Applications of Statistical Models and Artificial Neural Networks to Investigate Thermals in Turkey

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Abstract

This paper presents some applications of statistical models and artificial neural networks (ANN) to investigate thermals for two gliding regions in Turkey. ANN was used for modeling and prediction of favorable dry and wet thermal conditions. Long-term monthly, seasonal and annual averages of meteorological data (air temperature, solar radiation and sunshine duration) were used, in part, to 'teach' the ANN model. The ANN model exhibited skill with one-month-in-advance predictions; longer-range predictions were not attempted. By considering climate-change scenarios, predictions were made of these variables for the year of 2025.

Introduction

Daily programs during a gliding season are based on convection potential in the flight area. Vertical velocity, air temperature, wetness, vegetation cover, daily heating rate, incoming solar radiation, sunshine duration, instability condition and heat fluxes have a key role on prediction of flight lengths. Solar estimation methods have been successfully applied to seven climatologically different stations in Turkey.[1]

Artificial neural networks (ANNs) are systems of weight vectors, whose component values are established through various machine-learning algorithms. The algorithms take, as input, a linear set of patterns and produce, as output, a numerical pattern representing the actual output. ANNs mimic, somewhat, the learning process of the human brain. Instead of complex rules and mathematical routines, ANNs are able to 'learn' key information patterns within a multi-information domain. In addition, inherently noisy data do not present a problem, as ANNs are tolerant to noise variations. ANNs have been used in many engineering applications such as in control systems, in classification and in modeling complex process transformations. The advantages of ANN compared to classical methods are speed, simplicity and the capacity to learn from examples.[2, 3] In the last decade, some works about the use of ANN in solar data have been published.[4, 5, 6] This technique can be used in the modeling of complex physical phenomena.

The main aim of this study is to analyze temporal and spatial variations of air temperature, solar radiation, sunshine duration and climate changing effects on soaring conditions in Turkey.

Material and methods

Study area and data

The main training and experience flights of gliding schools are organized in the Central Anatolia and the Mediterranean Region in Turkey (Fig. 1). For this reason, two study areas and representative data sets recorded in two climatological stations (Eskişehir, Central Anatolia and Isparta, Mediterranean Region) are considered. Monthly and seasonal averages of air temperature (T), incoming solar radiation (SR) and sunshine duration (SD) between 1975 and 2009 in Eskişehir (39° 30' N, 30° 31' E, h = 800m above msl) and Isparta (37°46' N, 30°33' E, h = 997m above msl) are analyzed (Fig. 1). The long-term data also are analyzed for the interval between 1901 and 2001.[7a, 7b]

The Intergovernmental Panel on Climate Change (IPCC) climate scenarios of air temperature values for 2025 and seasonal variations of the North Atlantic Oscillations (NAO) are interpreted together with temporal and spatial variations of our data.

Methods

Statistical analyses of temporal and spatial variations of variables are analyzed by using SPSS and EXCEL packet programs. The MATLAB tool for ANN analyses are used to simulate meteorological data.

Measures-of-Position: Z-Score

The z-score indicates how far and in what direction a variable deviates from its distribution's mean, expressed in units of its distribution's standard deviation[8]. The Z-score method used is simply the standardization of a given monthly or seasonal value of the given parameter's time series X_j, such as X_1, X_2, … X_n. The standardized annual average air temperature (SMT), solar radiation (SSR) and sunshine duration (SSD) series, X_i is defined as;

$$\text{z-score} = (X_i - \mu)\,/\sigma \qquad (1)$$

where μ and σ values are long-term average and standard deviation of air temperature, solar radiation and sunshine duration for the two study areas between 1975 and 2006.

The standard score, or Z-score, is the number of standard deviations that a given value x is above or below the mean.[8] Z-scores are analyzed to define monthly and seasonal trends of variables.

Artificial Neural Network, basic structure and properties

Artificial neural networks differ from traditional modeling approaches; they are 'trained' to learn solutions rather than programmed to model a specific problem. They are usually used with problems that are intractable with traditional methods. They can 'learn' from examples, are fault tolerant in that they handle noisy and incomplete data, are able to deal with non-linear problems and, once 'trained', can perform predictions at high speed.

Neural networks are composed of simple elements operating in parallel (Fig. 2). These elements were inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. A neural network can be 'trained' to perform a particular function by adjusting the values of the connections (weights) between the elements. Commonly, neural networks are adjusted so that a particular input leads to a specific target output.

