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PREDICTING URBAN EXPANSION AND WATER RESOURCE DEPLETION IN JAIPUR: A GOOGLE EARTH ENGINE-BASED LAND USE AND LAND COVER CLASSIFICATION

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Abstract: -

Google Earth Engine (GEE) has emerged as a powerful tool for mapping land use and land cover (LULC) urban area changes in India. This study investigated urban expansion based on LULC changes in Jaipur City, Rajasthan, using Landsat 8 OLI/TIRS sensor data from 2014 and 2024, processed through Google Earth Engine (GEE). LULC classification was performed using GEE scripts, categorizing land into four classes: water, cropland, barren land, and built-up areas. The results show a significant increase in built-up areas from 8,118.59 sq km in 2014 to 54,638.60 sq km in 2024, while water bodies decreased from 2,302.50 sq km to 1,981.08 sq km during the same period. Cropland increased by 38,857.73 sq km, suggesting a trend of agricultural intensification, while barren land decreased by 85,056.31 sq km. The study also predicts LULC changes for the future decade from 2024 to 2034, revealing a significant reduction in water resources due to urbanization and an increase in built-up areas. The predicted GEE map shows a gradual decrease in cropland area, a steady decline in water area, a steady increase in buildup area, and a notable increase in barren land area. The accuracy of LULC prediction using GEE increased significantly, from 93.4% in 2014 to 99.945% by 2034. The findings suggest a trend of urbanization and agricultural intensification in the region, with barren lands being converted into agricultural areas and built-up areas. The study highlights the need for future landscape development with significant planning and resource management to address the potential water crisis in Jaipur City in India.

Keywords: Land use and land cover (LULC), Google Earth Engine (GEE), Landsat 8 OLI/TIRS, Built-up areas, Cropland, Barren, Water bodies cover

1. Introduction

Google Earth Engine (GEE) has emerged as a useful tool for mapping land cover and detecting changes in India. Several researchers have used GEE cloud-based infrastructure and huge satellite image collections to investigate trends in land use and land cover (LULC) across urban expansion in Rajasthan state of Indian areas. Recent research has indicated significant regional variations in LULC modifications, such as a decrease in agricultural regions in Gujarat State and an increase in water-covered surfaces in Jaipur City. GEE's

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precision in dealing with large-scale satellite data and effective monitoring of urban expansion are vital for sustainable urban development and resource management. The integration of GEE and machine learning (ML) approaches has enhanced its ability to detect small LULC changes over time. This advanced approach allows researchers to identify developing trends and patterns in land-use dynamics, providing useful information to decision makers and urban planners. Furthermore, GEE's cloud-based platform encourages collaborative research projects by facilitating data and methodology exchanges between scientists and institutions in India and throughout the world. The change of geographical features in every location is a continual process. Monitoring these changes is critical for efficient resource allocation. Urban areas, agricultural grounds, water bodies, and desolate territory have all changed as a result of increased human activity in certain locales. Jaipur was selected as the study region because of its fast rising population, which has led to increased urbanization from 2014 to 2034. This study investigates land use and land cover (LULC) changes in Jaipur City, Rajasthan. Landsat 8 OLI/TIRS sensor data from 2014 and 2024 were processed using Google Earth Engine. The LULC classification categorized land into water, cropland, barren land, and built-up areas. This paper is aims to investigate and predict the LULC changes using the GEE tool for the Jaipur City in Rajasthan, located at 26° 54' 27.0864" N and 75° 44' 22.7004" E, as the study area.

The research used data from Landsat 8 OLI/TIRS sensors and GEE Engine to extract land surface temperature and define the region of interest. The LULC studies in Jaipur city used data from Landsat Collection 2 Level-2 sensors from 2024 and 2014 is proposed in this paper to classify land use into four categories: water, cropland, barren land, and built-up. The accuracy of these classifications was assessed using a confusion matrix built into GEE.

It has been observed that significant infrastructure development and civilization growth takes place in the city localities and it has become and metropolitan in last decades. This urban growth has resulted in diminishing water resources and farmlands while also contributing to increased air pollution and the degradation of natural resources Anant Patel et al.[1]. Land use and land cover (LULC) maps illustrate shifting patterns in geographical areas by classifying various categories, such as urban development, agricultural fields, water resources, and uncultivated land. Google Earth Engine (GEE), a cloud-based platform, was employed to generate LULC classification maps Pande, et al [2]. Remote sensing data, particularly from the Landsat program, an ongoing initiative capturing satellite imagery of Earth, are widely used for land-cover mapping. GEE offers access to extensive datasets, machine learning algorithms for classifying areas such as forests, water bodies, urban developments, farmlands, and barren territories, and pre-processing functions applied to images prior to use Phan TN et al [3]. Land use and land cover change (LULC) signifies terrestrial modifications, primarily resulting from human impact on the environment. Tracking LULC changes is vital for geographical planning, with researchers utilizing this information to assess land transformation over time. Cloud computing is employed to integrate remote sensing and machine learning algorithms, mitigate cloud cover bias, and enhance the image processing speed Houda et al. [4]. As the population rises, the need for habitable land increases, resulting in the conversion of agricultural areas, water bodies, and

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uncultivated land into urban areas. These land types contribute to the environmental balance, but their reduction over time disrupts ecological systems Jonas et al [5]. Continuous LULC monitoring is essential to improve urban planning and environmental equilibrium. A decrease in agricultural land and water bodies can also impact the economy of specific geographic regions.

