comparatively humid areas of Japan, the field was irrigated to protect the crops against water shortage because of high infiltration of the sandy soil, so water stress did not occur during growing period. Additionally, heavy rain was experienced due to a typhoon during the last two weeks of the sunn hemp growing season (Takagi *et al*., 2009).

2.2. Methods

2.2.1. Artificial neural networks (ANN)

As stated in Lopez *et al*. (2001), ANN approach bases on finding out the input and output variables' relationship by studying previously recorded data. An ANN model consists of two phases which are training and testing phases. Input, hidden and output layers are required in an ANN. The input and output layers cover the nodes corresponding to input and output variables, respectively (Fig. 2). Every layer consists of a certain number of neurons. They are interconnected each of these by some weights. In the hidden layer, every neuron receives its input from the input layers according to Eq. (1):

$$y_j = \sum_{i=1}^{m} w_{ij} x_i \tag{1}$$

where y_j is the input value of the j^{th} neuron in the hidden layer, m is the number of neurons in the input layer, w_{ij} is established weight and x_i is the input value (Kaul *et al*., 2005).

Every neuron in the hidden layer gives output (O_j) through an activation function. O_j is the sigmoidal function in the form of:

$$O_j = f\left(y_j\right) = \frac{1}{1 + e^{\frac{-\left(y_j + b_j\right)}{\theta}}} \tag{2}$$

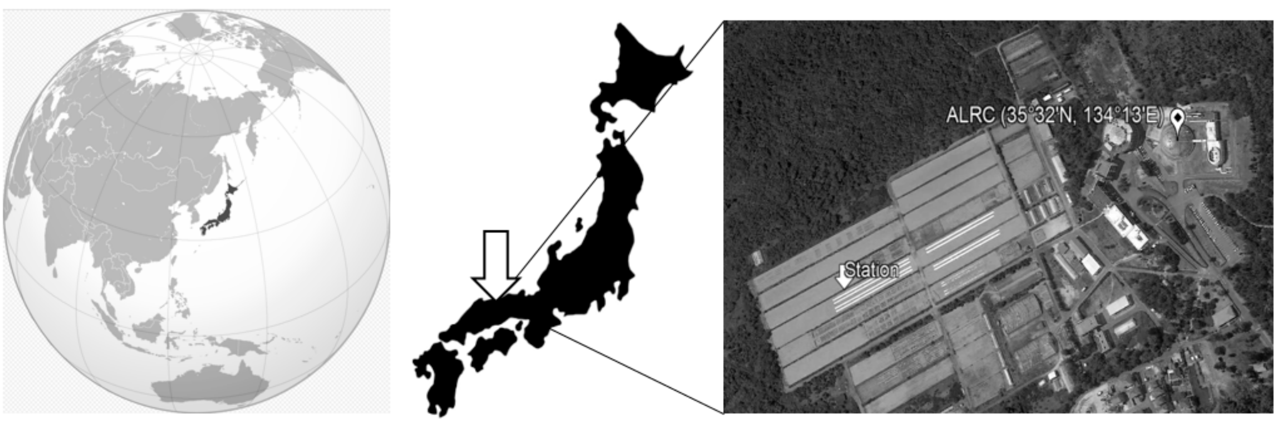

Fig. 1. Research area located at the ALRC, Tottori, Japan.
Fig. 1. Area di studio situata presso l'ALRC, Tottori, Giappone.

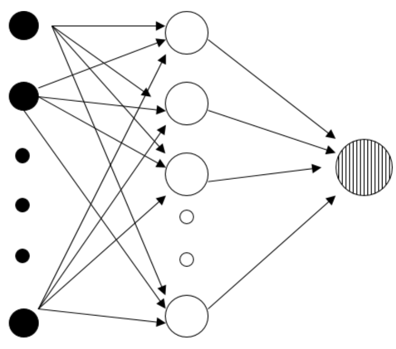

Fig. 2. A typical neuron with layers.
Fig. 2. Un neurone tipico con strati.

where $f(y_j)$ is the output of the neuron, b_j is the initial value and θ represents the bias (Hamidi and Kayaalp, 2008). Detailed theoretical description of the neural networks can be found in Haykin (1994).

In this study, back propagation neural network approach was used. The total sum of squared errors between measured and modeled values was minimized by tuning ANN parameters as used by van Wijk and Bouten (1999). The transfer function used for the hidden layer was the sigmoidal function.

