Estimating UV Erythemal Irradiance by Means of Neural Networks

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ABSTRACT

In recent years, there has been a substantial increase in attempts to model the flux of ultraviolet radiation (UV). UV irradiance at surface level is a result of the combined effects of solar zenith angle, surface elevation, cloud cover, aerosol load and optical properties, surface albedo and the vertical profile of ozone. In this study, we present the development of an artificial neural network (ANN) model that can be used to estimate solar UV irradiance on the basis of optical air mass, ozone columnar content, latitude, horizontal visibility data and cloud occurrence data such as type, coverage and height. ANN are widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems. They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, are able to deal with nonlinear problems and, once trained, can perform prediction and generalization at high speed. In this study, a multilayer perceptron network (MLP) consisting of an input layer, an output layer and one hidden layer was used. Training of the neural network was done using the Bayesian regulation back propagation algorithm. The study was developed using data from three stations on the Iberian Peninsula: Madrid and Murcia during the period 2000-2001 and Zaragoza in 2001. To train and validate the MLP neural networks, independent subsets of data were extracted from the complete database at each station. The results suggest that a MLP neural network using optical air mass, ozone columnar content, latitude and total cloud coverage provides the best estimates, with mean bias deviation and root mean square deviation of 0.1% and 18.0%, 1.6% and 19.6%, 0.1% and 14.6% at Madrid, Murcia and Zaragoza, respectively. Despite the dependence of the cloud radiative effect on cloud type, the use of additional information such as cloud type or cloud elevation did not improve these results. The performance of the developed ANN has been checked regarding its ability to estimate the UV index (UVI); results indicate that in more than 95% of the cases, the difference between estimated and measured values does not exceed one unit of UVI.

INTRODUCTION

Depletion of the Earth’s ozone layer is considered responsible for an increase in the solar ultraviolet (UV) irradiance reaching the surface (1). The solar UV irradiance includes wavelength bands from 100 to 280 nm (UV-C), which is completely absorbed in the Earth’s atmosphere, 280-315 nm (UV-B), partially absorbed by stratospheric ozone and 315-400 nm (UV-A), which makes up most of the UV irradiance at the surface. Although in outer space UV-B and UV-A account for about 7.5% of the solar total irradiance, at the surface they typically make up between 3% and 5% of the solar total irradiance (2). Numerous studies have investigated UV-B irradiance during the past two decades because of its harmful effects on biological systems (3-6). For human beings, the effect that has received most attention is the erythema, or sunburn, which is caused by an action spectrum (7) standardized in 1987 by the Commission Internationale de l’Eclairage (8). Using this action spectrum as a weighting factor for the UV radiation, one obtains the UV erythemal irradiance (UVER). Surface UVER is a result of the combined effects of solar zenith angle, surface elevation, cloud cover, aerosol loading and optical properties, surface albedo and vertical profile of ozone. The precise determination of the role of these parameters is quite difficult, and ground-based studies are important to improve our understanding of these effects. The high temporal and spatial variability of cloud cover and especially aerosols is responsible for much of the variability in UVER. In recent years, there has been a substantial increase in attempts to model the UV irradiance.

Unfortunately the cloud and aerosol characteristics determining radiation transfer are seldom known because of a general lack of observations, especially for the aerosols. Modeling the effect of clouds requires knowledge of cloud optical thickness and drop size distributions with high temporal and spatial resolution, information that is limited to specific sites and campaigns. Thus, a different approach, based on commonly accessible data, must be used to model UVER to obtain long time series or extended spatial distributions. This article is devoted to the study of cloud effects on UVER using information routinely registered in most meteorological stations: cloud type and amount, expressed in terms of fractional cloud coverage in octas (eighths), usually recorded every 3 h. This kind of approach has been followed in different studies (9-18). The approach followed in these studies included modeling
DATA AND MEASUREMENTS

The UVER observations, performed within the Spanish UV-B radiometric network, were recorded as half-hour average values. Martinez-Lozano et al. (20) reported a detailed description of this network. Yankee UVB-I radiometers are operated and maintained by the Spanish Meteorological Institute (INM). In the stations selected for this study, simultaneous observations of ozone columnar content were performed using the Brewer instrument operated within the same network at the selected locations. This allowed the use of locally measured ozone together with the cloud observations routinely performed at these stations following the World Meteorological Organization (WMO) guidelines.

