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An artificial neural network model application for the estimation of thermal comfort conditions in mountainous regions, Greece

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RESUMEN

En esta investigación, se aplicó un modelo de red neuronal artificial (ANN), para estimar las condiciones térmicas de las regiones montañosas de Gerania (MG) y de Nafpaktia (MN) en Grecia. La temperatura del aire y la humedad relativa fueron registradas de junio hasta agosto de 2007, en dos sitios seleccionados de cada región estudiada. Datos de los parámetros antes mencionados se usaron para calcular el índice termohigrométrico (THI), evaluando las condiciones de confort térmico como categorías. El modelo ANN, perceptrón multicapa (MLP), fue usado para estimar los valores del THI en los niveles de las alturas 1334 y 1338 m en MG y MN, respectivamente. Con base en la temperatura y en la humedad relativa de los niveles examinados a baja altitud (650 m en MG y 676 m en MN), teniendo en cuenta el tiempo de medición real (ATM). Los resultados del desarrollo y aplicación del modelo ampliado MLP indicaron una estimación más precisa de los valores THI en los estudios de las dos regiones durante un periodo de todo el día, comparado con la aplicación MLP sin el uso del ATM. También, el modelo ampliado, examinando el día entero, mostró estimaciones más precisas de los valores THI en el MG comparados con el MN. De manera similar, este modelo proporcionó una mejor estimación por separado del periodo, tanto durante el día (09h00min-20h00min) y durante la noche (21h00min-08h00min) en comparación con las estimaciones respectivas del THI, tomando en cuenta sólo la temperatura del aire y la humedad relativa como parámetros de entrada. Adicionalmente, la ampliación del modelo MLP fue mucho más eficiente para estimar los valores THI durante las horas del día, comparado con las horas de la noche en ambos MG y MN. También el modelo ampliado MLP fue capaz de estimar mejor los valores de THI en la clase Caliente en MG, como así mismo en la clase Confortable en MN.

ABSTRACT

In this research, an artificial neural network model (ANN) was applied to estimate the thermal comfort conditions in the mountainous regions of Gerania (MG) and of Nafpaktia (MN) in Greece. Air temperature and relative humidity were recorded from June to August 2007 at two selected sites for each study region. Data of the aforementioned parameters were used for the calculation of the thermohygrometric index (THI), from which thermal comfort conditions were evaluated as classes. The ANN model, the multilayer perceptron (MLP) was used for the estimation of THI values at the examined high altitude level (1334 and 1338 m in MG and MN, respectively) based on the temperature and the relative humidity of the examined low altitude level (650 m in MG and 676 m in MN), taking into account the actual time of measurement (ATM). The results of the development and application of this extended MLP model indicated more accurate estimations of THI values at the two study regions during the whole day period compared to the MLP application without the use of ATM. Also, the extended model, examining the whole day, showed more accurate estimations of THI values in MG compared to MN. Similarly, this model provided better estimations separately for both daytime (09h00min-20h00min) and nighttime (21h00min-08h00min) in comparison with the respective THI estimations taking into account only the air temperature and relative humidity as input parameters. Additionally, the extended MLP model was more efficient estimating THI values during daytime hours compared to nighttime hours in both MG and MN. Also, the extended MLP model was more capable in estimating better the THI values in the "hot" class in MG as well as in the "comfortable" class in MN.

Keywords: Artificial neural networks, air temperature, relative humidity, thermohygrometric index, mountainous Nafpaktia, Gerania mountains, Greece.

1. Introduction

Mountains cover about a quarter of the global land surface (Kapos *et al.,* 2000; Guan *et al.,* 2009). Mountainous regions hold a rich variety of ecological systems which are sensitive to environmental conditions (Jansky *et al.,* 2002) and appear to be very attractive to residents and tourists, particularly during the summer vacation period.

The effect of topography, the more complex relief and the composition of vegetation cause a spatial pattern of topoclimates in mountainous regions (Barry and Chorley, 2001). Therefore, in these regions the meteorological parameters such as air temperature, humidity, radiation and precipitation present large spatial variations (Barry and Chorley, 2001; Tang and Fang, 2006), and spatial modelling of the climate parameters is very important in evaluating environmental conditions (Chapman and Thornes, 2003; Guler *et al.,* 2007).

