

Estimating the Effect of TEC Data on Rain with Modelling and Wavelet Transformation Analysis

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Abstract. Events such as geomagnetic storms and solar winds cause significant changes and deterioration in the upper layers of the earth's atmosphere. These distortions have a significant effect on the waves and signals used by the satellites and radios we use. Based on different satellite observations, studies on geomagnetic storms, ionosphere TEC (Total Electron Content) samples, and GPS observations, we can obtain some measurements. Another important natural event in measuring temperature data and investigating its effects is rain. In this study, it is aimed to determine the effect of TEC change in the ionosphere on the daily precipitation for Izmir, Trabzon and Istanbul provinces of Turkey and to determine whether the success of the algorithms used for different regions will change according to the region, that is, the data. The temporal variation of TEC data for the period January 1–December 31, 2017 has been examined and modelled. In this study 60% of the one-year daily data was used for training, 20% for evaluation, and 20% for testing. In the first part of the study, wavelet transforms and large, medium, and small scale changes in TEC and precipitation data were examined. In the second part of the study, TEC data are modelled with artificial neural networks, support vector machines, and decision tree-based estimation methods. And in the last stage, machine learning algorithms and wavelet were used together to predict TEC data, and the prediction success ratio was tried to be related. There is a sufficient evidence of observed and estimated TEC data with alpha = 0, 05 significant level.

Keywords: Total Electron Concentration · Wavelet · Artificial Neural Network · Support Vector Machine · Decision Tree

1 Introduction

Today, data mining and machine learning are used in almost every field, from health to communication, from education to security. One of these fields is the TEC (Total Electron Content) field. With the estimation studies carried out in this field, we continue our daily

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lives with minimal interruptions, especially in the field of satellite and communication. Another important area is rain forecasting. It takes place in our lives as an important issue in many areas, from the drinking water we use in our daily lives to its use in agricultural areas.

When the recent academic studies are examined, it is seen that there are not many academic publications on whether there is a linear relationship between TEC and rain fall rate. The relationship between increasing and decreasing in TEC data is another important issue, and was examined. Within the scope of this study, similar studies in two areas were analyzed.

TEC causes an important error component in the global positioning system (GPS) by ionospheric delays. Ionospheric error can be reduced by a dual-frequency receiver using a linear combination. However, accurate ionospheric error modelling is required for single-frequency receivers. El-Diasty developed a short-term forecasting model based on a short data set [2]. In their study, they used five GPS stations with five-day ionospheric datasets along with time and location to develop the Wavelet network (WN)-based ionospheric model. He also made a comparison between the WN-based ionospheric model developed to validate the WN-based ionospheric model and the CODE, JPL, and IGS Global Ionospheric Map (GIM) models.

Sorkhabi used the deep learning method of artificial neural networks so that SF users could estimate the TEC value [10]. By using the ionosphere code observation method, which is a single-layer model, 24 permanent GNSS stations in the northwest of Iran were selected and modelled independently of the geometry called L4 between the satellite and the receiver with a linear combination. This modelling was used to train the error ANN with a hyperbolic tangential sigmoid activation function and two 5-day periods of high and low solar and geomagnetic activity intervals.

Estimating where and when space weather events such as solar flares and X-ray bursts are likely to occur in a given area of interest poses a significant challenge in space weather research. Asaly et al. have focused on X-ray time series predictions. In their study, they used a support vector machine to classify daily Total Electron Content spatial changes prior to solar flare events [1].

With the importance of knowing the extreme TEC values in readiness for dangerous ionospheric conditions, Nishioka and others have derived a cumulative distribution function of TEC to estimate the extreme TEC values that occur annually, every 10 years, and every 100 years in Japan. To estimate the extreme values of TEC, they examined their daily distribution using 22 years of TEC data from 1997 to 2018. They used two methods. In the first method, the distribution of slab thickness is artificially inflated to estimate excess TEC values. In the second method, excessive slab thicknesses are applied to estimate excessive TEC values [7].

