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RESEARCH ARTICLE / ARAŞTIRMA MAKALESI

Monitoring and Predicting of Land Use and Cover Change for the period 2000-2030 Using Remote Sensing Data and Cellular Automata Approach

Uzaktan Algılama Verileri ve Hücresel Otomata Yaklaşımı Kullanılarak 2000-2030 Dönemi Arazi Kullanımı ve Örtü Değişikliğinin İzlenmesi ve Tahmin Edilmesi

Gülşen Keçeli [1], Ender Buğday [2*]

[1] Ministry of National Defence, Directorate General for Mapping, Ankara, TÜRKİYE
[2] Çankırı Karatekin Üniversitesi Orman Fakültesi, Orman Mühendisliği Bölümü, Çankırı, TÜRKİYE
Corresponding Author/ Sorumlu Yazar *: ebugday@karatekin.edu.tr

Abstract

Understanding and characterize land use and land cover changes are crucial for informed decision-making in various management disciplines, including forestry, agriculture, industrial development, urban planning, rural and urban administration, and natural resource management. In this study, the land use and land cover (LULC) changes in İzmit province and its adjacent areas, undergoing rapid industrialization, were analyzed for the periods 2000-2010 and 2020 using Remote Sensing (RS) and Artificial Neural Network (ANN) methodologies. Additionally, a LULC projection for the year 2030 was generated and mapped. Within the scope of this study, land use changes across four categories (forest, water, agricultural, and built-up areas) were simulated utilizing elevation and slope variables derived from satellite imagery. Landsat 5 Thematic Mapper, Landsat 7 Enhanced Thematic Mapper Plus, and Landsat 8 Operational Land Imager satellite imagery were employed as data sources for the simulation. As a result of classified images Kappa values were calculated as 91% for 2000, 87% for 2010 and 94% for 2020. The validation value of the 2030 simulation was determined as 89.2%. This study project that, forest areas will decrease by 0.41%, agricultural areas by 4.38%, and water areas by 0.04%, while built-up areas in the industrial city of İzmit are expected to increase by 37.06% from 2020 to 2030. It is projected that forest and aquatic ecosystems are experiencing gradual spatiotemporal decline, whereas agricultural lands are undergoing a more rapid rate of reduction, a trend anticipated to persist.

Keywords: *Remote sensing, Land cover change, Artificial neural network, Landsat, Modeling*

Öz

Ormancılık, tarım, endüstriyel gelişim, şehir planlama, kırsal ve kentsel yönetim ve doğal kaynak yönetimi gibi çeşitli yönetim disiplinlerinde bilinçli karar alma için arazi kullanımı ve arazi örtüsü değişikliklerini anlamak ve karakterize etmek çok önemlidir. Bu çalışmada, hızlı bir sanayileşme süreci geçiren İzmit ili ve çevresindeki alanlardaki arazi kullanımı ve arazi örtüsü (AKAÖ) değişiklikleri, Uzaktan Algılama (UA) ve Yapay Sinir Ağı (YSA) metodolojileri kullanılarak 2000-2010 ve 2020 dönemleri için analiz edilmiştir. Ayrıca, 2030 yılı için bir AKAÖ projeksiyonu oluşturularak haritalanmıştır. Bu çalışma kapsamında, uydu görüntülerinden elde edilen yükseklik ve eğim değişkenleri kullanılarak dört kategorideki (orman, su, tarım ve yapılaşmış alanlar) arazi kullanım değişiklikleri simüle edilmiştir. Landsat 5 Tematik Haritalayıcı, Landsat 7 Geliştirilmiş Tematik Haritalayıcı Plus ve Landsat 8 Operasyonel Arazi Görüntüleyici uydu görüntüleri simülasyon için veri kaynağı olarak kullanılmıştır. Sınıflandırılmış görüntüler sonucunda Kappa değerleri 2000 yılı için %91, 2010 yılı için %87 ve 2020 yılı için %94 olarak hesaplanmıştır. 2030 simülasyonunun doğrulama değeri %89,2 olarak belirlenmiştir. 2030 simülasyonunun doğrulama değeri %89,2 olarak belirlenmiştir. Yapılan çalışma sonucunda sanayi kenti İzmit'te 2020-2030 yılları arasında orman alanlarının % 0,41, tarım alanlarının % 4,38, su alanlarının ise % 0,04 oranında azalacağı, yapılaşmış alanların ise % 37,06 oranında artacağı öngörülmektedir. Orman ve sucul ekosistemlerin kademeli olarak mekansal ve zamansal bir düşüş yaşadığı, tarım alanlarının ise daha hızlı bir azalma oranına maruz kaldığı ve bu eğilimin devam edeceği öngörülmektedir.

Anahtar Kelimeler: *Uzaktan algılama, Arazi örtüsü değişimi, Yapay sinir ağları, Landsat, Modelleme*

1. Introduction

Although the world's population growth rate varies regionally, the world population continues to increase. It is predicted that the world population will reach 8.5 billion people in 2030 United Nations, *Population 2030: Demographic Challenges and Opportunities for Sustainable Development Planning*.. Similarly, Türkiye's population, which was approximately 85 million in 2022, is projected to reach an estimated 90 million by 2030 TUIK, *The Results of Address Based Population Registration System 2022 in Türkiye.*. In light of the ongoing population growth, it is anticipated that land use patterns and associated changes will persist Aneesha Satya vd., "Future Land Use Land Cover Scenario Simulation Using Open Source GIS for the City of Warangal, Telangana, India".. Technology is actively used in decision

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support systems approaches, management, and planning that go through a continuous and rapid process Kwak vd., "A Large Scale Multi Criteria Suitability Analysis for Identifying Solar Development Potential".. Today, many simulation approaches such as Artificial Neural Network (ANN) have been developed to reveal the growth of urban areas and model land use/cover changes Guan vd., "Modeling Urban Land Use Change by the Integration of Cellular Automaton and Markov Model"; Almeida vd., "Using Neural Networks and Cellular Automata for Modelling Intra-urban Land-use Dynamics".. In Türkiye, urbanization has gained noticeable momentum after the 1980s. The number of people living in cities in Türkiye increased to 76% in 2010. Türkiye is among the top countries in the world in terms of the number of people living in cities and the urban population growth rate Uysal ve Maktav, "Landsat Verileri ve Lineer Spektral Ayriştirma (Unmixing) Yöntemi Kullanilarak Izmit Körfezi Çevresinde Kentsel Değişim Alanlarinin Belirlenmesi".. Because of the uncontrolled urbanization, industrialization and population growth in the last 50 years, it has caused negative effects especially on agricultural and forest areas. Such a situation is disturbing for human health and the environment due to environmental changes caused by people or natural events. As a result, the increasingly uncontrolled growth of the urban environment harms natural areas and human health; and causes land use and land cover changes.

Today, decision support systems, which are an important tool in the management of natural resources, in urban and rural areas, need to be understood and analyzed for their applicability Buğday ve Erkan Buğday, "Modeling and Simulating Land Use/Cover Change Using Artificial Neural Network From Remotely Sensing Data".. The pressure on forest areas is increasing gradually due to the increasing population and the problems it brings Elliott vd., "A Synthesis".. When considered in terms of the relationship between cities and forests, monitoring land use and land cover change can provide detailed and consistent information about the future Rimal vd., "Monitoring and Modeling of Spatiotemporal Urban Expansion and Land-Use/Land-Cover Change Using Integrated Markov Chain Cellular Automata Model"..

