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Spatio-Temporal Prediction of Urban Expansion Using Sentinel Data and ML-Model

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ABSTRACT

Rapid urbanization has significantly transformed Land Use and Land Cover (LULC) patterns worldwide, highlighting the necessity for continuous monitoring and prediction of urban growth to facilitate sustainable urban planning. This study proposes a spatio-temporal framework to analyze urban expansion in Tirunelveli, Tamil Nadu, India, through the integration of Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 optical satellite data using a Random Forest machine learning classifier. Spectral indices derived from optical imagery were integrated with SAR backscatter features to generate LULC maps for multiple temporal periods, enabling a comprehensive assessment of land-cover dynamics. The accuracy of the classified maps was evaluated through standard accuracy assessment techniques, confirming the reliability of the proposed framework. Post-classification change detection analysis revealed a consistent expansion of built-up areas over the study period, along with changes in vegetation, barren land, and other land-cover classes. Furthermore, based on the observed urban growth trends, future urban expansion was projected to support long-term urban planning. The findings demonstrate that the synergistic use of optical and radar remote sensing data coupled with machine learning provides an effective approach for monitoring urban dynamics and offers valuable insights for sustainable land-use planning and urban development strategies.

Keywords: Urban Growth, LULC, Sentinel-1, Sentinel-2, Random Forest, Remote Sensing, Change Detection, Tirunelveli.

1. INTRODUCTION

Land Use and Land Cover (LULC) changes significantly influence environmental conditions and sustainable development. Rapid population growth and developmental expansion continuously modify the Earth's surface, making it essential to monitor these changes for effective land resource management. Traditional land surveying methods are time-consuming and costly. Remote sensing offers an efficient alternative, enabling large-scale monitoring through satellite observations, while Google Earth Engine (GEE), a cloud-based geospatial platform, provides access to extensive satellite datasets and computational power for rapid analysis without requiring advanced infrastructure.

This study, part of the Spatio-Temporal Prediction of Urban Expansion Using Sentinel Data and ML Model project, analyzes LULC changes in Tirunelveli City using multi-temporal satellite data. It integrates Sentinel-1 SAR and Sentinel-2 multispectral imagery - Sentinel-2 identifies vegetation, built-up surfaces, and barren land, while Sentinel-1's radar data remains unaffected by cloud cover, together improving classification performance. A Random Forest classifier, chosen for its accuracy and reliability with multi-dimensional satellite data, is used for supervised classification into three classes - Vegetation, Barren Land, and Built-up Area - across 2016, 2019, 2022, and 2026, enabling calculation of temporal area variation. The resulting LULC maps and analysis support environmental monitoring, urban planning, and sustainable land management, demonstrating the effectiveness of integrating remote sensing, GIS, GEE, and machine learning.

2. METHODOLOGY

The proposed workflow includes satellite data acquisition, preprocessing, feature extraction, training sample preparation, Random Forest classification, accuracy assessment, change detection analysis, and urban growth prediction. The entire workflow was implemented on the Google Earth Engine [6] (GEE) cloud platform.

i) Study Area

The study focuses on the Tirunelveli region in Tamil Nadu, India. It is a prominent administrative and urban centre characterized by a heterogeneous landscape comprising built-up areas, vegetation, and barren land. The official administrative boundary shapefile of Tirunelveli was used to define the Region of Interest (ROI) and to clip all satellite datasets.