Here, the network was adjusted, based on a comparison of the output and the target, until the network output matched the target. Typically, many such input/target output pairs are used to 'train' a network. Batch training of a network proceeds by making weight and bias changes based on an entire set (batch) of input vectors. Incremental training changes the weights and biases of a network as needed after presentation of each individual input vector. Incremental training is sometimes referred to as "on line" or "adaptive" training.[3, 9, 10] Equations (2) and (3) describe input, hidden and output elements:

$$o_i^l\Big|_{i=1}^{K} = f^{\,l}\left\{\sum_{j=1}^{M} w_{ij}^l . o_j^l + b_i^l\right\}\Bigg|_{i=1}^{K} \qquad (2)$$

$$x_i^l\Big|_{i=1}^{K} = \left\{\sum_{j=1}^{M} w_{ij}^l . o_j^l + b_i^l\right\}\Bigg|_{i=1}^{K} \qquad (3)$$

where;

*p*j : jth input to the Neural Network,
*ol*i : ith output of the *l*th layer,
*bl*i : ith neuron's bias of the *l*th layer,
*wl*ij : weight from neuron j of the *l-1*th layer to neuron i in the *l*th layer,
f l : nonlinearity or activation function or the transfer function of the *l*th layer,
*xl*i : sum of the weighted inputs or net output of neuron i of *l*th layer,
K : Number of neurons in layer *l*,
M : Number of neurons in layer *l-1.*

There are different learning algorithms that can be applied to train a neural network. The most popular is the back-propagation algorithm. Standard back-propagation is a gradient descent algorithm. The best algorithm is usually chosen by trial and error. For the training of the ANN, the Levenberg-Marquardt (LM) feed-forward, back-propagation algorithm and log-sig activation function were used. In the feed-forward algorithm, the units were arranged as layers and the output data of a unit were transported to the next layer as inputs over the weights. The input layer transported the data with no change to units of hidden layers. Data processing was performed in hidden-and-output layer which formed the network output. With this structure, feed-forward networks carry out a non-linear static function. Feed-forward ANNs are trained with the back-propagation algorithm.[11]

This paper contains some information about ANN applications on seasonal variations of sunshine duration, solar radiation and air temperature values.

Analyses

Air temperature variations

Air temperature (especially maximum air temperature) is one of the important indicators of thermal quality in dry conditions. Increasing air temperature is associated with increasing surface temperature by conduction. When air temperature increases sufficiently, thermals and dry convection are produced. Analyses of air temperature with cloudiness, humidity and land surface characteristics, like vegetation cover, presents a more complete explanation of thermal strength. In the present paper, influences of vegetation cover, humidity and vertical temperature profiles (instability) on thermals have been neglected.

Based on temporal variations of air temperature, slightly increasing trends occurred in annual air temperature values at Isparta, and Eskişehir as seen in Fig. 3. These linear relationships are significant with n = 101, r = 0,42 and α = 0,01. The annual trend of temperature in Eskişehir is approximately equal to the trend detected at Isparta.

Solar radiation

Annual solar radiation values for each season between 1975 and 2009 are shown in Figs. 4 (a) and 4 (b). In general, decreasing trends have been observed at Eskişehir and Isparta in recent years with α values between 0,01 and 0,06.

Figures 5 (a) and 5 (b) show annual Z-score values (measure of position) of solar radiation at Eskişehir and Isparta between 1975 and 2009. In general, linear trends are opposite to each other at the two stations. There is a decreasing trend in solar radiation at Eskişehir and an increasing trend at Isparta with $\alpha = 0,06$.

Sunshine duration

Figure 6 shows annual sunshine duration in the study areas. Temporal variations are similar in spring and summer at both stations.

The increasing trend of Z-score values of sunshine duration at Eskişehir is higher than the same trend observed at Isparta (Fig. 7) with $0,05 < \alpha < 0,06$.

The negative linear relation between solar radiation and sunshine duration values at Eskişehir is unexpected (Fig. 8). A reason for the negative relation between solar radiation and sunshine duration recorded at Eskişehir may be associated with higher concentration of scattering particles (such as dust and smoke) and other local factors. This reason should be analyzed in detail.

Analysis of NAO and comparison with temporal variations

The North Atlantic Oscillation (NAO) is a climatic phenomenon in the North Atlantic Ocean of fluctuations in the difference of atmospheric pressure at sea level between the Iceland Low and the Azores High. It controls the strength and direction of westerly winds and storm tracks across the North Atlantic.[12]

The polynomial approximation of temporal NAO values is shown in Fig. 9 (degrees of freedom = 56). In recent years, negative NAO values have been observed.

