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Digital elevation modeling using artificial neural networks, deterministic and geostatistical interpolation methods

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ABSTRACT
The digital elevation model (DEM) is the name given to a digital structure used to indicate the surface. Determination of features such as elevation, basin slope and basin area are very important in engineering applications. These properties are determined by the DEM and their power to represent accuracy or truth is vital in engineering applications. In addition to the latitude (X), longitude(Y) coordinate information, altitude information is required, and intermediate values are determined by different methods for DEM. In this study, Mert River Basin Samsun (Turkey) was chosen as the application area. Heights are estimated from X, Y coordinate information. Three different Artificial Neural Networks, IDW and Kriging methods were used. Artificial Neural Networks (ANN) were analyzed with three different inputs. These are: (i) x coordinate information; (ii) y coordinate information; (iii) It is in the form of x and y coordinate information and are used Radial Based Artificial Neural Network, Multilayer Artificial Neural Network and Generalized Artificial Neural Network. X and Y coordinate information was used in IDW and Kriging interpolation methods. Results were evaluated using Coefficient of Determination (R^2), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) as comparison criteria. According to the modeling results: It was observed that the results of all methods reached a sufficient level of accuracy. Kriging method was found to be the most successful model, followed by IDW and ANN.

1. INTRODUCTION

Resource management, urban and rural planning, transportation planning, agriculture, forestry, watershed management, disaster risk assessment etc. Digital Elevation Model (DEM) is needed in many studies. In addition, basic topographic and morphological parameters derived from the DEM are needed. At the present time, Geographical Information Systems (GIS) enables the creation of DEM and the automatic derivation of topographic and morphological parameters from DEM (Fang and Wu 2007; Gocic and Trajkovic 2013; Klingseisen et al. 2008; Papik et al. 1998; Parlak et al 2006; Yan 2008, Yakar 2008; Yakar et al. 2009).

DEM is the numerical representation of the topography. The DEM contains some errors and uncertainties depending on the data generated and the model used. These errors systematically affect the details of the land derived from the DEM. For this reason, the correctness of the DEM must be investigated for the adequacy of the work to be performed (Usul and Paşaoğulları 2004; Wang et al. 2006).

Two methods are generally used when creating DEM. The first is the 3-dimensional images obtained by the remote sensing method. These images are a wide range of high precision data. Also, the relative and absolute precision accuracy is very low. Radar and laser scanners and other sensor are also available to achieve high precision, high resolution DEM. These transactions are generally costly. The second method is to scan the existing topography, using digital contour lines; access to the height data generated by DEM, data such as high efficiency, low cost, topographic maps related to the experiment, measuring the use of this method and achieving the desired results (Yan 2008).

When the important studies on numerical height

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modeling are examined; Demirkesen (2003) created the digital elevation model using satellite images of the Cumberland Drainage Basin in Kentucky, USA (Demirkesen 2003). Arslanoğlu and Özçelik (2005) modeled numerical heights using the contour lines of 1 / 25.000 scaled maps (Arslanoğlu and Özçelik 2005). Akçın et al. (2005) modeled the seabed topography with Artificial Neural Networks (ANN) (Akçın et al. 2005). Şahin and Yakar (2007) have created a numerical elevation model for 2 different regions from aerial photographs, IKONOS satellite images, elevation curves and radar scans. (Şahin and Yakar 2007). Karan et al. (2004) made surface modeling with Object-Information-Based Combinational-Photogrammetry technology using three-dimensional topographic data, two-dimensional aerial images and satellite images. (Karan et al. 2004). Hani et al. (2011) created the numerical height model with Granulometric analysis model (Hani et al. 2011). Çakır and Yılmaz (2014) made surface modeling using polynomials, multiquadric interpolation, feed forward neural network and ANFIS methods (Çakır and Yılmaz 2014). Schulmann et al. (2015) made topographic surface modeling using Landsat satellite image data and shadow and vision technique (Schulmann et al. 2015). Niederheiser et al. (2018) created a numerical model by using terrestrial image matching method to obtain the topographic features of the Alps region (Niederheiser et al. 2018). Khosa et al. (2019) used elevation modeling from land surface, empirical and satellite-based models using on-site observations in a semi-arid region in South Africa (Khosa et al. 2019). Zhang et al. (2020) made surface modeling with stochastic and micro grinding processes (Zhang et al. 2020). Demir and Ülke Keskin (2020) made surface modeling with multi-layered artificial neural network method and regression methods from ANN methods (Demir and Ülke 2020). In addition, surface models based on coordinate transformation are also made (Güllü et al. 2011; Konakoğlu et al. 2016; Lei and Qi 2010; Tierra et al. 2008)

