HYDROLOGICAL PROCESSES
Hydrol. Process. **23**, 442–450 (2009)
Published online 22 October 2008 in Wiley InterScience
(www.interscience.wiley.com) DOI: 10.1002/hyp.7153

Artificial neural network models for estimating regional reference evapotranspiration based on climate factors

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Abstract:

Evapotranspiration (ET) is one of the basic components of the hydrologic cycle and is essential for estimating irrigation water requirements. In this study, an artificial neural network (ANN) model for reference evapotranspiration (ET_0) calculation was investigated. ANNs were trained and tested for arid (west), semi-arid (middle) and sub-humid (east) areas of the Inner Mongolia district of China. Three or four climate factors, i.e. air temperature (T), relative humidity (RH), wind speed (U) and duration of sunshine (N) from 135 meteorological stations distributed throughout the study area, were used as the inputs of the ANNs. A comparison was conducted between the estimates provided by the ANNs and by multilinear regression (MLR). The results showed that ANNs using the climatic data successfully estimated ET_0 and the ANNs simulated ET_0 better than the MLRs. The ANNs with four inputs were more accurate than those with three inputs. The errors of the ANNs with four inputs were lower (with RMSE of 0·130 mm d^{-1}, RE of 2·7% and R^2 of 0·986) in the semi-arid area than in the other two areas, but the errors of the ANNs with three inputs were lower in the sub-humid area (with RMSE of 0·21 mm d^{-1}, RE of 5·2% and R^2 of 0·961. For the different seasons, the results indicated that the highest errors occurred in September and the lowest in April for the ANNs with four inputs. Similarly, the errors were higher in September for the ANNs with three inputs.

KEY WORDS artificial neural network; climate factors; Penman–Monteith; reference evapotranspiration

Received 12 January 2008; Accepted 20 August 2008

INTRODUCTION

Reference evapotranspiration (ET_0) is the basis for estimating crop evapotranspiration (ET_c) and computing crop irrigation water requirements. The modified Penman–Monteith (P-M) equation has been accepted universally for different time steps including hourly, daily and monthly for ET_0 (Allen *et al.*, 1998) and was recommended by the United Nations Food and Agriculture Organization (FAO) and the World Meteorological Organization (WMO). The method is able to provide consistent ET_0 values in many regions and climates (Allen *et al.*, 2005, 2006) and is widely used by agronomists, irrigation engineers and other scientists in field-practice and research (Chiew *et al.*, 1995; Jacobs and Satti, 2001; Garcia *et al.*, 2004; Temesgen *et al.*, 2005).

However, the main shortcoming of the P-M method is that it requires data on a large number of climatic variables which are unavailable in many regions. Numerous attempts have been tried to overcome difficulties associated with data availability for ET estimation. Magliulo *et al.* (2003) used a modified atmometer to measure ET_0 in Mediterranean environments. Class A pan evaporation records are often used in combination with GIS technology to estimate the regionally distributed ET_0 (Naoum and Tsanis, 2003). However, a great number of class A pan observation sites and labour effort for data collection and communication are required to improve estimates and spatial interpolation. The Priestley–Taylor equation (Priestley and Taylor, 1972) was reported to be able to estimate regional monthly ET_0, but needed the adjusting factor α adapted to different site conditions (Castellvi *et al.*, 2001). Subsequently, improved versions of the P-T were developed and make ET_0 estimates from reduced sets of inputs much closer to P-M values (Steiner *et al.*, 1991). Nevertheless, the superiority of the P-M method over the Priestley–Taylor equation was recently demonstrated (Utset *et al.*, 2004).

In the past decade, considerable attention had been paid to the application of artificial neural networks (ANNs) in diverse fields, such as system modelling, fault diagnosis and control, pattern recognition, financial forecasting, and hydrology (French *et al.*, 1992; Wen and Lee, 1998; ASCE, 2000a, b; Coulibaly, 2003). In recent years, ANNs have been applied in the field of evapotranspiration estimation (Sudheer *et al.*, 2002; Kisi, 2006a, b; 2008; Zanetti *et al.*, 2007; Jain, 2008). Kumar *et al.* (2002) developed ANN models for the estimation of ET, and they compared the ANN estimates with those of the Penman method. Although they used the gradient-descent algorithm, which often yields suboptimal solutions (Hagan and Menhaj, 1994; El-Bakyr, 2003) for the optimization of the ANN networks weights, they found

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that the ANN could predict ET better than the conventional method. Sudheer *et al*. (2003) and Trajkovic *et al*. (2003) reported on the performance of radial basis neural networks in ET estimation. Trajkovic (2005) used a temperature-based radial basis ANN for modelling ET. He compared the ANN results with those of the Hargreaves, Thornthwaite and reduced P-M methods and concluded that the radial basis ANN generally performs better than the other models in modelling the ET process. Recently, Kisi (2007) investigated the modelling of ET_0 using ANNs with the Levenberg–Marquardt (LM) training algorithm and concluded that ANNs could be employed successfully in modelling ET_0 from the available climatic data.

