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URBAN GROWTH PREDICTION WITH ARTIFICIAL NEURAL NETWORKS – KIRKLARELİ CASE STUDY

Azem KURU [1*]

[1:] Kırklareli Üniversitesi, Mimarlık Fakültesi, Şehir ve Bölge Planlama Bölümü.

Abstract

It is a necessity for a sustainable world to manage urban growth, where urban areas and urban populations are constantly increasing. Cities are growing vertically and horizontally over time due to the many factors that they have inhabited. If the spatial growth of cities is not guided correctly, it may have a negative impact on the sustainability of environmental resources as well as social and economic difficulties. In recent years, many models have been created to predict urban growth. In this study, spatial growth for Kırklareli was modeled by using artificial neural network technology. Urban boundaries detected by satellite images and aerial photographs in 1993 and 2017 were tested with artificial neural networks. As a result of the study, the usability of artificial neural networks as a tool to determine the future spatial boundary of cities has been detected.

Keywords: Artificial neural networks, urban growth prediction, urban growth modelling, GIS, Kırklareli.

YAPAY SİNİR AĞLARI İLE KENTSEL BÜYÜMENİN MODELLENMESİ- KIRKLARELİ ÖRNEĞİ

Özet

Kentsel alanların ve kentli nüfusunun sürekli arttığı günümüz dünyasında kentsel büyümeyi yönlendirmek sürdürülebilir bir dünya için zorunluluk arz etmektedir. Kentler içinde barındırdığı birçok etkenin etkisiyle zaman içerisinde yatayda ve dikeyde büyümektedir. Mekânsal olarak büyüyen kentlerin bu büyümesinin doğru yönlendirilmemesi çevresel kaynakların sürdürülebilirliğine olumsuz etki ettiği gibi sosyal ve ekonomik zorlukları da beraberinde getirmektedir. Son yıllarda kentsel büyümenin önceden tahmin edilebilmesi için birçok model oluşturulmuştur. Bu çalışmada yapay sinir ağları teknolojisi kullanılarak Kırklareli kenti için mekânsal büyüme modellenmiştir. 1993 ve 2017 uydu görüntüleri ve hava fotoğrafları yardımıyla tespit edilen kent sınırları yapay sinir ağları ile test edilmiştir. Çalışma sonucunda yapay sinir ağlarının gelecek dönemlerde kentin yayılma sınırlarının belirlenmesinde araç olarak kullanılabilirliği saptanmıştır.

Anahtar Kelimeler: Yapay sinir ağları, kentsel büyüme tahmini, kentsel büyüme modeli, CBS, Kırklareli.

[*] Sorumlu Yazar: azemkuru@gmail.com

1. INTRODUCTION

In today's world, the population of cities is continuously increasing, and in parallel, urban areas are growing spatially. Many elements shape the growth process. The individual preferences of the urban population, land prices, desire for closeness to urban facilities, income levels, social and cultural differences, and economic costs are some factors affecting the formation of the urban macroform. The interaction of these elements is the reason for the urban spatial expansion. In addition, many other factors affect the spatial growth of cities, such as public investments, land use, slope, aspect, hydrology, geological situation, agricultural capacity, proximity to transport links, and proximity to job areas. The spatial growth of cities harms natural resources and brings many social and economic costs to citizens and governments. In this respect, handling spatial growth is essential for sustainable urban development.

Many researchers studying urbanism emphasize the importance of modeling urban growth to guide the expansion of urban areas. Remote sensing (RS) and geographical information systems (GIS) can be said to be influential in developing urban growth models. With the help of modeling, it may be possible to understand complex urban systems better and proactively solve the problems before they occur. In addition, the model will provide greater convenience during the planning and help urban planners to increase the objectivity of planning (Maithani et al., 2007; Aydın, 2015; Ayazlı et al., 2011). As a result, various urban growth model has been built.

Using GIS and artificial neural networks (ANN), the Land Transformation Model uses social, environmental, and political criteria to predict urban land use changes simultaneously. Also, the individual contributions of every criterion to estimate land use change has been examined (Pijanowski et al., 2002; Pijanowski et al., 2005; Pijanowski et al., 2014). Change-Pattern-Value model aims to detect and characterize land use changes using several socioeconomic and remote sensing data. The model uses an artificial neural network to determine the main reasons for land use change (Dai and Wu, 2005).

Urban Expansion Model (UEM) was produced to predict urban spatial growth via geographic information systems, ANN, remote sensing, and various socioeconomic and environmental parameters. Socioeconomic and environmental parameters and built-up areas are used for inputs and outputs to train ANN. As socioeconomic and environmental parameters, transportation network, residential area, service center, open spaces, elevation, aspect, and slope selected (Pijanowski et al., 2009).

