Applications of Statistical Models and ANN to Define Onset and Organization of Thermals

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- Introduction
- Description of Study Area and Data
  - Study Area
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- Methods
  - Z Scores, Statistical Methods
  - Artificial Neural Network, Basic Structure
- Analysis
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Introduction

Daily programs of gliding activities are based on **convection potential** in 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.

Artificial neural networks **(ANNs)** are systems of weight vectors, whose component values are established through various machine-learning algorithms, which take as input a linear set of pattern inputs and produce as output a numerical pattern representing the actual output. ANNs mimic somewhat the learning process of a human brain. Instead of complex rules and mathematical routines ANNs are able to learn key information patterns within a multi-information domain. 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 capacity** to learn from examples, (Sırdaş, S. and A. D. Şahin,Tokgozlu, A., A. Şencan and Z. Aslan - Tulunay, E., T. Senalp, Y. Tulunay and Z. Aslan). In the last decade, some works about the use of ANN in solar data have been published, (Chouai, A.,S. Laugier., and D. Richon - Bechtler, H., M.W.Browne, P.K. Bansal., and V. Kecman - Pacheco-Vega, A., M. Sen, K. T. Yang., and R. L. Mc. Clain). 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 .

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Study Area

The main training and experience flights of gliding school are organized in Central Anatolia and 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 in this paper.

- Eskişehir ((39° 30' N, 30° 31' E, h=800m above msl)

- Isparta (37°46' N, 30°33' E, h = 997m above msl)

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

Data

- Monthly and seasonal averages of air temperature (T),
- Incoming solar radiation (SR),
- Sunshine duration (SD)

between **1975 and 2009**.

Re-analyzed data is also analyzed for the interval between **1901 and 2001**, (New, M.G., Hulme, M., and Jones, P.D; New, M.G., Hulme, M., and Jones, P.D).

IPCC climate scenarios of air temperature values for **2025** and seasonal variations of North Atlantic Oscillations **(NAO)** are interpreted together with temporal and spatial variations of data.

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Methods

Statistical analyses of temporal and spatial variations of variables are analyzed by using **SPSS and EXCEL** packet programs. **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 that variable deviates from its distribution's mean, expressed in units of its distribution's standard deviation. 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 monthly air Temperature **(SMT),** seasonal average of sun radiation **(SSR)** and sunshine duration (SSD) series, x_j is defined as;

$$Z\text{-score} = x_i = (X_i - \bar{X})/S_x \qquad (1)$$

The standard score, or Z-score, is the number of standard deviations that a given value x is above or below the mean, (TRIOLA, M. F). Z-scores are analyzed to define monthly and seasonal trends of variables.

Artificial Neural Network, Basic Structure and Properties

- Artificial neural networks differ from the **traditional modeling** approaches in that they are trained to learn solutions rather than being programmed to model a specific problem in the normal way.

- They are usually used to address problems that are **intractable** to solve with traditional methods.

- 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 non-linear problems, and once trained can perform predictions at very high speed.

Artificial Neural Network, Basic Structure and Properties

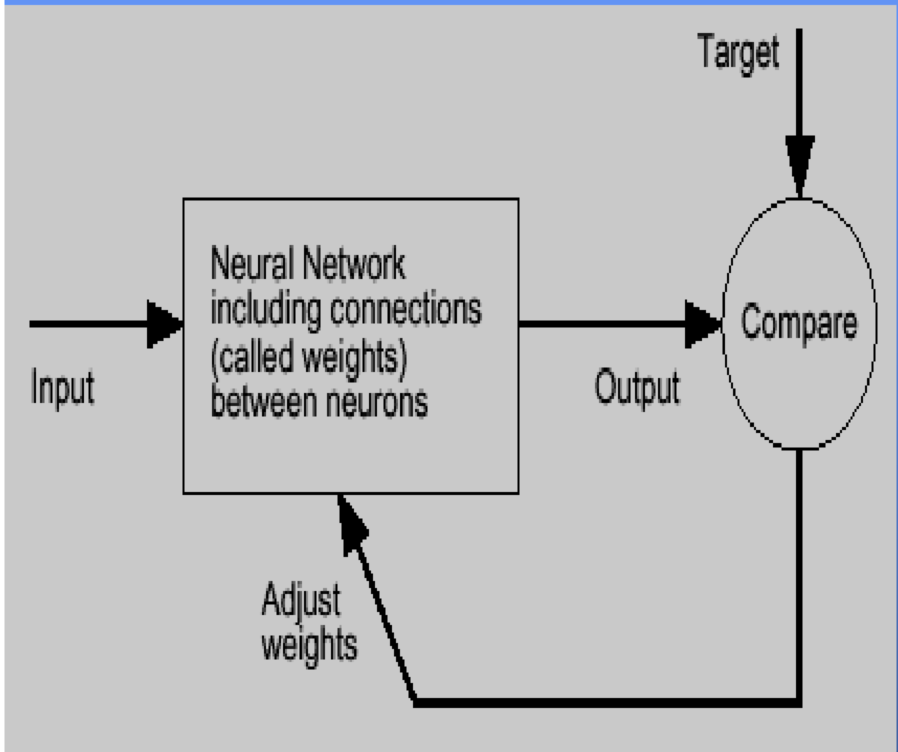

Figure 2- Basic structure(a)

Neural networks are composed of simple elements operating in parallel, (Fig. 2-a). These elements are 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, or trained,** so that a particular input leads to a specific target output. Here, the network is adjusted, based on a comparison of the output and the target, until the network output matches 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,(Tulunay, E., T. Senalp, Y. Tulunay and Z. Aslan - Fu, L.M. - Tsoukalas, L.H., and R. E. Uhrig).

Artificial Neural Network, Basic Structure and Properties

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

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

where;

