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Arazi Örtüsü ve Kullanımının Zamansal ve Mekânsal Değişiminin Yapay Sinir Ağları ile Modellenmesi: Kastamonu Örneği

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Öz

Sınırlı olan doğal kaynakların yönetiminde en uygun yöntemleri tespit etmek ve kullanmak, teknolojinin etkin kullanılmasıyla kaliteli bilgiyle kısa zamanda sonuca ulaşmak günümüzde son derece önemlidir. Uzaktan algılama (UA) teknikleri bu bakımdan çok etkili bir araç olarak kullanılmaktadır. Objelerle doğrudan temas olmaksızın çeşitli parametreler hakkında bilgiler edinmek hem zaman hem de maliyet açısından avantajlar sağlamaktadır. UA teknolojileri birbirinden farklı birçok disiplinde kullanılmaktadır. Bu teknolojilerin kullanıldığı en önemli uygulama alanlarından biri de uydu görüntüleri yardımıyla kentsel gelişimin izlenmesidir. Kentsel arazi kullanımının detaylı olarak belirlenmesi karar vericiler, planlayıcılar, uygulayıcılar ve araştırmacılar için etkili planlama faaliyetleri yürütebilmeleri açısından önemlidir. Bu çalışmada Kastamonu ili merkez ilçesine ait 1999 - 2016 yılları arasındaki arazi örtüsü ve arazi kullanımının değişimi incelenmiş; arazi kullanımı ve değişimi grupları oluşturulmuştur. Öncelikle çalışma alanına ait uydu görüntüleri kontrolsüz sınıflandırma metoduyla sınıflandırılmış ve doğruluk dereceleri hesaplanmıştır. Sınıflandırılan uydu görüntüleri Yapay Sinir Ağları (YSA) yaklaşımı ile çalışma alanının 2033 yılındaki muhtemel arazi örüsü, kullanımı ve değişimi modellenmiştir. Buna göre çalışma alanında 1999 yılı ile 2016 yılı arasında meydana gelen değişim; ormanlık alanlar için %7.8 azalma, su alanları için %10.8 artma, tarım alanları için %13.9 azalma ve yapılaşma alanları için %10.9 artma şeklinde gerçekleştiği tespit edilmiştir. Elde edilen sonuçlar ile arazi örtüsü ve arazi kullanımı değişiminin tespit edilmesi ve gelecekte nasıl bir seyir izleyeceğinin tahmin edilebilmesi için uygulanabilir pratik bir araç olduğu düşüncesine varılmıştır. Bu çalışmada kullanılan YSA yaklaşımının planlayıcı ve karar vericiler için önemli bir karar destek sistemi aracı olacağı öngörülmektedir.

Anahtar Kelimeler: Coğrafi Bilgi Sistemleri, Uzaktan Algılama, Arazi Örtüsü/Arazi Kullanımı, Yapay Sinir Ağları.

Modeling of Temporal and Spatial Changes of Land Cover and Land Use by Artificial Neural Networks: Kastamonu Sample

Abstract

Currently, it is very important to identify and use the most appropriate methods in the management of limited resources and to reach a conclusion in a short time period by using the technology in an effective manner to fastly obtain information in high quality. Remote sensing (RS) techniques are used as a very effective tool for this purpose. Obtaining information about various parameters without direct contact with the objects provides advantages in terms of both time and cost. RS technologies are used in various different disciplines. One of the most important application areas where these technologies are used is to monitor urban development by the help of the satellite images. Determination of urban land use in detail is important for decision-makers, planners, practitioners and researchers to conduct effective planning activities. In this study the change in land cover and land use between the years of 1999 and 2016 in the central district of Kastamonu was investigated; land use and exchange groups were formed. First, satellite images of the study area were classified by controlled classification method and their accuracy was calculated. The classified satellite images are used to model the probable land area, its usage and changes in 2033 by using Artificial Neural Networks (ANN) approach. According to this, changes in the field between the years of 1999 and 2016 are given as follows; 7.8% decrease for forest areas, 10.8% increase for water areas, 13.9% decrease for agricultural areas and 10.9% increase for construction areas. Based on the results, it was thought that it is a feasible and practical tool to determine the change of land cover and land use to predict the course of the future. The ANN approach used in this study is predicted to become an important decision support system for planners and decision makers.