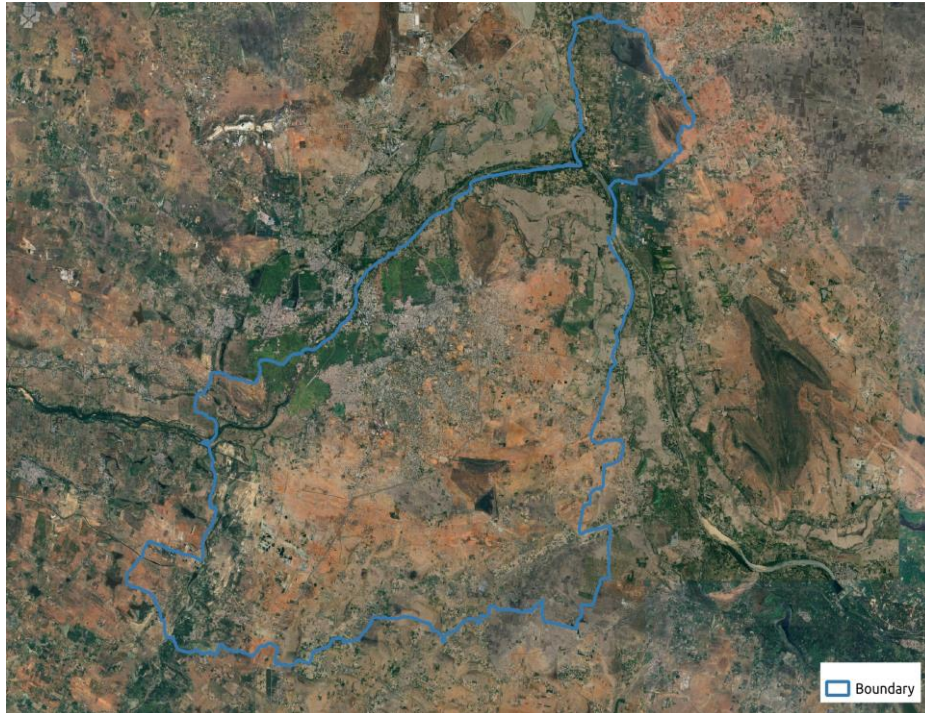


Fig.1. Tirunelveli Boundary

ii) Satellite Data Acquisition and Preprocessing

a) Sentinel-2 Optical Data:

Sentinel-2 [5] Level-2A multispectral imagery was used for optical data analysis. Six spectral bands were utilized: B2 (Blue), B3 (Green), B4 (Red), B8 (Near-Infrared), B11 (Short-Wave Infrared 1), and B12 (Short-Wave Infrared 2).

b) Sentinel-1 SAR Data:

Sentinel-1 [1] Ground Range Detected (GRD) Synthetic Aperture Radar (SAR) data was used to obtain radar backscatter information. VV and VH polarization bands were incorporated to provide complementary structural information and to reduce the limitations associated with cloud cover in optical imagery.

For each target year (2016, 2019, 2022, and 2026), the image collections were filtered according to the ROI and acquisition period. Sentinel-2 images with less than 20% cloud cover were selected, and a median composite was generated to obtain representative imagery for each study year. The resulting composites were clipped to the study-area boundary.

iii) Feature Extraction

A multi-source feature stack was constructed by integrating Sentinel-2 spectral bands, spectral indices, and Sentinel-1 SAR features.

Three spectral indices were derived from the Sentinel-2 imagery:

1. Normalized Difference Vegetation Index (NDVI):

$$NDVI = (NIR - Red) / (NIR + Red)$$

$$NDVI = (B8 - B4) / (B8 + B4)$$

2. Normalized Difference Built-up Index (NDBI):

$$NDBI = (SWIR - NIR) / (SWIR + NIR)$$

$$NDBI = (B11 - B8) / (B11 + B8)$$

3. Normalized Difference Water Index (NDWI):

$$NDWI = (Green - NIR) / (Green + NIR)$$

$$NDWI = (B3 - B8) / (B3 + B8)$$

In addition, Sentinel-1 VV and VH polarization bands and the VV/VH ratio were incorporated into the feature stack. The NDWI was included as an additional spectral feature to provide water- and moisture-sensitive information during land-cover discrimination. Therefore, the final multi-source feature stack consisted of 12 layers, including 6 Sentinel-2 spectral bands, 3 spectral indices (NDVI, NDBI, and NDWI) [10], 2 Sentinel-1 SAR bands, and 1 VV/VH ratio.

iv) Training and Validation Data

The study area was classified into three LULC classes:

- Vegetation
- Barren Land
- Built-up Area

Training polygons were manually digitized through visual interpretation of high-resolution reference imagery [8]. Balanced samples were collected for each class and randomly divided into 70% training and 30% validation datasets. The training samples were used for model development, while the independent validation samples were used to evaluate classification performance.

v) Random Forest Classification

A Random Forest (RF) classifier [4], an ensemble machine learning algorithm consisting of multiple decision trees, was employed for pixel-based LULC classification. The classifier was trained using 100 decision trees and the multi-source feature stack.

