Sentinel-2Driven Land Use Classification Using IRUNet,UNet,ResUNet for the Perungudi Region

Medhaa M
Computer Science
Vellore Institute of Technology, Chennai
Chennai, India
medhaa.m2022@vitstudent.ac.in

Janani P
Computer Science
Vellore Institute of Technology, Chennai
Chennai, India
janani.p2022@vitstudent.ac.in

***Abstract*—Accurate land use and land cover (LULC) classification is a critical baseline for management in sustainable urban planning, peri-urban monitoring, and environmental governance for urbanized landscapes that are rapidly changing. This paper proposes an integrated method to apply mapping and spatio-temporal analysis of LULC in the Perungudi area of Chennai and emphasizes temporal analysis as a way to understand urbanization and zones for amplifying urbanization. This pipeline involves a combination of manual annotation for ground truth preparation, conventional machine learning (Random Forest), and a high-performing deep ensemble framework (IRUNet - InceptionResNetV2 + UNet), engineered for addressing challenges presented by heterogenous urban landscape characteristics, seasonal change, and imbalancing classes of LULC outputs driven by atypical urbanization patterns. All spatial outputs (classified maps, statistics, and metrics) are systematically saved in a MongoDB database, which supports geo-tagged storage, and enables the extraction of data for interactive and visual FDA dashboards. The proposed workflow shows an improvement in segmentation accuracy and change-detection sensitivity compared to pixel-based protocols and provides an end-to-end approach for reproducible, scalable, and policy-relevant mapping of LULC to fast-growing peri-urban regions in India.**

***Index Terms*—Sentinel-2, Perungudi, land use classification, deep learning, IRUNet, UNet, InceptionResNetV2, MongoDB, geospatial database, feature-driven analytics, urban change detection.**

I. Introduction

The Chennai Metropolitan Region (CMR) has witnessed considerable spatial and demographic development over the last four years, affirming its position as one of the top urban growth corridors in India. Based on Census projections, the population in the metropolitan region grew from around 11.25 million in 2021 to nearly 12.29 million in 2024 (or an approximate demographic growth of around 9% over a relatively short time frame). Based on the Second Master Plan and recent land-use research by CMDA (Chennai Metropolitan Development Authority), built-up extent in southern and eastern areas, including Perungudi, Sholinganallur, and Thoraipakkam, expanded an estimated 16-18% between 2020 and 2024. Meanwhile, vegetative (i.e., trees, shrubs, etc.) and open water bodies decreased, about 8

Identify applicable funding agency here. If none, delete this.

To address these challenges, this study presents a systematic and reproducible remote-sensing workflow for multi-temporal land-use and land-cover (LULC) classification over the Perungudi region between 2020 and 2024, using Sentinel-2 multi-spectral imagery. The proposed pipeline incorporates accurately annotated ground-truth samples for training and validation, utilizes both classical (Random Forest) and deep-learning (IRUNet, an InceptionResNetV2–UNet hybrid) models for segmentation, and a MongoDB database to enable efficient, structured storage of model outputs and accompanying spatial statistics. The repository framework also supports either one-time visualizations or temporal visualizations through analytical dashboards, which provide quick and interpretable understanding of changing urban patterns based on remote-sensing data.

By integrating multi-temporal satellite observation and advanced segmentation architectures with a structured geospatial repository management framework, this study makes a contribution to the multi-scalar observation of urban land-cover transformations in Chennai that is scalable, transparent, and data-driven. The proposed way finds reliable and quantifiable information that is actionable and relevant in the context of urban policy and multi-scalar policy-based decision making in a rapidly transforming urban context.

II. Dataset and Preprocessing

A. Dataset Description

The level 2A surface reflectance dataset used in this study is taken from the Sentinel-2 Multispectral Instrument (MSI) (Copernicus Open Access Hub) and is available through Google Earth Engine (GEE). The collection ID: `COPERNICUS/S2_SR_HARMONIZED` The Sentinel-2 satellite has 13 spectral bands in the visible, near-infrared, and short-wave infrared, with a spatial resolution of 10 to 60 meters that can be used for land-use and vegetation classifications in a heterogeneous urban environment. Images were downloaded according to the 2023 time period, and were subsequently validated against manually annotated samples that were collected in 2024 to ensure that there was an adequate degree of agreement across the inter-annual time period being examined. The area of interest (AOI) was delineated as the Perungudi area of Chennai, India with geographic coordinates of (80.2305 E - 80.2605 E, 12.9605 N - 12.9805 N). The AOI is an important land transition corridor located near the Chennai IT Expressway and, as such, has ongoing vegetation to built-up cover transitions that were captured in past years.