Land use and land cover (LULC) are two terms that can be used separately because they include specific studies for different areas. Land use refers to "human activities on and related to land, usually not visible from direct view" Xu ve Li, "Land Use Carbon Emission Estimation and Simulation of Carbon-Neutral Scenarios Based on System Dynamics in Coastal City"., while land cover refers to "vegetation and artificial structures covering the land surface" Kaloudis vd., "Land Cover Changes in Evrytania Prefecture (Greece)".. The speed and spatial scale of human changes to the land surface, mostly in the form of land use and land cover changes, are unprecedented and so invasive that they are massively transforming a large part of the planet's land surface, affecting fundamental aspects of the earth's systems Alam vd., "Using Landsat Satellite Data for Assessing the Land Use and Land Cover Change in Kashmir Valley".. Identifying LULC changes is crucial for the proper management of natural resources and their management Mallupattu ve Sreenivasula Reddy, "Analysis of Land Use/Land Cover Changes Using Remote Sensing Data and GIS at an Urban Area, Tirupati, India".. As urban landscapes undergo perpetual transformation, land use patterns are correspondingly in a state of continuous flux. Consequently, the strain on natural resources intensifies, leading to detrimental exploitation. The construction of new urban structures can result in the degradation of nearby forests and agricultural lands, potentially leading to a reduction in natural areas or the complete loss of natural landscapes Yıldız, "İzmit Şehrinin Mekansal Gelişim Süreci Alternate title: Spatial Development Process of The City of Izmit.". Conventional approaches to demographic data collection, such as censuses and environmental sample analysis, may prove inadequate for sophisticated environmental research. Due to the myriad challenges associated with environmental issues and the complexity of managing multidisciplinary data, the deployment of advanced technologies such as Remote Sensing (RS) and Geographic Information Systems (GIS) is imperative. These technologies offer robust predictive capabilities and can effectively model these complexities. The approaches and techniques offer valuable information for the examination and monitoring of natural resources within the realm of environmental management Mallupattu ve Sreenivasula Reddy, "Analysis of Land Use/Land Cover Changes Using Remote Sensing Data and GIS at an Urban Area, Tirupati, India".. In this context, modeling approaches such as decision trees, machine learning, artificial neural network, etc. are frequently used Singh vd., "A Machine Learning-Based Classification of LANDSAT Images to Map Land Use and Land Cover of India"..

RS data are widely used to classify land cover and ensure the reliability of the corresponding area estimates Kim, "Land Use Classification and Land Use Change Analysis Using Satellite Images in Lombok Island, Indonesia".. RS and GIS are considered powerful, effective, and economical tools for land and other natural resources management. These technologies have proven their effectiveness in updating and managing spatial data in developing countries by providing the advantage of rapid data collection to regularly collect LULC information at a much lower cost than traditional ground survey methods Wang ve Maduako, "Spatio-Temporal Urban Growth Dynamics of Lagos Metropolitan Region of Nigeria Based on Hybrid Methods for LULC Modeling and Prediction"..

GIS and simulation approaches are effective and useful techniques that increase the clarity of research findings. RS is actively used to obtain data at varying resolution levels and for the requested date in with the target. With its multi-purpose analysis capability with GIS and its software, it offers significant advantages in terms of both presenting the current situation and planning processes. Simulation approaches, on the other hand, offer significant advantages in effective planning studies where necessary precautions are taken to predict possible changes in the future. Today, many simulation approaches such as Artificial Neural Network (ANN) have been developed to reveal the growth of urban areas and model land use/cover changes. The aim of planning studies is to forecast potential future challenges and to address them through anticipatory and proactive strategies Yazıcı vd., "Kentsel Büyümenin Modellenmesi ve Simülasyon Modelleri"..

The accelerated expansion of urban land utilization precipitates adverse transformations in land cover and land use patterns. The expansion of new territories for settlement and industrial purposes poses a direct threat to forested and agricultural lands. Furthermore, accelerated and unregulated urbanization and various environmental challenges can significantly impede the provision of essential services such as infrastructure, transportation, healthcare, education, and housing. This study examines the spatial development of İzmit post-2000, a period marked by the accelerated expansion of urban utilization in our country. It includes a comprehensive analysis of methodologies and procedural steps that could serve as foundational elements for sustainable urban management plans Yıldız, "İzmit Şehrinin Mekansal Gelişim Süreci Alternate title: Spatial Development Process of The City of Izmit.". The ANN methodology, a prominent decision support system, was employed in the analysis

Muhammad vd., “Spatiotemporal Change Analysis and Prediction of Future Land Use and Land Cover Changes Using QGIS MOLUSCE Plugin and Remote Sensing Big Data”.. Leveraging highly predictive modelling techniques Wang ve Maduako, “Spatio-Temporal Urban Growth Dynamics of Lagos Metropolitan Region of Nigeria Based on Hybrid Methods for LULC Modeling and Prediction”., extensive regions utilizing RS data Xu ve Li, “Land Use Carbon Emission Estimation and Simulation of Carbon-Neutral Scenarios Based on System Dynamics in Coastal City”., GIS software, and the ANN approach can yield more robust and effective predictive models compared to conventional methods Thodda vd., “Predictive Modelling and Optimization of Performance and Emissions of Acetylene Fuelled CI Engine Using ANN and RSM”..

This study estimated the 2030 LULC projection for the İzmit provincial center and its adjacent areas using RS data, GIS techniques, and the ANN approach. The LULC classifications for the study area projected for the year 2030 were simulated by utilizing Landsat satellite imagery from the years 2000, 2010, and 2020, encompassing data from Landsat 5, 7, and 8 in the study. This study is anticipated to provide valuable insights into the scientific appraisal of the benefits and drawbacks of forested regions near urban centers, thereby offering significant contributions to practitioners and policymakers involved in forest management.

2. Materials and Methods

2.1. Study area

The study area was carried out in the Marmara Region, İzmit city center and nearby forest area borders. The study area is located between 40050’14”- 40039’31” north latitudes and 29043’45”- 30007’56” east longitudes and covers an area of approximately 765.7 km^2 (Figure 1). İzmit is located on the eastern shore of İzmit Gulf, in the Çatalca-Kocaeli section of the Marmara Region. It is located at an important road junction in the Asia-Europe junction Anonymous, “Kocaeli Valiliği, Türkiye”.. İzmit province is an important industrial and commercial center of our country. Kocaeli topography is the large section in the north of İzmit Gulf that slopes from south to north and has a low degree of ruggedness. This part is opened by the valleys of the rivers heading towards the Black Sea and has the appearance of rolling hills. The high parts of the study area are located in the south around the Gulf of İzmit Anonymous, “Kocaeli Valiliği, Türkiye”.. The elevation of the hills in the north of İzmit province is approximately 350 meters above sea level. The main tree species in İzmit grove forests are broad-leaved beech and oak, coniferous black pine, maritime pine, and radiata pine Yıldız ve Döker, “İzmit Şehrinin Nüfus Gelişimi (The Population Changes of the City of İzmit)”.

Figure 1. Location of the study area.

The climate of İzmit and its surroundings can be said to be in a transitional area between the typical Mediterranean climate and the typical Black Sea climate. In İzmit and its surroundings, summers are hot and rainy; winters are cool and rainy, and generally warm. The number of days covered with snow does not exceed ten. In the summer months, sweltering heat is experienced on the Gulf Coast. The highest temperature measured in İzmit and its surroundings is 44.1 °C (July 13, 2000), and the lowest temperature is -18.0 °C (February 9, 1929). The annual average temperature in İzmit and its surroundings is 14.8 °C, and the annual precipitation varies by region but is between 768 and 1153 mm Başoğlu vd., “Performance Analyzes of Different Photovoltaic Module Technologies under İzmit, Kocaeli Climatic Conditions”.. In this study, Digital Elevation Model (DEM) and slope variables were used as spatial variables. In this context, DEM and Slope maps prepared for analysis are given in Figure 2.

The lowest elevation value of the study area varies between 0 m and 963.9 m, and the average elevation is 194.2 m. The lowest slope value of the study area varies between 0 º and 41.58º, and the average slope is 10.3º.

2.1. Methodology

In this study, Landsat7 ETM (dated 27/07/2000), Landsat5 TM (dated 31/07/2010), and Landsat8 OLI (dated 27/08/2020) satellite images with path-row values of 179-032 were used. Satellite images used in the study land use and land cover classification for these years in the study area were made using QGIS 2.18 and ArcGIS 10.3 software. In this study, satellite imagery underwent both atmospheric and geometric corrections prior to classification. Atmospheric correction was performed using atmospheric correction model in QGIS software, which minimized atmospheric effects such as scattering and absorption, ensuring more accurate reflectance values. Geometric corrections were applied with ground control points, ensuring alignment with the reference coordinate system and minimizing spatial distortions. For classification, we applied to QGIS supervised classification using maximum likelihood. The classification was based on spectral bands, which were selected to capture the relevant information for distinguishing land cover types. Classification was made as forest area, water area, agricultural area, and build-up area to be used in modelling. In the next stage, the obtained raster data were separated as random training (70%) and test data (30%) in the computer environment and modelled according to the ANN approach Srivastava vd., "Selection of Classification Techniques for Land Use/Land Cover Change Investigation".. With the ANN approach (Multi-Layer Perceptron), the past 10 years were taught to predict the year 2020 with the change information learned from previous years. The current year 2020 and the year 2020 obtained from the ANN approach will be compared and validated, and the predictive power of the model produced with this modelling approach - the performance of the model has been revealed. After acceptable model success was achieved in the last stage, the ANN modelling for the year 2030 was performed and the prediction process was completed. This process was downloaded from USGS web site (www.usgs.gov) based on the recent years of satellite images, Landsat satellite images will be downloaded, and the same steps will be repeated for recent years, and the model performance will be calculated and presented.