GEE's user-friendly interface and easy access of GEE (Paul et al [6]) have made it an essential resource for Indian researchers and government bodies, allowing them to perform extensive LULC studies without requiring significant computational power. The widespread availability of geospatial analysis tools has sparked an increase in research on regional and local LULC shifts, enhancing our understanding of India's varied landscapes. Moreover, combining GEE with other data types, such as socioeconomic indicators and climate information, has created new opportunities for cross-disciplinary research, enabling a more comprehensive approach for tackling complex environmental issues in India. In Gujarat, research utilizing Landsat 8 data processed through GEE revealed notable LULC changes between 2018 and 2023. Agricultural areas consistently diminished, while urban regions expanded rapidly. The total proportion of agricultural and forested land decreased slightly from 61.08% to 60.7%, whereas the water coverage increased from 4.07% to 5.13% (Jodhani et al., [7]). A separate study in Aurangabad City, India, employed a machine-learning algorithm (random forest) developed using GEE to categorize LULC. The findings showed that from 2015 to 2020, there was growth in water body area (11.24 km2), wasteland (66.30 km2), and urban area (36.70 km2), while vegetation cover declined (Pande et al., [8]). Notably, these studies reveal some inconsistencies in land cover trends across different parts of India. While Gujarat has experienced a reduction in bare land due to urbanization [7], Aurangabad has seen an increase in the wasteland area (Pande et al., 2023). This underscores the diverse and intricate nature of land cover changes across India's varied terrain. Recently GEE has demonstrated its effectiveness as a platform for examining LULC changes in India, offering high precision and efficiency in processing extensive satellite data. These investigations show the potential of this tool for monitoring urban growth, agricultural land loss, and alterations in water bodies and vegetation cover, which are vital for sustainable urban planning and resource management in India (as in Pande et al., [2] and [8]).

Therefore this study is aimed to investigate the classification and Prediction performance of LULC using the GEE engine. In the rest of this manuscript is organized as follows;

Initially need of LULC prediction is discussed in next section. Followed by the extended survey of the related literature in the section 3 including classification and change detection. The section 4 has presented the proposed LULC prediction system and GEE map gradation process. Section 5 has presented the results and outcomes of the classification and prediction for Jaipur city for last two decades. Finally, paper concluded the major findings in the section 6 including the discussion.

2. Need of LULC Investigations

This study is essential to environmental comprehension and sustainable planning. It offers foundational data on land usage and coverage, supports resource administration, tracks

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environmental shifts, and contributes to sustainable growth, urban development, disaster response, and climate change research. LULC cartography helps identify development zones, evaluate hazard susceptibility, and create risk-reduction plans. Additionally, these maps assist in identifying areas for climate change mitigation and adaptation efforts. LULC mapping is essential for conserving biodiversity as it identifies vital habitats and ecological pathways. These data will allow conservationists and decision-makers to create specific plans for safeguarding threatened species and preserving ecosystem vitality. Additionally, LULC information can be combined with other geographic data to develop comprehensive models that forecast future changes in land use and their potential effects on both the natural environment and human population.

Overall land uses along with the land cover investigation LULC is crucial for sustainable resource management, biodiversity conservation, and addressing climate change impacts. The assessment of LULC changes provides valuable insights into human-induced environmental alterations and their consequences on ecosystems and natural resources (Akodéwou et al., [9] 2020). LULC changes significantly impact various environmental factors. For instance, the conversion of natural vegetation to cultivated land in Ethiopia has led to increased soil erosion rates, altered hydrological balances, and changes in surface runoff and stream flow patterns (Negese, et al [10] 2021). Similarly, in China's Beijing-Tianjin-Hebei region, the expansion of built-up areas and decline of vegetated land resulted in a 5.1% increase in total water yield, highlighting the importance of LULC composition in water resource management (Li et al., [11], in 2018). LULC investigations are essential for informing policy decisions and guiding sustainable development strategies. The integration of multiple analysis techniques, such as intensity and trajectory analyses, provides a more comprehensive understanding of LULC changes and their underlying factors (Akodéwou et al., [9] in 2020). Additionally, the application of advanced technologies like deep learning and remote sensing has significantly enhanced the accuracy and efficiency of LULC monitoring and change detection (Rong& Fu, [12] 2023; and Thyagharajan et al [13] in 2017). These advancements enable better-informed decision-making for regional planning, environmental protection, and ecological security (Kanchan et al., [14] 2024; Yang, W. et al [15], 2021).

3. Literature Surveys

In recent time huge research have been using the GEE for the LULC investigations. The different studies have used various classifiers for improving the accuracy of prediction for their respective region of interest. Random forest (RF) classifier has emerged as a powerful and widely used tool for land use and covers classification and change detection. Multiple studies have demonstrated its effectiveness and superiority over other machine learning algorithms. RF classifiers consistently outperformed other classifiers in terms of accuracy across various studies. For instance, (Ouma et al., 2023) reported that RF achieved the highest overall average accuracy of 92.8% compared to other algorithms like SVM and MLP-ANN. Similarly, (Kasahun & Legesse, 2024) found that RF surpassed both support vector machine (SVM) and artificial neural network (ANN) with an average overall accuracy of 0.97 and kappa coefficient of 0.98. RF also exhibited better computational efficiency, with (Kasahun & Legesse, 2024) noting a processing time of just 6.33 seconds compared to 15 and