Keywords: Geographic Information Systems, Remote Sensing, Land Cover/Land Use, Artificial Neural Networks.

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1. Introduction

Remote sensing (RS) systems allow users to make decisions based on different situations and objectives by the help of strategy setting (Blackwell and Chen, 2009). Another important advantage of RS technology is to monitor the earth regularly and to operate in geographic areas that are difficult to access and control (Blumenthal,2013). Due to industrialization and rapid urbanization, many important factors like changes in the ecosystem, bio-diversity and regional climate change negatively affect cities, agricultural areas and forests. For this reason, the RS technique is used as an important tool in determining the temporal change of cities quickly and effectively (Zhang,2006).

At present, both the spatial and temporal analysis of land cover (LC) and its use is very common in terms of providing a contribution to decision support systems (Veldkamp and Verburg, 2004). Management of forest resources (Watson et al., 2000; Pocewicz et al., 2008), urban planning and management (Almeida et al., 2008; Brown et al., 2000), monitoring the development of agricultural areas (Lambin et al., 2000; Lakes et al., 2009) etc. changes in LC and its usage are examined. The detailed use of land use (LU) is critical to decision-makers, planners, practitioners and researchers. Studies are carried out by using the methods and approaches provided in both national and international literature, given as follows: Artificial Neural Network (ANN) in these areas (Gardner and Dorling, 1998; Kavzoglu and Mather, 2003; Dai et al., 2005; Almeida et al., 2008; Çiftçi et al., 2017; Martínez-Vega et al., 2017; Babu and Sudha, 2018), Cellular Automata (CA) (Li and Yeh, 2002; Almeida et al., 2008; Brown et al., 2012; Basse et al.; 2014), Support Vector Machine (SWM) (Kavzoglu and Colkesen, 2009; Were et al., 2015, Babu and Sudha, 2018; Jiménez et al., 2018), Markov model (Brown et al., 2000; López et al., 2001; Weng, 2002; Wu et al., 2006; Pocewicz et al., 2008; Fan et. 2008), Decision Tree (DT), Time Series (Seto and Fragkias, 2005), Data Mining (Tayyebi et al., 2014), Maximum Likelihood Classification Method (Sunar Erbek et al., 2004; Jiménez et al., 2018), Random Forests (Were et al., 2015), Machine Learning (ML) (Rogan et al., 2008).

ANN is defined as an information processing technique that can be used to simulate the working principles of the brain, such as to learn, to produce information and to make inferences (Öztemel, 2003; Elmas, 2011; Babapour et al., 2015; Buğday, 2018). It is necessary to monitor the LC and usage on a temporal and spatial scale and to teach the changes to the system by determining the changes and thus to observe the development in the light of the data obtained in the following years and to use the resources efficiently. In the management of natural resources, ANN can provide highly effective solutions. The first stage is to enter data into the system and to initiate the learning stage. Depending on the machine used and the processing power of this machine, the learning time varies. Several studies have shown that the predictions made with ANN have a very high predictive power (Fatemi, 2004; An et al., 2009). ANN approach provides a high-quality information and data platform for practitioners, planners and decision-makers and in addition to these, they also have very high rates of reliability. The widespread usage of ANN is caused because of the satisfactory level of reliability in the determination of changes in LU/LC.

In this study, it was aimed to determine the LU/LC change between the years of 1999-2016 in the central district of Kastamonu province by using satellite imagery and ANN approach and to model the changes in LU/LC in the near future. For this purpose satellite images of the study area were provided. After the limitation process, the infrared band was removed and controlled classification was made on the remaining bands and change in the satellite images of different dates is expressed in spatial form. In order to determine the change, LU/LC groups of two satellite images were formed over a period of 17 years. The satellite images classified as forest, water, agriculture and construction areas were taught with ANN approach and the LU/LC of the study area which includes the Kastamonu province was modelled for the 2033 year.

