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Assessment of Land Use Changes in Ahvaz and Their Impact on the Morphological Changes of the Karun River Using Landsat Time-Series Data

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Abstract:

Urban growth and development, especially in metropolitan areas, significantly impact the environment and natural resources. This study examines land use changes in Ahvaz and their effects on the morphological changes of the Karun River using a 20-year time series of Landsat satellite data (2000–2020). For this purpose, satellite images from the TM, ETM+, and OLI sensors were processed, and land use maps were extracted using the Maximum Likelihood Classification (MLC) algorithm. Additionally, riverbed changes were analyzed through hydro morphological indices and spatial analyses in a GIS environment.

The results indicate that over this period, urban areas expanded by 45%, while agricultural lands decreased by 27%. Furthermore, the Karun River’s width has narrowed by up to 15% in certain sections, with significant course shifts observed in central and southern Ahvaz. Change modeling using the CA-Markov model suggests that if the current trend continues, the river’s width may shrink by up to 20%, and urban areas could expand by 60% by 2030.

This study highlights the importance of using remote sensing and Geographic Information Systems (GIS) for effective water resource management and urban planning. It recommends implementing appropriate management strategies to mitigate the negative effects of land use changes.

1. Introduction

Rapid urban expansion, particularly in developing regions such as Ahvaz, presents numerous environmental challenges, including significant transformations in land use, ecosystem degradation, and disruptions to hydrological systems (Seto et al., 2011). The increasing footprint of impervious surfaces due to infrastructural development results in reduced groundwater recharge and elevated surface runoff, contributing to urban flooding and erosion (Arnold & Gibbons, 1996). Furthermore, the fragmentation of natural habitats and reduction in vegetation cover severely impact urban biodiversity and ecological resilience (McKinney, 2002).

The rapid pace of urbanization modifies the natural landscape, leading to soil sealing, disruption of natural drainage systems, and a decline in evapotranspiration. These changes are especially detrimental in semi-arid regions like Khuzestan, where water resources are already under stress (Shrestha et al., 2012). Urban expansion into agricultural and riparian zones also intensifies competition for water resources and encroaches upon floodplains, amplifying the risk of disaster events and hydrological instability.

Moreover, urbanization is closely linked with changes in river morphology, particularly through river straightening, bank encroachment, and construction of infrastructure such as bridges and embankments, which alter sediment dynamics and flow velocity (Walsh et al., 2005). These alterations not only impact the ecological functions of natural water bodies but also exacerbate flood risks, degrade water quality, and increase sedimentation rates (Paul & Meyer, 2001). Long-term consequences may include reduced river conveyance capacity and increased vulnerability of urban populations to hydrometeorological hazards.

The rapid pace of urbanization modifies the natural landscape, leading to loss of vegetation cover, soil sealing, increased surface runoff, and changes in riverine dynamics (Zhou et al., 2014). These alterations not only impact the ecological functions of natural water bodies but also exacerbate flood risks, degrade water quality, and increase sedimentation rates (Paul & Meyer, 2001).

The Karun River, as the longest and most voluminous river in Iran, serves as a critical ecological and economic artery for the region. However, increasing population density and industrialization in Ahvaz have imposed anthropogenic stresses on the river’s morphology. Observations indicate channel narrowing, bank erosion, and disrupted flow regimes in sections adjoining major urban growth (Falahatkar et al., 2018).

To understand and mitigate these impacts, it is essential to monitor spatial-temporal changes using advanced technologies. This study integrates satellite imagery analysis, GIS-based spatial modeling, and hydrological assessment to evaluate the extent and implications of land use changes on the Karun River. By examining the period from 2000 to 2020 and simulating future trends through predictive modeling, the research aims to contribute to sustainable urban development and river conservation strategies in Ahvaz.

