International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Evaluating Land Use and Land Cover Transformation Through Remote Sensing: A Study of The Purandar Lift Irrigation Area

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Abstract

The Purandar Lift Irrigation Scheme was started to reduce water scarcity in the semi-arid Purandar taluka, which lies between the Mula-Mutha and Nira rivers in Pune District, Maharashtra. This area gets low and unpredictable rainfall, usually between 400 to 600 mm, making water management a serious issue. The scheme covers four talukas—Purandar, Haveli, Daund, and Baramati—and includes several villages. This study focuses on change anyalses in land use and land cover (LULC) from the year 2005 to 2023 to understand how the irrigation project has affected the region over time.To determine LULC change detection, Remote Sensing and GIS techniques were used, with Landsat 7 Enchanced Thematic Mapper (ETM) and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared (TIRS) satellite images as the main data source. The Maximum Likelihood Classification (MLC) method was used for supervised classification, and the Kappa coefficient was used to check the accuracy of the results.

The anaylsis identify major changes in the landscape, especially a decrease in barren land by 8% and other class shows an increase in agricultural land and Built-up Area.These changes suggest that the irrigation scheme has been successful in improving water availability for farming and other uses. The results highlight the importance of tracking LULC changes to evaluate how well such irrigation projects work and how sustainable they are in the long run. This research gives useful information that can help improve water resource planning and management in the region.

Keywords: LULC, Purandar Lift Irrigation, Remote sensing and GIS, Kappa Coefficient

INTRODUCTION

Land is widely available,but it is a limited resource.Which is used for different essential services, like urbanisation, infrastructure development, the production of greater quantities of food, feed, fibre, and fuel, etc. Land use (LU) and land cover (LC) are the two individual terms predominantly used for classifying land. Land cover refers to the physical and biological cover of the Earth's surface, including natural elements such as forests, wetlands, water bodies, and urban areas ,while land use describes how the land cover is modified (e.g., agricultural land, built-up area, recreation area, wildlife management areas).[12]
Land Use and Land Cover (LULC) is essential for assessing environmental change and managing natural resources.It promotes sustainable planning in agriculture, forestry, water management, and urban development. Obtaining real-time information on land use and cover changes is challenging due to their dynamic nature. Traditional methods are time-consuming, arduous, expensive, and labour-intensive. The spatial variance of LULC raises doubts about the point data gathered using standard approaches. In current

times, satellite-based remote sensing technology has been created, which are of tremendous importance for preparing LULC maps and monitoring them at regular intervals of time .[14]
Land Use Land Cover (LULC) classification involves categorizing satellite or aerial imagery into meaningful land categories such as agriculture, forest, built-up areas, and water bodies. The main methods include visual interpretation, which is manual and expert-driven, and digital classification, which uses computer algorithms. [10] Digital classification can be supervised, where the user provides training data, or unsupervised, which relies on automatic clustering without prior labels. [11] Advanced methods like Object-Based Image Analysis (OBIA) and machine learning/deep learning (e.g., Random Forest, CNNs) are used for higher accuracy and complex patterns, especially with high-resolution data. [2] Hybrid approaches combine multiple techniques for improved results. The choice of method depends on data type, resolution, availability of training data, and project goals. [4]
Supervised and unsupervised classification are two fundamental approaches used in remote sensing for Land Use Land Cover (LULC) mapping. Supervised classification involves the use of labeled training data, where the user selects representative samples of known land cover types to train the algorithm. This method typically yields higher accuracy, especially when sufficient and accurate ground truth data are available. Algorithms such as Maximum Likelihood, Support Vector Machine (SVM), and Random Forest are commonly employed in supervised approaches. [10 & 11] Unsupervised classification, on the other hand, doesn't need any training data or prior knowledge. Instead, the algorithm groups image pixels into clusters based on their spectral similarity, and the user interprets these clusters post-classification. Techniques like K-Means and ISODATA are often used in unsupervised classification, making it useful for preliminary analysis or in areas lacking ground truth information. [9] While unsupervised methods are easier to implement, they often require further refinement and manual interpretation, whereas supervised classification is more reliable when accuracy and detail are critical. [11] After evaluating several LULC mapping approaches, it is clear that supervised classification is commonly used due to its superior accuracy in identifying specific land cover types, particularly in irrigated areas. This method enables the user to train the model with known reference data, making it appropriate for separating complex classifications such as irrigated and non-irrigated farmland.
Land Use Land Cover (LULC) mapping in semi-arid regions is vital for assessing the impact of water scarcity, land degradation, and changing agricultural patterns. These regions often rely heavily on irrigation due to limited and irregular rainfall. Accurate mapping helps monitor land transformations, evaluate the effectiveness of irrigation infrastructure, and inform sustainable land and water management policies. Remote sensing has become a key tool for this purpose, enabling large-scale observation over time. Multi-temporal satellite datasets such as Landsat, Sentinel-2, and MODIS are commonly used to capture seasonal and annual variations in vegetation, water bodies, and agricultural lands in semi-arid zones. [6]
Supervised classification techniques are among the most reliable approaches for LULC analysis in semi-arid and irrigated regions, particularly where land cover types may be spectrally similar but functionally distinct. These methods allow the use of training data derived from field surveys or high-resolution imagery to improve classification accuracy. Studies like [1] in Pakistan and [5] in the Indus Basin successfully applied Random Forest and phenology-based supervised classification to map irrigated and non-irrigated agriculture. Similarly, [13] used Landsat and MODIS data with supervised classification to map irrigated lands in California's Central Valley. In the Krishna River Basin in India, [7] employed MODIS NDVI time-series combined with ground truth data and Random Forest to produce irrigated area maps with over 80%

accuracy.
The incorporation of time-series data, phenological signatures, and vegetation indices like NDVI, SAVI, and EVI enhances the classification of irrigated areas in semi-arid environments. These approaches allow researchers to detect double cropping, differentiate irrigated from rainfed areas, and monitor land-use dynamics in response to climate variability and policy changes. Integration of machine learning techniques with high-resolution imagery, as demonstrated in studies across Iran[16], has promising results for decision-making in water-scarce regions. Overall, supervised classification methods, particularly when coupled with phenological and spectral data, provide a robust framework for LULC mapping in irrigation-dominated, semi-arid landscapes.
Water management is a major concern in the semi-arid Purandar taluka, which is located in Pune District, Maharashtra, between the Mula-Mutha and Nira rivers. The Purandar Lift Irrigation Scheme attempts to alleviate water scarcity in this area, which receives irregular and little rainfall, between 400 and 600 mm. The program includes villages from Haveli, Daundh, Baramati, and Purandar, and it covers four talukas. Purandar lift irrigation scheme is partially started in 2006 , where the 4 TMC water from Mula -Mutha river is lifted into this water scarcity region.The purpose of this study is to detect changes in land use and land cover (LULC) in the region between 2005 and 2023, with a particular focus on comprehending the effects of the irrigation project throughout that time.