p_j : j^{th} input to the Neural Network,

o_{li} : i^{th} output of the l^{th} layer,

b_{li} : i^{th} neuron's bias of the l^{th} layer,

w^l_{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,

x_{li} : 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

Artificial Neural Network, Basic Structure and Properties

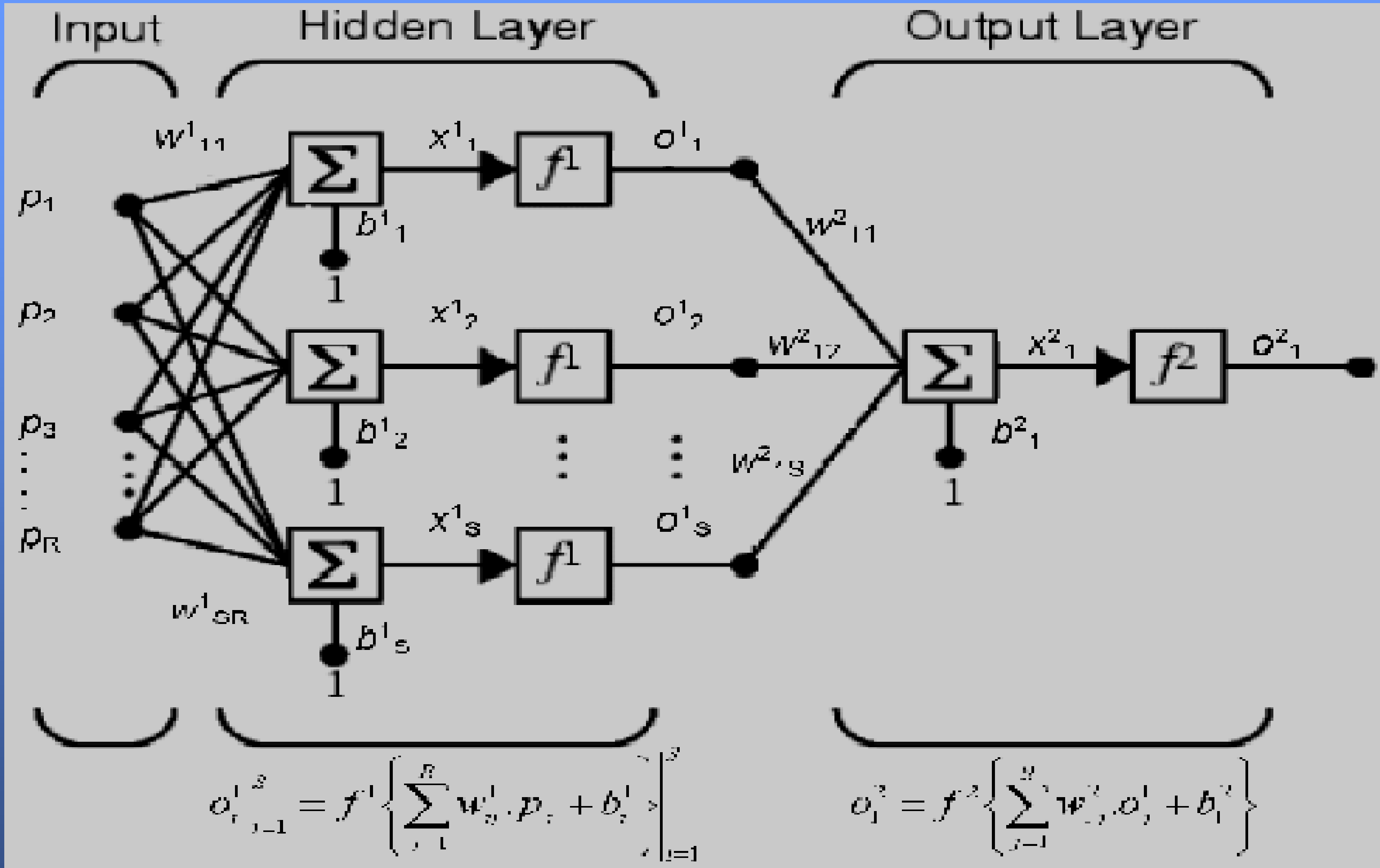

Figure 2- Properties of ANN (b)

Artificial Neural Network, Basic Structure and Properties

There are **different learning algorithms** that can be applied to train a neural network. The most popular of them 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, **Levenberg-Marquardt (LM)** feed forward back propagation algorithm and log-sig activation function was used.

In feed forward algorithm, the units are arranged as layers and **the output data** of a unit are transported to the next layer as inputs over the weights. The input layer transports the data with no change to units of hidden layers. Data processing is performed in hidden and output layer forming the network output. With this structure feed forward networks carry out a non-linear static function. Feed forward ANNs are trained with back propagation algorithm, (Lin, C.T., and C.S.G. Lee).

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

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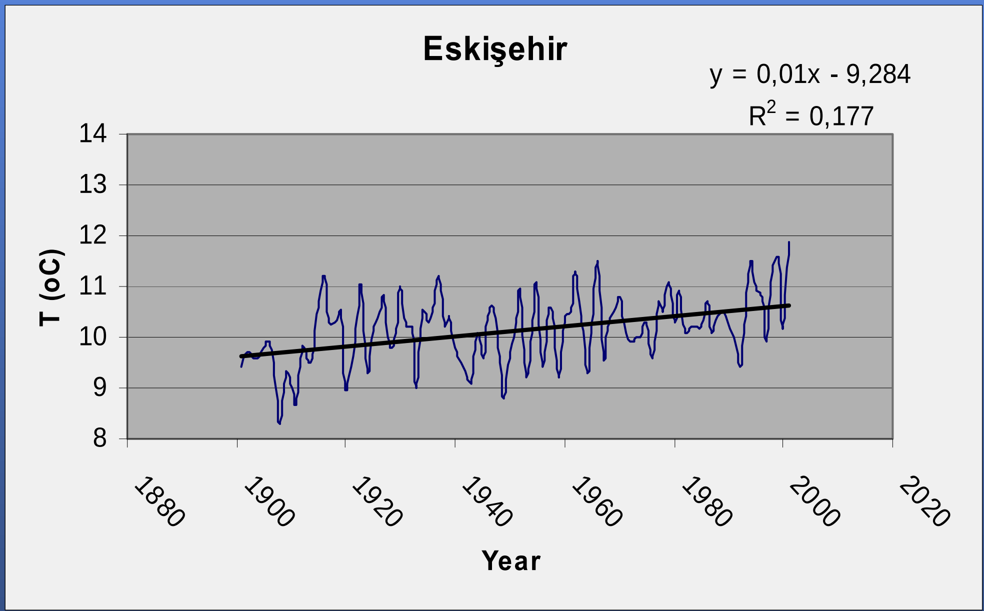
Analysis

Analyses of Air Temperature Variations

Slightly increasing trends have been observed in annual variations of air **temperature** values in **Isparta, and Eskişehir**, (Fig. 3). Annual trend of temperature variation in Eskişehir is approximately equal to the trend value observed in Isparta. Increasing air temperature values are associated with increasing insulation and soil temperature which have been **trigged earlier organizations of thermals** in atmospheric boundary layer.



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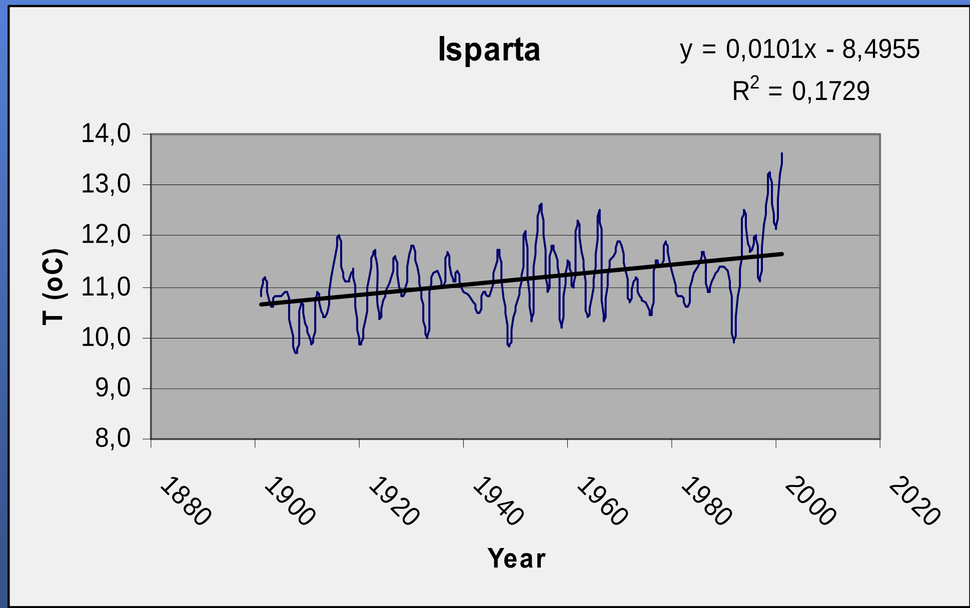
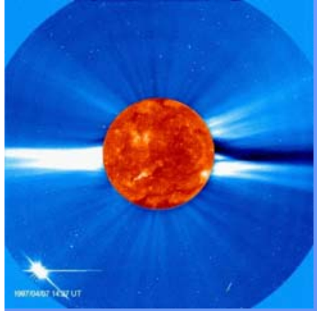