2.2.2. Surface conductance

In this study, the surface conductance was determined by rearranged Penman-Monteith equation (Monteith and Unsworth, 1990).

$$g_s = \frac{\gamma LE}{\rho C_p VPD} + \frac{g_a}{\left(\frac{\beta s}{\gamma} - 1\right)} \tag{3}$$

where g_s is the surface conductance (m s^{-1}), g_a is the aerodynamic conductance (m s^{-1}), ρ is the density of the air (kg m^{-3}), β is Bowen ratio, γ is psychrometric constant (kPa °C^{-1}), C_p is the specific heat at constant pressure (J kg^{-1} °C^{-1}), VPD is the vapor pressure deficit (kPa), s is the rate of change of saturation vapor pressure with temperature (kPa °C^{-1}).

The aerodynamic conductance is calculated by using following Eq. (4) based on wind speed (Jensen *et al.*, 1990):

$$g_a = \frac{k^2 u}{\ln\left(\frac{(z_m - d)}{z_o}\right)\ln\left(\frac{(z_m - d)}{z_{oh}}\right)} \tag{4}$$

where k is von Karman`s constant (0.41), u is wind speed (m s^{-1}) at height z (m), z_m (m) is the height of wind speed, z_o (m) is the roughness parameter for momentum, z_{oh} (m) is the roughness parameter for heat and water and d (m) is the zero plane of displacement. d, z_o and z_{oh} are calculated by the equations given below (Allen *et al.*, 1998):

$$d = h\frac{2}{3} \tag{5}$$

$$z_o = 0.123h \tag{6}$$

$$z_{oh} = 0.1 z_o \tag{7}$$

The latent heat flux (LE) was calculated by using Bowen Ratio Energy Balance (BREB) method as follows (Bowen, 1926):

$$\beta = \gamma\left(\frac{\Delta T}{\Delta e}\right) = \frac{H}{LE} \tag{8}$$

$$R_n - G - LE - H = 0 \tag{9}$$

$$LE = \frac{R_n - G}{(1+\beta)} \tag{10}$$

where R_n is net radiation (Wm^{-2}); G is soil heat flux (Wm^{-2}); LE is latent heat flux (Wm^{-2}); H is sensible heat flux (Wm^{-2}); ΔT is the temperature gradient (°C) and Δe is the vapor pressure gradient (kPa) over the height interval above canopy surface.

2.2.3. Jarvis type model

The surface conductance model was built by Jarvis (1976) and developed by Noilhan and Planton (1989). In this study, the surface conductance was calculated by following equation (Dickonson, 1984; Niyogi and Roman, 1997):

$$\frac{1}{g_s} = r_s = r_{smin} LAI^{-1} F_1 F_2^{-1} F_3^{-1} F_4^{-1} \tag{11}$$

where r_s is surface resistance (s m^{-1}), r_{smin} is the minimum surface resistance. Detailed information about the calculation of F_1, F_2, F_3 and F_4 as functions related to global solar radiation, soil water content, vapor pressure deficit and temperature, can be found in Niyogi and Roman (1997), Dickinson (1984) and Kimura *et al.* (2006).

3. MEASUREMENTS

Vertical gradients of T and RH were measured at fixed levels of 0.5, 1 and 1.5 m above the ground surface to apply BREB approach for the determination of actual evapotranspiration. For this aim, ventilated psychrometers were used to measure the variations of T and RH. The wind speed at 2 m was measured by a cup anemometer (3101-5, Young), though the wind direction was measured at a height of 3 m. In addition, a four component net radiometer sensor (MR40, EKO Inc.) was installed at 2 m high above the surface to measure short and longwave radiations. Soil heat flux was measured by two soil heat flux plates (PHF-01, REBS Inc.) installed at 2 cm depth. Moreover, the soil water content was measured at 0-30 cm depth at three different points in the field by using soil water content reflectometers (CS615, Campbell Sci.). Furthermore, precipitation was collected by a tipping bucket rain gauge (34-T, Ota Keiki). Whole data were collected at 10 and 30 min. intervals using a datalogger (CR23x, Campbell Sci.). Necessary information about components of the measurement system can be found in Takagi (2005) and Takagi *et al.* (2009).

