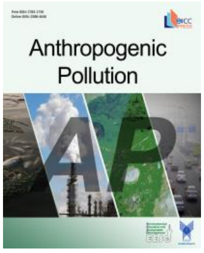

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Research Article

Assessment and Modeling of Land Use/Land Cover Change Dynamics in Anzali International Wetland, Iran

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Abstract

Natural and human activities in wetland ecosystems result in ongoing land use and cover alterations. Moreover, the quick population growth in these areas intensifies land use changes and the transformation of natural cover, leading to the conversion of wetlands for residential purposes and subsequent infrastructure development. This study used satellite data to investigate and model land use changes in the area surrounding Anzali international wetland from 2000 to 2023; it also employed the Markov chain model, logistic regression, and artificial neural networks to predict potential land use changes by 2050. To determine changes in land use area within the studied ecosystem, land use maps of Anzali International wetland were extracted from Landsat satellite data related to 2000, 2013, and 2023. Then the Support Vector Machine (SVM) classification algorithm was used to identify six classes of land use: agricultural lands, grasslands, forests, reedbeds, built-up lands, and water bodies. The accuracy of land use maps derived from satellite images was assessed using two metrics: overall accuracy and kappa coefficient, yielding values of 89.56% and 0.84 for 2000, 93.83% and 0.91 for 2013, and 98.14% and 0.97 for 2023. They were also validated based on the 30% hold-out sample (91 points) obtained through random stratified sampling. The analysis of the change detection matrix indicated that the most significant alterations in land use from 2000 to 2023 involved the conversion of water bodies to other land uses (which accounted for a net loss of 3,170 hectares, representing a 33.4% reduction compared to the water body area in 2000). In contrast, the area of changes in other land uses showed an increase during this period. Projections for 2050 suggest that current trends will persist and intensify, leading to a further drastic reduction in the area of this body of water to approximately 898 hectares (only 12.7% of its 2000 extent), ultimately reaching its lowest level. Other land uses, particularly reedbeds, are anticipated to increase significantly and expand to cover about 38.1% of the study area by 2050, becoming the predominant land use in the region, while agricultural lands will continue to occupy a substantial part of the area.

Keywords: Markov chain models; Logistic regression; Neural networks; Land Change Modeler (LCM); Anzali international wetland

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1. Introduction

Effective management of natural and man-made ecosystems, along with long-term planning, necessitates the prediction of land use changes through modeling techniques. The assessment of land cover changes is crucial for comprehending environmental processes at both regional and global levels. This topic has garnered great attention among researchers in environmental sciences, earth sciences, ecology, and related disciplines (Vella et al., 2025; Liu et al., 2023; Reddy et al., 2017; Jain et al., 2017; Tiwari et al., 2019; Mas et al., 2014; Mishra et al., 2014; Mas et al., 2014; Alaei et al., 2024; Mohammadi, et al. 2023). Land use changes result from a complex interplay of physical, biological, economic, and social factors. These factors significantly influence erosion processes, enhance surface runoff, and alter regional biodiversity. Land use changes, shaped by physical, climatic, economic, and social factors, significantly affect both the temporal and spatial status of local communities in coastal areas. Rapid population growth, urban development, and tourism activities are expected to substantially alter the current land use and cover of these regions in the future (Yuan et al., 2005; Joshi et al., 2011; Rawat et al., 2013; Kaliraj et al., 2017).

The analysis of land use change patterns relies on identifying the parameters that influence these changes and then modeling the changes for medium-term and long-term decision-making and planning. Consequently, it is increasingly essential to establish regulations and relationships that facilitate the transformation of land uses and accurately forecast future development processes. Nevertheless, the identification and modeling of land use and land cover changes have always faced serious challenges. Some of these challenges include the absence of precise, current, comprehensive, and systematic data on land surface, the intricacy of detecting changes, and the time-consuming and expensive nature of conventional methods. Recent advancements in remote sensing systems have made it easier to provide regular images with acceptable spatial resolution across various spectral bands, rendering these systems effective tools for monitoring land surface changes (Farshidi et al., 2022). Remote sensing technology plays a crucial role in environmental and natural resource research by offering timely information, consistent coverage, and cost efficiency. Specifically, medium-resolution images, such as Landsat images, are notable for their availability over extensive areas, continuous access, cost-free nature, and up-to-date information (Yousefi et al., 2018).

There are numerous models for predicting and modeling changes in land use and land cover, the most important of which include Cellular, Land Change Modeler (LCM), GEOMOD, STCHOICE, and CA Markov Automata. Simulation maps generated from these models help researchers understand, detect, and predict trends in changes and potential environmental issues. However, a major challenge in this field is the validation of model outputs. The rate of change in the study area, along with the patterns of land use and cover changes, influences the precision of the simulation outcomes derived from a model (Mas et al., 2014). Conversely, varying the parameters and criteria used as inputs will yield different outputs from the model. The appropriate selection of parameters in the modeling and change prediction process significantly influences the accuracy and validity of the results, often more so than the choice of model itself. Therefore, it may be somewhat misleading to discuss the superior accuracy of one model over others (Pontius and Malanson, 2005).

It is difficult to compare the current models of land use and cover change because each model presents various options to the user at each phase of execution, and the user's selections may influence the validity of the outcomes (Mas et al., 2014). Therefore, comparing the accuracy of the existing methods proves challenging. LCM is one of the most commonly used models for modeling land use changes (Areendran et al., 2017; Onate-Valdivieso and Sendra, 2010).

Many studies have modeled land use changes, some of which will be reviewed here. In a study entitled "Evaluation and Prediction of Land Use Changes Using the CA_Markov Model," Karimzadeh Motlagh et al. (2022) modeled and predicted the temporal and spatial patterns of land use change in the drainage basin of Zayandeh Rud by using the cellular automata and Markov chain models. They analyzed land use changes from 1996 to 2018, simulated projections for 2030 and 2050, and proposed some scenarios for future land use changes. Dehghani et al. (2023) conducted a study entitled "Evaluation of land use changes using multispectral satellite images and artificial neural networks." They employed multispectral satellite images and artificial neural networks to evaluate land use changes in Aligudarz, Iran, over 9 years from 2013 to 2021 using Landsat 8 satellite images of the OLI sensor. Tajadod et al. (2024) conducted a study entitled "Optimization of Sentinel 1 and 2 data classification methods by combining spectral indices (Case study: Anzali wetland)." Their results showed that the integration of Sentinel 1 and 2 data yielded superior outcomes compared to the combination of Sentinel 2 data with spectral indices. Specifically, the kappa coefficients were 0.91, 0.84, 0.79, and 0.97, while the overall accuracies were 92.99%, 87.43%, 83.80%, and 97.90% for the four study periods (2016, 2017, January 2022, and July 2022, respectively). These figures significantly surpass those obtained from the combination of Sentinel 2 data with spectral indices. In another study