In mountainous regions there are many problems in obtaining the precise meteorological data because the network of the meteorological stations in the middle and high altitudes is sparse due mainly to difficulties in installing and maintaining the measuring instruments (Friedland *et al.*, 2003; Tang and Fang, 2006). Thus, researchers who are interested in the environmental conditions of the aforementioned regions are often forced to estimate the meteorological parameters on the basis of data collected from nearby lower-altitudes areas (Tang and Fang, 2006). For this reason, there has recently been a large number of studies which use geostatistical and regression techniques. Bolstad *et al.* (1998) developed regression models with more accurate estimations of air temperature in specific sites and in local scale than either kriging or lapse models, using data of regional network stations in the southern Appalachian mountains of North America. Guler *et al.* (2007) used air temperature and precipitation data in order to develop climate-elevation regression methods by the use of geographical information systems at the regions with more complex topography in Samsun, Turkey. Also, general models were constructed using geographical and terrain characteristics (e.g. altitude, slope aspect), dominant regional climate features and their interactions in mountainous regions of Taiwan and China (Ranhao *et al.*, 2008; Guan *et al.*, 2009).

The accuracy of these methods can generate estimations depending on the complexity that underlies the spatial structure of the field (Snell *et al.*, 2000). One robust computational technique, the artificial neural network (ANN) model (Shank *et al.*, 2008) is characterized by a high potential of complex, non-linear and time-varying input-output mapping (Dibike and Coulibaly, 2006). ANN models are based on the biological neuron connections which are found in human brains. They are repeatedly exposed to inputs and vary in terms of strength of the connections between neurons based on these inputs (Shank *et al.*, 2008). Furthermore, the ANN allow the data to define the functional form while the regression techniques allow the data to assume this form (Ustaoglu *et al.,* 2008) and thus, ANN models provide satisfactory predictions of meteorological parameters (e.g. air temperature) compared to multiple linear regression methods (Chronopoulos *et al.,* 2008; Ustaoglu *et al.,* 2008).

Thermal comfort is defined as the condition of mind which expresses satisfaction with the thermal environment, absence of thermal discomfort or conditions in which 80 or 90% of humans do not express dissatisfaction (Yilmaz *et al.,* 2007). Meteorological variables such as air temperature, humidity, wind speed, radiation as well as behavioral variables such as clothing and activities influence thermal comfort conditions which can be evaluated by using a lot of indices for this purpose. Some of them are based on the heat balance equation (rational indices) while others are based on objective or subjective estimation of human thermal stress (empirical indices) and on direct measurements of environmental parameters (direct indices) (Chronopoulou-Sereli and Chronopoulos, 2011).

The rational indices display a more comprehensive estimation of thermal comfort conditions than others since they integrate a large number of environmental and behavioral variables. On the other hand, the disadvantages of rational and empirical indices are focused on their complexity, since too many variables are involved, on their difficulty to implement in work places and on the fact that some of them require invasive measurements, not feasible for daily use. Another disadvantage of rational indices is that some of their parameters must be considered as constant because there is not a practical way of recording them, e.g. the case of heat stress index (HSI) which is based on constant skin temperature of 35 ºC (Epstein and Moran, 2006).

In contrast the direct indices are more user-friendly and applicable than rational and empirical ones (due to their use of common environmental variables), including the widely used biometeorological index, the thermohygrometric index (THI) as modified by Nieuwolt (1977), which requires only temperature and humidity data (Toy *et al.*, 2007). This index is derived from the discomfort index which combines wet-bulb temperature and dry-bulb temperature in a scale that simulates the human thermal sensation for the hot period of the year (Thom, 1959). The aforementioned index has been used daily for more than four decades and has been suggested as a universal heat stress index by Epstein and Moran (2006). The same suggestion can be accordingly made for THI which, as already mentioned, is derived from discomfort index.

Although in recent years many applications have been reported for the estimation of meteorological variables (Tolika *et al.*, 2007; Shank *et al.*, 2008; Ustaoglu *et al.*, 2008; Liu *et al.*, 2009; Smith *et al.*, 2009), the only information for the estimation of human thermal comfort conditions in mountainous regions, to our knowledge, has been reported by Kamoutsis *et al.* (2010). The regional features, the physical environment and the thermal comfort affect the decisions of tourists (Lin and Matzarakis, 2008) for their destinations. This study focuses on the estimation of thermal comfort conditions in two mountainous regions with a sparse network of meteorological stations, the Gerania mountains and the mountainous Nafpaktia in Greece using ANN models.

2. Materials and methods

2.1 Study regions and measurement sites

This study was conducted in two mountainous regions of Greece in the southeastern part of Europe. The first one, Gerania mountains (altitudes up to 1341 m) which is included in the Natura 2000 network (Manoli, 2008), is located in east continental Greece, in the Prefectures of West Attica and Korinthia (Fig. 1a, c) about 60 km from Athens, the capital of Greece. Dense forests of *Pinus halepensis* dominate at altitudes up to 850 m in these mountains, while sites with higher altitudes are forested by *Abies cephalonica*, at a good conservation status, thus creating a natural environment of great aesthetic value and of utmost ecological importance. The region of Gerania mountains (MG) is unexploited and abandoned with no industrial activities. It appears to have a great importance for recreation and tourist activities because of its relatively small distance from Athens combined with the possibility to accomodate a singnificant percentage of Athens population.

