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A GEOAI APPROACH FOR LAND USE LAND COVER CHANGE ANALYSIS OF BHILWARA DISTRICT, RAJASTHAN

Richa Sharma
Department of Computer Science
Research Scholar,
Sangam University, Bhilwara, Rajasthan
richa.sharma@sangamuniversity.ac.in

Dr. Vikas Somani
Department of Computer Science
Research Dean ,Professor & Head of dept.,
Sangam University, Bhilwara, Rajasthan
vikas.somani@sangamuniversity.ac.in

Abstract: To comprehend and measure changes in land use and land cover (LULC) in the Bhilwara district of Rajasthan, India, this study summarizes previous research on the use of Geographic Artificial Intelligence (GeoAI) and associated geospatial methodologies. Higher computational structures that effectively manage massive spatial inputs and generate precise maps of dynamic landscapes are required due to the fast growth of urban and agricultural areas in semi-arid Indian districts. This summary explains how GeoAI, which combines AI models with remote sensing and geographic data, improves conventional techniques for identifying, categorizing, and projecting LU/LC changes across time. The theoretical underpinnings of GeoAI, recent case studies in Bhilwara and related areas, methodological developments, and future research prospects are some of the major topics covered.

Keywords: Remote Sensing, LULC, Geospatial data, Classification, Spatial data

I. Introduction

Changes in land use and land cover (LULC) are imp-ortant markers of environmental change and the effects of human activity on terrestrial ecosystems. Semi- arid climate conditions combine with growing urbanization, agricultural expansion, and mining operations in areas like Bhilwara, Rajasthan, creating unique spatial patterns that call for precise mapping and (ML) and deep learning (DL) inside spatial analysis.

This paper reviews the theoretical basis of GeoAI, the current state of LULC research in and around Bhilwara, and the potential of GeoAI to improve LULC monitoring and forecasting.

II. Review of Literature

Land Use Land Cover (LULC) change analysis is crucial for monitoring environmental and urban transformations, especially in semi-arid regions such as Rajasthan. Traditional remote sensing and GIS techniques have been widely used to map LULC changes using multi-temporal satellite imagery and indices such as NDVI [1], [2]. These methods provide foundational insights but are limited by manual interpretation and moderate classification accuracy [2].

In Rajasthan, studies report increasing built-up areas and declining vegetation in districts including Bhilwara, accompanied by rises in land surface temperature (LST) [3], [4]. Conventional supervised classification

techniques used in such kind of studies are frequently limited in predictive capability and scalability [4]. To deal with such kind of issues, **machine learning (ML) algorithms**, such as Random Forest (RF) and Support Vector Machine (SVM), have been applied, offering improved accuracy and better handling of complex land cover patterns [5], [6]. Integration temporal analysis of landscape change, urban growth, and land cover dynamics.

Key features of GeoAI include:

- **Automated feature detection** from multispectral and hyperspectral imagery.
- **Semantic segmentation** that labels each pixel with meaningful land cover categories.
- **Predictive modeling**, allowing forecast of future LULC changes.
- **Fusion of multi-source data** for richer spatial insights.

Compared to traditional supervised classification, GeoAI models especially deep learning, architectures can handle large variability in land cover patterns and perform with high accuracy across diverse landscapes.

with cloud-based platforms like Google Earth Engine (GEE) further enhances large-scale, multi-temporal analysis [7].

The emergence of **Geospatial Artificial Intelligence (GeoAI)** integrates RS, GIS, and machine learning for automated feature extraction, semantic segmentation, and predictive LULC modeling [8], [9]. While GeoAI shows promising results in regional and global studies, its application at the district level in India, particularly Bhilwara, remains limited, highlighting a research gap addressed by the present study [9].

III. GeoAI:Conceptual Framework and Applications

GeoAI refers to the integration of **AI techniques** such as ML, DL, and data mining with geospatial data analytics to process spatial phenomena captured in satellite imagery, aerial photography, and GIS databases. It extends conventional GIS by incorporating algorithms capable of learning patterns and features directly from complex spatial datasets.

Foundational work on GeoAI highlights its deployment in remote sensing tasks such as scene classification, object detection, and semantic segmentation, where convolutional neural networks (CNNs) and other deep models extract spatial patterns from imagery data. GeoAI's focus includes not only improved classification accuracy but also enhanced. temporal analysis of landscape change, urban growth, and land cover dynamics.