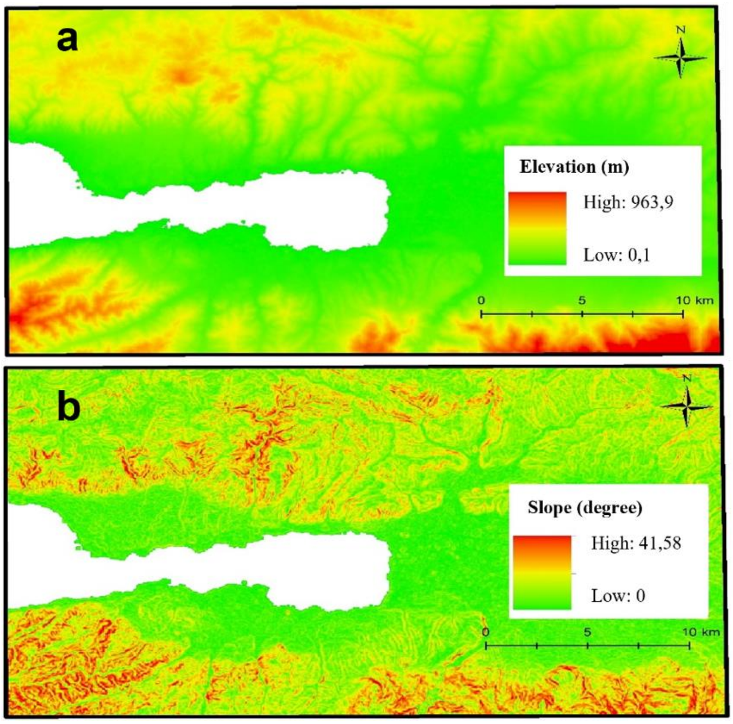


Figure 2. Study Area (a) Digital Elevation Model and (b) Slope map.

2.1.1. Data processing

Satellite images of the study area in 2000, 2010, and 2020 were downloaded free of charge from USGS web site (www.usgs.gov). DEM data obtained from the current ASTER-GDEM digital elevation model of the study area boundaries was also obtained from this web address. DEM and slope classes were used as topographic variables of the study area, and these calculations were created using ArcGIS 10.3 and QGIS 2.18 software on the DEM data.

Land use classification elements are categorized as forest, water area, agricultural land, and build-up areas. The QGIS software was used to obtain a prediction map and validation was performed. The data related to the study was compiled, reported and presented in the findings section of the study. The workflow of the study is given in Figure 3.

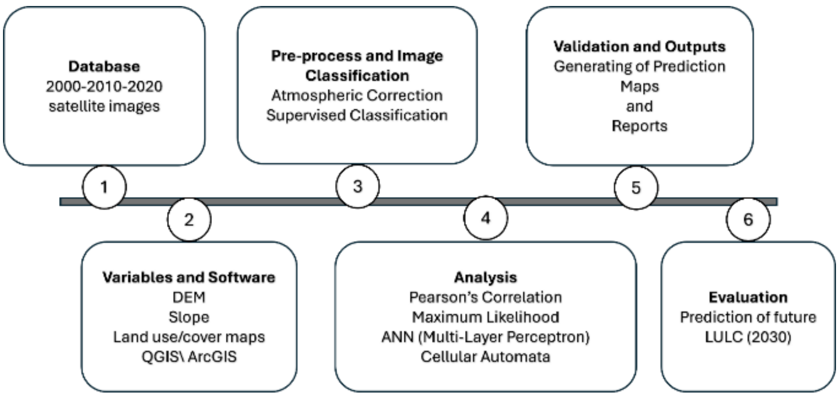


Figure 3. The workflow of the study.

2.1.2. Determination of land use and land cover change

The MOLUSCE plugin within QGIS software was employed to analyze changes between sequential images, thereby enabling future predictions. MOLUSCE, developed as an integral tool in the ever-evolving QGIS GIS software, facilitates the examination of land use and land cover changes over various periods, generating models for future projections. This plugin is compatible with QGIS 2 versions. MOLUSCE provides a user-friendly interface, replete with specific menus, commands, and functions. Additionally, it operates efficiently without requiring a high-performance processor, making it highly valued for delivering rapid and effective insights. Consequently, it holds substantial potential for planning activities Bolat ve Doğan, "Uzun Dönemli (1984-2020) Arazi Kullanımı Değişiminin Tespiti ve Modellemesi (2035)"; Gao vd., "Spatiotemporal Change Analysis and Prediction of the Great Yellow River Region (GYRR) Land Cover and the Relationship Analysis with Mountain Hazards"..

The study area was delineated into four land cover categories: forest, water, agriculture, and built-up. Landsat5 TM (acquired on 31/07/2010), Landsat7 ETM (acquired on 27/07/2000), and Landsat8 OLI (acquired on 27/08/2020) satellite images, corresponding to Path-Row 179-032, were utilized in this study. To enhance classification accuracy, images from July and August were selected because their cloud cover was less than 10%. Before classification, atmospheric and geometric corrections were conducted using QGIS 2.18 software. A supervised classification approach was employed, utilizing the maximum likelihood classification (MLC) algorithm. Employing this algorithm, the spectral characteristics of each class were learned and identified using training data. Subsequently, every pixel within the confines of the study area was classified into one of these designated classes.

The classification's accuracy was evaluated, using a confusion matrix and metrics like Overall Accuracy, Kappa Coefficient, Producer's Accuracy, and User's Accuracy in this study. The Kappa coefficient (κ), a measure of agreement between predicted and actual classifications, was computed using the following formula Cohen, "A Coefficient of Agreement for Nominal Scales". (Equation 1):

$$\kappa = \frac{O_A - p_e}{1 - p_e} \tag{1}$$

where O_A represents the sum of classified samples divided by the total number of samples, and Pe is derived from the aggregate sum of the LULC classifications across the four categories and their corresponding validation samples, divided by the square of the total pixel count Cohen, "A Coefficient of Agreement for Nominal Scales".. The Kappa values obtained for the image classifications were 0.91 for the year 2000, 0.85 for the year 2010, and 0.94 for the year 2020. These high Kappa values indicate substantial agreement and suggest the classifications' reliability. Consequently, these results underscore the method's potential to provide significant advantages in planning activities.

2.1.3. Simulation and validation process

Integrating ANN within the MOLUSCE plugin in QGIS creates a sophisticated workflow for analyzing and predicting LULC changes. This workflow leverages the computational power of ANN – Multi Layer Perceptron (MLP) algorithm to model complex, non-linear relationships between various spatial variables and LULC changes over time. The MLP algorithm represents a class of ANN characterized by multiple layers of nodes, or neurons, through which data passes in a unidirectional manner - from input to output. The architecture of the MLP algorithm typically consists of an input layer, one or more hidden layers, and an output layer. Each layer is fully connected to the subsequent layer, enabling the network to learn complex mappings between inputs and outputs. The initial step involves preparing spatial data, including historical LULC maps, and relevant driving factors (elevation and slope). These datasets serve as inputs to the ANN model. The ANN model is trained using historical LULC data Rimal vd., "Monitoring and Modeling of Spatiotemporal Urban Expansion and Land-Use/Land-Cover Change Using Integrated Markov Chain Cellular Automata Model"; Alam vd., "Using Landsat Satellite Data for Assessing the Land Use and Land Cover Change in Kashmir Valley".. The ANN consists of multiple layers, including an input layer (representing spatial variables), one or more hidden layers, and an output layer (predicting LULC categories). The relationship between input variables $X = [\ x1, x2, \ldots, xn]$ and the LULC output Y is modelled through the network's weights and activation functions. The ANN training process minimizes the error function E using a backpropagation algorithm, which iteratively adjusts the weights W to reduce the difference between the predicted and actual LULC values Bishop, *Neural Networks for Pattern Recognition*. (Equation 2):