Although previous research has demonstrated that ANNs can obtain satisfactory results for simulating ET_0, most of these ANNs were trained and tested using data from the same station and were adaptable for that station with detailed climatic data. It is not practical to train ANNs for every station of a large region. Consequently, it is necessary to develop regional ANN models using data from many stations for ET_0 estimation. In addition, in existing applications of ANNs for estimating ET_0, the applicability of ANNs had not been analysed in different climate regions and different seasons. In this study, ANN models for ET_0 in three different climatic areas with arid, semi-arid and sub-humid climate in the north of China were developed using available climatic data from many stations, and the precision of ANN models with different inputs were compared. At the same time, the simulation results from different areas were compared in order to evaluate the applicability of ANNs to estimate different ET_0.

MATERIALS AND METHODS

Study area and data

The Inner Mongolia district, located in northern China (37°24′–53°23′N, 97°12′–126°04′E), was selected as the study area, has a total area of $118 \cdot 3 \times 10^4$ km^2, and occupies about 1/8 the total area of China (Figure 1). Overall, the study area has a relatively arid and rainless climate with average temperature of 0–8 °C and annual precipitation of 50–450 mm. However, the evaporation is intense and exceeds 1200 mm every year in most of the study area. In particular, there are 5–20 days with sand storms, but relatively fewer sand storms in the eastern part of the study area. The study area can be divided into three sub-regions according to their climatic conditions, which are arid, semi-arid and sub-humid areas from west to east, respectively. The range of values for the climate factors in each area is listed in Table I.

There are 135 meteorological stations in the study area, with 40, 60 and 35 stations in arid, semi-arid and sub-humid areas, respectively (Figure 1). Four climate factors, including daily average air temperature (T), relative humidity (RH), wind speed (U) and duration of sunshine (N), solar radiation in every month for the growth period of the main crops were collected from April to September for 30 years (1970–2000) by the Inner Mongolia Weather Bureau. In every station, the monthly average values of the 30 years for every climate factor were supplied to calculate ET_0 using the P-M method and were used to train the ANN.

Reference evapotranspiration (ET_0)

The P-M method was developed by defining the reference crop as a hypothetical crop with an assumed

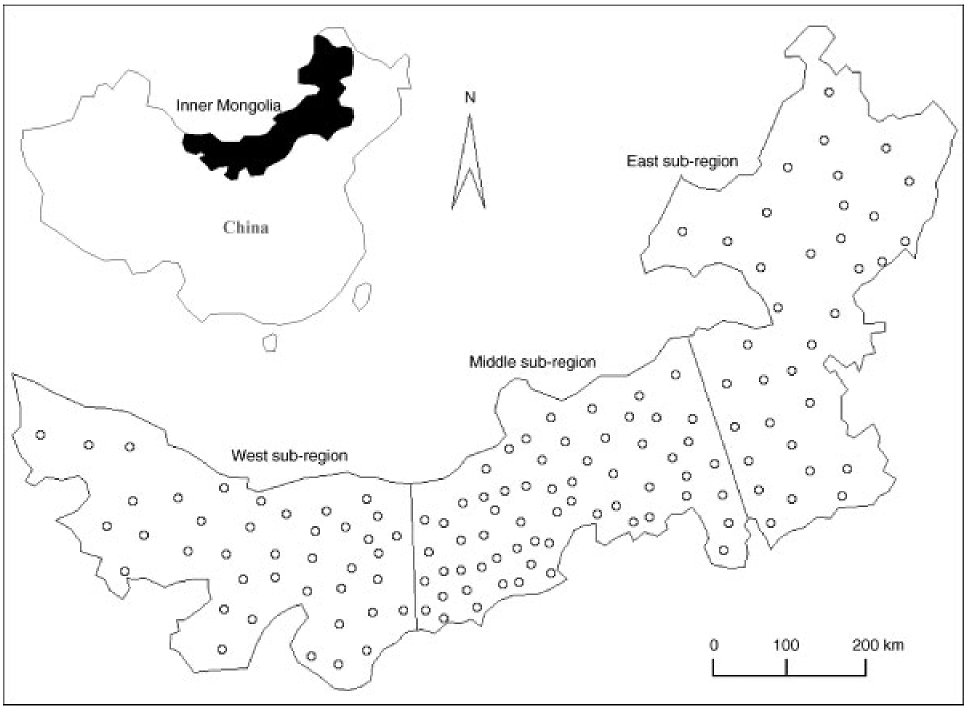

Figure 1. Location of the meteorological stations in arid (west sub-region), semi-arid (middle sub-region) and sub-humid (east sub-region) areas of Inner Mongolia, China

DOI: 10.1002/hyp

Table I. Range of the four climate factors temperature (T), humidity (RH), wind speed (U) and duration of sunshine (N) with ET_0 in arid, semi-arid and sub-humid areas of Inner Mongolia district, China