B. Rationale for Dataset Selection

Sentinel-2 was preferred over other satellite options such as Landsat 8 or MODIS due to its improved spatial resolution (10 m) and increased revisit time frequency (5 days). These features allow for object level segmentation which is common for dense urban mapping (particularly in a heterogeneous area like Perungudi where mixed pixels are frequent and fine-scaled features, such as rainwater lagoons or close residential plots, needed to be adequately captured). To some extent, this helped as Sentinel-2 is a normalized Level-2A product, preliminary atmospheric correction has been done on copyright free bands, and each image collection has bands depicting cloud-mask quality. Observations could also demonstrate consistent radiometric and temporal characteristics across images for the multi-year study

C. Data Preprocessing in Google Earth Engine

The study utilized Sentinel-2 Multispectral Instrument (MSI) Level-2A surface reflectance collection imagery derived from the Copernicus Open Access Hub, hosted in Google Earth Engine (GEE), catalog identifier COPERNICUS/S2_SR_HARMONIZED. The Sentinel-2 data set, with 13 spectral bands in the visible, near-infrared, and short-wave infrared ranges and spatial resolutions of 10 m - 60 m, is suitable for land-use and vegetation differentiation in mixed urban landscapes. Imagery was acquired during 2023, and new in situ samples were manually labeled based on ground-truthing in the 2024 calendar year for inter-annual comparison and compatibility. The area of interest (AOI) is the Perungudi area of Chennai, India (80.2305 E - 80.2605 E, 12.9605 N - 12.9805 N), which is also notable as a land-transition corridor adjacent to the Chennai IT Expressway and ongoing change from vegetation to built-up cover to a lesser extent than prior years. A. Dataset Description The level 2A surface reflectance dataset used in this study is taken from the Sentinel-2 Multispectral Instrument (MSI) (Copernicus Open Access Hub) and is available through Google Earth Engine (GEE). The collection ID: COPERNICUS/S2_SR_HARMONIZED. The Sentinel-2 satellite has 13 spectral bands in the visible, near-infrared, and short-wave infrared, with a spatial resolution of 10 to 60 meters that can be used for land-use and vegetation classifications in a heterogeneous urban environment. Images were downloaded according to the 2023 time period, and were subsequently validated against manually annotated samples that were collected in 2024 to ensure that there was an adequate degree of agreement across the inter-annual time period being examined. The area of interest (AOI) was delineated as the Perungudi area of Chennai, India with geographic coordinates of (80.2305 E - 80.2605 E, 12.9605 N - 12.9805 N). The AOI is an important land transition corridor located near the Chennai IT Expressway and, as such, has ongoing vegetation to built-up cover transitions that were captured in past years. B. Rationale for Dataset Selection Sentinel-2 was preferred over other satellite options such as Landsat 8 or MODIS due to its improved spatial resolution (10 m) and increased revisit time frequency (5 days). These features allow for object level segmentation which is common for dense urban mapping (particularly in a heterogeneous area like Perungudi where mixed pixels are frequent and fine-scaled features, such as rainwater lagoons or close residential plots, needed to be adequately captured). To some extent, this helped as Sentinel-2 is a normalized Level-2A product, preliminary atmospheric correction has been done on copyright free bands, and each image collection has bands depicting cloud-mask quality. Observations could also demonstrate consistent radiometric and temporal characteristics across images for the multi-year study.

D. Manual Annotation and Ground-Truth Creation

Furthermore, four spatially diverse tiles measuring 256 pixels by 256 pixels (almost 2.56 km by 2.56 km each) were extracted to denote urban, water, vegetation, and wasteland land covers based on the centroid locations manually collected for the region. They were subsequently annotated using polygon digitization in GEE for the reference year of 2024, and then exported as GeoTIFFs for model training and evaluation.

Polygon digitization was conducted for the 2024 Sentinel-2 composite within GEE where the polygons were comprehensive representation of high quality reference, and classified as Urban, Vegetation, Water Body and Wasteland Land Covers, through exerting quality control of polygons with high- resolution Google Earth

