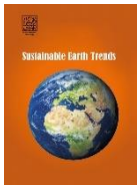
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Land use/land cover change modeling and prediction using artificial neural networks: A case study of the Birjand watershed

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ABSTRACT

Human development and land transformation have turned land use and land cover (LULC) change into one of the major global environmental challenges, affecting essential biogeochemical cycles such as water, carbon, and energy. This study aims to model and predict LULC changes in the Birjand watershed, located in eastern Iran, using an Artificial Neural Network (ANN) within the Land Change Modeler (LCM) framework. Landsat satellite imagery (TM and ETM+) was used to detect historical changes, while eight explanatory variables digital elevation model, slope, soil texture, and distance from roads, rivers, faults, residential areas, and agricultural lands were applied to simulate transition potentials for the 2000–2010 calibration period. A Markov chain analysis was then employed to estimate the probability of transitions between land use classes, and predicted maps were generated for 2020. The results revealed that barren lands were predominantly converted into residential areas, reflecting rapid urban expansion. Validation of the simulated 2020 map against observed data indicated strong model performance, supported by accuracy metrics such as the Kappa coefficient and Overall Accuracy. Based on the validated model, LULC projections for 2040 show a continued decline in agricultural lands alongside the expansion of urban and barren areas. The projected areas amount to approximately 73.82 km² of agricultural land, 68.81 km² of urban land, and 3,282.39 km² of barren land. These projections underscore the urgent need for sustainable land-use planning and management strategies to minimize environmental degradation in arid regions.

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1. Introduction

Human development and land transformation have turned land use and land cover (LULC) change into one of the major global environmental challenges, affecting essential biogeochemical cycles such as water, carbon, and energy (Weng and Hu, 2009). Attention to these changes has increased due to their significant environmental consequences, including biodiversity loss, habitat fragmentation, and land degradation (Kuemmerle, 2009). Human activities have accelerated the conversion of natural lands into agricultural and urban uses, leading to the deterioration of ecological integrity (Kamusoko and Aniya, 2007; Kehrestaghi and Jafarian, 2011). These processes have substantial impacts on natural resources such as water, vegetation, soil, and food production, highlighting the critical role of proper land use management in minimizing adverse environmental effects (Abbas et al., 2010). Therefore, land evaluation and management should be prioritized according to land suitability and ecosystem functionality (Huston, 2006). Unplanned land use changes are among the most serious environmental issues in Iran, where during the past four decades, rapid and uncontrolled land conversions have occurred due to population growth and socio-economic pressures (Arekhi and Niyazi, 2009). Remote sensing data and satellite imagery provide a valuable means of analyzing such transformations, such as rangeland degradation

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and the expansion of agricultural lands (Shataei and Ghanbari, 2009). Modeling LULC dynamics is a key approach for understanding the rate and pattern of degradation, biodiversity loss, and habitat fragmentation, and it contributes to spatial planning and sustainable management of ecosystems (Lambin, 1997; Prez-Vega et al., 2012).

Various models have been developed to predict land use transitions, including the Land Change Modeler (LCM), GEOMOD, CA-Markov, and DINAMICA (Mas et al., 2014). Remote sensing data, when integrated with Geographic Information Systems (GIS), serve as a robust framework for detecting, mapping, and modeling spatiotemporal changes (Bakr et al., 2010; Abd El-Kawy et al., 2011; Mendoza et al., 2011). Among these, the LCM, developed within the TerrSet (formerly IDRISI) software, provides a systematic platform for evaluating historical land cover transitions and simulating future changes (Schulz et al., 2010). It operates through four main stages: change analysis, transition potential modeling, future projection, and validation (Pelorosso et al., 2011; Gholamalifard et al., 2014).

Transition potential modeling is a fundamental step in LCM that estimates the likelihood of conversion from one land use class to another, based on explanatory spatial variables such as topography, soil type, distance to roads, rivers, and settlements (Vega-Perez et al., 2012). The use of Artificial Neural Networks (ANNs) enhances this process by enabling the model to capture nonlinear relationships among variables and improve prediction accuracy (Weng and Hu, 2009).

Recent advances in LULC modeling demonstrate increasing effectiveness of combining machine-learning techniques (especially ANN / MLP) with spatial modeling frameworks (CA-Markov or hybrid CA-ANN / LCM-based approaches) across diverse geographical and socio-environmental contexts. For example, in Ethiopia the Goang Watershed study (2023) applied an MLP–CA-Markov model to forecast LULC dynamics until 2060 and documented substantial transitions among forest, shrubland, cropland, and built-up areas. In the Upper Omo–Gibe River Basin, another 2023 study utilized a CA-ANN model to analyze land-use transitions over 1991–2022 and produce future scenarios, confirming the model's suitability for long-term environmental planning.

In arid/semi-arid regions, the relevance of such hybrid models is particularly evident. In the El-Fayoum Governorate (Egypt), an integrated ANN+CA-Markov framework provided reliable projections under rapid urbanization and agricultural intensification pressures. Similarly, in 2024 a CA-ANN based study forecasted LULC changes in a tropical coastal region with high accuracy, supporting sustainable land-use planning in vulnerable habitats.

Beyond traditional CA–Markov hybrids, recent methodological innovations have emerged. A 2024 study combined neural-network based cellular automation with global remote-sensing datasets to map and forecast LULC over wide areas, illustrating the potential for integrating big-data platforms in land-use monitoring. Furthermore, novel architectures such as combining transformer encoders, convolutional neural networks (CNN), and cellular automata have been proposed for urban land change simulation-offering improved spatiotemporal modeling of land-use dynamics.

Applications are not limited to academic research: a 2024 CA–ANN analysis in Brazilian urban centers demonstrated practical applicability of these hybrid models for urban expansion studies. Also, a 2024 study (Mehra & Swain) employed an ANN-based cellular automation to simulate LULC up to 2040, reporting acceptable accuracy (Kappa ~0.77, OA ~86.8 %), which strengthens confidence in predictive outputs.

Taken together, these works show that ANN-based spatial modeling-whether using CA–Markov, CA-ANN hybrids, or advanced neural-network architectures-offers a robust, flexible, and accurate framework for analyzing and forecasting LULC changes. The present study applies exactly this approach to the Birjand watershed-a semi-arid region with low precipitation and a mix of plains and mountains-making the method especially suitable for capturing complex, nonlinear land-use dynamics under environmental pressures.