	Arid area	Semi-arid area	Sub-humid area
Temperature (°C)	9·13 ~ 23·42	4·25 ~ 19·61	1·49 ~ 19·35
Humidity (%)	28·5 ~ 48·3	41·8 ~ 68·5	46·0 ~ 75·4
Wind speed (m s^{-1})	2·85 ~ 3·79	2·13 ~ 3·75	2·10 ~ 3·45
Duration of sunshine (h)	9·09 ~ 10·53	8·38 ~ 9·59	7·68 ~ 9·30
ET_0 (mm day^{-1})	4·62 ~ 7·22	3·35 ~ 5·11	2·80 ~ 4·65

height of 0·12 m having a surface resistance of 70 s m^{-1} and an albedo of 0·23, closely resembling the evaporation of an extensive surface of green grass of uniform height, actively growing and adequately watered. The FAO-PM equation recommended for daily reference evapotranspiration ET_0 (mm day^{-1}) estimation (Allen *et al*., 1998) may be written as:

$$ET_0 = \frac{0{\cdot}408\Delta(R_n - G) + \gamma(900/(T+273))u_2(e_s - e_a)}{\Delta + \gamma(1 + 0{\cdot}34u_2)} \quad (1)$$

where R_n is the net radiation at the crop surface (MJ m^{-2} day^{-1}), G the soil heat flux density (MJ m^{-2} day^{-1}), T the air temperature at 2 m height (°C), u_2 the wind speed at 2 m height (m s^{-1}), e_s the vapour pressure of the air at saturation (kPa), e_a the actual vapour pressure (kPa), Δ the slope of the vapour pressure curve (kPa/°C) and γ is the psychrometric constant (kPa/°C). A complete set of equations was proposed by Allen *et al*. (1998) to compute the parameters of Equation (1) according to the available weather data and the time step computation, which constitute the P-M method. In this study, every day of month was assumed have same ET value and mean daily ET_0 calculated by P-M method were regarded as the measured values which were used to train and test the ANNs.

Artificial neural network (ANN) technology

The ANN technology is an alternative to estimating nonlinear systems. Of the many ANN architectures, the back-propagation network (BP) is by far the most popular (Haykin, 1998). The network consists of layers of parallel processing elements, called neurons, with each layer being fully connected to the preceding layer by interconnection strengths, or weights W. Figure 2 illustrated a three-layer neural networks consisting of layers i, j and k, with the interconnection weights W_{ij} and W_{jk} between layers of neurons.

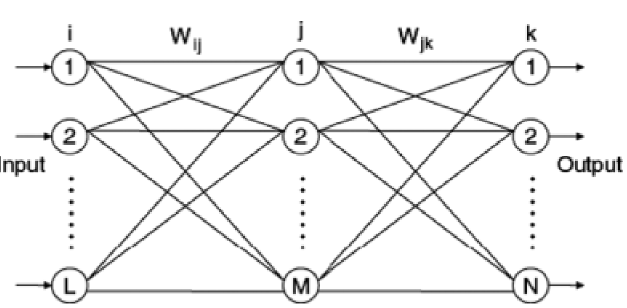

Figure 2. Three-layer feed-forward ANN architecture

The activation value at ith neuron in nth layer $a_i{}^n$ is given by the following equation.

$$a_i^n = \sum_{j=1}^{m} W_{ji}^n O_j^{n-1} + b_i^n \quad (2)$$

where $W_{ji}{}^n$ is weight of the link between the ith neuron in the nth layer and the jth neuron in the $(n-1)$th layer; $O_j{}^{n-1}$ the output of the jth neuron in the $(n-1)$th layer; $b_i{}^n$ the bias of the ith neuron in the nth layer; and m the number of neurons in the $(j-1)$th layer. The activation value of a neuron is used to obtain the output value of that neuron through the transfer function. The general functional form of the sigmoidal logistic transfer function used in this study (and is the most commonly used nonlinear transfer function) is given by:

$$f(t) = 1/(1 + \exp(-t)) \quad (3)$$

where t represents the weighted sum of the input for a node in the hidden layer, and exp denotes the natural exponential function. The function value of each neuron in the output layer was obtained by propagating the effect of input through layers. The ANN was trained under supervision with the LM algorithm, which uses Newton's method for approaching the error function minimum, given by

$$E = \sum_P \sum_m (y_i - O_i)^2 \quad (4)$$

In this case, y_i is the ANN computed output of sample i and O_i the observed output of sample i; P is the number of training patterns or data sets.

In this study, the data were divided into three distinct data sets for the purpose of ANN training, verification, and validation. During network learning, the training samples were processed through the ANN, and the connection weights were adjusted adaptively until a minimum acceptable error was achieved between the predicted and the observed output. Intermittently during training, the verification data set was processed through the ANN to ensure that it was not over-fitting the training set. Following training, the ANN was tested with the validation data set to assess how well it had learned to generalize system behaviour.