Inyurt et al. aimed to estimate the daily ionospheric total electron content (TEC) using the Gaussian process regression (GPR) model and multiple linear regression (MLR) in their work. First of all, the daily TEC values of two Global Navigation Satellite System (GNSS) stations in Turkey were collected from 2015 to 2017. The performance of the GPR model is compared with the classical MLR model using Taylor diagrams and relative error plots. Six models with various input parameters were realized for both GPR and MLR techniques [4].

Tang et al. studied accurate corrections for ionospheric total electron content (TEC) and early warning information, and a short-term ionospheric prediction model for global navigation satellite system (GNSS) applications under the influence of space weather. They used a new machine learning model, the Prophet model, to predict the global ionospheric TEC [11].

Iyer and Mahajan recommend using the regression method to estimate TEC using an online machine learning model with new training data at regular intervals in their work. They tested the model for both quiet and disturbed days for the IISC, Bangalore, India location near the magnetic equator. The model is adaptive and chooses the appropriate regression method to reduce computation time and make it suitable for short-term predictions in real time [5].

Lei et al. proposed two different new methods for estimating TEC data based on time. (1) Introduced the Bidirectional Gate Repeater Unit BiGRU to enhance capabilities to predict TEC with both past and future time step. (2) To highlight critical time step information, an attention mechanism was used to give weight to each time step. Using Deep Neural Network (DNN), Artificial Neural Network (ANN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Bidirectional Long Short-Term Memory (BiLSTM) and Gated Repetitive Unit (GRU) as machine learning algorithms estimation of TEC ta has been carried out [12].

Benoit et al. conducted a study on the estimation of TEC data over a 6 year period. Linear Regression, Polynomial Regression, Support Vector Machine algorithms were used as estimation algorithms and Elastic Net regularization method was used to reduce the RMSE value [13].

Momin et al. present statistical distributions of rain velocity measured in Malaysia with integration times of 10 s, 20 s, 30 s, 1 min and 2 min. The ITU-R P.618–13 estimation method was used to estimate the rain attenuation of the ground-to-satellite link using the rain rate measured with integration times of 10 s, 20 s, 30 s, 1 min and 2 min [14].

Ahuna et al., together with their studies containing 4 years of data, conducted a study to predict the rain precipitation situation. They tried to increase the success ratio by using back propagation neural network (BPNN) in examinations made in different regions [15].

Sodunke et al., in their study, studied the effects of rain during the communication of satellite devices. In this study, the estimation of precipitation in a particular region at different times was made. In this study, the Feed Forward Neural Networks (FFNN) algorithm was used as the estimation method [16].

Nandi et al., time series prediction of rain attenuation from rain velocity measurement during rain was made for the temperate place Vigo, Spain using Synthetic Storm Technique (SST) for Ka and Q band signal. Rain velocity and rain attenuation data for the three-year measurement period from 2016 to 2018 were used to test the validity of the SST model at the current location [17].

Eyigüler analysed Magnetic and Electric field variations during Geomagnetically active days over Turkey. This paper covers same result on Geomagnetically induced currents (GIS) at mid-latitudes magnetic field perturbations are in the order of 0.5 nT/s and near vicinity of Bozcaada and Çanakkale in Turkey [19].

This paper shows some result of temporal variation of TEC data in selected areas in Turkey. Advanced machine learning helps to understand and to model temporal variation of daily TEC data.

2 Data and Study Area

2.1 Data Set

This study was carried out to cover the cities of Istanbul, Izmir and Trabzon within the borders of the Republic of Turkey in 2017. The dataset contains 365 rows. The data set consists of 3 columns of daily TEC data, historical data, rain fall rate (mm/m^2) data and rain series transformed with the Wavelet technique.

2.2 Study Area

TEC values based on in this study cover the cities of Istanbul, Izmir and Trabzon in Turkey. TEC data is taken from Germany's open source IMPC DLR (Ionosphere Monitoring and Prediction Center) site. These values are TEC values taken daily for 1 year from 01.01.2017 to 31.12.2017.