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30 seconds for SVM and ANN respectively. Interestingly, while RF generally performed well, some studies highlighted the benefits of ensemble approaches. (Ouma et al., [16], 2023) demonstrated that a post-classification multiclass fusion technique improved overall LULC classification accuracy by more than 2% compared to using RF alone. (Elmahdy & Mohamed [18], 2023) also explored an ensemble approach combining RF and SVM, achieving an F1-score of 0.99. Finally, RF has demonstrated to be a reliable and accurate classifier for LULC research in a variety of geographical locations. Its capacity to handle multidimensional data, resistance to overfitting, and computing efficiency make it ideal for large-scale LULC mapping and change detection. However, ensemble methods that combine RF with other algorithms show promise for further improving classification accuracy. Citation: et al [19] has used the LULC investigation using the SVM classifier and for LandSat 8 achieves the accuracy of 92%. Although, the accuracy of any classifier highly depends on the selection of their ROI and overall instances. Zhewen Zhao et al [20] utilized ML algorithm in GEE to generate reliable LULC maps from satellite data, with RG outperforming CART, SVM, and RF with 98.68% accuracy. Omarzade et al [21] have proposed comparison of GEE performance for SVM based classifier for Northern Iran region and have achieved the accuracy around 90-95%.The use of the RF is a strong candidate for specific used of LULC ROI investigation in GGE due to its high accuracy, computational efficiency, ability to handle complex, multi-dimensional data, resistance to overfitting, versatility across geographical contexts, ensemble potential, compatibility with GEE, and interpretability. Its accuracy rates varied from 92.8% to 97%, and it can be combined with other algorithms for improved accuracy. However, specific project requirements and ensemble methods may offer additional benefits.

A. Change detection

Some of the key approaches include remote sensing techniques that are widely used for LULC change detection, utilizing multispectral satellite imagery from sensors, such as Landsat TM, ETM+, and OLI (Aslami et al [22], 2018; Lu et al., [23] 2019). Both pixel-based and object-based classification methods are employed to create thematic maps and detect changes (Dingle Robertson et al [24], 2011). Object-based approaches have shown advantages in producing more uniform and meaningful LULC objects, although they may struggle with small, rare classes (in the [24] 2011). Advanced techniques, such as spatiotemporal data fusion (STF) methods, have been developed to overcome challenges such as cloud contamination and obtain same-season LULC maps for different years (Lu et al., 2019). Some studies have proposed robust multitemporal change detection frameworks to address issues such as scale changes, noise, and geometrical distortions when using images from different These approaches, combined with GIS techniques and multi-temporal satellite imagery, provide valuable tools for monitoring and predicting LU and changes, and sustainable land management and urban planning strategies (Song et al., [25] 2018). Interestingly, geo-statistical features extracted from bitemporal images have shown promise in eliminating the effects of forest phenology on classification results. Semivariogram parameters and indices derived from NDVI images have demonstrated high accuracy in detecting LULC changes, while disregarding and changes caused no-logical differences

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(Silveira et al., [26] 2018). In conclusion, LULC change detection methods continue to evolve, incorporating machine-learning algorithms such as Support Vector Machines [26], cellular automata-Markov models [23], and enhanced Intensity Analysis (Deng & Quan, et al [27] in 2023).

The city of Jaipur has undergone considerable transformations in its land use and land cover (LU-LC) patterns, with a marked expansion of developed areas replacing green spaces and undeveloped land. Mourya, et al. [28] (2021) has investigated the LILC detection and analysis for the Jaipur city lonely but their analysis is focused on agricultural crop-based classification. They estimated predicted land accuracy of 92.4% during 2020-2030 periods. Research conducted from 2008 to 2011 indicated a significant increase in land surface temperature (LST) across all LULC categories (Gupta et al., [29] 2020). The average temperature rise was about 2.6°C in winter and 1.47°C in summer. Notably, the proportion of impervious surface area (ISA) showed an upward trend across various LU-LC categories, indicating rapid urban expansion in Jaipur. This growth of built-up areas has significantly influenced LST variations (Gupta et al., 2020). The research also examined seasonal differences in LST across different LU-LC types, shedding light on the urban heat island (UHI) effect in Jaipur. In summary, the rapid urbanization of Jaipur has resulted in substantial changes to LULC patterns, leading to elevated LST and potential UHI effects. These results underscore the importance of implementing sustainable urban planning approaches to reduce the negative impacts of urbanization on the local climate and environment. Additional research should examine long-term trends and investigate potential mitigation strategies to address the challenges posed by urban growth in Jaipur.

4. Proposed LULC Production System

Jaipur City is selected as the study area for this research which is in the state of Rajasthan. Situated at 26.907524 latitude and 75.739639 longitudes, Jaipur's GPS coordinates are 26° 54' 27.0864" N and 75° 44' 22.7004" E. Several cities in Rajasthan, including Alwar, Kota, Ajmer, Pushkar, and Bhagalpur, as well as Matura and Agra in Uttar Pradesh, are in close proximity to Jaipur. Jaipur is approximately 270 km from New Delhi, India's capital. The location of Jaipur in India is illustrated in Figure 1. The first map is then further used to extract the local region of interest which is Jaipur city in study as illustrated in the Figure 2. The research utilized data from Landsat 8 OLI/TIRS sensors that underwent atmospheric correction. The land surface temperature was extracted from these sensors. To define the region of interest (ROI), The following Google Earth Engine (GEE) snippet was employed to define the region of interest:

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Figure 1The GEE Indian Map locating Jaipur District extracted via ee.ImageCollection("LANDSAT/LC08/C02/T1_L2")