In designing a robust and accurate ANN model, the modeller must address a number of important factors, including the type and structure of the neural network, the

DOI: 10.1002/hyp

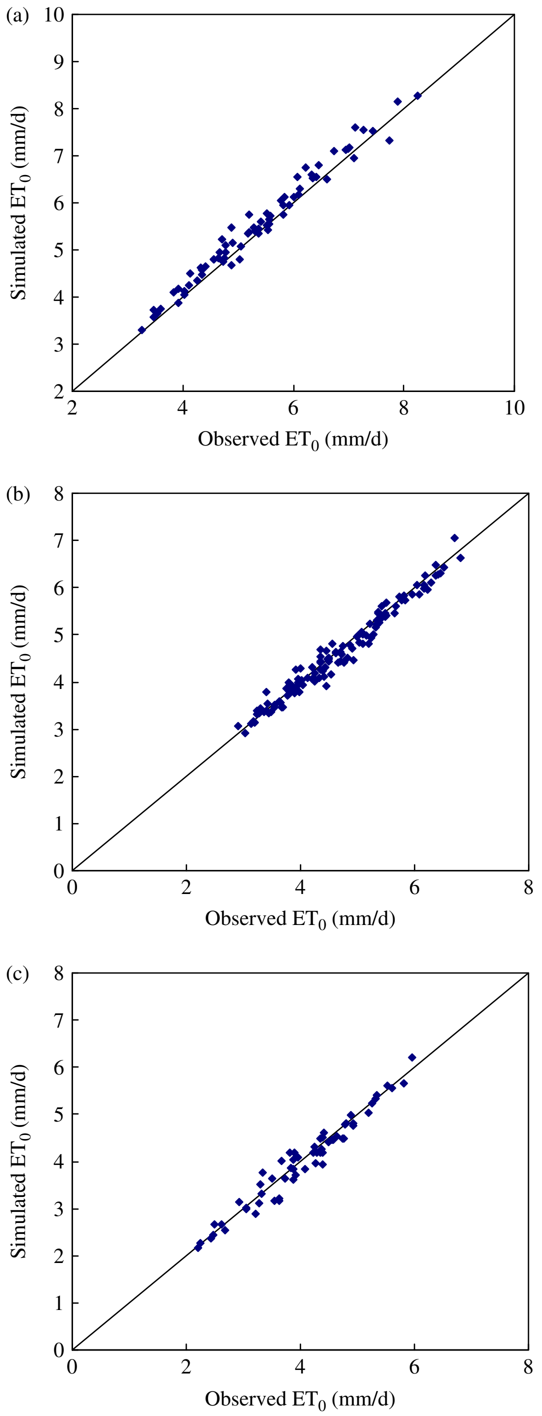

Figure 3. Observed and estimated ET_0 using ANNs with four inputs in arid (a), semi-arid (b) and sub-humid (c) areas of Inner Mongolia, China

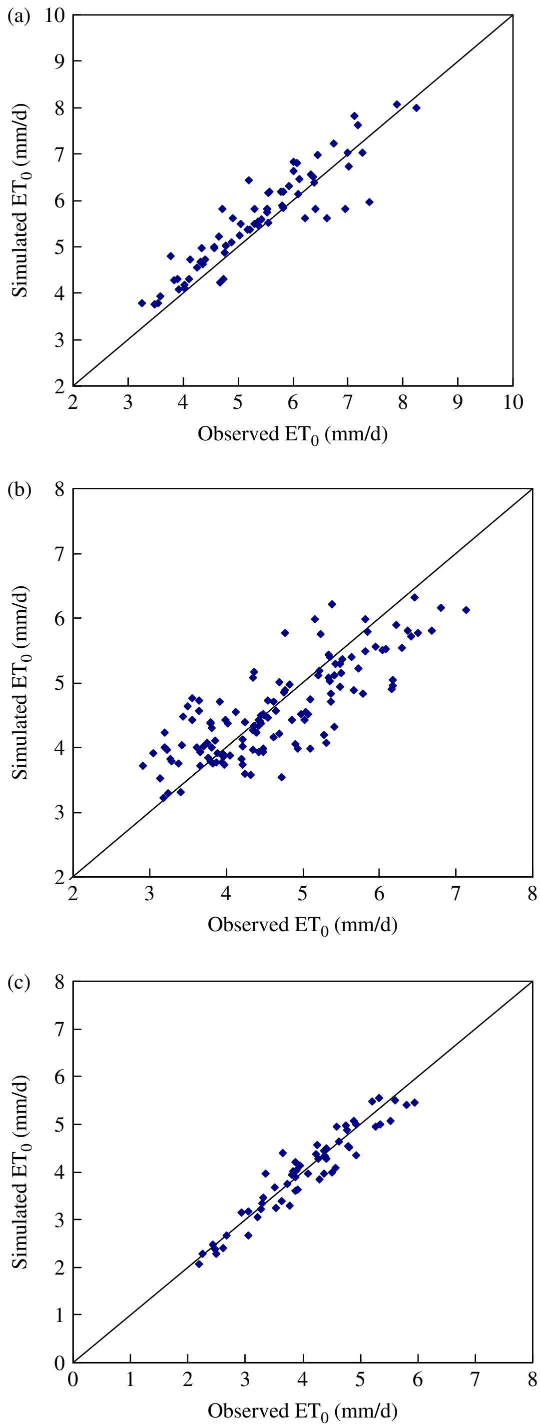

Figure 4. Observed and estimated ET_0 using ANNs with three inputs in arid (a), semi-arid (b) and sub-humid (c) areas of Inner Mongolia, China

input prediction variables used, and data pre-processing. This was generally accomplished through a combination of best professional judgment, heuristic rules, and trial and error.

