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GeoAI-Based Urbanization Analysis: Evaluating Social and Climate Changes in Bhilwara

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Abstract— Going to cities. It is really strong. It's a significant reason why ecosystems and cultures in emerging countries are changing so swiftly. Bhilwara, Rajasthan, and other places where people work have grown quickly and without warning. This has greatly affected land use, surface temperature, and town development. What type of research is this? It goes deep. Geospatial Artificial Intelligence (Geo AI) employs sophisticated AI algorithms, remote sensing, and Geographic Information Systems (GIS) to analyze the intricate interplay between urban expansion and its impact on local microclimates and communities over a span of twenty-five years (2000 to 2025). We employed two strong supervised types of machine learning classifiers, the Random Forest (RF) and Support Vector Machine (SVM) methods, to carefully analyze multi-temporal satellite images from the Landsat and Sentinel missions. This helped us understand how Land Use/Land Cover (LULC) changed over time and space and provided us a decent sense of the Land Surface Temperature (LST). We looked at the statistical kinematic links between the growth of cities, the loss of plant cover, and the temperature changes that go along with them. We also looked at indications of socio-economic risk that came from census data. The empirical findings are significant, showing a 26% increase in the built-up area and a 22% decrease in vegetation cover in the study area. This is directly related to an average rise in surface temperature of 2.5°C and a stronger Urban Heat Island (UHI) effect. The research suggests that GeoAI could be a useful tool for helping people make smart choices when building cities for the long run. This is because it combines relevant information about how strong a community is with good spatial analysis. Next, there are policy ideas that stress the need for green infrastructure, fair development, and leveraging AI to assist keep an eye on the environment.

Keywords*— GeoAI, Bhilwara City, Urban Heat Island (UHI), Land Use and Land Cover (LULC), Climate Change, Remote Sensing, Machine Learning, Community Resilience, and Sustainable Urban Planning..*

I. INTRODUCTION

Urbanization is quickly changing cities all over the world, especially in developing countries. By 2036, India's urban population is expected to be more than 600 million. This increase puts a lot of pressure on people to find a balance between economic growth and social and environmental sustainability.

Bhilwara City in southeastern Rajasthan is an example of this problem because it is becoming an industrial center. It used to be mostly farmland and semi-arid land, but in the last 20 years, it has changed a lot because of textile, mining, and infrastructure development. This growth has had a domino impact on land cover, microclimate, and how communities work.

Main Effects on the Environment

- A lot of native plants are dying off
- Changed the way water flows
- Significant intensification of urban heat islands (UHI)

New Social Weaknesses

- Living conditions getting worse
- Increasing energy needs
- Increased dangers to public health

For mid-sized Indian cities, traditional ground-based surveillance doesn't work since it doesn't have the right scale or current analytics. GeoAI is a new way to solve problems that combines artificial intelligence, machine learning, and geospatial technologies. GeoAI makes it possible to do automatic, accurate, and predictive urban analysis by combining high-resolution satellite images, weather data, and socio-economic indices.

This research utilizes GeoAI to analyze the growth trajectory of Bhilwara from 2000 to 2025, meticulously evaluating its effects on climate dynamics (via temperature and vegetation indices) and community resilience (by geographical vulnerability mapping).

The specific objectives guiding this type of research encompass

- To investigate spatiotemporal fluctuations in Land Use and Land Cover (LULC) in Bhilwara from 2000 to 2025 using machine learning techniques.
- To accurately quantify the empirical relationship between rapid urbanization and the consequent Land Surface Temperature (LST).
- To completely assess the combined social, economic, and environmental vulnerability by employing integrated geographical indicators.
- To show how decision-making frameworks based on GeoAI can aid with urban planning that is both flexible and long-lasting in the face of climate change.