4. RESULTS AND DISCUSSION

4.1. Observations

During the growing season of sunn hemp, the leaf area index (LAI) was periodically measured. The maximum LAI at the end of the period was 3.52. All meteorological variables were measured from 1st of August (DOY 214) to 8th of October 2004 (DOY 282). It has been observed that the mean temperatures were in a decreasing trend within this period, as expected. With the beginning of the rainy season, an expected decrease also occurred in VPD. SWC values generally followed the variations in P+I. Time series of the daily averaged meteorological factors (input variables) and daytime (R_n>0) energy balance components which were determined from 10-min data during the growing period were given in Fig. 3. Meteorological data could not be measured for four days because of some unexpected technical problems. At the early stages of the period, in August, the VPD was high, but it showed a decreasing trend until the end of the period (Fig. 3). As a result of heavy rain, the VPD decreased. This situation caused raise in soil water content on many days in September and October.

During the period, daily mean T at 2 m was about 25 ˚C and ranged from 18 to 30 ˚C. Because the last days of the period encountered the typhoon season, the lowest T was measured. T was decreasing gradually toward the end of the period. Daily average RH was about 81% ranged from 64 to 95%. As a consequence of heavy rain, RH showed a tendency for increase in September and October, when T dropped during the same period. The

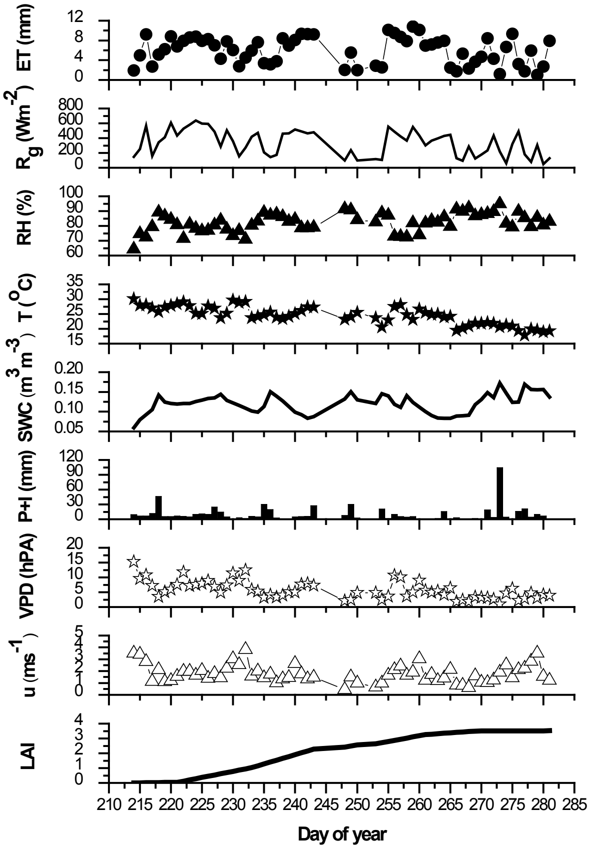

Fig. 3. Time series of daily averaged meteorological factors and daytime energy balance components.

Fig. 3. Serie temporali di dati meteorologici medi giornalieri e componenti del bilancio energetico diurno.

total irrigation and precipitation amounts were 172 and 408.5 mm during the period. Totally, 187 mm rainwater fell in the last 11 days (during the typhoon season) of this experiment period. Missing meteorological data were filled by using data recorded at the fixed meteorological station of ALRC located about 300 m away from the experiment field. Daily mean wind speed (u) at 2 m height was 1.8 m s^{-1} and reached up to the maximum value of 3.8 m s^{-1}. After beginning of the measurements, daily mean SWC increased due to the irrigation and precipitation. SWC at 0-30 cm depth was 0.12 m^3 m^{-3} and showed an increasing trend. At the end of the period, SWC reached up to 0.17 m^3 m^{-3}. The amount and distribution of the P and I resulted in temporary increases in SWC during this growing period. Because of irrigation, precipitation, increasing temperature and radiation, daily total evapotranspiration of sunn hemp was about 6 mm. Furthermore, daily mean VPD ranged from 1 hPa to 15.3 hPa with an average value of 5.7 hPa (Takagi *et al.*, 2009).