The trained model was applied to the feature composites corresponding to 2016, 2019, 2022, and 2026 to generate the respective LULC maps. Classification performance was evaluated using the independent validation dataset and a confusion matrix. Overall Accuracy and the Kappa Coefficient were calculated to assess the reliability of the classification results.

vi) Change Detection and Urban Growth Analysis

Post-classification comparison was performed to quantify LULC transitions across the study years. The analysis primarily focused on the conversion of other land-cover classes into the Built-up class. Built-up area statistics were calculated for each study year in km² and hectares.

Temporal changes were analyzed for the intervals 2016–2019, 2019–2022, and 2022–2026 to determine the pattern and rate of built-up expansion. The spatial distribution of the detected changes was also examined to identify the major directions and patterns of urban growth within the study area.

vii) 2030 Urban Expansion Prediction

Future urban expansion for the year 2030 is estimated based on the historical built-up growth trend observed between 2016 and 2026. The increase in built-up area across the different study periods was analyzed to determine the prevailing growth trend.

A linear extrapolation approach was applied to the observed historical trend to estimate the potential built-up extent for 2030. The resulting prediction provides a baseline scenario for understanding future urban expansion and can support urban planning and sustainable development strategies in the Tirunelveli region.

3. RESULTS AND DISCUSSION

The proposed methodology was applied to multi-temporal satellite data for the years 2016, 2019, 2022, and 2026. The Random Forest classifier was used to generate LULC maps containing three classes: Vegetation, Barren Land, and Built-up Area. The classified outputs were subsequently analyzed to determine the temporal variation and spatial expansion of built-up areas.

A. LULC Classification Results

The LULC classification results provide the spatial distribution of Vegetation, Barren Land, and Built-up Area for the selected study years. The comparison of the classified maps shows a gradual increase in the extent of built-up areas during the study period.