The latitude and longitude information is as follows (Table 1 and Fig. 1):

Table 1. Geographic Description of Study Area

No	Study Area	Latitude	Longitude
1	Istanbul	41.0082° N	28.9784° E
2	Izmir	38.4333° N	38.4333° N 27.1528
3	Trabzon	41.0052° N	39.7179° E

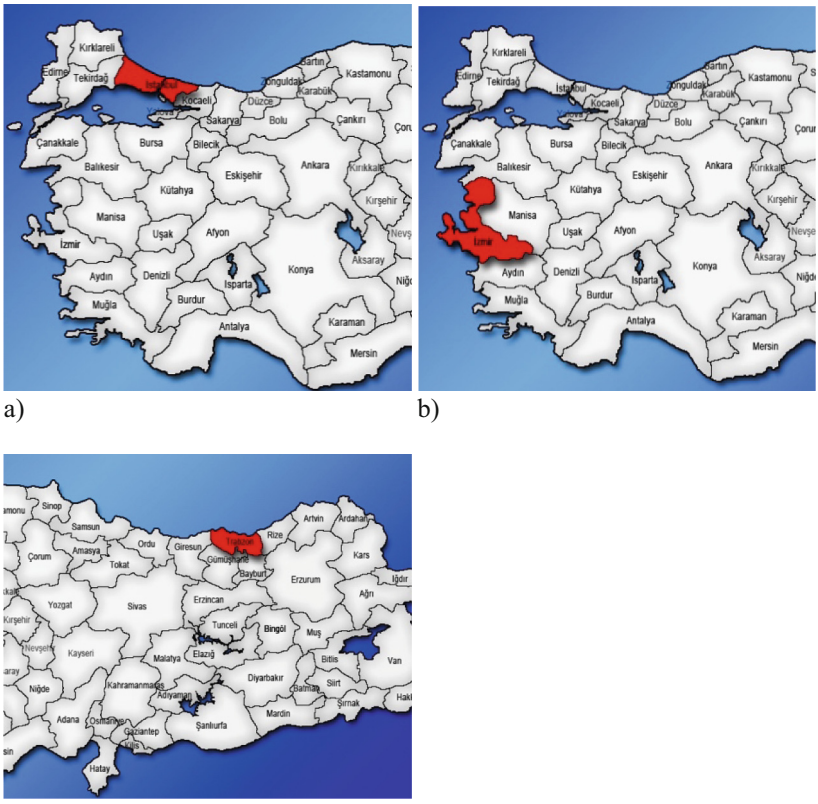

Fig. 1. Study Area, a) İstanbul, b) İzmir, c) Trabzon

3 Models and Algorithms

3.1 TEC – Total Number of Electrons

The number of free electrons per unit area up to 1000 km from the ground is called TEC, that is, the total number of electrons. The main factors affecting the total number of electrons are as follows [8].

1. Geographical Location
2. Seasons
3. Local time difference
4. Magnetic activities
5. Variability in extreme ultraviolet radiation

The smallest value in the total number of electrons occurs at midnight, while the largest value occurs at noon. In addition, the total number of electrons increases from north to south [8].

In local TEC determination studies, the following formulas for differential code differences for satellites and receivers are obtained by taking the differences of signals

between each satellite and receiver. Formula 1 is used for satellites and formula 2 for receivers. [8].

$$P_4 = P_{1J}^{\dot{I}} - P_{2J}^{\dot{I}} = d_{ion,1,J}^{\dot{I}} - d_{ion,2,J}^{\dot{I}} + DCB^{i} + DCB_J \tag{1}$$

$$L_4 = L_{1J}^{\dot{I}} - L_{2J}^{\dot{I}} = \left(d_{ion,1,J}^{\dot{I}} - d_{ion,2,J}^{\dot{I}}\right) - \lambda\left(b_{1,J}^{\dot{I}} - b_{2,J}^{\dot{I}}\right) - \lambda(N_{1,J}^{\dot{I}} - N_{2,J}^{\dot{I}}) \tag{2}$$

The ionospheric spherical harmonic functions in formula 3 should be applied to find the VTEC value, that is, E (β,s) at the desired latitude and longitude [8].

$$\sum_{n=0}^{n_{max}} \sum_{m=0}^{n} \widetilde{P_{nm}}(\sin\beta)(a_{nm}\cos(ms) + b_{nm}\sin(ms)) \tag{3}$$

3.2 Methods of Completing the Missing Data

Istanbul TEC data consists of two columns. The first column shows the day information, the second swarm shows the total electron count obtained as a result of the ionosphere observations. It is of great importance to define missing data such as NaN and unknown in databases.