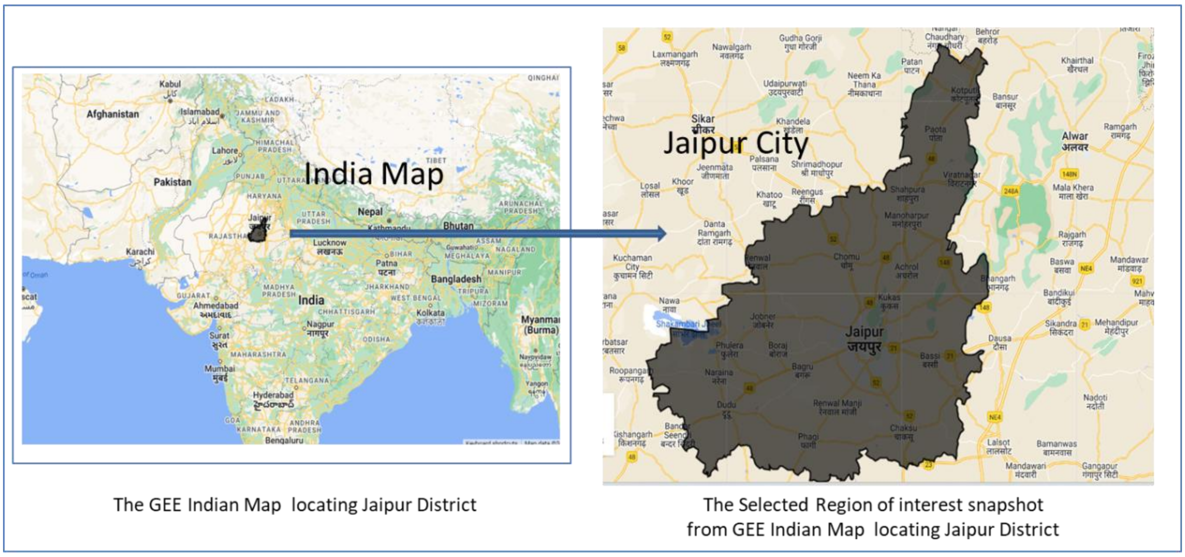

Figure 2 GEE extracted local region of interest (ROI) which is Jaipur city under study

4.1 LULC Proposed Methodology

The Land Use and Land Cover (LULC) studies made use of data from Landsat Collection 2 Level-2 sensor of year 2024 and 2014 of Jaipur city. For study the change take four classes' water, cropland, barren land and buildup. By the use of GEE scripts the LULC was classified. To study the change in the classes perform the following:

a) Image selection

b) Make the classes and training samples.

c) Perform classification by running the classifier.

Accuracy Assessment:

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The authenticity of both LULC classification maps was denoted by the use of confusion matrix that was built into GEE. The confusion matrix calculates the accuracy of classification. The accuracy is calculated by the total of correct classifications divided by the total number of classifications. The classification of 2014 and 2024 for the four classes (water, buildup, barren land and cropland) is produced.

Change detection

A change area for four classes was calculated from initial year 2014 and final year 2024. The flow of computing the change is shown in the following flow chart (Figure 3).

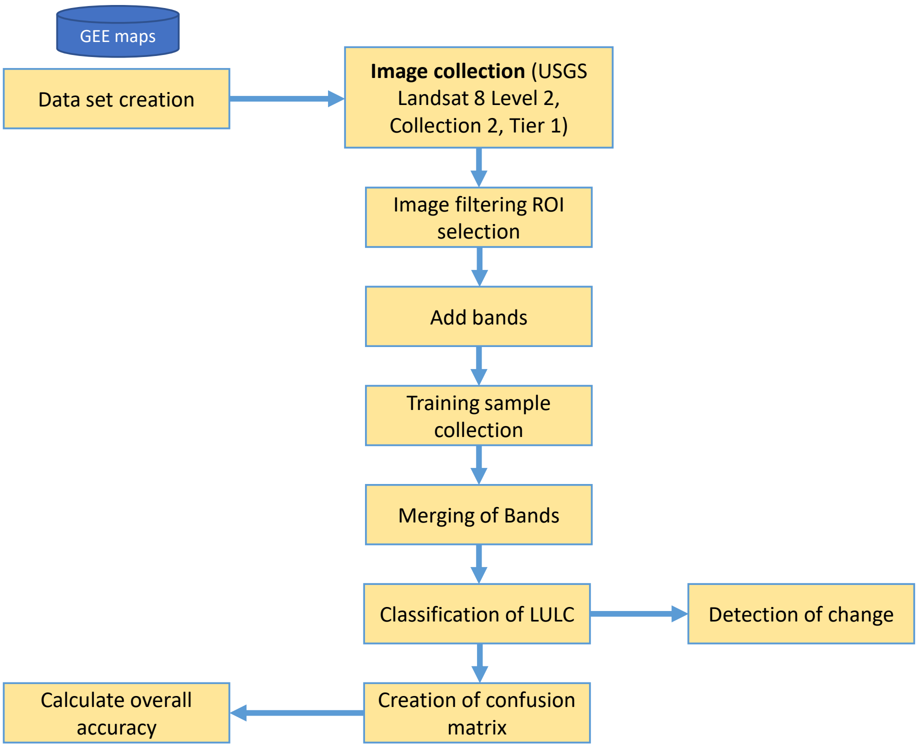

Figure 3: Methodology LULC prediction flow chart using GEE

5. Results and Discussion

This study have contributed in two pass, first pass have investigated the LULC classification using GEE for the Jaipur city map from 2014 to 2024. The second parts of the study have presented the prediction results for the precise change estimate for futuristic decade from 2024 to 2034. Prediction ultimately aims to early warn the administration to well plan for future.

5.1 Dataset and Study Area Description

Study employed Landsat Collection 2 dataset, which contains global Level-2 science products for surface reflectance and temperature, derived from individual scene analysis available at https://www.usgs.gov/landsat-missions/landsat-collection-2-level-2-science-products.The study area is capital of Rajasthan, the biggest land-based state in India, is Jaipur, which is often referred to as the "pink city." It is renowned for its extensive history and is one of the ten largest metropolitan areas in the nation. An important milestone was

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reached on June 6, 2019, when Jaipur was certified as a World Heritage Site by the UNESCO World Heritage Committee. This honor was given to Jaipur along with six other cultural sites that were concurrently inscribed to UNESCO's World Heritage List

5.2 LULC Classification

The Figure 4 representing the 2014 land use and land cover (LULC) map of the Jaipur region, categorized into built up, water, cropland, and barren land. It includes names of towns, cities, and color codes for built up areas, water, cropland, and barren land. The dominant land cover is bare land, suggesting arid conditions. The map is likely used for environmental planning, land management, or studying land use patterns over time. The GGE proportional input goggle Map of a LULC for 2024 in the Jaipur area is displayed in Figure 5. Essential components include a key showing land cover categories, geographic positions, and color-coded representations. The projection suggests dry or semi-dry conditions, with densely populated areas clustered around urban hubs. Additionally, the map illustrates visible farmland and water features, emphasizing the region's agricultural and hydrological resources.