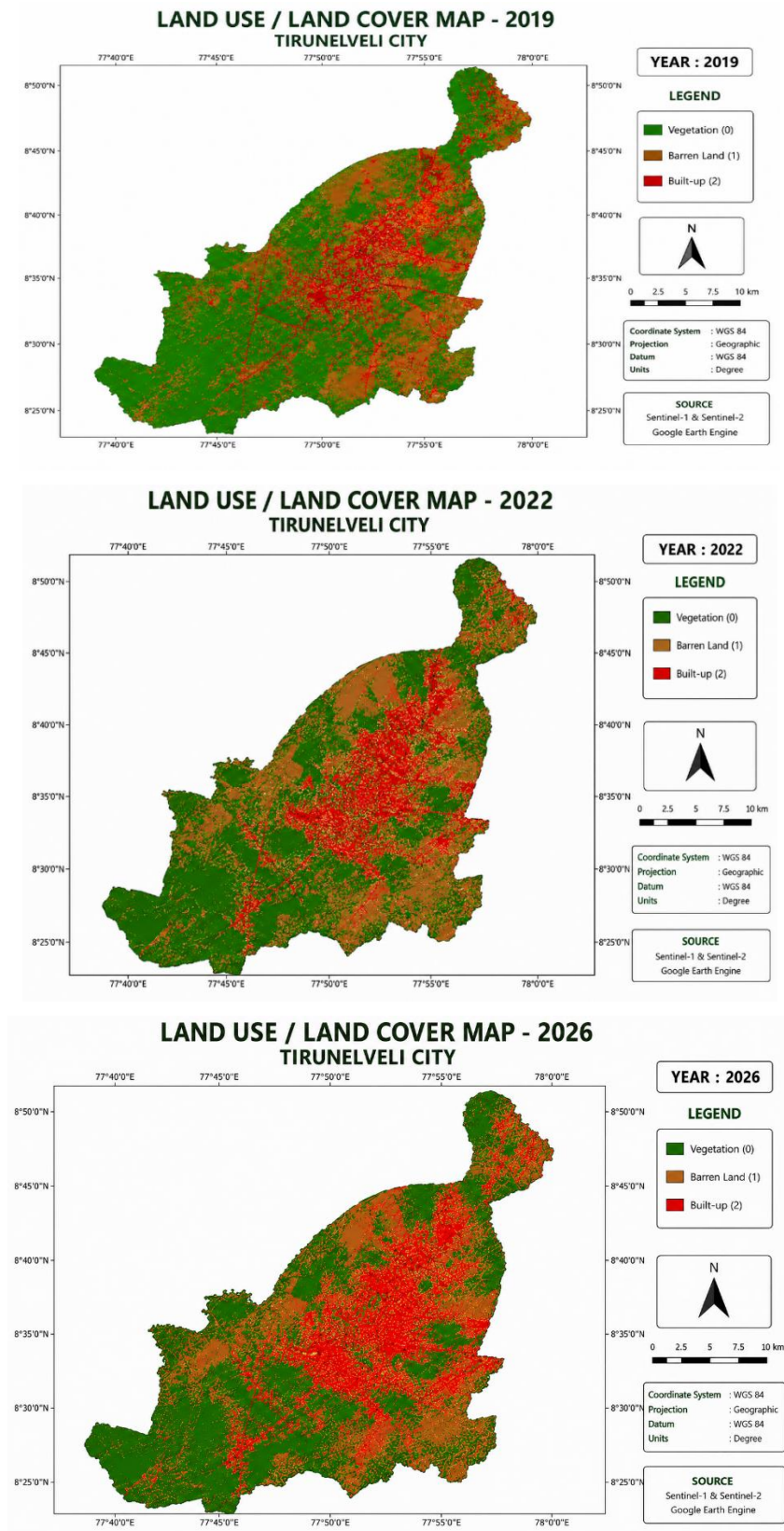


Fig. 2. Multi-temporal LULC classification maps of Tirunelveli (2016, 2019, 2022, 2026).

The multi-temporal classification demonstrates that urban development has resulted in the conversion of portions of vegetation and barren land into built-up areas. The changes observed between the different years provide the basis for further urban growth and change detection analysis.

B. Classification Accuracy

The performance of the Random Forest classifier [3] was evaluated using validation samples and a confusion matrix. The obtained overall accuracy was 94.23%, indicating that the classifier provided reliable results for the selected LULC classes.

Parameter	Result
Overall Accuracy	94.23%

Table 1: Accuracy

The accuracy result indicates that the integration of Sentinel-1 radar features, Sentinel-2 spectral information, and derived indices provided effective input features for LULC classification.

C. Built-up Area Analysis

The built-up class was extracted from the LULC maps and its area was calculated for each study year. The results are presented below.

Year	Built-up Area (km ²)
2016	70.93
2019	81.86
2022	85.40
2026	102.91

Table 2: Built-up Area

The built-up area increased from 70.93 km² in 2016 to 102.91 km² in 2026. Therefore, the total increase in built-up area during the study period was approximately 31.98 km². The growth between successive periods was 10.93 km² from 2016 to 2019, 3.54 km² from 2019 to 2022, and 17.50 km² from 2022 to 2026. These results demonstrate a clear overall increasing trend in built-up development.

D. Change Detection

Change detection was performed by comparing the classified LULC information between 2016 and 2026. The analysis identifies areas where the land-cover class changed during the study period.