SLEUTH model consists of the slope, land use, exclusion, urban extent, transportation, and hillshade variables and one of the modified cellular automata models. It interprets urban growth by four primary rules: new spreading center, transportation-oriented, organic, and self-generated. It also has five growth parameters: diffusion, breed, slope resistance, road gravity, and spread, and every parameter has a value range of 0-100. Under these circumstances, there are five steps to implement SLUETH in an urban area: compilation, data preparation, calibration, estimation, and evaluation of outputs. Many researchers use the model for various urban and regional unique areas (Silva ve Clarke, 2002; Watkiss, 2008; Xibao et al., 2006; Xi et al., 2009; Wu et al., 2009; Rafiee et al., 2009).

Urban Growth Boundary Model used raster formatted seven parameters such as roads, green spaces, slope, aspect, elevation, facilities, and constructed area. This model uses geographic information systems, remote sensing, and neural networks to predict urban extents. It was calibrated for Tehran city, and 80% accuracy of the growth boundary has reached (Tayyebi et al., 2011). Maithani et al., 2007 developed a pixel-based urban spatial growth model with the help of ANN, GIS, and RS. They used five variables: proximity to main roads, secondary roads, proximity to the urban core, proximity to the urban built-up boundary, and amount of constructed area in a neighborhood of five hundred meters. In the study, the number of perfect correct matches for the model calibrated for Saharanpur City was found 66%.

Berberoglu et al. (2016) performed a comparative study within cellular automata based on several models in Adana. The compared models are Markov chain, SLEUTH, logistic regression, regression trees, and ANN. When the model with the best results becomes SLEUTH with a kappa accuracy of %75, logistic regression and artificial neural network become the least well-predictive. Triantakonstantis and Stathakis (2015) applied the ANN-based model to Athens. Using 1990 and 2000 freely available Corine land cover data, they predicted the 2006 urban growth boundary and later compared it with the actual 2006 situation. The used parameters are proximity to roads and urban areas, slope, and elevation. The kappa accuracy of the prediction is 63%.

Mohammady et al., (2014) tried calibrating an artificial neural network-based model for Sanandaj City. They use elevation, slope, proximity to main transportation networks, residential areas, centers and sub-centers, and green areas variables. Using Landsat imagery of the year 2000, they simulated urban growth for 2006 and compared it with the current 2006 urban layout. Percent correct match for the simulation 2006 found 90%. Grekousis et al. (2013) performed a fuzzy logic and ANN-based model for the Athens Metropolitan Area.

Park et al. (2011) compare several land suitability index maps created using logistic regression, analytical hierarchy process, frequency ratio, and artificial neural network. To predict land use change, slope, elevation, aspect, proximity to roads and urban areas, road ratio, current land use, legal constraints, and environmental scores were used. After comparing all selected methods' accuracy, the artificial neural network-based model gives the best results.

Moghaddam and Samadzadegan (2009) use an artificial neural network to select effective parameters for cellular automata-based urban growth models. Historical data used for training the model; the historical amount of built-up environment in the neighborhood, agricultural suitability and proximity to the urban center, suburban center, roads, highway, and water body parameters were used for training to clear up land use change drivers for Esfahan.

Similarly, Yeh and Li, (2002) and Li and Yeh, (2001) propose a cellular automata model that transition rules defined thanks to artificial neural network methods. The amount of development in a 7x7 pixel neighborhood, agricultural suitability, and proximity to urban areas, suburban areas, roads, highways, and railways derived from historical remote sensing data are used. Almeida et al. (2008) use cellular automata and ANN to model urban growth for one of Sao Paulo's small towns. They use an artificial neural network to define transition rules of cellular automata. In addition to these studies, many other urban growth models have been developed of artificial neural network methods (Zhang, 2016; Zhou, 2012; Almeida and Gleriani, 2005; Guan and Clarke, 2005; Liu and Lathrop, 2002; Maithani, 2009; Wang and Mountrakis, 2011).

ANN are preferred for solving problems in many areas, such as forecasting, modeling, vehicle routing, traveling salesman problems, clustering, classification, etc. ANN has developed in artificial intelligence. It is an estimating tool that relies on dependent and independent variables such as regression and similar methods. The main difference between ANN and statistical methods is that neural networks do not make any assumptions about statistical distribution or data properties. Another essential feature is that it produces more relevant results than traditional statistical models in modeling complex data since it is a non-linear estimation method (Fischer, 1992).

ANN comprise many simple processing units connected by adjustable weights. Contrary to traditional methods, relationships between variables can be caught and learned from examples, even if they are unknown or difficult to understand. ANN are alternative computation tools that can generalize, comprehend, classify, and adapt to changing conditions in a data set (Maithani et al., 2007).