$$E(W) = \frac{1}{2}\sum\nolimits_{i=1}^{m} (Y_i - Y^{\wedge}{}_i) \tag{2}$$

where Yi is the actual LULC category, $Y^\wedge i$ is the predicted LULC category, and m is the number of training samples. Once trained, the ANN model predicts future LULC changes based on the input spatial variables. The MOLUSCE plugin utilizes the trained ANN to simulate LULC scenarios for future time periods. The predicted LULC map $L^\wedge t$ for time t is generated Bishop, *Neural Networks for Pattern Recognition*. as (Equation 3):

$$\mathrm{L}^\wedge{}_t = f(X_t, W) \tag{3}$$

where Xt represents the spatial variables at time t, and Wdenotes the optimized weights from the training phase. The accuracy of the ANN-MOLUSCE model is evaluated using statistical measures such as the Kappa coefficient and overall accuracy. These metrics compare the predicted LULC maps with actual LULC data to assess the model's performance. The ANN-MOLUSCE workflow is built around a process where spatial variables, such as land use types, elevation, and other geographical data, are input into an ANN. Within the ANN, these inputs are processed through multiple layers, where each layer applies a set of weights to the data. These weights are essentially numbers that adjust the importance of each input as the data moves through the network. Additionally, bias values are added at each layer to help fine-tune the predictions. The data then passes through an activation function, which introduces non-linearity, allowing the network to model more complex relationships. The final output is a predicted category of LULC, such as whether a particular area is likely to be forest, agricultural land, or built-up Aneesha Satya vd., "Future Land Use Land Cover Scenario Simulation Using Open Source GIS for the City of Warangal, Telangana, India".. This entire process is integrated with the MOLUSCE plugin, which specializes in spatial analysis, making it possible to effectively model and predict how land use and land cover might change over time. The combination of these tools allows for more accurate and reliable predictions, which are crucial for making decisions in areas like urban planning, environmental conservation, and sustainable development.

In this study, ANN for the simulation of the possible LULC change from 2010 to 2030, which are widely used in the international literature, were preferred in the learning process with 1000 iterations, neighborhood value 3x3 pixels, learning rate 0.001, hidden layer 10 and momentum value 0.050 and five iterations were preferred.

The CA modelling approach is an algorithm that simulates real nature data and evaluates stochastic, nonlinear, and spatial processes in this context Tong ve Feng, “A Review of Assessment Methods for Cellular Automata Models of Land-Use Change and Urban Growth”.. Due to this capability, it has become one of the most preferred methods in modelling land use change. It creates modelling results based on defined rules Canpolat ve Dağli, “ELAZIĞ İLİ’NDE ARAZİ KULLANIMI DEĞİŞİMİ (2006-2018) VE SİMÜLASYONU (2030)”.. The CA approach is the expression of the representation of development in different steps, where the space is expressed by dividing it into cells and based on the change of these cells over time. The development of cells, the effect of neighboring pixel cells, and the characteristic features of the pixels themselves are important. Complicated systems can be explained with a basic mathematical approach. With this approach, the development of the land can be estimated according to the land class expressed by each cell using spatial information and dynamics Subedi vd., “Application of a Hybrid Cellular Automaton - Markov (CA-Markov) Model in Land-Use Change Prediction: A Case Study of Saddle Creek Drainage Basin, Florida”.. In the realm of LULC modelling, each cell within a CA grid represents a discrete parcel of land, characterized by a specific land use or cover type. The evolution of each cell's state over time is governed by a set of transition rules, which are influenced by the cell's current state as well as the states of its neighboring cells. These transition rules encapsulate the complex ecological, socio-economic, and environmental processes that drive land use transformations, such as urbanization, deforestation, or agricultural expansion Chopard and Droz, “Cellular Automata Model for the Diffusion Equation”.. The CA model operates through iterative processes, wherein the grid's state is updated at each time step, allowing it to effectively capture the spatiotemporal dynamics of land cover change. Furthermore, the integration of CA with GIS significantly enhances its utility in LULC studies by incorporating real-world spatial data into the model Behera vd., “Modelling and Analyzing the Watershed Dynamics Using Cellular Automata (CA)–Markov Model – A Geo-Information Based Approach”.. This integration facilitates the calibration of transition rules using empirical data, thereby improving the accuracy and reliability of the simulations.

Validation assesses the accuracy and reliability of the model by comparing its outputs with independent datasets, using metrics such as Kappa coefficient or Area Under the Curve (AUC) Kerner vd., “Cellular automata approach to three-phase traffic theory”; Kamusoko vd., “Rural Sustainability under Threat in Zimbabwe – Simulation of Future Land Use/Cover Changes in the Bindura District Based on the Markov-Cellular Automata Model”..

To validate the results, the real map for 2020, obtained by classifying the current image, was compared with the simulated map for 2020. The simulated map was generated using QGIS software and data trained with an ANN for the 2000 to 2020 change analysis.

3. Results and Discussion

3.1. Classification of Satellite Images

In the study, satellite imagery was categorized into four distinct classes utilizing the supervised classification method. Subsequently, the accuracy of the land use and land cover information derived from the classified satellite images was assessed in relation to actual values. The Kappa coefficient, indicative of the classification's success, was calculated to further evaluate the precision (degree of accuracy) of the classification process Table 1.

Table 1. Supervised classification accuracy levels and Kappa values.

Classification	Accuracy score (%) in 2000	Accuracy score (%) in 2010	Accuracy score (%) in 2020
Forest	95.96	97.50	99.25
Water	98.85	99.83	99.72
Agriculture	85.35	83.5	92.5
Built-up	96.87	93.4	89.42
Kappa value	0.91	0.87	0.94

The classification efficacy of forest, water, agricultural, and built-up areas for the years 2000, 2010, and 2020 demonstrated a high level of acceptance, with Kappa values calculated at 91%, 87%, and 94%, respectively. Upon evaluating the Kappa values, it was ascertained that the classifications were conducted with a high degree of accuracy. Notably, the lowest Kappa value was observed in 2010, which is hypothesized to be attributable to the utilization of the Landsat 5 TM satellite imagery in the study.

3.2. Land use – Land cover change and validation

In this study, to elucidate land use and land cover changes, DEM and slope map data were utilized as spatial variables, calculated within the QGIS environment, and saved in raster format. Following classification, Pearson’s Correlation method was employed to determine the relationship between these variables. Markov Chain (MC) transition matrices Kamusoko vd., “Rural Sustainability under Threat in Zimbabwe – Simulation of Future Land Use/Cover Changes in the Bindura District Based on the Markov-Cellular Automata Model”. were used to calculate the probability of transitions between land classes, resulting in the creation of change maps for the periods 2000-2010 and 2010-2020 (Figure 4 and Figure 5). In these change maps, transitions among the four classes are depicted as pixel transitions between classes. To facilitate understanding of these changes, distinct primary colors were assigned to each class, with transitions to other classes represented by gradients from dark to light shades of the primary colors.

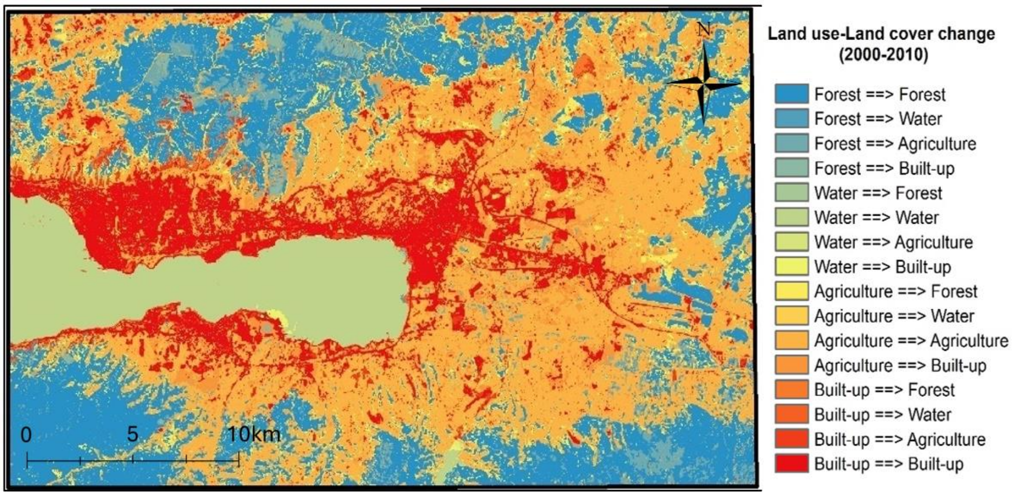


Figure 4. The LULC change map between 2000-2010

Table 2. Land use and land cover change rates in the study area between 2000-2010.