10.57647/AP.2026.1001.07

entitled "Simulation and prediction of landscape pattern of Zhuzhou Wetland using LCM model," Zhan et al. (2021) systematically analyzed land use changes in Zhuzhou Wetland from 2006 to 2016 to protect, utilize, and scientifically manage urban wetland resources. They also employed LCM to simulate and predict the changes by using Landsat series remote sensing images and additional data. Their findings demonstrated that land uses around the urban Zhuzhou Wetland will be continuously changing until 2021. Kimario et al. (2024) conducted a study entitled "Assessment of Future Wetland Degradation in the Drainage Basin of the Vamirov River from 2020 to 2050 Using Remote Sensing Images and CA-Markov Chain Model." They introduced an integrated approach that combines GIS, remote sensing, CA-Markov chain modeling, neural networks, and logistic regression to evaluate the effects of land use/land cover dynamics on wetland degradation based on land use/cover maps from 2000, 2013, and 2023. Masalvad et al. (2025) carried out a study entitled "Prediction of Land Use Changes and Ecosystem Service Impacts Using CA-Markov Techniques and Machine Learning." Their results revealed a responsive correlation between ecosystem service valuation (ESV) and land-use and land-cover change (LULCC), whereby alterations in land use immediately influence the availability and quality of ecosystem services Esavi and Rezaei (2014) used Landsat data to evaluate the spatial and temporal land use changes in Suldus Wetland in order to understand the effects of drought on this ecosystem from 1989 to 2013. Their findings demonstrated a significant decrease in the wetland area in 2000, which marked the severest drought in the studied period. They also reported that the discharge of chemical fertilizers caused eutrophication and finally led to the overgrowth of aquatic plants in this wetland. In a similar study, Maleki et al. (2018) used the OLI (Landsat 8) data to investigate changes in land cover and water body in Hamoon Wetland in a period of one year. The results showed that OLI, with an 18-day rotation, can adequately monitor changes in water resources.

Many studies have investigated the watershed of Anzali Wetland (Attarchi, et al. 2021; Aghsaei, et al., 2020; Badamfirooz et al., 2019; Mousazadeh, et al., 2015; and Shakerir, et al., 2019).

However, this study presents a distinctive approach by integrating three modeling techniques—Artificial Neural Networks (ANN), Logistic Regression (LR), and the CA-Markov chain—within a single framework to project land use/cover changes in Anzali Wetland. While previous studies have mainly focused on individual models or shorter time spans, this study covers a 23-year period (2000-2023) and provides a comparative assessment of these models' performance for long-term forecasting until 2050. This integrated and comparative methodology aims to offer a more robust understanding of change dynamics and to identify the most reliable predictive tool for this critically endangered ecosystem, thereby informing more effective conservation and urban planning strategies. This study aims to emphasize the necessity of urban planning strategies that prioritize ecosystem preservation and promote sustainable urban growth.

2. Materials and methods

2.1. Study area

Anzali International Wetland is located in the southwest of the Caspian Sea at 37.4689° N, 49.3537° E, covering an area of 193 km2. The area of this water ecosystem ranges from 150 to 200 km2, influenced by climatic conditions and water level in the Caspian Sea (Ahmadzadeh et al., 2023). Anzali international wetland is among the 27th international wetlands in Iran recognized by the Ramsar Convention Bureau since 1975, alongside 18 other wetlands, (Fig. 1).

Anzali international wetland borders the Caspian Sea to the north, Soumehsara to the south, Pirbazar to the east, and Kapourchal and Abkenar to the west. Because of different geographical characteristics, climate conditions, and biodiversity levels, Anzali weland is divided into four regions: eastern, central, western, and southwestern (Siahkesheem). The central region of Anzali wetland comprises a large body of water, encompassing the Selke and Sorkhankpl wildlife refuges, as well as the wetland's outlet to the sea. The eastern region of Anzali weland is predominantly covered with decomposing aquatic vegetation and represents one of the most polluted and shallow regions of this ecosystem. The Chukam Wildlife Refuge is situated in this region of the wetland. The deepest part of Anzali international wetland is found in the western region, which comprises a large body of water (Javdankherad et al., 2011). The recent reduction in water depth has diminished the connection between Siahkesheem and other regions of the wetland. Field observations indicate that this reduction, along with the decline in water levels, has enabled residents on the periphery of the wetland to encroach upon various sections of Siahkesheem, thereby diminishing the width of the wetland in this area (Modaberi and Shokohi, 2019). Anzali wetland is one of the most important wetlands in Iran, located on the southern coast of the Caspian Sea and in proximity to the cities of Anzali and Rasht. It is divided into four areas: aquatic, vegetal, marshland, and coastal. The wetland receives inflow from multiple rivers, notably the Sefid-rud River, and exhibits significant biodiversity, encompassing various plant and animal species, including migratory birds and fish. Nevertheless, Anzali international wetland faces serious threats such as water pollution, habitat destruction, and climate change, which necessitate effective protection and management measures.

3. Methodology

3.1. Data

The land use maps of the Anzali Wetland watershed were derived from Landsat satellite images from 2000, 2013, and 2023, utilizing TM, ETM+, and OLI sensors, respectively, to quantify changes in the study area. Landsat 8 satellite reference images were utilized to develop the land use map for 2023. Table 1 presents the specifications of the images used for developing the land use maps. The data obtained were at Level 1, which lacked radiometric correction. However, systematic geometric correction was implemented using ground control points, and adjustments for displacement errors due to the area's topography were applied. Data were assessed for radiometric errors through the display of individual bands and various color combinations. The geometric integrity of the images was also verified by integrating vector layers of roads and waterways derived from topographic maps, along with control points obtained from images (Google Earth) and ground sampling locations. This study employed the Quick Atmospheric Correction (QUAC) within the ENVI environment to perform atmospheric correction on existing data and remove anomalies that could lead to classification errors. Unlike physics-based methods whose accuracy is directly dependent on sensor calibration and measurement geometry, QUAC performance remains relatively stable despite increases in sensor and measurement uncertainties. Moreover, in contrast to physics-based methods that necessitate specific bands for the correction of water absorption and airborne particle scattering, QUAC applies to any set of visible-near-infrared (VNIR-SWIR) wavelengths (Perkins et al., 2012). The QUAC method was selected for its computational efficiency and acceptable accuracy for land cover classification purposes, as it does not require complex atmospheric parameters that are often unavailable for historical imagery like the Landsat 5 TM data from 2000.