Öztürk et al. (2010) have studied digital elevation data sources and structures, sources of errors in Grid DEM, observation of slope, view, flow direction, flow sum, basin-sub basin, drainage network from GIS and DEM, and effect of grid-DEM's resolution on self-derived topographic and morphological data in their study (Öztürk et. al. 2010). Demirkesen (2003) made hydrological analysis by using the DEM data obtained from the satellite images belonging to that region in order to help the land arrangement and planning in urban and rural areas. As a result of the analysis, the flood zones were determined depending on the rainfall amount to the region (Demirkesen 2003). Çakır (2015) used a functional test surface as an application area. The surface created is a rugged terrain consisting of mountains and pits. After specifying 80 fulcrums and 30 test points for this test surface in random distribution, optimal DEM models to represent the surface have been developed with Polynomials, Multicuadic Interpolation, Feedforward Artificial Neural Networks (F-ANN) and Adaptive Network Based Fuzzy Inference Systems (ANFIS). As a result of their work, F-ANN and ANFIS methods are more successful than polynomials and multicharistic interpolation methods in determining DEM (Çakır 2015). Yaprak and Arslan (2008) investigated the usability of deterministic and Kriging interpolation methods in surface modeling to determine geoid with GPS and Leveling method. Gümüş and Şen (2017) obtained surface models of lands with different topographic features using IDW and Kriging methods and interpreted the results using analysis of variance (ANOVA). In the current study, the 14362 digital elevation model data are used. 14362 data were randomly sorted in excel. Then A (as training data 90% - as testing data 10%), B (80% -20%), C (70% -30%), D (60% -40%), E (50% -50%) were divided into training-test packages. Coordinate information was prepared as single x, single y and x, y, respectively, and z output data was produced. The objective of the study is to estimate the elevation point at any ungauged location in the Mert River. Artificial Neural Network models and two different well- known interpolation methods (IDW and Kriging) are used for this purpose.

2. MATERIALS AND METHOD

2.1. Material

The Mert River (latitude: 41.279 and longitude: 36.352) located in the central district of Samsun and poured into the Black Sea was selected as the study area. The study area is shown in Figure 1.