	2000		2010		2000-2010	
	km^2	%	km^2	%	Δ (km^2)	Δ (%)
Forest	230,98	30,17	227,08	29,66	-3,90	-0,51
Water	74,77	9,76	73,31	9,57	-1,46	-0,19
Agriculture	352,75	46,07	325,73	42,54	-27,02	-3,53
Built-up	107,20	14,00	139,58	18,23	32,38	4,23
Total	765,70	100	765,70	100	-	-

The distribution of temporal and spatial changes in land use and land cover in the study area between 2000 and 2010 is given in Table 2. As of the year 2000, analysis of Table 2 indicates that the forested area encompassed 230.98 km², representing 30.17% of the total study area. The water bodies covered 74.77 km², accounting for 9.76% of the total area, while agricultural lands extended over 352.75 km², constituting 46.07%, and built-up areas occupied 107.20 km², making up 14%. By 2010, the forested area had decreased to 227.08 km², corresponding to 29.66% of the total area. The water bodies covered 73.31 km², or 9.57%, the agricultural lands decreased to 325.73 km², representing 42.54%, and the built-up areas expanded to 139.58 km², which constituted 18.23% of the total study area.

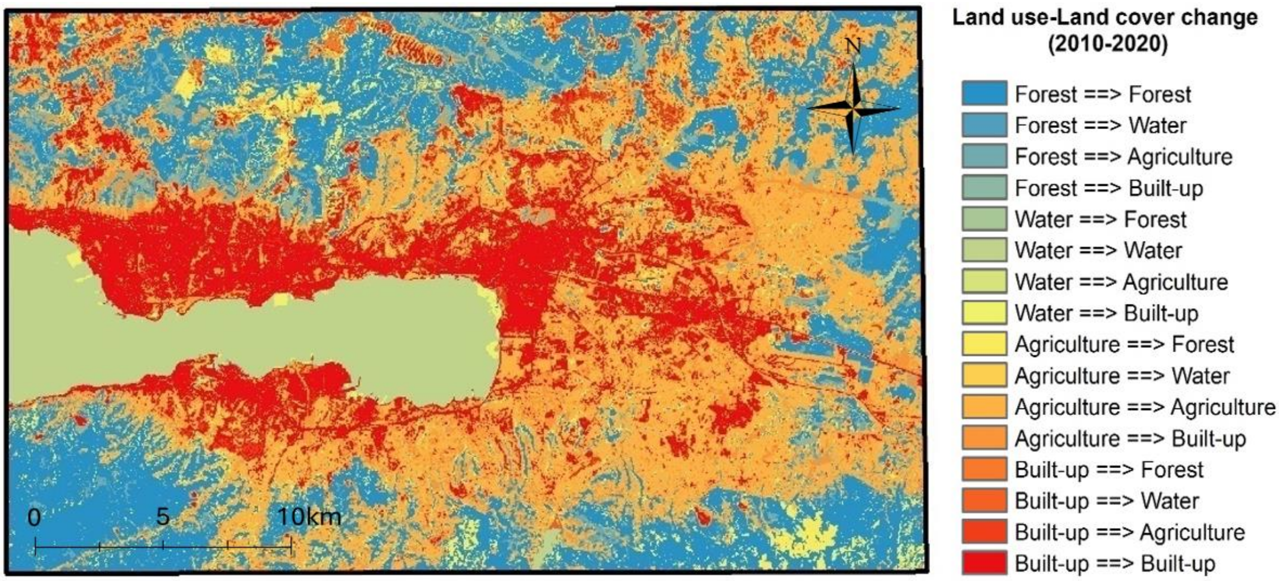


Figure 5. The LULC change map between 2010-2020.

Table 3. Land use and land cover change rates in the study area between 2010-2020.

	2000		2010		2000-2010	
	km²	%	km²	%	Δ (km²)	Δ (%)
Forest	230,98	30,17	227,08	29,66	-3,90	-0,51
Water	74,77	9,76	73,31	9,57	-1,46	-0,19
Agriculture	352,75	46,07	325,73	42,54	-27,02	-3,53
Built-up	107,20	14,00	139,58	18,23	32,38	4,23
Total	765,70	100	765,70	100	-	-

The distribution of temporal and spatial changes in land use and land cover in the study area between 2010 and 2020 is given in Table 3.

An examination of Table 3 reveals that in 2010, the forested area was calculated to be 227.08 km², constituting 29.66% of the total study area. Similarly, the water area was determined to be 73.31 km², comprising 9.57% of the total area; the agricultural area was 325.73 km², representing 42.54%; and the built-up area was 139.58 km², accounting for 18.23%. By 2020, the forested area had decreased to 220.11 km², or 28.75% of the total area; the water area slightly declined to 73.25 km², or 9.56%; the agricultural area reduced to 288.42 km², or 37.67%; while the built-up area increased to 183.91 km², representing 24.02% of the total study area.

Within the study area, it was observed that forest and agricultural regions diminished between 2000-2010 and 2010-2020, whereas built-up areas expanded. The water area, while not exhibiting significant overall change, experienced a reduction. The LULC maps for the years 2000, 2010, and 2020 are presented in Figure 6, Figure 7 and Figure 8 respectively.

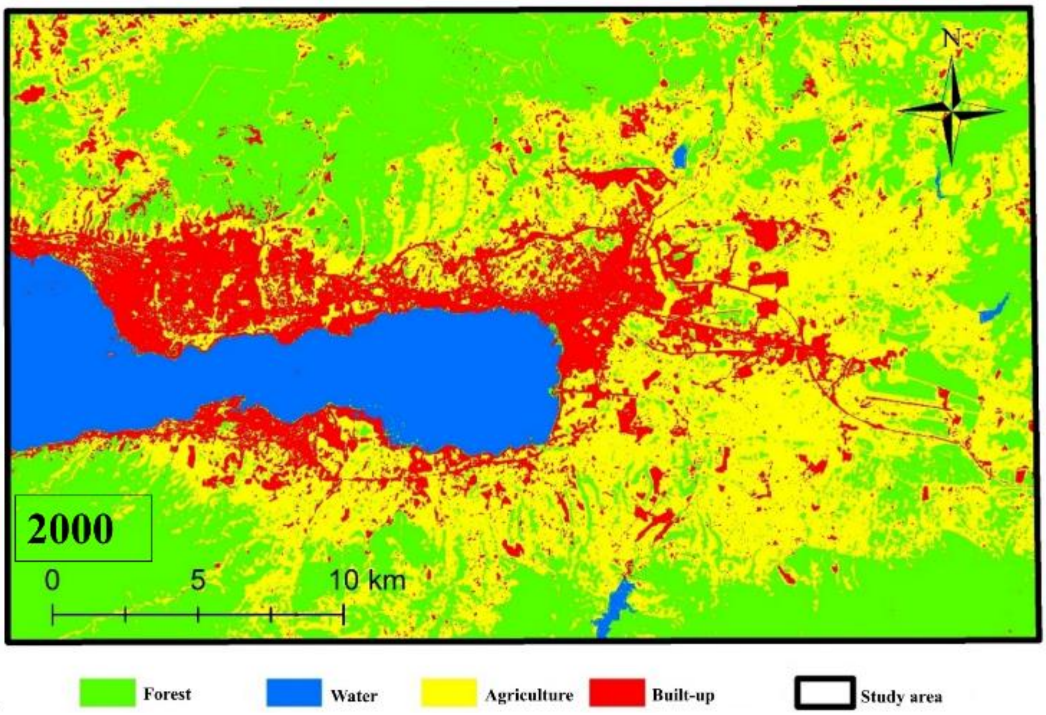


Figure 6. Land use and land cover map of 2000.