Figures 10 (a) and 10 (b) present linear relationships between NAO and air temperature values at Eskişehir and Isparta. Increasing (positive) NAO values are accompanied by decreasing annual average air temperature values. Further, positive correlations between NAO and solar radiation are evident in spring, summer and winter. But, there is a negative relationship between the two variables in autumn. By considering the periodicity of NAO fluctuations, higher temperature values are expected at the two study areas in future years.

Climate scenarios

The Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) was examined for the top-of-atmosphere radiation changes as carbon dioxide and other greenhouse gases built up between 1950 to the present and the expected buildup to 2100. Through the first period, there was an increase in net radiation absorbed and this tendency is expected during the second period, as well.

The Earth's climate is strongly affected by the reflection, absorption and transmission of solar radiation by the atmosphere.[12-17] Climate models have been used with future scenarios of forcing agents (e.g., greenhouse gases and aerosols) to make a suite of projected climates. The different forcings of the four IPCC scenarios are reflected in different model surface temperature responses. For example, the constant 20th century forcing shows the least increase in future surface temperature, the B1 and A1B scenarios displays moderate increases and the A2 scenario results in the largest response. After the year 2100, the B1 and A1B scenarios were extended another 100 years with the forcings fixed at year 2100 values.[18] The A2 storyline and scenario family describes a heterogeneous world. While there is a large increase in the greenhouse effect from increasing greenhouse gases and water vapor (as a feedback), this is offset to a large degree by a decreasing greenhouse effect from reducing cloud cover and increasing radiative emissions from higher temperatures.[13, 14]

Figures 11 (a) and (b) show expected climate changing effects on air temperature values at Isparta for four different A2 scenarios. The estimated air temperature values are 1-4^{o}C higher than current values. Average annual air temperature changes present increasing trends up to 2025 under A2 scenarios in the two study areas. Correspondingly, it is estimated that incoming solar radiation and sunshine duration will increase as well.

Analyses of ANN

The ANN method was applied to forecast incoming solar radiation (SR) and sunshine duration (SD) values in the study areas. Forecasts of the two variables using MATLAB were made for one month in advance. Eighty-percent of the data was used for running the ANN. Scatter diagrams of the forecast and observed solar radiation values at the two stations are shown in Figs. 12 (a) and 12 (b). The fitted lines have slopes close to 45° passing through the origin illustrating the excellent correlation between the predicted and measured values.

Figures 13 (a) and 13 (b) present a one-month-ahead forecast versus observed sunshine duration values with linear fit lines. Twenty-percent of the data was used for testing the ANN method. The results are shown in Figs. 12 and 13 where $n = 84$, $0,94 < r < 0,97$. It can be seen that the forecasted and observed values have excellent correlations with the confidence level $\alpha = 0.01$.

Results and conclusions

Long-term data (1950-2006) shows a negative relationship between annual average air temperature and NAO variations in study areas: in general, increasing positive NAO values corresponded to decreasing temperatures. These results suggest the following effects on soaring conditions over the study areas assuming the NAO values continue to decrease in the next decade: increasing average air temperature values leading to better thermals.

Incoming solar radiation and NAO relationships are positive in spring, summer and winter. There is a negative relationship between the two parameters in autumn. In the next decade, decreasing values of NAO indexes are expected. Thus, this trend in NAO is expected to be accompanied by the decreasing trends of solar radiation in spring, summer and winter but an increasing trend in autumn.

According to the results of the correlation analysis, there is a positive linear relation between sunshine duration and NAO indices in Mediterranean (Isparta) and Central Anatolia (Eskişehir) areas in spring and winter. In summer and autumn this relation is negative. In the next decade decreasing values of NAO indexes are expected, hence these trends would be accompanied by increasing values of sunshine duration in summer and autumn.

In this paper, ANN was successfully applied to predict, one month in advance, solar radiation and sunshine duration values at Isparta and Eskişehir. The R^2-value for the predicted-vs-observed solar radiation and sunshine duration is greater than 0,89 which shows the sufficient evidence of this relation with $\alpha = 0.05$. The models 'learned' the shape of the inherent nonlinearities and the system reached the correct operating point. Errors using these models are well within acceptable limits. This suggests that ANN can be used for modeling in this field.