The Yankee UVB-I radiometer is a broadband (280–315 nm) Robertson–Berger type radiometer. The spectral response of the instrument is designed to approximate the spectral response of the human skin to UV (8). The maintenance of the calibration constant of the instruments included in the Spanish UV-B radiometric network is described in the study of Martinez et al. (20). The experimental uncertainty of this instrument is about 8.9% (21,22).

Three-hourly observations of cloud type, cover and height were obtained from the INM meteorological stations where the radiometers are installed. In this study, we also used the horizontal visibility data determined by meteorological observers in decameters (dm).

Data were registered at Madrid (40°27′N, 3°44′W, 580 m above sea level [a.s.l.]) and Murcia (38°10′N, 1°10′W, 69 m a.s.l.), during the period 2000–2001, and Zaragoza (41°38′N, 0°55′W, 250 m a.s.l.), during 2001. To avoid instrument deviations from the ideal cosine law, we limited our study to solar elevation angles greater than 10°; in any case, the UVRB values measured for larger zenith angles are relatively small.

ARTIFICIAL NEURAL NETWORKS

The human brain is composed of neurons that provide us with the ability to apply our previous experiences to our actions (23,24). ANN are computing algorithms that mimic the four basic functions of these biological neurons. These functions are to receive inputs from other neurons or sources, combine them, perform operations on the result and output the final result.

According to Haykin (23), a neural network is a massively parallel-distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the human brain in two respects; the knowledge is acquired by the network through a learning process and interneuron connection strengths known as synaptic weights are used to store the knowledge. A rather interesting feature of ANN is the fact that once a network was set up, it can learn in a self-organizing manner that emulates the brain functions such as pattern recognition, classification and optimization (23–26).

An ANN is characterized by its architecture, training or learning algorithm and activation function. The architecture describes the connections between neurons. It consists of an input layer, an output layer and generally, one or more hidden layers in-between as depicted in Fig. 1. This figure shows one of the commonly used networks, namely, the layered feed-forward neural network with one hidden layer. In its simple form, each single neuron is connected to other neurons of a previous layer through adaptable synaptic weights. Knowledge is usually stored as a set of connection weights. Training is the process of modifying the
connection weights in some orderly fashion using a suitable learning method. The network uses a learning mode, in which an input is presented to the network along with the desired output and the weights are adjusted so that the network attempts to produce the desired output. The weights after training contain meaningful information, whereas before training they are random and have no meaning (19).

The layers in these networks are interconnected by communication links that are associated with weights that dictate the effect on the information passing through them. These weights are determined by the learning algorithms, which lead to the categorization of the ANN (25). Thus the fixed-weight ANN do not need any kind of learning. On the other hand, the training of the so-called supervised ANN is based on input data only. This means that the networks learn using experience gained from previous inputs. Finally, supervised ANN use both input and output data in the training process. This form of ANN has greater flexibility and, in fact, is the most commonly used. The multilayer perceptron (MLP) ANN fall in this category in which the weights are updated for every set of input–output data. The neural network software was written using the Neural Network Toolbox of MATLAB 6.0 (27).

Three types of data files are required: a training data file, a test data file and a validation data file. The first and the last should contain representative samples of all cases the network is required to handle, whereas the test file may contain about 10% of the cases contained in the training file. During training, the network is tested against the test file to determine accuracy, and training should be stopped when the mean average error remains unchanged. This is done to avoid overtraining, in which case the network learns perfectly the training patterns but is unable to make predictions when presented an unknown training set.

Whereas the number of input and output neurons is determined by the respective number of input and output parameters of the current application, the choice of the number of hidden layers in-between and their size depends on the task and is made on the basis of experience. When there are too few hidden neurons, the neural network will not be able to solve the learning problem. If there are too many, convergence of the learning algorithm will be slowed or may even be compromised because of local minima. In addition, because of the large number of parameters, there is a risk of overfitting in this case: the neural network can learn too precisely the patterns in the learning set and exhibit mediocre performance on new situations. Concerning nonlinearity, even a neural network with one hidden layer is already able to reproduce any nonlinear functional dependence between the input and target data.