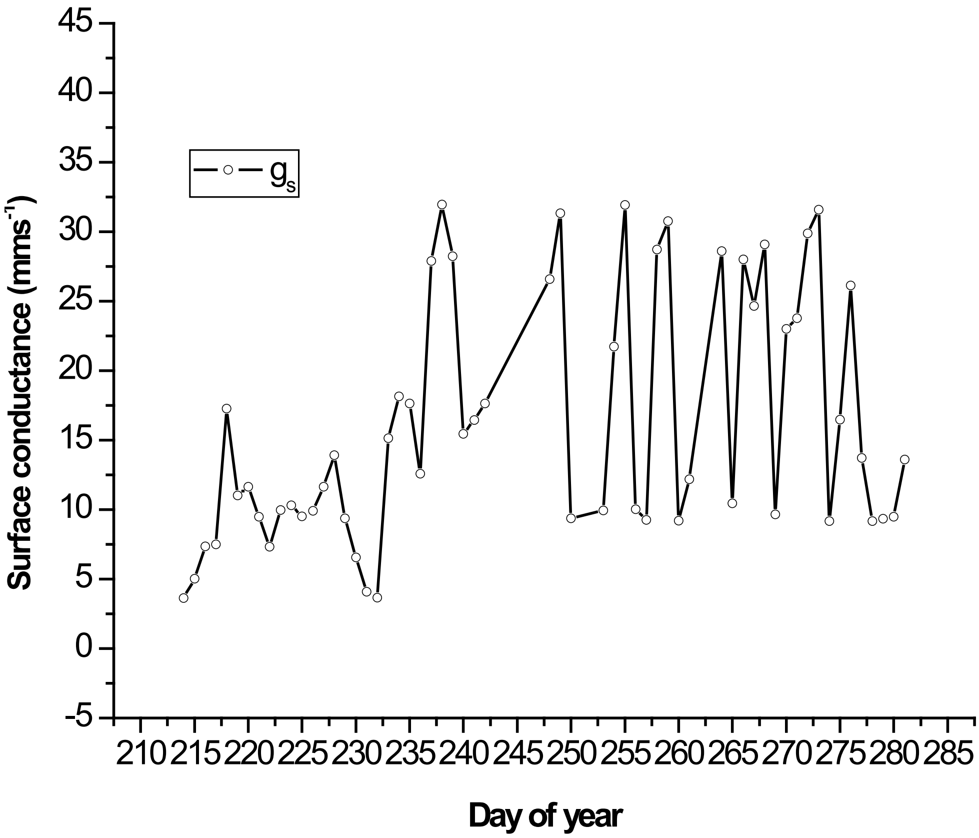

Fig. 4. Time series of surface conductance.
Fig. 4. Serie temporale della conduttanza di superficie.

4.2. Surface conductance of sunn hemp

As Dirks and Hensen (1999) reported, the surface conductance plays an essential role regarding energy and mass exchanges between the environment and plant. It is also important for designation of LE and CO_2 assimilation. In this study, it has been calculated by rearranging the Penman-Monteith equation. In order to calculate surface conductance, first, the actual evapotranspiration was calculated by BREB method. b, LE and H were calculated by using Eqs. (8), (9) and (10), respectively. Secondly, g_a was calculated by Eq. (4). Then, raw flux data were checked by using Ohmura (1982) criterion and some unacceptable data were rejected in order to avoid the errors in the estimation of fluxes of sunn hemp. Finally, g_s was calculated by using Eq. (3).

Daily total evapotranspiration was lower as expected at the early phenological stages in August than the values at the flowering and maturity stages in September and October. In the last part of the measurements, the heavy rain caused high soil moisture. Besides, evapotranspiration (ET) was increased with crop growth. The total amount of actual ET for whole growing season was around 350 mm. Eventually, it can be mentioned that the highest ET during the growing season can be attributed to the highest soil moisture and precipitation amount. Daytime average global solar radiation was about 334 W m^{-2} and varied from 50 to 636 W m^{-2}. Additionally, the daytime average R_n was about 231 W m^{-2} with a maximum value of 405 and a minimum of 32 W m^{-2} over the period. It can be said that R_g showed a decreasing trend from the beginning to the end of the measurement period. Furthermore, the daytime average soil heat flux was about 28 W m^{-2}.

The results showed that most part of the available energy was used by ET of the sunn hemp. Temporal variation of the calculated surface conductance is presented in Fig. 4. The daytime averaged aerodynamic and surface conductance were about 31 mm s^{-1} and 16.7 mm s^{-1}, respectively. g_s value was lower in August than in September and October. These can be explained with the development of crop and increasing of the transpiration in the second half of the period as reported by Takagi *et al.*, (2009).

