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ASSESSMENT OF BIOCLIMATIC COMFORT USING ARTIFICIAL NEURAL NETWORK MODELS – A PRELIMINARY STUDY IN A REMOTE MOUNTAINOUS AREA OF SOUTHERN GREECE

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Summary: This work presents an artificial neural network (ANN) model-based approach to assess bioclimatic conditions in remote mountainous areas using a relatively limited number of microclimatic data from easily accessible meteorological stations. Seven meteorological stations were established in the mountainous area of Samaria Forest canyon (Greece). ANN models were developed to predict air temperature and relative humidity for the five most remote stations of the area using data only from two stations located in more easily accessible sites. Measured and model-estimated data were compared in terms of the determination coefficient, the mean absolute error and residuals normality. Then, the developed ANN models were used to predict values of the thermohygrometric (THI) bioclimatic index on hourly basis for the five most remote stations using the model-predicted air temperature and humidity data and to evaluate the comfort THI categories. These results were then compared to THI classes obtained using the measured air temperature and relative humidity data recorded at the stations. Results showed that appreciable percentages of successful forecasts were achieved by the ANN models, indicating therefore that ANNs, when adequately trained, could successfully be used in practical applications of bioclimatic comfort in remote mountainous areas.

Key words: microclimate, artificial neural networks, thermal comfort, thermohygrometric (THI) index

1. INTRODUCTION

Human thermal comfort conditions may be assessed through a number of theoretical and empirical indices requiring usually a larger or smaller number of input microclimate parameters (Mayer 1993). In several cases, however, meteorological data in the desired or required spatial resolution are not readily available, e.g., in mountain regions due to the complex terrain, or due to the sparse network of the meteorological stations. In such cases, there is a need to estimate data for meteorological parameters not recorded at several locations from observations of the same variable recorded at other sites. Spatial data interpolation and process-based techniques have, however, important limitations in complex terrain areas (e.g. Tveito and Schöner 2002) whereas sometimes much simpler methods are used (e.g. Tang and Fang 2006).

Recently, artificial neural network (ANN) models have been started to be used for spatial data interpolation (Chronopoulos et al. 2008, Cheng et al. 2002, Rigol et al. 2001). ANN applications to various bioclimatic aspects is, however, still limited (e.g. Grinn-Gofroń and Strzelczak 2008, Incerti et al. 2007, Sánchez Mesa et al. 2005) despite their increasing use in various atmospheric studies (e.g. Tsiros et al. 2009, Wang and Lu 2006, Dimopoulos et al. 2004, Chaloulakou et al. 2003). In general, ANNs contain no critical assumptions about the nature of spatial data and are well suited to processing noisy data and handling non-linear modeling tasks (Openshaw and Openshaw 1997). The purpose of the present preliminary study is to illustrate the development and application of ANN models to assess bioclimatic comfort in a series of sites inside a remote mountainous canyon based on meteorological values recorded at reference stations located in easily accessible areas.

2. MATERIALS AND METHODS

2.1. Study area and microclimatic data

The application site is the canyon of Samaria, a mountainous forest, located in the southwest part of Crete Island in southern Greece. The canyon extends from 35°18'27"N and 23°55'06"E to 35°14'40"N and 23°58'01"E, covering a total distance of about 18 km. The only way to cross the canyon is on foot and only during the summer. The entrance of the canyon is closed during the winter, because of the danger of falling rocks and flood. The dataset used consists of measured mean hourly temperature and humidity data for 7 meteorological stations established in the canyon for the purposes of the present study and for the following time periods: 12/6/2003 – 4/8/2003, 6/8/2004 – 15/9/2004 and 20/6/2005 – 27/10/2005. Fig. 1 shows the terrain of the study area and the locations of the meteorological stations along the canyon. The geographic coordinates of the locations of the stations are given in Table 1 whereas typical statistics of the measured air temperature and relative humidity data are shown in Table 2.