Constructive learning algorithms (28) are being investigated to automatically determine optimal neural network architectures. However, in current applications, the number of intermediate neurons is usually decided heuristically. In this study, the optimal number of hidden neurons is determined empirically as the minimum number of neurons yielding satisfactory predictive performance on a test set, without leading to overfitting or unacceptably long learning times.
Table 1. Statistical results of the validation of each of the developed ANN. We include the results obtained with the ANN on the basis of the complete set of input variables and those obtained with a simplified ANN model that excludes the visibility, VIS, as input variable.

<table>
<thead>
<tr>
<th>Stations</th>
<th>UVER$_{meas}$ mW m$^{-2}$</th>
<th>N</th>
<th>b</th>
<th>$R^2$ (%)</th>
<th>MBD (%)</th>
<th>RMSD (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLP with VIS</td>
<td>Madrid 01</td>
<td>92</td>
<td>1350</td>
<td>0.995 ± 0.002</td>
<td>0.99</td>
<td>-0.1</td>
</tr>
<tr>
<td></td>
<td>Murcia 01</td>
<td>107</td>
<td>976</td>
<td>0.994 ± 0.004</td>
<td>0.95</td>
<td>1.4</td>
</tr>
<tr>
<td></td>
<td>Zaragoza 01</td>
<td>94</td>
<td>532</td>
<td>0.995 ± 0.003</td>
<td>0.99</td>
<td>-0.09</td>
</tr>
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<td>MLP without VIS</td>
<td>Madrid 01</td>
<td>92</td>
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<td>1.5</td>
</tr>
<tr>
<td></td>
<td>Murcia 01</td>
<td>106</td>
<td>981</td>
<td>0.990 ± 0.004</td>
<td>0.95</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>Zaragoza 01</td>
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<td>0.99</td>
<td>-0.05</td>
</tr>
</tbody>
</table>

The selection of training data has a vital role in the performance and convergence of the neural network model. An analysis of historical data for identification of variables that are important to the process is important. Plotting graphs to check whether the charts of the various variables reflect what is known about the process for operating experience and for discovery of errors in data is very helpful. In our case, we have used the previous experience in modeling UVER (18). To select the input variables to the ANN for estimations of UVER, it is interesting to consider that at a specific site, the main factor causing variation of the UV irradiance is variation of solar elevation. Observed daily and yearly variations are dominated by this factor. Total ozone and clouds are of second-order importance for the variation.

**CLOUDLESS CONDITIONS MODEL**

**ANN design**

Because of the great influence of clouds on UVER, we have considered the convenience of developing a set of ANN for cloudless conditions before the development of an ANN for all sky conditions. Thus we have developed a model for the UVER under cloudless conditions. This model, although locally dependent, allows the estimation of cloudless UVER using input data routinely measured in meteorological networks. Thus, as a first step we developed a particular model at each location. The variables considered for this model were the optical air mass, m$_o$, total columnar content of ozone, L, and the horizontal visibility, VIS, a variable measured in meteorological networks that can be considered as a surrogate for the atmospheric aerosol load.

Figure 2 shows the MLP used to estimate UVER under cloudless conditions. It consists of three layers: the input layer that includes three neurons (corresponding to the parameters that influence UVER), the hidden layer that consists of four neurons and, finally, the output layer that consists of a unique neuron corresponding to UVER, the estimated UVER.

The training of the ANN has been done using 80% of the cloudless skies data measured in 2000 (Madrid and Murcia) or 2001 (Zaragoza). The remaining 20% of the data corresponding to the previous data sets has been used as the test data set. These two subsets have been selected using a random process. In fact, these test data sets are used to select among 10 possible ANN obtained after the corresponding trainings at each location. The idea is to select, at each location, the ANN that provides the lowest root mean

Figure 4. Histograms of the differences between measured and estimated UVI, UVI$_{meas}$ - UVI$_{exp}$, for each one of the data set used. A: MLP network developed for Madrid. B: MLP network developed for Murcia. C: MLP network developed for Zaragoza.
square deviation (RMSD) between estimated and measured values corresponding to the test data set. Initial weights used in the ANN training are randomly selected, and circumstances could lead in some cases to a low level of convergence. Thus, the use of the test data allows selection of the best-trained ANN among the 10 obtained.