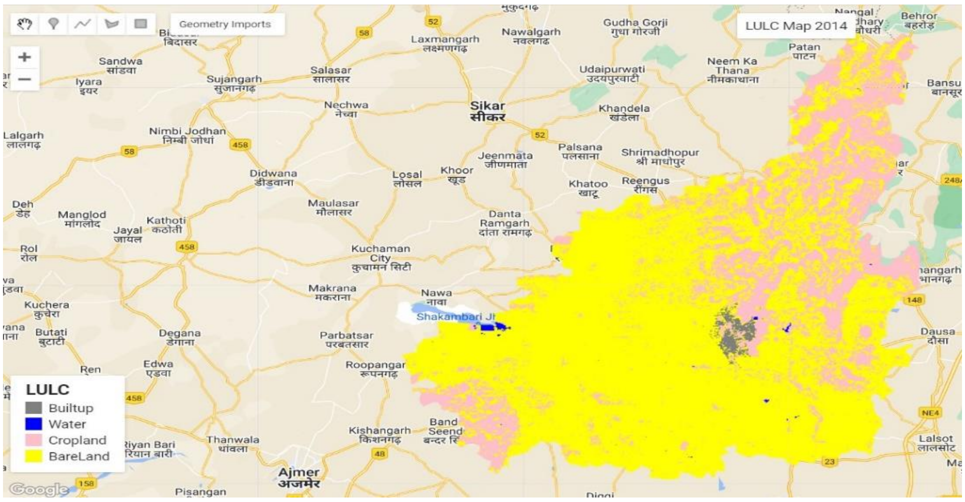

Figure 4: LULC land map for the 2014 for the Jaipur region-

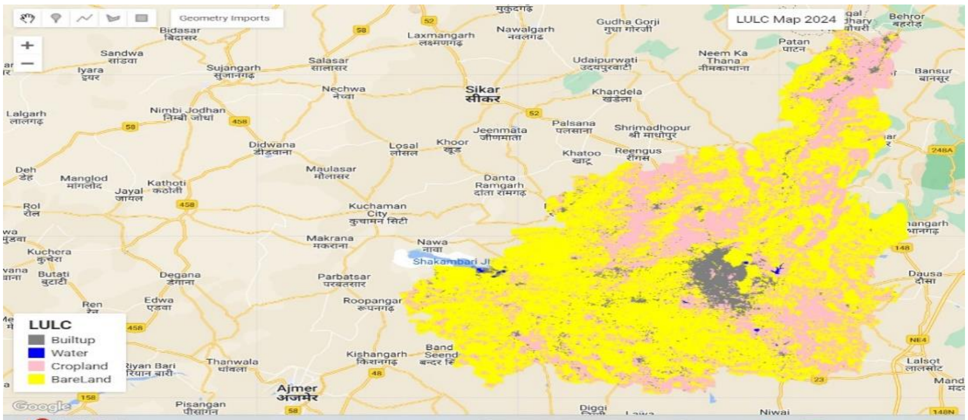

Figure 5: LULC land map after 10 years for 2024 for the Jaipur region

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The LULC classification is done for year 2014 and 2024 for classes' water, cropland, and barren and built up. In this classification we found that built up is very much increased from 2014 to 2024 and already there is very less area of water class in 2014 and it more decreased in 2024. Crop land is increased from 2014 to 2024 and barren land is decreased in already stated years. Figure 4 and Figure 5 is denoting the classification map of 2014 and 2024 for all four classes.

The change determined and the results of prediction are presented in Figure 6, respectively, to the input maps in Figure 4 and Figure 5. Land use and land cover (LULC) changes between 2014 and 2024 showed a significant increase in built-up areas, increased agricultural intensification, and the conversion of barren land to cropland and built-up areas is predicted. The central region shows a concentration of built-up areas, whereas the region around Sikar is dominated by cropland. Barren land constitutes a significant portion of the remaining area, especially north of Sikar. The analysis suggests a trend of urbanization and agricultural intensification in the region, with barren lands being converted into agricultural areas and built-up areas. Overall it can be observed that proposed approach using GEE is capable of successfully predicting the LULC changes.