4.3. Training and testing of ANN and MLR models

In this study, the MATHLAB was used to create an ANN model for predicting the daily average surface conductance of sunn hemp crop. In order to test the ANN and MLR models, total data were split into training and testing data. The ANN model was trained by randomly selected 70% of the whole data. Remaining portion (30%) of the total data were used in order to test the ANN model. A total of 45 daily averaged data, which are calculated from 30-min measured data (totally 2577 data for 64 days) were used for training the model and remained part of data were applied for testing the model. Input and output variables were normalized within the range of 0.1 and 0.9 by using following equation and then normalized data were trained and tested by ANN and MLR.

$$x_i = \left[0.1 + 0.8\frac{\left(x - x_{min}\right)}{\left(x_{max} - x_{\min}\right)}\right] \tag{12}$$

In training and testing of the ANN model, the number of epochs, the learning rate and hidden layers used in the optimization were 100, 0.30 and 2, respectively.

In the study, the back-propagation algorithm in ANN approach was used for training several multi-layer neural networks to estimate the daily average values of g_s. In the first step, the surface conductance of sunn hemp was modeled by ANN, MLR and Jarvis (1976) approaches as a function of global solar radiation, soil water content, vapor pressure and temperature; and then leaf area index was added to this combination. Finally, all variables such as the daily average air temperature, relative humidity, wind speed, vapor pressure deficit, soil water content at 0-30 cm depth; daily total precipitation and irrigation; daytime net radiation and daily leaf area index data had been used as inputs in ANN and MLR to train and test the data set. In order to find a relationship between g_s and input data, the network consisted of eight inputs, five neurons in two hidden layers and one neuron in the output layer. The training procedure was continued until the error function approached to a minimum value in ANN. After finishing the training, the developed model was tested. The output was the surface conductance calculated by ANN (g_{sANN}), MLR (g_{sMLR}) and Jarvis approaches (g_{sJRV}). After the training and testing, performance of the developed model by ANN (g_{sANN}) was compared with the developed model by g_{sMLR}, g_{sJRV} and surface conductance in the Penman-Monteith equation, which was calculated by Eq. (3). The performance of ANN, MLR and Jarvis type models was examined by looking at the average absolute relative error (AARE), root mean square error (RMSE) and determination coefficient (r^2). AARE of g_s was calculated using relative error (RE) given in Eq. 13 and 14.

$$RE = \frac{\left(g_s - g_{smodel}\right)100}{g_s} \tag{13}$$

$$AARE = \frac{1}{n}\sum_{i=1}^{n}\left|RE\right| \tag{14}$$

The surface conductance was estimated in Takagi *et al.* (2009) earlier. It was found that daytime hourly average g_s was highly related to R_n by ANN and MLR approach, when daytime hourly data were used as input and output. However, in this study, daytime averaged energy fluxes, daytime surface conductance data, daily averaged meteorological variables, daily total precipitation and irrigation were used. Additionally, in this study, input variables including LAI and R_g (instead of R_n) for modeling of g_s were twice more than the input variables used in Takagi *et al.* (2009) study.

The relationships between each of the variables with g_s were examined separately. Fig. 5 represents the response of g_s to variables (u, RH, P+I, LAI, T, SWC, VPD, R_g, ET). The lines (dotted line for linear and straight line for nonlinear fittings) show the fittings of the functions for the data. As seen in Fig. 5, the variability of the g_s of sunn hemp depends highly on VPD, RH and u. The g_s increased when VPD, u decreased and RH increased; as expected. The g_s was high when T was low and LAI was high. The g_s value increased, while P+I increased. The response of g_s to the variability of T was similar to as reported by Kimura *et al.* (2006). The effects of R_g and SWC were weak on the g_s of sunn hemp during the measurement period. Despite of high SWC, g_s and ET values during the measurement period, a quite low relationship could be obtained between SWC and g_s.

By using this data set, it has been found that the highest determination coefficient (r^2=0.35) was estimated by MLR method for g_s in the training period when VPD and RH used together as inputs. In the test period, the MLR method estimated slightly higher r^2 (0.68). Similarly, the MLR for combination of VPD, RH and u gave better relationships (r^2=0.45) in the training period (Tab. 1). The MLR for combination of R_g, VPD, SWC and T, which are also meteorological input parameters in Jarvis type of model, showed a determination coefficient of (r^2) 0.40 with a high RMSE in training period, whereas r^2 was 0.82 in test period. Adding LAI into the combination of R_g, VPD, SWC and T caused to increase the relationship (r^2=0.49) in the training period. The MLR model had the highest r^2 with a value of 0.57 when all meteorological factors (VPD, RH, u, R_g, T, SWC, LAI, P+I) were considered as inputs. It increased between the training and test periods of the model (Tab. 1).