In this study, the LCM integrated with ANN was used to model and predict LULC changes in the Birjand watershed. ANN was chosen due to its ability to capture complex, nonlinear relationships among multiple driving factors, providing high predictive accuracy and flexibility without strict parametric assumptions. The novelty of this work lies not

only in using ANN with spatial drivers such as topography, soil texture, and proximity variables-which is common in recent LULC studies-but also in applying this framework specifically to the arid and semi-arid Birjand watershed, incorporating region-specific topographic, soil, and anthropogenic factors, and validating the model with multi-temporal, high-resolution satellite imagery. This integrated, data-driven approach enhances predictive accuracy and provides valuable insights for sustainable land management and environmental planning in heterogeneous and rapidly changing arid landscapes.

2. Material and methods

2.1. Study area

The Birjand watershed, located in eastern Iran within South Khorasan Province (32°48′ N, 58°11′ E), was selected as the study area. It covers approximately 3,435 km² and includes both plains and mountainous zones. Elevation ranges from 1,180 m to 2,720 m above sea level. The Birjand plain has an average annual precipitation of about 140 mm and a mean temperature of 16.5 °C, classifying the region as arid (Fig .1).

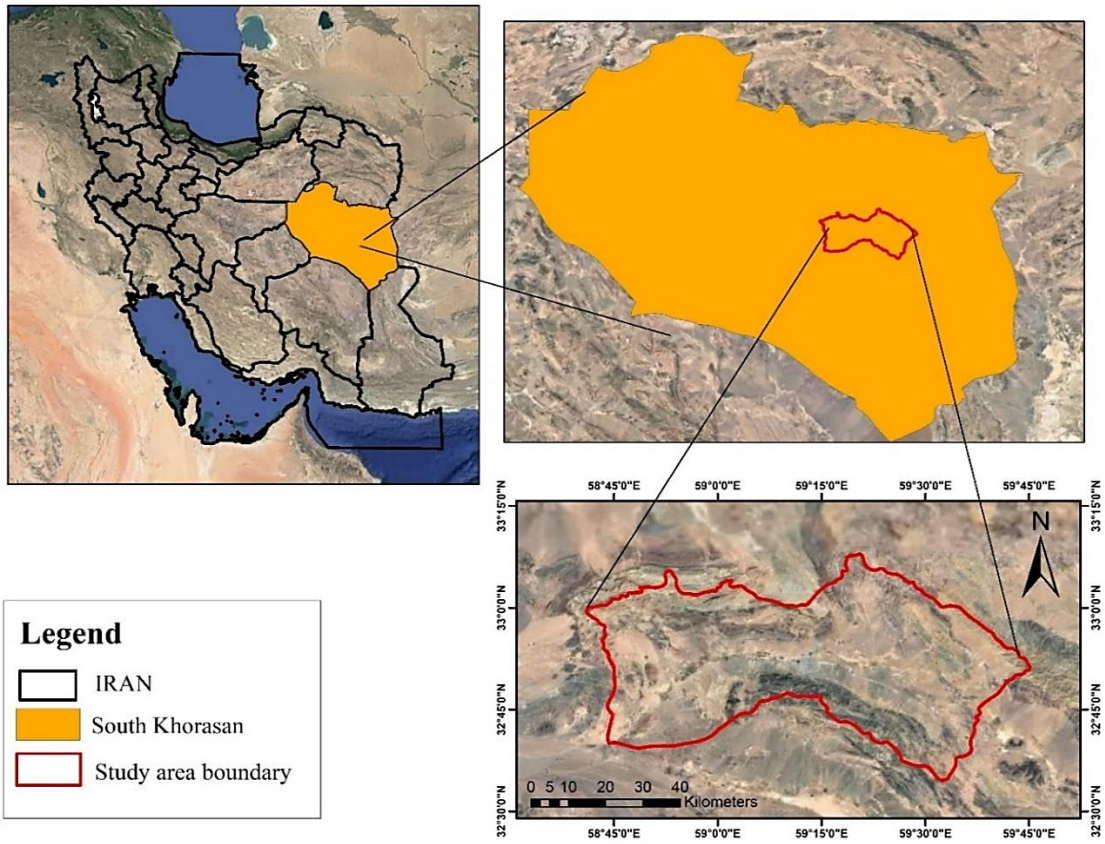


Fig. 1. Geographic location of the study area.

2.2. Accuracy assessment of LULC maps

To analyze LULC dynamics, multi-temporal land-use maps are required to represent conditions at different times. Following preprocessing and classification of Landsat imagery for land-use change simulation and map production, the accuracy of the results must be evaluated. In this study, accuracy assessment particularly after image processing-was carried out using the following approaches: (i) verification with known field data when available, by comparing classified outputs against ground-truth points for each class; (ii) evaluation using color-composite imagery, enabling qualitative and quantitative appraisal by an interpreter; and (iii) standard assessment with field/reference data, considered the most robust method, in which sampling points collected from the ground (here, using Google Earth and existing maps) are used to compute accuracy metrics such as overall accuracy and the Kappa coefficient.

2.3. Implementation of the land change modeler (LCM)

Implementation of the Land Change Modeler (LCM):
LULC modeling for 2000, 2010, and 2020, and prediction for 2040, were performed in TerrSet (IDRISI). The software integrates remote-sensing inputs with change-analysis and predictive algorithms. The workflow comprised three main stages:

1. Change analysis, comparing two dates to detect dominant transformations;
2. Transition-potential modeling, estimating the likelihood of conversions among classes using an Artificial Neural Network (ANN, specifically a Multilayer Perceptron);
3. Change prediction, simulating future LULC using historical transitions via a Markov chain model coupled with the ANN.

This explicit description clarifies the specific machine-learning approach applied, addressing model selection and its role in predicting LULC dynamics.
LULC modeling in the Birjand watershed was performed using TerrSet (IDRISI) in three stages. Historical change analysis identified dominant transformations (2000–2010). Transition potentials were estimated using an Artificial Neural Network (ANN) with eight explanatory variables, and a Markov chain was then applied to generate the 2020 prediction map, which was validated prior to forecasting LULC changes to 2040. This ANN–Markov approach efficiently captures nonlinear transitions and historical trends.