The characteristics of the ANN can be listed as follows while varying according to the model network and used algorithms (Öztemel, 2006; Openshaw, 1998):

- An artificial neural network is a machine learning system. Traditional programming and artificial intelligence methods have entirely different methods of information processing.
- The ability to run with missing data makes them vulnerable to fault tolerance. The network will continue to work if some of its cells become corrupted and fall into an unstable state. Conventional computers often need complete data.
- ANN can produce results even if there is incomplete data in samples after training; traditional systems can not work with missing information.
- They can be self-organizing and learning. It is possible that ANN can adapt to new situations and can constantly learn new events.
- In ANN, information is spread. In other words, the whole network characterizes the event it is learned.
- ANN can only run with numerical data. Symbolic data expressions must be translated into numerical values.
- It can be used in shape overarching, classification, and pattern recognition.
- Non-linear problems in complex systems can be solved by ANN.
- The procedure of ANN is quite easy because no need an exact equations or expressions.
- Normal distribution of dataset is not necessary.
- Different measurement scales and types can be used.
- Redundancy is not a problem in ANN.

ANN usually consists of three layers containing different numbers of neurons: an input layer, a hidden layer, and an output layer. All neurons except those in the network's input layer collect input from the weighted links connected to them and generate an activation in response to collected values (Zhou, 2012; Aydın, 2015; Topuz, 2008).

There are no accepted rules for the architecture of ANN. While ANN with fewer hidden layers are insufficient for solving complex problems, the excessive number of hidden layers creates uncertainty. After the number of hidden layers is determined, the problem is confronted by not deciding how many neurons will be present in each layer. The amount of input layer is same as the amount of variables in the system. Accordingly, the number of output layers can be defined by the desired number of outputs. The important issue is to define the number of neurons in hidden layers. The traditional matrix algorithm indicates that matrix sizes must be equal to the number of inputs or outputs. Yet, no proof exist on how many neurons can be found most efficiently in the hidden layer. It is decided by the trial and error learning method (Ataseven, 2013; Almeida et al., 2008; Fletcher and Goss, 1993; Li and Leh, 2001; Guan and Wang, 2005).

Different types of neural networks exist. One of the most frequently employed ANNs is the multi-layer perceptron (MLP) neural network. Three layers—input, hidden, and output—make up MLP's architecture. It is primarily used to find non-linear relationships. By introducing the input in a feed-forward form, which spreads through the hidden layer and the output layer, ANN algorithms calculate weights for input values, input layer nodes, hidden layer nodes, and output layer nodes. Weights connected to each connection alter the signals as they propagate between nodes. The receiving node adds the weighted inputs from every node connected to it in the preceding layer. This node's output is then calculated as a function of its input, or "activation function.". Before the data reaches the output layer, it is subjected to numerous weighted summations as it moves from node to node. The backpropagation algorithm, the most widely used training algorithm, is used to determine the weights in an ANN. The initial weights are chosen at random by the backpropagation algorithm, which then contrasts the calculated output with the anticipated output for each observation. The mean squared error is a measure of how different the calculated output values are from the expected values across all observations. A generalized delta rule is used to adjust the weights after the network has received all observations (Rumelhart et al. , 1986) in order to spread the network's total error across all of its nodes. Until the error stabilizes at a low level, this process of feeding forward signals and back-propagating the errors is repeated iteratively (in some cases, many thousands of times). (Pijanowski et al., 2002; Özcan, 2015) (Figure 1).

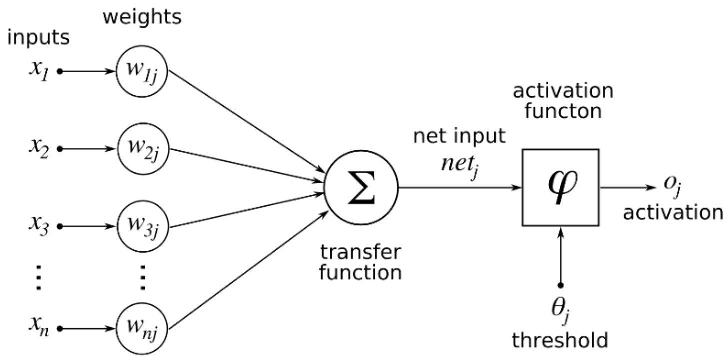

Figure 1. The architecture of Multi-Layer Perceptron Neural Network (Pijanowski et al. 2002; Özcan, 2015)

One of the essential advantages of the ANN is its ability to generalize. The dataset should divide into three groups; the training set used to train the net; the validation set used to determine the neural network performance; and the test set used to check the overall performance of an ANN (Almeida et al., 2008).