[b]0.48

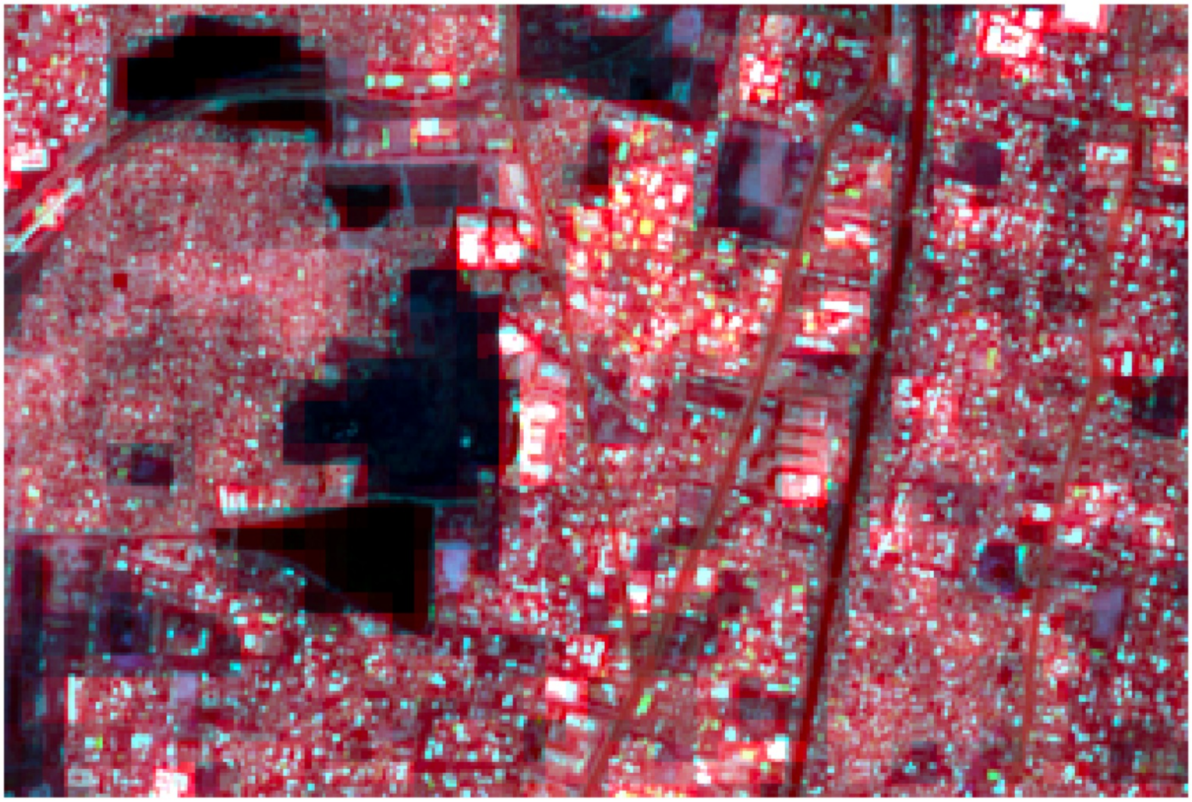


Fig. 1: Sentinel-2 composite (Perungudi, 2023).