Specific expectations from this study are:

- Larger values of maximum surface air temperatures are expected to produce improved thermals if the surface dew-point temperatures and vertical distribution of temperatures remain constant.[16] Accordingly, the trend of dew-point temperatures corresponding to the air temperatures in Fig. 3a was found to be almost zero; the monthly average range and standard deviation were quite low, $1,2^{o}C$ and $0,3^{o}C$, respectively. Thus, the expected larger surface air temperatures should be associated with deeper convective boundary layers.
- Practical significance of the results for gliding activities are:

i) Increasing sunshine duration in both study areas,

ii) Most of the training activities of Turkish Air League have been carried in Eskişehir. The expected increasing trend of sunshine duration at both locations would positively effect flight duration.

iii) From the point of view of the organization of dry thermals, the better flying conditions are expected at Isparta rather than Eskişehir based on the future scenarios.

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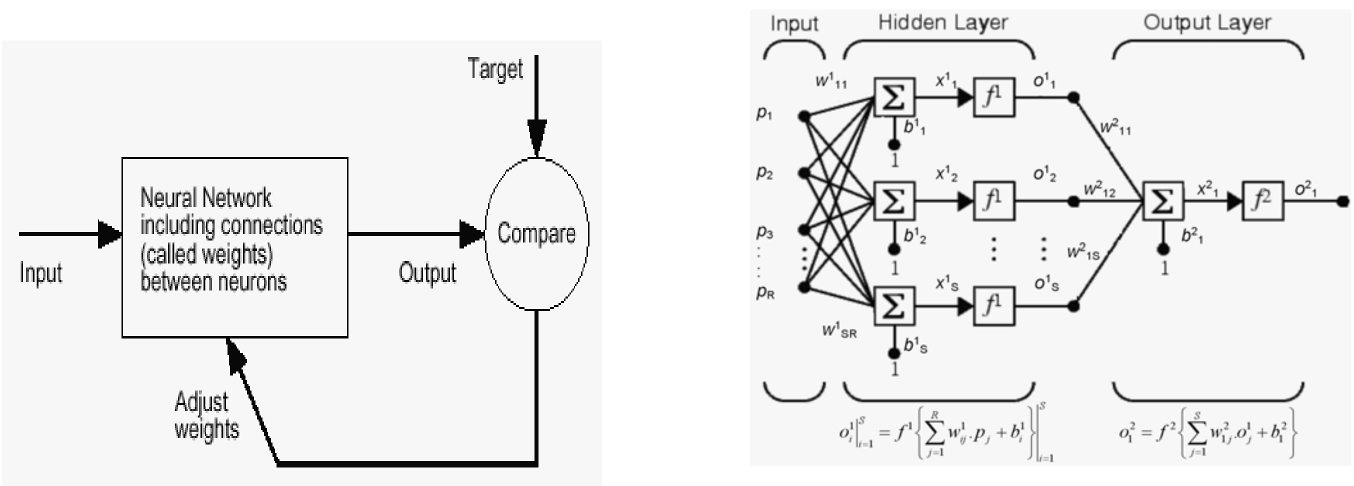
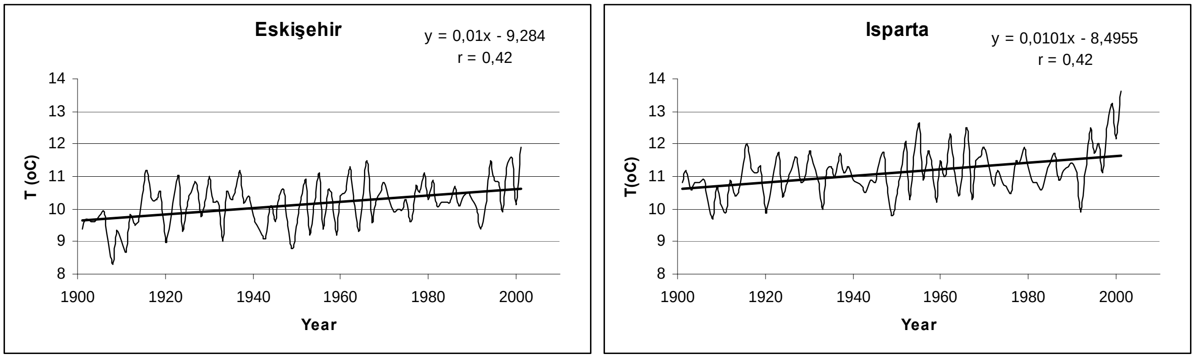
[18]IPCC Fourth Assessment Report: Climate Change, 2007