2. Material and Method

Material

In this study Kastamonu is chosen as a sample area because it was observed that there is urban growth, there are changes in usage of agricultural land changing over the time and forest areas occupy a large place in the land cover (LC). This study was carried out in an area of 135 km^2 that covers the central district of Kastamonu province. Kastamonu central district is surrounded by Devrekani and Seydiler towns from the north, Taşköprü town from the east, Çankırı city and Tosya town from the south, Araç, İhsangazi and Daday towns from the west. The working area is located between 35°48” and 42°01” north latitudes and 32°43” and 34°37” east longitudes (Figure 1).

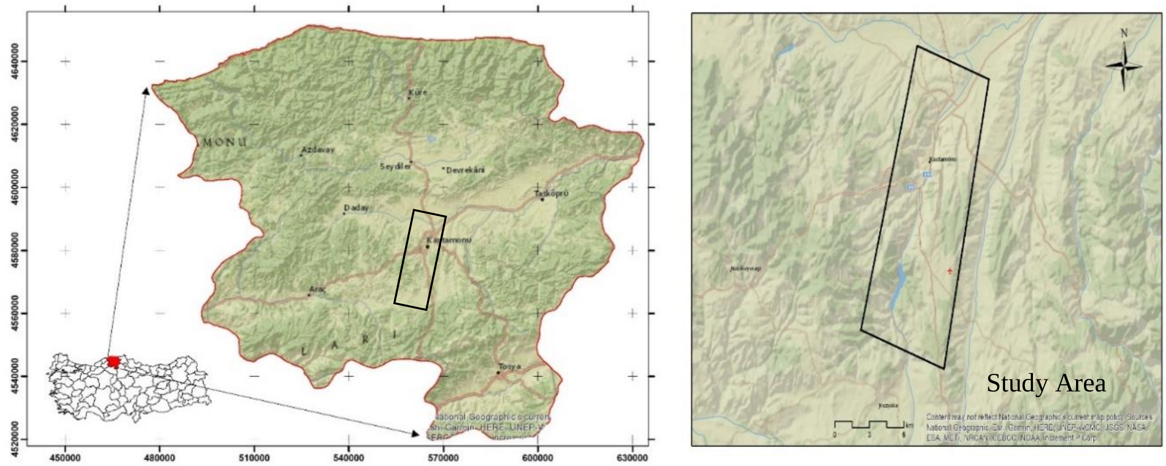

Figure 1 Location of study area

Method

Landsat 1 is the first satellite of NASA that used for ground observation research was installed in 1972 to orbit around the world. Lastly, Landsat 8 OLI was launched in 2013. Landsat 8 OLI can obtain medium-level resolution images from 15 to 100 m (URL-1).

In this study, Landsat 5 TM dated 17 June 1999 and Landsat 8 OLI (path/row: 177/31) satellite images dated 22 November 2016 were used. Before the classification process, the images were processed with the processes like pre-processing and enrichment. The classified satellite images were selected from the images of summer and autumn months. In this way, agricultural areas and forest areas could be more easily identified while reference points are taken.

Land Cover/Land Use Modeling. Determination of current land cover/land use (LC/LU) data and its change is an essential element for the decision makers to comprehend the system and to produce models in terms of planning and management studies. The differences in LU are the most important triggers of environmental changes that cause the transformation of the earth (Nicolas et al., 2014). Changes in decisions take place in the direction of the economic, social, political, cultural and environmental processes. Therefore, man is important element besides the natural processes during these changes are occurred.

Land Cover. The land cover consists of earth cover of the land, for example, vegetation, areas covered with water, naked soil and so on. Recognition of LC is important for border detection and preparation of maps, monitoring studies, management of resources and planning. On the other hand, LC information is important in terms of establishing a basis for the change in monitoring studies.

Land Use. The definition of land use is related to what the land serves. Settlement area, wildlife environment or agricultural areas which include the purpose of use and the definition of different LU changes over time constitutes the subject of LU.

As a result of monitoring the LU change whether a land carries the required features or not is determined and there is a balance tried to be provided by looking at the other LU with the light of the related data. In this way areas do not comply with the usage situation can be avoided and also this information is used for the development of regional protection and development strategies.