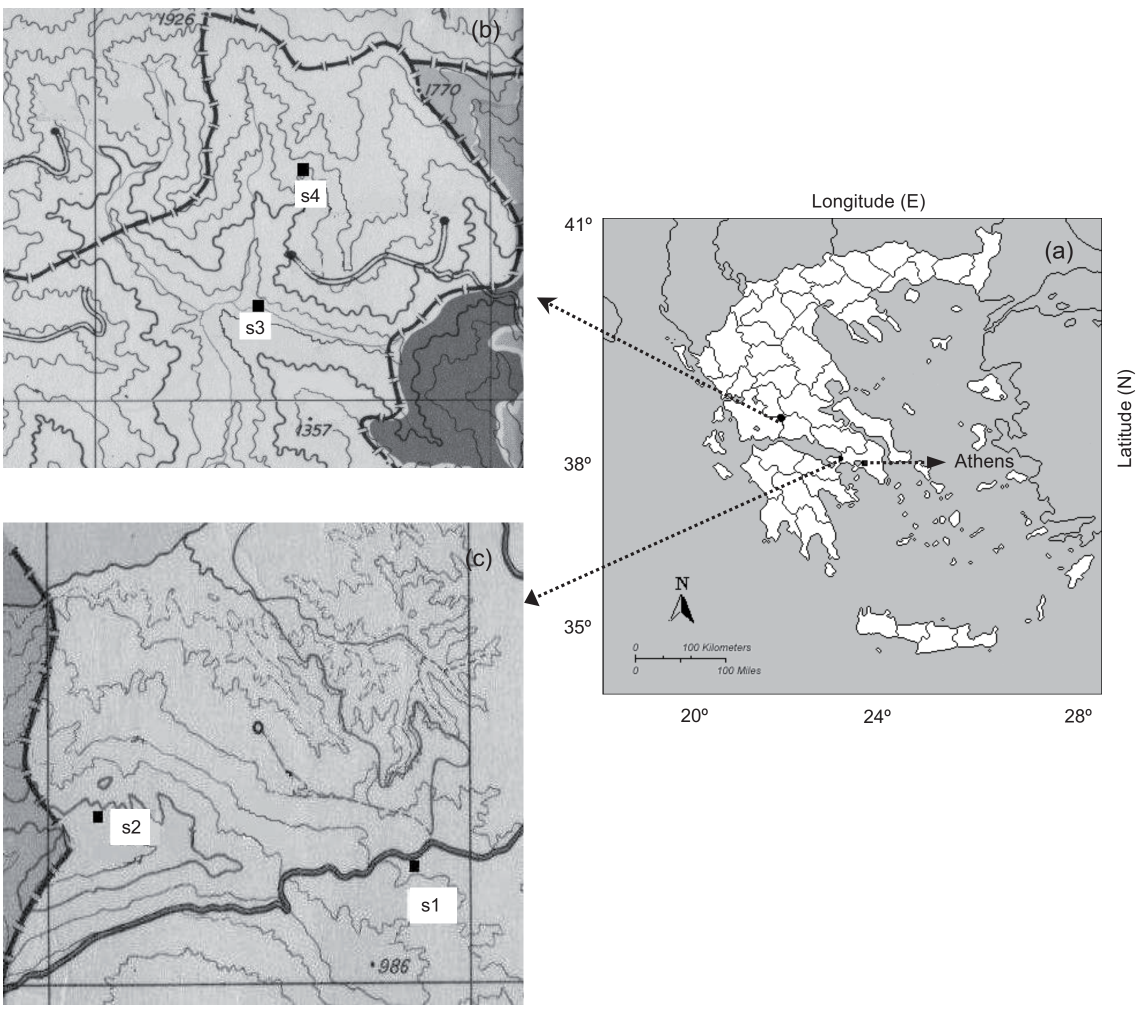

Fig. 1. Location map of the examined regions, in Greece (a) and maps of the study sites (■ s1, s2, s3, s4) in Mountainous Nafpaktia (b) and in Gerania mountains (c) the scale in Figs. 1b,c is 1:200 000.

The second region comprised a wide part of mountainous Nafpaktia (MN) districts, with altitudes ranging from 676 to 1338 m (Fig. 1a, b) in the Municipality of Apodotia, Prefecture of Aitoloakarnania, in west continental Greece, about 350 km from Athens. This region is unexploited and is characterized by rich biodiversity (flora and fauna) with great development potential. It is known for its beautiful beech forest (*Fagus silvatica* L.), the southernmost beech forest in Europe. In MN, few commercial, industrial or other human activities exist and it could be a reliable alternative tourist destination for rest and recreation (Matsoukis *et al.*, 2009).