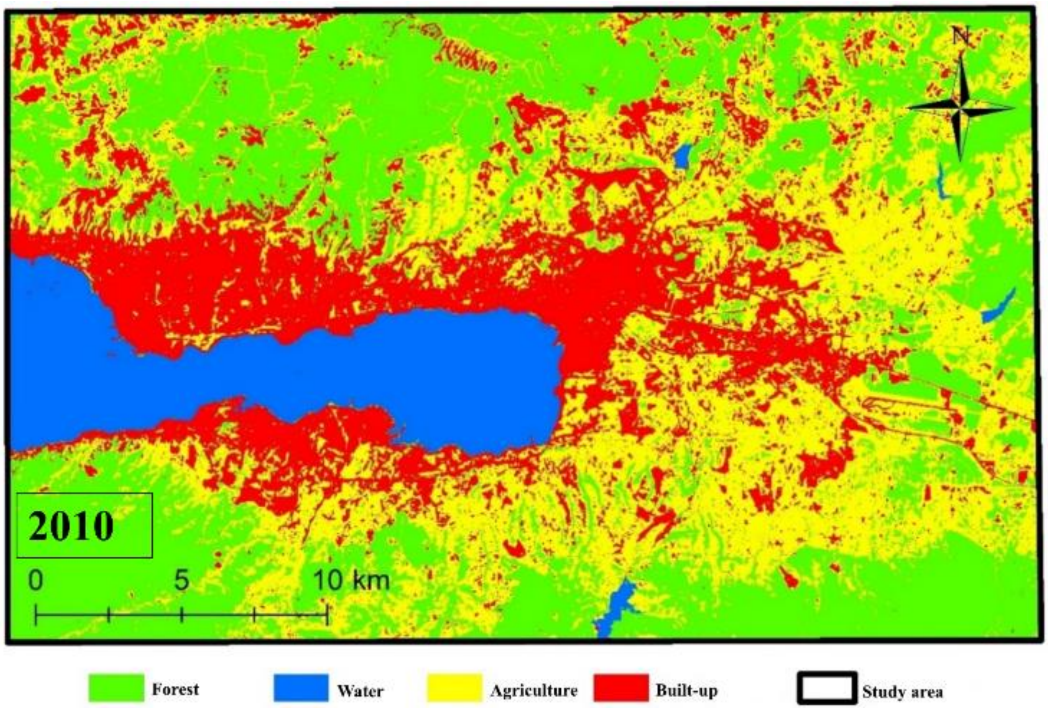


Figure 7. Land use and land cover map of 2010.

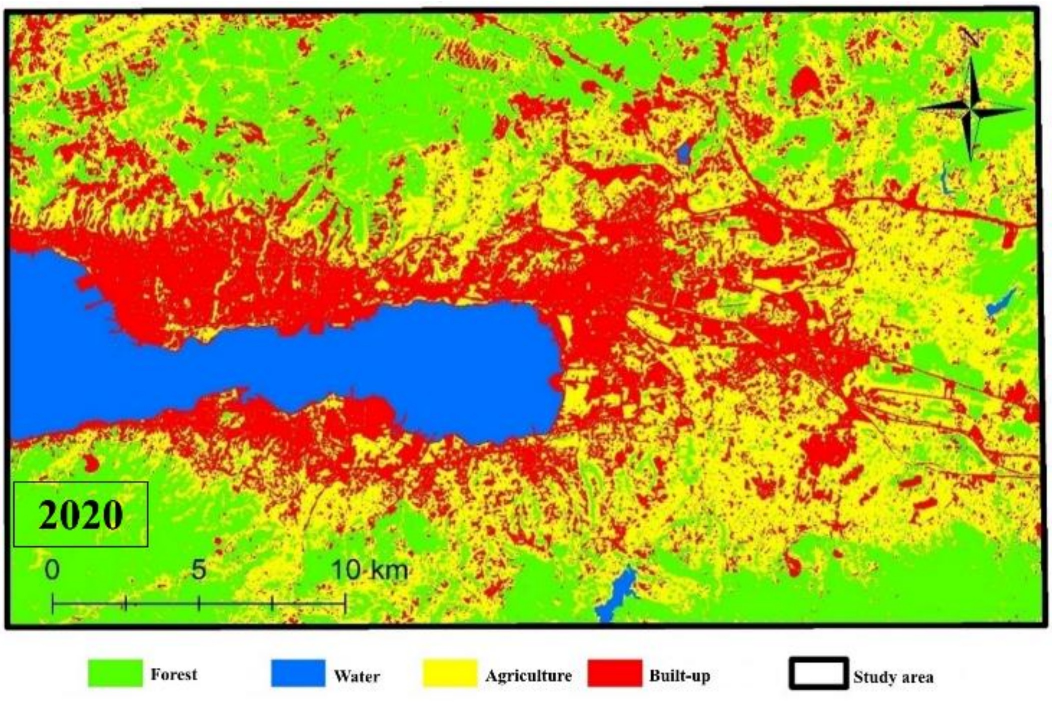
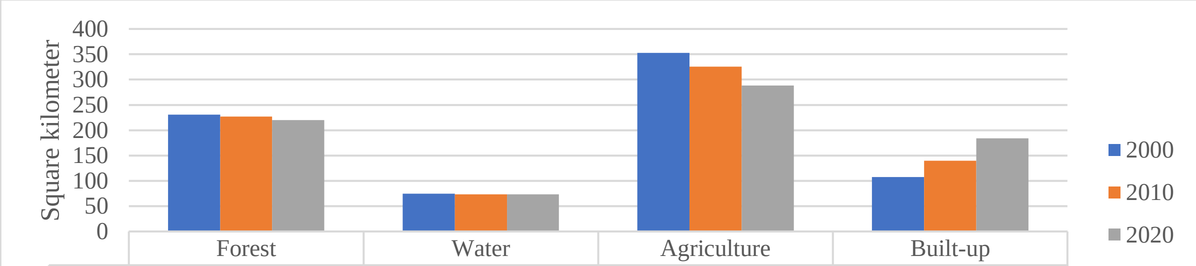


Figure 8. Land use and land cover map of 2020.

Table 4. Land use and land cover change rates in the study area between 2000-2020.

	2000		2000-2010		2010		2010-2020		2020	
	km^2	%	Δ (%)	Δ (km^2)	km^2	%	Δ (%)	Δ (%)	km^2	%
Forest	230,98	30,17	-0,51	-3,90	227,08	29,66	-0,91	-6,96	220,11	28,75
Water	74,77	9,76	-0,19	-1,46	73,31	9,57	-0,01	-0,06	73,25	9,56
Agriculture	352,75	46,07	-3,53	-27,02	325,73	42,54	-4,87	-37,31	288,42	37,67
Built-up	107,20	14,00	4,23	32,38	139,58	18,23	5,79	44,33	183,91	24,02
Total	765,70	100			765,70	100			765,70	100

According to the analysis results obtained, the changes observed between 2000, 2010, and 2020 are summarized in Table 4. An analysis of Table 4 reveals a general declining trend in forest and agricultural areas, a lack of significant change in water areas, ana notable increasing trend in built-up areas. The alterations in land use for the years 2000, 2010, and 2020 are illustrated in Figure 9.



	Forest	Water	Agriculture	Built-up
2000	230,98	74,77	352,75	107,2
2010	227,08	73,31	325,73	139,58
2020	220,11	73,25	288,42	183,91

Figure 9. Land use/cover change between 2000-2010-2020.

The forest area exhibited a consistent decline over the study period, decreasing from 230.98 km² in 2000 to 220.11 km² in 2020 when Figure 9 is examined. This reduction represents a total decrease of 10.87 km², indicating a steady loss of forested land. Similarly, the agricultural area also experienced a notable decrease, with the area shrinking from 352.75 km² in 2000 to 288.42 km² in 2020. This reduction of 64.33 km² reflects a substantial decline in agricultural land over the two decades. In contrast, the built-up area demonstrated a significant increase. The built-up region expanded from 107.2 km² in 2000 to 183.91 km² in 2020, representing an increase of 76.71 km². This growth suggests a marked expansion in urbanization and infrastructure development during the study period. The water body area remained relatively stable, with only minor fluctuations. The area slightly decreased from 74.77 km² in 2000 to 73.25 km² in 2020, indicating a negligible reduction over the twenty-year span. Overall, the data indicates a trend towards increased urban development at the expense of forested and agricultural lands, while water bodies have remained largely unchanged.

3.3. Simulation process

In this study, to simulate the predicted LULC changes between 2020 and 2030 using the ANN approach, the years 2000 and 2010 were initially incorporated into the training process. This training involved 1,000 iterations, a 3x3 (9-pixel) neighborhood size, a learning rate of 0.001, 10 hidden layers, and a momentum value of 0.050. During the training phase, the minimum validation total error (MinValidation Overall Error) recorded for 2010 was 0.09471, with a corresponding validation Kappa value (Current Validation Kappa) of 87%. A simulation map was then generated. In the validation phase, the LULC map classified for 2020 was compared with the simulated LULC maps derived from the ANN learning process through Cellular Automata over five iterations. The validation results indicated that the ANN approach achieved a prediction accuracy of 91.1% (Figure 10).