[b]0.48

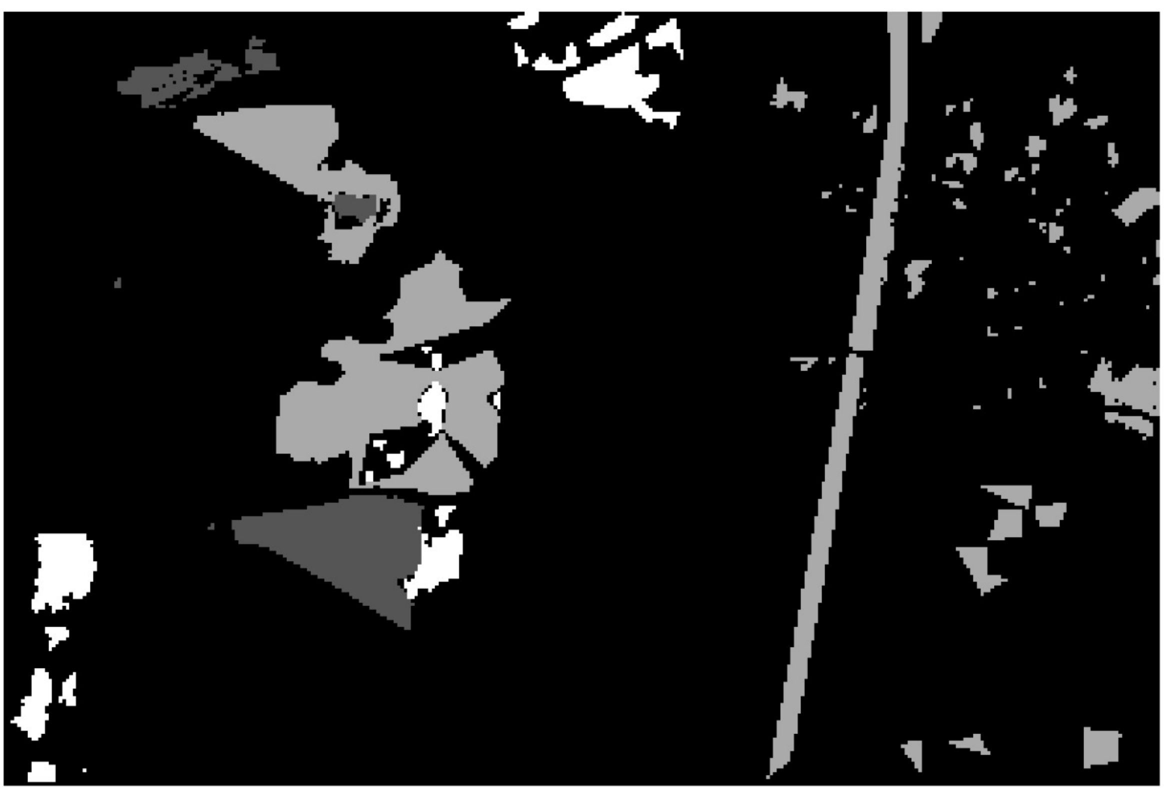
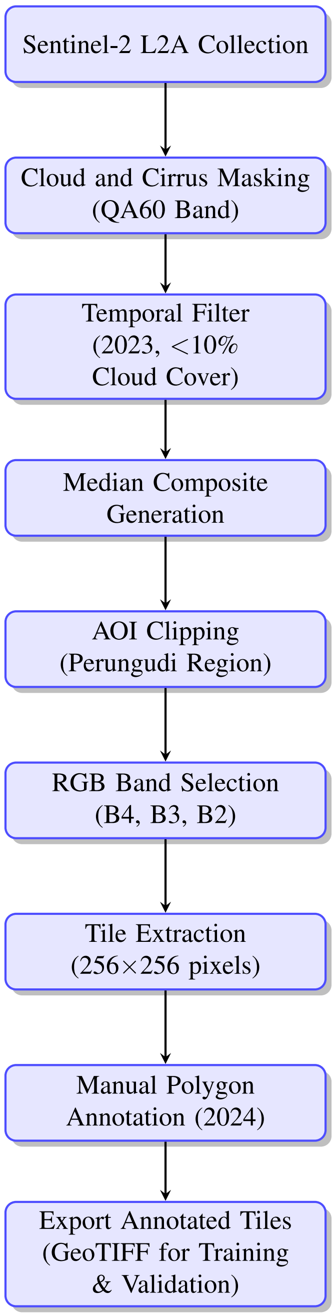


Fig. 2: Annotation mask (Perungudi, 2024).

imagery and municipal Cadastral maps. The reference dataset provides the basis for supervised training and validation for the comparative Random Forest and IRUNet-based classification models described in the following sections.

Fig. 3: Schematic overview of the GEE preprocessing workflow.



III. Literature Review

Considerable improvement of remote sensing based land use and land cover (LULC) classification has been possible because of high-resolution satellite missions such as Sentinel-2 and the use of deep learning. These technologies have allowed for more accurate and up-to-date analysis of heterogeneous landscape scales, especially in urban and peri-urban areas where smaller classification distinctions are critical for successful spatial planning and sustainable development. Ba et al. used deep learning models to model LULC dynamics over time (using multi-years of satellite imagery) and successfully modeled urban land change in different cities across Africa. They demonstrated that CNNs perform significantly better than traditional pixel-based classifiers and highlighted the importance of carefully curating training data and ensuring reproducibility for mapping over time. Guzder-Williams et al. similarly focused on demonstrating the generalizability of Sentinel-2 deep learning models used for intra-urban mapping across cities from around the globe. They showed the impact of heterogeneous urban mosaics and how open-access datasets and U-Net architectures addressed this scalability challenge. In 2025, researchers focused on high-density urban areas to develop a strong deep learning classifier using data augmentation to support improved discrimination between built-up, vegetation, and water classes in segmented Sentinel-2 imagery, with a strong focus on mitigation of shadow and mixed-pixel effects. From a data infrastructure perspective, Niua et al. investigated hybrid NoSQL approaches tailored for storage and querying of large-scale geospatial data, and concluded that distributed architectures and federated OLAP capabilities provided faster analytics for continental and global LULC products that facilitate streamlined incorporation into real-world decision-making dashboards. With regards to methodology improvements, Kumar et al. suggested a spectral unmixing and downscaling algorithm for Sentinel-2 data which is a major advancement in feature discrimination within morphologically challenging urban termination areas. Alzubaidi et al. applied transfer learning with deep CNNs on Landsat data as well, detailing that despite having a coarser spatial resolution architectural deep features pre-trained with transfer learning, have better classification accuracy for certain forestry and agricultural classes than with Landsat data by itself across different spatial and spectral characteristics - pushing forward the need for multi-sensor data fusion. Benhammou et al. contributed the ”Sentinel2GlobalLULC” dataset, which is a comprehensive and consensus-annotated benchmark dataset for global-scale geospatial analysis using deep learning frameworks. In another case, Sawant et al. also introduced a large spatial level LULC dataset for Indian conditions, underlying the specifics of dense urban-rural transition complexities while providing policy-relevant urban management applications. Karra et al. coupled