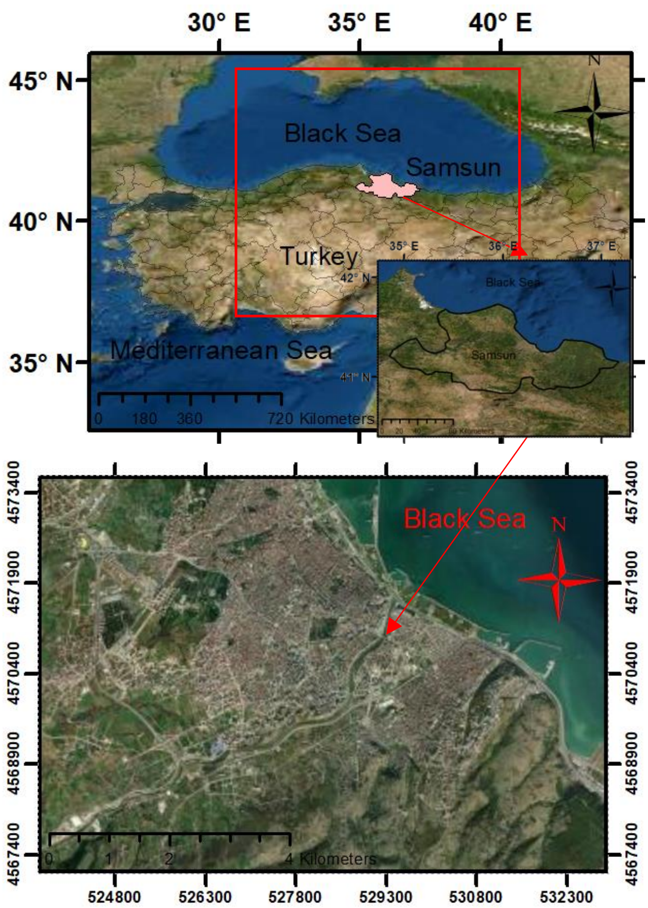

Figure 1. Study Area

The data modeled in the study is the current map height data obtained from the central municipalities of Samsun (Canik-Ilkadım). These data are defined in the

ED-50 coordinate datum with a scale of 1/1000 and were obtained from aerial photographs.

Table 1. Statistical information of data

	X	Y	Z
Number of Data (N)	14362	14362	14362
Minimum value (m)	4568584.581	528296.486	0.07
Maximum value (m)	4572051.156	530920.692	238.130
Skewness Coefficient	0.008	0.0579	1.429
Standard deviation	889.701	686.639	52.355
Average	4570318.492	529557.428	43.688

2.2. Methods

2.2.1. Multi-Layered Artificial Neural Network

Multi-layer Artificial Neural Networks (MANN) consists of an input layer, one or more hidden (intermediate) layers, and an output layer where information is input. MANN has transitions between layers called forward and backward propagation. In the forward propagation phase, the output and error value of the network are calculated.

In the back-propagation phase, the inter-layer link weight values are updated to minimize the calculated error value (Arı and Berberler 2017). The MANN model uses the backpropagation learning algorithm, which is the generalization of the least squares algorithm in linear perception. Back propagation consists of backward steps in which the output of the network is determined by the algorithm that defines advanced forward information and the error caused by the emergence of the weights is reduced. In the feed-forward step, the inputs of the training set are sent to the input layer of the network. The input layer contains neurons that receive these inputs. Therefore, the number of neurons in the input layer must be the same as the number of input values in the data set. Neurons in the input layer transmit the input values directly to the hidden layer. Each neuron in the hidden layer calculates the total value by adding the threshold value to the weighted input values and multiplies them with an activation function, then transmits them to the next layer or directly to the output layer. The weights between the layers are initially chosen randomly. The error value is calculated by comparing the output values of the network with the expected output values. The multi-layer sensor model consists of an input (X_1, X_2, X_3,….., X_n), a hidden, and an output layer (Y). Each layer may also have one or more processing elements. The processor elements in the input layer act as a buffer that distributes the input signals to the processor elements in the intermediate layer. The intermediate layer processor elements use the outputs of the previous layer as inputs. With all inputs, weights are multiplied and total. This value is then passed through a transfer function and the output value of that neuron is calculated. These operations are repeated for all the processor elements on this floor. These operations are repeated for all processor elements in this layer. The processor elements in the output layer also act as intermediate layer elements and the network output values are calculated. This model is also known as feed forward ANN's as the information flow is in the forward direction (Gemici et al. 2013). Different learning algorithms are used to train the network The activation function processes the net input to the cell and determines the output that the cell will generate for that input. One of the most used activation functions in applications is the Sigmoid-type activation function (Gemici et al. 2013). The formula of the function is shown in Equation (1). The most active site of the function is between 0.2 and 0.8.