Figure 10. ANN learning curves and validation for the years 2000-2010 and 2010-2020.

In the study, a simulation for the projected 2030 LULC was conducted by applying the ANN approach to classified satellite images from 2000 and 2010. Following the data training with ANN, utilizing information acquired through remote sensing techniques, a LULC simulation map for 2030 was generated (Figure 11). During the learning phase for the 2030 LULC simulation map, the minimum validation overall error was recorded at 0.08176, while the current validation Kappa value was 89.2%.

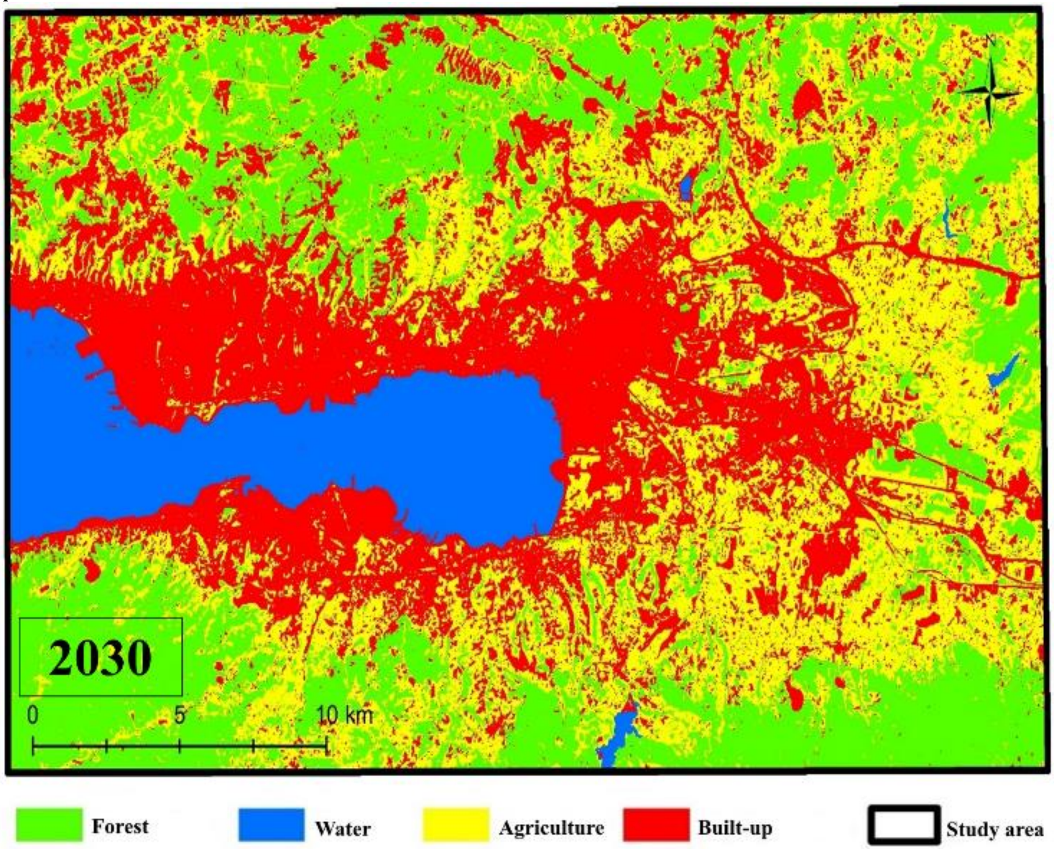


Figure 11. Land use and land cover simulation map projected for 2030.

Table 5 presents a comparison between the land classes depicted in the 2030 LULC simulation map generated through this study and the findings derived from the LULC map created using the current 2020 satellite imagery.

Table 5. Estimated LULC change between 2020 and 2030.

	2020 (km^2)	2030 (km^2)	Change Δ (km^2)	Change Δ (%)
Forest	220,11	216,98	-3,13	-0,41
Water	73,25	72,86	-0,39	-0,04
Agriculture	288,42	254,89	-33,53	-4,38
Built-up	183,91	220,97	37,06	4,84
Total	765,70	765,70	-	-

It is projected that forest areas will experience a decrease of 3.13%, reducing from 220.11 km^2 to 216.98 km^2 by 2030. Water areas are expected to diminish by 0.39 km^2, decreasing from 73.25 km^2 to 72.86 km^2. Agricultural areas are anticipated to contract by 33.53 km^2, declining from 288.42 km^2 to 254.89 km^2. Conversely, built-up areas are forecasted to increase by 37.06 km^2, rising from 183.91 km^2 to 220.97 km^2, which represents a growth of 4.84%. These projections are detailed in Table 5. The graph illustrating the results of this study is presented in Figure 12.

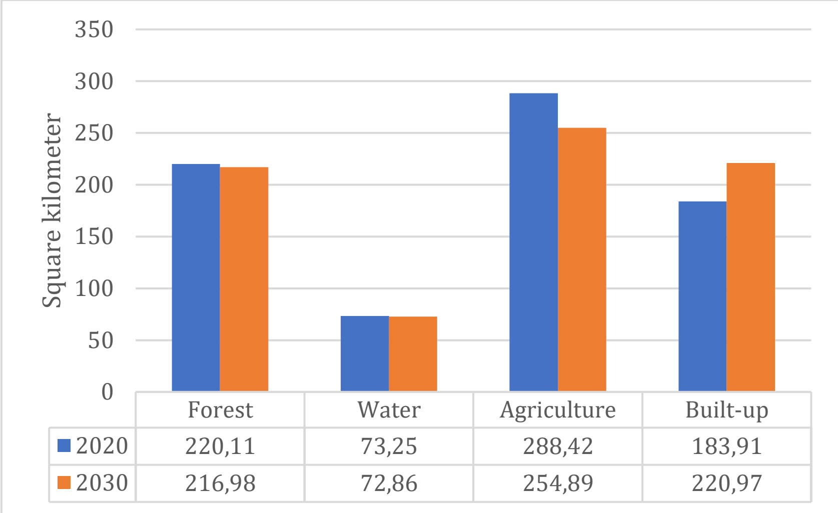


Figure 12. Land use and land cover simulation map projected for 2030.

In 2020, the forest area was recorded at 220.11 km², while the water body covered 73.25 km² when Figure 12 is examined. Agricultural land encompassed 288.42 km², and built-up areas spanned 183.91 km². By 2030, a slight reduction in the forest area is projected, decreasing to 216.98 km². Water bodies are expected to contract marginally to 72.86 km². The agricultural area is forecasted to diminish to 254.89 km². Conversely, built-up areas are anticipated to expand significantly to 220.97 km². This data suggests a trend towards a reduction in forest and agricultural lands, coupled with a slight decrease in water bodies, while built-up areas are projected to increase substantially. The observed shifts reflect ongoing changes in land use patterns, likely influenced by urban expansion and development activities.