Table 1 The geographic coordinates of the locations of the stations

Station	Longitude (Eastern)	Latitude (Northern)	Elevation
S_1	23°55'06"	35°18'27"	1200 m
S_2	23°56'10"	35°18'24"	640 m
S_3	23°56'53"	35°18'00"	490 m
S_4	23°57'31"	35°17'29"	340 m
S_5	23°57'44"	35°16'56"	290 m
S_6	23°58'04"	35°15'29"	190 m
S_7	23°58'01"	35°14'40"	120 m

Table 2 Statistics of the measured air temperature (°C) and relative humidity (%) data: mean and standard deviation (S.d.) values

Station		12/06/2003 to 04/08/2003		06/08/2004 to 15/09/2004		20/06/2005 to 27/10/2005	
		Mean	S.d.	Mean	S.d.	Mean	S.d.
S_1	Temp. (°C)	22.0	3.0	18.8	4.5	18.1	4.8
	RH (%)	38.3	9.5	51.9	19.8	59.9	16.0
S_2	Temp. (°C)	28.1	3.6	24.4	5.3	23.2	6.1
	RH (%)	33.8	12.4	37.6	15.4	44.0	19.6
S_3	Temp. (°C)	26.8	3.9	24.9	4.4	23.4	5.4
	RH (%)	34.7	12.3	38.4	13.4	45.8	20.5
S_4	Temp. (°C)	26.5	3.8	24.9	4.0	23.7	4.3
	RH (%)	35.2	12.2	38.3	12.2	51.0	23.1
S_5	Temp. (°C)	26.8	4.1	25.3	4.1	23.8	5.7
	RH (%)	39.0	14.1	40.0	13.0	50.8	24.5
S_6	Temp. (°C)	26.3	3.3	25.4	3.2	24.2	4.6
	RH (%)	46.9	15.5	46.1	13.5	47.6	17.2
S_7	Temp. (°C)	27.2	2.8	25.9	3.0	25.5	4.5
	RH (%)	44.1	13.4	45.5	12.9	48.3	15.4

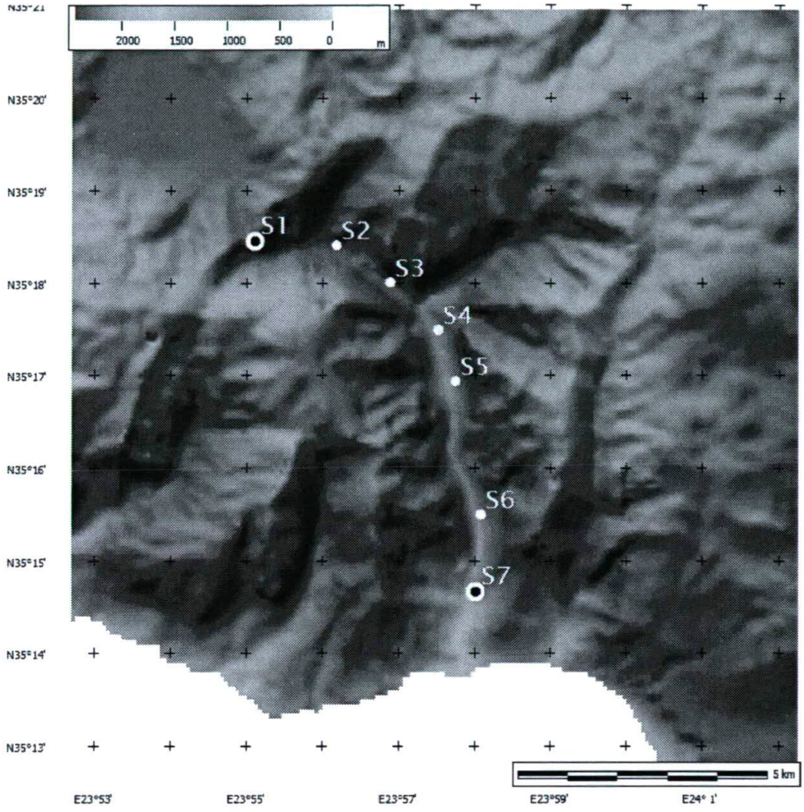

Fig. 1 Terrain of the study area and locations of the meteorological stations along the canyon

2.2. The biometeorological index

To assess human thermal comfort, the well known thermohygrometric (THI) index was used. THI was developed by Thom (1959) and was supported by a later work of Clarke and Bach (1971). THI is a simple index suitable for open spaces. For the calculations, the THI equation with air temperature (°C) and relative humidity was used along with the THI categories according to Kyle (1994):

$$THI = T - (0.55 - 0.0055 \cdot RH) \cdot (T - 14.5) \tag{1}$$

where T: ambient air temperature (°C); RH: ambient relative humidity (%).