2. MATERIAL AND METHODS

2.1. Study Area

The small-medium-sized Kırklareli city was chosen as the study area. The Kırklareli province is in the area of transition from Marmara to Europe and a neighboring border with Bulgaria. Bulgaria surrounds it in the north, the Black Sea in the east, Istanbul in the southeast, Tekirdağ in the south, and Edirne in the west (Figure 2).

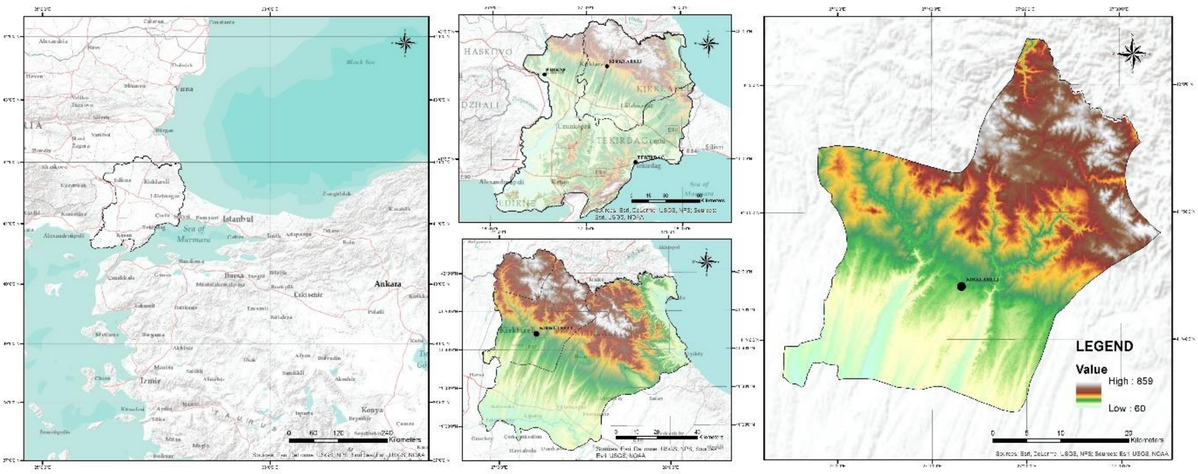

Figure 2. Location Map of the Study Area

While the city's population was about 60.000 in 2007, it had a population of 80.000 in 2016 (Turkstat, 2017) (Figure 3). Large-scale investments in the city are one of the main reasons for increasing the urban population and causing spatial expansion. The establishment of Kırklareli University in 2007 brought vitality to the economic life of the city and led the city to develop rapidly. At this point, there is a need for well-planned urban development for sustainable urban growth.

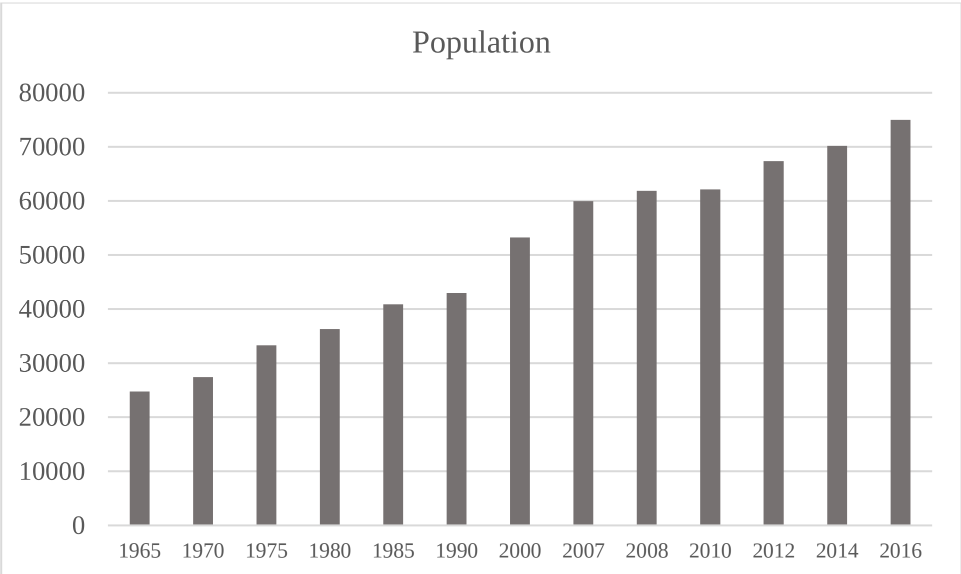

Figure 3. Population Growth in Study Area.