Two sites of the same orientation (southwest) in each study region were selected. The selection was mainly based on different altitude. There were two levels, each with similar altitudes, for both study regions. The first level comprised the altitudes 650 and 676 m and the second level, 1334 and 1338 m (Table I). The orientation, altitude, latitude and longitude of each site were evaluated using a mobile global positioning system (Garmin eTrex Vista) and checked against 1:50 000 topographic maps.

Table I. Study sites in Gerania and Nafpaktia.

Sites	Altitude (m)	Latitude	Longitude	Dominant vegetation
		Gerania mountains		
s1	650	38º 00´ 59.2´´ N	23º 10´ 58.5´´ E	*Pinus halepensis*
s2	1334	38º 01´ 16.0´´ N	23º 08´ 02.4´´ E	*Abies cephalonica*
		Mountainous Nafpaktia		
s3	676	38º 43´ 05.1´´ N	21º 57´ 36.8´´ E	*Abies cephalonica*, *Cercis siliquastrum, Pistacia terebinthus*
s4	1338	38º 44´ 29.5´´ N	21º 58´ 34.2´´ E	*Abies cephalonica*

2.2 Measurements and quantification of thermal conditions

Air temperature and relative humidity were monitored simultaneously every 15 min by sensors with data loggers (Hobo type Pro, H08-032-08, accuracy ±0.2 ºC at 25 ºC and ±3% relative humidity over 0 ºC to 50 ºC), one for each site, for the summer period between 23 June and 28 August 2007. The instruments were tested in the laboratory against appropriate sensors for a period of five days while being exposed to the same range of temperature and humidity. These initial tests revealed no drift errors for any of the sensors. The data loggers were enclosed in appropriate shelters screened from rainfall and direct solar radiation and mounded under trees 1.5 m above the ground surface. The shape of the shelters allowed acceptable air ventilation.

Regarding air temperature and relative humidity data, hourly basis averages were calculated for each study site and for the whole experimental period. These averages were used for the calculation of the average hourly values of the thermohygrometric index (THI) (Toy *et al.,* 2007) according to the equation:

$$\mathrm{THI}\ (^{\circ}\mathrm{C}) = t - [(0.55 - 0.0055f)(t - 14.5)] \tag{1}$$

where t = air temperature (ºC) and f = relative humidity (%). This index was selected for our study because it is friendly and easily applicable and is based on data of environmental parameters which exist in the majority of the meteorological stations of our country. Another reason for THI selection is its suitability to provide a more detailed approach to summer biometeorological conditions in mountainous areas (Kamoutsis *et al.,* 2007; Manoli, 2008), by using the available data set. The above THI values were used for the evaluation of classes of human thermal comfort (Table II) as modified from Toy *et al.* (2007).

Table II. Relation of human thermal comfort class with thermohygrometric index (THI).

Human thermal comfort class	THI value (ºC)
Cold	–1.7 to +12.9
Cool	+13.0 to +14.9
Comfortable	+15.0 to +19.9
Hot	+20.0 to +26.4
Very hot	+26.5 to +29.9

2.3 Neural network modelling

A commonly used neural network model, the multilayer perceptron (MLP), was used to evaluate the estimated THI values at high altitude based on the air temperature and the relative humidity values at the lower altitude, in both MG and MN. This model can effectively be used to evaluate microclimate conditions in remote mountainous canyons (Chronopoulos *et al.,* 2008). A recent study showed that, the MLP model (initial) can be applied satisfactorily for the estimation of the THI values at high altitude during daytime hours using as input parameters the air temperature and the relative humidity (Kamoutsis *et al.,* 2010). Our study comprises an extension of the initial neural network model using as an input parameter an additional factor (extended model): the actual time of the measurement (ATM). The extended model was applied and tested for the whole day and separately for both daytime (09h00min-20h00min) and nighttime (21h00min-08h00min). This model was compared with the reported initial model (Kamoutsis *et al.,* 2010). Additionally, the MLP model was assessed by comparing the estimated percentages of the THI values for every thermal comfort class in relation with their actual occurence.

For MLP training, firstly the backpropagation (Rumelhart *et al.,* 1986; Fahlman, 1988; Fausett, 1994) and then the conjugate gradient descent algorithms (Fletcher and Powell, 1963; Fletcher and Reeves, 1964) were used in two phases. The activation function, for the hidden units as well as the output unit, is the logistic sigmoid function. A trial-and-error approach was also applied to select the best network architecture. One hidden layer with various numbers of nodes formed each network. The training set consisted of half of the data, the selection set of a quarter of the data and the test set of the remaining quarter of the data randomly assigned.

The best MLP neural network structure for our study (network structure: 3:3-8-1:1) was selected after trying all different three layer MLP networks (1 up to 3 input variables, 1 output variable and 1 up to 9 hidden layer neurons). The training method was carried out in two phases. In the first phase, the algorithm backpropagation was used, while in the second the conjugate gradient descent algorithm was used.