Fig. 2 shows the different stages of this study, including the preparation of LULC maps based on satellite data (from 2000 to 2023), as well as the triple models for predicting land uses by 2050.

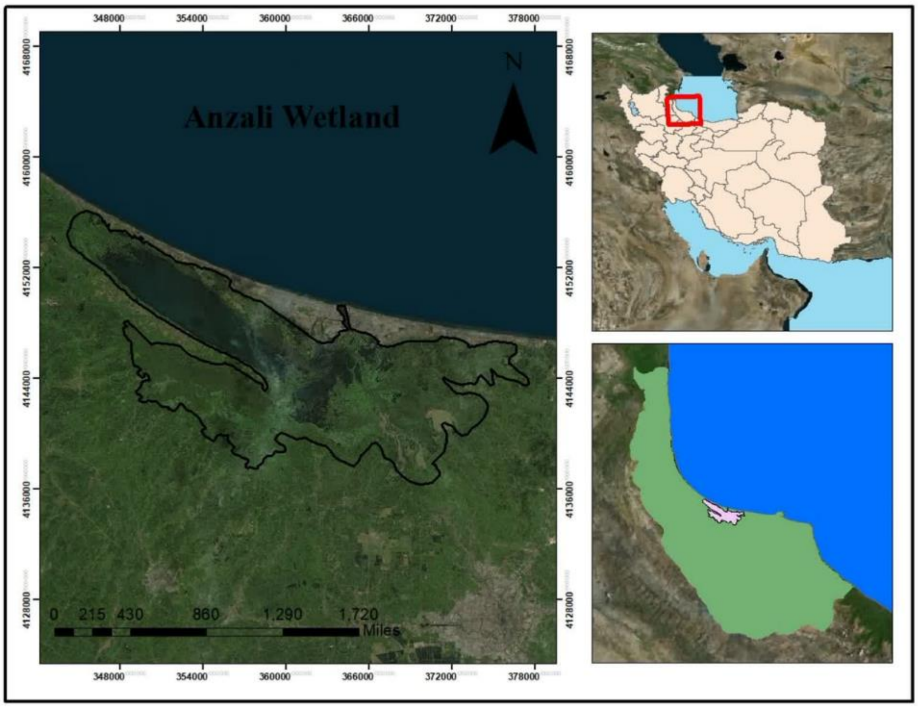

Figure 1. Geographical position of Anzali International wetland, Guilan Province, Iran

Table 1. Specifications of images utilized for developing land use maps in the Anzali international wetland

Satellite	Sensor type	Date of imaging	Path	Right-of-way (ROW)	Spatial resolution	Reference
Landsat 5	TM	06.30.2000	166	34	30 m	USGS
Landsat 8	OLI	05.25.2013	166	34	30 m	USGS
Landsat 8	OLI	08.17.2023	166	34	30 m	USGS

10.57647/AP.2026.1001.07

3.2. Satellite data classification and land use mapping

Satellite images were analyzed and categorized through a supervised classification method to provide evidence of LULCC. This study employed the support vector machine (SVM) algorithm to classify satellite images. A total of 303 ground truth points were collected through a combination of field surveys (for 2023) and interpretation of high-resolution Google Earth imagery (for historical years). These points were randomly divided, with 70% (approximately 212 points) used for training the classifier and 30% (approximately 91 points) reserved for validation of the final land use maps. The algorithm's output was then utilized for modeling in subsequent stages. This study employed three land use prediction models to forecast land use in the regions adjacent to Anzali International Wetland. The neural network and logistic regression models were executed in the open-source QGIS utilizing the MOLUSCE module, while the CA-Markov chain model was performed in IDRISI. For the ANN and LR models in MOLUSCE, a set of spatial driving variables was used to train the change prediction. These variables included distance from roads, distance from settlements (built-up areas), distance from the wetland core (water body), slope, and elevation. The accuracy of land use maps derived from satellite images was assessed using two metrics: overall accuracy and kappa coefficient, yielding values of 89.56% and 0.84 for 2000, 93.83% and 0.91 for 2013, and 98.14% and 0.97 for 2023. In all three methods, the validation and verification of the model involved entering data from 2000 to 2013 into the models. A prediction was subsequently generated for 2023, which was then compared with the actual data and the classification map for 2023. The subsequent step was generating a prediction for 2050 for each of the models.

CA-Markov model: CA-Markov is a combined LULC prediction model that integrates a Cellular Automata (CA) and a Markov Chain. This model utilizes autonomous cells to identify and represent the dynamics of complex systems through simple rules, thereby enabling spatial modeling of the system's future. CA-Markov models are recognized as effective instruments for LULCC prediction. These models utilize transition probability matrices to forecast land use changes from the past to the future. In this model, the Markov chain by itself is insufficient for modeling the spatial distribution of LULCC. Therefore, the integration of a Markov chain with cellular automata effectively considers the spatial and geographical structure of these changes. The outcomes of this procedure facilitate the simulation of LULCC maps for subsequent years (Douandji et al., 2025).

Logistic regression (LR): The Weight of Evidence (WoE) is a bivariate statistical technique developed by Bonham-Carter and Agterberg (1990). This method evaluates the likelihood of an event occurring by examining the ratio of presence to absence of each category of predisposing factors. In this method, each class is allocated either W+ or W−. The weight W+ indicates the positive influence of predisposing factors on a potential natural hazard, whereas the weight W− denotes their negative influence. The weights are derived from specific formulas that enhance the accuracy and transparency of event probability analysis (Bonham-Carter and Agterberg 1990).

Artificial neural network (ANN): The neural network method is widely used to investigate land use and cover (Hashemi, 2016). This method preprocesses data from land use categories, including agricultural lands, grasslands, forests, reedbeds, built-up lands, and water bodies, through dummy coding into independent variables represented as 0 and 1 (Zeshan et al., 2021).

3.3. LULCC modeling

This study employed LR and ANN to model and predict LULC in 2025. To this end, an LCM model was developed by creating a probability matrix and identifying areas of change through the Markov chain model. It involved developing sub-models for various land use transitions based on significant regional changes and utilizing descriptive variables via the MLP method. Additionally, it included the creation of change probability maps and forecasting future land use alterations. This stage involved analyzing changes in various land use classes in the area surrounding Anzali Wetland for the periods 2000-2013 and 2013-2023, as well as forecasting land use changes for 2050.

4. Results

The accuracy of the final land use maps derived from satellite images was assessed using two metrics: overall accuracy and kappa coefficient, yielding values of 89.56% and 0.84 for 2000, 93.83% and 0.91 for 2013, and 98.14% and 0.97 for 2023. They were also validated based on the 30% hold-out sample (91 points) obtained through random stratified sampling.