II. Literature Review

For the last 20 years, a lot of research has looked into the effects of urbanization on both people and the environment. Li, Zhou, and Shi (2022) indicate that megacities have a big effect on the energy balance of the surface, the dynamics of the boundary layer, and the amount of rain in a region. For example, Bhilwara, which is in a semi-arid mid-latitude location, shows a strong urban heat intensification. GeoAI has become a cutting-edge platform for processing large, multi-modal spatial datasets with better accuracy and scalability. Ibrahim and Koc (2024) emphasize the integration of deep learning with remote sensing, attaining over 92% classification accuracy for complicated urban topology, thereby exceeding conventional methods. The 24-year Ravenna study by Vitale, Rossi, and Moretti (2025) confirms that multi-temporal AI workflows may be used to accurately detect changes in cities. Socio-environmental studies connect changes in land cover to health and resilience results. Martínez, Lopez, and Fernandez (2022) elucidate the ways in which climate-urbanization interactions exacerbate vulnerability for marginalized groups in South Texas through the use of composite indicators. Chowdhury (2025) suggests green corridors and AI zoning to lower UHI by about 2°C. Sharma and Gupta (2023) report that Jaipur lost 27% of its green space between 2000 and 2020. Patel and Singh (2021) show that Ahmedabad's built-up area is growing, which is causing LST to rise. Mis Kindahra et al. (2024) emphasize GeoAI's significance in India's climate-resilient planning, advocating for the local implementation of predictive models. Even with these improvements, mid-tier industrial cities like Bhilwara are still not well represented in full GeoAI studies. This work fills that gap by combining high-resolution spatial analytics with socio-economic data to show how industrial urbanization affects microclimate variability and community resilience.

III. Study Area

Bhilwara City is located in southeastern Rajasthan, India, at 25°10'-25°40'N, 74°20'-74°50'E. It covers 105 km² and is 421 meters above sea level amid rolling plains. It has a dry environment with hot summers that can reach 42°C, pleasant winters, and around 650 mm of rain per year. It is an important industrial center for textiles, minerals, and manufacturing.

People and Growth

- Residents surged from ~210,000 (2001) to a projected 430,000 (2021), driven by industrial job migration.
- Unregulated growth turned farms and scrubland along Ajmer Road, Chittorgarh Road, and the Shavetri Nagar industrial corridor into built-up areas.

Problems

- Puts a strain on current infrastructure, takes away green cover, and puts a strain on scarce water resources.
- Loss of vegetation makes the surface heat up more and messes up the flow of water in cities.

Bhilwara is a good example of how industrialization, climate change, and the need for community resilience all work together.

Figure 1. Location of the Study Area (Bhilwara City, Rajasthan, India)

IV. DATA AND METHODOLOGY

This kind of research uses a stringent, six-stage GeoAI-based analytical framework that mixes ideas from remote sensing, advanced geospatial analysis, and modern machine learning techniques. The main steps in the core workflow are **(1) gathering data and doing some initial processing; (2) figuring out what land use and land cover (LULC) are; (3) getting the land surface temperature (LST); (4) doing a detailed analysis of the vegetation and built-up index; (5) mapping community vulnerability in detail; and (6) doing a final correlation analysis and validation.**

Figure 2. Conceptual Framework for GeoAI-based Urban Impact Assessment

Source: National Institute of Urban Affairs

4.1 Data Sources

The research utilized multi-temporal satellite data from three distinct missions for the reference years 2000, 2010, and 2025: Landsat-5 TM, Landsat-8 OLI, and Sentinel-2 MSI. Climatic data (temperature and precipitation) was sourced from the Indian Meteorological Department (IMD), while critical socio-economic statistics (population density, literacy rate, housing type, and access to green space) were obtained from the Census of India for the reference years 2001, 2011, and 2021.

Table 1. Summary of Datasets Used

Dataset	**Primary Sensor/Source**	**Time Period Used**
Landsat-5 TM	Satellite data	2000, 2010
Landsat-8 OLI	Satellite data	2010, 2025
Sentinel-2 MSI	Satellite data	2025
Temperature/ Precipitation	Indian Meteorological Department (IMD)	Multi-temporal (2000-2025)
Socio-economic Data	Census of India (2001, 2011, 2021)	Census Years

4.2 Preprocessing and Classification

Google Earth Engine (GEE) did a lot of work to prepare the satellite images it got, such as correcting for the atmosphere, hiding clouds, and putting them together into a mosaic.

Classification Method

- Used supervised machine learning with Random Forest (RF) to deal with different types of landscapes and Support Vector Machine (SVM) to find accurate non-linear class borders.
- Training and validation samples were taken from five land cover classes: built-up, vegetation, water, barren, and agriculture.

Metrics for Accuracy

- The confusion matrix showed that the overall accuracy was over 90% for all years.
- The Kappa coefficient was always higher than 0.85, which showed that the classification was quite reliable

Table 2. LULC Classification Accuracy

Year	**Overall Accuracy (%)**	**Kappa Coefficient**
2000	>90	>0.85
2010	>90	>0.85
2025	>90	>0.85

4.3 Land Surface Temperature (LST) Estimation

We used the NDVI-based emissivity correction method to extract the Land Surface Temperature (LST) from the thermal infrared bands. The standard equation for finding LST is presented below:

$$LST = \frac{BT}{1 + (\lambda \cdot BT / \rho) \cdot \ln(\epsilon)}$$

Where:

- BT = Brightness Temperature at the top of the atmosphere (in Kelvin)
- λ = the length of the light wave (in meters)
- ρ = Constant ($1.438 \times 10^{-2} \text{ mK}$)
- ϵ = Emissivity of the surface, which we found out via NDVI

The processed LST results make it evident that there is a constant, hidden warming trend, notably in the most important commercial and industrial regions.