Figure 1 The locations of the stations (two study areas) in Turkey



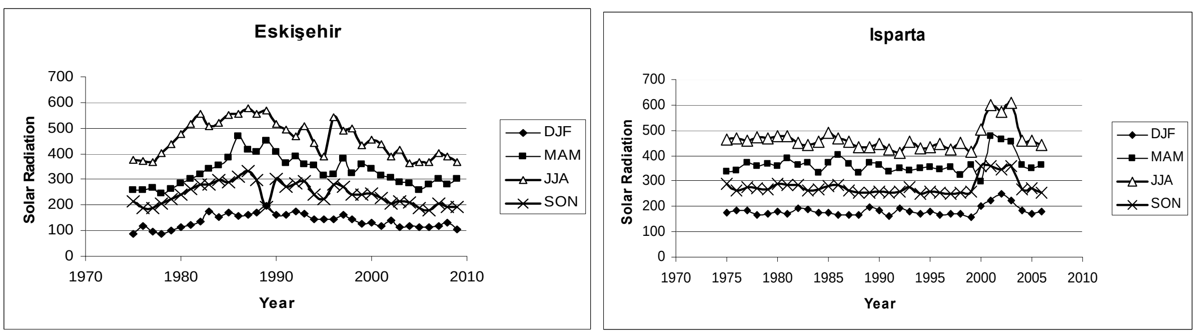
(a) (b)

Figure 2 Basic structure (a) and properties of ANN (b)[3]



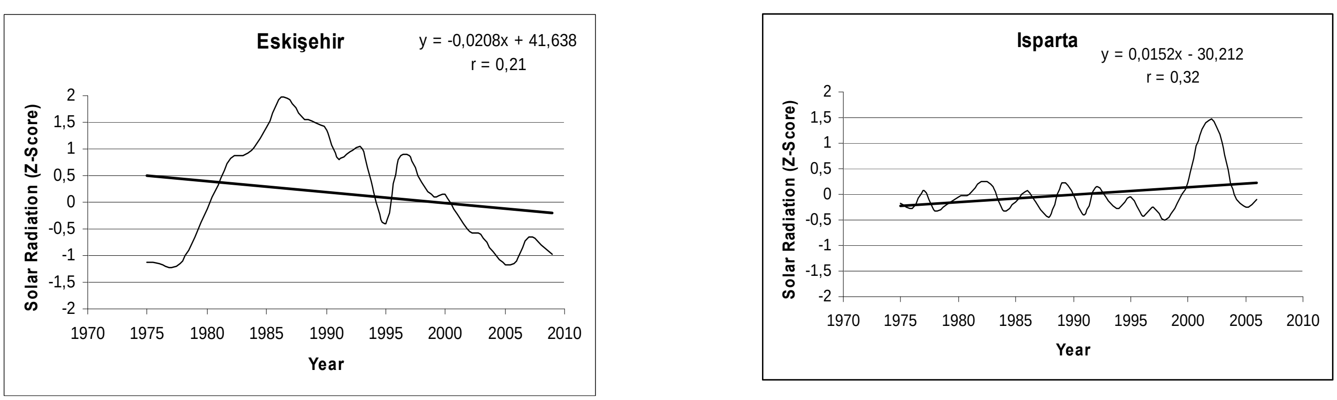
(a) (b)

Figure 3 Annual air temperature at Eskişehir (a) and at Isparta (b) between 1901 and 2001, (α = 0,01)



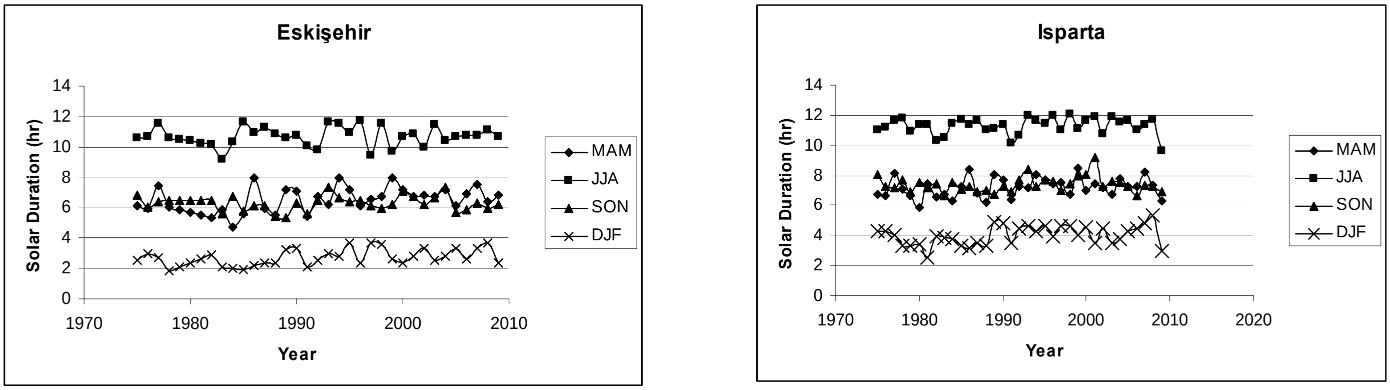
(a) (b)

