RELATIVE HUMIDITY MODELING WITH ARTIFICIAL NEURAL NETWORKS

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Abstract. Air humidity has great importance for living beings, especially plants. Air humidity controls vaporisation on earth's surface and transpiration of plant leaves. Additionally, it prevents most of the radiation from the sun and reflected sun rays from reaching the ground and prevents excessive heating or cooling. The purpose of this study is to predict relative humidity as an important climate parameter, based on annual total precipitation, average ambient temperature, and altitude. Regression and artificial intelligence network models were developed by using monthly average temperature, total precipitation, and altitude parameters obtained from 177 meteorological stations in Turkey to predict relative humidity. When analysed, the model developed with the artificial neural network method had greater predictive power ($R^2 = 0.84$) than the model developed with multiple linear regression ($R^2 = 0.76$). In this study may be applicable in climate conditions that are similar to those in Turkey.
Keywords: *Turkey, multiple linear regression, ANNs, humidity, climate*

Introduction

The amount of water in the air is referred to as air humidity. Air humidity is important for the development of plants and prevents most of the radiation from the sun and reflected sun rays from reaching the ground, thus preventing excessive heating or cooling. When the relative humidity of air decreases, the transpiration rate of plants increases. This causes decreased turgor pressure in plant cells. The relative humidity ratio in ambient air should be greater than 65% for turgor pressure to be balanced. If the relative humidity of air constantly decreases, transpiration increases; if water absorbed by the roots fails to correspond to water lost via transpiration, plant stomas will close and decrease transpiration. In this case, the gas exchange necessary for photosynthesis and respiration will fail, and as a result plant growth will either slow or completely stop (Cox et al., 2016).

The transpiration rate of plants is affected by sunlight, wind, air humidity, air pressure, and the amount of water in soil. During winter months, temperature and light intensity are relatively low. Therefore, the transpiration rate decreases and plants need less water. Generally, in places where temperatures are at low levels during summer or winter, plants need less water, whereas in places where temperatures are higher, plants need more water (Rohli and Vega, 2013).

Additionally, air relative humidity has an important role in storage of products. If relative air humidity in a barn is high, the amount of water in stored products will increase. Increased water retention will lead to product losses due to excessive heating, decay, and rotting (Pixton, 1982).

Because air humidity has an effect on water loss in an ecosystem, it is important in terms of ecology. Therefore, ground humidity is considered as a criterion in determining climate type. For example, places with more than 80% relative humidity are characterised as rain forests, whereas places with less than 20% humidity are characterised as extremely dry climates (Clarke, 1954).

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Air humidity controls vaporisation on the earth's surface and transpiration of plant leaves. As vaporisation and transpiration increase, the amount of water decreases inside root sections and on the ground surface. Fog as air humidity is important for dry regions. Although there may be no precipitation events in deserts for years, fog in the air supports plant survival. However, higher relative humidity or foggy and cloudy weather can cause various types of fungus that cause different diseases in plants to grow and spread, thus decreasing agricultural yield in humid regions (Yurtseven, 1999; Kanber et al., 1992).

Air humidity thus has great importance for living beings, especially plants. Yet, in analysing previous studies regarding prediction of climate parameters, there were few studies on relative humidity prediction. The purpose of this study is to predict relative humidity as an important climate parameter for ecologic studies, based on certain measurements that are believed to be related to relative humidity: annual total precipitation, average ambient temperature, and altitude.

Prediction models developed in this purpose are based on classical regression analysis (Tokar and Johnson, 1999) and artificial neural networks (ANNs) (Al-Alawi et al., 1998; Luk et al., 2000; Kumar et al., 2002; Çelik et al., 2016) that are increasingly important in recent years. Multiple linear regression techniques are the most widely used statistical tools for discovering the relationships among variables. ANNs are considered nonlinear statistical data modeling tools where the complex relationships between inputs and outputs are modeled or patterns are found. ANNs have been very useful in many aspects of climatical research and modeling in recent years (Terzi and Keskin, 2010; Keskin et al., 2011).