$$y = F(v) = \frac{1}{1+e^{-v}} = \frac{1}{2}[\tanh(\frac{v}{2})-1] \tag{1}$$

2.2.2. Radial Based Artificial Neural Networks

Radial-based ANN (RBANN) concept was introduced into the literature in 1988 by Broomhead and Lave. ANN model and Radial-based functions have been developed by considering the effect-response states of neuron cells in human nervous system (Okkan and Dalkılıç 2012). It is possible to see the The digital elevation model (DEM) is a numerical structure used to indicate the surface. It is possible to view the training of RBANN models as a curve fitting approach in multidimensional space (Partal et al., 2008; Poggio and Girosi 1990). Thus, the educational performance of the RBANN sample turns into a problem of finding the closest result to the data in the output vector space and thus an interpolation problem (Okkan and Dalkılıç 2012). RBANN structure generally consists of input layer, hidden layer and output layer similar to ANN structure. However, unlike other ANNs, the data is subjected to radial based activation functions and a nonlinear cluster analysis when passing from the input layer to the hidden layer. The structure between the hidden layer and the output layer functions as in other ANN types and the actual training takes place in this layer. In the RBANN model we used, the problem was solved with purelin function.

2.2.3. Generelization Regresion Artificial Neural Network

The Generalized Regression Artificial Neural Network (GRANN) proposed by Specht (1991) does not require an iterative training procedure as in the back-propagation method (Sürel, 2006). GRANN estimates any function between input and output vectors using training data. As the training set expands, the prediction error decreases to zero (Alp and Cığızoğlu, 2004). As known by definition, regression estimates the most probable value of a dependent variable based on the independent variable x, given the training set x. The regression method estimates y to minimize common square error. GRANN is a method that estimates the common probability density function of x and y when a training set is given. The system is generally ideal since the Common Density Function is obtained without any pre-acceptance from the data (Alp & Cığızoğlu, 2004; Kesikoğlu et. al. 2020; Öztürk et. al. 2022). If the common probability density function of f (x,

y) is known, the regression of the dependent y variable according to the independent x variable is given in Equation (2).

$$E\left[y|X\right]=\frac{\int_{-\infty}^{\infty} yf(X,y)dy}{\int_{-\infty}^{\infty} f(X,y)dy} \quad (2)$$

2.2.4. Inverse Distances Weighted

Inverse Distance Weighted (IDW) is one of the most preferred non-geostatistics methods. This method is an interpolation technique used to determine the cell values of unknown points using the values of known sample points. Since it produces estimates only from neighboring points, it makes a local intermediate value estimation. The method is based on the fact that the nearby points have a greater weight on the surface to be interpolated than the distant points. The cell value is calculated by observing the various points moving away from the cell of interest and depending on the increase in distance. The predicted values are a function of the distance and the size of the points in the neighboring neighborhood, and as the distance increases, the importance and effect on the cell to be estimated decreases (Taylan and Damçayırı, 2016).

$$F(x,y)=\sum_{i=1}^{n} w_i f_i \quad (3)$$

$$w_i=\frac{h_i^{-p}}{\sum_{j=1}^{n} h^{-p}{}_i} \quad (4)$$

The weights used to estimate the function are expressed as any exponent of the distance in inverse proportion to the distance.

In the Equations 3-4; (Krige, 1951)
p; Known as force parameter and show exponent,
h_i; Spatial distance between sample points and interpolated points,
w_i; Weights are doing and the sum of the values must be 1.
f_i= Known altitude values.

2.2.5. Kriging Method

The kriging method is a geostatistical interpolation method that estimates the optimum values of data at other points using data from known nearby points. The most important feature that distinguishes Kriging from other methods is that a variance value can be calculated for each estimated point or area. This is a measure of the reliability of the predicted value (Yaprak and Arslan, 2008).

The estimation by the Kriging interpolation method has two stages: (i) adaptation to a model: creation of variograms and covariance functions, this is based on the autocorrelation model and (ii) estimation: estimation of the unknown (Öztürk and Kılıç 2016).

Equation 5 used in kriging;

$$N_p=\sum_{i=1}^{n} P_i * N_i \quad (5)$$

Where;
n = Number of points in the model,
N_i = N_p, The geoid undulation values used in the calculation of
N_p = The required undulation value
P_i = The weight values for each N_i value used in the calculation of N_i.

Kriging technique provides more objective results than other estimation techniques and also gives minimum variance and standard deviation of estimation.