2.4. LCM framework

The Land Change Modeler (LCM) provides a structured platform to (i) analyze multi-date LULC changes, (ii) model transition potentials driven by key explanatory variables, and (iii) predict future LULC by combining spatial likelihoods (e.g., ANN outputs) with temporal transition probabilities (e.g., Markov chain).

2.4.1. Change analysis

Classified land-use maps for 2000, 2010, and 2020 were prepared, and gains/losses as well as net changes for each class were quantified at both regional and pixel scales to support urban and environmental planning.

2.4.2. Transition-potential modeling

Transition-potential modeling estimates the probability that one class will convert to another. Explanatory variables considered in this study included distance to roads, rivers, and residential areas, along with slope, elevation (DEM), soil texture, and distance to agricultural lands; these variables were selected for their demonstrated influence on observed changes. Model performance was evaluated using training/testing errors and the Kappa statistic.

2.4.3. LULC prediction

Using the LCM model (ANN+Markov) calibrated with observed 2000–2010 LULC data, the 2020 LULC map was first simulated and validated against the actual 2020 map. Here, “calibrated” means that the model parameters were adjusted and trained using historical LULC data to accurately capture transition potentials between land-use classes. The validated model was then used to forecast LULC for 2040 based on the historical transitions.

3. Results and discussion

For supervised classification, training samples were selected using a simple random sampling method to ensure appropriate spatial distribution across the entire watershed. The samples were assigned to three main land-use/land-cover classes considered in the study. Using the Maximum Likelihood Classification (MLC) method, eight land-use classes were identified within the study area. The classified LULC maps for the years 2000, 2010, and 2020 are presented (Fig. 2), while the overall accuracy and Kappa coefficient values derived from the change-detection analysis are summarized in Table 1.

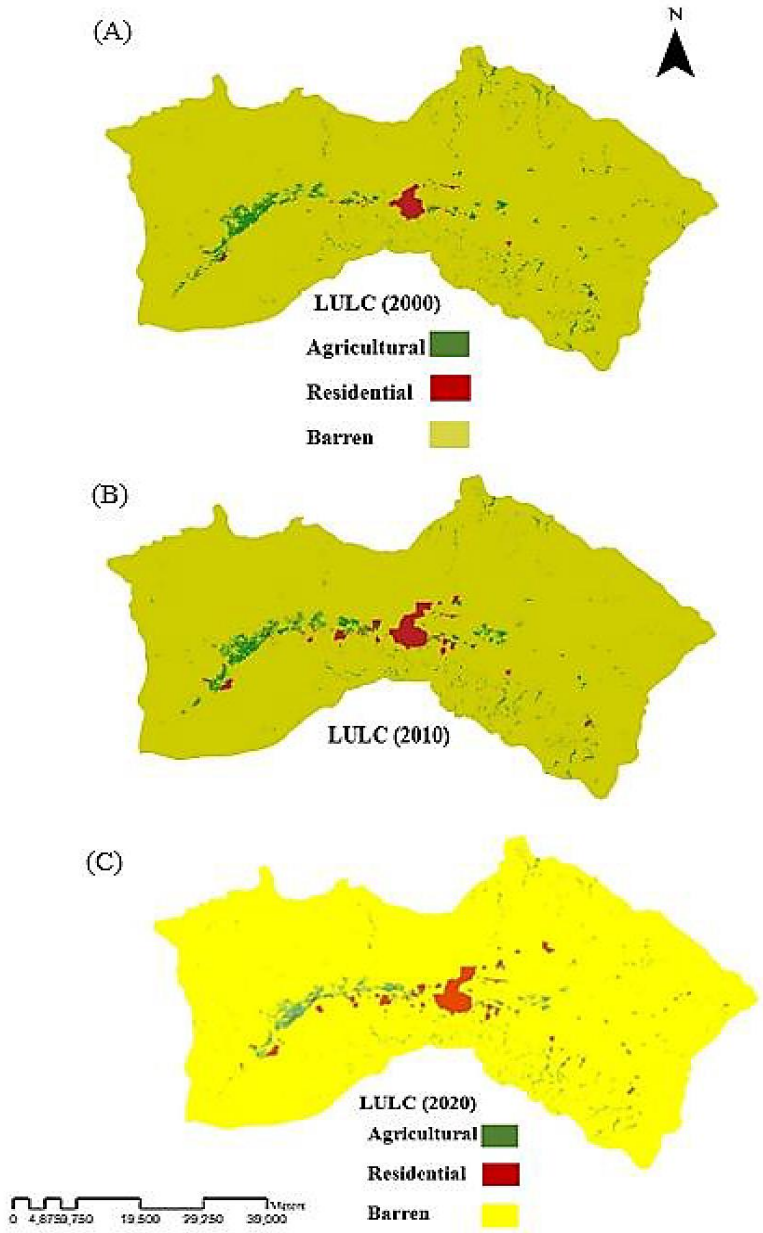


Fig. 2. Classified land-use/land-cover maps for the years (A) 2000, (B) 2010, and (C) 2020.

3.1. Accuracy assessment of land-use/land-cover maps

One of the most common methods for evaluating classification accuracy is to compare the results with ground truth data. In this approach, a number of sample pixels are selected and compared with the corresponding reference data to verify classification reliability. After the land-cover classification and preparation of land-use maps comprising three main classes: barren land, residential areas, and agricultural lands for the years 2000, 2010, and 2020, the results were validated using ground-truth information derived from Google Earth. The accuracy assessment results for these three years, including the overall accuracy and the Kappa coefficient, are presented in Table 1.

Table 1. Accuracy assessment results for classified LULC maps (2000, 2010, 2020).

Accuracy Index	2000	2010	2020
Overall Accuracy (%)	90.87	89.79	97.03
Kappa Coefficient	0.876	0.835	0.913

3.2. Change detection

Change detection is a powerful tool for evaluating and modeling land-use and land-cover dynamics. This process enables rapid assessment of increases and decreases across different land-use classes through graphical representation of spatial changes. In this study, after preparing LULC maps for the years 2000, 2010, and 2020, land-cover changes were detected and quantified using the Change Analysis panel of the LCM module. This panel allows the calculation of net changes for each land-use class over multiple time intervals.