3.4. Discussion

The trends over the last ten years show a clear pattern of diminishing forest and agricultural lands, with a simultaneous increase in built-up areas and significant impacts on water bodies. This transformation underscores the complexities and challenges posed by LULC changes, as urbanization often takes precedence over environmental sustainability Leulmi vd., "Assessment of the Effect of Land Use and Land Cover (LULC) Change on Depth Runoff"; Sharma vd., "Impact of Land Use and Land Cover on Urban Ecosystem Service Value in Chandigarh, India".. Numerous international studies have reported analogous trends to those identified in this research Blakime vd., "Dynamics of Built-Up Areas and Challenges of Planning and Development of Urban Zone of Greater Lomé in Togo, West Africa"; Naikoo vd., "Analyses of Land Use Land Cover (LULC) Change and Built-up Expansion in the Suburb of a Metropolitan City".. In regions experiencing rapid urbanization, the expansion of built-up areas has been pronounced, primarily driven by urban sprawl, population growth, and economic development Singh vd., "A Machine Learning-Based Classification of LANDSAT Images to Map Land Use and Land Cover of India".. Empirical research conducted in regions such as Southeast Asia and Africa consistently indicates similar patterns of urban expansion, often at the cost of agricultural and forested areas Nasir vd., "Modelling Past and Future Land-use Changes from Mining, Agriculture, Industry and Biodiversity in a Rapidly Developing Southeast Asian Region"; Rachman vd., "Insights from 30 Years of Land Use/Land Cover Transitions in Jakarta, Indonesia, via Intensity Analysis".. Within the scope of this study, a slight reduction in both forest and agricultural areas is projected by 2030, a trend commonly observed globally, particularly in developing nations. The decline in forest cover is frequently attributed to factors such as logging, agricultural expansion, and urbanization Kullo vd., "The Impact of Land Use and Land Cover Changes on Socioeconomic Factors and Livelihood in the Atwima Nwabiagya District of the Ashanti Region, Ghana".. Moreover, agricultural lands are often subject to conversion into urban areas or may be abandoned due to urban encroachment Pande vd., "Intertwined Impacts of Urbanization and Land Cover Change on Urban Climate and Agriculture in Aurangabad City (MS), India Using Google Earth Engine Platform".. Comparable situations have been documented in studies across South America, Southeast Asia, and certain regions of Africa, where forests and agricultural lands are increasingly supplanted by urban infrastructure Anand ve Oinam, "Future Land Use Land Cover Prediction with Special Emphasis on Urbanization and Wetlands"; Benavidez-Silva vd., "Future Scenarios for Land Use in Chile"; Muchelo vd., "Patterns of Urban Sprawl and Agricultural Land Loss in Sub-Saharan Africa".. This study also anticipates a slight decrease in the extent of water bodies. In some regions, reductions in water bodies have been linked to urbanization, water abstraction, and climate change Mohibul vd., "Assessing Land Use/Land Cover Transformation and Wetland Decline in Birbhum District, West Bengal"; Patel vd., "Novel Approach for the LULC Change Detection Using GIS & Google Earth Engine through Spatiotemporal Analysis to Evaluate the Urbanization Growth of Ahmedabad City".. Contrarily, certain studies have documented increases in artificial water bodies, such as reservoirs or dams, particularly in areas focused on irrigation or hydroelectric energy Buğday ve Erkan Buğday, "Modeling and Simulating Land Use/Cover Change Using Artificial Neural Network From Remotely Sensing Data"; Ahialey vd., "LULC changes in the region of the proposed Pwalugu hydropower project using GIS and remote sensing technique"; Zafar vd., "Trend Analysis of the Decadal Variations of Water Bodies and Land Use/Land Cover through MODIS Imagery".. In summary, our study mirrors broader global trends in LULC changes, predominantly driven by urbanization and development. However, it is crucial to recognize that these dynamics can vary significantly based on regional policies, environmental conservation efforts, and socioeconomic factors. The analysis showed that the results obtained from the study area were similar to the results commonly encountered in the national and international literature Muhammad vd., "Spatiotemporal Change Analysis and Prediction of Future Land Use and Land Cover Changes Using QGIS MOLUSCE Plugin and Remote Sensing Big Data"; Liu vd., "The Climatic Impacts of Land Use and Land Cover Change Compared among Countries"; Petit ve Lambin, "Impact of data integration technique on historical land-use/land-cover change: Comparing historical maps with remote sensing data in the Belgian Ardennes”.. It was determined that forest and agricultural lands generally turned into constructed areas.

The results from this study mirror broader global trends in land use and land cover (LULC) changes, predominantly driven by urbanization and development. Several international studies have reported analogous patterns of diminishing forests and agricultural lands, with a simultaneous increase in built-up areas. For instance, a study in Nigeria's Oba Hills Forest Reserve found that the forest cover has progressively diminished over the years due to population growth and human activities, such as the conversion of forest land for non-forest uses Bukoye vd., “Land Use Land Cover Dynamics of Oba Hills Forest Reserve, Nigeria, Employing Multispectral Imagery and GIS”.. Similarly, research in the central highlands of Ethiopia showed a significant decrease in forest and grassland areas between 1973 and 2020, with a corresponding increase in agricultural land, settlements, and bare land Shiferaw vd., “Effect of Forest Cover Change on Ecosystem Services in Central Highlands of Ethiopia”.. The decline in forest cover is often attributed to factors like logging, agricultural expansion, and urbanization. A study in the Yangtze River basin in China found that urban construction accounts for the highest proportion of forest loss, as the expansion of cities encroaches into surrounding forests Zhu ve Zhu, “Study on Spatiotemporal Characteristic and Mechanism of Forest Loss in Urban Agglomeration in the Middle Reaches of the Yangtze River”.. Comparable situations have been documented in South America, Southeast Asia, and parts of Africa, where forests and agricultural lands are increasingly supplanted by urban infrastructure Van Vliet, “Direct and Indirect Loss of Natural Area from Urban Expansion”; Van Der Laan vd., “Mitigation of Unwanted Direct and Indirect Land-use Change – an Integrated Approach Illustrated for Palm Oil, Pulpwood, Rubber and Rice Production in North and East Kalimantan, Indonesia”; Molinario vd., “Contextualizing Landscape-Scale Forest Cover Loss in the Democratic Republic of Congo (DRC) between 2000 and 2015”.. Moreover, the conversion of agricultural lands into urban areas or their abandonment due to urban encroachment has been observed in various regions. A review of land-use intensification found that cropland expansion in forest frontiers is often market-driven, while management intensification is more often fueled by technological development Van Vliet, “Direct and Indirect Loss of Natural Area from Urban Expansion”.. The impact of these LULC changes on water bodies is also a concern. Some studies have linked reductions in water bodies to urbanization, water abstraction, and climate change Haas vd., “Satellite Monitoring of Urbanization and Environmental Impacts—A Comparison of Stockholm and Shanghai”; Rohatyn vd., “Differential Impacts of Land Use and Precipitation on ‘Ecosystem Water Yield’”.. Conversely, increases in artificial water bodies, such as reservoirs or dams, have been documented in areas focused on irrigation or hydroelectric energy Rohatyn vd., “Differential Impacts of Land Use and Precipitation on ‘Ecosystem Water Yield’”.. It is crucial to recognize that these dynamics can vary significantly based on regional policies, environmental conservation efforts, and socioeconomic factors. For example, a study in the Brazilian Amazon highlighted the need for strategies to address legal and illegal deforestation, such as bringing social and environmental safeguards to infrastructure plans, consolidating positive incentives for sustainable commodity production, and fully implementing forest protection legislation Moutinho vd., “Achieving Zero Deforestation in the Brazilian Amazon”.. In summary, the findings of this study are consistent with the broader global trends in LULC changes, characterized by the diminishment of forests and agricultural lands, the expansion of built-up areas, and the impacts on water bodies. These patterns are driven primarily by urbanization and development, with variations depending on regional contexts and policy interventions.

4. Conclusions

In this study, land use and land change maps obtained with remote sensing techniques (supervised classification) approach using Landsat satellite images for the years 2000, 2010, and 2020 were used to reveal the change in LULC. A simulation of temporal and spatial change was produced for the year 2030 with the MLP-ANN approach. In addition, spatial and spatial change was revealed in the study area where the urban settlement center with dense forest assets is located.

As a result; in the LULC change model (2000-2030) made for the area where İzmit center and its close vicinity are located; forest areas are expected to increase from 230.98 km² to 220.11 km²; It has been determined that agricultural areas have decreased from 352.75 km² to 288.42 km² by 1.42% forest area and 8.4% agricultural area, respectively, water areas were 74.77 km² in 2000, 73.31 km² in 2010 and 73.25 km² as of 2020, water areas have generally decreased very slightly, this supports the opinion that drought and water budgets have decreased due to global climate change, and built-up areas have increased by 10.02% from 107.2 km² in 2000 to 183.91 km² in 2020. It is thought that this increase is also an expected situation since İzmit province is one of our important industrial cities. When we look at the 2030 estimates, it is thought that built-up areas will increase and can be 220.97 km². Considering that cities with developed industries have a larger population, it is predicted that the results of the study can be realized.

The ANN method and the use of the CA simulation approach preferred in this study have been one of the features that increase modelling performance. This approach is an effective tool for determining the LULC change in more detail, and since the high classification success also increases the success of the model, it will increase the accuracy of the predictions.

It is thought that in future studies if different satellite images are used with higher resolution and more precise data, both the classification and the prediction power of the model to be produced will be further increased. The prediction approaches used in this study can be improved by using different criteria and approaches, and the success of the LULC change prediction can be increased.

Ethics committee approval and conflict of interest statement

This article does not require ethics committee approval. This article has no conflicts of interest with any individual or institution.

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Author Contribution Statement

The authors declare no conflict of interest. The authors confirm their contributions as follows: G.K. was responsible for the original draft, conducting tests, validation, and providing resources. E.B. was responsible for writing, review, editing, and supervision.

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