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IV. Land Use Land Cover Research in Bhilwara District

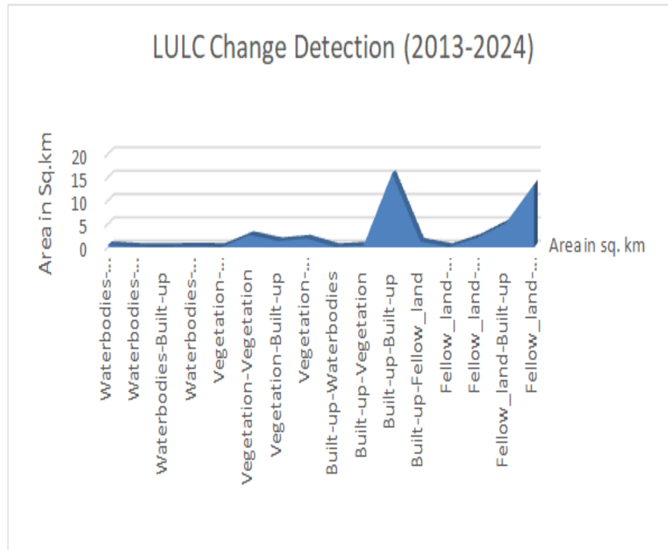
4.1 Remote Sensing and GIS Studies

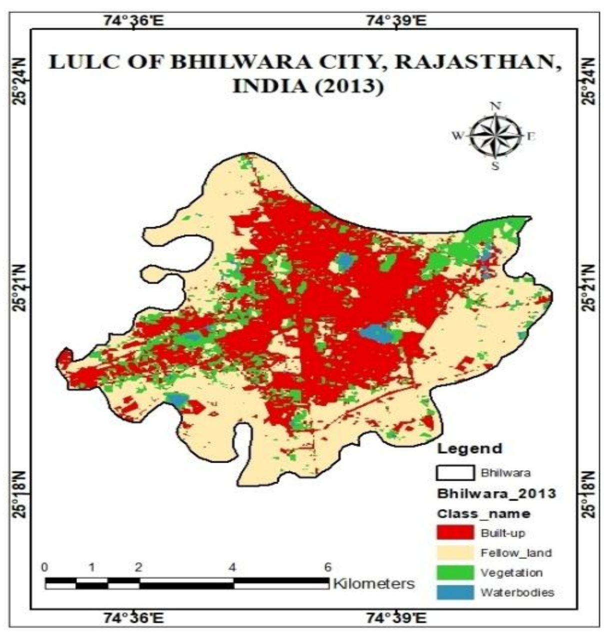
Several studies have employed remote sensing and GIS to monitor LULC changes in Bhilwara district:

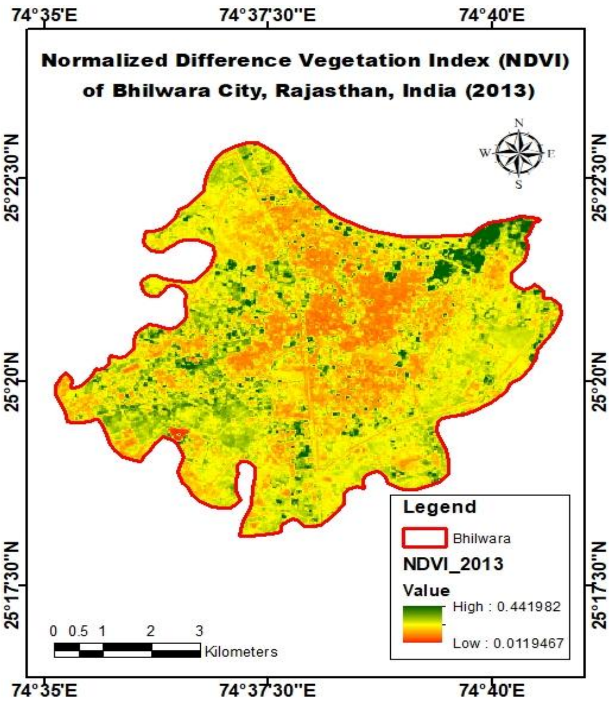
- A **2024 study** applied LULC classification and **NDVI (Normalized Difference Vegetation Index)** analysis to quantify urban expansion and vegetative health in Bhilwara city. The research reported significant increases in built-up areas accompanied by declines in cropland and deciduous forest, indicating ecological stress and a need for sustainable planning.