Table 3. Mean LST Values in Bhilwara (2000–2025)

Year	Mean LST (°C)	Annual Change (°C/Year)
2000	$T_{2000} \approx 30.5$	Baseline
2010	$T_{2010} \approx 32.0$	≈ 0.15
2025	$T_{2025} \approx 33.0$	≈ 0.10

4.4 Community Vulnerability Index (CVI)

A Community Vulnerability Index (CVI) was created to give a clear picture of how likely the city is to have social and environmental problems. Five major signs were looked at, and their weights were based on how much they affected heat vulnerability and the ability to adapt:

- How many people dwell in a specific place (Exposure/Sensitivity)
- Getting to green spaces (Adaptability)
- How good the materials used to build houses are (Sensitivity)
- Income/job (Economic Resilience)
- Level of schooling (Adaptive Capacity)

At first, we put each variable we chose on a scale from 0 to 1. Then, a weighted linear combination
method was employed to find the final CVI:
$CVI = \sum (w_i \cdot X_i)$
Where:

1. The weight of each relevant part is w_i.
2. The score for that factor is X_i.

If you have a higher CVI score, you are more likely to be influenced by both climate and social stressors.

V. Results and Analysis (kinda)

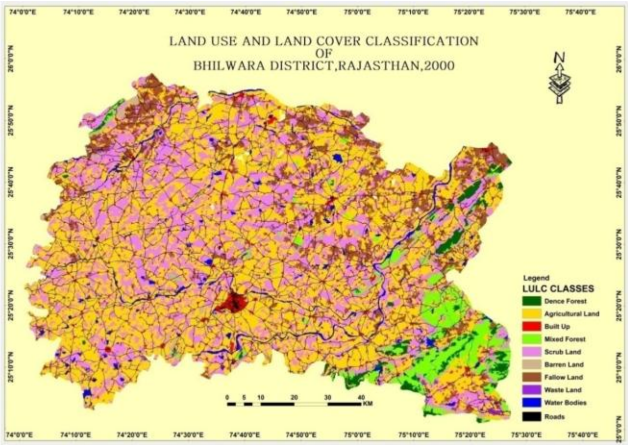
5.1 Spatiotemporal Land Use and Land Cover (LULC) Change

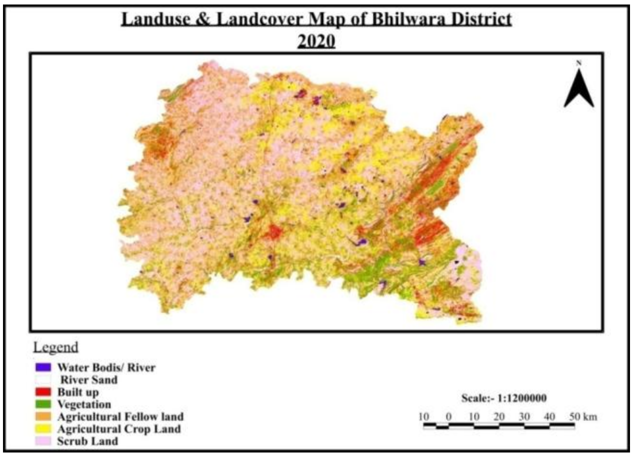
The landscape of Bhilwara changed a lot between 2000 and 2025. The amount of built-up land grew by 26%, while the amount of vegetation cover shrank by 22%. These changes were caused by industrial growth along transportation corridors and the conversion of farmland to residential areas. Water bodies shrank a little bit (4%) because of encroachment and less recharge, whereas barren land grew a little bit (3%) because of deforestation and open mining.