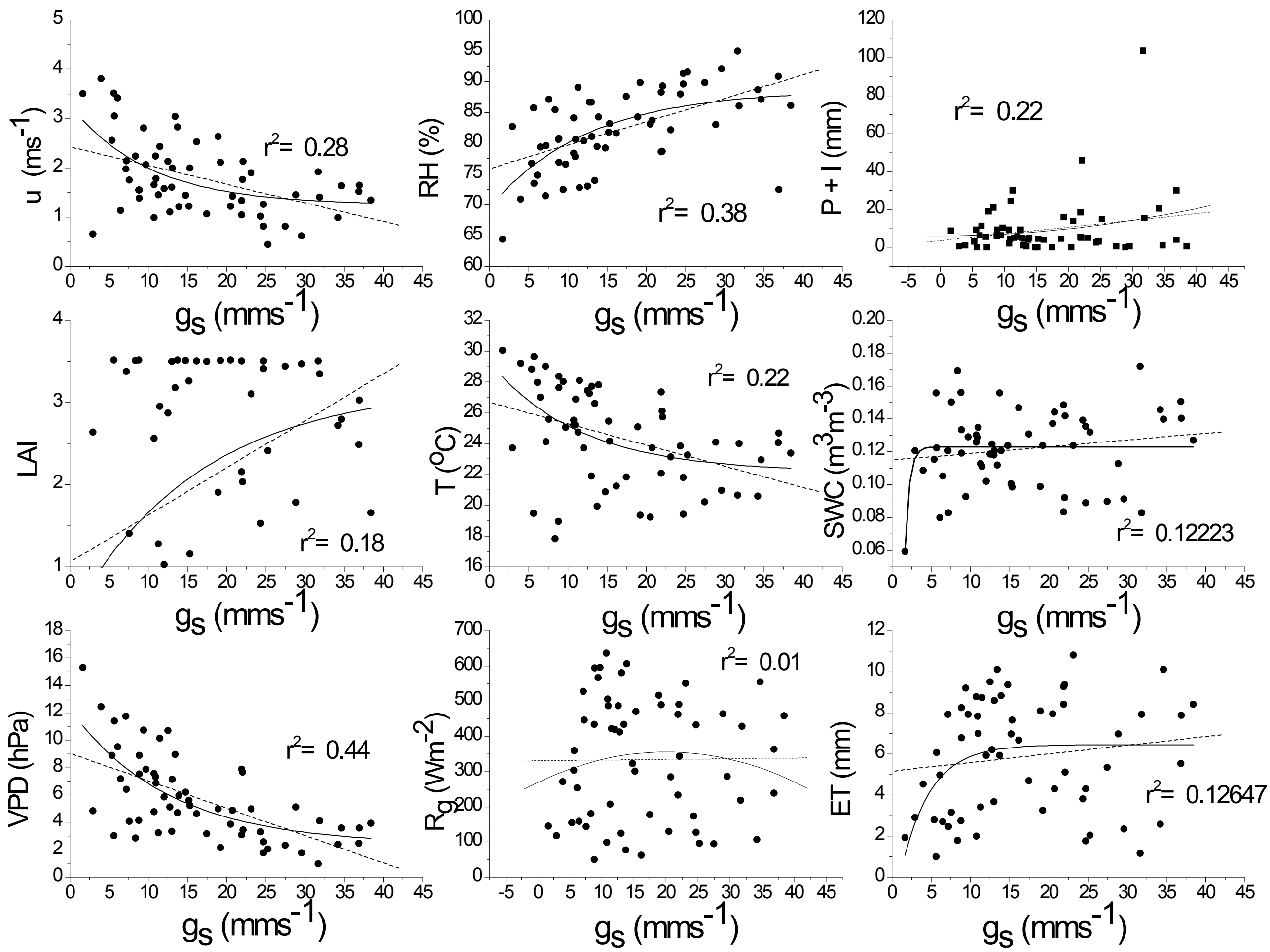

Fig. 5. Response of gs to the variables.
Fig. 5. Risposta delle conduttanza a diverse variabili ambientali.

Tab. 1. Performance criteria of the MLR model in the train and test periods.
Tab. 1. Criteri di rendimento del modello MLR e nei periodi di allenamento e test.

	Train data r^2	RMSE	Test data r^2	RMSE
g_s-VPD, RH	0.35	7.77	0.68	6.14
g_s-VPD, RH, u	0.45	7.16	0.43	8.68
g_s-VPD, T, SWC, R_g	0.40	8.43	0.82	3.81
g_s-VPD, T, SWC, R_g, LAI	0.49	6.73	0.59	8.49
g_s-VPD,T,RH,u,R_g,LAI,P+I,SWC	0.57	7.13	0.72	6.85

RMSE = Root mean square error - Errore quadratico medio.