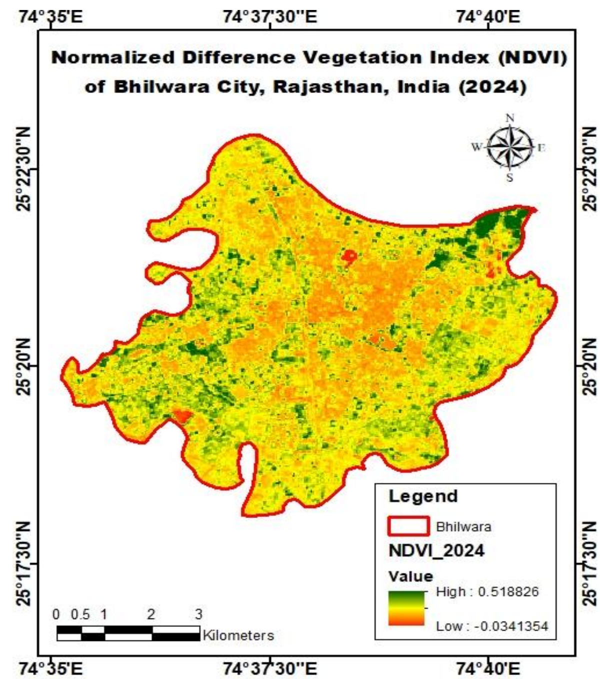
LULC and NDBI analyses in Bhilwara showed a strong correlation between built-up and vegetation, emphasizing how land cover transformationaffects local microclimates.

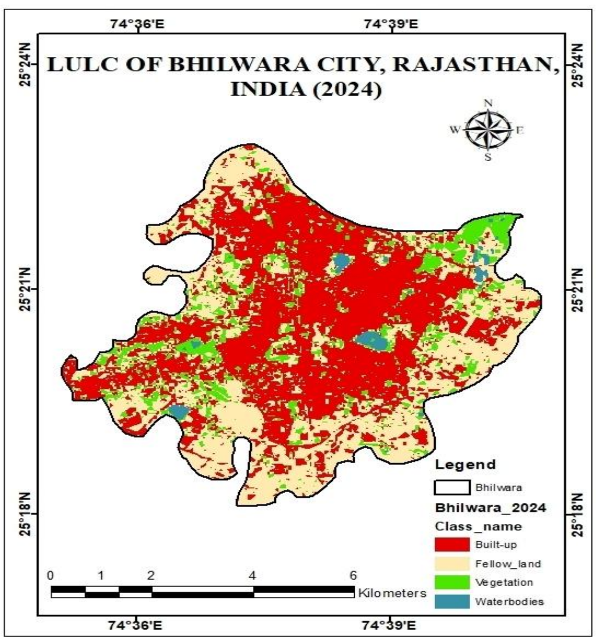
These case studies display that **spatial classification and change detection techniques** using satellite imagery and GIS remain essential for evaluating landscape transformations at district and regional scales.











4.2 Emerging AI-Enabled Research

Few published works specifically applying GeoAI in Bhilwara were identified; however, a broader trend is emerging where AI-driven geospatial analysis is integrated with traditional GIS workflows:

- An ongoing research effort proposes integrating **AI and machine learning** within GIS to forecast urban growth patterns and land use dynamics in Bhilwara, highlighting a move toward predictive frameworks that anticipate future land cover scenarios.
- ile not Bhilwara-specific, hybrid approaches using **machine learning with object-based detection to predict LULC changes** illustrate methods that could be transferable to Bhilwara studies, emphasizing the need for advanced computational models in similar semi-arid Indian contexts.