Database. In the digitization of the satellite images, numerical data with a spatial resolution of 30 meters were obtained from earthexplorer.usgs.gov address that covers the boundaries of the study area and they were transferred to GIS environment. The distances to the roads and the road map were prepared in the GIS environment and they were calculated in QGIS 3.0 software. LU is examined in 4 groups as forest, water, agriculture and construction area.

Remote sensing(RS) is monitoring, detection and recording of the object or situation from a remote location (Weng, 2010). Nowadays information is obtained from various types of satellites with various spatial, temporal, radiometric and spectral resolutions. RS technologies enable the monitoring of large areas, fast data transfer, easy storage of information related to the area and to work in the digital environment. At the same time, integrated use with GIS allows systematic renewal and monitoring of changes and multi-band sensors to receive data in electromagnetic spectrum regions that human eyes cannot perceive makes RS methods more valuable (Duran, 2007).

In order to reveal spatial and temporal changes in the study area firstly, QGIS 3 software was used to download images of 1999 and 2016 and to transfer them to digital media. Atmospheric correction was performed thanks to this software and image registration and verification was performed with the help of local reference points. The LU classes were classified as forest, water, agricultural land and construction areas and the controlled classification method was applied and the spatial and percentage of each class were calculated separately for 1999 and 2016. The Kappa values for the classification successes of the satellite images of these years were calculated by using this software. The Kappa coefficient (Cohen, 1960) is calculated by the following equation:

$$k = N\sum_{i=1}^{m} C_{ii} - \sum_{i=1}^{m} Nr_i \cdot Nc_i / N^2 - \sum_{i=1}^{m} Nr_i\, Nc_i$$

In this equation:

m: Total number of rows in error matrix
Nri: i. Total number of pixels in a row
N: Total number of pixels in the matrix
Cii: i. Number of pixels in rows and columns
Nci: i. Total number of pixels in the column

After this stage, the satellite images which are classified by using the MOLUSCE (Modules for Land Use Change Evaluation) component of QGIS software were inspected according to the distance spatial factor and changes in LC and LU were estimated for 17 years later (2033). Pearson's correlation method (a statistical method) was used to determine whether there is a linear relationship between two numerical measurements and if any it is used to determine the direction and severity of this relationship.

For the satellite images of 1999 and 2016, LU/LC change was calculated by taking spatial factors into account for two different time periods. The ANN model approach is preferred in which is also used for estimation of spatial distributions in 2033. Here class statistics refer to the beginning and final LU areas and the transition matrices refer to the ratio of pixels as LC/LU that varies from one to another. Markov Chain transition matrices-In the next stage Markov Chain (MC) transition matrices were calculated. The transition matrices include the possibility of changing from one land class to another land class and by the help of these matrices number of pixels of each LU class can be calculated. Transition matrices were obtained depending on the satellite images used in the study area and the distance factor of the roads.

In ANN approach while modeling the potential transition learning speed, maximum number of iterations, hidden layers and momentum properties are used. Here the neighbourhood defines the number of neighbouring pixels around the current pixel and the number of pixels is preferred as 3X3 in this study. Learning speed, momentum and maximum number of iterations define learning parameters. The high learning rate and high momentum allow quick learning but the learning process may be unstable. Small learning rate and momentum mean stable but slow learning and small learning was preferred in this study. A hidden layer and a network of 12 neurons are created as the number of hidden layers. After the calculation of errors in training and validation sets the graph was transferred. In order to measure the minimum error amount of validation set, a minimum validation general error was obtained. Delta general accuracy calculation was performed to indicate the difference between the minimum error obtained and the current error. The kappa value was calculated for the current verification. In this process, the learning algorithm analyzes the accuracy achieved in the training and validation sets of the samples and it stores the best neural network in the memory. The training process is completed when the best accuracy is reached.

Simulation can be expressed by evaluating the interface according to the processing of the non-changeable 0 and change up to 100 units. In this study simulation process was made for 2033 and a resulting simulation map was obtained.

3. Results and Discussion

Classification of satellite images was downloaded from the plug-in menu of the QGIS software by the help of the Semi-Automatic Classification plug-in and it was classified by controlled classification technique. Accordingly, classes and distributions of satellite imagery from 1999 and 2016 are given in Table 1.