Comparison of regression and ANN models have shown that the performance values of the ANN models are better than the regression models in general (Yadav and Chandel, 2014; Kumar et al., 2015).

Materials and methods

Turkey is located in the northern hemisphere, between 36°-42° N and 26°-45° E. More than half of the country has an altitude of more than 1,000 m. Approximately one third of the country is covered with medium-height plainlands, highlands, and mountains, and 10% is at low altitude. The highest and most mountainous areas are located on the eastern side of the country. The most rugged area in the north is the North Anatolian Mountains, and the roughness of south, east, and southeast regions is caused by the Toros Mountains. The highest mountain in the country is Mount Ağrı, at 5,166 m. The largest plains are Çukurova, Konya Plains, and Harran Plains. The longest river with a spring source and flowing into the sea is Kızılırmak with a length of 1,355 m. The largest natural lake is Van Lake with an area of 3,713 km². Atatürk Dam Lake is the largest artificial lake with a 817 km² area. The largest island is Gökçeada with a 279 km² surface area. Total land area is 770,760 km², and total water area is 9,820 km² (Şahin, 2006).

Turkey is located between a temperate zone and sub-tropical zone. Although Turkey is surrounded by seas on three sides, differences in mountain elongation and land forms cause different climate types with different properties. The coastal section of Turkey has a temperate climate because of the tempering effect of the sea. The North Anatolian Mountains and Toros Mountain range prevent the mild sea climate from penetrating to

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the inner regions. Therefore, the inner regions of the country have a continental climate (Atalay, 1997).

Due to climate differences by location and geographical properties, natural vegetation consists of various plant formations, including forests, shrubs or bushes, or weeds. These plant groups that show humid, semi-humid, or dry characteristics based on the effects of climate differ in geographical spread, morphology, ecology, and floristic properties. In Turkey, there are approximately 12,000 plant taxa (Günal, 2013).

This study attempts to predict relative humidity by using certain parameters (average annual total precipitation, average ambient temperature, and altitude) collected between 1987-2017 from 177 large climate stations in Turkey. The location of these stations is given in *Figure 1*.