2. Materials and Methods

2.1 Methodology

The methodology consists of integrating remote sensing techniques with spatial analysis tools. Landsat imagery (2000–2020) from TM, ETM+, and OLI sensors was pre-processed for radiometric and geometric corrections. MLC was used for land use classification into urban, agriculture, water, and barren lands. River morphology was analysed using spatial metrics in a GIS environment. Finally, CA-Markov modelling was employed for predictive mapping of future land use and river morphology scenarios.

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2.2 Study Area

Ahvaz lies in Khuzestan Province, Iran, at 31°20'N and 48°40'E. Covering an area of over 18,000 hectares, it is a major industrial and population center intersected by the Karun River. The region's hot climate and strategic location make it highly susceptible to both natural and anthropogenic pressures.

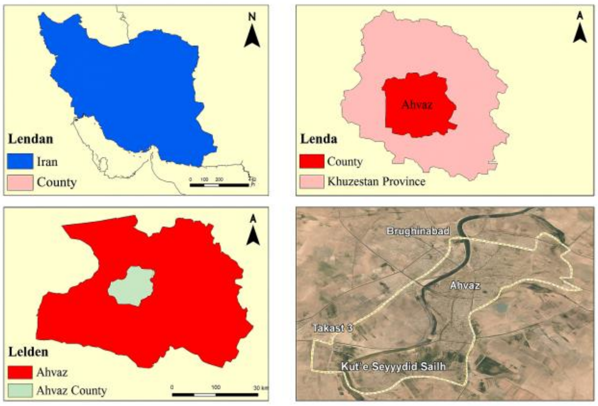

Figure 1. Ahvaz lies in Khuzestan Province

2.3 Data Acquisition and Processing

Landsat images were obtained from USGS Earth Explorer. Preprocessing steps included atmospheric correction using FLAASH, geometric rectification, and mosaicking. Ancillary data such as cadastral maps and land cover surveys aided in validation.

Before utilizing satellite imagery, it is necessary to correct any errors that may have occurred during data acquisition or transmission. When using imagery, particularly when high-accuracy interpretation is desired, it is essential to apply **geometric** and **radiometric corrections**, depending on the objectives of the study (Richards & Jia, 2006). Geometric corrections usually begin with enhancing the image resolution, which depends on factors such as the spectral band, spatial and radiometric resolution, and the physical characteristics of surface features.

In **visual interpretation**, higher-resolution images assist analysts in achieving more accurate results. Moreover, suitable image clarity is important for identifying control points and selecting training samples during classification. To achieve this, **image enhancement techniques** are employed. In this study, the **2% linear stretch method** was used. Preprocessing is generally carried out to prepare the data for classification and varies depending on the data type. Each data type requires specific preprocessing techniques. The main preprocessing steps for classification include:

- **Radiometric correction**
- **Geometric correction**
- **Band reduction**
- **Image calculations**
- **Filtering**

Raw remote sensing images typically contain geometric errors and pixel value inaccuracies. Geometric errors relate to spatial distortion, while radiometric errors concern pixel intensity values. Although some of these errors are corrected at ground receiving stations, the images must still be reviewed by users to identify and correct residual errors. Generally, satellite image corrections are divided into **geometric** and **radiometric** corrections.

2.4 Land Use Classification

The satellite images from 1989, 1994, 2001, 2006, 2011, and 2016 were classified using the Maximum Likelihood Classification (MLC) method, a robust and widely adopted supervised classification technique grounded in statistical probability theory. MLC assigns each pixel to the class it most likely belongs to, based on the mean and covariance of training data drawn from each category. This method is particularly effective for land cover analysis where distinct spectral signatures are observed.

To ensure classification accuracy, training samples were manually selected from the study area through visual interpretation and field data. These samples were chosen with high precision and homogeneity to prevent misclassification caused by mixed pixels. The minimum number of training samples per class followed the standard guideline of at least 10 times the number of bands used.