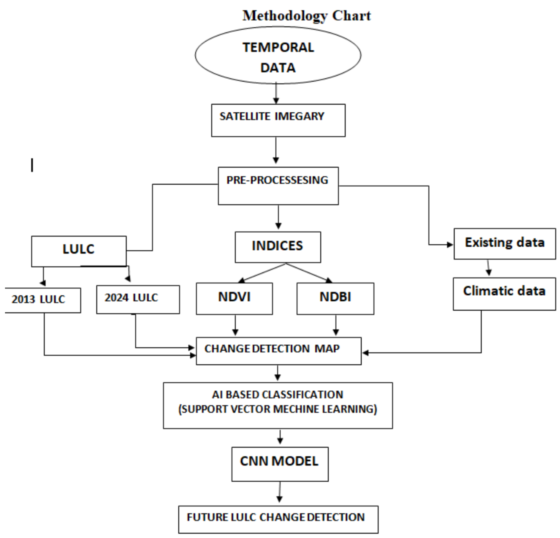
These emerging GeoAI approaches signal a shift in LULC research paradigms toward scalable, data-driven methodologies that can operate on high-resolution satellite data and provide near real-time change detection.

V. Methodological Integration: GeoAI and Geospatial Techniques

To harness GeoAI for LULC change detection, a typical workflow integrates multiple components:

1. **Data Acquisition**: Multi-temporal satellite data (e.g., Landsat, Sentinel) provide spectral bands for varying time periods.

2. **Pre-processing**: Radiometric and atmospheric corrections prepare images for reliable analysis.
3. **Feature Extraction**: Vegetation indices like NDVI and built-up indices inform change metrics over time.
4. **AI-based Classification**: Deep learning models (e.g., CNNs) or ensemble algorithms (e.g., random forest, SVM) classify land cover with high accuracy.
5. **Change Detection and Validation**: Temporal comparisons reveal the extent and trend of LULC transitions. Statistical validation (e.g., accuracy matrices) ensures reliability.



GeoAI enhances these workflows by enabling **end-to-end automation**, adaptive learning from large datasets, and deep feature learning that surpasses traditional pixel-based methods.

VI. Challenges and Future Directions

While GeoAI offers significant advantages, several challenges persist in its application to LULC-

- **Data limitations**: High-resolution datasets may not be uniformly available across all time periods for rural and semi-urban Indian districts like Bhilwara.**Model generalizability**: Deep learning models trained on one region may not transfer effectively to another without domain adaptation techniques.
- **Computational resources**: Running deep learning models on large geospatial datasets requires substantial processing power.

Future research should prioritize:

- **Local training datasets** from Bhilwara and adjacent regions to improve model relevance.
- **Integration of socio-economic variables** with GeoAI predictions to understand drivers of land change.
- **Policy-oriented tools** that translate LULC analysis into guidance for regional planning and sustainable land management.

VI. Result and discussion:

Conclusion

By enhancing conventional GIS and remote sensing methods with cutting-edge AI capabilities, GeoAI offers a revolutionary paradigm in LULC change analysis, as this research summary demonstrates. Existing remote sensing studies in the Bhilwara district show notable land changes associated with urbanization and environmental effects.

2013	2024	Change_detection	Area in sq. kr
Waterbodies	Waterbodies	Waterbodies-Waterbodies	0.463236
Waterbodies	Vegetation	Waterbodies-Vegetation	0.106859
Waterbodies	Built-up	Waterbodies-Built-up	0.070189
Waterbodies	Fellow_land	Waterbodies-Fellow_land	0.147479
Vegetation	Waterbodies	Vegetation-Waterbodies	0.086488
Vegetation	Vegetation	Vegetation-Vegetation	2.638404
Vegetation	Built-up	Vegetation-Built-up	1.3109
Vegetation	Fellow_land	Vegetation-Fellow_land	1.872531
Built-up	Waterbodies	Built-up-Waterbodies	0.061232
Built-up	Vegetation	Built-up-Vegetation	0.362684
Built-up	Built-up	Built-up-Built-up	15.809558
Built-up	Fellow_land	Built-up-Fellow_land	1.221504
Fellow_land	Waterbodies	Fellow_land-Waterbodies	0.040236
Fellow_land	Vegetation	Fellow_land-Vegetation	2.081174
Fellow_land	Built-up	Fellow_land-Built-up	5.198123
Fellow_land	Fellow_land	Fellow_land-Fellow_land	13.53666

The use of GeoAI can improve LULC study accuracy, scalability, and interpretability through automated categorization, predictive modeling, and deeper feature extraction. Sustainable land use planning and addressing landscape issues in semi-arid districts like Bhilwara require ongoing development of localized GeoAI applications and interdisciplinary partnerships

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