Sentinel-2 imagery with deep learning approaches, detecting types of urban deprivation and accomplishing global LULC mapping with kappa scores and accuracies exceeding 90%. Kramarczyk and Hejmanowska provided an important evaluation of U-Net models for agricultural LULC mapping using ground truthing and Sentinel-2 time series, demonstrating that high-quality temporally and spectrally composited images allows U-Net models to produce accurate and trustworthy classifications in peri- urban and agricultural landscapes. Taken together, these studies provide evidence that state-of-the-art CNN and U-Net/IRUNet architectures, high-quality datasets, scalable hybrid database systems, and robust benchmarking processes represent a solid foundation for operational LULC mapping using Sentinel-2 imagery across diverse landscapes. This foundation allows for rapid regional applications (such as the Perungudi urban analysis described here) based on development of best practices in model development, validation, and mainstream integration with geospatial information systems for improved environmental monitoring and urban planning.

IV. Digital Image Processing

The project uses advanced digital image processing of Sentinel-2 multispectral satellite images for fine land cover classification in the Perungudi region of Chennai. It utilized Sentinel-2 Level-2A surface reflectance data consisting of 13 spectral bands from visible to shortwave infrared wavelengths, owing to its fine spatial resolution (10m) and high temporal revisit frequency (5 days) which allowed for object-level segmentation necessary for capturing heterogeneity of urban environments and transitions between land cover types.

In Google Earth Engine, preprocessing steps included atmospheric correction, cloud and cirrus masking using bitwise operations of QA60 band, cloud masked image compositing across 2023 annual period to derive median composite images. The composite raster was normalized again by scaling the reflectance values across the 0 - 1 range for inputting into the downstream model. Important spectral indices; Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Normalized Difference Built-up Index (NDBI), were also calculated to improve discrimination between vegetation, water bodies, and built up features.

Ground-truth polygons were manually annotated for the primary land cover classes; water, agriculture, wasteland, urban using Google Earth Engine's polygon digitizing tools based on high-resolution Pauling and from the input cadastral maps. The annotated polygons were the basis for model building.

This digital image processing method for land cover segmentation was effective, in spite of seasonal changes and the urban environment. Visualizing the classified land use image on the internet was accompanied by exporting the normalized satellite composite image and label masks to be saved as GeoTIFF images for further off-line usage and for advanced deep learning modelling, such as IRUNet explained elsewhere in the paper. This method provides an example for a standardized approach through remote sensing pre-processing, calculation of spectral indices, and machine learning classification to provide a reliable spatial knowledge and can be applied for urban planning and environmental assessments.

V. Data Analysis

This sections highlights the exploratory data analysis (EDA) results focused on spatial structure, class distribution and geostatistical properties of labeled land use data for the Perungudi region. EDA is an important prerequisite to model development and training, and reliability of model output and interpretation relies on good EDA.

A. Vector and Raster Data Visualization

Figure 4 showcases the vector data comprising manually annotated polygons for major land use categories (Urban, Vegetation, Waterbody, Wasteland), digitized using high-resolution Google Earth Engine (GEE) overlays and Cadastral maps. This high-quality reference dataset enables robust supervised classification workflows. Figure 5 displays the corresponding raster-based Sentinel-2 image composite, evidencing spectral and spatial variability crucial for downstream segmentation. Overlaying these datasets (Figure 6) strengthens the spatial alignment and provides ground-truth validation for class boundaries.