The input data were separated in three sets. The first training set comprises 802 values, the second selection set comprises 400 values and the last testing set comprises 400 values. After applying the sensitivity test for the input variables, we found that all three variables used (actual measurement time, *t*, *f*) are significant to our model at $p < 0.05$.

3. Results and discussion

The results of various tests that have been performed using the extended MLP model indicated better estimations of the THI values at high altitude compared with the original MLP model for the whole day. Specifically, the coefficients of determination (R^2) between observed and estimated THI values at high altitude were higher ($R^2 = 0.80$ in MG and $R^2 = 0.75$ in MN) than those ($R^2 = 0.73$ in MG and $R^2 = 0.61$ in MN) of the initial model. Also, the mean absolute errors (MAE) were lower (MAE = 0.817 ºC in MG and MAE = 0.934 ºC in MN) using the extended model compared to those (MAE = 0.994 ºC in MG and MAE = 1.130 ºC in MN) with the original model. Also, the extended model, showed more accurate estimations of the whole-day THI in MG, resulting in higher R^2 and lower MAE values compared to MN.

Similar results with the application of the extended *MLP* model for daytime hours were obtained in both MG (R^2=0.95, MAE = 0.36 ºC) and MN ($R^2 = 0.77$, MAE = 0.76 ºC) in comparison with the application of the original MLP model (Kamoutsis *et al.,* 2010) in both regions ($R^2 = 0.88$, MAE = 0.58 ºC in MG, $R^2 = 0.69$, MAE = 0.87 ºC in MN). At nighttime (21h00min-08h00min), the extended MLP model indicated slightly better estimations of the THI ($R^2 = 0.55$, MAE = 1.25 ºC in MG and $R^2 = 0.60$, MAE = 1.11 ºC in MN) in comparison with the original model ($R^2 = 0.50$, MAE = 1.30 ºC in MG and $R^2 = 0.38$, MAE = 1.37 ºC in MN).

Additionally, the extended MLP model was more efficient in estimating the THI in daytime hours (09h00min-20h00min) compared to nighttime hours (21h00min-08h00min) in both MG and MN, resulting in higher R^2 and lower MAE during daytime in relation to nighttime. Also, greater variations in estimated-observed data in MN compared to MG, particularly during nighttime, were observed throughout the whole period of the experiment (Fig. 2a, b). This fact can be attributed, partly, to the different rate of the nocturnal radiative cooling under calm clear sky conditions (Oke, 1999) due to the change in the dominating plant species (Geiger *et al.,* 2003) from the low to the high altitude, at both study regions (Table I). Less accurate estimations during nighttime in MN compared to MG using the MLP original model were reported by Kamoutsis *et al.* (2010).

Five classes of THI values were found Very Hot, Hot, Comfortable, Cool and Cold. Note that the class Very Hot was detected only at low altitude (650 m in MG and 676 m in MN). The use of more complex indexes (MCI) to our study, like predicted mean vote (PMV), physiological equivalent temperature (PET) and others, may probably offer more sensitivity to our results, because of their higher number of classes for human thermal comfort than THI. However, the requirement for more meteorological parameters to estimate the MCI such as global radiation, mean radiant temperature, wind speed etc. (Chronopoulou-Sereli and Chronopoulos, 2011), along with the absence of appropriate instruments for their measurement in the majority of the meteorological stations of our country synthesize a restrictive factor of MCI use because the comparison of the results with these from other regions in Greece will not be possible.

The percentages of success and of appearance for the estimated THI values for t he classes Hot, Comfortable, Cool and Cold using the extended MLP model for the whole day period at high