Table 1 Classes and distributions of accuracy ratios of satellite imagery for 1999 and 2016.

Classification	1999 Accuracy (%)	2016 Accuracy (%)
Forest areas	91.4	95.8
Water areas	99.7	97.8
Agricultural areas	83.2	66.1
Built-up areas	84.4	82.9
Kappa value	**0.84**	**0.82**

When Table 1 is examined, it is seen that areas except the agricultural areas are classified with high accuracy. The reason for this low value in these agricultural areas is some parts of the areas are thought of as orchards. The classification processes were successfully completed with the rates of 82% and 84% for 1999 and 2016 respectively.

Table 2 shows the classes of LC/LU in which are formed after classification. As seen in Table 2, forest areas were determined as 49.5%, water areas as 1.1%, agricultural areas as 33.2% and construction areas as 16.2% as of 1999. As of 2016, forest areas were determined as 41.7%, water areas were determined as 11.9%, agricultural areas were determined as 19.2% and construction areas were determined as 27.2%. During the past 17 years, forest areas have decreased by 7.8%, water areas have increased by 10.8%, agricultural areas have decreased by 14% and construction areas have increased by 11%. LC/LU maps containing the study area are given in Figure 2.

Table 2 Classes and distributions of land for 1999 and 2016

	Pixel	%	ha	Pixel	%	ha
Forest areas	74648	**49.5**	6718.3	17290057	**41.7**	5656.7
Water areas	1705	**1.1**	153.5	4960426	**11.9**	1622.9
Agricultural areas	50037	**33.2**	4503.3	7953724	**19.2**	2602.2
Built-up areas	24505	**16.2**	2205.5	11305928	**27.2**	3698.9
Total	150895	**100**	13580.6	41510135	**100**	13580.6

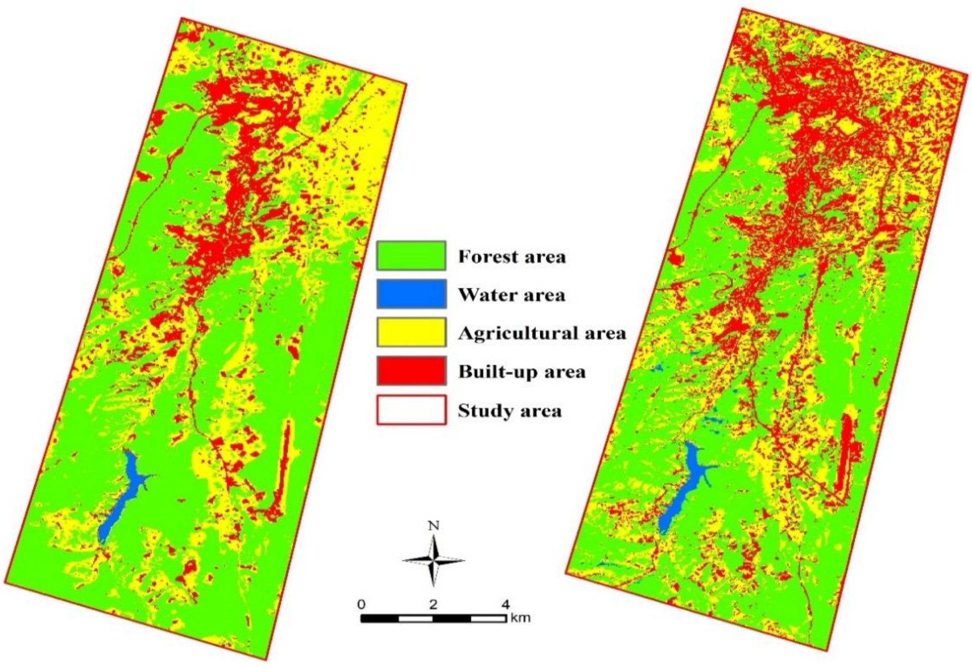

Figure 2 Land use and land cover for 1999 and 2016.

After the classification method called as correlation assessment, the correlation classification was made according to Pearson's Correlation method. In this evaluation "distance to the roads" classified with 500 m zones factor was chosen and it was formed in raster format (Figure 3). The classified image of the beginning that belongs to 1999 and the last image that belong to the year 2016 and the distance data of the roads are overlaid. After the controls were completed the LC/LU changes were calculated. The statistics for the classes are given in Table 2.