Development of artificial neural networks (ANNs)

The regional ANN model for estimating ET_0 were developed using data from multiple stations. From the temporal viewpoint, the data from April to September were set as a sample. In this study, six ANNs were trained and tested for the arid, semi-arid and sub-humid areas of Inner Mongolia, because of the variable effect of climate factors on each sub-region. For each sub-region, two ANNs, one with four inputs and one with three inputs, were developed. To take advantage of the generalization ability, the meteorological stations were divided randomly into two sets for the purpose of training and validation. In detail, about two-thirds of the stations were used to train the ANNs and the other one-third to test the ANNs. As a result, the input–output data (i.e. climate factors and ET_0) from 26, 40 and 23 stations

DOI: 10.1002/hyp

were used to train ANNs and the remainding 14, 20 and 12 stations to test the ANNs for the arid, semi-arid and sub-humid areas, respectively. The ANNs development was performed with Matlab 6·5.

A LM algorithms was used for training. Intermittent verification during ANN training was performed to avoid overtraining. That is, network learning was verified periodically with the verification data set during training, and this process was repeated until the verification errors began to increase. At this point, after approximately 5000 epochs, the training was terminated, with the corresponding set of nodal connection weight values saved. Following this development phase, the ANN models were validated with the third unique data set to evaluate ANN prediction capability (Figures 3 and 4).

Statistical indices used to evaluate the goodness of fitting

In this study, statistical indices were used to provide quantitative analysis of ANN and MLR modelling performances. The R^2 measures the degree to which two variables were linearly related. *RMSE* and *RE* provided different types of information about the predictive capabilities of the model. The *RMSE* tends to emphasize big departures of estimates from the measurements, whereas the *RE* is a proportional measure of the error, as it is weighed over the mean of measurements. *RMSE, RE* and R^2 were defined as:

(a) The the root mean square error (*RMSE*):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(y_i - O_i)^2}{m}} \tag{5}$$

where m is the number of observations, and O_i and y_i are, respectively, the ith observed (calculated with the FAO-PM method) and predicted (using the ANN procedure) data.

(b) The relative error (*RE*):

$$RE = \frac{RMSE}{\overline{O}} \tag{6}$$

where $\overline{O}$ is the average value for O_i with $i = 1, 2, \ldots, m$.

(c) The coefficient of determination, R^2:

$$R^2 = \frac{\left[\sum_{i}^{m}(y_i - \overline{y})(O_i - \overline{O})\right]^2}{\sum_{i=1}^{m}(y_i - \overline{y})^2 \sum_{i=1}^{m}(O_i - \overline{O})^2} \tag{7}$$

where $\overline{y}$ and $\overline{O}$ are the averages of the data arrays of y_i and O_i.

RESULTS AND ANALYSIS

ANN models with four inputs

The weather parameters considered for ANN models with four inputs were daily air temperature (T), relative humidity (RH), wind speed (U) and duration of sunshine (N). The output was the daily ET_0 calculated with FAO-PM method. Similar to many researchers (Ozgur, 2007), we decided the optimal node number in the hidden layer of the network using a trial and error method by considering *RMSE, RE* and R^2 values from the test sample. In this study, nine ANNs with four inputs were trained and tested for the three areas (Table II). The results indicated that all ANNs with four inputs used to calculate ET_0 performed well in the study area and had low errors, with an average *RMSE* of 0·231 mm day^{-1}, 0·134 mm day^{-1} and 0·170 mm day^{-1}, *RE* of 4·4%, 2·9% and 4·5%, and R^2 of 98·6%, 98·5% and 97·3% for the arid, semi-arid and sub-humid areas, respectively. At the same time, the changes in errors for ANNs with different numbers of hidden nodes for each area were small and the variance of *RMSE* for ANNs with different numbers of hidden nodes were $1·82 \times 10^{-5}$ mm day^{-1}, $5·01 \times 10^{-6}$ mm day^{-1} and $7·29 \times 10^{-6}$ mm day^{-1}, respectively. Overall, ANN models appear to be effective for estimating ET_0. Furthermore, ANNs with four inputs were more adaptable to semi-arid and sub-humid areas and had relatively high errors from the *RMSE* and *RE* viewpoints. Considering the three error statistics values,

Table II. Test errors (*RMSE, RE*, R^2) of ANN models with four inputs when computing ET_0 in arid, semi-arid and sub-humid areas of Inner Mongolia, China