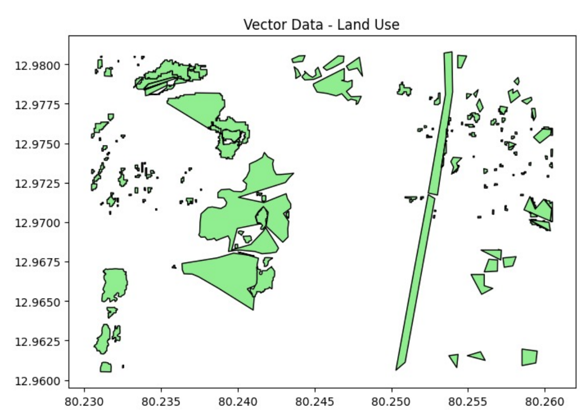


Fig. 4: Vector data of the annoated polygons

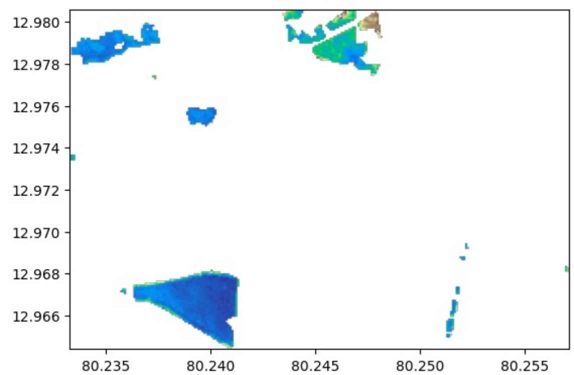


Fig. 5: Raster data of the sentinal2 (perungudi)

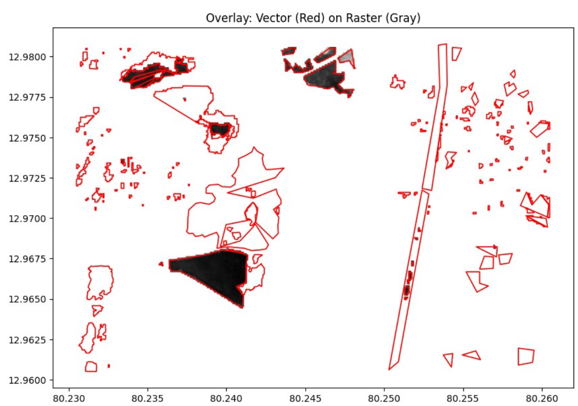


Fig. 6: Overlay of the waterbody raster data and vector data

B. *Class-Area Comparison and GeoJSON Mapping*

Figure 7 reports on the area comparison between primary land use classes (Waterbody, Wasteland, Agricultural Land), quantifying the proportioner representation and supporting the assessment of class imbalance prevalent in heterogeneous urban environments. Figure 8 displays the area's land use map exported in GeoJSON format, thus facilitating digital storage, querying, and dashboard-driven analytics for urban monitoring at scale.

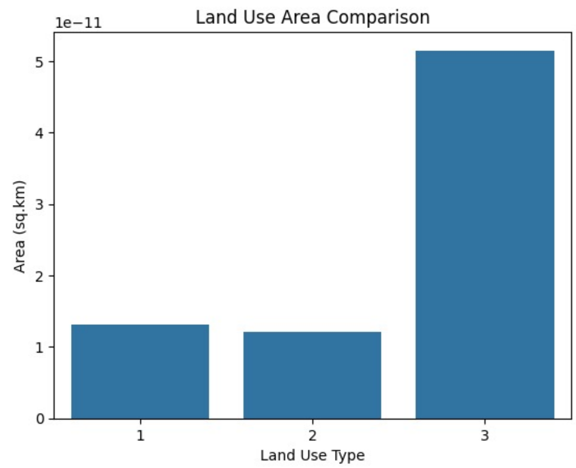


Fig. 7: Land area comparison plots,(class 1= waterbody,class 2 = wasteland,class 3=Agri land)