The final change detection map represents the following transitions:

- No Change
- Vegetation → Built-up
- Barren Land → Built-up
- Built-up → Vegetation
- Built-up → Barren Land

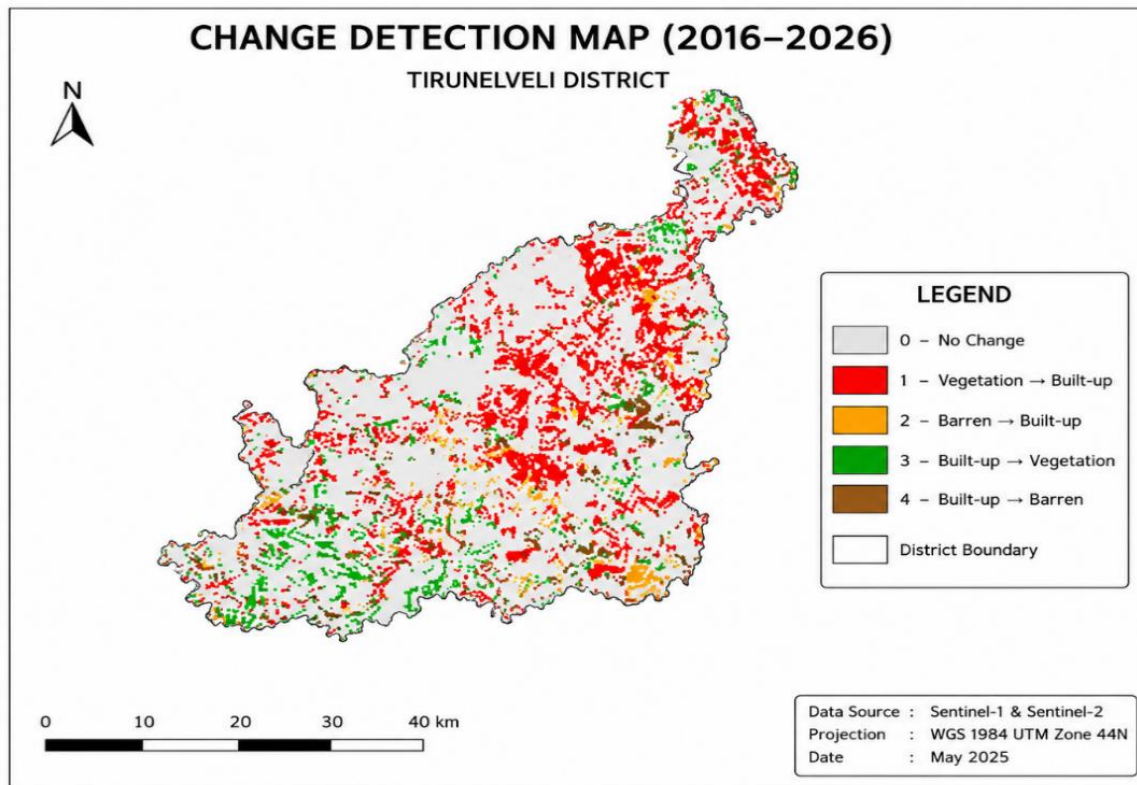


Fig. 3. LULC change detection map of Tirunelveli from 2016 to 2026.

The change detection results provide a clear spatial representation of the areas affected by land-cover transformation. In particular, the conversion of vegetation and barren land into built-up areas indicates the spatial pattern of urban expansion during the study period.

E. Urban Growth Analysis

The temporal built-up area results indicate that Tirunelveli experienced considerable urban growth between 2016 and 2026. The built-up area increased from **70.938 km² in 2016 to 102.914 km² in 2026**, resulting in an overall increase of **31.976 km²** during the study period. The built-up area increased by **10.928 km²** during 2016–2019, **3.541 km²** during 2019–2022, and **17.507 km²** during 2022–2026. Among the analyzed intervals, the highest built-up growth occurred during **2022–2026**, indicating an accelerated pattern of urban expansion during the later period.

F. 2030 Urban Expansion Prediction

future urban expansion of Tirunelveli was estimated based on the historical built-up area growth observed from 2016 to 2026. The built-up area showed a continuous increasing trend across the study periods, with the most substantial increase observed during the later period. This historical growth pattern was used to estimate the potential extent of future built-up development.