The greatest land use change from 2000 to 2013 was a 57.6% reduction in water bodies, which were transformed into other land uses. However, other land uses exhibited an increase in this period as follows: reedbeds by 4.6%, built-up lands by 51.1%, agricultural lands by 51.6%, grasslands by 0.62%, and forests by 64.2%. The results also indicated that the area of forests increased from 992 to 1,246 hectares (39.5%), grasslands from 580 to 612 hectares (0.62%), reedbeds from 5040 to 6020 hectares (4.6%), agricultural lands from 6622 to 8,010 hectares (51.6%), and built-up lands from 1,180 to 1,253 hectares (51.1%) during this period. Conversely, water bodies decreased from 9,490 to 8,617 hectares (57.6%).

The greatest reduction in land use from 2013 to 2023 was a 13.9% reduction in water bodies, which were transformed into other land uses such as reedbeds, grasslands, built-up lands, forests, and agricultural lands. By contrast, other land uses showed an increase in this period as follows: reedbeds by 1.63%, grasslands by 0.23%, built-up lands by 0.61%, forests by about 0.39%, and agricultural lands by 1.96%. Moreover, the wetland's water body diminished from 8,617 to 6,320 hectares, representing a reduction of 3.6% over this period.

This study employed the CA-Markov model in QGIS, LR, and ANN to model and predict LULCC in 2050. In addition, land use maps from 2000 and 2013 were used to forecast the land use map for 2023, which was subsequently utilized to develop the 2050 land use map (Fig. 3). This figure below presents change trends in the five land uses of Anzali Lagoon from 2000 to 2050.

A matrix of change probability and a matrix of potential change areas (Table 4) were developed to facilitate the prediction process. Finally, a prediction map for 2023 was developed based on the established sub-models and maps of change probability transfer.

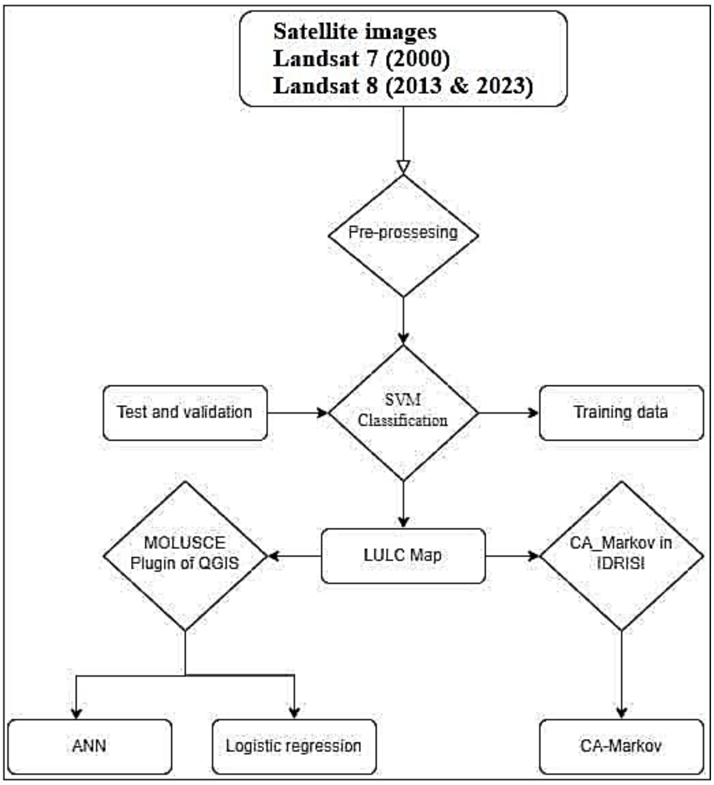

Figure 2. A schematic view of the research process

Table 2. Area and percentage of different land use classes in the studied period

Land Use Category	2000	%	2013	%	2023	%	2050	%
Reed Bed	5,040	19.7	6,020	26.1	6,925	27.73	9,125	38.1
Grassland	580	1.91	612	2.53	690	2.76	1,257	3.41
Agriculture	6,622	24.57	8,010	32.08	8,500	34.04	8,962	36.08
Built-up Area	1,180	4.72	1,253	5.01	1,630	5.62	2,848	6.42
Water Body	9,490	38.04	8,617	34.47	6,320	25.34	898	12.67
Forest	992	3.14	1,246	5.39	1,325	5.78	1,462	6.47

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This study employed the CA-Markov model in QGIS, LR, and ANN to model and predict LULCC in 2050. In addition, land use maps from 2000 and 2013 were used to forecast the land use map for 2023. Fig. s 6, 7, and 8 show the predicted maps for 2050. Fig. 6 presents the classification of the study area by CA-Markov model for 2023; moreover, Fig. s 7, 8, and 9 show the predicted maps of land use changes in the study area by 2050 based on ANN, LR, and CA-Markov, respectively.

The results of validating the accuracy of LR and ANN in predicting LULCC for 2023 and 2050 are shown in Tables 3 and 4 and Fig. s 9 and 10.