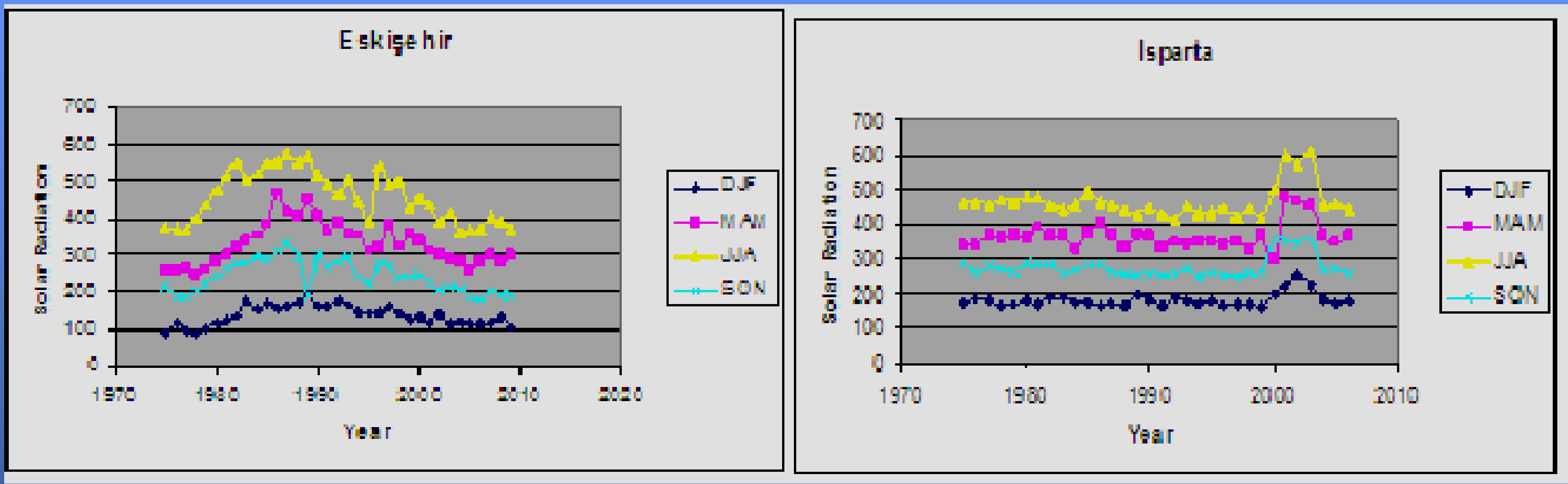
b

Figure 3- Annual variation of air temperature in Eskişehir (a) and in Isparta (1975-2009)



Analyses of Solar Radiation

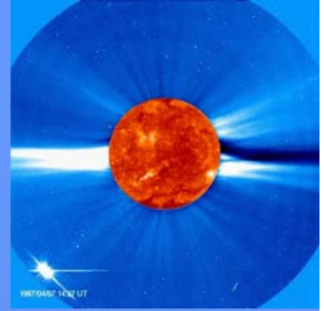
Annual variations of **solar radiation** values for each seasons between 1975 and 2009 are shown in Fig. 4. In general, **decreasing trends** have been observed in Eskişehir and Isparta in recent years .



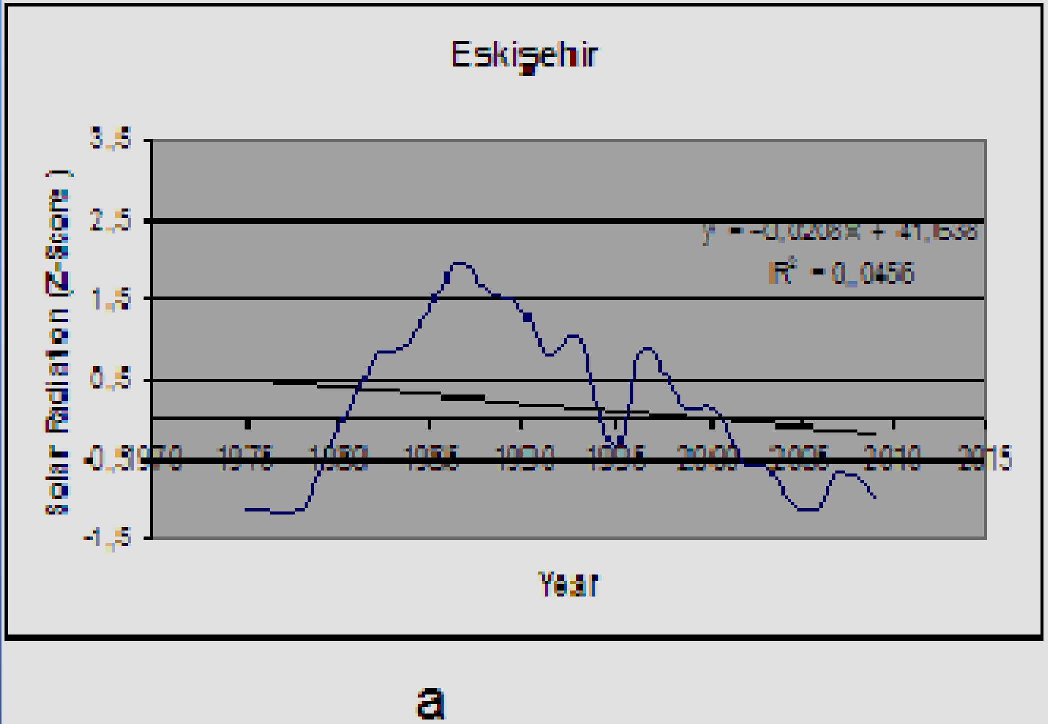
a **b**

Figure 4- Seasonal Variation of Solar Radiation (cal/cm²) in Eskişehir (a) and in Isparta (b)

Analyses of Solar Radiation



Figures 5 (a) and (b) show annual variation of **Z-score values** (measure of position) of **solar radiation** in Eskişehir and Isparta between 1975 and 2009. In general linear trends are opposite with each other in two stations. There is decreasing trend in solar radiation in Eskişehir.



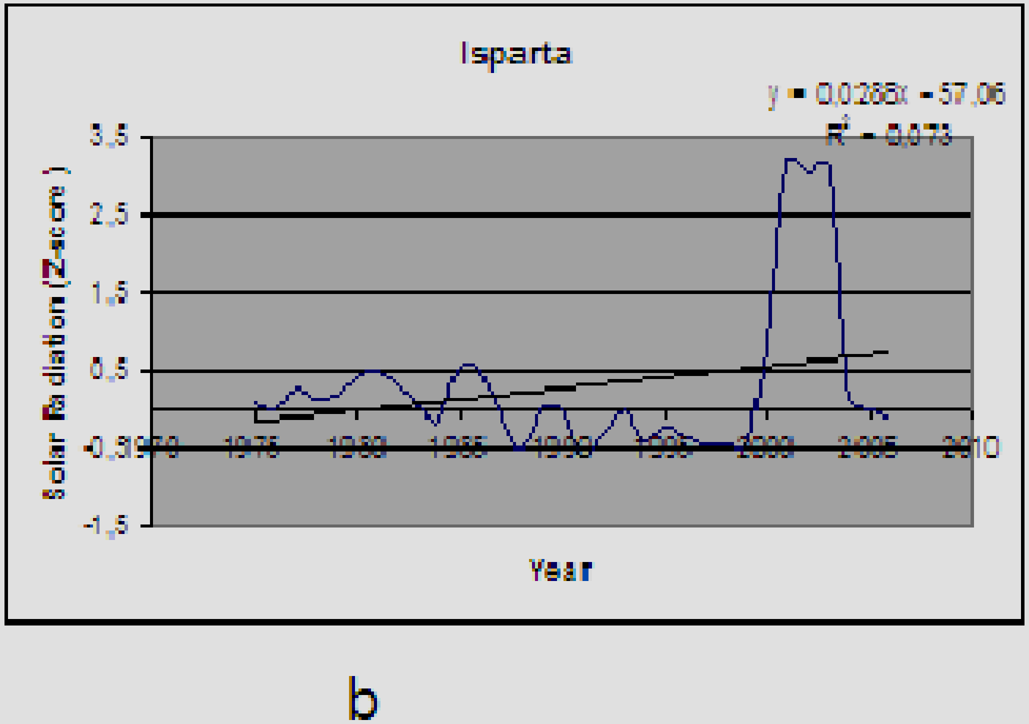


Figure 5- Annual Z-score Variation of Solar Radiation (cal/cm²) in Eskişehir (a) and in Isparta