	Arid area			Semi-arid area			Sub-humid area		
	RMSE (mm d^{-1})	*RE* (%)	R^2	*RMSE* (mm d^{-1})	*RE* (%)	R^2	*RMSE* (mm d^{-1})	*RE* (%)	R^2
ANN (4,4,1)	0·238	4·4	0·986	0·138	3·1	0·983	0·175	4·9	0·97
ANN (4,5,1)	0·233	4·4	0·987	0·136	3·1	0·983	0·174	4·9	0·97
ANN (4,6,1)	0·226	4·3	0·987	0·136	3·1	0·984	0·173	4·7	0·972
ANN (4,7,1)	0·225	4·3	0·987	0·135	2·9	0·986	0·173	4·7	0·972
ANN (4,8,1)	0·223	4·2	0·987	0·134	2·8	0·985	0·171	4·5	0·973
ANN (4,9,1)	0·23	4·4	0·986	0·134	2·8	0·986	0·169	4·5	0·975
ANN (4,10,1)	0·232	4·4	0·986	0·13	2·7	0·986	0·162	4·1	0·977
ANN (4,11,1)	0·238	4·5	0·985	0·131	2·9	0·986	0·165	4·2	0·974
ANN (4,12,1)	0·237	4·5	0·985	0·131	2·9	0·986	0·17	4·4	0·974

the optimal structures of ANNs were 4-8-1, 4-10-1, 4-10-1 for the arid, semi-arid and sub-humid areas, respectively, and the *RMSE, RE* and R^2 were 0·223 mm day^{-1}, 4·2% and 98·7% for the arid area, 0·130 mm day^{-1}, 2·7% and 98·6% for the semi-arid area and 0·162 mm day^{-1}, 4·1% and 97·7% for the sub-humid area, respectively.

ANN models with three inputs

In some regions, the four climate factors could not be collected simultaneously, so it was important for calculating ET_0 to establish an empirical model using a few climatic data items. In this study, ANN models with three climate factors as inputs were trained and tested to evaluate the feasibility of ANNs with fewer inputs. The correlation analysis showed that N, T and U had a relatively weak relationship with the local ET_0 for the arid, semi-arid and sub-humid areas, respectively (Table III). Therefore, the selected inputs combinations for ANNs were T, RH and U for the arid area, RH, U and N for the semi-arid area, and T, RH and N for the sub-humid area. Similar to the ANNs with four inputs, 10 ANNs with three inputs for each area were trained and tested to determine the optimal network structure. Compared with the ANNs with four inputs, the ANNs with three inputs had higher errors, with an average *RMSE* of 0·450 mm day^{-1} for the arid area, 0·443 mm day^{-1} for the semi-arid area and 0·224 mm day^{-1} for the sub-humid area (Table IV). At the same time, the changes in *RMSE* in the 10 ANNs were more obvious than in the ANNs with four inputs, and the variances were $1·52 \times 10^{-4}$ mm day^{-1}, $6·84 \times 10^{-4}$ mm day^{-1} and $2·86 \times 10^{-5}$ mm day^{-1} for the arid, semi-arid and sub-humid areas, respectively. Thus, the defaulted factor, i.e. N, T and U for the arid, semi-arid and sub-humid areas, respectively, influenced the precision of the ANNs. The impact of U on the performance of the ANNs was relatively weak in the sub-humid area. The average *RMSE* of the three-input ANNs increased by 0·22 mm day^{-1}, 0·31 mm day^{-1} and 0·05 mm day^{-1} compared with those for the four-input ANNs for the arid, semi-arid and sub-humid areas, respectively. Similar to ANNs with four inputs, ANNs with three inputs had the highest precision in the sub-humid area. Considering the three error statistics, the optimal numbers of hidden nodes were 9, 5 and 6 for the arid, semi-arid and sub-humid areas, respectively. Correspondingly, the optimal structures of the ANNs were 3-9-1, 3-5-1 and 3-6-1 for the three areas, respectively. The *RMSE, RE* and R^2 were 0·438 mm day^{-1}, 9·3% and 82·2% for the arid area, 0·365 mm day^{-1}, 8·1% and 90·4% for the semi-arid area, and 0·21 mm day^{-1}, 5·2% and 96·1% for the sub-humid area, respectively.

Accuracy of ANNs in different seasons

With the variations of climate in different seasons, the sensitivity of ET_0 to climate factors was different. Generally, the accuracy of empirical models for ET_0 estimation changes with the seasons. In this study, the accuracy of the ANNs in the different seasons was also analysed.

Errors statistics including *RMSE, RE* and R^2 from April to September for ANNs with four inputs and three inputs are listed in Table V and Table VI, respectively. Overall, there were lower errors in every month for ANNs with four inputs than for those with three inputs. From

Table III. Correlation coefficients between climate factors including temperature (T), humidity (RH), wind speed (U) and duration of sunshine (N) and ET_0 in arid, semi-arid and sub-humid areas of Inner Mongolia district, China

	Temperature	Humidity	Wind speed	Duration of sunshine
Arid area	0·61	−0·91	0·68	0·55
Semi-arid area	0·5	−0·9	0·68	0·75
Sub-humid area	0·85	−0·83	0·53	0·58

Table IV. Test errors (*RMSE, RE*, R^2) of ANN models with three inputs when computing ET_0 in arid, semi-arid and sub-humid areas of Inner Mongolia, China