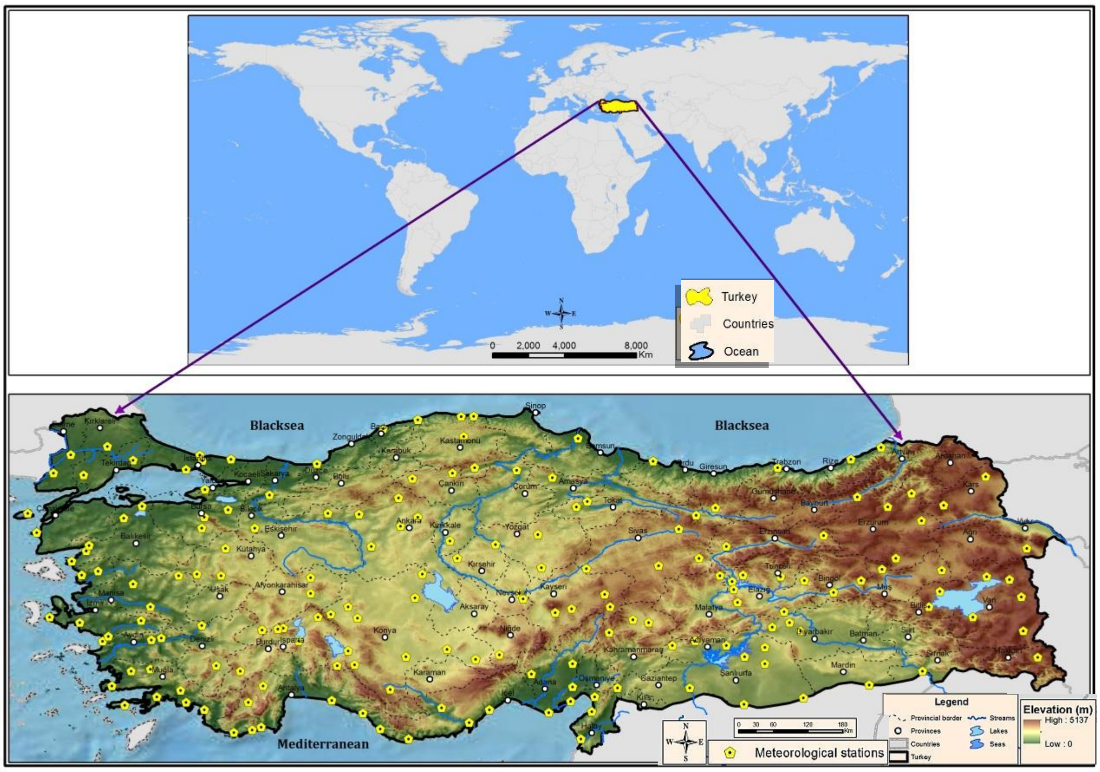

Figure 1. *Study area*

Regression analysis, which forms the basis of the multiple linear regression model adopted in the study, enables the development of a model of the relationship between dependent and independent variables; this model enables predictions (Kalıpsız, 1994).

The multiple linear regression model used in the analysis is presented in *Equation 1*.

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \varepsilon i \quad \text{(Eq.1)}$$

In this model, Y is the dependent variable, X_1 is temperature, X_2 is precipitation, and X_3 is altitude, b_0 is where the regression curve intersects the y axis, b_1 is the regression coefficient for the first independent variable, b_2 is the regression coefficient for the

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second independent variable, b_3 is the regression coefficient for the third independent variable; εi is a random error variable for zero average, and $\sigma 2$ is variance.

Today, artificial intelligence applications are used for predicting meteorological events. Successful results were found especially in applications with artificial neural networks (Keskin and Terzi, 2006; Kumar et al., 2002; Saplıoğlu and Çimen, 2010; Zealand et al., 1999).

The artificial neural network (ANN) adopted in this study was developed based on learning with trial and generalisation concepts of the human brain. The biologic neural system can be explained as a three-layered system that constantly receives information, interprets this information, and produces decisions for this interpretation. Receiver neurons turn a stimulus within the organism or from the outside world into electrical signals that transfer information. Reaction neurons turn electrical impulses created by the brain into appropriate reactions as organism output. *Figure 2* shows a block diagram of a neural cell (neuron) (Öztemel, 2003).

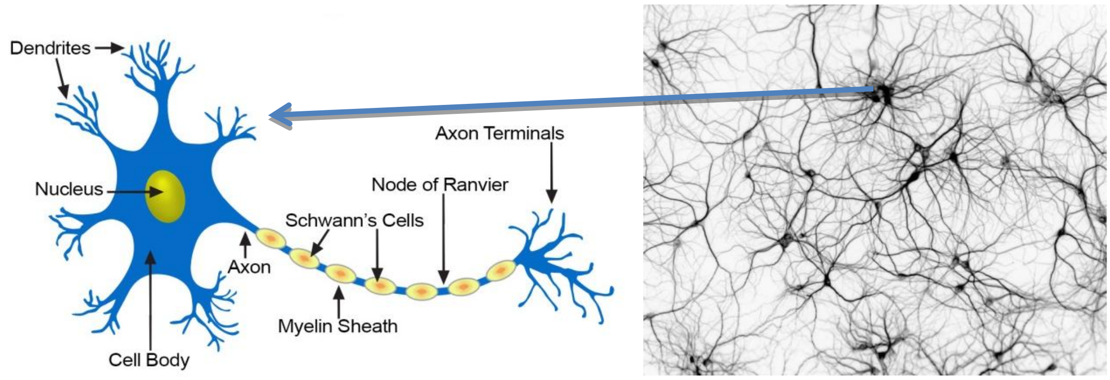

Figure 2. *Structure of neuron. (Anonymous, 2018a, b)*

An artificial neuron cell consists of five main components: inputs, weights, summation (uniting) function, activation (transfer) function, and output. Inputs are outside-world information to an artificial neuron cell. Information received from the outside world or a previous layer are sent to the artificial neuron cell as input. Weights indicate the importance of the information sent to an artificial cell and the effect on the neuron. These are coefficients determining the effect of inputs received by the artificial neuron. The summation function calculates net input to a cell. The value obtained from the summation function is processed by a linear or non-linear derivable activation function, and the output of operation elements is calculated. Activation functions enable curvilinear matching between input and output units. Out value is the value obtained after application of the activation function (Elmas, 2003; Öztemel, 2003).