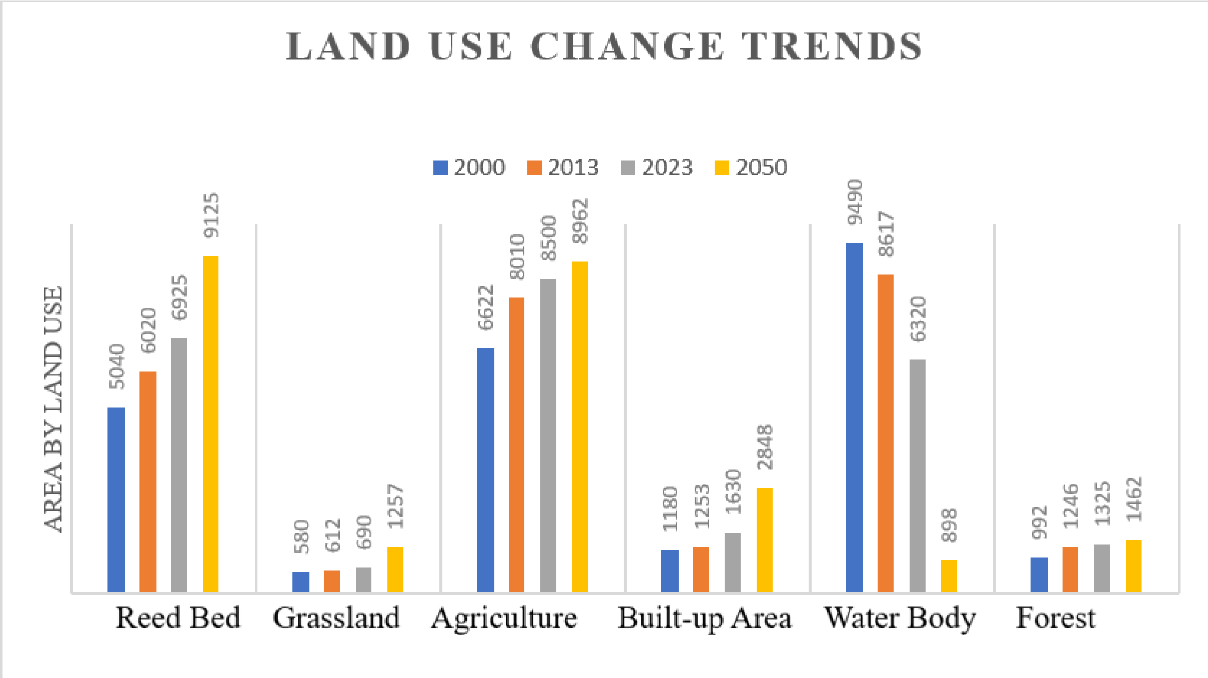

Figure 3. Land use/cover changes (LUCC) (hectares)

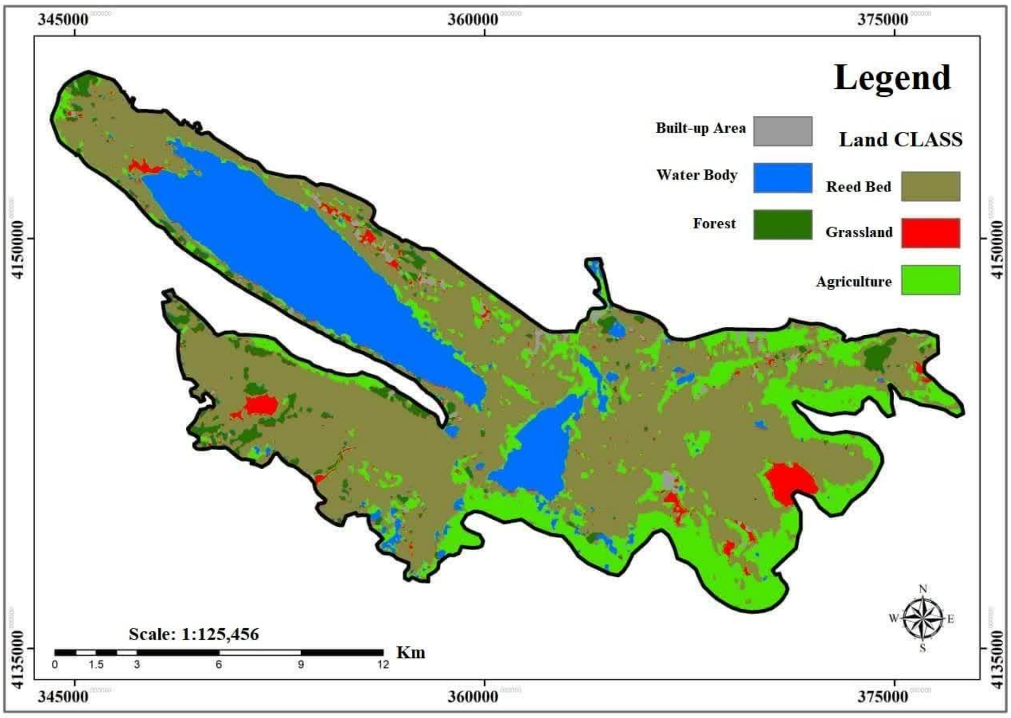

Figure 4. Classification of the study area by ANN (2023)

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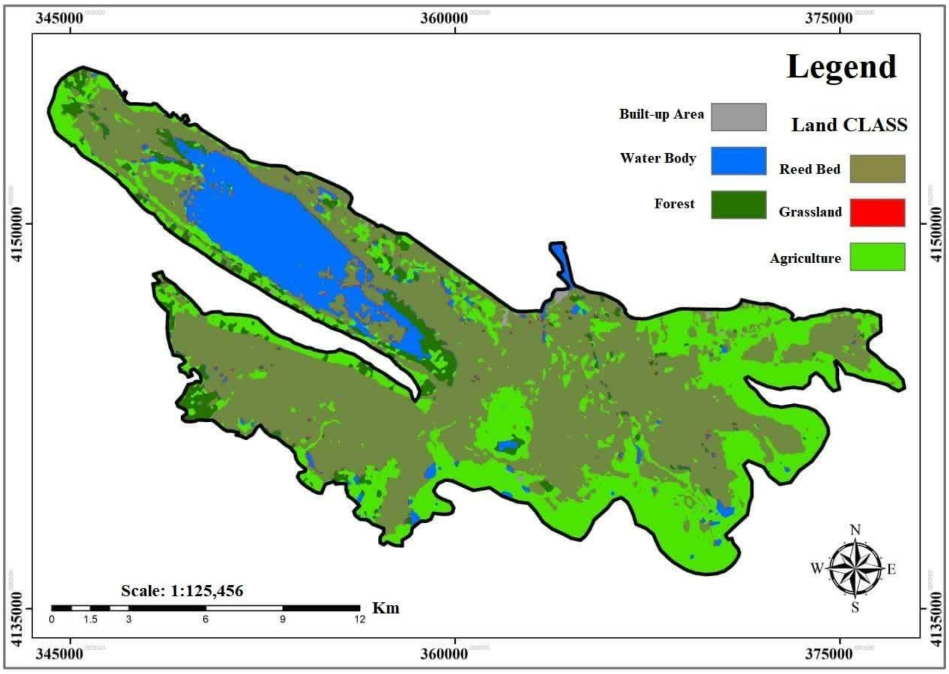

Figure 5. Classification of the study area by LR (2023)