The land surface was categorized into five distinct land use/land cover (LULC) classes: vegetation cover, urban areas, industrial zones, barren lands, and water bodies. These categories reflect the major land cover types in the Ahvaz region and provide a suitable basis for temporal change detection and spatial modelling.

To enhance class differentiation and feature visibility, False Color Composites (FCCs) were applied. FCC 742 (bands 7–red, 4–green, 2–blue) was used for the years 1989 to 2011, and FCC 753 (bands 7–red, 5–green, 3–blue) was employed for the 2016 image acquired by the OLI sensor. In both composites, vegetation appears in green tones, aiding in its visual identification, while built-up and barren areas are depicted in varying shades of pink and grey.

After training data selection, the separability of classes was assessed using the Jeffries–Matusita (J-M) index, a statistical metric for evaluating spectral distinction between classes. Most classes achieved the maximum separability value of 2.0, indicating minimal spectral overlap and high confidence in the classification results.

To further verify classification performance, confusion matrices and Kappa coefficients were used for each year. The results revealed classification accuracies ranging from 85% to 91%, reflecting the consistency and reliability of the methodology across the multi-temporal dataset.

The land use maps generated through this process enabled the analysis of spatiotemporal trends, showing a clear pattern of urban expansion and agricultural land decline in Ahvaz. These classified images served as inputs for subsequent spatial modelling and river morphological analysis in the study.