Based on the observed temporal growth trend, the built-up area of Tirunelveli is predicted to reach **133.589 km² by 2030**. The prediction indicates that urban expansion is likely to continue beyond 2026, resulting in further conversion of available non-built-up land into built-up areas.

The 2030 prediction provides a forward-looking baseline for understanding the potential spatial extent of urban growth. The predicted expansion can assist urban planners and decision-makers in identifying areas that may experience future development and in formulating sustainable land-use and urban management strategies for the Tirunelveli region.

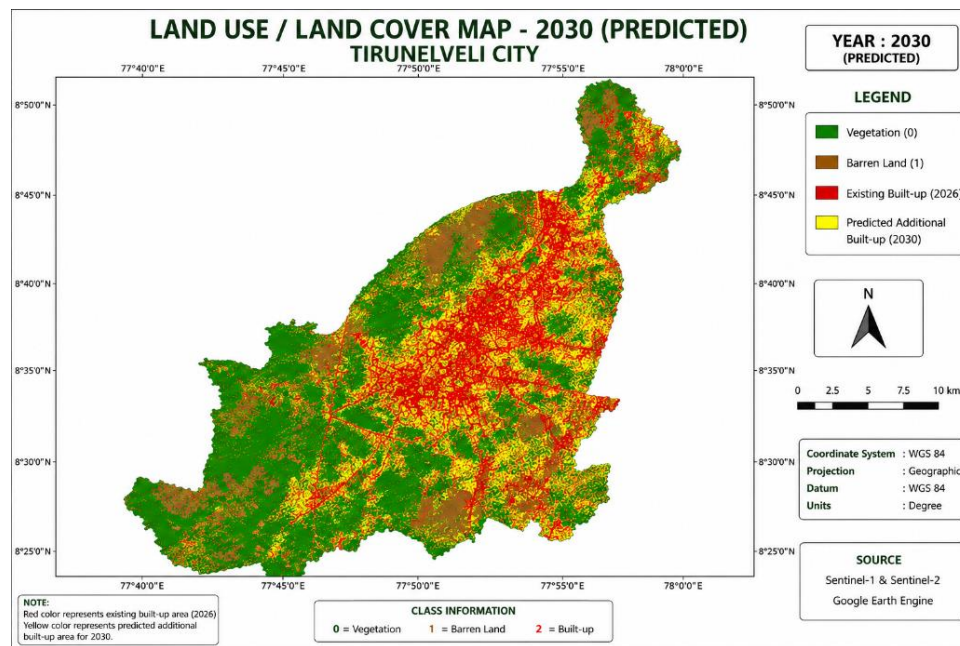


Fig. 4. 2030 Urban Expansion Prediction

4. CONCLUSION

This study presented a remote sensing[2,7] and machine learning-based framework for analyzing and predicting spatio-temporal urban expansion in Tirunelveli, Tamil Nadu, using integrated Sentinel-1 and Sentinel-2 satellite data. The built-up area increased from **70.938 km² in 2016 to 102.914 km² in 2026**, resulting in an overall increase of **31.976 km²** during the study period. The change-detection analysis revealed a continuous pattern of built-up expansion across the study area. Based on the observed historical growth trend, the built-up area is predicted to reach **133.589 km² by 2030**. The results demonstrate the usefulness of integrating optical and radar remote sensing data with machine learning for monitoring urban growth and providing a baseline for future land-use planning and sustainable urban development.

5. FUTURE ENHANCEMENTS

1. Higher-resolution satellite data can be integrated to identify finer-scale urban features and improve the precision of built-up boundary detection.
2. Advanced machine learning and deep-learning models can be incorporated to improve the accuracy of urban expansion prediction beyond the trend-based 2030 estimate.
3. Additional factors such as road networks, population growth, and infrastructure development can be integrated with the satellite-derived features to further improve prediction reliability.

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