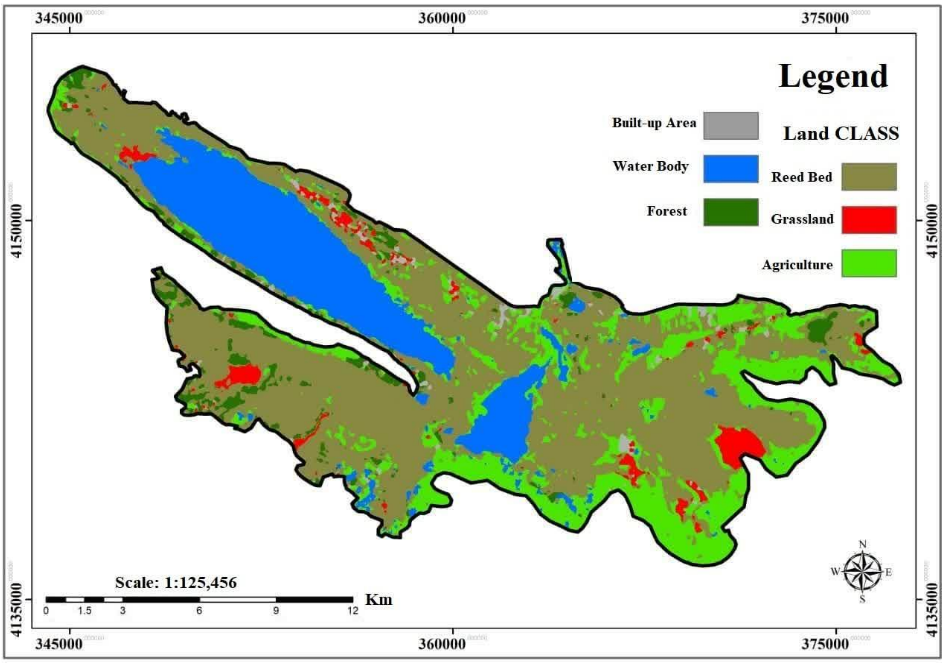

Figure 6. Classification of the study area by CA-Markov model (2023)

Table 3. Verification of LULCC prediction for 2023 by LR, ANN, and CA-Markov in the study area

Land use classes	LR	ANN	CA-Markov
Reedbeds	6610	6520	6675
Grasslands	552	588	618
Agricultural lands	6018	5918	6168
Built-up lands	1848	1633	2062
Water bodies	8598	8378	8612
Forests	1365	1347	1463

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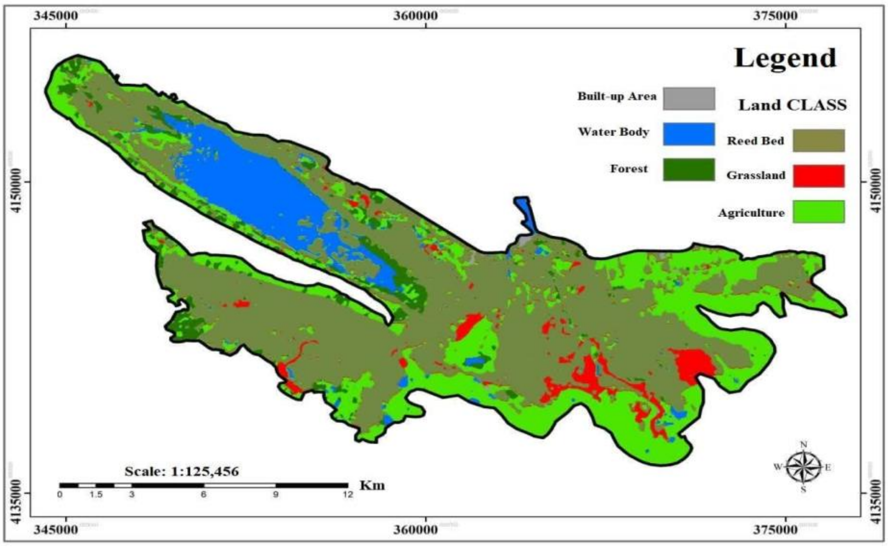

Figure 7. Predicted image of the study area using ANN (2050)

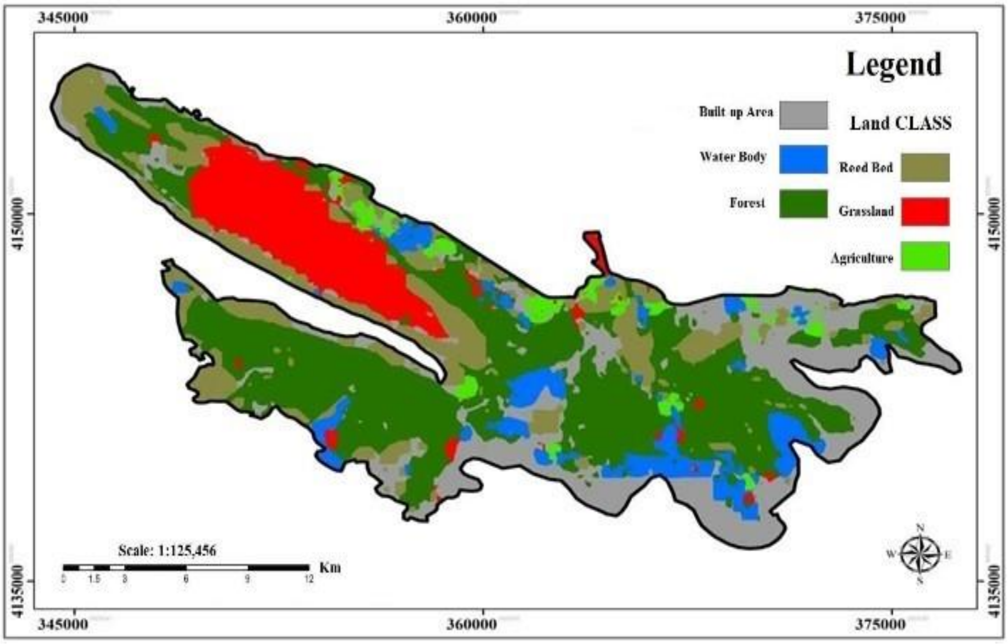

Figure 8. Predicted image of the study area using LR (2050)

Table 4. Verification of LULCC prediction for 2050 by LR, ANN, and CA-Markov in the study area

Land use classes	LR	ANN	CA-Markov
Reedbeds	5460	5493	5518
Grasslands	80	76	494
Agricultural lands	8504	8943	9346
Built-up lands	1216	1224	1238
Water bodies	8713	7860	8782
Forests	1383	947	1416

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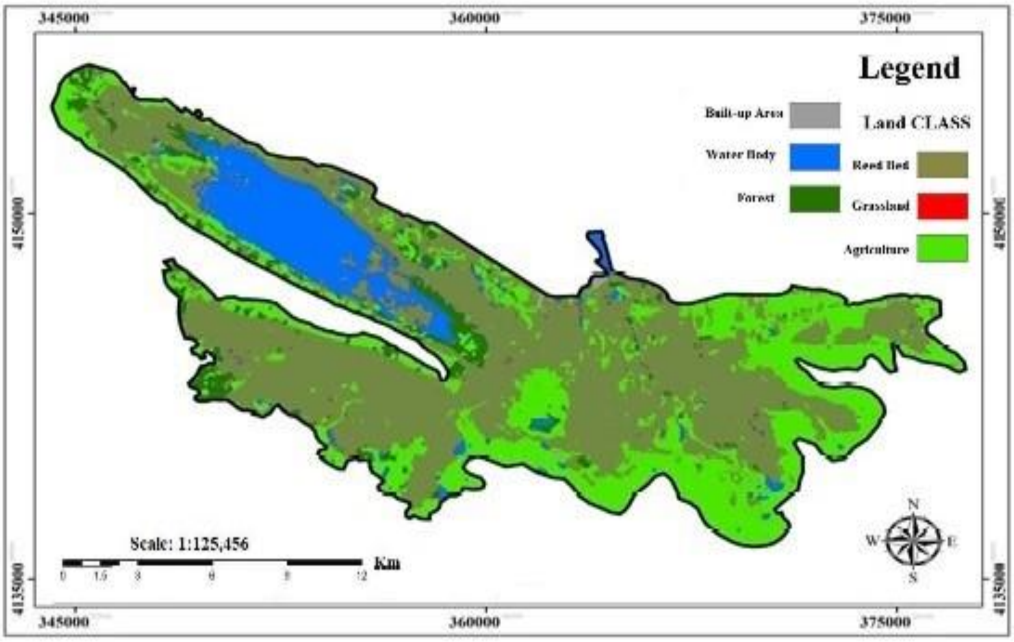