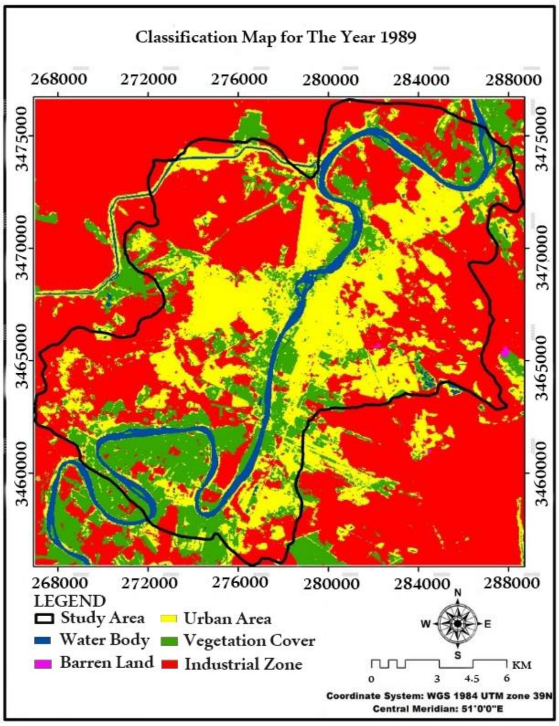

Figure 2. Land Use/Land Cover Classification Map for the Year 1989

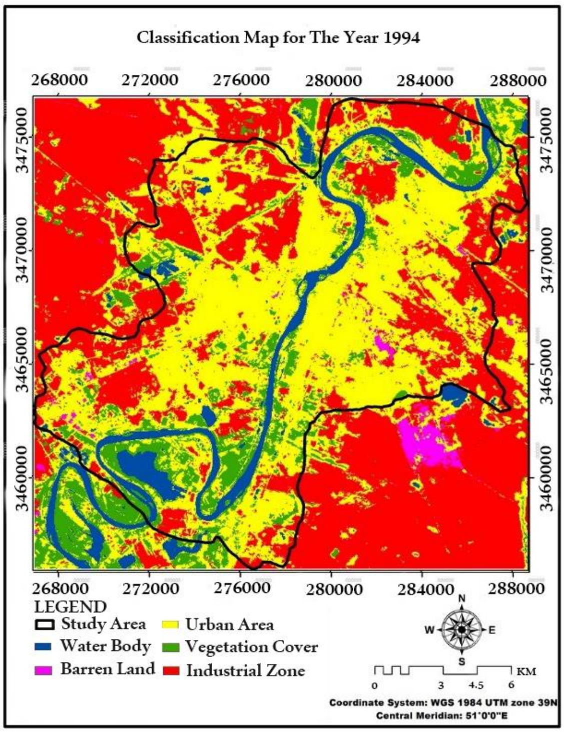

Figure 3. Land Use/Land Cover Classification Map for the Year 1994

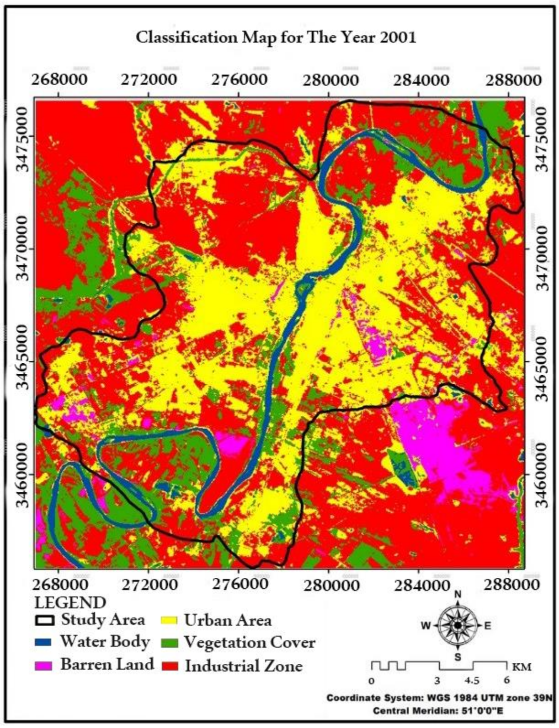

Figure 4. Land Use/Land Cover Classification Map for the Year 2001

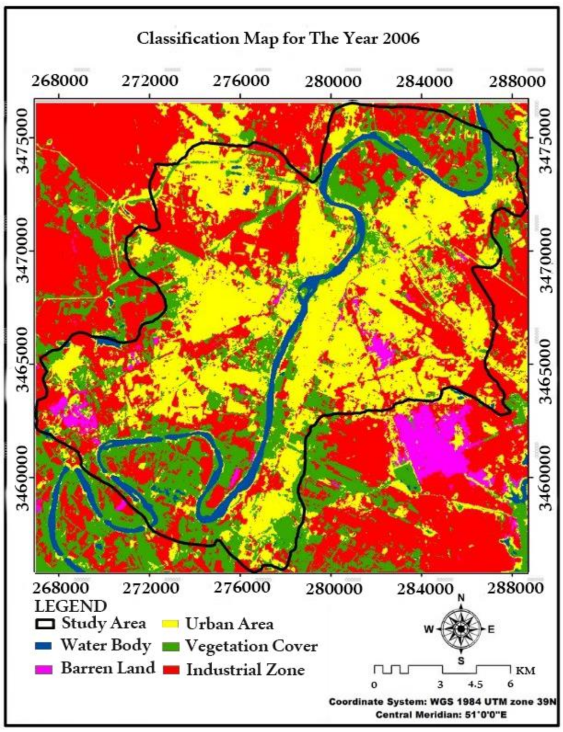

Figure 5. Land Use/Land Cover Classification Map for the Year 2006

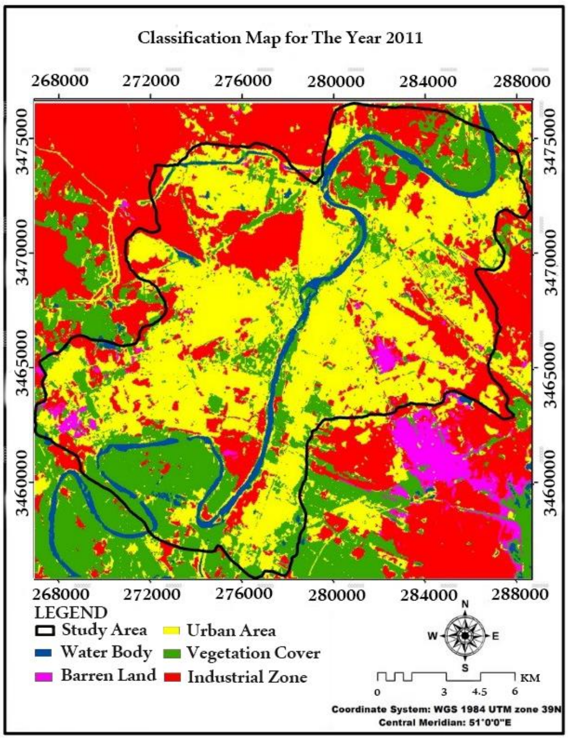

Figure 6. Land Use/Land Cover Classification Map for the Year 2011

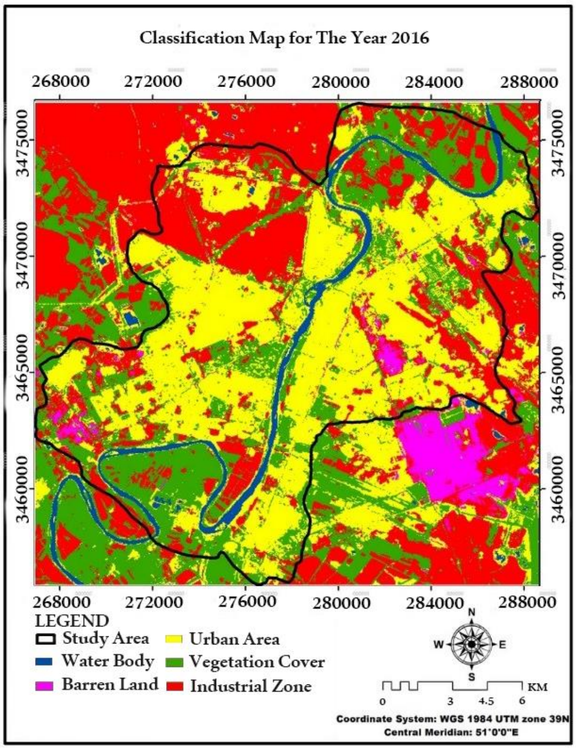

Figure 7. Land Use/Land Cover Classification Map for the Year 2016

Land Use Area

The total land use area of the study region is 45,025.26 hectares. Since changes have occurred in the extent of each land use class during the period from 1989 to 2016, the status of the area for each land use class in different years is presented in Table 1.

Table1. Area of Land Use Classes in Different Years (per hectares)

Land Use Class	1989	1994	2001	2006	2011	2016
Vegetation Cover	7,446.87	4,362.12	6,474.15	10,225.26	11,007	12,146.94
Urban Areas	10,097.64	17,447.49	12,573.09	12,817.80	15,531.31	14,279.40
Industrial Areas	24.03	567.27	1,819.89	1,326.24	1,490.04	1,665.45
Barren Lands	25,685.19	19,841.94	22,590.09	19,006.92	15,712.47	15,610.32
Water Bodies	1,771.83	2,806.74	1,568.34	1,649.34	1,474.74	1,323.45

Validation of Land Use Maps

To validate the generated land use maps, training samples from the classified classes were prepared for each year and then compared with reference land use maps of the corresponding years. For accuracy comparison, an error matrix was first created, and then Kappa coefficient and overall accuracy were calculated. Due to the large volume of the error matrices and their outputs, only the Kappa and overall accuracy values are presented in Table 2. According to the results in Table 4-2, the classification achieved relatively good accuracy, with an average Kappa accuracy of 86% and an average overall accuracy of 91% across all generated land use maps.