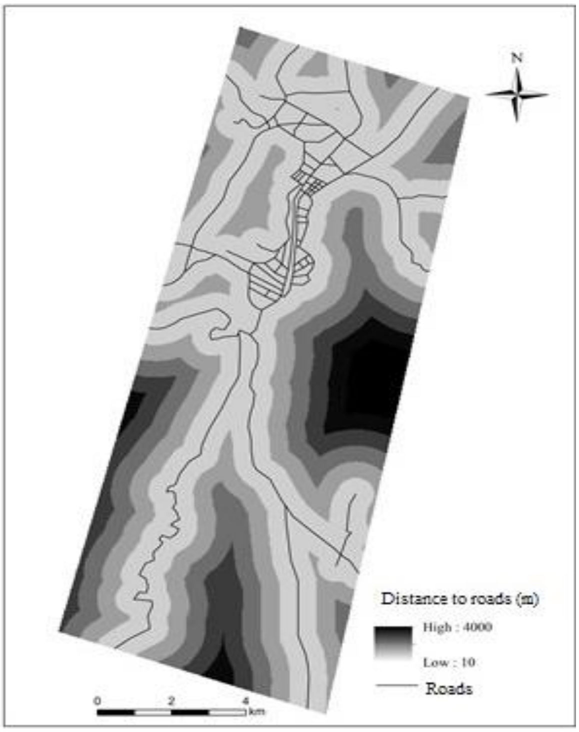

Figure 3 Routes of study area.

When Table 2 is examined it was determined that there is a positive and negative change in LC and its usage from the year 1999 to 2016. While forest areas and agricultural areas are decreased by 7.8% and 14% respectively, there was an increase of about 11% in the water area and building areas. LC/LU change- In this study, change map was created by using satellite images and distance to the paths as a factor. The change was given as a combination of the transitions of the four classes used. There are different colours assigned to each land class and the change to the other areas were expressed in different shades of the same colour. The change map is given in Figure 4.

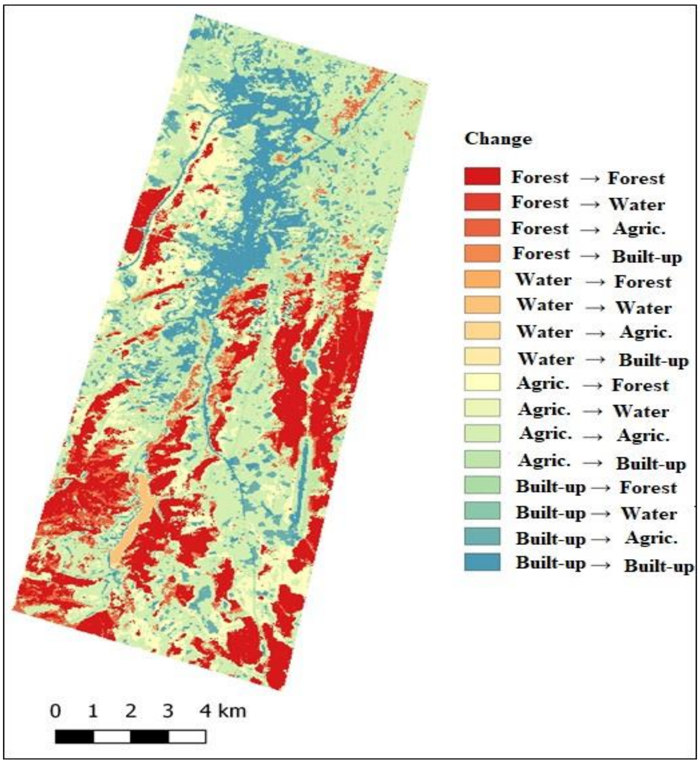

Figure 4 Change map of study area.