	Arid area			Semi-arid area			Sub-humid area		
	RMSE (mm d^{-1})	*RE* (%)	R^2	*RMSE* (mm d^{-1})	*RE* (%)	R^2	*RMSE* (mm d^{-1})	*RE* (%)	R^2
ANN (3,3,1)	0·468	10	0·809	0·442	9	0·874	0·226	5·5	0·953
ANN (3,4,1)	0·462	9·9	0·805	0·377	8·3	0·902	0·223	5·5	0·958
ANN (3,5,1)	0·458	9·7	0·803	0·365	8·1	0·885	0·221	5·4	0·961
ANN (3,6,1)	0·458	9·8	0·793	0·435	8·7	0·873	0·21	5·2	0·961
ANN (3,7,1)	0·442	9·6	0·812	0·452	8·8	0·872	0·225	5·5	0·953
ANN (3,8,1)	0·44	9·5	0·811	0·458	8·8	0·873	0·228	5·6	0·951
ANN (3,9,1)	0·438	9·3	0·822	0·475	9·3	0·867	0·222	5·4	0·955
ANN (3,10,1)	0·445	9·7	0·813	0·474	9·3	0·876	0·224	5·6	0·954
ANN (3,11,1)	0·442	9·7	0·81	0·476	9·4	0·871	0·229	5·8	0·947
ANN (3,12,1)	0·45	9·8	0·804	0·475	9·4	0·879	0·229	5·8	0·948

DOI: 10.1002/hyp

Table V. Test errors of the optimal ANN with four inputs in different seasons in arid, semi-arid and sub-humid areas of Inner Mongolia, China

	Months	April	May	June	July	August	September
Arid area	*RMSE* (mm d^{-1})	0·156	0·226	0·212	0·174	0·28	0·331
	RE(%)	3·6	3·5	3·2	2·7	5·2	7·9
	R^2	0·965	0·952	0·989	0·996	0·998	0·968
Semi-arid area	*RMSE* (mm d^{-1})	0·085	0·174	0·195	0·128	0·088	0·129
	RE(%)	2·3	3·2	3·7	2·5	2	3·3
	R^2	0·973	0·984	0·986	0·996	0·989	0·975
Sub-humid area	*RMSE* (mm d^{-1})	0·06	0·162	0·235	0·12	0·155	0·25
	RE(%)	1·6	3·6	5·2	3	4	7·6
	R^2	0·995	0·984	0·994	0·993	0·978	0·984

Table VI. Test errors of the optimal ANN with three inputs in different seasons in arid, semi-arid and sub-humid areas of Inner Mongolia, China

	Months	April	May	June	July	August	September
Arid area	*RMSE* (mm d^{-1})	0·23	0·518	0·554	0·435	0·401	0·57
	RE (%)	5·1	9·2	8·4	7·3	7·8	13·7
	R^2	0·71	0·408	0·567	0·8	0·896	0·772
Semi-arid Area	*RMSE* (mm d^{-1})	0·365	0·544	0·425	0·562	0·254	0·55
	RE(%)	10	10	7·5	10·8	5·9	15·8
	R^2	0·278	0·465	0·848	0·86	0·818	0·64
Sub-humid Area	*RMSE* (mm d^{-1})	0·193	0·295	0·251	0·2	0·152	0·254
	RE(%)	5·6	6·1	5·1	4·5	4	7·6
	R^2	0·963	0·905	0·892	0·936	0·932	0·922

April to September for the arid and semi-arid areas and from April to July for the sub-humid area, the differences in errors from the two ANN models were obvious, but the differences were small for the period August to September for the sub-humid area.

For the ANNs with four inputs, the errors changed significantly across the different months. In the three area, the ANNs all had the lowest precision in September, with the *RMSE, RE* and R^2 of 0·331 mm d^{-1}, 7·9% and 0·968, 0·129 mm d^{-1}, 3·3% and 0·975, and 0·250 mm d^{-1}, 7·6% and 98·4% for the arid, semi-arid and sub-humid areas, respectively. The relative accuracy of ANNs for all three sub-regions in April was higher and the *RE* was 2·6%, 2·3% and 1·6% for the arid, semi-arid and sub-humid areas, respectively. In the period from May to August, the *RE* of ANNs was 2·7–5·2%, 2·0–3·7% and 3·0–5·2% for the arid, semi-arid and sub-humid areas, respectively, and the change was relatively small. Therefore, it could be concluded that the ANNs with four inputs estimated ET_0 from April to August well, but the errors were relatively higher and significant in September. This can be attributed to the characters of the weather in September, which is cooler and different from the other months.

Similar to the ANNs with four inputs, the errors of ANNs with three inputs had the lowest precision in September for the study area, especially for the arid and semi-arid areas, where the *RE* of the ANNs were 13·7% and 15·8%, respectively. For the other five months, no significant trends were found in the change of the precision of ANNs with three inputs. This was because the impact of the defaulted factor, i.e. N, T and U for the arid, semi-arid and sub-humid areas, on estimated E_0 was different for the different months. For example, the absence of N made errors in the ANNs for the arid area increase in May and June, but relatively little in the other months. In the semi-arid area, the increases in ANN errors were more obvious in April than in the other months due to the default T. Different from the arid and semi-arid areas, the default U did not decrease the precision of ANNs significantly from June to September, whereas the decrease of precision was relatively obvious in April and May. Overall, the accuracy of ANN models for ET_0 estimation changed with seasons. As a result, an ANN with four or three inputs could be selected to estimate ET_0 in different seasons and climate areas, dependent on accuracy requirements.