Study Area

Geographically, the study area lies within the coordinates of 18.00° to 18.30° N latitude and 74.00° to 74.30° E longitude. This locates it in the eastern part of the Pune district, which is characterized by dry plains interspersed with undulating terrain and some hill ranges, particularly in Purandar taluka. These physical features have both constrained and shaped agricultural practices in the region for decades. In areas like Baramati and Daund, the terrain is relatively flatter, allowing for easier water flow and farming operations. However, in hilly areas like Purandar, efficient water conveyance and distribution become more technically challenging, necessitating the use of lift irrigation systems.
The climate of the region is typical of the semi-arid Deccan Plateau. Summers are hot and dry, while winters are cooler with more favorable conditions for certain crops. The erratic and often insufficient monsoon rainfall means that natural water availability is highly uncertain.

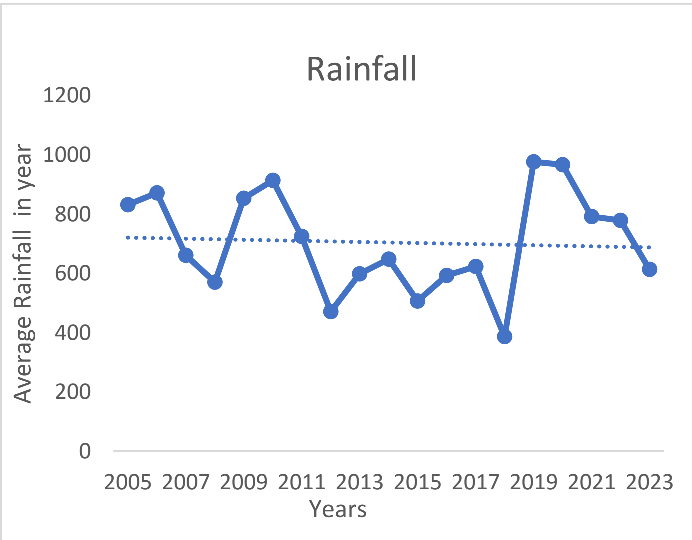


Figure 1: Location map

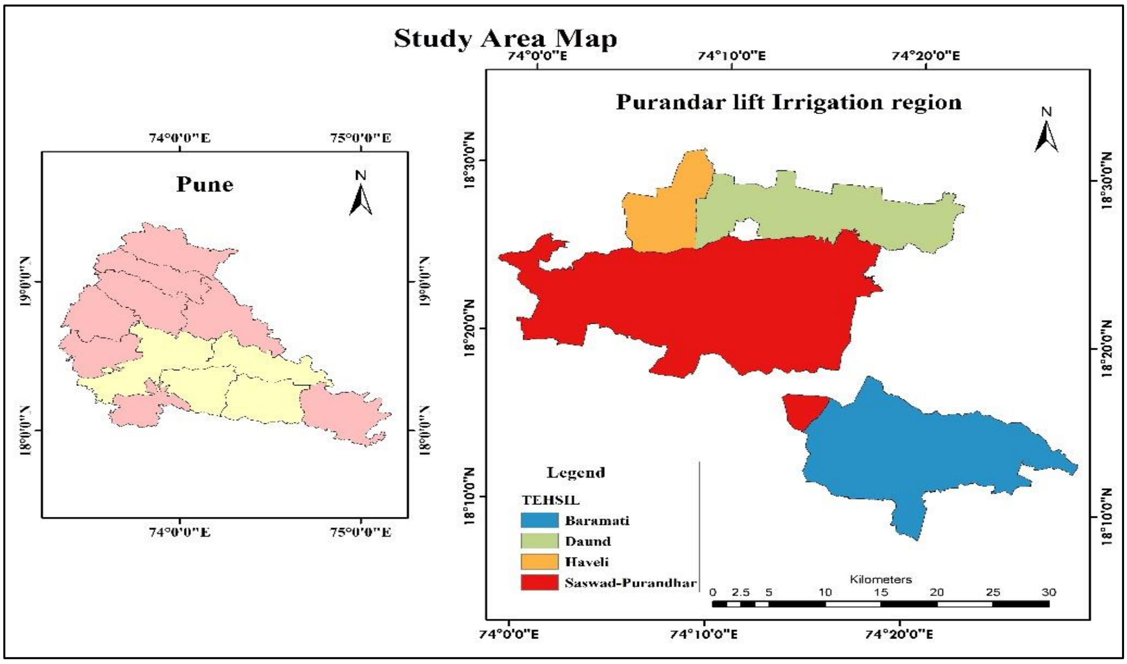


Figure 2 : Rainfall Chart

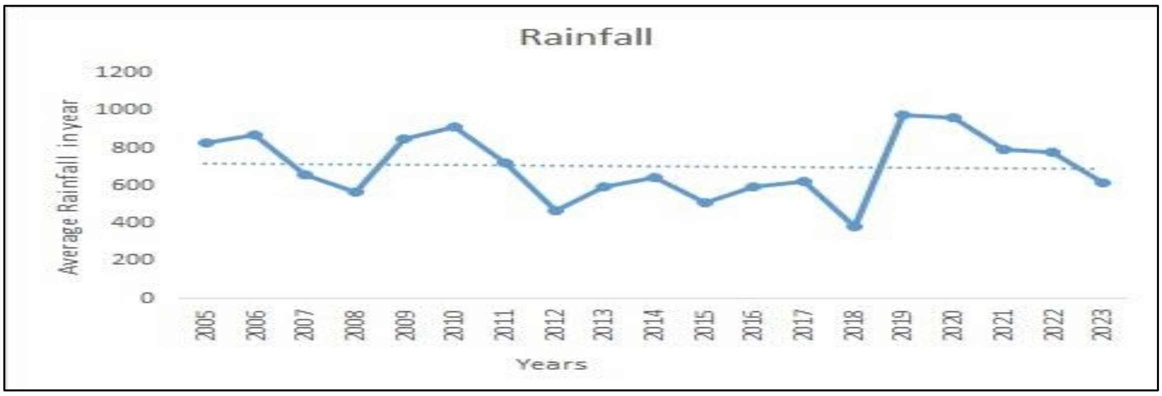


Figure 3: Geomorphology

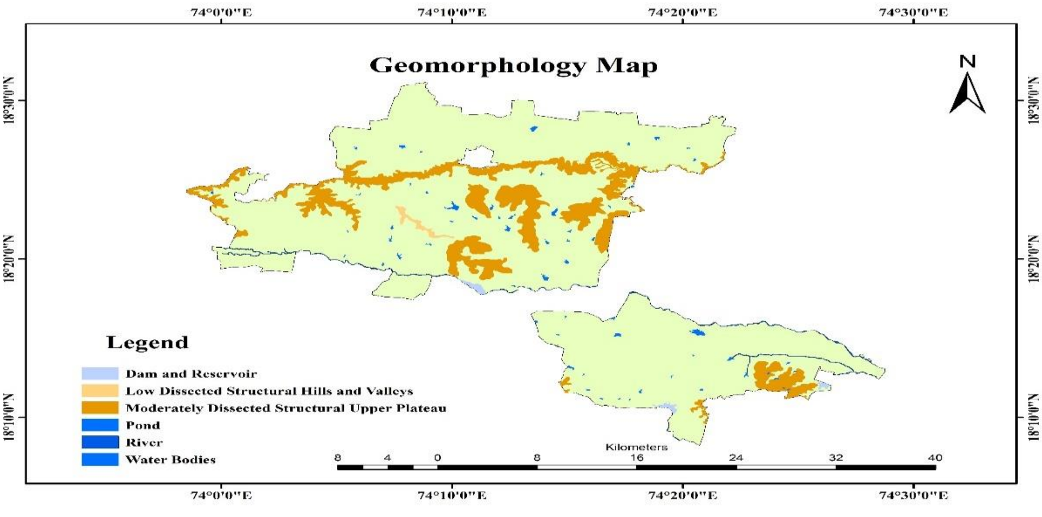


Figure 4: Geology

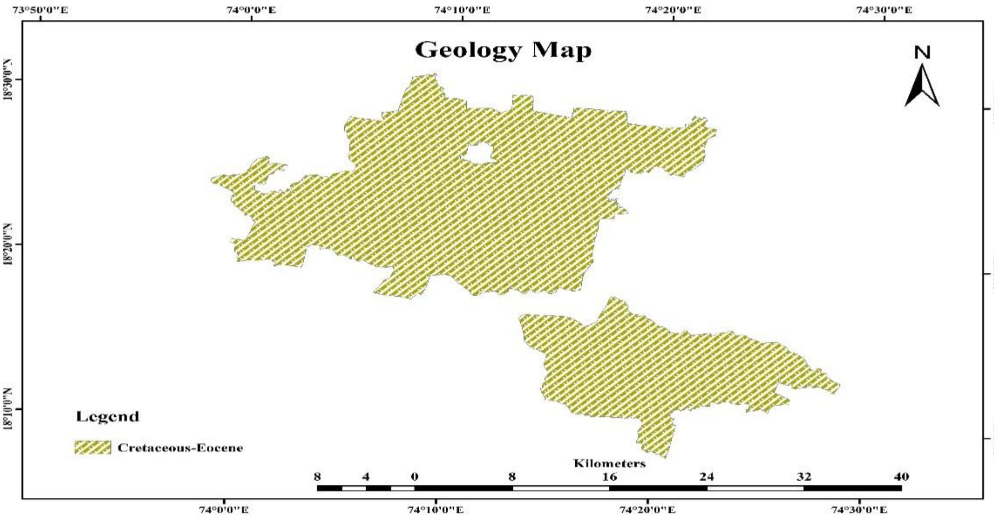


Figure 5: Drianage Network

This situation puts severe pressure on groundwater resources, which are being depleted at an alarming rate due to overuse for irrigation, especially in high-demand zones like Baramati where commercial crops such as sugarcane and grapes are