Input and corresponding output information are fed into ANNs, and the neural network is trained to learn the relationship between input and output. ANNs can be grouped as feedforward and feedback or recurrent based on information flow type. In a feedforward network structure, information flows forward. Generally, in a feedforward network, there is one input layer, one or two hidden layers, and outputs layers. These networks are called multi-layered feedforward networks (Schalkoff, 1997).

Additionally, ANNs learn with supervised, unsupervised, and reinforcement learning. Back propagation algorithms in supervised learning have two types of connections. In the first form, corresponding outputs for certain inputs are computed in

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a forward connection and by using weights. In the second form, the connection is backwards; to minimise errors on output layers, weights are organised backwards. A feedforward operation transfers data on the input layer to the first hidden layer. In all these stages, the number of computing elements in each layer is important (Elmas, 2003).

Because there is no operation on the input layer of ANNs, the number of computing elements on input and output layers depends completely on the applied problem. The number of hidden layers and number of computing elements on hidden layers can be determined through trial and error, but the number of neurons on input and output layers is considered (Şen, 2004).

In ANNs, network input and output can be pre-processed to increase the efficiency of network training. This operation is called normalisation. In the literature, there are various data normalisation practices. This model adopted one of the most common methods, Min-Max, and data were reduced to between 0 and 1 (Jayalakshmi and Santhakumaran, 2011).

Results

In this study, regression and ANN models were developed to predict relative humidity in 177 regions in Turkey that have different geographical and climate conditions. Meteorological data of the past 30 years (1987-2017) in the 177 regions were obtained from Turkish State Meteorological Service (TSMS) and used for modelling (*Table 1*).

Table 1. *Descriptive statistics of sample plots*

	N	Minimum	Maximum	Mean	Std. Error	Std. Deviation	Variance
Altitude (m)	177	2	2400	722.93	45.062	599.516	359419.779
Precipitation (mm)	177	196.3	2279.5	627.146	20.6666	274.9511	75598.131
Temperature (°C)	177	3.7	20.2	13.169	0.2809	3.7367	13.963
Relative humidity (%)	177	46.7	82.0	63.338	0.4920	6.5455	42.843

Multiple regression analysis was used to determine the collective effect of dependent variables (temperature, precipitation, and altitude) on the independent variable (relative humidity). Based on multiple regression analysis, a mathematical equation with statistical significance of $p < 0.001$ and an R^2 value of 0.76 was computed (*Eq. 2*; *Fig. 3*).

$$RH(\%) = 105 - (2.477x\text{Temp.}) + (0.005xPrecip.) - (0.017xAltit.) \quad \text{(Eq.2)}$$

The Neural Network Toolbox plug-in for MATLAB was adopted to create the ANN model. In this ANN model, three input parameters (temperature, precipitation, altitude) and one output parameter (relative humidity) were predicted. When the model was structured, a 3-input, 1-output Levenberg-Marquardt (LM) algorithm was used for predicting relative humidity. First, on average 70% of data were used as “input” to train the network, 20% were used for testing the developed model, and 10% were used for validation purposes.

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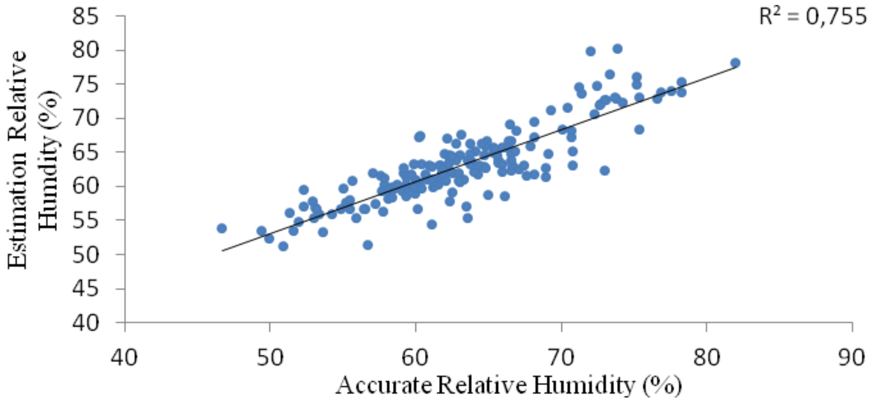