Figure 4 Seasonal averages of solar radiation (cal/cm^2) at Eskişehir (a) and at Isparta (b), (1975-2006)



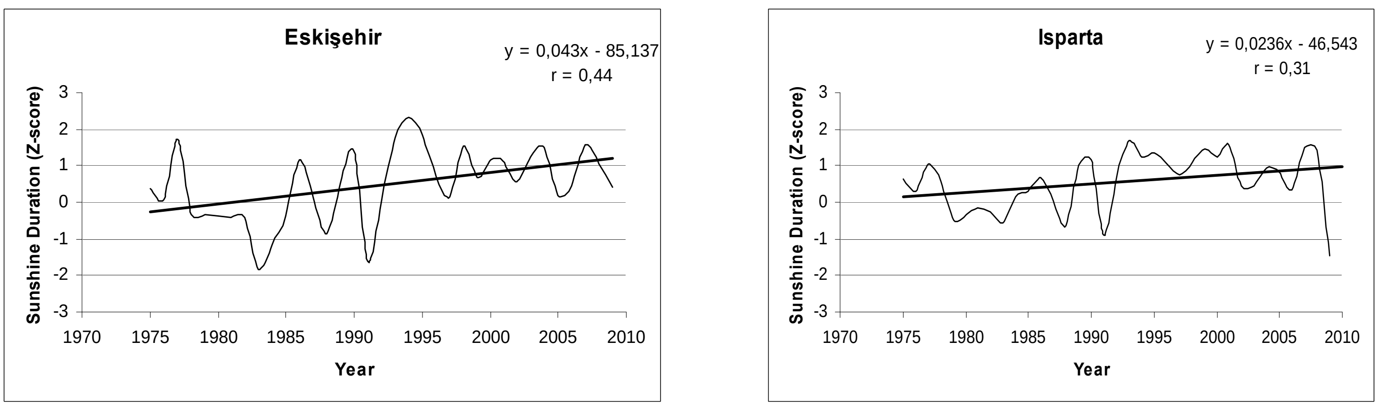
(a) (b)

Figure 5 Annual z-scores of solar radiation (cal/cm^2) at Eskişehir (a) and at Isparta (b), (α = 0,06)



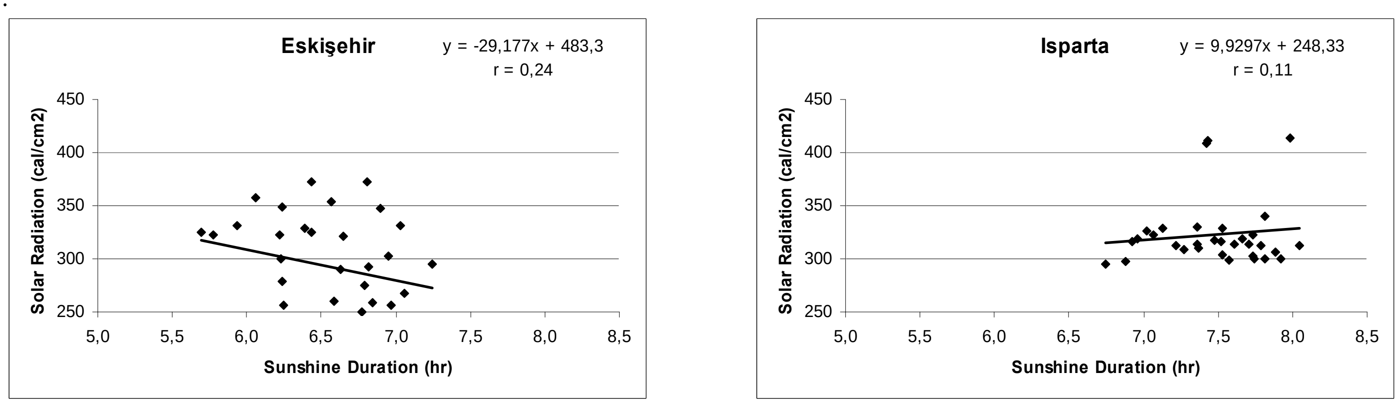
(a) (b)