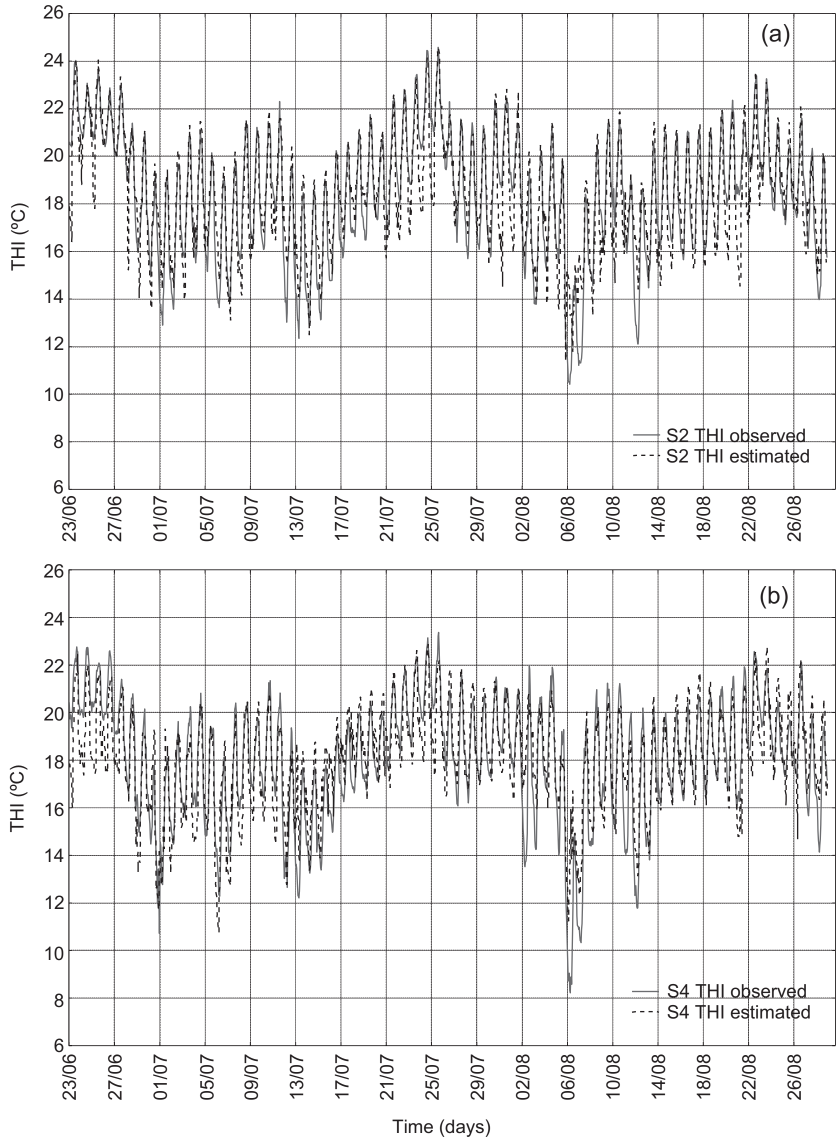

Fig. 2. Observed and estimated THI values in high altitude (alt.) level (s2, s4) vs. low alt. level using the multilayer perceptron model (air temperature, relative humidity and actual time of measurement as input parameters) in Gerania mountains (a) and in mountainous Nafpaktia (b), Greece, from 23 June to 28 August 2007. High alt. level: alt. 1334 and 1338 m at the s2 site in MG and at the s4 site in MN, respectively.

altitude of the examined regions (s2 at MG and s4 at MN) are presented in Figure 3. The model was more successful estimating the Hot class at the s2 site (1334 m) because of the larger percentage of success (25.1 %) and appearance (30.5 %) of the THI (Fig. 3a) compared to those (Fig. 3b) at the s4 (1338 m) site (14.6 % success and 22.4 % appearance). The percentages of success and appearance for the predicted THI in the Comfortable class of the s4 site (Fig. 3b) at MN were

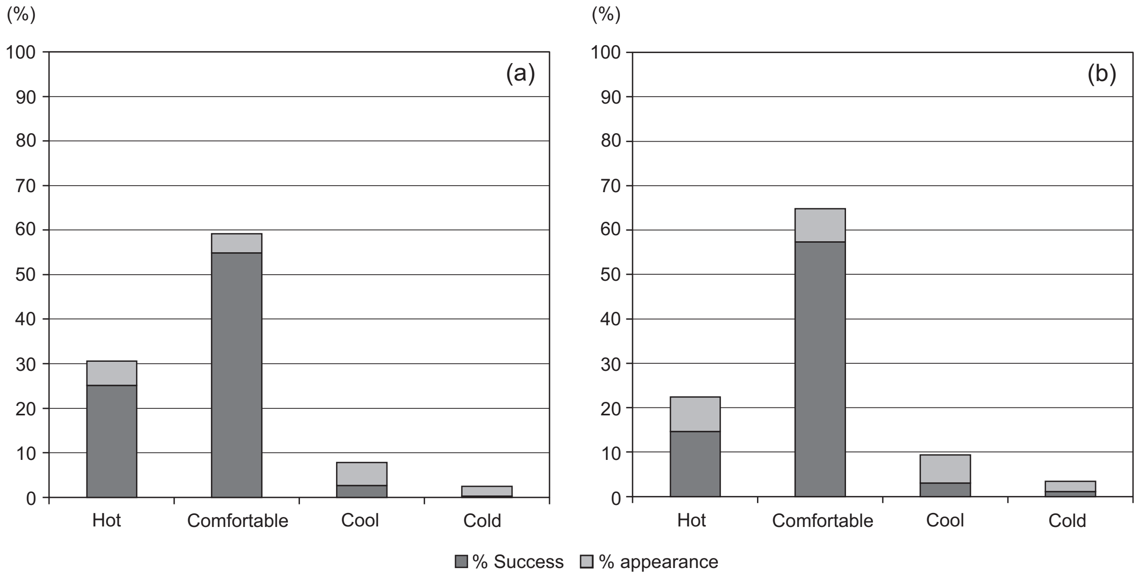

Fig. 3. Percentages of successes and of appearance for the estimated THI values in each thermal comfort class at the high altitude (alt.) level in Gerania mountains (a) and mountainous Nafpaktia (b), Greece, from 23 June to 28 August 2007. Low alt. level: alt. 650 and 676 m in MG and MN, respectively. High alt. level: alt. 1334 and 1338 m in MG and MN, respectively.