2.3. The Artificial Neural Network (ANN) models

An artificial neural network involves a network of simple processing elements (artificial neurons) which can exhibit complex global behavior, determined by the connections between the processing elements and element parameters. For modeling, the multilayer perceptron (MLP) artificial neural network model was adopted whereas for model training the back propagation algorithm was used (Rumelhart et al. 1986). Figure 2 shows a rough schematic figure of the MLP ANNs that were used in the present study. There is an input layer, a hidden layer of five units and the output layer. The connections between the layers are feedforward only and their weights and thresholds are determined by the training procedure of the neural network. The training set consisted of ½ of the data, the selection set of ¼ of the data and the test set of the remaining ¼ of the data, randomly assigned.

For the MLP, the output with one hidden layer is given by:

$$f(x)=\phi^{s}\left(\sum_{i=1}^{I} w_{is}\phi^{i}\left(\sum_{e=1}^{n} w_{ei}x_{e}+w_{0}\right)+w_{s}\right) \tag{2}$$

where I is the number of hidden nodes, n is the number of input variables, w_{ei} and w_{is} are the weights of the input-to-hidden and hidden-to-output layer, w_0 and w_s are the corresponding thresholds (bias), ϕ^i and ϕ^s are the units' activation functions.

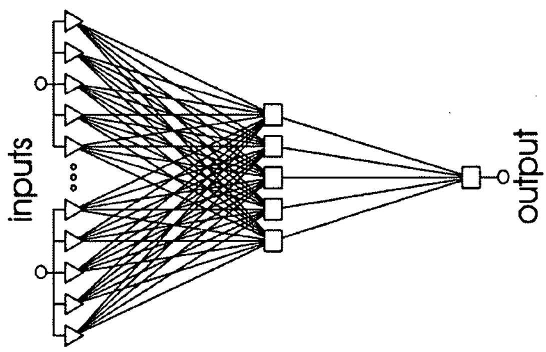

Fig. 2 General schematic figure of the MLP Artificial Neural Networks that were used.

The activation function for the hidden units as well as the output unit is the logistic sigmoid function $\phi(x)=\left(1+e^{-x}\right)^{-1}$. A major consideration in the use of MLP for model building is the determination of the optimal architecture of the network (number of inputs, number of layers and number of nodes per layer). Usually, a trial-and-error method is applied to test various alternative models. The model networks developed in the present study use one hidden layer with 5 nodes since it was found that this is the number of layers that gives the best results on the selection set.

3. RESULTS AND DISCUSSION

The first step was to develop ANN models to predict air temperature and humidity for the most remote stations of the area, $S_2 - S_6$, using data only from stations S1 (entrance of the canyon) and S_7 (end of the canyon), located in more easily accessible areas. Measured and estimated data of both air temperature and relative humidity were compared in terms of the determination coefficient (R^2) and the mean absolute error (MAE). It was found that R^2 values range from 0.7 to 0.9 for air temperature and from 0.7 to 0.8 for relative humidity; MAE values range from 0.9 to 1.8 °C and 5 to 9%, for air temperature and relative humidity, respectively. The normality of the residuals was also examined using the Shapiro-Wilk normality tests and it was found that residuals have a normal distribution. In addition, the results of the ANN models were compared to results obtained from regression analyses. The multiple linear regression was used just to compare the ANN results with this widely accepted methodology and to examine the efficiency of ANNs. The multiple linear regression had the same inputs as the neural networks used in this study.