Analyses of Sunshine Duration

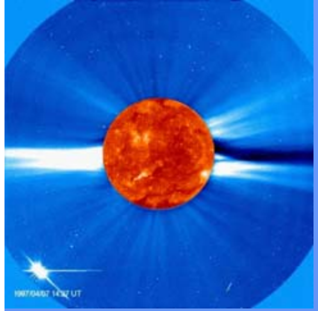


Figure 6 shows annual variation of sunshine duration in study areas. Temporal variations are very similar in spring and summer in both stations.

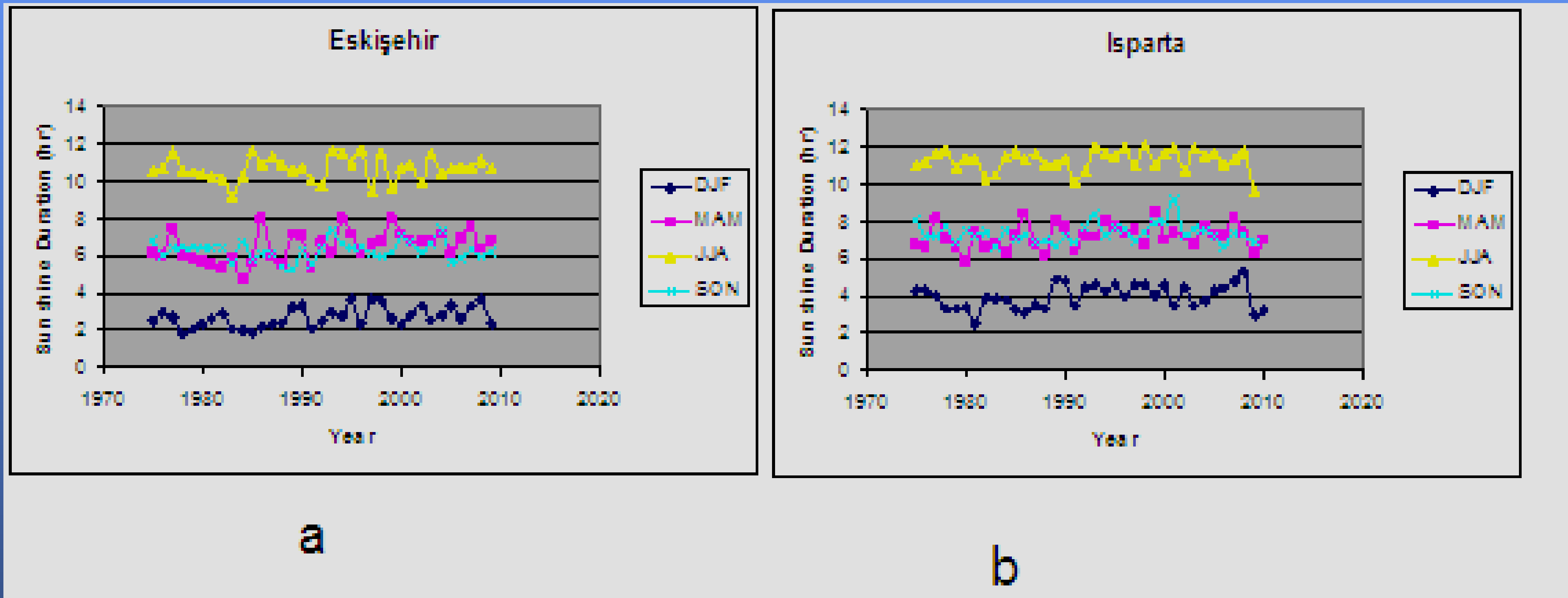
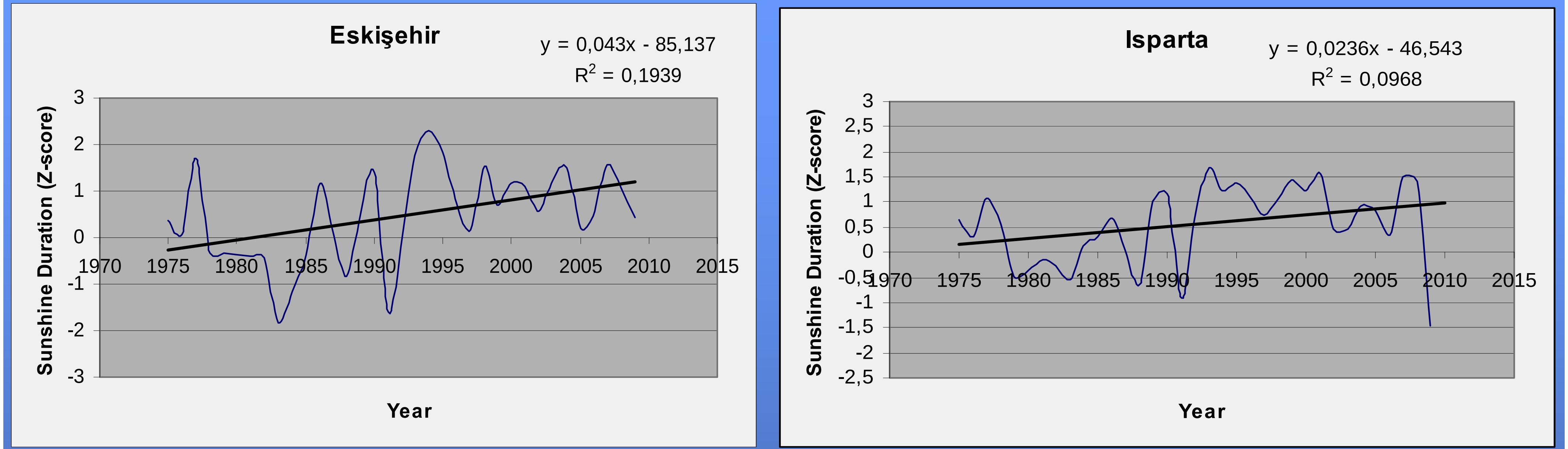


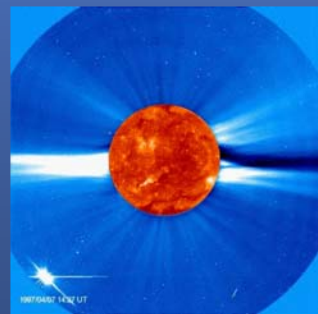
Figure 6- Annual Variation of Sunshine Duration (hr) in Eskişehir (a) and in Isparta (b)