Figure 6 Annual sunshine duration (hr) at Eskişehir (a) and at Isparta (b)



(a) (b)

Figure 7 Annual Z-Score variations of sunshine duration (hr) at (a) Eskişehir, (α = 0,05) and at (b) Isparta, (α = 0,06)



(a) (b)

Figure 8 Solar radiation (cal/cm^2) and sunshine duration (hr) at (a) Eskişehir, (α = 0,07) and at (b) Isparta, (α = 0,15)

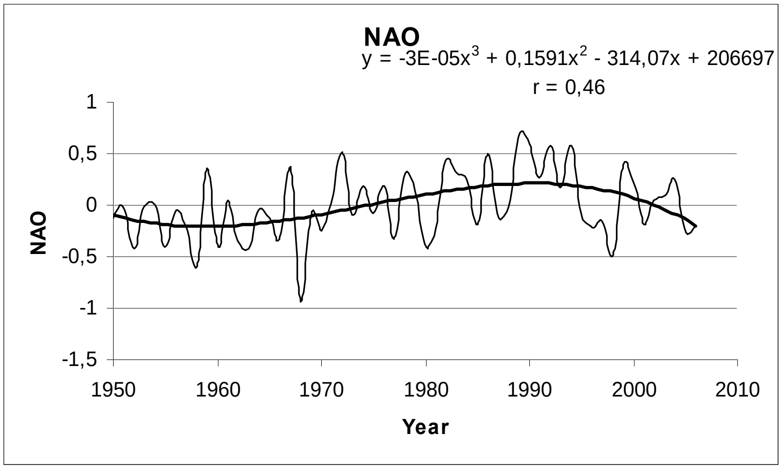
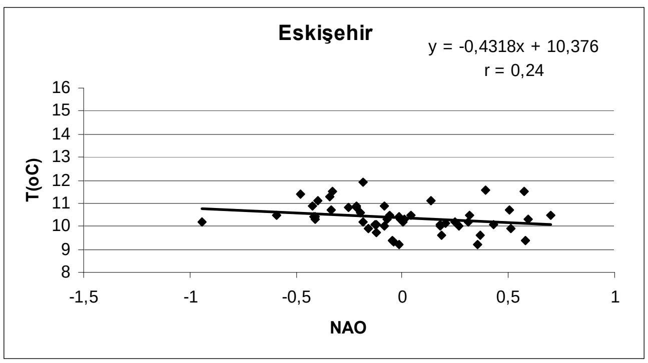
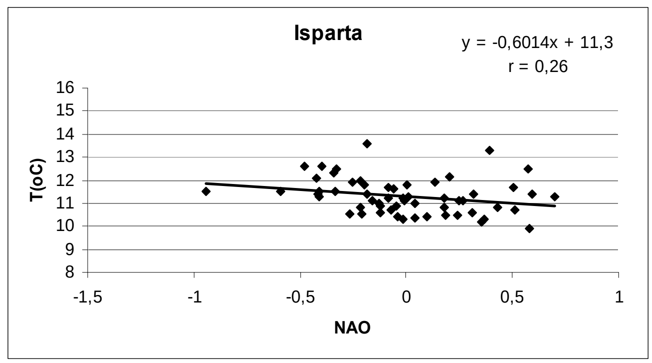


Figure 9 Actual NAO values and polynomial approximation of NAO

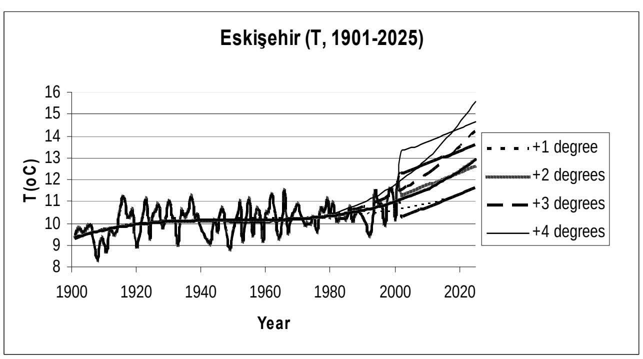


(a)