Table 2. Validation of Land Use Classification Maps

Land Use Map Year	Overall Accuracy (%)	Kappa Accuracy (%)
1989	89	84
1994	91	86
2001	90	85
2006	93	87
2011	93	89
2016	91	85
Average	**91%**	**86%**

2.5 Change Detection

In this study, land use changes have been analysed across five distinct time intervals: 1989–1994, 1994–2001, 2001–2006, 2006–2011, and 2011–2016. Each period has been separately examined to detect and describe spatial and temporal shifts in land use. Additionally, cumulative changes over the entire study period from 1989 to 2016 have been monitored to understand long-term trends and transformations in the landscape. The analysis aims to identify the dynamics of urban expansion, vegetation cover, industrial growth, barren land reduction, and fluctuations in water bodies. The graph in Figure X visually represents the magnitude of increase or decrease in each land use class throughout the period from 1989 to 2016. Among all time intervals, the most notable changes were observed between 1989 and 1994, particularly in the urban areas and barren lands categories. During this time, urban land cover showed a sharp upward trend, reflecting rapid urban expansion, while barren lands experienced a marked decline, likely due to land conversion for development or agriculture.

Subsequent sections detail these patterns of change for each period under investigation.

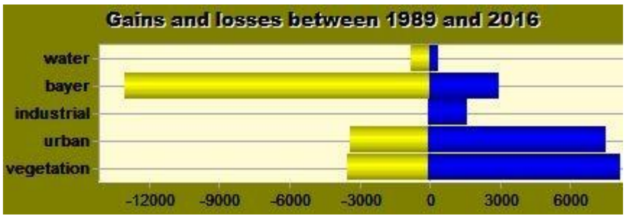

Figure 8. Land Use/Land Cover change detection

2.6 River Morphological Extraction

Following the land use classification, the Karun River was extracted from the classified land use maps. For this purpose, areas classified as water bodies were isolated from other land use classes using ArcGIS software. Subsequently, mean filtering techniques were applied to eliminate water features located outside the main channel of the Karun River. As a result, the morphological structure of the Karun River was extracted for each year under study.

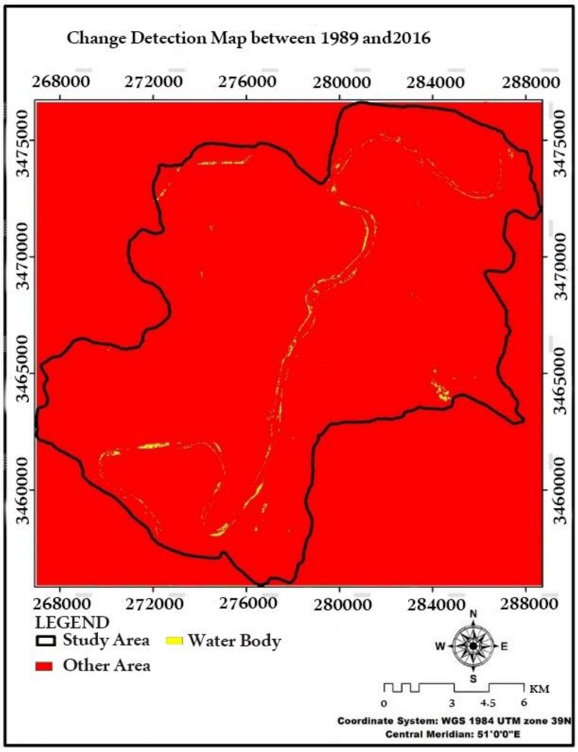

Figure 9. Land Use/Land Cover change detection Karun River

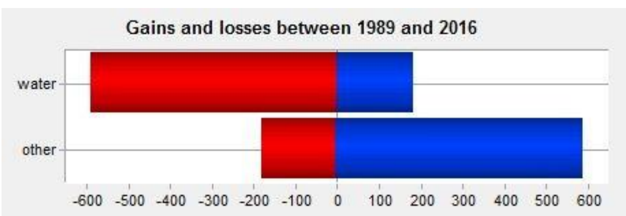

Figure 10. Land Use/Land Cover change detection Karun River

2.7 Modelling with CA-Markov

The CA-Markov model simulated 2021 scenarios based on 2011–2016 transitions. Transition probability matrices were derived, and neighbourhood rules were defined. Results projected a continuation of urban growth and further river narrowing. Model validation used simulated 2016 against actual 2016with high similarity indices.