Fill – missing code is used to fill in missing data in MATLAB. 6 methods are used most frequently in MATLAB.

1. Fill missing (A, 'previous'): It is a method of filling the missing entries with the previous entry.
2. Fill missing (A, movmethod, window): a method of filling in missing entries using a moving window average or median with window length.
3. Fill missing (A, fillfun, gapwindow): Fills in the gaps of missing entries using a special method fill – fun, specified by a function descriptor, and a fixed window surrounding each gap from which padding values are calculated and must have the input arguments, and fillfun, which are vectors containing length sample data, length sample data locations, and missing data locations and the positions in it are a subset of the vector of sample points (Fig. 2).

3.3 Multilayer Perceptron Neural Networks Algorithm (MLP NN)

Artificial neural networks (ANNs) are in a network-like structure formed by neurons that make up the nervous system of humans. ANNs are divided into two as the most known types. In ANN, the model consisting of three input layers and an output layer is called Single-Layer Neural Networks (SLNN), while the model consisting of input, output and hidden layers is called Multi-Layer Perceptron Neural Networks (MLP NN). MLP NN was used in this study. Multilayer Perceptron Neural Networks have a feed-forward structure and are a simple and reliable type of ANN. Output values from MLP NN must be binary. Binary results mean that the output values in the output layer are Yes/No, 0/1, True/False etc. means [3, 9] (Fig. 3).

344	4.5085	
345	4.9495	
346	5.9215	
347	4.7205	
348	NaN	
349	NaN	
350	NaN	
351	NaN	
352	NaN	
353	5.0835	

a)

344	4.5085	
345	4.9495	
346	5.9215	
347	4.7205	
348	4.7810	
349	4.8415	
350	4.9020	
351	4.9625	
352	5.0230	
353	5.0835	

b)

Fig. 2. Missing Data from the File

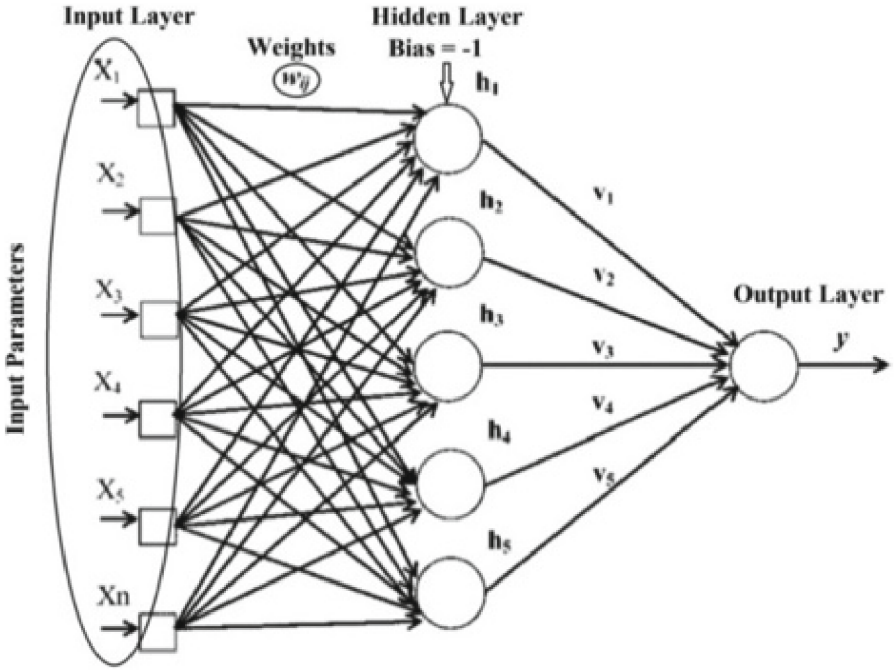

Fig. 3. MLP NN Structure's Flow

3.4 Support Vector Machine (SVM)

One of the main differences between Artificial Neural Networks (ANNs) and SVM is that SVM trains any system focusing on a single solution (a single optimal solution), while