Analyses of Sunshine Duration



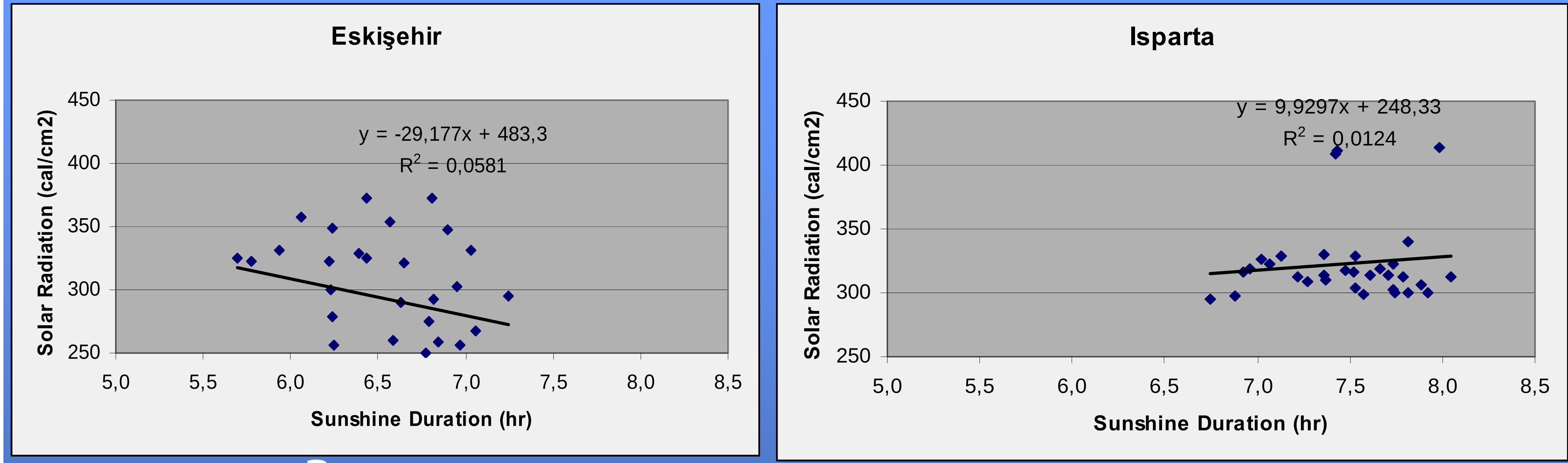
a b

Figure 7- Annual Z-Score Variations of Sunshine Duration (hr) in Eskişehir (a) and in Isparta (b)



Increasing trend of z-score values of sunshine duration in Eskişehir is higher than the same values observed in Isparta, (Fig. 7).

Analyses of Solar Radiation and Sunshine Duration



a b

Figure 8- Scattering Diagram of Solar Radiation (cal/cm2) and Sunshine Duration (hr) in Eskişehir (a) and in Isparta (b)

The negative linear relation between solar radiation and sunshine duration values in Eskişehir is very interesting. The reason of the negative relation between solar radiation and sunshine duration recorded in Eskişehir would be associated with higher concentration of scattering particles (such as water vapor) and other local factors. This relation should be analyzed in detail, (Fig. 8).

Analyses 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, (Tokgözlü, A., and Z. Aslan,).

Moving average simulation of NAO values is shown in Figure 9. Moving average smoothing is with **5 years average** values (lag = 5 years) of NAO indices. In recent year negative NAO values have been observed.

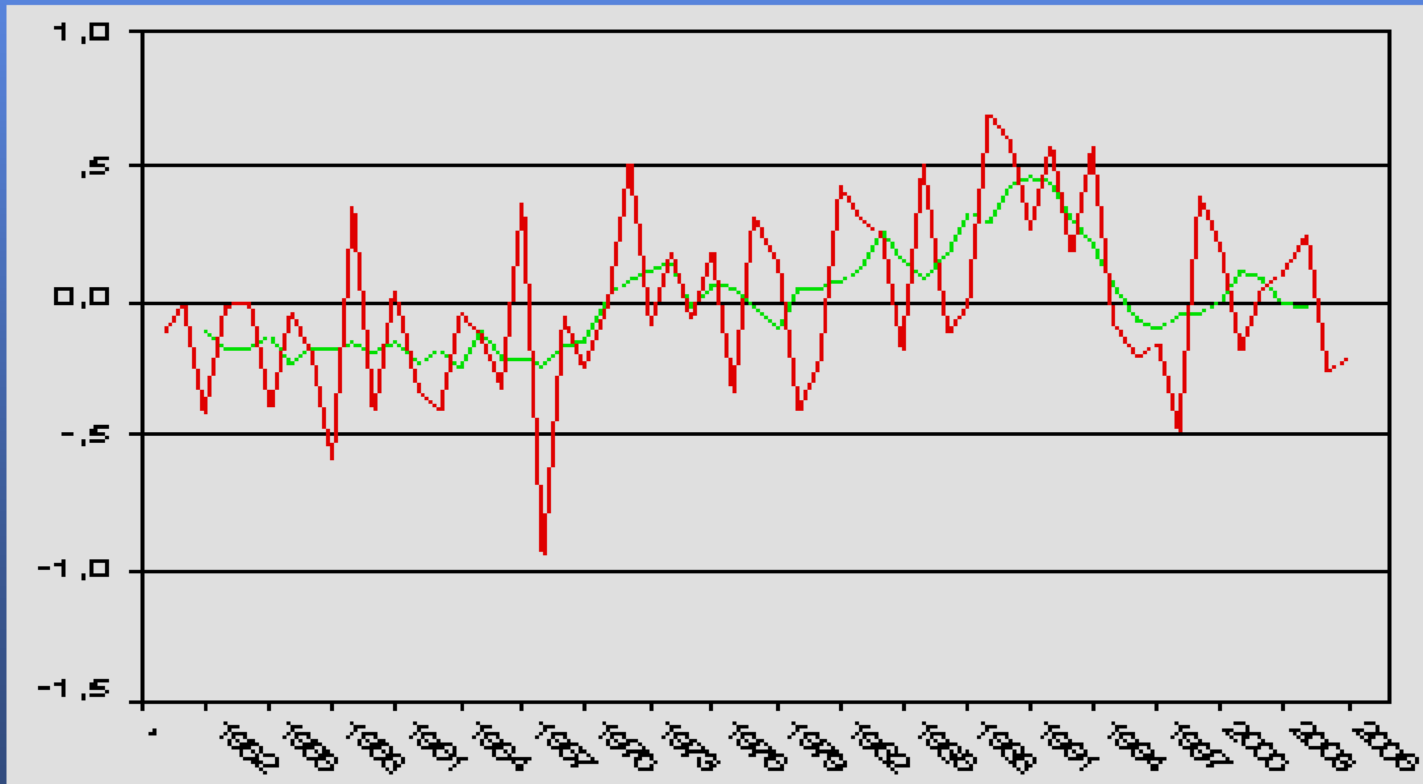
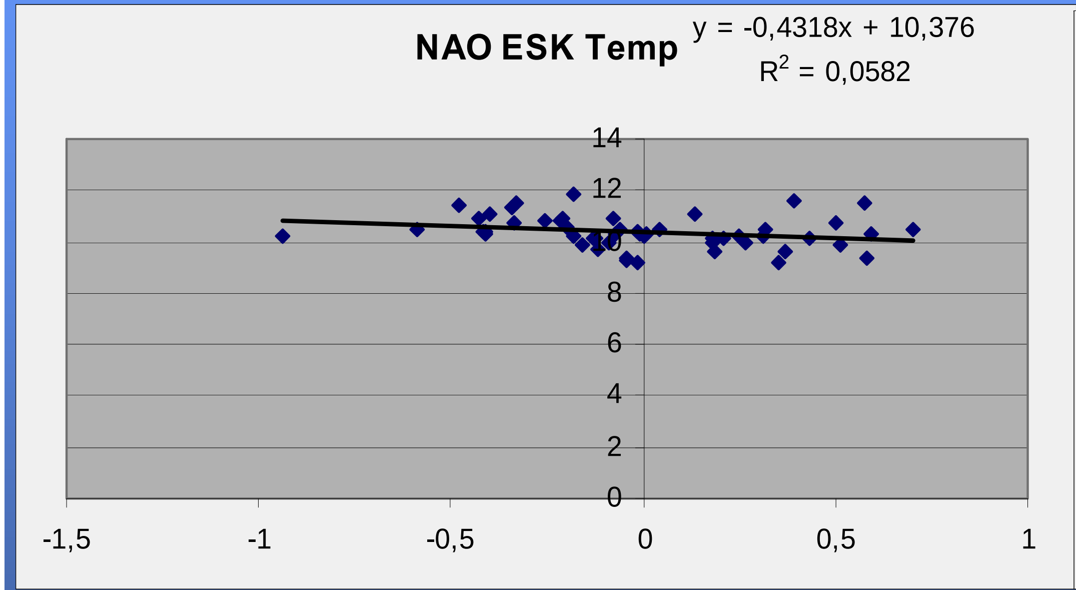
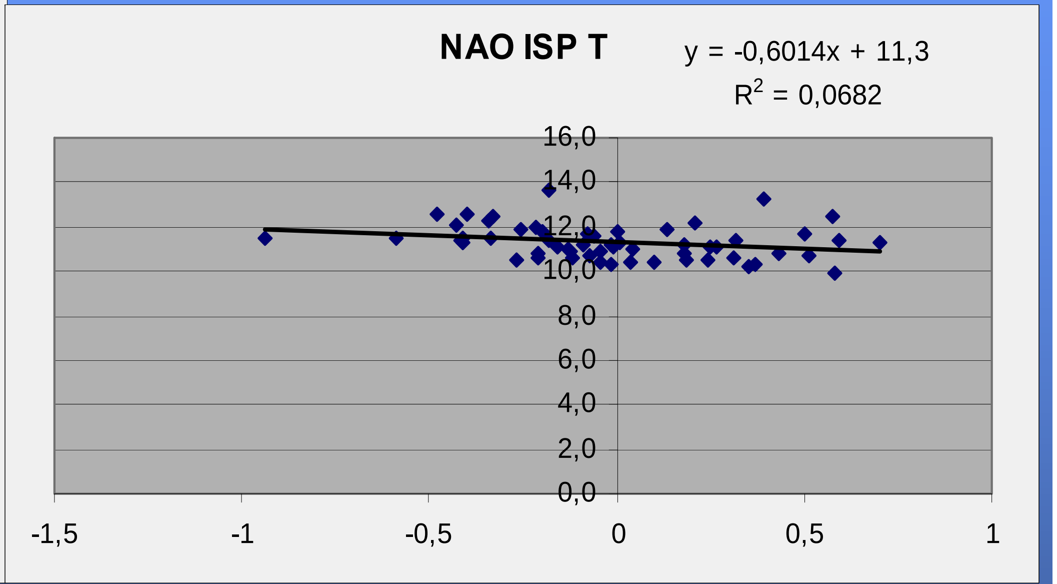