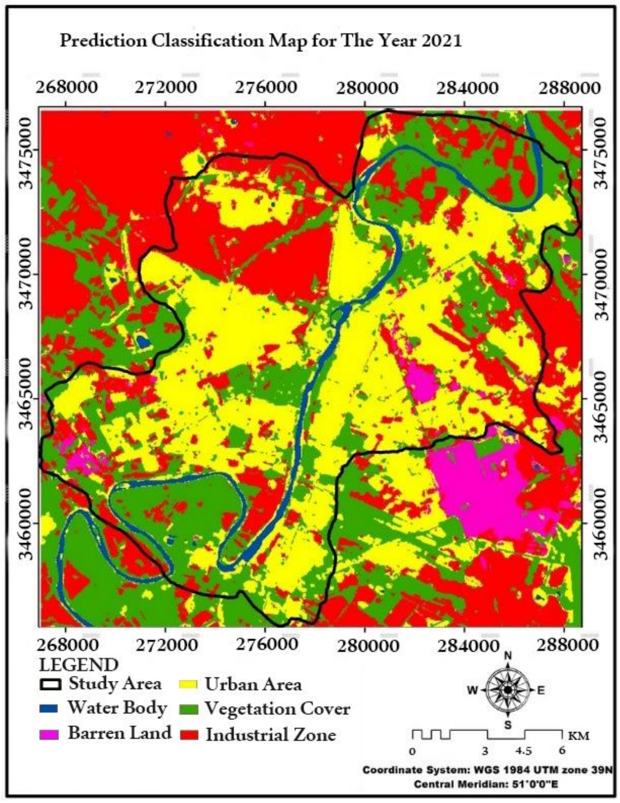

Figure 11. Land Use/Land Cover CA-Markov model simulated for 2021.

3 Conclusion

This study highlights the transformative effects of urbanization on land use and river morphology in Ahvaz, demonstrating how the expansion of human settlements and infrastructure has reshaped the landscape and influenced ecological stability. By analyzing multi-temporal satellite data and applying classification models such as logistic regression and artificial neural networks through the LCM framework, the research revealed significant changes between 1989 and 2016. These include a notable increase in urban areas and a concurrent decline in vegetative and agricultural land cover. While the classification accuracy was acceptable—with Kappa statistics ranging from 84% to 89%—limitations such as misclassification and underrepresentation of certain land cover transitions indicate the need for model refinement.

The findings underscore the necessity of integrating geospatial technologies into urban planning and environmental management. The degradation of natural and agricultural spaces in favor of urban expansion calls for immediate policy interventions. These include stricter zoning laws, implementation of river conservation projects, and the promotion of green infrastructure. Sustainable urban development should incorporate buffer zones along riverbanks, afforestation initiatives, and controlled urban growth strategies to mitigate adverse environmental effects. Water resource management must also be prioritized to address sedimentation, pollution, and disruptions to hydrological cycles caused by unchecked development.

Looking ahead, future research should leverage high-resolution satellite imagery, advanced machine learning classification techniques, and socio-economic data integration to enhance both the accuracy and applicability of land use monitoring. The application of artificial intelligence and deep learning in remote sensing can further improve detection and predictive modeling. Moreover, the inclusion of climate change scenarios and hydrodynamic modeling could provide deeper insights into the long-term impacts of land use transformation. A data-driven, interdisciplinary approach that combines advanced geospatial tools, effective policy design, and community engagement is essential for ensuring sustainable urban growth and preserving vital environmental resources in regions like Ahvaz.

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