Comparison of ANN with multi linear regression (MLR)

Typically, ANN models are compared with other empirical models to further assess their performance. There are many empirical models for ET_0, but they are generally valid only under specific climatic and agronomic conditions, and cannot be applied under conditions different from those for which they were originally developed. Multilinear regression (MLR), a simple method, has been used to estimate ET_0 in many regions where climatic data is missing (Jensen *et al.*, 1990; Alexandris and Kerkides, 2003). In this study, MLR models with four inputs and three inputs were

Table VII. Comparison of errors between ANN models and multi-regression (MLR) in arid, semi-arid and sub-humid areas of Inner Mongolia, China

		Arid area		Semi-arid area		Sub-humid area	
		ANN	MLR	ANN	MLR	ANN	MLR
Four inputs	*RMSE* (mm d^{-1})	0·223	0·246	0·13	0·16	0·162	0·202
	RE(%)	4·2	4·9	2·7	3·7	4·1	5·2
	R^2	0·987	0·978	0·986	0·978	0·977	0·961
Three inputs	*RMSE* (mm d^{-1})	0·438	0·529	0·365	0·563	0·21	0·273
	RE(%)	9·3	10·2	8·1	12·7	5·2	6·9
	R^2	0·822	0·853	0·885	0·743	0·961	0·93

developed to compare their results with those of the ANNs for each area. The results are listed in Table VII for the *RMSE, RE* and R^2 statistics for the three areas. Both four- and three-input ANN models outperformed the corresponding MLRs in the three areas in terms of the various performance criteria. For example, the *RMSE* of ANNs with four inputs decreased by 0·023 mm day^{-1}, 0·030 mm day^{-1} and 0·040 mm day^{-1} compared with that of MLRs for the arid, semi-arid and sub-humid areas, respectively.

Similarly, the accuracy of ANNs with three inputs was higher than MLRs with three inputs, and this was obvious, especially in the arid and semi-arid areas where the *RMSE* of ANNs decreased by 0·091 mm day^{-1} and 0·198 mm day^{-1}, respectively, compared with that of the MLRs. Furthermore, reduction of climate factors diminished the accuracy of ANNs less than that of MLRs. This is attributed to the ability of the ANNs to model non-linear relationships. This study showed that the ANNs performed well in ET_0 calculation, a complex and non-linear problem, in arid and semi-arid areas even with incomplete inputs. For the sub-humid area, however, MLRs and ANNs gave very similar results. This implies that an empirical MLR model, with T, RH and N, may provide equally good results to those of the ANN model in sub-humid area.

CONCLUSIONS AND DISCUSSION

ANNs for ET_0 estimation in three areas with arid, semi-arid and sub-humid climate were trained and tested. The inputs were conventional climate factors. Compared with MLR models, ANNs with both four inputs (T, RH, U and N) and three inputs performed satisfactorily in estimating regional ET_0. ANNs with three inputs had significantly larger errors than those with four inputs for arid and semi-arid areas. The accuracy of the ANNs developed for the arid area was lower than those developed for the other areas. In the sub-humid area, however, ET_0 was simulated well by ANNs with only the three climate factors T, RH and N (i.e. no wind speed data).

Although ANN models can be used to estimate regional ET0 based on climate data, it must be pointed out that performance of the ANN also depends on the training algorithm, transfer function, net structure (hidden neurons), and so on. Generally, a back propagation algorithm is used to train ANNs because of its simplicity. In some examples, however, the back propagation algorithm may become trapped in a local optimum. In addition, the transfer function can also affect the performance of ANNs. Similar to ANNs for ET_0 estimation, a sigmoidal logistic was used for the transfer function in this study. Both training algorithm and transfer function can produce uncertainty in ANNs. The performance of ANNs with different training algorithms and transfer functions for ET_0 estimation will be investigated in a future study. Trial and errors method were often used to determine the number of hidden neurons in the ANN. This study showed that errors in ANN models change little when the number of hidden neurons is increased. Generally, the simplest ANN (i.e. fewest hidden neurons) is selected for use.

The accuracy of ANNs for estimating ET_0 was different in the different seasons. The ANNs with four inputs had small errors in April when the temperature is relatively low, but had the most evident errors in September. ANNs with four inputs could be selected for use in the season when the temperature is low. The impact of N and T on ANN results was obvious in the arid and semi-arid areas, in which ANNs with three inputs had lower accuracy in every month compared with that of the four-input ANNs. Similar to the ANNs with four inputs, the precision of the ANNs with three inputs was lowest in September in arid and semi-arid areas. However, in the sub-humid area, the ANNs with three inputs simulated ET_0 from June to September well, with an accuracy almost equal to that of ANNs with four inputs.

Summarizing, ANN models with conventional climate factors can be used to estimate regional ET_0 satisfactorily in arid, semi-arid and sub-humid areas, although the precision changes with the seasons. When four or three conventional climate factors are collected, daily ET_0 at any site in the study regions can be estimated using the corresponding regional ANN model.

ACKNOWLEDGEMENT

This research was supported by the National Natural Science Foundation of China (NSFC) Project No.50769004 and National Key Technology R&D Program of China No.2007BAD88B04.

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DOI: 10.1002/hyp