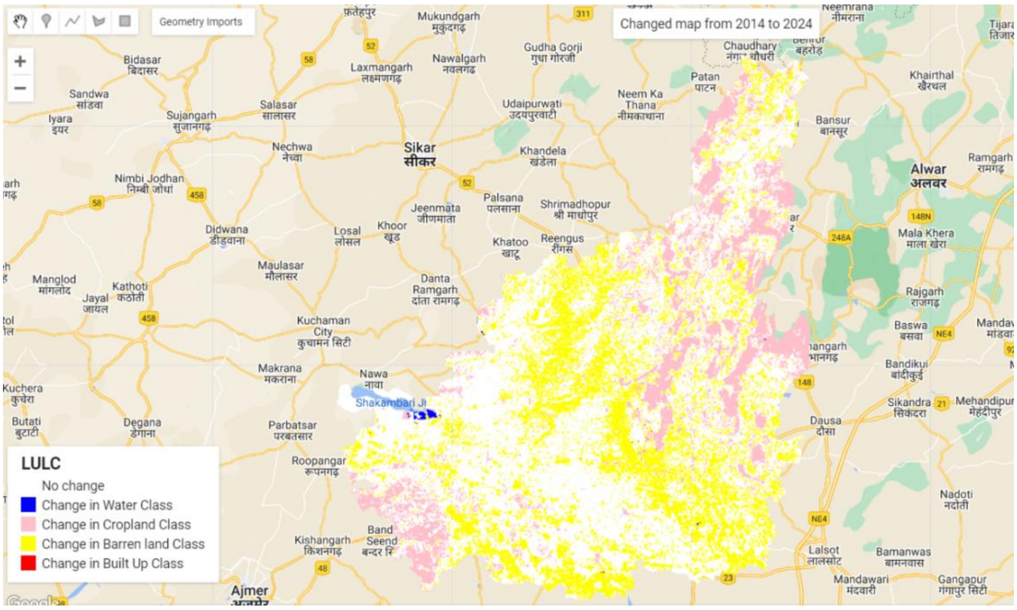

Figure 6: Changed map of all classes from 2014 and 2024.

From the comparison of the Figure 5 and Figure 6 it can be clearly observed that due to the rapid growth of urbanization and civilization in the city the water availability is significantly reduced. And the Barren land is also gravelly occupied during the decade from, 2014-2024. This imposes the grate significant challenge for futuristic land planning. This statement is justified based on the statistical performance comparison based on area utilization.

Table 2 Performance evaluation of the Classification Accuracy Assessment

Property	Water	Cropland	Barren land	Buildup

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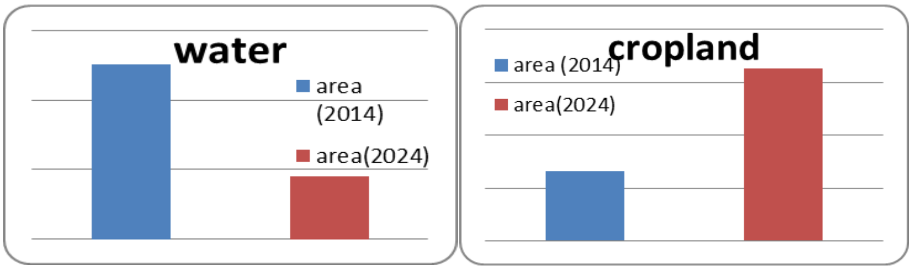
Area (sqkm)(2014)	2,302.50	3,26,382.49	7,87,633.11	8,118.59
Area (sqkm)(2024)	1,981.08	3,65,240.22	7,02,576.80	54,638.60
Percentage changes	- 13.9596	+11.9055	-10.7989	673

Table 2 lists the results of the Classification Accuracy Assessment. This table illustrates a comparative analysis of various land-use categories (Water, Cropland, Barren land, and buildup) between 2014 and 2024, with areas measured in square kilometers. The table provides a side-by-side comparison of land use classifications for 2014 and 2024. Analysis of the data revealed a reduction in the areas occupied by water bodies and barren land, whereas cropland and built-up regions expanded. These changes may be attributed to factors such as urban development, agricultural growth, or shifts in environmental conditions. Table 2 is showing the area of different classes in 2014 and 2024, the water class is decreased in 2024 up to 321.42 sqkm, cropland is increased by the 38,857.73 sqkm, and barren land is decreased by 85,056.31 sqkm. There is very much increment of build-up in 2024 which is up to 46,520.01 sqm.

The further celearity of class wise change detection is justified using the bar graphs in Figure 7 over the four different classe or features. It is clearly observed from the Figure that the 13.9596 % water resource reduction is observed in last one decade. This signifies the grater water crises in Jaipur city and localities in coming future. The agricultural land uses have significantly increases by 11.9055 %. This is also required to predict the continuous land change prediction for next decade in advance for efficient planning



a) Water class from 2014 to 2024 b) Cropland class from 2014 to 2024

a) Barrenlad in 2014 to 2024 b) Buildup in 2014 to 2024

Figure 7 Graphical representation of the land area cover detection in Sq Kms for four classes of data

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The Beren land has been reduced by 10.7989 % t is because there is significant builtup

For accuracy assesment we compute a confusion matrix for 2014 and 2024 and calculate the accuracy.

Actual Classes

		0	1	2	3
Pridicted Classes	0	29	0	0	0
	1	0	26	0	0
	2	0	1	82	2
	3	0	0	10	47

Figure 8 confusion matricx for the data calsssifcation of GEE map 2014

0-Water class, 1-Cropland class, 2-Barrenland, 3-Buildup

An analysis of the confusion matrix using the RF classifer provided, the perfromance is evaluated based on the accuracy, precision, and recall for each class. The classification accuracy for four different classes are quanttitatlvlly evaluated based on the Accuracy, Precision and Recall parameters defied as follows;

$$Accuracy = Auc = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} * 100 \quad (1)$$

$$Precision = Pres = \frac{Tp}{Tp + Fp} * 100 \quad (2)$$

$$Recall = Sensitivity = Se = \frac{Tp}{Tp + Fn} * 100 \quad (3)$$

Where,

Tp is an acronym for accurately predicted events for every class.
Tn stands for inaccurately predicted events for every class.
Fp is instances that were intended to belong to one class but ended up in another.

Fn Instances that are projected to be in a different class but actually belong to another.

Based on the confusion matrix we do caclulate the Fp, Fn as

$$Fp = \sum_{Col=1}^{n} \text{Coloumn value} - Tp\ col \quad (4)$$

$$Fn = \sum_{Row=1}^{m} \text{Row value} - Tp\ row \quad (5)$$

Recall and Precision are very essential parameters whenever multiclass classification problem is solved. As the represeted the instances pridicteed class vise.