In the present study, the Birjand watershed was analyzed over a ten-year period (2000–2010) to assess land-use transitions and to establish the basis for model prediction. The 2020 land-use map was employed for model validation, and the forecast for 2040 was generated based on the three temporal datasets (2000, 2010, and 2020). The change detection procedure began with the Change Analysis tab in TerrSet, which was used to identify areas of increase and decrease in the three major land-use classes barren, residential, and agricultural within the watershed boundary for the studied years (2000, 2010, and 2020).

3.2.1. Land-use conversion and net change between classes

During the study period from 2000 to 2010, significant changes occurred in land-use patterns within the Birjand watershed. According to Fig. 3, the increase and decrease trends for each land-use class were clearly identified, illustrating the net change in area for each category during this interval.

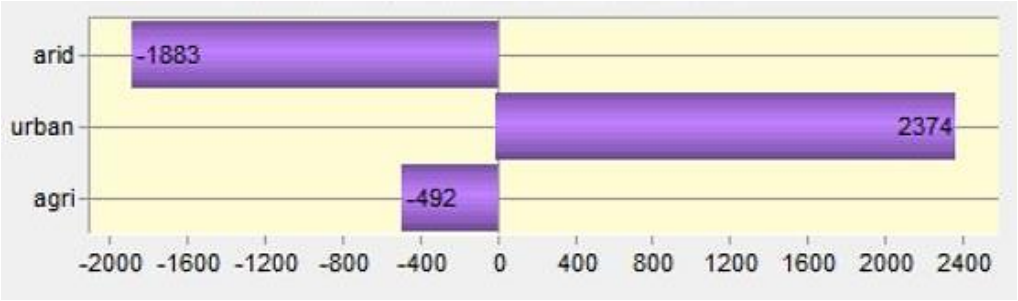


Fig. 3. Net changes in the studied land-use classes (2000–2010), expressed in hectares.

These changes mainly involved an increase in residential land use, which expanded by 2,374 hectares in 2010 compared to 2000. This growth was largely associated with the implementation of the Maskan-Mehr (National Housing Development) project. Using the "Contributions to Net Change in Urban" option, and as illustrated in Fig. 4, it was observed that the largest conversion occurred from barren lands to residential areas, amounting to 2,332 hectares, while the conversion from agricultural lands to residential areas was approximately 43 hectares.

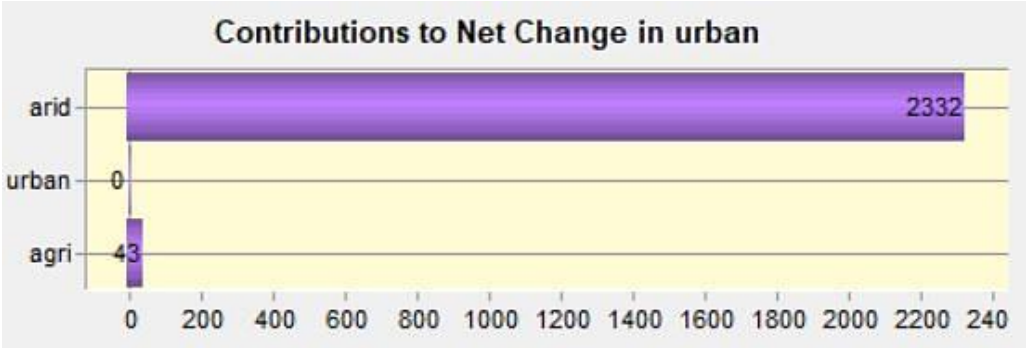


Fig. 4. Net changes in residential land use (2000–2010), expressed in hectares.

During this period, a significant decline in agricultural land use was observed, indicating a decrease of 492 hectares. Fig. 5 illustrates the conversion of 449 hectares of agricultural lands into barren areas and 43 hectares into residential areas.

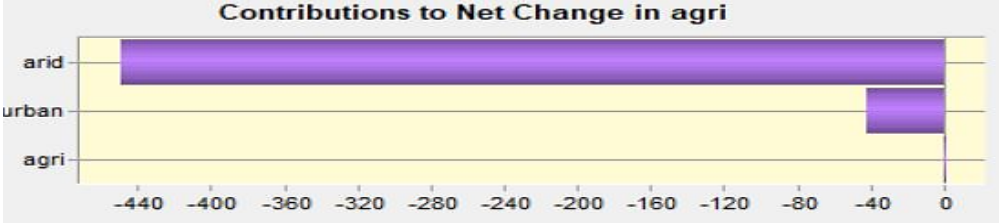


Fig. 5. Net changes in agricultural land use (2000–2010), expressed in hectares.

During the study period, barren land use decreased by 1,883 hectares. According to Fig .6, a total of 2,332 hectares of barren land was converted into residential areas, while 449 hectares of agricultural land were transformed into barren land.

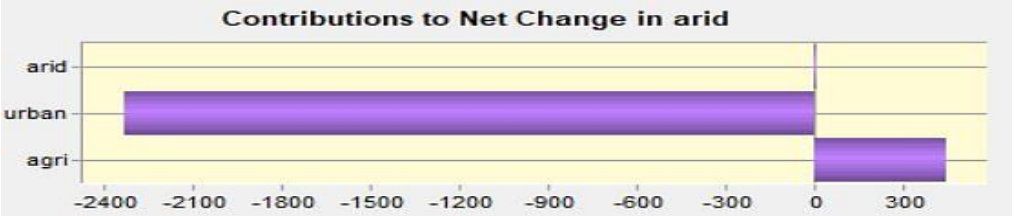


Fig. 6. Net changes in barren land use (2000–2010, hectares) simulated using a calibrated ANN–Markov model.

Table 2. Land-use/land-cover transitions (2000–2010) simulated with ANN–Markov.

Classification	Area (ha)	Category
Decrease	116.46	1
No Change	2,394.63	2
Increase	2,490.75	3

3.3. Land-use change maps

To analyze the trend of land-use and land-cover changes, the Land Change Modeler (LCM) was applied. Using maps of persistence (no change) and transition maps, the model generated various land-use change maps illustrating spatial dynamics across the study area. The results of this modeling indicated that, during the different time periods, the Birjand watershed experienced major transformations characterized primarily by the conversion of barren lands into residential areas and a reduction in agricultural lands, as illustrated in Fig. 7.