Figure 3. *The relationship between accurate and estimation relative humidity (%)*

To determine the number of hidden layers and hidden neurons, various trials were conducted. The model with 1 hidden layer and 10 neurons provided the best results. Sigmoid activation function was used between layers. A maximum iteration number of 12 was obtained. In each execution, the algorithm was stopped after 6 epochs (*Fig. 4*). To determine the relationship between training data and output results obtained after training, regression analysis was applied. Analysis indicated an R^2 value of 0.84. Similarly, analysis was conducted on test data, validation data, and all data, with R^2 values of 0.83, 0.79, and 0.84, respectively (*Fig. 4*).

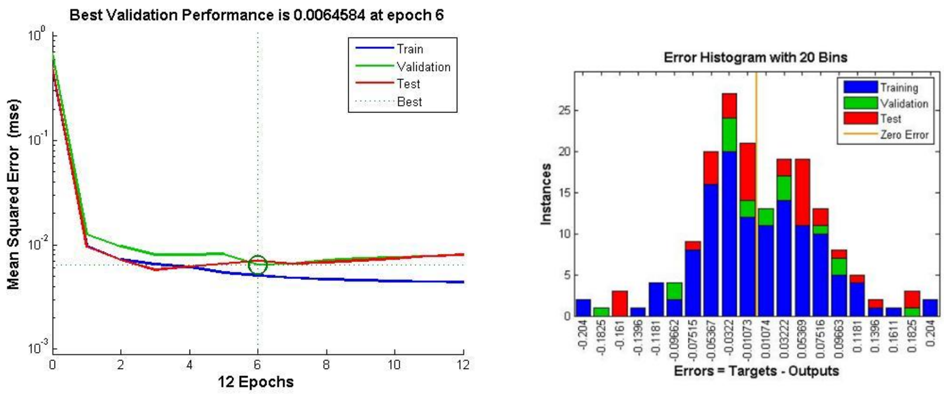

Figure 4. *Best validation performance and error histogram of model*

To determine the relationship between training data and output results obtained after training, regression analysis was applied. Analysis result indicated R^2 value of 0.84. Similarly, analysis were conducted on test, validation, and on all data and R^2 values were found 0.83, 0.79, and 0.84 respectively (*Fig. 5*).

Discussion and conclusions

The purpose of this study was to predict certain parameters thought to related to relative humidity. To predict relative humidity, various models were developed by using temperature, precipitation, and altitude parameters. Calculated values for the model and

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real values were compared with statistical methods. Comparison results indicated that predicted and measured relative humidity values had good fit.