ANN compares multiple solutions and trains by finding the best optimal solution. This is an advantage for SVM in terms of getting the result more practical and faster, but also a disadvantage as it focuses on a single solution. SVM works similar to MLP NN working logic. If this similarity is explained in more detail, firstly the dataset (whether passively or dynamically obtained from experimental results) is introduced to the algorithm. Then the attributes are evaluated in turn. Although the determination of the features is not for MLP NN, it has been seen that this algorithm is very important for classifying the outputs. Then, training and test datasets are created based on the real dataset. In another similarity, MSE is calculated in order to control and evaluate the system performance, as in the MLP NN algorithm [6] (Fig. 4).

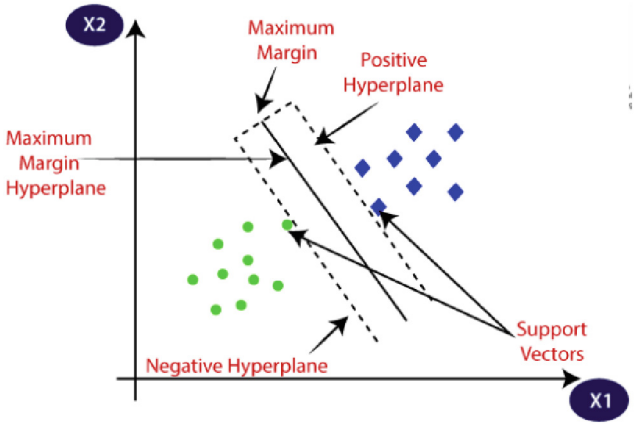

Fig. 4. Example Decision Boundary of SVM [21]

3.5 Decision Tree

KA, detects statistically significant data groups in the data set and shows these significant relationships in the form of tree diagrams. Because this notation is easy and understandable, it is used in many machine learning applications. KA, which consists of input and output data sets, works with a supervised learning method. In this supervised structure, KA detects the connection between input and output. In the KA structure created, there are roots, branches, leaves and the nodes between them. Data belonging to the same class are in leaves on the same branch. In the leaf on a branch, there are result values corresponding to all possible output classes [18] (Fig. 5).

3.6 Wavelet Method

A wave is usually referred to an oscillating function of time or space, such as sinusoid. Wave transformation of signals has proven to be extremely valuable in mathematics, science, and engineering, especially for periodic, time-invariant, or stationary phenomenon. A wavelet is a small wave with finite energy, which has its energy concentrated in time

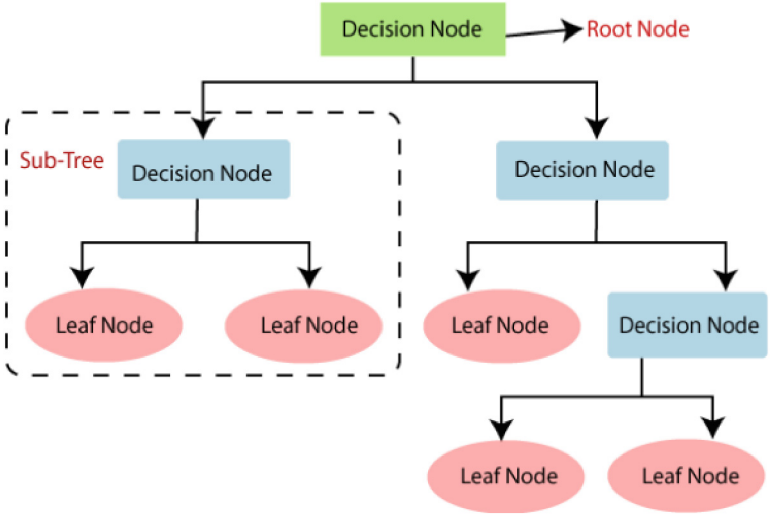

Fig. 5. Genel structure of Decision Tree [21]

or space to give a tool for the analysis of transient, non-stationary, or time-varying phenomenon. The wavelet still has the oscillating wavelike characteristics, but also has the ability to allow simultaneous time, or space, and frequency analysis with a flexible mathematical foundation. Following figures illustrate the difference between wave and wavelet [20] (Fig. 6).