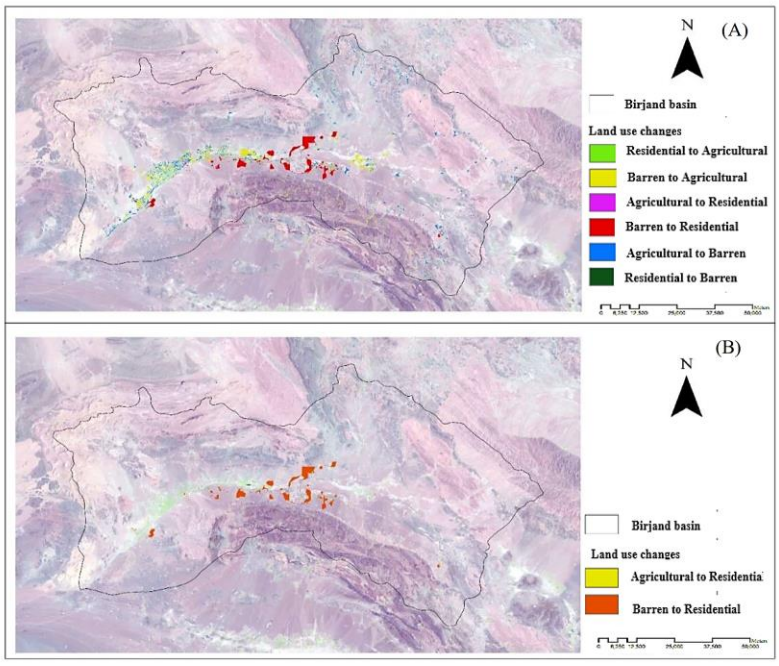


Fig. 7. Detected land-use change maps under the LCM model: (A) overall land-use changes, (B) conversions to residential land use.

3.4. Spatial trend of residential land-use changes

The spatial trend of land-use changes, particularly in the central parts of the Birjand watershed, indicates that the highest rate of conversion to residential land use occurred in these areas. Regions with gentle slopes and close proximity to urban centers, main roads, and power transmission lines exhibit the greatest potential for residential expansion and urban development. These spatial patterns of growth are illustrated in Fig. 8.

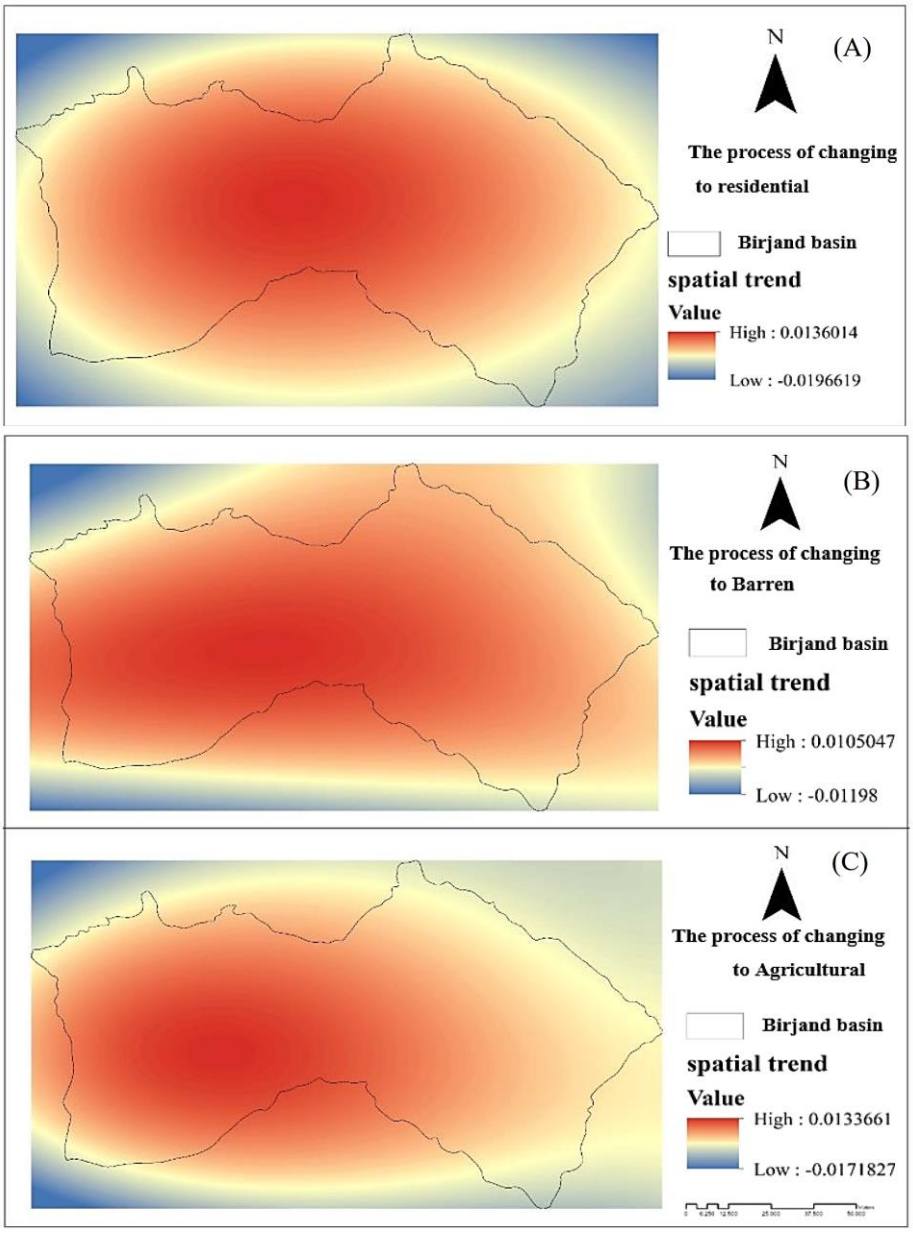


Fig. 8. Spatial trend of land-use changes during 2000–2010: (A) conversion to residential, (B) conversion to barren, and (C) conversion n to agricultural land use.