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Table 4 Class vise True Positives and Negatives assessment for 2014 map

Class Parameter	Class 0 -Water	Class, 1 -Cropland	Class, 2 -Barrenland	Class 3 -Buildup
Tp	29	26	82	47
Tn	0	0	1	0
Fp	0	1	10	2
Fn	0	0	2	10

Table 4 Class vise performance evaluation of the % parametric assessment for 2014

Class Parameter	Class 0 -Water	Class, 1 -Cropland	Class, 2 -Barrenland	Class 3 -Buildup
Precision	100	96	89	96
Recall	100	100	97	82

The results of the extrected confusion matrix (CFM) highlights the importance of looking at precision and recall for each class individually, rather than relying solely on overall accuracy, it gives insights into the model's strengths and weaknesses in classifying each land cover type. It is clearly noted that Random Forest (RF) classifiers demonstrate high performance, achieving an accuracy of 0.93 for the 2014 data map. The model exhibits notable precision and recall for Water and Cropland categories. However, it struggles with Barrenland classification, missing some instances and showing lower recall, which suggests misclassification issues for this particular class.

Actual Classes

		0	1	2	3
Pridicted Classes	0	38	0	0	0
	1	2	71	0	0
	2	0	3	156	13
	3	0	4	19	111

Figure 9 confusion matricx for the data calsssifcation of GEE map 2024

0-Water class, 1-Cropland class, 2-Barrenland, 3-Buildup

The confusion matrix is a ML tool used to evaluate the performance of a classification model. The proposed classification model classifies different land cover types into three categories:

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Water with 38 instances, 173 Cropland, 172 Barrenland, and total 134 instances of Buildup. The matrix interprets each row as the actual class and each column as the predicted class. The most significant confusion is between "Barrenland" and "Buildup." The confusion matrix helps identify strengths and weaknesses of the classification model, guiding future improvements.

The analysis in the Figure 9 of confusion matrix of 2014 represented the accuracy and precision of a classification model based on a confusion matrix shows that the model has an overall accuracy of approximately 72.7%. The total samples for each class are 517, and the total number of true positives (TP) is 38. The overall accuracy is 376/517, or 0.727. The precision for each class is 95% for water, 91% for crops, 89% for barrenland, and 89% for building. A higher precision indicates fewer false positives, and it is important to calculate true positives, false positives, true negatives, and false negatives for a better understanding of the matrix.

The accuracy of land use/land cover (LULC) classification for 2024 is presented in Table 5, categorized by four classes. These classes nclude water, cropland, barren land, and buildup, with the table displaying accuracy, precision, and recall for each. The classification demonstrates high accuracy across all land use types. Water classification achieves flawless recall (100%) and near-perfect precision (95%). Cropland exhibits exceptional accuracy (94.7%), with high precision (91%) and recall (97%). Barren land also shows strong performance, with 92% precision and 98% recall. Buildup has a slightly lower accuracy (85%), although its high recall (96%) indicates that most buildup areas are correctly identified. To summarize, the LULC classification model performs effectively, with the only notable weakness being a somewhat lower precision for the Buildup class. The consistently high recall values demonstrate that the model successfully identifies most instances of each land cover type.

Table 5 Class vise LULC classifacction accuracy for the year 2024 map

Class	**Accuracy**	**Precision**	**Recall**
Class 0 - Water	94.7%	95%	100%
Class 1 - Cropland		91%	97%
Class 2 – Barren land		92%	98%
Class 3 - Buildup		85%	96%

In order to test the accuracy of method the results are also pridicted for the next futureistic decade too.

5.3 LULC Prediction Results

This section has contributed to predicting LULC charges for the future decade from 2024 to 2034 in advance. The data from Landsat 8 OLI/TIRS [30], sensors and GEE Engine is captured and desired ROI as selected are illustrated. The results of the predicted GEE map for 2034 is shown in Figure 10. A significant reduction in water resources is observed in Figure

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10, which is a warning to plan the rate of urbanization across the city. This is due to the exponentially increasing rate of built-up areas across the city. In order to investigate the prediction for next 10 years slightly higher boundaries of the Jaipur city are considered expecting the more expansion of city lad area. This may leads to more number of instances.

The confusion matrix for prediction model is given in the Figure 11 and exceptionally high accuracy and class-wise precision and recall are observed. The confusion matrix have presented the slight imperfections are likely due to a very small number of misclassifications. The results suggest a very effective classification model. Overall accuracy represents the proportion of correctly classified instances across all four classes Based on the confusion matrix the precision and recall of each class are calculated and presented as quantitative comparison in Table 6.