Tab. 2. Performance criteria of the ANN model in the train and test periods.
Tab. 2. Criteri di rendimento del modello MLR e nei periodi di allenamento e test.

	Train data r^2	RMSE	Test data r^2	RMSE
g_s-VPD,RH	0.37	2.75	0.48	2.75
g_s-VPD,RH,u	0.50	2.36	0.26	3.05
g_s-VPD,T,SWC,R_g	0.87	1.95	0.63	2.34
g_s-VPD, T, SWC, R_g, LAI	0.81	1.97	0.79	2.27
g_s-VPD,T,RH,u,R_g,T,LAI,P+I,SWC	0.91	3.02	0.30	7.76

The performance criteria of the ANN model for the train and test periods were given in Tab. 2. The highest determination coefficient (r^2=0.37) in training period was estimated by ANN approach for g_s when VPD and RH were inputs. If we considered u as the combination of VPD and RH, resulting correlation sharply increased.

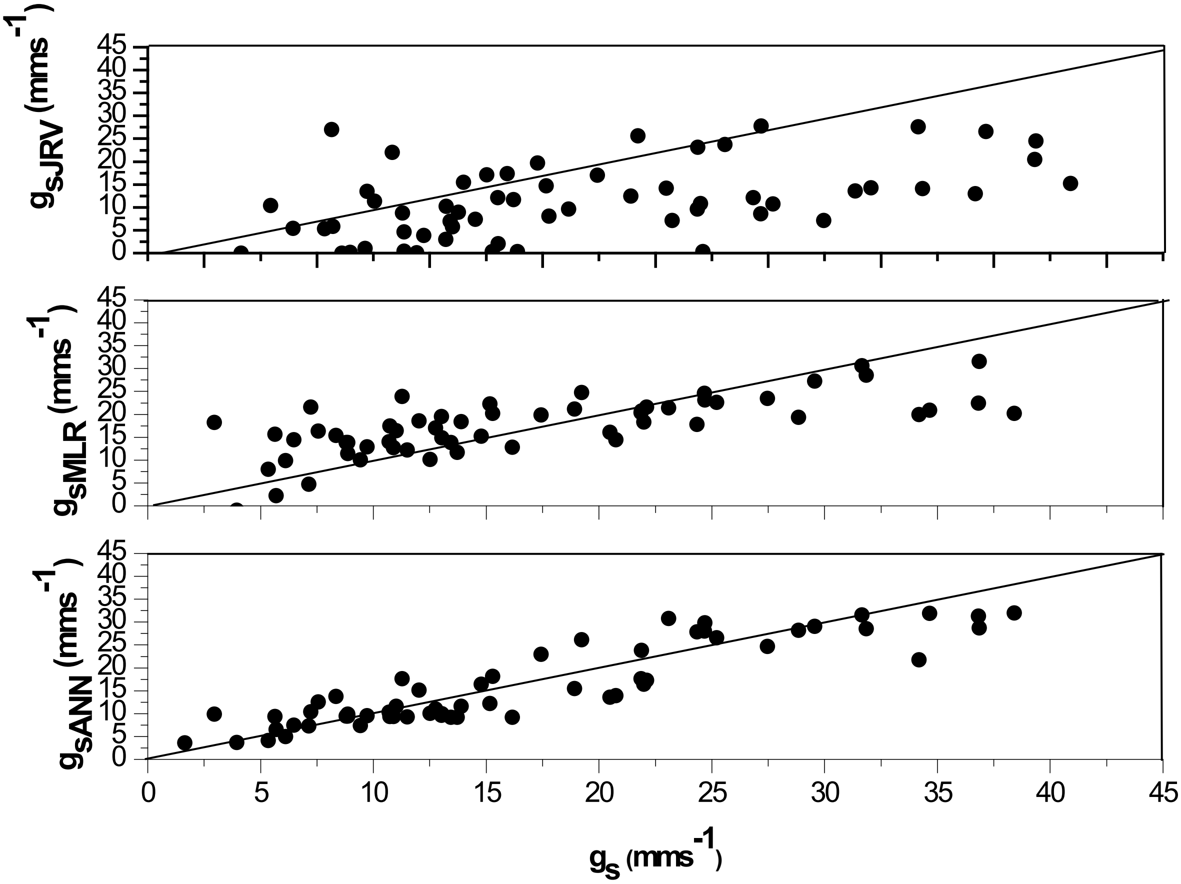

Fig. 6. The model g_s by ANN, MLR and JRV.
Fig. 6. Il modello della conduttanza su base ANN, MLR e JVR.