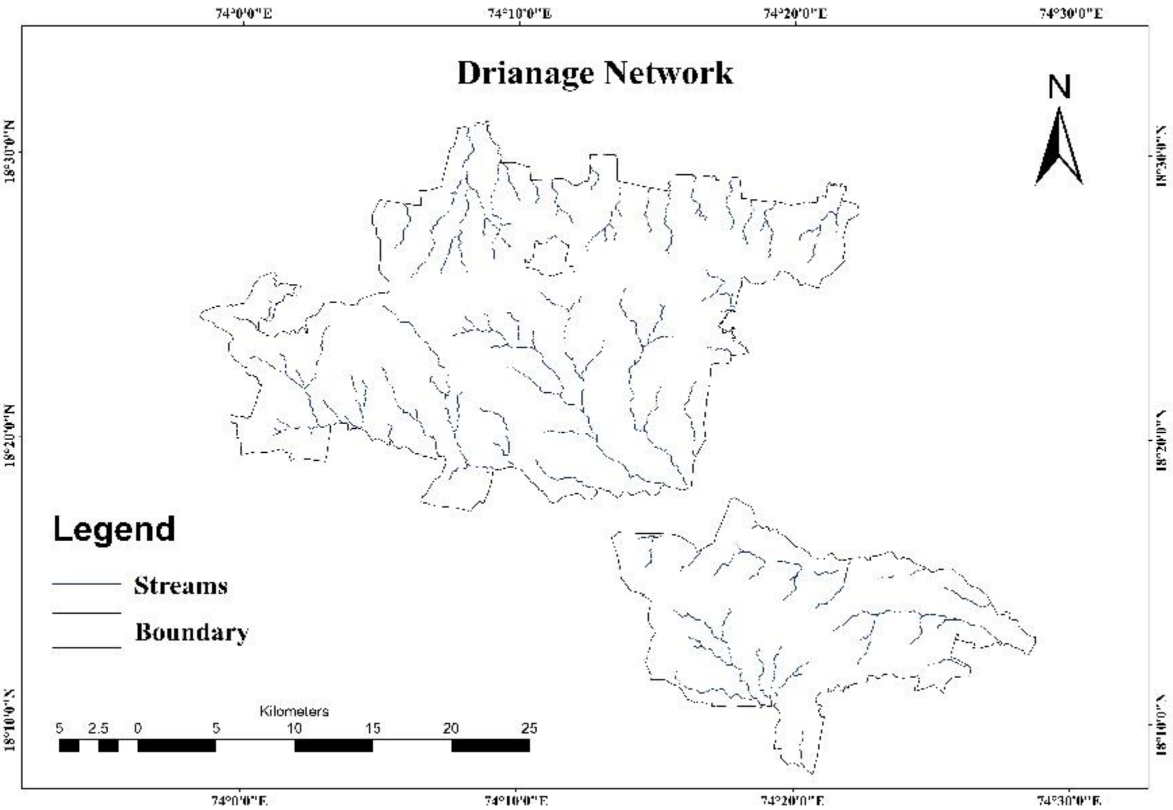


Figure 6: Methodology Flowchart

grown. This over-reliance on groundwater is not sustainable in the long term, and hence, the Purandar Lift Irrigation Scheme was conceptualized to bring surface water from external sources to meet agricultural needs.

Material and Methods

To evaluate the change in purandar lift irrigation area. The data used in this research incorporates two satellite images Landsat 7 Enchanced Thematic Mapper (ETM) and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared (TIRS) acquired on 7 nov 2005 and 26 dec 2023 respectively both the images had a spatial resolution of 30 meters. These time sereis of landsat images were aquired during the period of rabi season and are freely avilable from Landsat archive from United States Geological Survey (USGS).

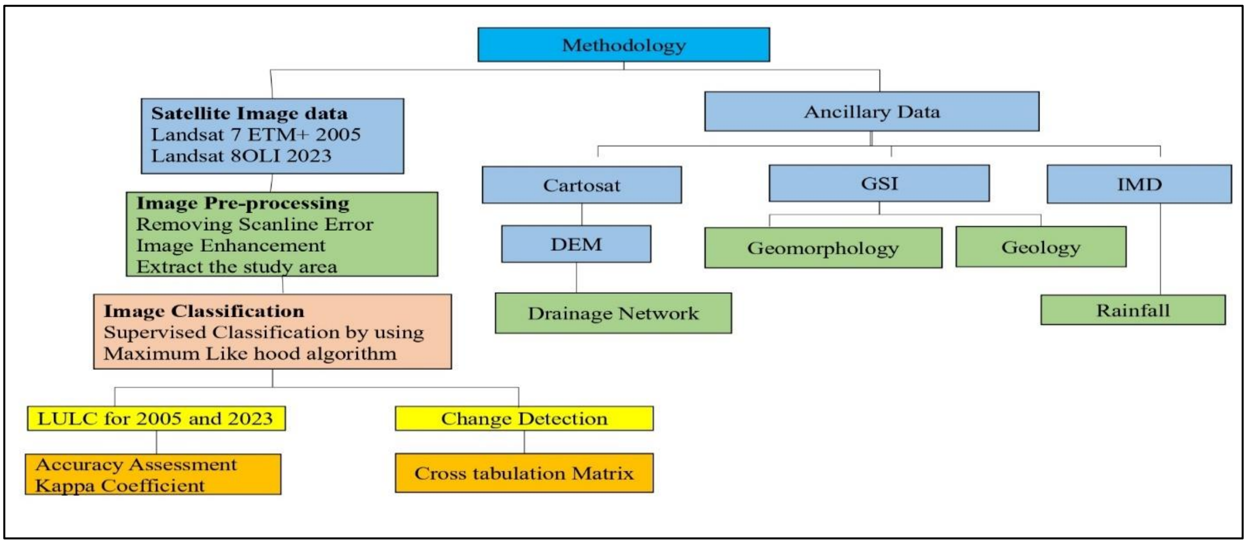


Figure 7: LULC 2005

The satellite imagery used in this study, comprising Landsat 7 ETM+ (2005) and Landsat 8 OLI (2023), underwent a series of pre-processing steps to ensure geometric and radiometric consistency before classification. Landsat 7 ETM+ data, affected by the Scan Line Corrector (SLC) failure post-2003, exhibited scan line errors that resulted in missing data stripes across the imagery. To correct this, a gap-filling procedure was applied using local histogram matching and mask-based interpolation methods within QGIS software. This approach restored the missing pixels by referencing neighboring valid values and adjacent scene data, thereby improving the image quality for further analysis.

Supervised classification using the Maximum Likelihood algorithm was applied to Landsat 7 (2005) and Landsat 8 (2023) imagery to categorize the land into five LULC classes: Agriculture, Built-up Area, Barren Land, Vegetation, and Water Body. Training samples were created using visual interpretation of high-resolution Google Earth imagery and field observations. These samples were used to train the classifier in ArcGIS 10.8 Classification accuracy was quantitatively evaluated using a confusion matrix derived from stratified random sampling of 132 to 131 ground truth points. The overall classification accuracy was accompanied by the Kappa coefficient (κ), which adjusts for the likelihood of agreement occurring by random chance. The Kappa statistic, widely used in remote sensing accuracy assessments, offers a more realistic evaluation of classification performance than overall accuracy alone. The Kappa statistic provides a measure of agreement between the classified data and the reference data, correcting for chance agreement. It is defined as:

$$\text{Kappa Coefficient} = \frac{(\text{Po} - \text{Pe})}{(1 - \text{Pe})}$$

where
po is the observed accuracy
pe is the expected accuracy due to random chance.
A Kappa value closer to 1 indicates strong agreement. The classification results achieved a Kappa coefficient of 0.90 and 0.89, indicating substantial to almost perfect agreement.
To assess the spatio-temporal land use/land cover (LULC) changes between 2005 and 2023, a cross-tabulation (transition) matrix was generated using classified satellite imagery. This matrix identifies transitions between different LULC classes, including persistence, gain, loss, and net change.
Let Cij represent the area that changed from class i (in year 2005) to class j (in year 2023).

- **Persistence** (unchanged area within class i):

$$P_i = C_{ii}$$

- **Gain** (new area gained by class j):

$$G_j = \sum_{i \neq j} C_{ij}$$

- **Loss** (area lost from class i to others):

$$L_i = \sum_{j \neq i} C_{ij}$$

- **Net Change**:

$$N_i = G_i - L_i$$

Where:
- i and j refer to LULC classes such as Agriculture, Built-up, etc.
- All values are in square kilometers.
  The actual analysis and image processing were done using ArcMap 10.8 software. This software was also used to create thematic maps (maps that show different land cover types) and to perform area calculations.