As mentioned previously, the number of neurons in the input and output layers is dictated by the number of input and output variables. For the hidden layer, we have used an empirical procedure testing different combinations and selecting the one that provides the best results, in terms of convergence and RMSD.

**Validation of the cloudless skies model**

As mentioned above, the design of an ANN requires the use of three data sets, the training and test data sets used in training and selecting the best ANN and the validation data set, which is an independent data set used to characterize the predictive capability of the ANN. In our study, we have used the data sets recorded in 2001 to validate the ANN obtained for Madrid and Murcia. In the case of Zaragoza because of the limitations in the available data set we have used the complete year 2001 as validation data set.

Figure 3 shows the scatter plot of estimated versus measured cloudless values for the three data sets. The performance of the models was evaluated using the RMSD and the mean bias deviation (MBD). These statistics allow for detection of both the differences between experimental data and model estimates and the existence of systematic over- or underestimation. Linear regression between estimated and measured values was also computed. The linear fitting was forced through zero, thus the slope (b) provides information about the relative over- or underestimation associated with the model. Finally, the coefficient of determination ($R^2$) gives an evaluation of the experimental variance explained by the model.

Table 1 shows results of these analyses, including the statistics previously described together with the number of cloudless data included in each data set and UVER$_{avec}$, the cloudless average value for UVER.

The slope of the linear regression between estimated and measured values is close to unity in all cases, thus indicating the goodness of the fit. On the other hand, the variance explained for the models is better than 99% at Zaragoza and Madrid, with slightly worse results for Murcia. It is evident that the local models provide estimates at different places with negligible MBD. It is interesting to note that the RMSD and MBD values obtained with these simple models were of the same order as those obtained in other studies of UVER or UV-B irradiance. Thus, Josefsson and Landelius (17) developed a cloudless empirical model that provided estimates of UVER with a RMSD about 8.7%. On the other hand, Dworin and Steinberger (29) developed a model based on the parametric model proposed by Ibala (30) that provided estimates of UV-B with an MBD of about 6%. Using empirical models developed with the same data sets, Alados-Arboledas et al. (18) have obtained slightly higher MBD and similar RMSD for each of the considered stations, MBD of about −3.0%, 1.9% and 0.2% and RMSD of 10%, 14.8% and 8.4%, for Madrid, Murcia and Zaragoza, respectively.

**Estimation of the UV Index**

For public education on the potentially harmful effects of the UV-B irradiance, an index called UV Index (UVI) has been introduced during the past years. The UVI itself is an irradiance scale computed by multiplying the UVER in W m$^{-2}$ by 40. Thus the clear sky value at sea level in the tropics would normally be in the range 10−12 (250−300 mW m$^{-2}$) and 10 is an exceptionally high value for northern midlatitudes. This scale has been adopted by the WMO and World Health Organization and is in use in many countries. UV intensity is also described in terms of ranges ranging from low values (less than 4) to medium (4−7), high (7−9) and extreme (9+).

To show the performance of the MLP model when used to estimate UVI, Fig. 4 shows the histogram of the differences between UVER$_{exp}$ and UVER$_{est}$, estimated and measured UVI. It is interesting to note that this test shows the reliability of a given model, developed at a given location, when applied at the different locations. In this case, we have used the whole data set available at each location. Thus, the percentage of cases with a maximum deviation of one unit of UVI, by under- or overestimation,
CLOUDY CONDITION MODEL

ANN design

There are various studies addressing the estimation of cloud effects on solar UV irradiance as a function of either the observed cloud amount (11,13–15,18,31–34), the cloud effect on other spectral

Figure 6. Scatter plot of estimated versus measured UVER using the ANN models developed at each location for cloudy conditions.