Modeling of change with artificial neural networks(ANN) –In this study, Multi-Layer Perceptron (MLP) ANN method was used in order to reveal the potential of LC transition that expresses the possibility of migration of land in the future. In this method, neighbourhood feature was preferred as 9 (3X3) pixel size, learning rate 0,1, the iteration number is 100 and the maximum moment is 0.5. At the end of the learning process, the minimum validation error was calculated as 0.01081 and the validation kappa value was 0.81. ANN learning curve is given in Figure 5.

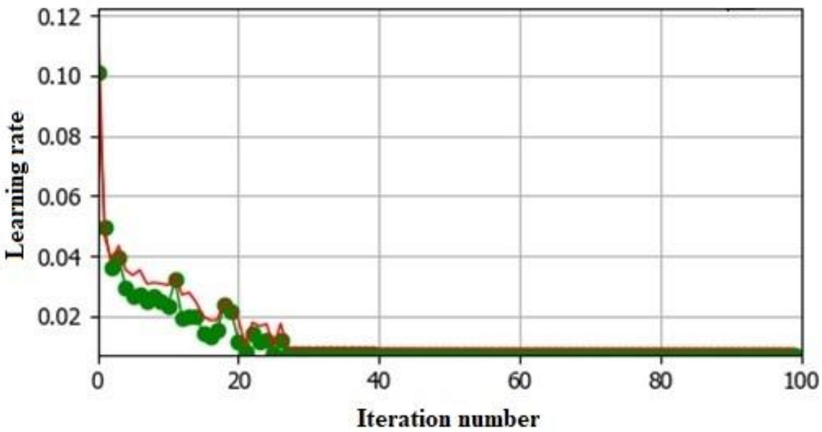

Figure 5 ANN learning curve.

Simulation of LC/LU–The final stage of the study is a simulation process and mapping, it took place after this learning phase. At the end of the learning period by considering the past 17 years of the period, estimated LC and LU of the center of the Kastamonu province in 2033 is given in Figure 6.

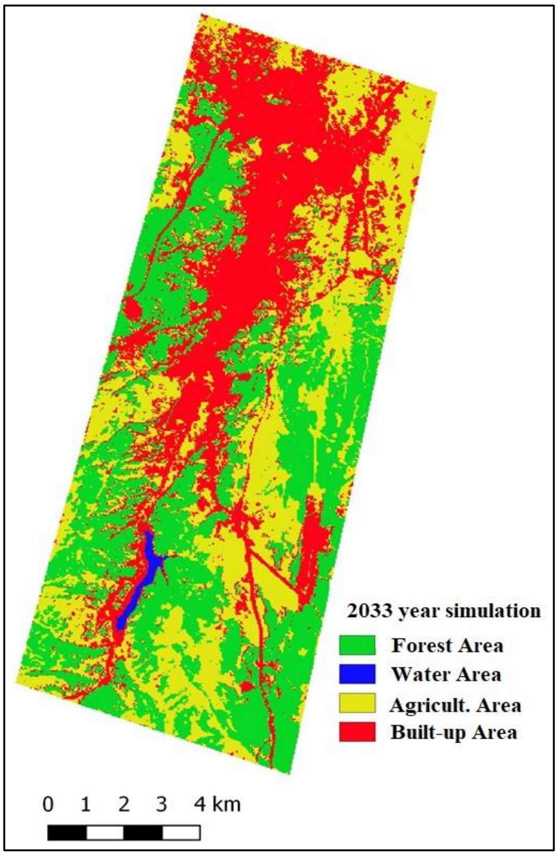

Figure 6 Estimated land cover and land use model for 2033.

Estimated land classes and their distributions in the simulation of 2033 that obtained as a result of the analysis are given in Table 3 in terms of % and ha.

Table 3 Estimated land classes and distributions in simulation for 2033

	2033 year	
	%	ha
Forest areas	35.3	4794.0
Water areas	16.7	2265.0
Agricultural areas	16.2	2203.1
Built-up areas	31.8	4318.5
Total	100	13580.6

For the year 2033, the rate of forest areas was estimated to be 35.3%, water area was estimated to be 16.7%, the agricultural area was estimated to be 16.2% and building area was estimated as 31.8%. When the results of the simulation are evaluated together with the forest, water, agriculture and construction areas belong to 1999 and 2016, the general trend is that the forest and agricultural areas will decrease and the water and construction areas will increase (Figure 7). The remarkable factor in the increase in water areas is the increase of dams in the region over the years.