3. APPLICATIONS

Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and determination coefficient (R^2) were used as comparison criteria. The formulas of the criteria are given in the Equations 6-7-8.

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Z_o-Z_e)^2} \quad (6)$$

$$MAE=\frac{1}{N}\sum_{i=1}^{N}\left|Z_o-Z_e\right| \quad (7)$$

$$R^2=\left(\frac{N*\left(\sum Z_o*Z_e\right)-\left(\sum Z_o\right)*\left(\sum Z_e\right)}{\sqrt{\left(N*\sum Z_o^2\right)-\left(\sum Z_o\right)^2*\left(N*\sum Z_e^2\right)-\left(\sum Z_e\right)^2}}\right)^2 \quad (8)$$

The distribution of the data used in the analysis is different for each package. Packages A (training data 90% - test data 10%), B (80% - 20%), C (70% - 30%), D (60% - 40%), E (50% - 50%). Table 2 shows the distributions.

Table 2. Table of data distributions

Packages	Training Data %	Test Data %
A	90	10
B	80	20
C	70	30
D	60	40
E	50	50

Table 3-7 shows the analysis results according to the comparison criteria of the test set of the A, B, C, D, E package respectively.

All analysis results are given in the tables below. When the results were examined, the Kriging method was the first to reach the best results in both training and test data in all packages. RMSE = 1.121, MAE = 0.635, R^2 = 0.999 in the B package. Secondly, the IDW, GRNN and RBANN method has achieved the best result. Finally, the MANN method solves the problem most accurately.

Table 3. A pack test data results

Test	Method	Input		
A (10%)		(i; x)	(i; y)	(ii; x,y)
RMSE	MANN	32.878	45.769	18.430
	RBANN	35.406	29.130	10.224
	GRANN	**32.699**	**45.634**	**2.357**
	Average	33.661	40.178	10.337
MAE	MANN	24.182	35.126	12.766
	RBANN	28.225	23.882	6.794
	GRANN	**24.036**	**34.951**	**1.278**
	Average	25.481	31.320	6.946
R^2	MANN	0.595	0.213	0.873
	RBANN	0.529	0.681	0.961
	GRANN	**0.599**	**0.218**	**0.998**
	Average	0.574	0.371	0.944

Table 4. B pack test data results

Test	Method	Input		
B (20%)		(i; x)	(i; y)	(ii; x,y)
RMSE	MANN	33.515	46.934	18.326
	RBANN	36.323	29.447	10.376
	GRANN	**33.360**	**46.762**	**2.315**
	Average	34.399	41.048	10.339
MAE	MANN	24.633	35.784	12.774
	RBANN	28.230	24.027	6.677
	GRANN	**24.480**	**35.603**	**1.282**
	Average	25.781	31.805	6.911
R^2	MANN	0.598	0.211	0.880
	RBANN	0.528	0.690	0.961
	GRANN	**0.602**	**0.217**	**0.998**
	Average	0.576	0.373	0.947

Table 5. C pack test data results

Test	Method	Input		
C (30%)		(i; x)	(i; y)	(ii; x,y)
RMSE	MANN	33.334	47.325	18.188
	RBANN	36.303	34.099	10.319
	GRANN	**33.222**	**47.157**	**2.292**
	Average	34.286	42.860	10.267
MAE	MANN	24.506	36.097	12.660
	RBANN	28.853	27.844	7.085
	GRANN	**24.267**	**35.963**	**1.279**
	Average	25.875	33.301	7.008
R^2	MANN	0.607	0.208	0.883
	RBANN	0.534	0.589	0.962
	GRANN	**0.609**	**0.213**	**0.998**
	Average	0.583	0.337	0.948