57.3% and 64.8%, respectively, that is, these percentages were slightly larger than the respective ones of s2 (Fig. 3a) at MG (54.9 % success and 59.1 % appearance). The percentages of the values of the THI corresponding to the Cool and Cold classes were smaller than the respective ones of the rest two classes. Therefore, the extended MLP model provides closer estimations of the THI values in the Hot class in MG, while the THI values classified as "Comfortable" can be evaluated more accurately in MN compared to MG.

4. Conclusions

This study estimates the thermal comfort conditions, using an artificial neural network model, the multilayer perceptron (MLP), at high altitude (1334 m in MG and 1338 m in MN), based on the meteorological parameters recorded at low altitude (650 m in MG and 676 m in MN), using as input variables the actual measurement time, the air temperature and the relative humidity (extended model). The results of this MLP extended model indicated more accurate estimations of THI values at the two study regions during the whole day period.

Similarly, this extended model provided better estimations separately for both daytime (09h00min-20h00min) and nighttime (21h00min-08h00min) in comparison with the THI estimations from the original model (only air temperature and relative humidity as input parameters). The extended MLP model was more efficient estimating THI values during daytime than nighttime in both MG and MN. Additionally, the MLP model was more successful estimating the THI values in the Hot class in MG and in the Comfortable class in MN. The extended MLP model (air temperature, relative humidity and actual time of measurement as input parameters) could be applicable to other mountain regions and, in general, in mountain research for the estimation of various meteorological indices.

References

Barry R. J. and R. J. Chorley, 2001. *Atmosphere, weather and climate*. 8 ed., Routledge, Taylor & Francis Group, London, UK, 422 pp.

Bolstad P. V., L. Swift, F. Collins and J. Régnière, 1998. Measured and predicted air temperatures at basin to regional scales in the southern Appalachian mountains. *Agr. Forest Meteorol.* **91**, 161-176.

Chapman L. and J. E. Thornes, 2003. The use of geographical information systems in climatology and meteorology. *Prog. Phys. Geog.* **27**, 313-330.

Chronopoulos K. I., I. X. Tsiros, I. F. Dimopoulos and N. Alvertos, 2008. An application of artificial neural network models to estimate air temperature data in areas with sparse network of meteorological stations. *J. Environ. Sci. Heal.* A **43**, 1752-1757.

Chronopoulou-Sereli A. and I. Chronopoulos, 2011. *Biometeorology-bioclimatology applications to the configuration of outdoor spaces.* Ziti Publications, Thessaloniki, Greece, 238 pp.

Dibike Y. B. and P. Coulibaly, 2006. Temporal neural networks for downscaling climate variability and extremes. *Neural Networks* **19**, 135-144.

Epstein Y. and D. S. Moran, 2006. Thermal comfort and the heat stress indices. *Ind. Health* **44**, 388-398.

Fahlman S. E., 1988. Faster-learning variations on back-propagation: an empirical study. In: *Proceedings of the 1988 Connectionist Models Summer School* (D. Touretzky, G. E. Hinton and T. J. Sejnowski, Eds.). Morgan Kaufmann Publishers, San Mateo, CA, 38-51.

Fausett L., 1994. *Fundamentals of neural networks*. Prentice Hall, New York, USA, 461 pp.

Fletcher R. and M. J. D. Powell, 1963. A rapidly convergent descent method for minimization. *Comput. J.* **6**, 163-168.

Fletcher R. and C. M. Reeves, 1964. Function minimization by conjugate gradients. *Comput. J.* **7**, 149-154.

Friedland A. J., R. L. Boyce, C. B. Vostral and J. T. Herrick, 2003. Winter and early spring microclimate within a mid-elevation conifer forest canopy. *Agr. Forest Meteorol.* **115**, 195-200.

Geiger R., R. H. Aron and P. Todhunter, 2003. *The climate near the ground*. Rowman & Littlefield Publishers Inc., Maryland, USA, 602 pp.

Guan B. T., H. W. Hsu, T.-H. Wey and L.-S. Tsao, 2009. Modelling monthly mean temperatures for the mountain regions of Taiwan by generalized additive models. *Agr. Forest Meteorol.* **149**, 281-290.