Figure 9- Moving average approximation of NAO values

Analyses of NAO and comparison with temporal variations

Figure 10 (a) and (b) presents **linear relation** between **NAO and air temperature values** in Eskişehir and Isparta. **Increasing** (positive) NAO values are accompanied by **decreasing** annual average air temperature values.





a **b**

Figure 10- Linear relation between NAO and air temperature values in Eskişehir (a) and in Isparta (b)

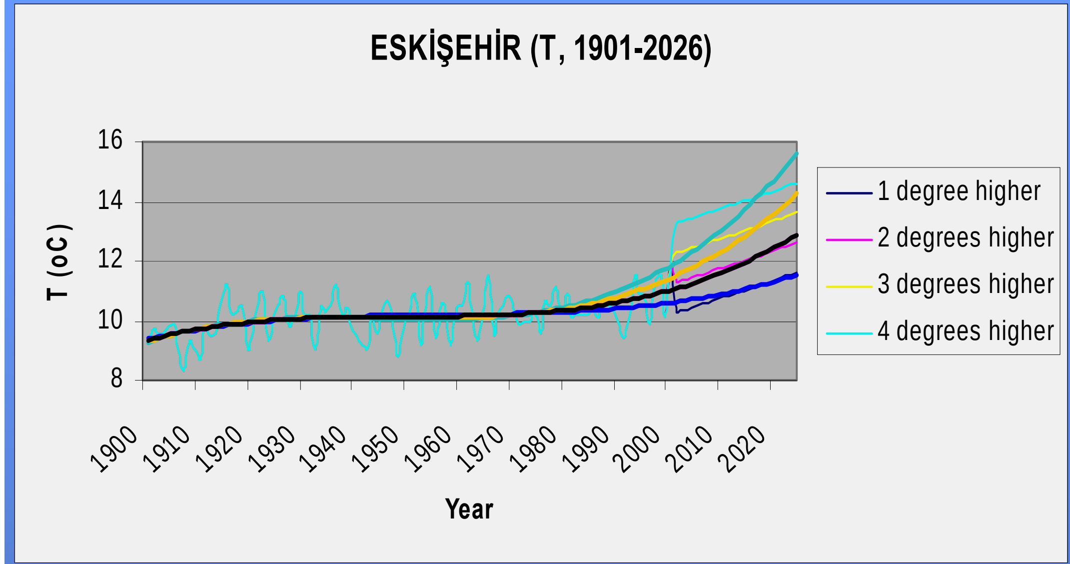
Positive relations between NAO and solar radiation have been observed in spring, summer and winter. There is a **negative relation** between two variables in autumn. By considering the periodicity of NAO fluctuations, higher temperature values have been expected at two study areas in following years.

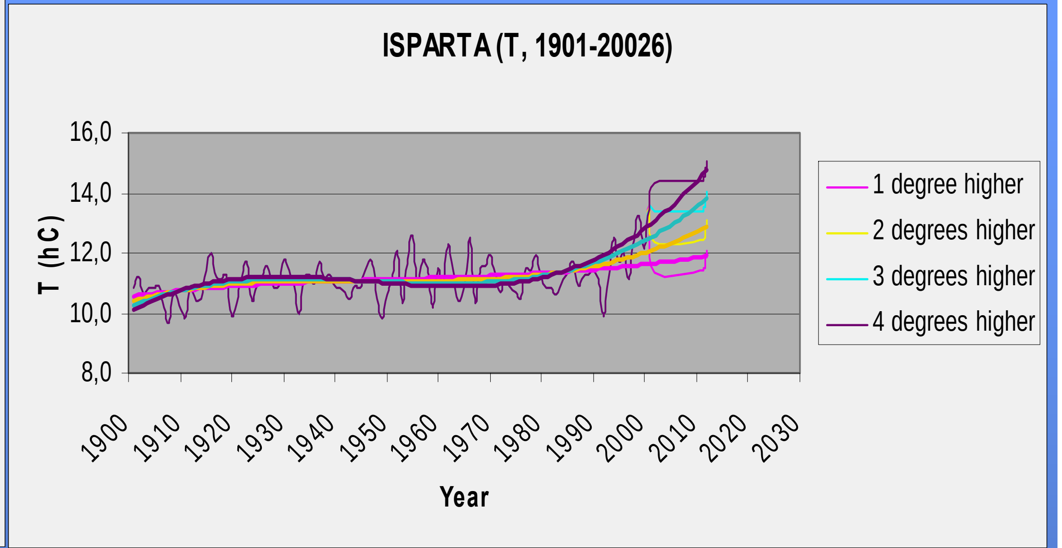
Climate Scenarios

The Intergovernmental Panel on Climate Change **(IPCC)** Fourth Assessment Report **(AR4)** are examined for the top of atmosphere radiation changes as carbon dioxide and other greenhouse gases build up from 1950 to 2100. There is an **increase** in **net radiation absorbed**.