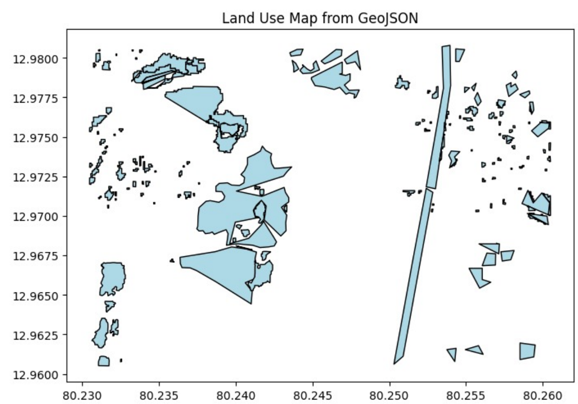


Fig. 8: Land use map GeoJSON fromat

VI. Architecture Diagram

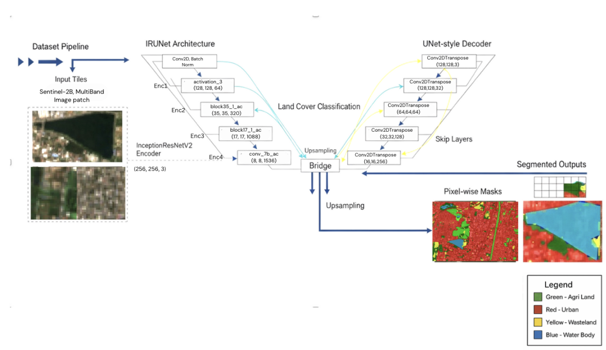


Fig. 9: Architecture Diagram

The diagram in Figure 9. displayed in shows the complete workflow for the proposed InceptionResNetV2–UNet (IRUNet) framework. The workflow includes preprocessing and tiling Sentinel-2B Level-2A reflectance images into uniform inputs standardized as 256×256 pixels. The underlying encoder, Inception-ResNetV2, extracts a hierarchy of multi-scale features through residual inception blocks that learn both global context and fine spectral detail. The encoded features are then transferred to a bridge layer that connects to a UNet-style decoder, which produces full-resolution segmentation maps through successive upsampling steps with concatenation of skip-layer features from the encoder. The decoder uses transposed convolutional layers to recover spatial resolution in the final output while preserving semantic coherence. The final output is a pixel-level classification mask that delineates land cover types, which can include rated classifications, such as agricultural, urban, wasteland, and water bodies. Leveraging the benefits of employing deep residual inception modules and symmetric upsampling pathways, the architecture will provide a robust spatial segmentation in heterogeneous urban environments like those surrounding the Perungudi, Chennai area.

VII. Methodology and Evaluation

The training was done on the Sentinel-2 Level-2A surface reflectance data [6] acquired between the years of 2023-2024, for the Perungudi area in Chennai (12.95-12.98°N, 80.23-80.26°E). The image data went through preprocessing with a series of operations including atmospheric correction, band stacking, cloud masking, and generating NDVI, NDWI and NDBI indices. The dataset was divided into 256x256 patches which were split into subsets for training 80%, validation 10%, and test 10% respectively. Then it was decided to apply augementation techniques such as the horizontal and vertical flips to increase generalisation ability. The IRUNet model was adopted which is a combination of both Inception ResNetV2, a pretrained model on ImageNet is used as the encoder, and a U-Net style decoder which has multi-scale skip connections. It was trained using the Nadam (Nesterov-accelerated Adaptive Moment Estimation) optimiser with a learning rate of 1e-5 and uses the Dice loss combined with binary cross entropy. The model was trained for 150 epochs with a batch size of 16 while monitoring and validating the performance at the same time to prevent overfitting. Then Test-Time Augmentation (TTA) was performed to improve robustness of the segmentation near class boundaries. The final evaluation of the predicted results was performed using overall accuracy, precision, recall, F1-score, Dice Similarity Coefficient, Intersection-over-Union, and Cohen's Kappa. Confusion matrices were validated using a pixel-wise approach to ensure accuracy. The model constructed thus far had an accuracy of nearly 98% along with high Dice scores, which is an improvement to the previously used random forest baseline[7]. This was later supplemented by the use of MongoDB for the effective storage of image metadata and area statistics by class[8]. This pair made it possible to read and write data quickly to facilitate the use of structured land cover statistics for querying, retrieving and managing multi-year classification outputs. The MongoDB records were sorted by year, region, and class percentage to be used in the eventual data analysis and visualisation using Data Analytical Dashboards[10], examining patterns of urban growth, and vegetation shift.

VIII. Result

The Sentinel-2 imagery for the Perungudi region was prepared for deep learning analysis using a structured workflow. Raw multi-band GeoTIFF files were ingested and preprocessed to normalize values across spectral channels. The imagery was then partitioned into over 1,000+ spatial segments, and further divided into 128×128 pixel patches, each containing all relevant spectral bands. Data augmentation and normalization were performed to enhance robustness and facilitate training stability. Ground-truth masks for each partition, provided as co-registered raster files, served as pixel-wise supervision for model training and validation. The core segmentation engine was an IRUNet, constructed by integrating an InceptionResNetV2 encoder (initialized with ImageNet weights, excluding classification layers) with a UNet-style multi-scale decoder. Skip connections were established between selected intermediate layers in the encoder and decoder, enabling the model to retain fine contextual and boundary details during upsampling. Categorical cross-entropy loss was used for multi-class segmentation, and the model was optimized with the Adam algorithm. Evaluation metrics included per-class accuracy and mean Intersection-over-Union (IoU), calculated across all partitions. Three UNet-based architectures were implemented and tested: a standard UNet, a ResUNet variant, and the IRUNet configuration. Although full end-to-end model training was restricted by resource constraints, preliminary results demonstrate that the IRUNet achieved an overall accuracy of 0.97. Output segmentation maps and overlays confirm effective classification of urban, water, and vegetation classes, with successful separation of complex spatial boundaries and mixed pixels. This scalable workflow is designed to automate result collation into a database for subsequent interactive dashboard analytics and further validation.