For visualizing results in graphs and for making tables and additional calculations—like measuring how much land cover changed over time—Microsoft Excel was used.

RESULTS AND DISCUSSION

LULC Pattern of Purandar Lift Irrigated Area in 2005

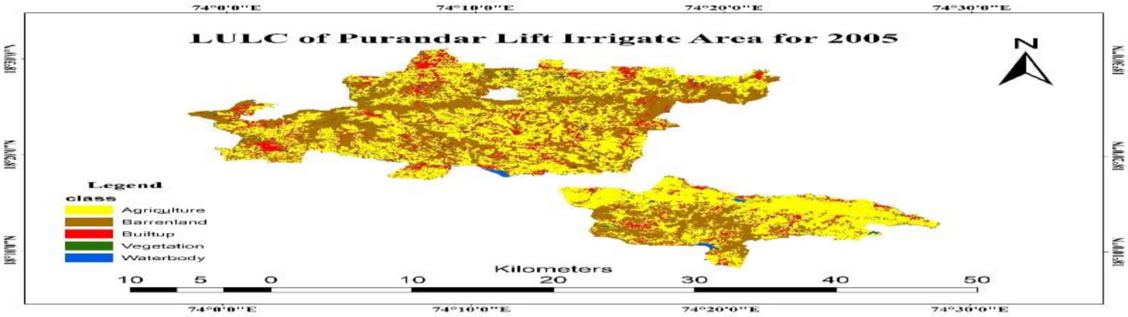


Figure 8 : Percentage chart 2005

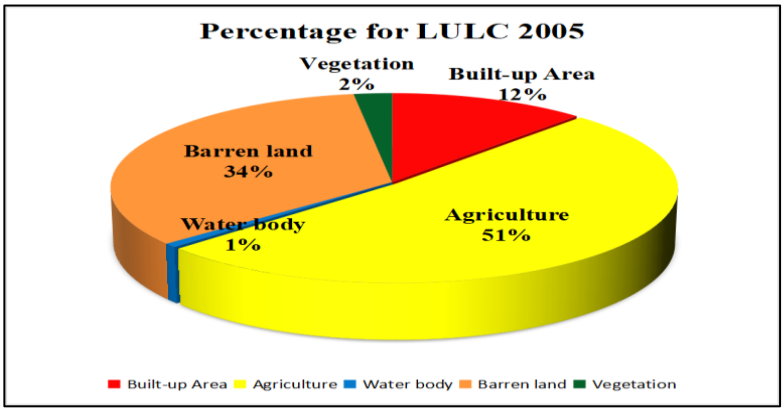


Figure 9: LULC 2023

Agriculture dominates land use, accounting for more than half of total area (51.45%). This depicts a terrain primarily reliant on agriculture or crop production. Barren land is the second most major group, accounting for 33.57%, indicating that a large amount of the land is unproductive or underused, potentially due to rocky, sandy, or deteriorated soils. Built-up Area accounts for 11.95%, indicating a moderate level of urban or infrastructure development. Vegetation and water bodies cover relatively tiny areas: 2.30% and 0.71%, respectively. This could signify a lack of forested or green areas, as well as a scarcity of natural water resources.

LULC Pattern of Purandar Lift Irrigation Area in 2023

Agriculture is the most common land use, accounting for more than half of the region. (55.69%) This means that the area is largely rural and heavily reliant on agriculture for a living and food production. It implies that barren land accounts for 25.06% of the total, implying that it is either unproductive or badly deteriorated. Buit-up Area accounts for 14.07%, indicating moderate urban development. Vegetation and water bodies cover a relatively modest area, 4.03% and 1.12%, respectively.

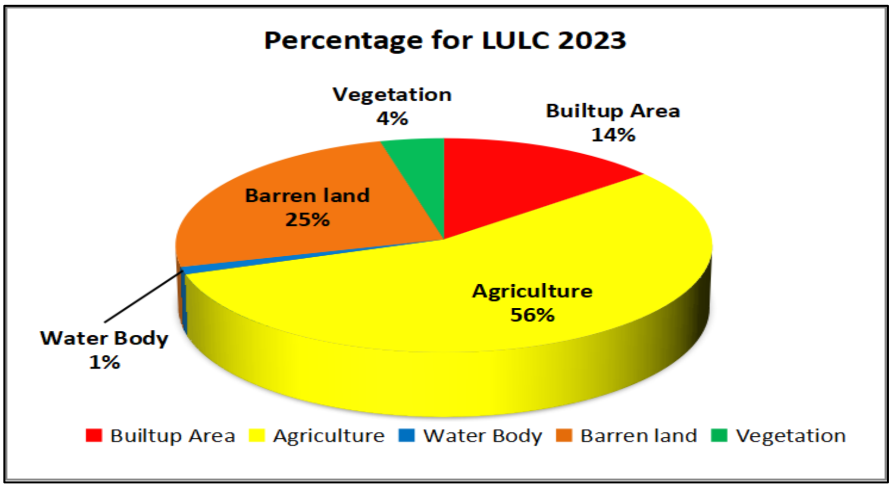


Figure 10: Percentage chart 2023

LULC Change detection from 2005 to 2023:

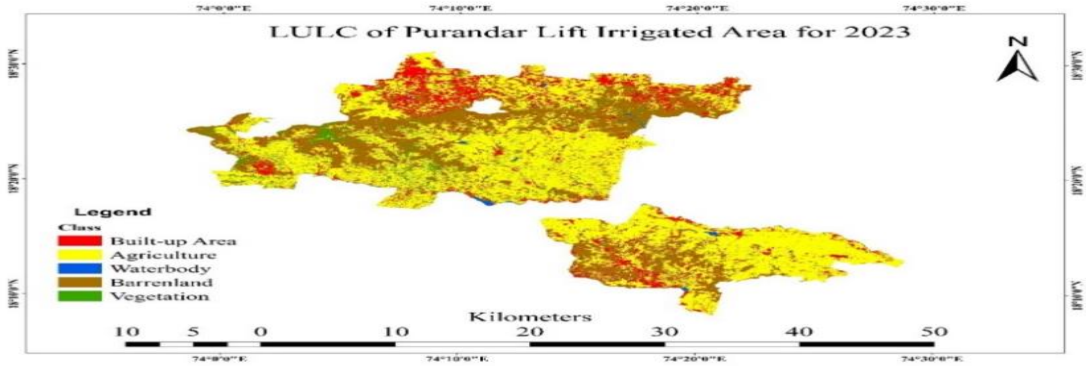
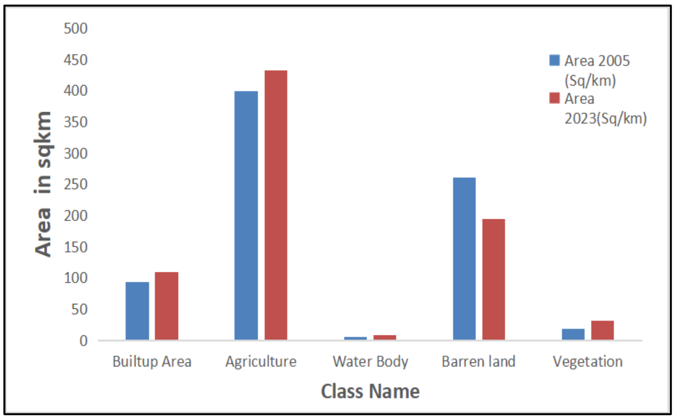


Figure 11: LULC change of 2005 and 2023



Between 2005 and 2023, the region's land use changed significantly, reflecting patterns in development, environmental restoration, and resource management. The built-up area grew by 16.47 square kilometres (17.76%), suggesting urban expansion fuelled by population growth and infrastructure development. Agricultural area also increased by 32.81 square kilometres (8.22%), most likely due to rising food demand and the conversion of barren land into agriculture. Water bodies increased by 57.75% (3.20 square kilometres), indicating successful water conservation efforts such as the construction of ponds, reservoirs, and rainwater harvesting systems. Meanwhile, unproductive land reduced dramatically by 66.23 square kilometres (25.42%), indicating a good trend towards productive land use.Notably, vegetation cover increased the most, by 75.10% (13.44 sq.km), showing efficient regeneration, natural regrowth, and environmental management. Overall, these developments represent a positive shift characterised by urban growth, enhanced agricultural activity, ecological restoration, and sustainable land use practices.

LULC_2005/LULC_2023	Agriculture	Barren land	Built-up Area	Vegetation	Water body	Total (2023)
Agriculture	289.52	80.85	52.17	7.66	1.42	431.62
Barren land	41.29	134.94	11.75	5.28	0.93	194.19
Built-up Area	49.8	31.36	23.52	3.46	0.86	109
Vegetation	14.48	10.97	4.31	1.4	0.17	31.33
Water body	3.61	2.04	0.82	0.09	2.09	8.65
Total (2005)	398.7	260.16	92.57	17.89	5.47	774.79

Table 1: Cross tabulation matrix

Change in Agriculture

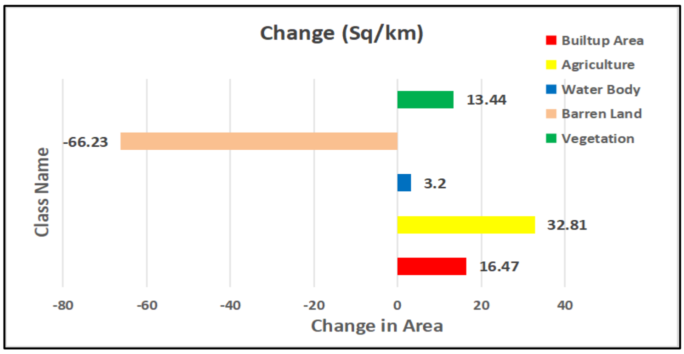


Figure 12: Change in area

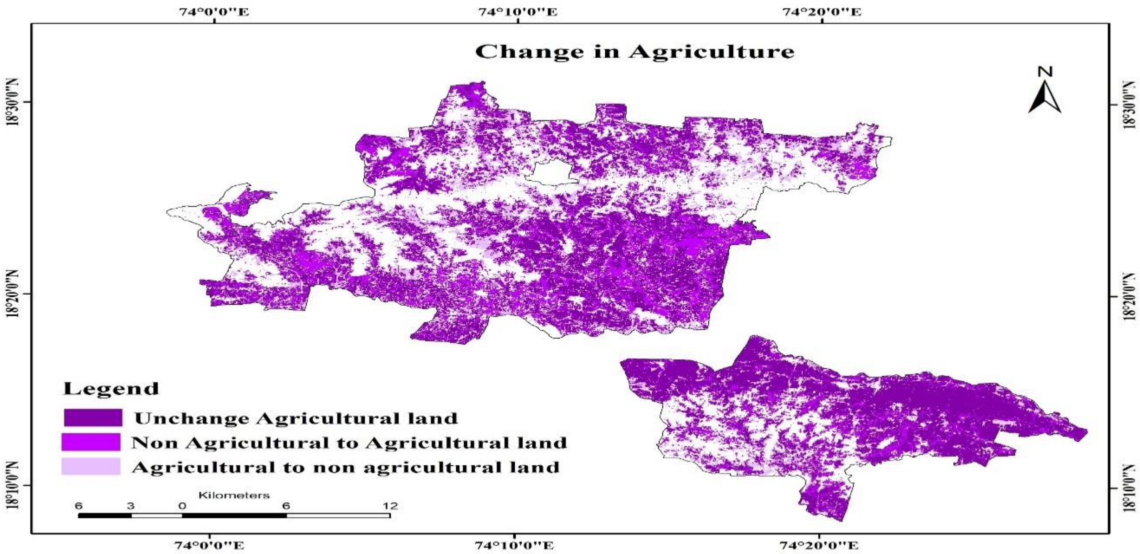


Figure 13: Agricultural changes

Fig13 represents the change in Agricultural land in Purandar lift irrigated area. The dark color area is indicating unchanged agricultural land which area is about 289.52 square kilometers and the light dark color area is Non agricultural area to agricultural land mainly 142.1 square kilometers, finally the lighter color area is an Agricultural area to a Non agricultural area 109.18 square kilometers. From the cross-tabulation, it can be said that a major part of agricultural land converted to Built up area and Barren land which approx 12.5% and 10% respectively from 2005 to 2023 which may be the result of changing pattern of livelihood activities of farmers. This shows that agriculture is under pressure from both urban expansion and environmental degradation.The agricultural land in Purandar lift irrigated region has increased by approximately 32.92 square kilometers. This indicate the net positive transformation, potentially due to improved irrigtion, policy support, or economic motivation for farmer.