2.2. Data Preparation

As explained in the first part of the study, in the literature on ANN, many different variables have been used to estimate the boundaries of the urban built-up area (Almeida et., al, 2008; Li and Yeh, 2001; Park et al.,2011; Pijanowski et al., 2002; Berberoglu et al., 2016; Yeh and Li, 2002; Triantakonstantis and Stathakis, 2015; Tayyebi et al., 2011; Mohammady et al., 2014; Moghaddam and Samadzadegan, 2009; Grekousis et al., 2013; Maithani et al., 2007; Yang et al., 2008). This study used proximity to main roads, the built-up area, the city center, and the amount of built-up area in a 7x7 pixels neighborhood as input data (Figure 4). First, the study area was divided into 100x100 meters square cells with a total of 15,641, and the cells were converted to point data based on their geometric centers. In the second step, data were entered for each of the six criteria in each cell center.

Digital elevation model data (DEM), which NASA provides as open source, was used to obtain slope and aspect analyses. Firstly, the data obtained are referenced to the coordinates of WGS 1984, 35N, which is the geographic location of the study area. The downloaded DEM data with a size of 26x26 m pixels were converted to 100x100 meters dimensions based on the cell centers used in the study. Then, the slope and aspect data were obtained using raster surface analysis in the ArcMap environment. The transportation network in the study area was determined for years 1993 and 2017 using satellite images, online maps, and aerial photographs. A score was assigned for each cell in the study area according to the degree of closeness to the roads with the help of the Euclidean distance tool in ArcMap.

The city's built-up area boundaries have been obtained by satellite images, online maps, and aerial photographs for two different years, 1993 and 2017. Firstly, aerial photographs and satellite images have been geographically referenced and rectified for two years. Later, the boundaries of the city's built-up areas were created manually. The distance of each cell outside the boundary was calculated the same as transportation. To create proximity to the city center, the administrative facility located in the geographically central point of the city was taken as the basis. The distance value assignment was made to each cell according to the designated center cell. The amount of built-up in the 7x7 unit neighborhood was obtained with the aid of the ArcMap focal tool.

Using variables, two independent data sets for the study area were obtained for 1993 and 2017. In the last stage before data entry to the model, every cell within the boundary of the 1993 and 2017 built-up area was assigned a score of 1, and for each cell outside the boundary of the built-up area score of 0 was assigned (Figure 5).

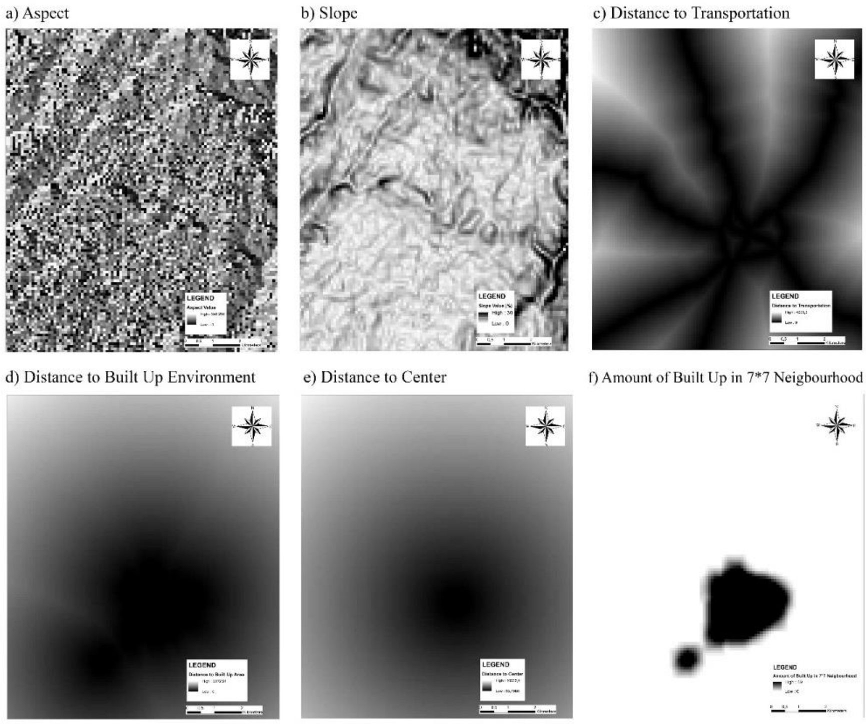

Figure 4. Variables Used for Training Artificial Neural Network Model.