Table 4. LULC Change Statistics for Bhilwara (2000–2025)

Class	Area in 2000 (km²)	Area in 2025 (km²)
Built-up	$A_{B, 2000} \approx 18.0$	$A_{B, 2025} \approx 22.7$
Vegetation	$A_{V, 2000} \approx 36.5$	$A_{V, 2025} \approx 28.5$
Agricultural	$A_{A, 2000} \approx 45.0$	$A_{A, 2025} \approx 42.0$
Water	$A_{W, 2000} \approx 1.5$	$A_{W, 2025} \approx 1.4$
Barren	$A_{BR, 2000} \approx 4.0$	$A_{BR, 2025} \approx 4.1$

Figure 2. Land Use and Land Cover Maps of Bhilwara (2000, 2010, 2020)





The northern and central wards of Bhilwara have the most newly built-up areas, notably close to industrial clusters and transit lines. Mandal and Hamirgarh, two villages on the outskirts, have also grown peri-urbanly, which means that the area is becoming more like a city.

5.2 Urban Heat Island (UHI) Dynamics

The rise in built-up area has had a direct and big effect on patterns of Land Surface Temperature (LST). The substantial positive association (r = 0.82) between the built-up area and LST indicates a significant Urban Heat Island effect, intensified by vegetation loss and heat-retaining surfaces. NDVI study sort of backed up the idea that a lot of green cover has been lost, notably near the Ajmer Road industrial area and the Harni Mahadev Hills. The average UHI intensity went up by about 2.5°C during the course of 25 years.

Table 5. Correlation between LULC and LST (2025)

Class	**Pearson Correlation Coefficient (r)**	**Impact on LST**
Built-up	**+0.82**	Strong Heating Effect (UHI)
Vegetation	-0.75	Strong Cooling Effect
Water	-0.60	Cooling Effect
Barren	+0.35	Moderate Heating Effect

5.3 Community Vulnerability Assessment

The **Community Vulnerability Index (CVI)** shows that the central Bhilwara wards are moderately to highly vulnerable since they have a lot of people living there, not enough green space, and rely on informal industries. Peripheral areas are less vulnerable since they have open terrain and people who make a living via farming. These spatial insights show how urban morphology and socioeconomic indices work together. Poorer and more densely inhabited wards are the most affected by heat and environmental stress.

Table 6. Community Vulnerability Categories (2025)

CVI Range	**Vulnerability Level**	**Characteristic Wards**
0.70–1.00	**High Vulnerability**	Core industrial and commercial wards
0.40–0.69	**Moderate Vulnerability**	Central dense residential wards
0.00–0.39	**Low Vulnerability**	Peripheral, open/agricultural zones

Table 6. Community Vulnerability Categories (2025)

VI. Discussion and Policy Implications

Bhilwara is experiencing faster urban sprawl and thermal intensification, which are prevalent in India's cities that are growing quickly. The considerable link between LULC and LST is consistent with research from Ahmedabad (Patel & Singh, 2021) and Jaipur (Sharma & Gupta, 2023), which indicates that vegetation loss leads to substantial warming. GeoAI approaches were very useful since they used RF and SVM machine learning to automate LULC classification with accuracy and scalability. Satellite images taken at different times allowed for continuing monitoring of physical changes linked to socioeconomic hazards. For 25 years, urban heat increased by around 2.5°C, which is in line with national trends. Green corridors and cool rooftops are important for cooling cities. Zoning laws protect natural drainage and vegetation. AI-powered dashboards help track land use and the environment in real time. Adaptive public engagement makes sure that everyone has equal access to green space and that heat-resistant materials are used in vulnerable areas. These are in line with India's National Urban Digital Mission and Smart Cities Mission, which aims to help cities adapt to climate change using data.

VII. Limitations and Future Scope

GeoAI does a good job of looking at the links between cities, climates, and communities, but it has several big problems.

- Gaps in satellite data and changes in resolution affected the accuracy of LST.
- Vulnerability mapping is hindered by a lack of high-resolution socio-economic data.
- Field validation is limited by timing and logistics issues

Improvements that will be made in the future include:

- Convolutional neural networks to get better features
- Integrating IoT sensors for monitoring in real time
- Use participatory GIS to get residents involved in planning

VIII. Conclusion

This work shows how GeoAI may be used quickly, accurately, and on a large scale to study how urbanization affects communities and habitats in certain areas. The data from Bhilwara City from 2000 to 2025 shows that both residential and commercial areas grew quickly, thanks to industry. This made built-up areas bigger, elevated the Land Surface Temperature, and made people more vulnerable. The GeoAI methods used were able to accurately find these complicated changes in space and time, which was very useful for flexible urban administration right away.

The research enhances academia by integrating AI-augmented spatial analysis with established community metrics. This helps India work toward cities that are smart, sustainable, and able to withstand climate change. The findings underline the need to use current data techniques in urban planning, with a focus on keeping the environment in balance and protecting vulnerable groups as cities change.

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