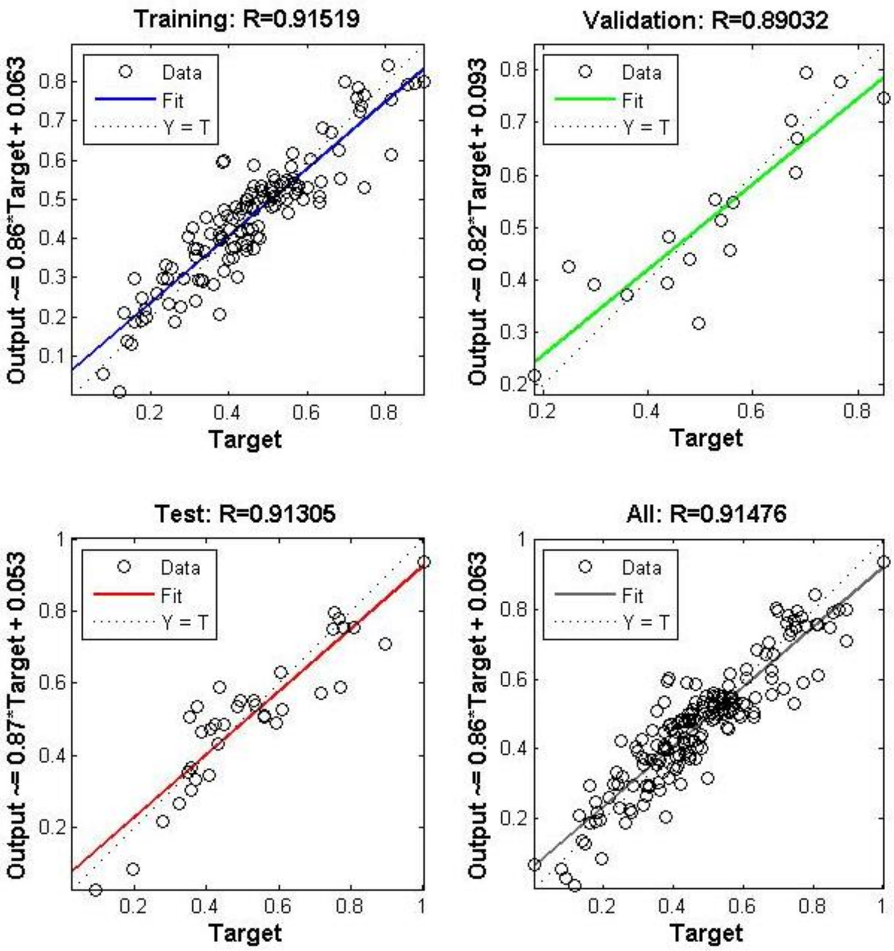

Figure 5. *Target and output relations of ANN model*

When analysed, the model developed with the ANN method had higher predictive power than the model developed with multiple linear regression. Similarly, Tokar and Johnson (1999) conducted a study to predict daily flow rate and used an ANN method with precipitation, temperature, and snow melting data. They compared results obtained from statistical regression and the ANN model and determined that the ANN model provided an extremely systematic approach. Kumar et al. (2015) predicted monthly average global solar radiations by using some parameters in ANNs and regression models. Comparison of ANNs and regression models have shown that the performance values of the artificial neural network models are better than the regression models as in this study. Yadav and Chandel (2014) predicted average global solar radiations by using some parameters in ANNs and regression models. ANNs had better performance than regression model too.

Similar studies were conducted by different researchers to predict other climate parameters. Erkaymaz and Yaşar (2011) predicted temperature by using water vapour pressure, relative humidity, wind, and air pressure parameters in an ANN method. In another study, Terzi (2006) predicted daily water temperatures of Eğirdir Lake by using

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daily air temperature, solar radiation, and relative humidity parameters in ANNs, Saplıoğlu and Çimen (2010) predicted missing daily precipitation of Portland by using measured daily precipitation parameters in ANNs.

Nastos (2014) predicted maximum daily precipitation for the next coming year of Athens (Greece) by using some parameters in ANNs. Correlation coefficient between the measured and predicted maximum daily precipitation were found to be 0.48. Deo and Şahin (2015) determined of feasibility of the ANNs for predicting the monthly Standardized Precipitation and Evapotranspiration Index (SPEI). In this purpose, a total of 30 ANN models were developed with 3-layer ANNs by them.

They ever that the ANNs was a useful data-driven tool for forecasting monthly SPEI based on performance evaluation measures. Ramasamy et al. (2015) predicted wind speeds with ANNs. Temperature, air pressure, solar radiation and altitude are taken as inputs for the ANNs to predict daily mean wind speeds. Correlation coefficient between the measured and predicted wind speeds was found to be 0.98.

Applying this study in Turkey under different geographic and climate conditions is important as these models can also be applied in climate conditions that are similar to those in Turkey. Additionally, when of the models was investigated, the strength of the model with ANN model was much higher than regression analysis; therefore, it is believed that the ANN model can be used for relative humidity prediction.

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