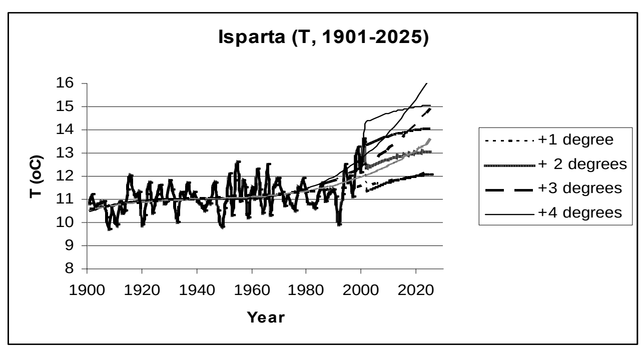


(b)

Figure 10 Linear relation between NAO and air temperature values at (a) Eskişehir and (b) Isparta, (α = 0,05)

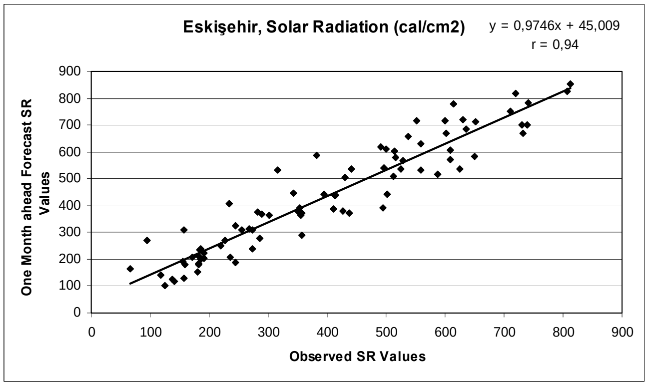


(a)

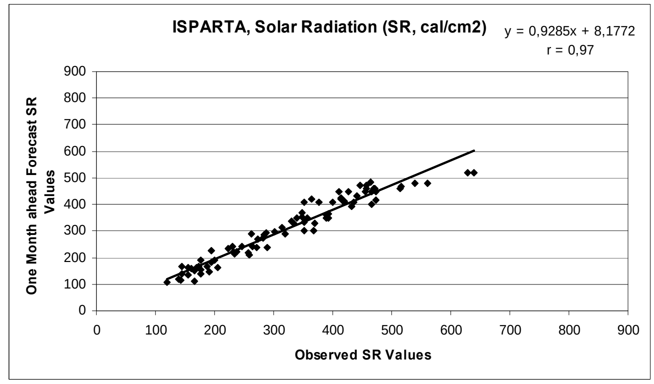


(b)

Figure 11 Climate scenarios for air temperature values at Eskişehir (a) and at Isparta (b)

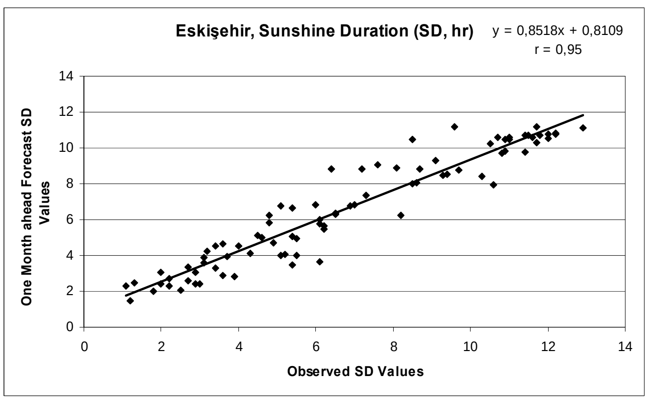


(a)

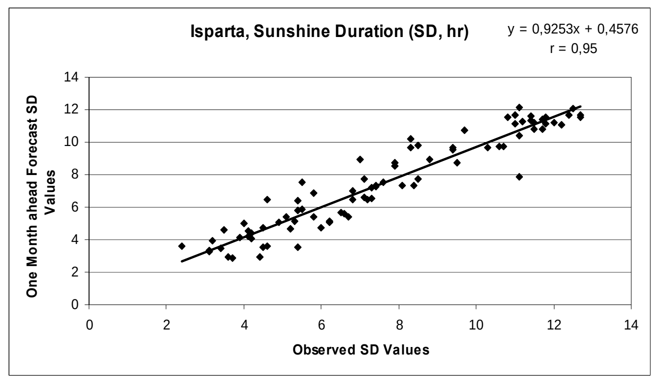


(b)

Figure 12 Forecast and observed solar radiation values with the linear fit at Eskişehir (a) and at Isparta (b), (α = 0,01)



(a)



(b)

Figure 13 Forecast and observed sunshine duration values with the linear fit at Eskişehir (a) and at Isparta (b), (α = 0,01)