Figure 9. Predicted image of the study area using CA-Markov (2050)

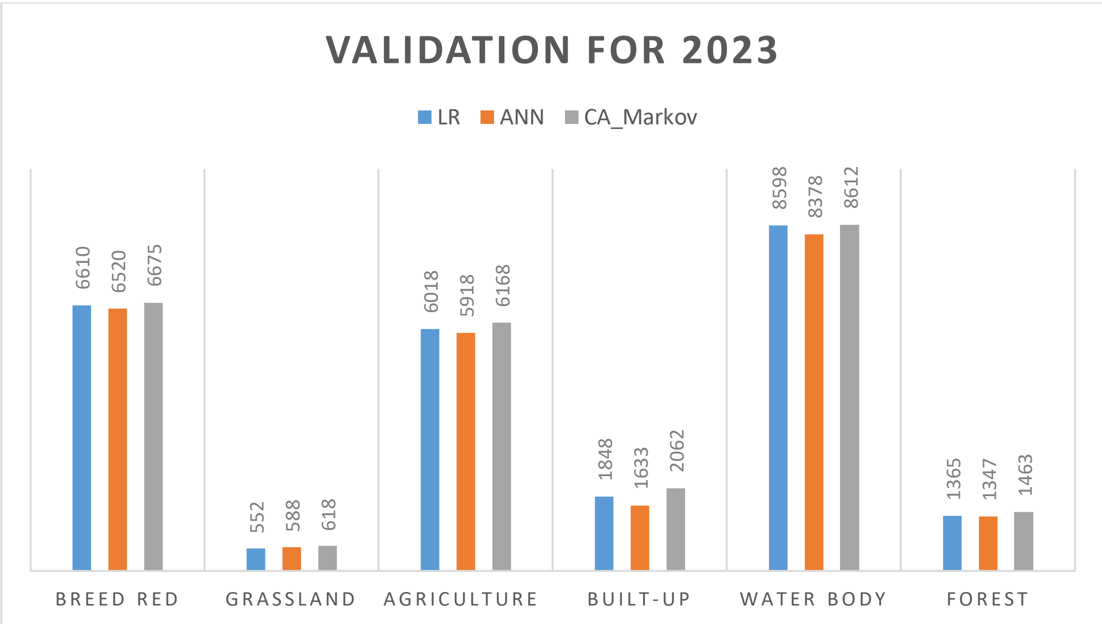

Figure 10. Accuracy of ANN, LR, and CA-Markov in predicting the 2023 LULCC in the study area

5. Discussion and conclusion

Coastal areas experience dynamic changes in land use and cover due to escalating pressures from both natural and human activities, something that is clearly observed in the study area. During the study period, a significant portion of the land surrounding Anzali International Wetland has been converted to agricultural lands and built-up areas, which adversely affects the environment and increases the vulnerability of local ecosystems.

Land use or land cover transition denotes the dynamic transformation and alteration of land characteristics over time, influenced by human or natural activities (Amin and Fazal, 2012). Land features undergo continuous transformation influenced by environmental sustainability and the needs of local communities (Kumar and Jayappa, 2009, 2017). A UNDP report from 2007 indicates that the human population in coastal areas has doubled over the past 40 years, with a similar growth rate anticipated for the next 40 years. Rapid population growth intensifies

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LULCC, facilitating the transition to residential uses and infrastructure development. Coastal areas have undergone significant alterations in recent decades resulting from human activities, which have adversely affected ecosystem services and the natural functioning of ecosystems, leading to concerning impacts and consequences in these regions (Small et al., 2000).

This study utilized satellite images from various time periods to prepare land use maps, allowing for the analysis of land use change trends in the study area from 2000 to 2023 across three distinct periods. The CA-Markov model was employed in QGIS to model land use changes, providing the conversion ratios of various uses and enabling future predictions. Additionally, it facilitated the identification of transitions between different use classes across the study period. The results of modeling LULCC in this study showed that digital satellite images can efficiently assess LULCC trends, serving as a foundation for evaluating environmental changes in various studies. The CA-Markov model is a commonly used method for simulating and forecasting LULV\CC. This approach integrates the spatial dynamics of cellular automata with the temporal analysis of Markov chains (Memarian et al., 2012). CA-Markov models can serve as valuable instruments for future planning because they effectively simulate intricate land use changes across various categories while considering spatial and temporal dynamics. Moreover, these models can predict future changes and identify transition probabilities between various land cover types by analyzing historical land use data under the established spatial norms and relationships (Komaki et al., 2023). Factors such as population growth, GDP, and topographic features can be added to CA-Markov models to elucidate the determinants of land use change and improve prediction accuracy (Zhang et al., 2023). A key limitation of this study was the use of the SVM classifier. Due to the spectral complexity of Anzali Wetland, particularly the confusion between reedbeds and certain agricultural crops, this ecosystem is recommended to be addressed by object-oriented classification or ensemble algorithms like Random Forest, potentially yielding higher classification accuracy.