Change in barren land:

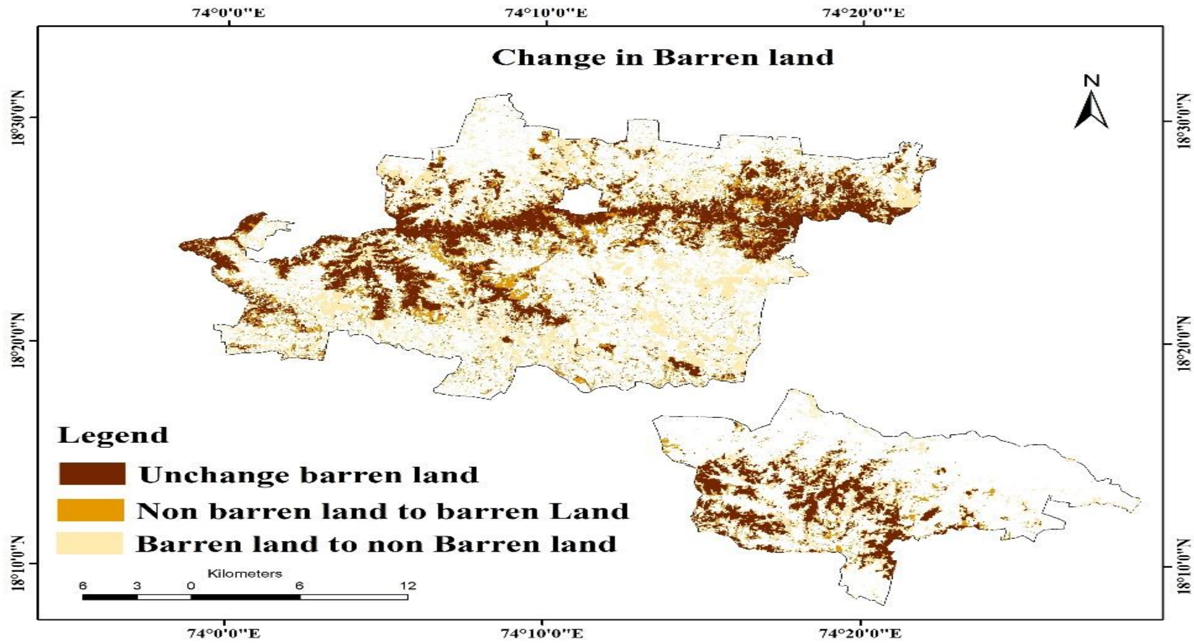


Figure 14 : Barren land changes

Major change have occured in Barren land. Fig14 represent the change in barren land , where unchnged barren land is 134.94 square kilometers is represented by dark brown color. Non barren to barren land is 59.25 square kilometers shown by light
barown color and Barren to non barren land is 125.22 square kilometers is represent by lighterbrown color. From cross tabulation it indicates that barren land is converted to majorily into agricultural and built-up area possible due to land reclamation, afforestation and irrigation Project for 2005 to 2023. Barren land has decreased by 65.97 square kilometers overall.This indicates a positive trend a significant portion of previously barren land has been converted into more productive uses.

Change in Built-up Area:

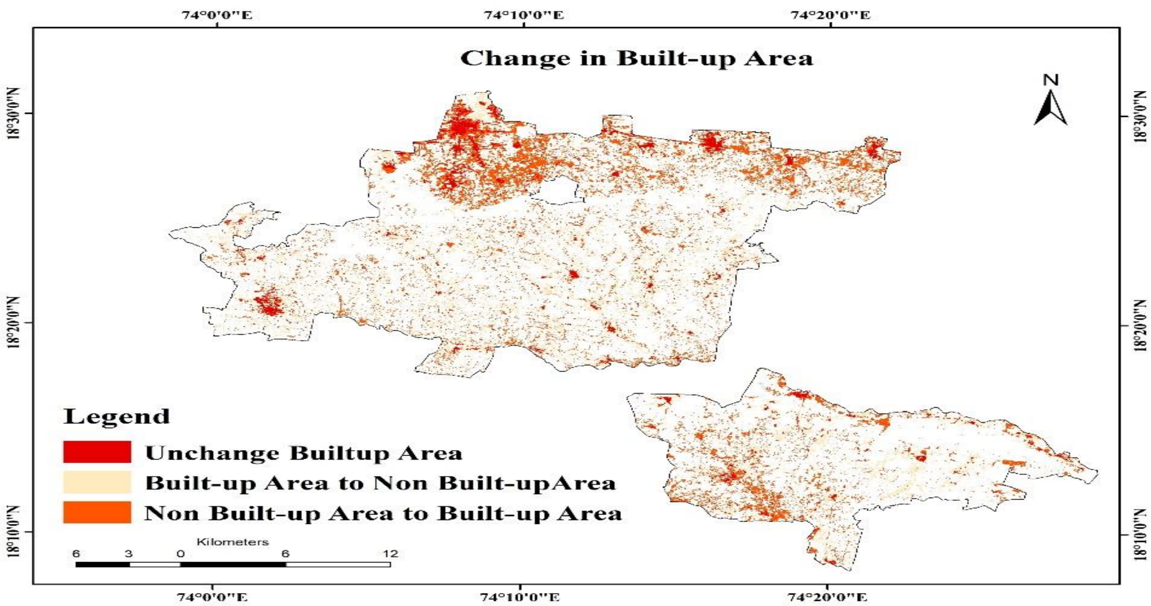


Figure 15: Built-up area changes

Fig 15 represent tthe change in Built-up area from year 2005 to 2023. Unchange Built-up area is 23.52 square kilometers dark red color and Built-up to non built-up area is 69.05 square kilometers by light red color. There is a net increase of 16.43 square kilometers in built-up area. There is clear urban growth, likely driven by infrastructure and population dynamics. This type of analysis is crucial for urban planning, zoning, and land management in areas influenced by irrigation projects like Purandar.