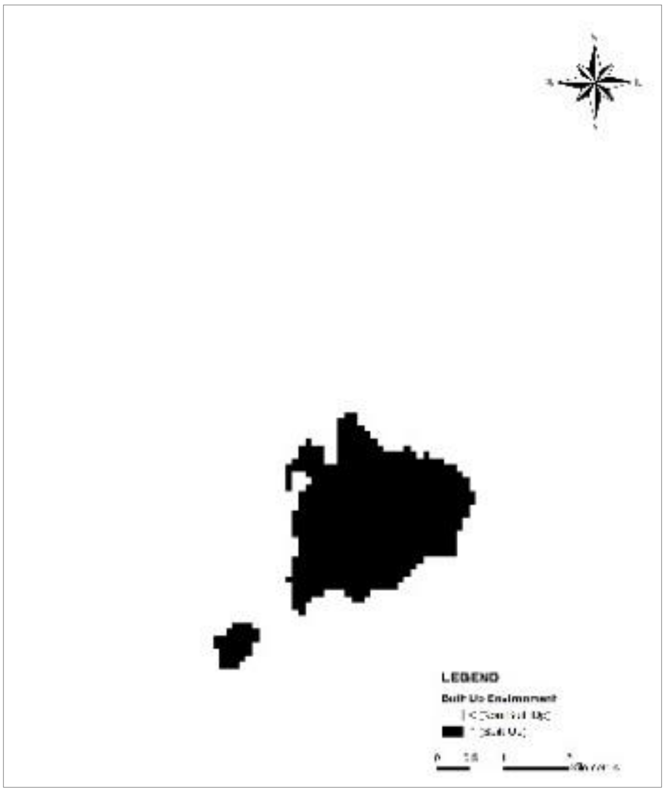

Figure 5. Built-Up Area in 1993

2.3. Application of the Model

In the model's training, six variables belong to the year 1993, and the built-up status of each cell, depending on these variables, has been used. Once the training was completed, the built-up status for 2017 was predicted using six variables of the year 2017, which were never included in the model. In the last stage, the actual urban boundary of 2017 was compared with the built-up status predicted by the model, and the accuracy was evaluated.

Matlab 2013a Artificial Neural Network Fitting Tool was used for modeling. In fitting problems, it needs a neural network to map between a set of numeric inputs and a set of numeric targets. The Neural Network Fitting Tool will help the user to select data, create and train a network, and evaluate its performance using mean square error and regression analysis.

The table data representing each cell spatially referenced in the ArcMap environment was transferred to the Matlab 2013a program (Mathlab, 2018). The slope, aspect, distance to the highway, distance to the built-up area, distance to the center of the city, and the amount of the built-up area in the 7x7 unit neighborhood were used as input data in the model. 70% of the total 15,410 pixels (10,948) were used for training, 15% (2,346) were used for validation, and 15% percent (2,346) were used for testing.

The number of hidden layers in similar models has been selected in various ways (Mohammady et al., 2014; Pijanowski et al., 2002). The excessive number of hidden layers causes overtraining in the model and causes the degree of gravity to fall, while the fewer hidden layers increase the difficulty of estimation(Yeh and Li, 2002; Almeida et al., 2008). In this model, the number of hidden layers is selected as six in parallel with the number of input variables (Yeh and Li, 2002; Li and Yeh, 2001) (Figure 6). Levenberg-Marquardt back-propagation (trainlm) method was used for training. The model is run this way and stops automatically when the maximum error count is reached (Figure 7). The completed trained model was saved to use in 2017 data.