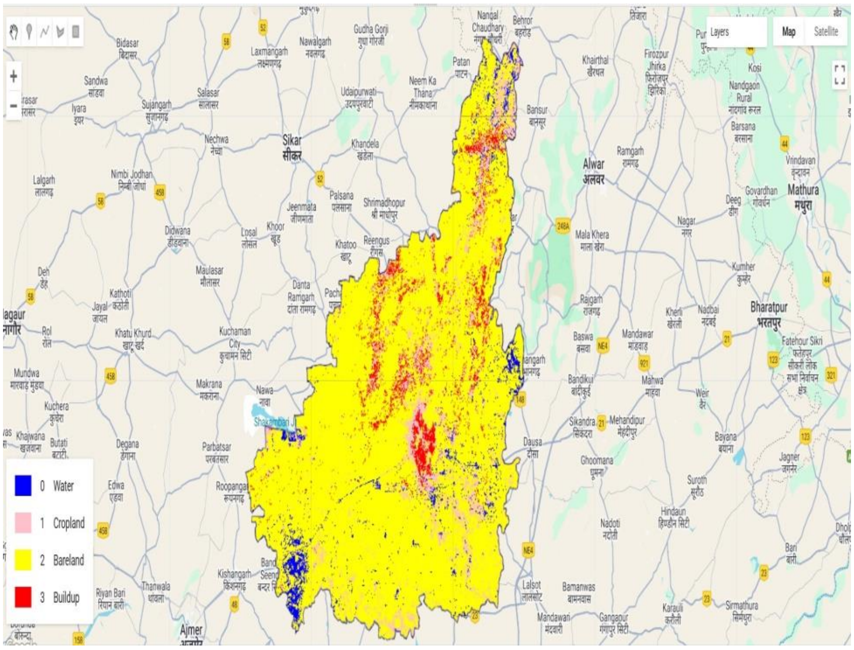

Figure 10 Pridicted GEE Changed map of all classes from 2024 and 2034

Actual Classes

Pridicted Classes	0	1	2	3
0	1329	0	0	0
1	0	2348	0	1
2	1	0	2437	0
3	2	0	1	2365

Figure 11 confusion matricx for the data pridiction using GEE map 2034

0-Water class, 1-Cropland class, 2-Barrenland, 3-Buildup

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Table 6 Class vise LULC classifacction quantitative perfromance for 2034 prediction

Class	**Precision**	**Recall**
Class 0 - Water	99.7%	100%
Class 1 - Cropland	99.96%	99.87%
Class 2 – Barrenland	100%	99.96%
Class 3 - Buildup	99.96%	99.92%

To justify the above results the class vise prediction results are in the Figure 12 for predicted changes in LULC from 2014 to 2034. Trends include a gradual decrease in cropland area, a steady decline in water area, a steady increase in buildup area, and a notable increase in Barrenland area.

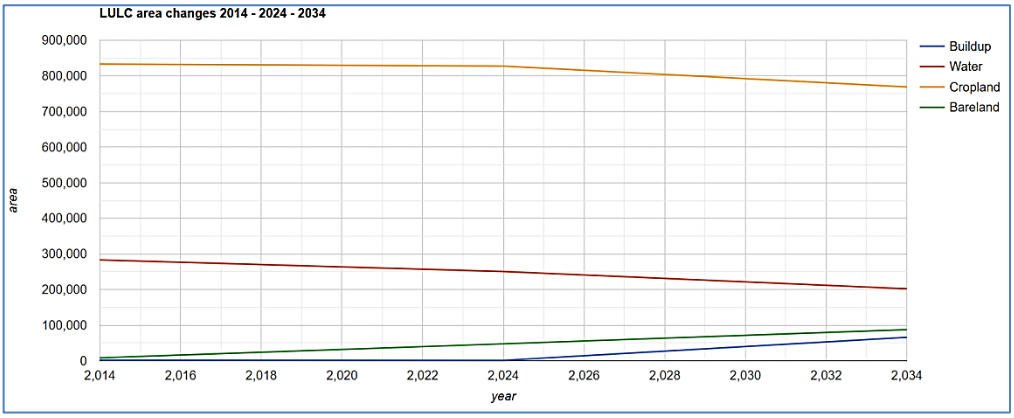

Figure 12 results of the GGE based predicted LULC changes from duration of 2014 tto 2034

Table 7 Comparison of prediction Accuracy and Buildup area for last three decades using GEE

Class Parameters	Year 2014 Map	Year 2024 Map	Year 2034 Map
Accuracy	93.4%	94.7%	99.945%
Builtup Area (sqkm)	8,118.59	54,638.60	102204.6304

Table 7 compares the accuracy of Land Use/Land Cover (LULC) prediction using Google Earth Engine over three decades: 2014, 2024, and 2034. The accuracy increased significantly, from 93.4% in 2014 to 99.945% by 2034. The built-up area also increased significantly, reaching 102,204.6304 sq.km in 2034. The data shows a strong positive correlation between time and accuracy since there is significant increase in built-up area, suggesting potential urbanization or land development trends. The growth in 2024-2034 is especially notable,

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showing approximately a doubling of the built-up area compared to just 2024.Table 6 Accuracy comparison for the three decades for LULC prediction using GEE

6. Conclusions and Future Scopes

This study investigates land use and land cover (LULC) changes in Jaipur City, Rajasthan, using Landsat 8 OLI/TIRS sensor data from 2014 and 2024, processed through Google Earth Engine (GEE). LULC classification was performed using GEE scripts, categorizing land into four classes: water, cropland, barren land, and built-up areas. It is concluded that Built-up areas increased significantly, while water bodies and barren land decreased from 2014 to 2024.The results show a significant increase in built-up areas from 8,118.59 sq km in 2014 to 54,638.60 sq km in 2024, while water bodies decreased from 2,302.50 sq km to 1,981.08 sq km during the same period. Cropland increased by 38,857.73 sq km, suggesting a trend of agricultural intensification. Also it is observed that the barren land decreased by 85,056.31 sq km.

The study predicts Land Use/Land Cover (LULC) charges for the future decade from 2024 to 2034, revealing a significant reduction in water resources due to urbanization and an increase in built-up areas. The predicted GEE map shows a gradual decrease in cropland area, a steady decline in water area, a steady increase in buildup area, and a notable increase in barrelland area. The accuracy of LULC prediction using Google Earth Engine increased significantly, from 93.4% in 2014 to 99.945% by 2034. The growth in 2024-2034 is particularly notable, with approximately a doubling of built-up area compared to 2024.

The findings suggest a trend of urbanization and agricultural intensification in the region, with barren lands being converted into agricultural areas and built-up areas.Change detection denote the modifications that are occur in different classes (water, cropland, barreland and buildup) from 2014 to 2024 we already discussed that there is increment and decrement in area of these classes. So that we are showing that there is very much increment in buildup class from 2014 to 2024 so according to this, builtup will increased in next years also. Water class area is decreased regularly and water class is converted in other class mainly in builtups. So in future it will be water crisis the Jaipur city. Thus it is propsoed to decelop the future kans scape with significant planning and resorice management. In future other agricultural class can be classifed including crop and farma land uses. Also other classifers perfromance can be compared for same ROI to.

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