Change in vegetation and waterbody

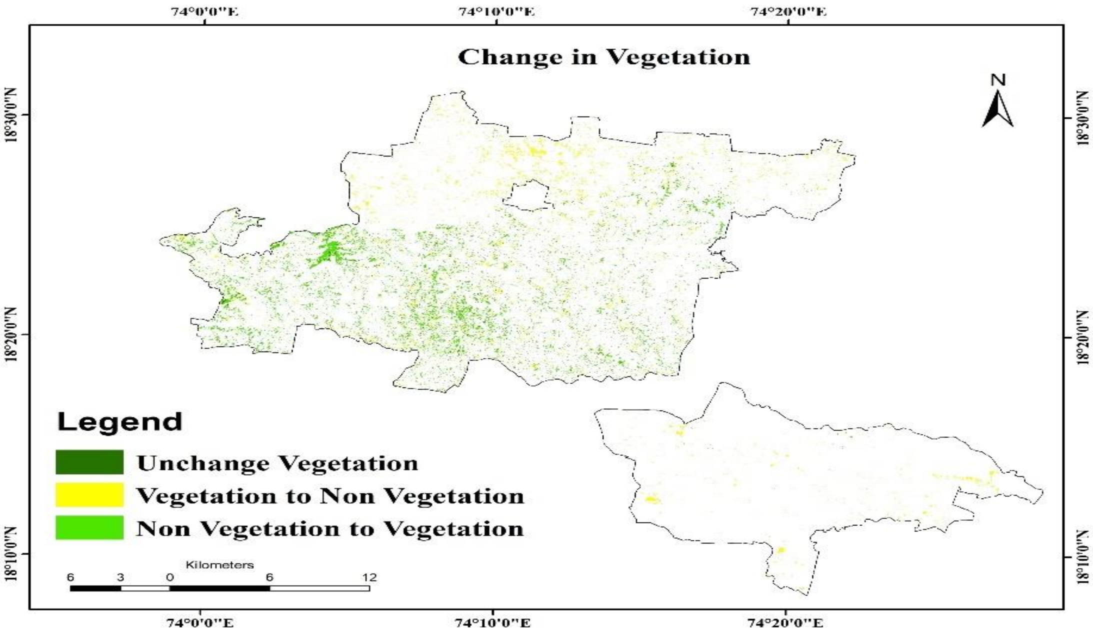


Figure 16: Vegetation Land changes

Fig 16 shows change in vegetaion and water body where unchanage vegetation is depicted in red color and water body is 1.4 and 2.09 square kilometers and change in non vegetation to vegetation is

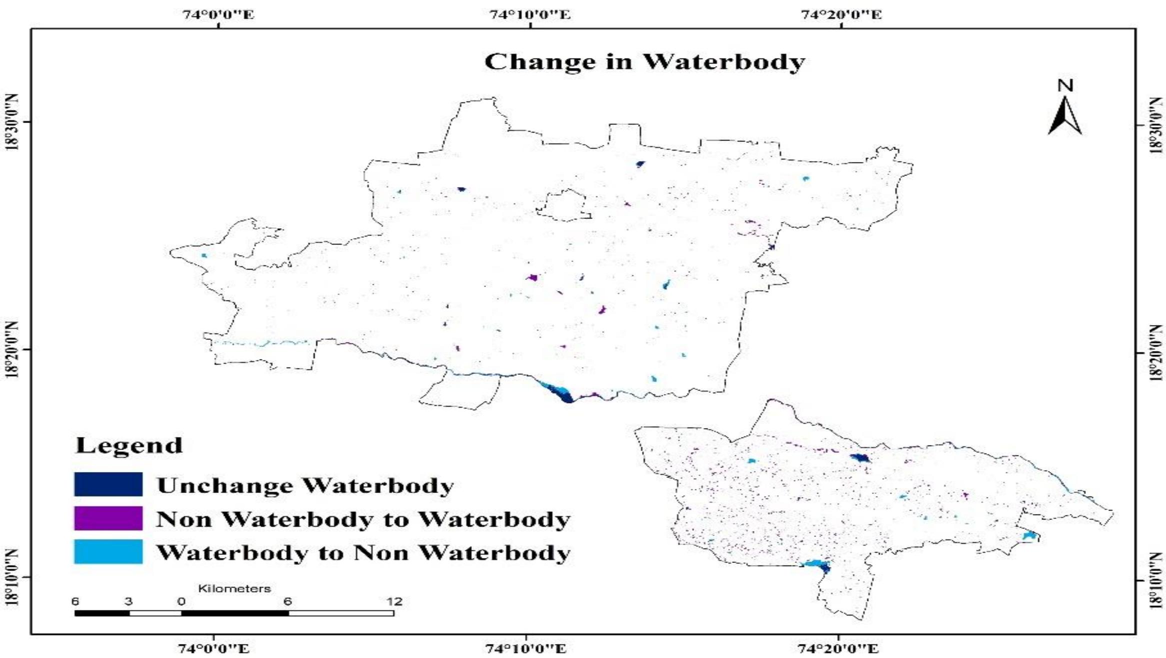


Figure 17: Waterbody land changes

29.93 square kilometers and vegtation to non vegetation is 16.49 square kilometers. where for water body it shows that Non waterbody to water body is 6.56 square kilometers and water body to non water body is 3.38 square kilometers form cross tabulation Vegetation in 2023 increased slightly with most gains from Agricultural land and Barren land through afforstation and natural recovery which is the sign of high ecological turnover. There is a net increase in water bodies by 3.18 square kilometers depict in Fig 17 a positive outcome for water availability and regional hydrology.

Conclusion

The comparative analysis of LULC percentages from 2005 to 2023 reveals significant land transformation over the 18-year period. The most notable changes include an increase in agricultural land from 51.44% to 55.69% and built-up areas from 11.94% to 14.07%. This suggests a trend toward intensified agricultural activity and urban expansion, likely driven by population growth and development needs. Additionally, the rise in vegetation (from 2.3% to 4.03%) and water bodies (from 0.71% to 1.12%) reflects positive environmental management, such as afforestation efforts and improved water resource conservation.

Conversely, barren land experienced a considerable reduction from 33.59% to 25.06%, indicating that previously unused land has been repurposed for agriculture, settlement, or ecological restoration. Overall, the data illustrates a shift toward more productive and managed land use, reflecting both developmental pressures and environmental sustainability efforts. These changes underscore the need for balanced land-use planning to ensure continued development while preserving ecological integrity.

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