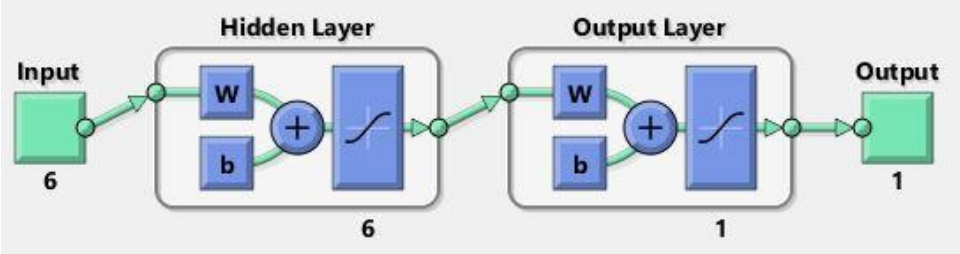

Figure 6. Architecture of Artificial Neural Network Model

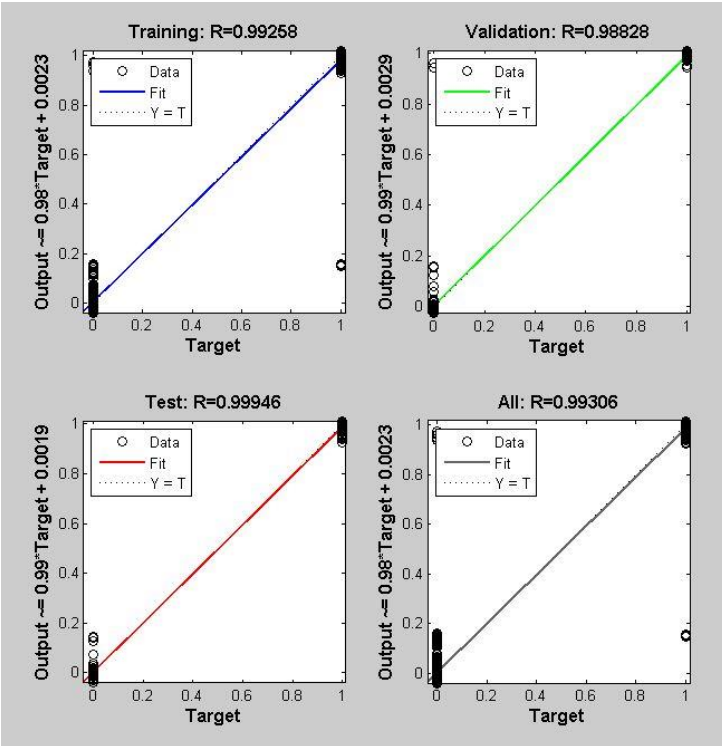

Figure 7. Regressions of Artificial Neural Network Model

Finally, the model trained by using the six variables belongs the year 1993 was simulated using the variables belongs the year 2017 that were not previously included in the model. The simulated built-up area for 2017 was not included in the model and is expected to be predicted by the model. Table 1 shows a sample proportion of the dataset for 2017, while Figure 8 shows the variables used. The actual and predicted built-up area in 2017 can be seen in Figure 9.

Table 1. Sample Table for Variables and Predictions in 2017.

Pixel Code	Slope (%)	Aspect	Distance to Main Roads (meters)	Distance to Built Up Area (meters)	Distance to center (meters)	Amount of Built-Up Area in 7x7 Neighbourhood	Built-Up	Predicted by Model
7089	2,06	59,04	248,00	190,21	1541,74	9,00	0,00	0,00
7537	0,73	186,34	255,19	0,00	1541,74	33,00	1,00	1,00
7068	2,22	217,57	553,89	38,04	1541,74	17,00	0,00	0,01
4907	2,02	153,44	26,90	80,70	1541,50	12,00	0,00	0,00
7301	4,63	240,26	340,25	0,00	1541,50	20,00	1,00	0,98
4880	2,80	191,31	565,53	60,15	1541,50	23,00	0,00	0,00
7316	2,92	183,81	579,43	407,06	1541,50	0,00	0,00	0,00
5944	7,04	108,44	60,15	53,80	1539,15	17,00	0,00	0,00
7540	1,27	315,00	513,91	110,91	1539,15	16,00	0,00	0,00
5714	9,03	125,54	60,15	60,15	1534,21	16,00	0,00	0,00
7538	3,50	270,00	358,88	38,04	1534,21	29,00	0,00	0,05
7539	2,38	318,01	456,50	107,60	1534,21	22,00	0,00	0,00
5829	9,38	124,11	53,80	53,80	1533,50	17,00	0,00	0,00
7418	5,15	181,98	137,16	0,00	1533,50	31,00	1,00	0,99
4310	2,22	265,60	76,08	0,00	1529,48	49,00	1,00	0,99
4766	4,52	285,95	458,08	0,00	1529,48	30,00	1,00	0,99

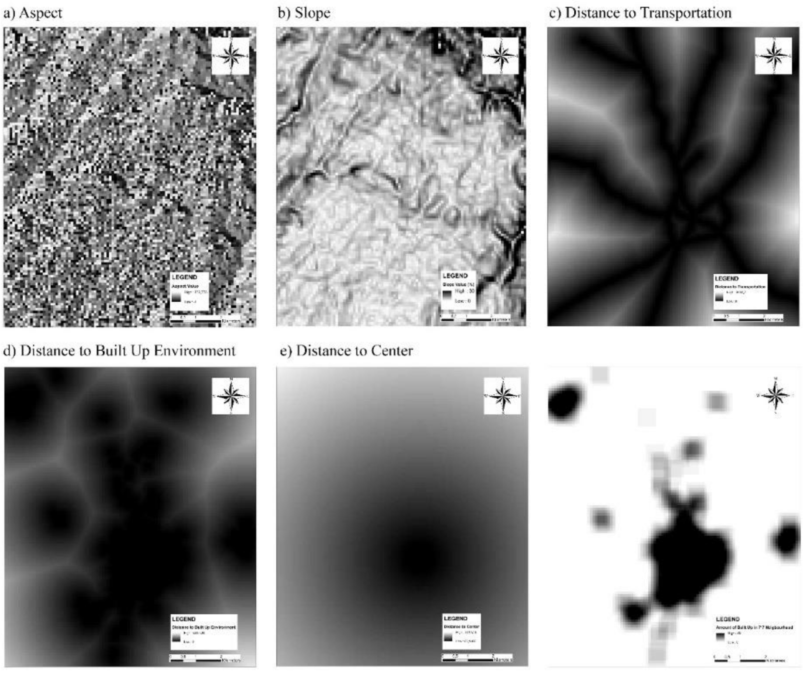

Figure 8. Variables Used to Predict Built-Up Environment for 2017

The study area is divided into 15,410 cells in total. In 2017, the actual number of built-up cells was 1,154 (7%). In the estimates made for 2017, 1,191 cells were found to have built-up (in the range of 0.5-1.00). The 1,129 cells were correctly estimated in the context of the current 2017 data, while 62 cells were incorrectly estimated. When the model results are subjected to a general evaluation, the existing settlements in 2017 are correctly estimated at 94%. The results were tested by statistical method and correlation analysis and reached the Pearson correlation of 0,904.