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, (Trenberth, K. E., and J. T. Fasullo - Cağlar, N., A. Tokgözlü and Z. Aslan, Application of Wavelet in Analyses of Solar Radiation and Solar Energy Potential).

Climate Scenarios





a b

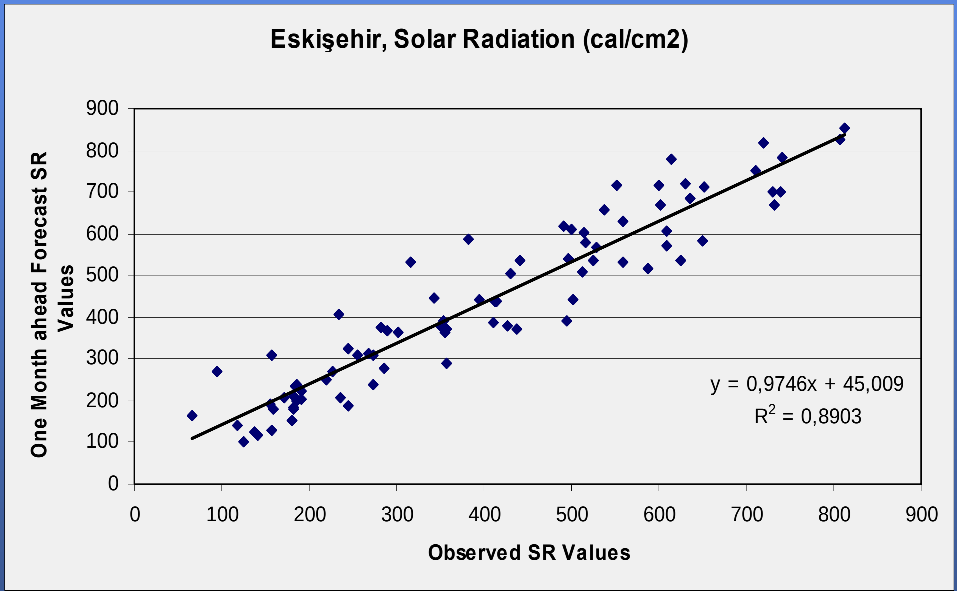
Figure 11- Climate scenarios for air temperature values in Eskişehir (a) and Isparta (b).

Figures 11 (a) and (b) show some **climate changing effects** on air **temperature** values in Isparta for four different (A2) scenarios. The estimated air temperature values are **1-4°C higher** than current values. Average Annual Air Temperature changes present **increasing trends up to 2025** under A2 Scenarios in two study areas. Correspondingly, it is estimated that incoming solar radiation and sunshine duration would be increased in following decade.

Analyses of ANN

ANN method was applied to **forecast incoming solar radiation** (SR) and **sunshine duration** (SD) values in study areas. Forecast of two variables using MATLAB was made **one month in advance.**

Scatter diagrams of the **forecast and observed** solar radiation values in two stations are shown in Figures 12 a and b. Fitted line has slopes close to **45°** passing through the origin.



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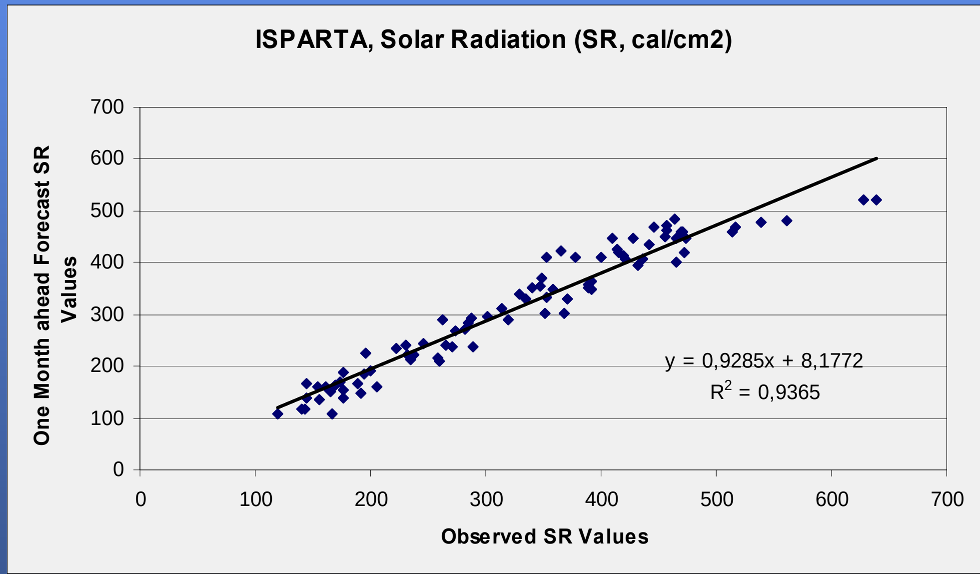
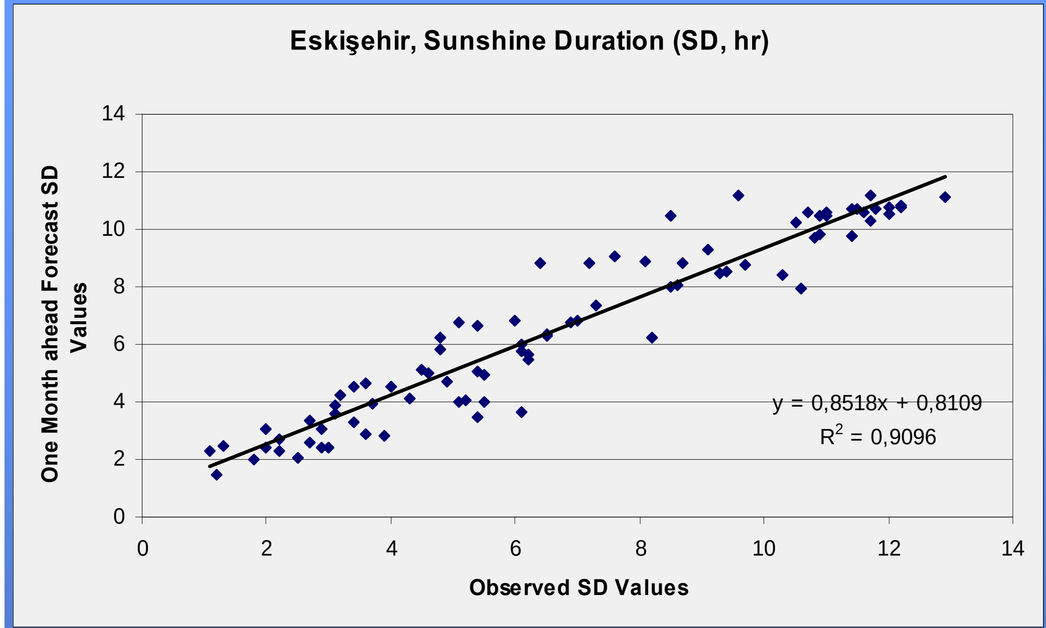


b

Figure 12- Scatter Diagrams of the Forecast and Observed Solar Radiation Values with the Linear Fit Line in Eskişehir (a) and Isparta (b)