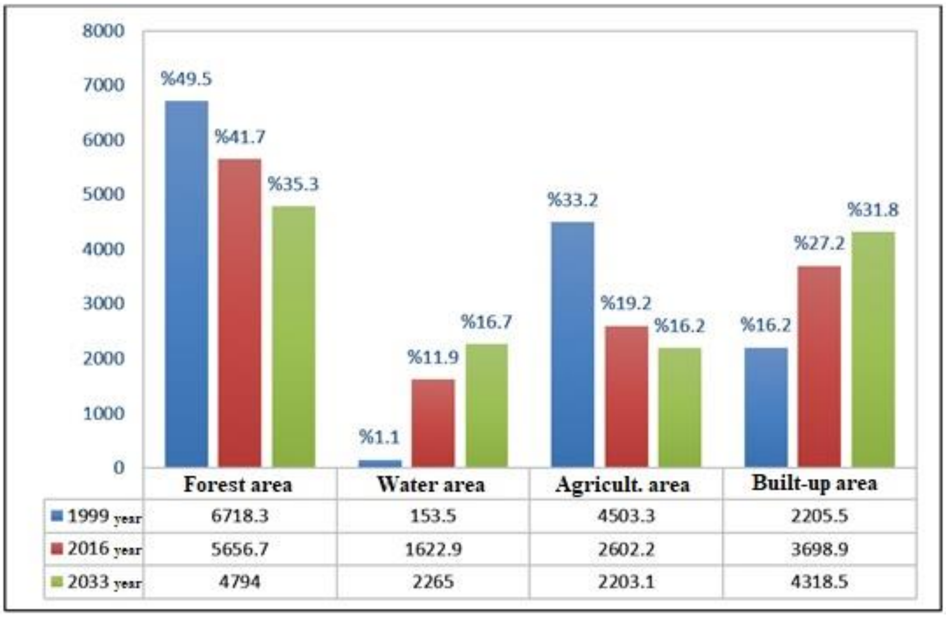

Figure 7 Comparison of the results of 1999, 2016 and 2033

4. Conclusion

The increase in the use of natural resources has revealed the necessity of the sustainability principle for the use of these future resources. One of the important parameters of a healthy implementation of sustainability is the determination of spatial and temporal changes in land cover/land use(LC/LU). Nowadays these changes can be determined more effectively and consistently and possible use in future can be calculated.

In this study, the change of LC/LU of 17 years (1999 and 2016) of Kastamonu Central district was calculated and simulated by using ANN images recorded in different time periods. In order to reveal the change satellite images of 1999 and 2016 were digitized and atmospheric correction was applied. Image registration and verification process were carried out with the help of the local reference points. The LU classes were classified as forest, water, agricultural land and construction areas and the controlled classification method was applied and the spatial and percentage distributions of each class were calculated separately for 1999 and 2016. The kappa value of the satellite images of these years was calculated as 82% and 84% respectively.

For the satellite images of 1999 and 2016, the distance variable to the roads as a spatial factor was used in two different time periods and the land change was calculated. ANN was used to estimate spatial distributions of the year 2033. In the modeling of potential transition of ANN approach, the neighbourhood was selected as 3X3, learning speed was selected as 0.1, maximum number of iterations was selected as 100, hidden layer cell number was selected as 10 and momentum value was selected as 0,5. Learning was determined with 81% accuracy. Since increasing the number of parameters affects learning, it is thought that these differences originate from the size of the study area. In this study, the simulation process was applied for 2033 and the resulting simulation map was obtained.

It is certain that the first condition for preserving the existing resources is to protect resources and use them without consuming them completely and to transfer them to future generations will be provided by the reasonable decisions that directed to development. Learning the changes in LU and continuous follow-up is very important to determine the feasibility of future decisions and policies (forestry, agriculture, urbanism, etc.). In future studies to use parameters of the study area and to use parameters that are suitable for this purpose, to compare different estimation models and to make maximum use of the opportunities of technology will make a significant contribution to decision-makers, practitioners and planners for stronger predictions.

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