Guler M., B. Cemek and H. Gunal, 2007. Assessment of some spatial climatic layers through GIS and statistical analysis techniques in Samsun Turkey. *Meteorol. Appl.* **14**, 163-169.

Jansky L., J. D. Ives, K. Furuyashiki and T. Watanabe, 2002. Global mountain research for sustainable development. *Global Environ. Chang.* **12**, 231-239.

Kamoutsis A., A. Matsoukis, I. Charalampopoulos and A. Chronopoulou-Sereli, 2007. Biometeorological conditions in mountainous communities and adjacent urban center in Greece by the use of indices: The case study of mountainous Nafpaktia district. In: *Developments in Tourism Climatology*, 3rd International Workshop on Climate, Tourism and Recreation, (A. Matzarakis, C. R. de Freitas and D. Scott, Eds.). Commission on Climate, Tourism and Recreation International Society of Biometeorology, Freiburg, Germany, 144-149.

Kamoutsis A., A. Matsoukis, K. Chronopoulos and E. Manoli, 2010. A comparative study of human thermal comfort conditions in two mountainous regions in Greece during summer. *Global Nest J.* **12**, 401-408.

Kapos V., J. Rhind, M. Edwards, M. F. Price and C. Ravilious, 2000. Developing a map of the world's mountain forests. In: *Forests in sustainable mountain development: A state-of-knowledge report for 2000*. (M. F. Price and N. Butt, Eds.) CAB International Publishing, Wallingford, USA, 4-9.

Lin T.-P. and A. Matzarakis, 2008. Tourism climate and thermal comfort in sun Moon, Lake, Taiwan. *Int. J. Biometeorol.* **52**, 281-290.

Liu X., X. Mei, Y. Li, Q. Wang, J. R. Jensen, Y. Zhang and J. R. Porter, 2009. Evaluation of temperature-based global solar radiation models in China. *Agr. Forest Meteorol.* **149**, 1433-1446.

Manoli E., 2008. Investigation of bioclimatic conditions and perspectives of development in Gerania mountains. M. Sc. Thesis. Athens, Greece: Department of Sciences, Agricultural University of Athens, 87 pp.

Matsoukis A., A. Kamoutsis and A. Chronopoulou-Sereli, 2009. Air temperature and thermal comfort conditions in mountainous and urban regions. *Int. J. Sus. Dev. Plann.* **4**, 357-363.

Nieuwolt S., 1977. *Tropical climatology: An Introduction to the climates of the low latitudes*. John Wiley and Sons, Chichester, New York, USA, 207 pp.

Oke T. R., 1999. *Boundary layer climates*. Routledge, Taylor Francis Group, New York, USA, 459 pp.

Ranhao S., Z. Baiping and T. Jing, 2008. A multivariate regression model for predicting precipitation in the Daquing Mountains. *Mt. Res. Dev.* **28**, 318-325.

Rumelhart D. E., G. E. Hinton and R. J. Williams, 1986. Learning representations by back-propagating errors. *Nature* **323**, 533-536.

Shank D. B., G. Hoogenboom and R. W. McClendon, 2008. Dewpoint temperature prediction using artificial neural networks. *J. Appl. Meteor. Climatol.* **47**, 1757-1769.

Smith B. A., G. Hoogenboom and R. W. McClendon, 2009. Artificial neural networks for automated year-round temperature prediction. *Comput. Electron. Agr.* **68**, 52-61.

Snell S. E., S. Gopal and R. K. Kaufmann, 2000. Spatial interpolation of surface air temperatures using artificial neural networks: Evaluating their use for downscaling GCMs. *J. Climate* **13**, 886-895.

Tang Z. and J. Fang, 2006. Temperature variation along the northern and southern slopes of Mt. Taibai, China. *Agr. Forest Meteorol.* **139**, 200-207.

Thom E. C., 1959. The discomfort index. *Weatherwise* **12**, 57-60.

Tolika K., P. Maheras, M. Vafiadis, H. A. Flocas and A. Arseni-Papadimitriou, 2007. Simulation of seasonal precipitation and rain days over Greece: a stastistical downscaling technique based on artificial neural networks (ANNs). *Int. J. Climatol.* **27**, 861-881.

Toy S., S. Yilmaz and H. Yilmaz, 2007. Determination of bioclimatic comfort in three different land uses in the city of Erzurum, Turkey. *Build. Environ.* **42**, 1315-1318.

Ustaoglu B., H. K. Cigizoglu and M. Karaca, 2008. Forecast of daily mean, maximum and minimum temperature time series by the three artificial neural network methods. *Meteorol. Appl.* **15**, 431-455.

Yilmaz S., S. Toy and H. Yilmaz, 2007. Human thermal comfort over three different land surfaces during summer in the city of Erzurum, Turkey. *Atmósfera* **20**, 289-297.