This study indicated that remote sensing technology, through the provision of multi-temporal images, serves as an effective foundation for monitoring LULCC. The analysis of changes in the water body of Anzali international wetland over the study period revealed a reduction in the wetland's area during the periods 2000-2013, 2013-2023, and 2000-2023. The study findings demonstrated significant changes in land use over the past 23 years (2000 to 2023). There was a notable increase in the area of reedbeds and agricultural lands, with agricultural lands expanding from 6,622 hectares in 2000 to 8,500 hectares in 2023. By contrast, the area of water bodies has diminished in this period. The expansion of reedbeds and agricultural land, coupled with the reduction of grasslands and forests, may yield both beneficial and detrimental impacts on the region's environment and economy. To achieve sustainable management of natural resources, it is essential to thoroughly analyze these changes and implement suitable policies to mitigate negative impacts and enhance positive outcomes. Similar to other coastal regions around the world, population concentration is particularly evident around the Caspian Sea, which increases the demand for land for housing, infrastructure, and other urban uses. Population density growth results in the transformation of natural or agricultural lands into urban areas, causing habitat loss and alterations in land cover (Nouri et al., 2008). According to projections, the current patterns will persist and become more pronounced by 2050. It is anticipated that the area of the "water body" will continue to shrink and eventually reach its lowest point. On the other hand, it is expected that "reedbeds" would grow considerably and take over as the primary land use in the area. The notable expansion of reedbeds, concurrent with the shrinkage of the open water body, is a critical finding. This dynamic is likely driven by eutrophication, the increase of nutrients (nitrogen and phosphorus) from urban and agricultural wastewater entering the wetland. This process promotes the rapid growth of aquatic vegetation like reeds, which gradually encroach upon and replace open water areas, a phenomenon observed in other degraded wetlands worldwide.

It is noteworthy that Phragmites australis plays a major role in the eco-hydrological currents of wetlands because it has predominated the vegetation cover of these ecosystems. The predomination of this species increases evapotranspiration in shallow lakes and wetlands 1 to 7 times compared to water bodies lacking vegetation (Zhang et al., 2021). This plant can grow in a wide range of ecosystems from oligotrophic wetlands to highly contaminated lakes and wetlands (Březinová and Vymazal, 2014). Ahmadzadeh et al. (2023) studied the trophy status of Anzali Lagoon using TSI and reported that this index increased from 59.51 in 1994 to 65.10 in 2018, accompanied by a reduction in the water area of this ecosystem from 5283.9 ha to 4183.92 ha in the same period. TSI value also demonstrated the eutrophic status of Anzali Lagoon.

"Agricultural lands" will also keep growing and still make up a sizable part of the region. Additionally, "built-up lands" and "grasslands" will grow more quickly than they did in the past. It is also anticipated that "forests" will expand nearly continuously. The area of Anzali international wetland is exhibiting a declining trend

10.57647/AP.2026.1001.07

attributed to population growth, heightened water extraction from the wetland's feeding sources, intensified agricultural utilization, and increasing water removal from the drainage basin for urban, agricultural, and industrial purposes. Population growth in the region surrounding Anzali Wetland directly correlates with increased demand for resources and land, potentially leading to further encroachment on wetland areas. National and regional policies, such as those aimed at agricultural expansion, urban development, or conservation, significantly shape these dynamics. For example, the prioritization of development over conservation can exacerbate the conditions in this wetland and accelerate its destruction. Economic factors, including shifts in the agricultural sector, tourism development, or industrial growth, also influence land use decisions. An increase in economic activities that rely on converting natural habitats or a decrease in funding for conservation efforts would accelerate the predicted changes. Therefore, the model's predictions are not merely extrapolations of past trends but are implicitly influenced by the assumption that current policy directions and socio-economic drivers will continue or evolve in predictable ways. Future studies are recommended to explore scenarios based on different policy interventions or economic trajectories to provide a more nuanced understanding of these influences. On the other hand, the large amount of organic matter entering Anzali Wetland through Zarjoob and Gohar Rood can destroy the habitat of birds and fish and waterlogging by agricultural lands (Maghsoudi Shaghaghi, et al., 2025).

The water level of the Caspian Sea has consistently declined over recent decades, resulting in a decrease of over three meters since the beginning of the past solar century. Although the overall trend of the Caspian Sea water level is declining, certain areas experience increases due to climate change, particularly influenced by variations in water flow from rivers such as the Volga. Population growth adversely impacts land resources, leading to the conversion of natural land uses to residential and other forms of man-made development. Therefore, it is necessary to implement projects that effectively evaluate LULCC in order to monitor and manage the natural and environmental resources in these regions. The findings of this study are consistent with those of Rasouli et al. (2012), who examined the effects of the Caspian Sea level decline on coastal areas. Their results indicated that roughly 185 km² of coastal land in Babolsar, Iran, is being lost, underscoring the significant effects of Caspian Sea level fluctuations on land availability and suggesting the necessity for adaptive land management strategies. The substantial land loss directly impacts agricultural and residential zones, highlighting the necessity for policy interventions to mitigate potential displacement and economic disruptions.

The study of LULCC offers pertinent information for the management of coastal resources. Consequently, it is crucial to establish suitable information infrastructures on a national or regional scale for the administration of coastal resources in the face of population pressure. The conditions in the study area indicate a serious alteration in the natural landscape and land utilization. The significant reduction in water resources, coupled with the unregulated growth of agricultural lands, reed beds, and urban areas, poses a critical threat to the environmental sustainability of the region. The predicted decrease in water body area to 898 hectares by 2050, as indicated in Table 2, represents a significant ecological and potentially socio-economic challenge for Anzali Wetland. This projection signifies a loss of approximately 87.3% of the current water body area (compared to the area in 2000), highlighting an alarming trend of wetland degradation. The implications are profound: reduced biodiversity, diminished capacity for flood regulation, impaired water quality, and potential impacts on local livelihood dependent on the wetland's resources (e.g., fishing and tourism). A comparison of this finding with governmental development plans, such as the biogeochemical project or various wetland restoration programs, reveals a critical divergence. While these programs aim to protect and restore wetland ecosystems, the current trajectory of predicted land use change suggests that these restoration efforts without substantial and effective interventions may be insufficient to counteract the pressures driving wetland loss. For instance, the biogeochemical project cannot achieve complete success if it focuses on improving water quality and reducing the load of pollutants but fails to adequately address the physical encroachment and conversion of water bodies to other land uses. Similarly, restoration programs need to be scaled up and effectively implemented, potentially coupled with stricter land-use regulations and enforcement, to counteract the drivers of degradation identified in this study. The study findings strongly suggest that current development and conservation strategies may need re-evaluation and intensification to meet the ambitious goals of national wetland protection, particularly concerning the preservation of vital water bodies within Anzali Wetland.

These alterations may diminish biodiversity in aquatic ecosystems, heighten soil erosion, intensify water scarcity issues, and exacerbate local climate change. If this trend continues in the absence of sustainable water resource management and land use planning, the study area will face serious environmental and economic challenges in the future. The region is transitioning to a heavily human-impacted ecosystem characterized by significant

10.57647/AP.2026.1001.07

limitations on natural water resources. This trend suggests a persistent rise in encroachment and pressure on the lands adjacent to Anzali international wetland in the future. These conditions necessitate active land use planning and management.

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Authors Contribution
All authors have contributed equally to prepare the paper.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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