Analyses of ANN



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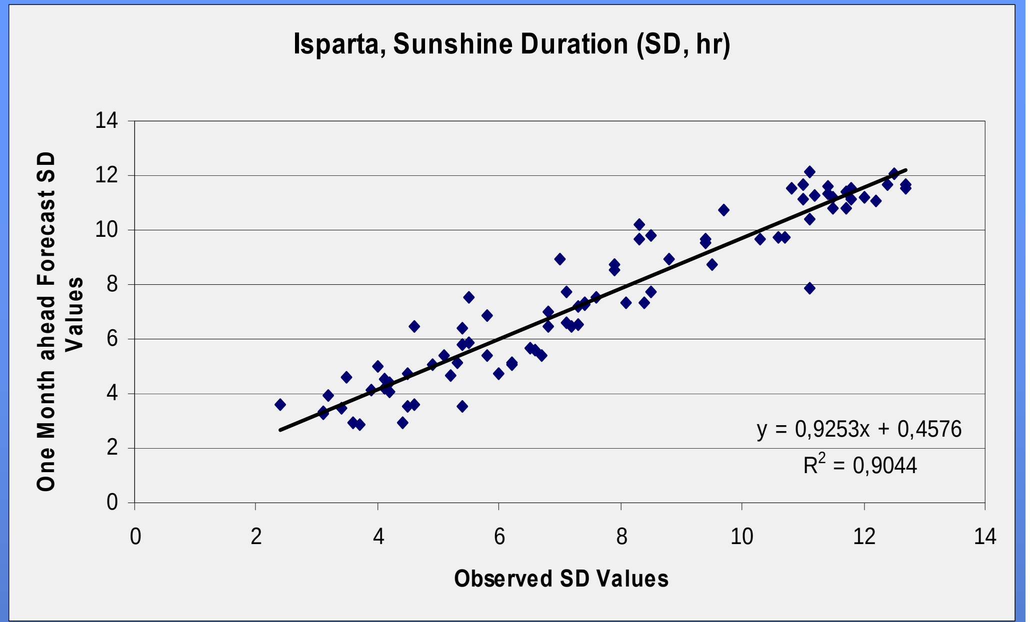

b

Figure 13- Scatter Diagrams of the Forecast and Observed Sunshine Duration Values with the Linear Fit Line in Eskişehir (a) and Isparta (b).

Figures 13 (a) and (b) presents **one month ahead forecast** versus observed **sunshine duration** values with linear fit line.

There is a sufficient evidence of all relations with the confidence level α = 0,05.

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Results and Conclusion

- Long term data (1950-2006) **shows negative relations** between annual average air **temperature** and **NAO** variations in study area: increasing positive NAO values correspond to decreasing values in general. These results suggest the following effects on soaring conditions over the study area: By assuming the NAO values continue to decrease in the next decade it will be resulting with the **increasing of average air temperature** values. These trends will be associated with **more dry thermals** organizations.

- Incoming **solar radiation** and **NAO** relations are **positive** in spring, summer and winter. There is a **negative** relation between two parameters in **autumn.**

- In the following decade hence decreasing values of NAO indexes are estimated, these trends would be accompanied by the **decreasing trends** of **solar radiation in spring, summer and winter** but an increasing trend in **autumn.**

Results and Conclusion

- 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 following decade hence decreasing values of NAO indexes are estimated, these trends would be accompanied by **increasing values of sunshine duration in summer and autumn.**

- In this paper, ANN is successfully applied to determine solar radiation and sunshine duration values in Isparta, Eskişehir and near vicinity. The **R^2-value** for the predicted solar radiation and sunshine duration is greater than 0,89 which shows the **sufficient evidence** of this relation with $\alpha = 0{,}05$. The ANN model learned the shape of the inherent nonlinearities and the system reached the correct operating point. Errors reported when using these models are well within acceptable limits which clearly suggest that **ANN** can be used **for modeling** in this field.

Specific results

- Thermo dynamic structure and organization of convection are very complex in the earth atmosphere and surface conditions. For this reason heating processes of the earth surface by solar radiation is related to meteorological processes in many different scales. Liquid water content (LWC) of clouds decreased with increasing temperature, suggesting that global warming may be related to the decrease of LWC within the clouds to some degree, (Sırdaş, S. and A. D. Şahin). For the next decade at two study areas the similar situation (decreasing ratio of LWC), increasing air temperature and sunshine duration would be estimated in soaring period.

- Thermal pressure of the surface is important than temperature variation, (Sigrist, B.). Temperature increase is too wide spread because of some little variation of cumulative irradiance. Sigrist analyzed thermal maps based on irradiation and temperature. There are some surface factors reducing temperature. Surface temperature is a better indicator than irradiance. Temperature increases are equal to the difference from cumulative irradiance to radiation losses. Local irradiation primarily depends on the direction of sun (geographic position, date and hour) and the atmosphere (altitude and turbidity). Sigrist analyzed radar data by interpreting topographic and elevation maps together. Similarly, in the present paper, a complex structure of incoming solar radiation variations is observed in Eskişehir and near vicinity.

Specific results

- By applying more statistical analyses, thermal index (strength of thermals) can be constructed on the basis of arithmetic average and standard deviation variations (Z-scores) of sunshine duration and air temperature. Solar irradiation and sunshine duration ranges can be determined for each study areas.

- By applying ANN method observed and the one month advance forecast values of solar radiation and sunshine duration are compared. Solar radiation and sunshine duration can be modeled by data driven approaches such as Neural Networks.

- The higher values of maximum air temperature observations are good indicators of trigging and organization of thermals, (Tokgozlu, A. and Z. Aslan). Higher trigger temperatures are associated with higher convective layers and organization of favorable dry or wet thermals in the atmospheric boundary layer.

- At the end of this study, future scenarios and temporal variation of variables which play an important role on thermalling have been analyzed; ANN simulation and tele-connections of these variations with NAO were discussed.

SUMMARY

The detailed information on the intensity of solar radiation at a given region is important to analyze variation of **soil trigger temperature** and **strength of thermals.** This paper presents some applications of statistical models and artificial neural networks **(ANN)** to define onset and organization of thermals. ANN has been used in the field of dry and wet convection for modeling and prediction of favorable thermal conditions for selected regions and **gliding schools** in Turkey. Long term monthly, seasonal and annual **averages of meteorological data** (air temperature, solar radiation and sunshine duration) have been used. By considering **climate changing scenarios,** prediction of these variables for the year of **2025** has been analyzed. In ANN model, multiple hidden architectures have been used. Errors reported when using these models are well within **acceptable limits** which clearly suggest that ANN can be used for modeling of actual solar radiation values based on monthly and seasonal average solar radiation values in this field. The higher values of air temperature observations are good indicators of trigging and organization of thermals. Higher trigger temperatures are associated with higher convective layers and organization of favorable dry or wet thermals in the atmospheric boundary layer. At the end of this study, future scenarios and temporal variation of variables which play an important role on thermals have been analyzed and, tele-connections of these variations with NAO were discussed. The favorable gliding conditions are available in late spring, summer and early autumn in Turkey. The period of gliding activities at study areas would increase under A2 Climate Changing Scenarios.

Keywords: Solar Radiation, Air Temperature, ANN, NAO, Thermalling, Climate Changing.

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THANK YOU