a) Built Up Area in 2017 b) Predicted Built Up Area in 2017

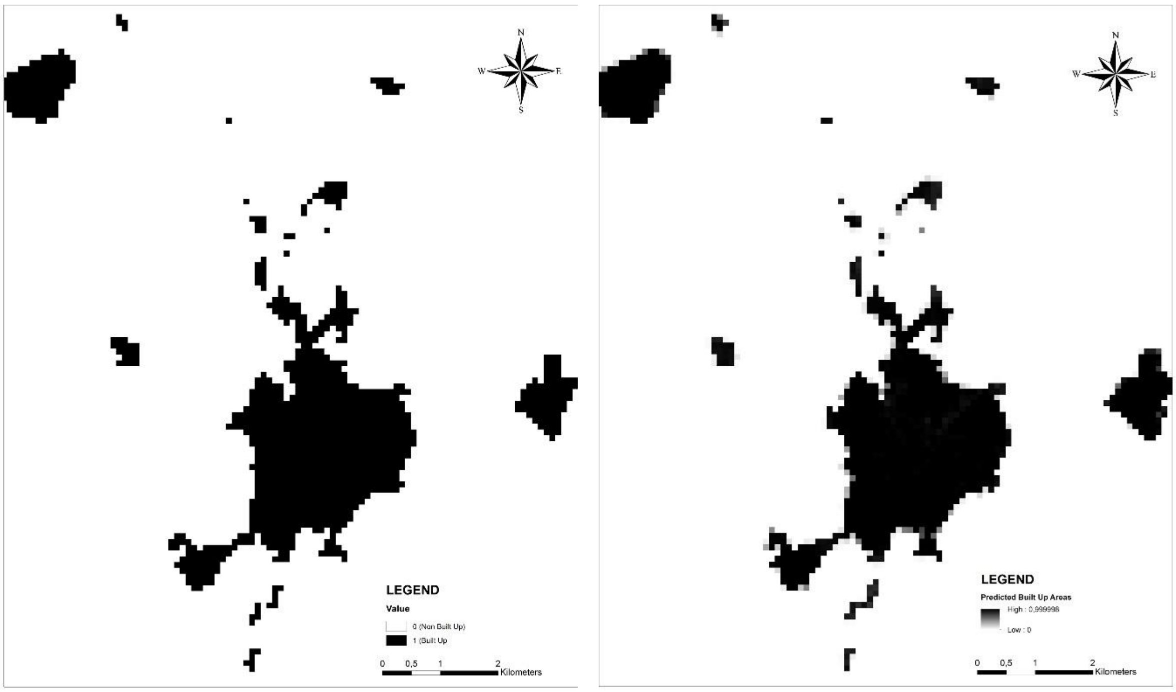

Figure 9. Real and Predicted Built-Up Area in 2017.

3. DISCUSSION AND CONCLUSION

For the Kırklareli, slope, aspect, proximity to transportation, proximity to the city center, proximity to the built-up area, and the amount of built-up area in the 7x7 unit neighborhood, which were considered essential factors for urban spatial expansion were taken as input data for the artificial neural network model. In 1993, the city's existing built-up area was thought to be a target data for the model. The model was trained with the data belongs in 1993. In the next phase, six variables belonging to 2017 were entered as input data to the model. Still, the 2017 built-up area was not included in the model to measure the model's predictive ability. The model, which was trained by data belongs in 1993, was used to predict the built-up area for 2017 by using the data belongs in 2017.

When it is considered that many factors direct a city's spatial development, a comprehensive model is needed to obtain higher accuracy. For future scenarios, when the variables for that year are known, the city's spatial development can be predicted using the ANN model.

It is known that the spatial expansion of cities is driven by many social, cultural, economic, and physical elements. Modeling urban growth in urban space where many factors exist is a challenging and complex process. However, in the literature, there are studies to predict the spatial growth of cities using simplified methods. Modeling spatial growth and predicting urban development directions is essential for sustainable urban development. It will be possible to take precautions on issues encountered in the future and to prevent problems that are difficult to return after they have occurred by producing proactive policies.

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