3.5. Modeling of transition potential

To model the transition potential of future land-use changes, land-use maps from the years 2000 and 2010 were utilized. In this stage, three sub-models were developed to predict the likelihood of conversion among major land-use categories: (1) barren to residential, (2) agricultural to barren, and (3) barren to agricultural. Additionally, eight driving variables influencing land-use changes slope, soil texture, and distance from residential areas, roads, rivers, faults, agricultural lands, and elevation (DEM) were selected as model inputs. These explanatory variables were incorporated into the model to improve the accuracy of transition potential estimation. The spatial distribution of these variables is illustrated in Fig. 9.

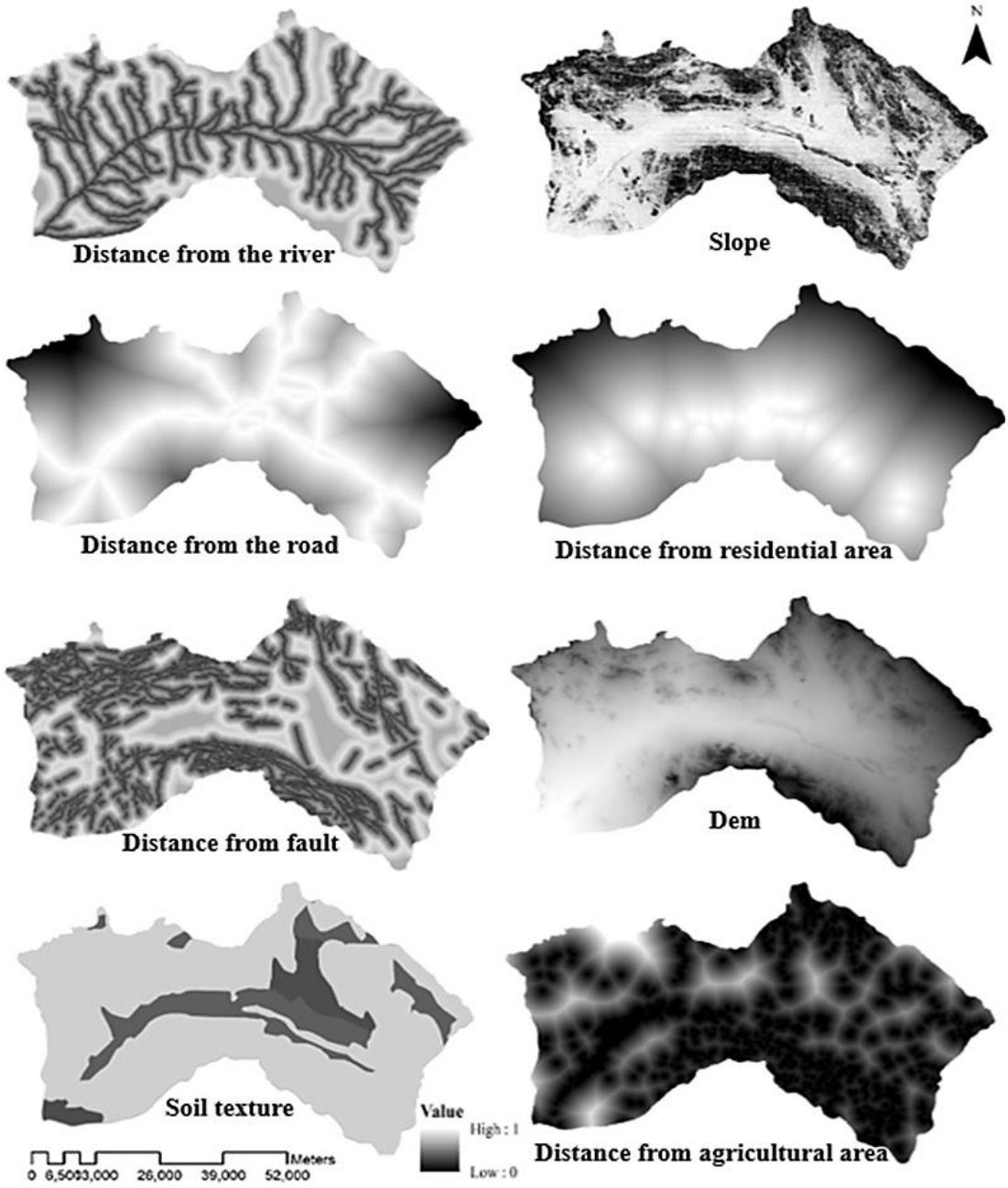


Fig. 9. Fuzzified maps of independent variables used in the LCM model, standardized and converted to transition suitability scores.

All explanatory variables used in the LCM model were standardized and fuzzified to represent their suitability for LULC transitions (see Fig. 9). Continuous variables such as elevation, slope, and distances to roads, rivers, and faults were normalized to a 0–1 scale using linear or sigmoidal fuzzy membership functions, depending on the expected influence on land-use change. Categorical variables, including soil texture, were assigned discrete membership values reflecting their contribution to specific LULC transitions. This fuzzification process ensures that the ANN can effectively learn complex, nonlinear relationships between the explanatory variables and land-use change probabilities.

3.5.1. Predictive ability of input variables

The Cramer's V coefficient determines the suitability of each variable for inclusion in the model to predict future land-use changes. When this coefficient exceeds 0.15, the variable is considered eligible for modeling; if it exceeds 0.40, it indicates that the variable has a strong explanatory power in describing the spatial changes observed in the study area. This means that the influence of such a variable on land-use

transitions is highly significant. It should be noted that some variables with a Cramer's V value below 0.15 may still be included in the model if, based on expert judgment, they are known to have a meaningful influence on land-use dynamics within the region. The four variables with the highest Cramer's V coefficients are presented in Table 3.

Table 3. Cramer's V coefficients of the explanatory variables used in the LCM model.