The values of the determination coefficients and the mean absolute errors for the two different modelling techniques are shown in Tables 3 and 4, for the air temperature and the relative humidity, respectively. The comparison indicates, in general, the superiority of the ANN models, especially in the case of the relative humidity estimations.

Table 3 Air temperature estimations at the remote stations: determination coefficients (R^2) and mean absolute error (MAE) of the linear regression and the ANN models

Station	**Multiple Linear Regression Model**		**ANN Model**	
	R^2	**MAE, °C**	**R^2**	**MAE, °C**
S_2	0.89	1.5	0.90	1.4
S_3	0.89	1.4	0.89	1.3
S_4	0.69	1.9	0.72	1.8
S_5	0.85	1.6	0.86	1.6
S_6	0.91	1.0	0.92	0.9

Table 4 Relative humidity estimations at the remote stations: determination coefficients (R^2) and mean absolute error (MAE) of the linear regression and the ANN models

Station	**Multiple Linear Regression Model**		**ANN Model**	
	R^2	**MAE, %**	**R^2**	**MAE, %**
S_2	0.79	6.7	0.83	5.6
S_3	0.75	7.3	0.80	6.3
S_4	0.65	9.7	0.73	8.6
S_5	0.65	10.3	0.73	8.9
S_6	0.79	4.7	0.80	4.6

The next step was to use the developed ANN models to predict bioclimatic data values using the model-predicted air and humidity data for the five most remote stations S_2 – S_6. The ANN-predicted values of THI were then used to estimate the THI categories of human comfort; results in terms of relative frequencies are shown in Table 5. The final step was to compare these results to the THI classes obtained using the measured air temperature and relative humidity data recorded at the five stations S_2 – S_6 (Table 5). The comparison in Table 5 shows that appreciable percentages of successful forecasts were achieved by the ANN models. The highest successful rate is achieved for station S_6 located in the vicinity of the sea. In addition, five THI classes were found in both cases, with the largest percentage to be associated with the 'Cool' class. With the exception of the 'Comfortable' class, all other classes appear in small percentages in both cases. It should be noted, however, that the parameters of wind speed and radiation were not considered in the present study since reliable data of those parameters are not always available for remote areas despite the fact that their variability is expected to affect significantly the thermal stress conditions. Reliable data of those parameters were not available for the study area so there was no other way of using another biometeorological index. This is also the reason that a simple, yet widely applied, biometeorological index was used in the present study.

Table 5 The relative frequencies of the THI classes for the various stations (a) calculated using the ANN model-estimated air temperature and humidity data values and (b) calculated using the measured air temperature and humidity data values. THI classes are according to Kyle (1994).

Station	Very Hot 26.5≤THI≤29.9		Hot 20≤THI≤26.4		Comfortable 15≤THI≤19.9		Cool 13≤THI≤14.9		Cold -1.7≤THI≤12.9	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
S_2	0.8	2.1	1.5	3.6	24.4	31.1	56.2	61.0	1.7	2.2
S_3	0.2	0.9	2.2	3.3	19.9	26.8	62.7	68.6	0.4	0.4
S_4	0.0	0.2	0.3	1.2	16.7	28.8	64.9	69.1	0.0	0.7
S_5	0.2	1.1	1.5	3.3	16.2	25.0	64.9	69.6	0.5	1.0
S_6	0.0	0.0	0.1	0.8	18.8	21.5	74.2	77.0	0.4	0.7

4. CONCLUSION AND RECOMMENDATIONS

The results of the present study revealed that there was a satisfactory capability to estimate, through the use of ANN models, the level of thermal comfort in remote mountainous areas using relatively limited data of air temperature and humidity from easily accessible meteorological stations, assuming ANNs were adequately trained. The present study focused on estimating actual conditions at five remote stations from the actual conditions at two reference stations; a future study should investigate the development of appropriate ANN procedures to make timely extrapolations into the future in order for the models to be used for forecasts of bioclimatic conditions. In addition, future studies should focus mainly on comparing ANN model results to results obtained from the use of more complex bioclimatic indices since in several cases the variability of wind speed and radiation fluxes is expected to modify more the thermal stress conditions than air temperature and humidity.

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