Figure 7. Histograms of the differences between measured and estimated UVI, $UVI_m - UVI_{exp}$, for each one of the data set used. A: MLP network Type I with VIS developed for Madrid. B: MLP network Type I with VIS developed for Murcia. C: MLP network Type I with VIS developed for Zaragoza.
ranges of solar irradiance (35–37) or a combination of the two (38). One other study (39) used additional information on the cloud field obtained by sky cameras.

In our study, we approach the estimation by training an MLP ANN with architecture similar to that used in the cloudless model previously described. Therefore, we included the parameters used in the cloudless skies approach and a set of additional input parameters describing clouds. Three different approaches have been considered by including various input data routinely obtained from meteorological stations. MLP Type I uses a single input variable, the total cloud amount in octas, (c). MLP Type II uses as input variables the amount of low-, medium- and high-level clouds, cL, cM, cH, together with the altitude of the lowest layer, H1. Finally, MLP Type III uses the same input variables used in Type II but excluding the altitude of the lowest layer.

Figure 5 shows the scheme of the MLP network used in this case. The number of input neurons depends on the type of cloud information used as input. For the hidden layer, we have selected five neurons following an empirical procedure as in the case of the cloudless model. For the training and test data sets we have followed a procedure similar to the one followed with the cloudless model but including all cloudy sky cases.

Validation of the ANN developed for all sky conditions

Table 2 shows the results obtained for the ANN models developed for all sky conditions, including cloudless and cloudy conditions, at each station. In a similar manner to the one followed in the validation of the cloudless models, we have used the data measured in 2001 at each station. It is evident that the three types of models used for cloudy conditions provide similar results. The MBD values are rather low, whereas the associated RMSD are slightly greater than those obtained for cloudless conditions. This suggests that the cloud information retrieved routinely by meteorological observers do not provide enough information to fully describe the radiative effect of clouds (18).

The results shown correspond to those obtained using visibility, VIS, as one of the input parameters. But it is important to note that the use of a simplified model excluding this input variable provides results similar to those shown in Table 2. On the other hand, it is evident that the model with the simplest information concerning cloud cover, model Type I, provides results similar to those obtained using the most complete information, Type II.

Figure 6 shows the scatter plots of estimated versus measured values for the ANN models Type I developed at each location. It is evident that scatter is distributed symmetrically and centered along the 1:1 line but with higher variability than that shown in Fig. 2 for the cloudless models.

Estimation of the UVI

Figure 7 shows the performance of the ANN (Model Type I) trained to estimate UVEx under cloudy conditions when used to estimate the UVI. In each case, we have tested the performance of the model developed at a given location versus all available data sets. Despite the differences, all the models present similar results, thus the number of cases with deviation between UVI measured and UVI estimated greater than one unit of UVI is lower than 8%. These results are slightly worse than those obtained under cloudless conditions but it is interesting to note that the model used at any one location can be used within an acceptable confidence interval for different locations.

CONCLUSIONS

Design and analysis of ANN models based on MLP for the estimation of UVEx, both for cloudless and cloudy conditions, demonstrate the feasibility of this tool for estimating UVEx. The mean bias deviation (MBD) obtained with the models is close to zero, under cloudless and cloudy conditions. On the other hand, the RMSD increases under cloudy conditions as a result of the higher complexity of cloud effects on this radiative flux, together with difficulties associated in the retrieval of appropriate information on the cloud field. To solve this last problem, new methods to observe the cloud field in a more objective manner than that followed by human observers are under development. In particular, a study under development includes the use of a sky camera alongside with the UV-B instrumentation to register the sky conditions with higher frequency. This system could offer additional information on the cloud field by means of image processing techniques applied to the whole sky images.

Our results show that this kind of model can estimate the UVEx with great accuracy; only for 8% of the cases did the difference between estimated and measured values exceed one unit of UVEx.

We consider that this study developed during a 2 year period at two of the selected places provides appropriate variability in cloud conditions together with statistical validity. However, the limited frequency of cloud cover used in this study represents a limitation to study certain aspects of such estimation models, including sun elevation and cloud type dependence.

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