Variable	Overall Coefficient	Residential Land	Barren Land	Agricultural Land
Distance from Residential Areas	0.2711	0.3579	0.3201	0.1322
Distance from Roads	0.1400	0.1263	0.2049	0.0000
Soil Texture	0.1374	0.1961	0.1315	0.0000
Distance from Agricultural Lands	0.2001	0.3432	0.0538	0.0000

After evaluating the Cramer's V coefficients, the variables with low correlation values indicating a weak relationship between the variable and land-use classes and a limited ability to explain observed changes were excluded from the modeling process. Consequently, the transition potential modeling for the sub-models was conducted using the four most influential variables: distance from residential areas, distance from roads, soil texture, and distance from agricultural lands.

3.5.2. Transition potential modeling using the multilayer perceptron (MLP) artificial neural network

In these maps, the transition potential from one land-use type to another is illustrated spatially. The transition potential maps were generated through the application of the Artificial Neural Network (ANN) using the Multilayer Perceptron (MLP) algorithm. These maps depict the likelihood of conversion between different land-use categories based on the selected explanatory variables. It should be noted that the transition potential maps were produced after multiple iterations of training and validation, ensuring optimal calibration accuracy. The resulting potential transition maps obtained from the ANN model are shown in Fig. 10.

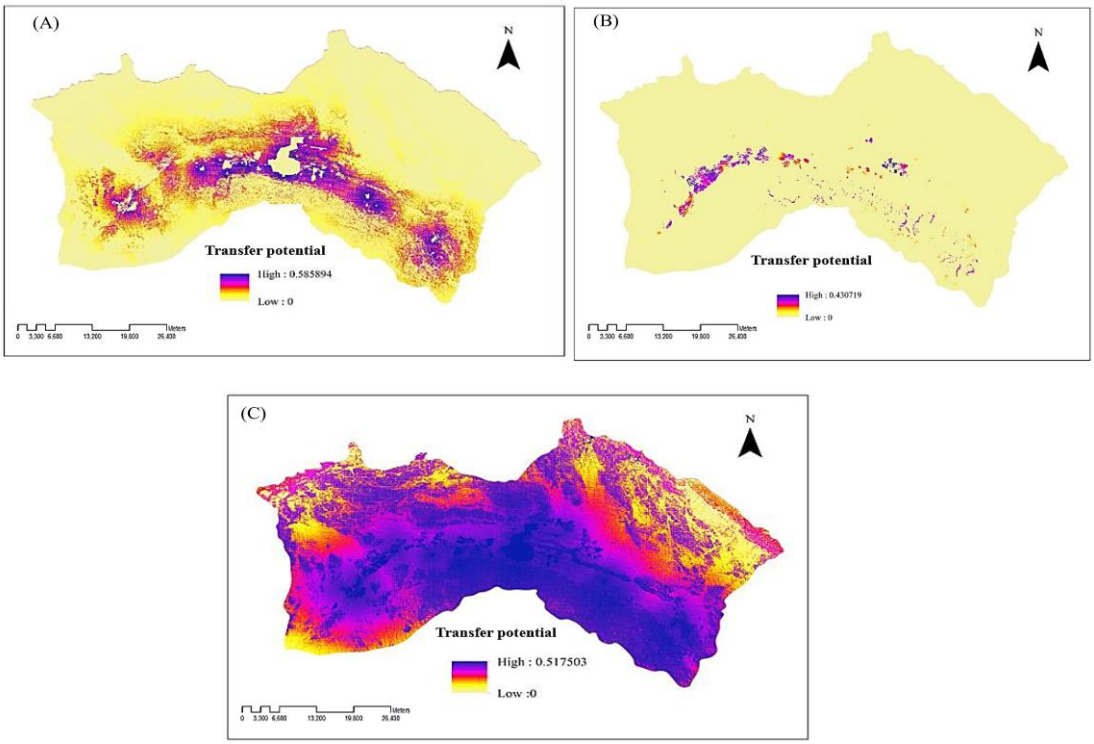


Fig. 10. (A) Transition potential map of barren to agricultural land use, (B) transition potential map of agricultural to barren land use, and (C) transition potential map of barren to residential land use.

3.6. Validation of transition potential modeling

The accuracy of the transition potential modeling was evaluated using three performance indicators: training error, testing error, and validation accuracy. These metrics were used to assess how effectively the Artificial Neural Network (ANN) predicted land-use transitions. Lower training and testing errors indicated better model calibration and higher predictive reliability.

3.7. Prediction of land-use/land-cover changes

Using the hard prediction model, the land-use prediction maps for the years 2020 and 2040 were generated. Comparison of the simulated maps with the actual reference data demonstrated that the predictions accurately represented the observed land-use change trends. The 2040 prediction model revealed that residential areas are expected to continue expanding, while agricultural lands are projected to decrease further, indicating ongoing urban growth and agricultural land degradation within the Birjand watershed.