Table 6. D pack test data results

Test	Method	Input		
D (40%)		(i; x)	(i; y)	(ii; x,y)
RMSE	MANN	33.316	46.948	18.080
	RBANN	350.732	33.814	9.902
	GRANN	**33.154**	**46.745**	**2.711**
	Average	139.067	42.502	10.231
MAE	MANN	24.437	35.847	12.554
	RBANN	308.732	27.552	6.438
	GRANN	**24.170**	**35.656**	**1.307**
	Average	119.113	33.018	6.766
R^2	MANN	0.600	0.207	0.882
	RBANN	0.101	0.589	0.965
	GRANN	**0.604**	**0.213**	**0.997**
	Average	0.435	0.336	0.948

Table 7. E pack test data results

Test	Method	Input		
E (50%)		(i; x)	(i; y)	(ii; x,y)
RMSE	MANN	33.279	46.857	17.947
	RBANN	35.675	35.816	10.349
	GRANN	**33.119**	**46.690**	**2.613**
	Average	34.024	43.121	10.303
MAE	MANN	24.377	35.925	12.542
	RBANN	28.268	27.698	6.890
	GRANN	**24.126**	**35.759**	**1.308**
	Average	25.590	33.127	6.913
R^2	MANN	0.599	0.206	0.884
	RBANN	0.540	0.536	0.961
	GRANN	**0.603**	**0.212**	**0.998**
	Average	0.581	0.318	0.947

Table 8. IDW and Kriging (KRI) methods data results

PACKS	Method	RMSE	MAE	R^2
A	IDW	1.638	0.881	0.999
	KRI	1.115	0.639	0.999
B	IDW	1.540	0.862	0.999
	KRI	1.121	0.635	0.999
C	IDW	1.129	0.651	0.999
	KRI	1.427	0.782	0.999
D	IDW	2.207	0.970	0.998
	KRI	1.763	0.677	0.998
E	IDW	2.158	1.012	0.998
	KRI	1.687	0.701	0.998

4. DISCUSSION

In the study of Demir and Keskin, multilayer artificial neural network and regression analysis were applied, and they used the data package as training (80%) and testing (20%). Multilayer neural network gave better results. However, a comparison between artificial neural networks was not carried out in the study. In this study, we have done modeling with different data packages using 3 different artificial neural network methods. According to the comparison criteria, the results of the generalized artificial neural network gave closer results than the multilayer artificial neural network. This study demonstrates the accuracy between training and testing, as well as supporting and enhancing the work of Demir and Keskin (Demir et al., 2020).

5. CONCLUSION

In the study, 14362 coordinate data were modeled using artificial neural network and interpolation techniques. IDW and Kriging methods from interpolation techniques, Radial Based Artificial Neural Network, Multilayer Artificial Neural Network and Generalized Artificial Neural Network methods were used in artificial neural network methods. Data in ANN A (90% -10%), B (80% -20%), C (70% -30%), D (60% -40%), E (50% - 50%) rates of training and testing packages, and the study was carried out for three different input combinations.

When the results are examined; It was determined that the Kriging method gave the best modeling (with the least error) in the A, B, D and E packages, and the IDW method showed the best modeling in the C package. While the R^2 values are close to each other, error values are listed as follows; RMSE values of the results of the packet, the order is as follows; A package = 1.115 and B Package = 1,121 with Kriging C Package = 1.129 with IDW method. The ranking of MAE values are; A package = 0,639, B package = 0,635 with Kriging method, C Package= 0.651 with IDW. Then comes the Generalized Artificial Neural Network for all packets then Radial-Based Artificial Neural Network, and finally the Multilayer Artificial Neural Network.

While it is observed that the results of the modeling made with 2 inputs from the GRANN models give an R^2 value close to each other, the order is as follows; C package = 0.9982, B package = 0.9981 A package = 0.9979. RMSE values of the packets also gave similar results, the order is as follows; C package = 2.2924 B Package = 2.3146, A package = 2.3572. The ranking of MAE values are; A package = 1.2777, C package = 1.2788, B Package = 1.2820.

Author contributions

Esra Aslı Çubukçu: Methodology, Application, Writing-Original draft preparation, **Vahdettin Demir:** Conceptualization, Methodology, Application, Reviewing and Editing. **Mehmet Faik Sevimli:** Last Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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