Similarly, adding R_g into the input list of VPD, T and SWC gave significant increase in the ANN model performance for train (r^2=0.87) and test (r^2=0.63) periods. Considering LAI with the input combinations of VPD, SWC, T and R_g showed a slight decrease in the performance of the ANN model in the training period and an increase in the test period. As seen in Tab. 2, adding P+I, RH, and u to the input combination of VPD, LAI, SWC, R_g, T resulted in an rise of ANN model performance for train period. In this case, it had the highest r^2 with a value of 0.91. When using VPD, T, SWC, R_g and LAI in test period, the highest relationship (r^2=0.79) was obtained, compared to MLR model (Tab. 2).

The actual g_s values calculated from Eq. 3 were compared to the performance of the Jarvis model. In addition, the g_s modeled using only variables considered in the Jarvis model (VPD, T, SWC, Rg, LAI) by ANN and MLR were compared with the actual g_s. The performance of the model g_s by ANN (g_{sANN}) was compared to the model g_s by multiple regressions (g_{sMLR}), Jarvis type (g_{sJVR}) and the g_s in Eq. (3) (Fig. 6). As seen in Fig. 6, the MLR model overestimated the g_s slightly, when g_s was lower than about 20 mm s^{-1} and underestimated when g_s was higher than about 20 mm s^{-1}. The relationship between actual g_s and g_{sMLR} was represented with a determination coefficient of 0.53. The Jarvis model underestimated the actual g_s and the relationship between g_s and g_{sJRV} was weak (r^2=0.26). In contrast, application of ANN approach on g_s gave very close relationship with the g_s (r^2=0.80) with a value of 26.54 % AARE during the period. It has been found that ANN has higher accuracy compared to classical method MLR and Jarvis type model (Fig. 6). Finally, it has been estimated that the Jarvis type of model gave the lowest relationship with the actual g_s.

After using the MLR between the meteorological and crop variables, which are independent variables, and surface conductance as dependent variable, it had been found that g_s increased when LAI, T, RH increased and VPD, u decreased.

5. DISCUSSION

In this study; ANN, MLR and Jarvis approaches have been applied for conductance during the measurement period of sunn hemp crop. ANN approach was compared to MLR, which is the traditional statistical technique and to Jarvis model as one of the commonly used approaches in the modeling of surface conductance. For training of the input data, eight variables were used in order to model the surface conductance. By using hourly daytime data calculated from 10-min averaged data, the surface conductance was modeled by ANN in Takagi *et al.* (2009). In that case, it was found that hourly averaged g_s was highly related to the hourly averaged R_n, whereas weak relationship was found between g_s and VPD, G, T. In our study, however, the daily averaged meteorological data, R_g and LAI were also used as inputs for the modeling of daytime averaged surface conductance of sunn hemp. The results showed that the daytime averaged surface conductance was mainly influenced by the variation of VPD, RH and u. A low determination coefficient (0.53) between g_s and all input variables had been found by using MLR analysis as a better relationship between daytime average g_s and all input variables was estimated by the ANN approach. Furthermore, the g_s seems to be affected slightly by SWC. This might be resulted from the high SWC, which is generally related to precipitation and irrigation. Using the same methodology in our study, Alves and Pereira (2000) also applied the Jarvis model and calculated the r_s by relating it with major meteorological parameters that affect the energy and mass transfers between the surface and atmosphere in the Penman-Monteith equation. The authors obtained satisfactory relationships between r_s, R_n and VPD which were represented with determination coefficients higher than 0.9. The finding of Shen *et al.* (2007) is also consistent with the results of this study.

Consequently, the ANN approach simulated the g_s better than MLR and Jarvis approaches, when the same meteorological variables were used for modeling as in Jarvis model. Adding LAI to this input combination like in Eq. (11), ANN gave high correlation with g_s for all cases. Finally, the ANN approach showed a better improvement against traditional statistical technique, when the same variables in the Jarvis model was considered for modeling. For this reason, it can be said that the ANN approach produced more accurate prediction for surface conductance than the Jarvis and MLR approaches. These results indicate that the ANN approach can be used for the estimation of non-linear time series and dynamic conditions.

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