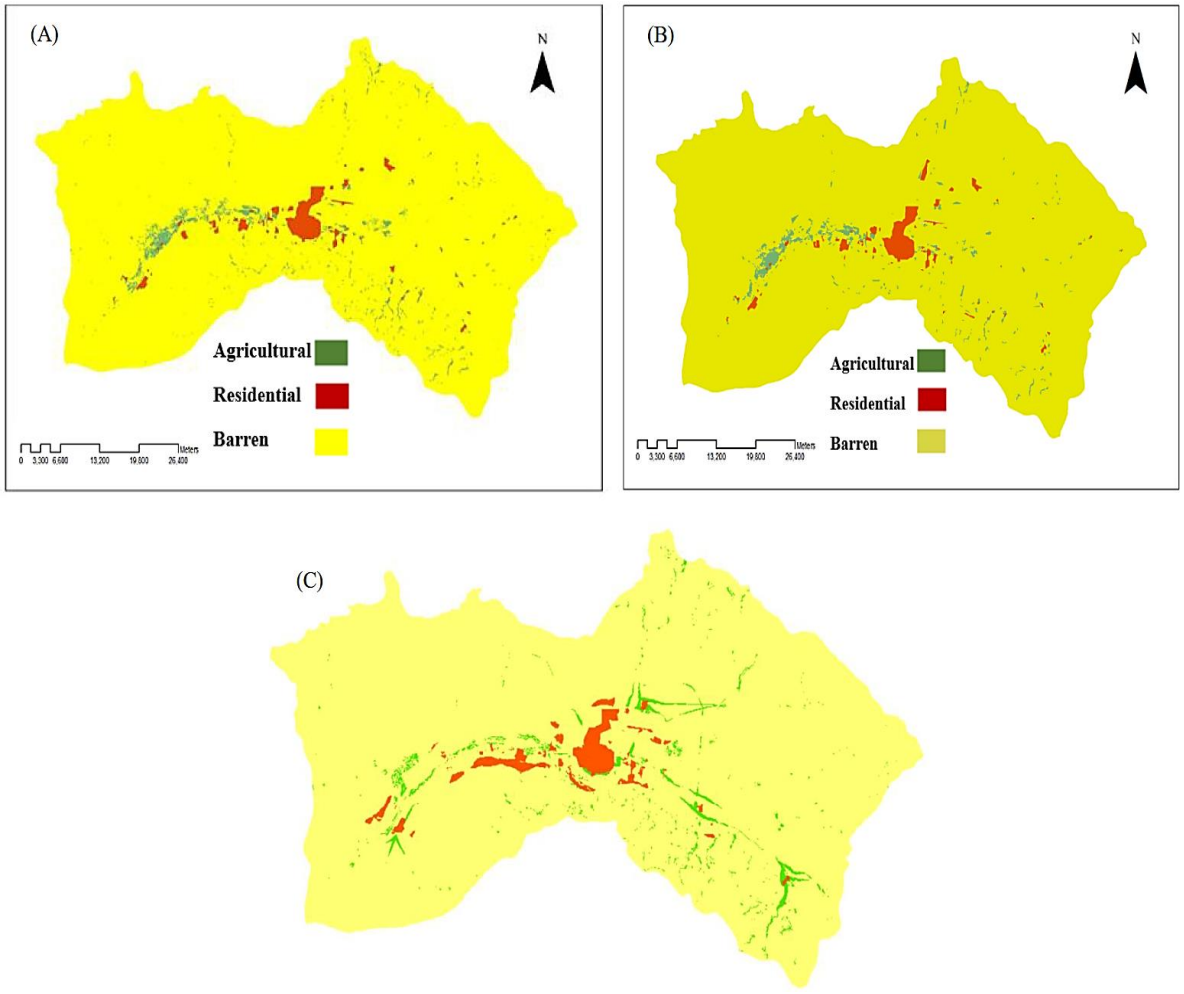


Fig. 11. (A) Reference land-use/land-cover map for 2020, (B) predicted land-use/land-cover map for 2020, and (C) predicted land-use/land-cover map of the Birjand watershed for 2040.

The study revealed significant LULC changes in the Birjand watershed during 2000–2010, including expansion of residential areas and declines in agricultural and barren lands. The ANN–Markov model effectively captured these transitions and provided accurate predictions for 2020 and 2040 (Fig. 11). However, the model has limitations, as it relies mainly on biophysical and proximity variables, excluding socio-economic, demographic, or climate drivers, and assumes past trends continue into the future. Future research could integrate these additional drivers, explore advanced machine-learning architectures, and perform scenario-based analyses to improve predictive performance and support sustainable land management in arid and semi-arid regions.

4. Conclusion

Proper management of natural resources in different regions is essential to minimize the environmental damage caused by land-use changes. Long-term prediction of such changes is a prerequisite for achieving sustainable management and mitigating environmental degradation by allowing decision-makers to plan based on potential future scenarios. In this study, the Land Change Modeler (LCM) was used to model land-use and land-cover changes in the Birjand watershed. The strength of the Artificial Neural Network (ANN) lies in its ability to model nonlinear relationships and handle complex datasets (Weng and Hu, 2009). Essentially, the ANN represents an empirical model that defines the relationship between the dependent variable (extent of land-cover change) and the independent variables (driving factors) (Weng and Hu, 2009). The explanatory variables used in this study included digital elevation model (DEM), distance from roads, distance from faults, distance from residential areas, distance from rivers, distance from agricultural lands, slope, and soil texture. These variables have also been applied in previous research (Schulz et al., 2010; Gholamalifard et al., 2014), demonstrating their significance in land-use change modeling. Neghaban et al. (2019) evaluated urban physical development and expansion into geomorphologically restricted areas using the LCM model and concluded that residential areas in prohibited zones have increased. Heidarizadeh and Behbahani (2019) assessed the performance of the LCM and GEOMOD models for simulating land-use changes and found Kappa coefficients of 0.82 and 0.70, respectively, identifying LCM as the more accurate model. Shakeri et al. (2019) used the LCM to analyze land-use changes in the Anzali Wetland Basin and projected changes up to 2045, showing that the most significant transformation was the conversion of forest lands to agricultural use, while urban land use continued to increase. Mohammad-Yari et al. (2019) modeled land-use changes in Behbahan County and reported an ROC value greater than 0.94 for all sub-models, with rangeland degradation being the dominant change and agricultural expansion being the most significant. Niakan Lahiji et al. (2018) examined land-use changes in Lahijan County between 1984 and 2016 and found considerable forest loss, indicating a continuing trend of deforestation. Perma et al. (2017) analyzed land-cover change modeling in the Gilan-e-Gharb forests of Kermanshah Province using the ANN-based transition potential approach, reporting a validation accuracy of 83.09% and a Kappa coefficient of 0.79. Taheri et al. (2014) applied the ANN and Markov chain models to simulate land-use changes in Tabriz County for 2016 and 2021, showing that between 1988 and 2011, urban and residential areas expanded mainly at the expense of rangelands, agricultural lands, and barren areas, with predicted urban growth reaching 1,037 ha by 2016 and 2,033 ha by 2021. The results indicate substantial LULC changes in the Birjand watershed between 2000 and 2010, with the most significant alterations in residential, barren, and agricultural lands. Predictions for 2040 suggest continued expansion of urban and barren areas, with projected areas of 7,382.25 ha (agriculture), 6,880.5 ha (urban), and 328,239.25 ha (barren). The high overall Kappa coefficient (0.82) confirms the reliability of the ANN–LCM model. For land-use planning and management, these findings highlight the need to prioritize sustainable urban expansion, protect agricultural lands, and implement restoration strategies for degraded barren areas. Future studies could enhance model precision by using higher-resolution imagery, additional calibration periods, and exploring the weighting of driving variables, as well as comparing alternative prediction models and classification methods to support robust LULC forecasting.=

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