4 Results

In this section, you can observe the results of the application for the cities of Istanbul, Izmir and Trabzon. For each province, an application was made with artificial neural networks, support vector machines, and decision tree-based estimation, which are machine learning algorithms. The r2, mse and rmse values of each application are listed. Then, the rain data was transformed with Wavelet as d1, d2, d3. With this transformed wavelet data, machine learning algorithms work as a hybrid model to increase the success ratio (Table 2).

Table 3 Shows comparison of model results for estimating daily variation of TEC. Result of Support Vector Machine shows better and much reliable results with alpha = 0,10.

Table 4 Shows comparison of model results for estimating daily variation of TEC. Result of AAN (d2 hybrit model) shows better results with alpha = 0,05.

Table 4 Shows comparison of model results for estimating daily variation of TEC. Result of Decision Tree (d3 hybrid model) shows better results with alpha = 0,01.

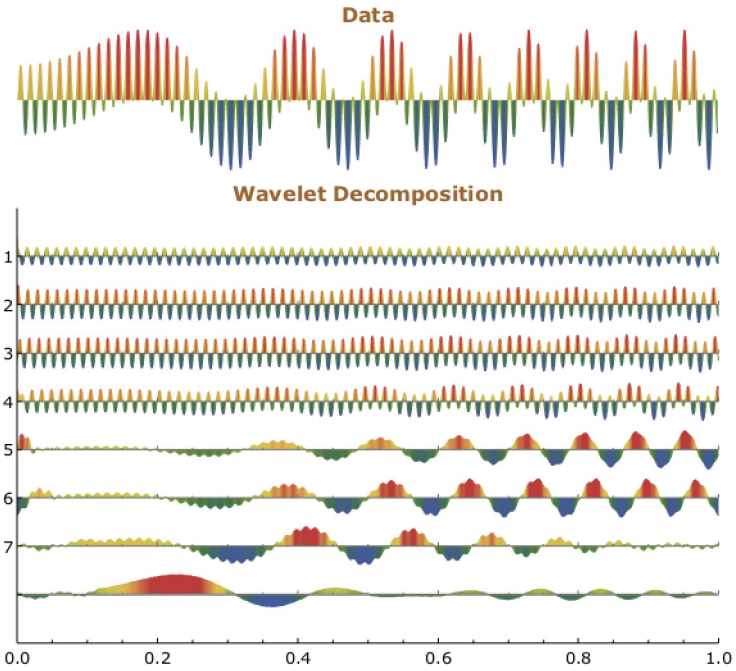

Fig. 6. Example of Visualize Wavelet transform using common x axis plot

Table 2. Comparison of Model Results for Izmir

Machine Learning Algorithm	Artificial Neural Network	Decision Tree	Support Vector Machine
r	−0.0001	−0.01	−0.02
mse	59.6231	0.9871	0.9945
rmse	6.5206	0.9935	0.9972
Machine Learning Algorithm D1	Artificial Neural Network	Decision Tree	Support Vector Machine
r	−0.0001	0.32	0.09
mse	935.2481	67.441	90.816
rmse	22.1084	8.2123	9.5298
Machine Learning Algorithm D2	Artificial Neural Network	Decision Tree	Support Vector Machine
r	−0.0051	0.36	0.00

(*continued*)

Table 2. (*continued*)

Machine Learning Algorithm D2	Artificial Neural Network	Decision Tree	Support Vector Machine
mse	19.3029	63.1	99.027
rmse	3.4068	7.9435	9.9512
Machine Learning Algorithm D3	Artificial Neural Network	Decision Tree	Support Vector Machine
r	−0.0137	0.23	−0.04
mse	19.1358	0.000	104.7
rmse	2.9027	8.8086	10.232

Table 3. Comparison of Model Results for Trabzon

Machine Learning Algorithm	Artificial Neural Network	Decision Tree	Support Vector Machine
r	0.00083	−0.02	−0.14
mse	0.3648	29.461	32.781
rmse	0.4906	5.4278	5.7255
Machine Learning Algorithm D1	Artificial Neural Network	Decision Tree	Support Vector Machine
r	−0.0230	0.57	0.34
mse	0.0926	12.314	18.959
rmse	0.2587	3.5091	4.3542
Machine Learning Algorithm D2	Artificial Neural Network	Decision Tree	Support Vector Machine
r	−0.0004	0.46	0.20
mse	0.1176	15.629	23.052
rmse	0.3095	3.9534	4.8012
Machine Learning Algorithm D3	Artificial Neural Network	Decision Tree	Support Vector Machine
r	−0.0369	0.16	−0.02
mse	4.9844	24.309	29.48
rmse	2.1198	4.9304	5.4295

Table 4. Comparison of Model Results for Istanbul

Machine Learning Algorithm	Artificial Neural Network	Decision Tree	Support Vector Machine
r	0.12	−0.18	−0.01
mse	724.83	974.84	832.58
rmse	26.923	31.222	28.854
Machine Learning Algorithm D1	Artificial Neural Network	Decision Tree	Support Vector Machine
r	0.32	0.19	0.40
mse	0.67781	0.81789	0.59808
rmse	0.823289	0.90437	0.77335
Machine Learning Algorithm D2	Artificial Neural Network	Decision Tree	Support Vector Machine
r	−0.0004	0.46	0.20
mse	0.1176	15.629	23.052
rmse	0.3095	3.9534	4.8012
Machine Learning Algorithm D3	Artificial Neural Network	Decision Tree	Support Vector Machine
r	0.75	0.82	0.82
mse	0.24969	0.18411	0.18209
rmse	0.49968	0.42908	0.42672

5 Conclusions

This study was carried out within the scope of several purposes. First of all, it is determined whether there is a relationship between the TEC-historical data and temporal variation of precipitation. If there is a relationship, estimating it and increasing the accuracy by using the estimation rate as a hybrid of Wavelet and machine learning algorithms. And finally, by examining the data of three different cities of Turkey with the same algorithms, it is observed how the performances of the algorithms change according to the changing data set.

As a result of the study, it has been determined that there is a linear partial relationship between TEC-historical data and rain. Although this situation is at different rates for all 3 cities, it has been observed that there is a strong relationship to a certain extent.

It has been determined that the prediction accuracy rate has increased significantly in some provinces with the use of machine learning algorithms first and then the Wavelet signal analysis method performed in the application part. It has been determined that the ANN algorithm for the city of Trabzon works with the wavelet d1 frequency and the rmse ratio is 0.82, which is the most appropriate algorithm. With the DT algorithm, D2, $r = 0.36$ value was reached for the city of Izmir. Likewise, D2, $r = 0.57$ values were reached for the city of Trabzon with the DT algorithm. It has been determined that the

support decision tree algorithm works most efficiently for the city of Izmir and it is the most appropriate algorithm with an rmse ratio of 0.99. It has been determined that of the Decision Tree (d3 hybrid model) algorithm works most efficiently for the city of Istanbul, and it is the most appropriate algorithm with an rmse ratio of 0.45.

When we analyzed the outputs of the application work, it was revealed that the algorithms did not perform the same for every dataset, even though they were working with similar datasets for the same problem. With this result, it has been observed that different problems work with different accuracy rates by different algorithms, and that the success ratio of algorithms with different data in the same problem significantly changes.

Significant levels have been changes from 0,01 to 0,10 for three selected study areas with TEC data observations and estimations.

As a result of the study, the results of the three targeted cases were reached. After this study, other studies can be done to increase the reliability of the results. First of all, performance conditions can be observed by working with different machine learning algorithms in these regions. As another study, the dataset of 2017 from this study can be expanded and a wider dataset by using long term results can be examined. Finally, with the expansion of the data set, performance conditions can be compared by working with deep learning algorithms, which is an approach covered by the field of machine learning.

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