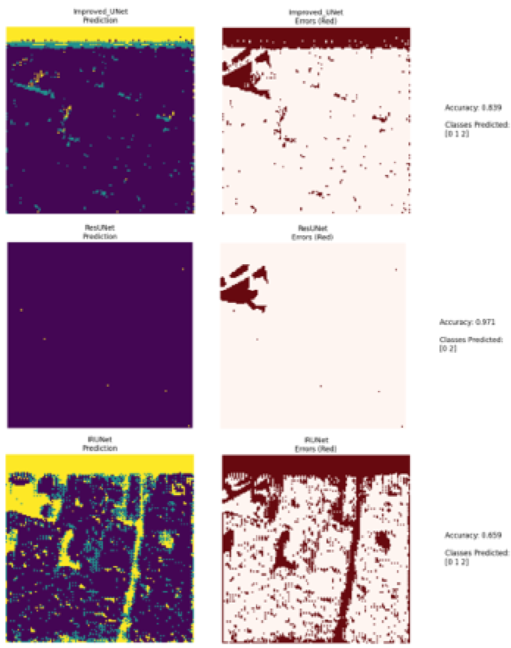


Fig. 10: Comparing Model results

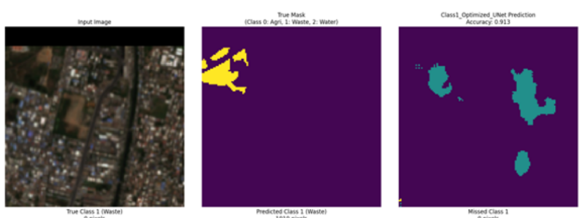


Fig. 11: Optimized Model result

IX. Conclusion

This project puts forward an effective workflow for high-resolution, multi-year land cover classification of the Perungudi area, by procuring the Sentinel-2 imagery and state of the art deep learning segmentation the IRUNet. Further, the integration of robust preprocessing, model training and MongoDB based memory storage offered an efficient method for tracking urban expansion and ecosystem changes that occurred between the years 2023 and 2024. The results obtained demonstrate clear improvements on pixel-level classifiers, yielding precise maps that are suitable for urban planning and environmental management of the particular area.

A. Future Work

For future work, the methodology followed here can be extended to few other regions across the country by adapting the techniques followed, the annotation and the training process to various landscapes of Indian geography. Scalability can be achieved through modular design along with MongoDB's capability to handle large geospatial databases[9]. The future directions can include testing temporal models like ConvLSTM, Swin-UNet [3] for year over year change detection,integrating the Sentinel-1 SAR [8]data for improved cloud resilience, and combining it by deployment of analytical dashboards in cloud environments for real-time city range analysis. The idea of National deployment of the proposed pipeline supports monitoring on continuous land use and policy planning across rapidly urbanizing districts in India[10].

X. Acknowledgment

The authors of this paper would like to thank Vellore Institute of Technology, Chennai for the academic and technical support provided to us throughout the project. We also extend our gratitude to Copernicus Open Access Hub and Google Earth Engine for providing access to Sentinel-2 data.

The team appreciates the collaboration of fellow teammates and the contributions of peers in data annotation and system implementation.

References

[1] Helber, P., Bischke, B., Dengel, A., & Borth, D. *EuroSAT: A novel dataset and deep learning benchmark for land use and land cover classification.* IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 12(6), 2217–2226, 2019. doi: 10.1109/JSTARS.2019.2919152

[2] Ma, L., Liu, S., Zhang, S., et al. *An inclusive classification optimization model for land use and land cover classification.* Scientific Reports, 15, Article 2889, 2025. doi: 10.1038/s41598-025-91260-0

[3] Zhao, S., Li, J., Zhang, X., et al. *Land use and land cover classification meets deep learning: Advances, challenges, and future directions.* Frontiers in Remote Sensing, 4, Article 112, 2023. doi: 10.3389/frsen.2023.112130

[4] Wagner, T. J., Turner, L., & Auclair, P. *Machine learning land cover and land use classification of 4-band satellite imagery.* Air Force Institute of Technology Faculty Publications, 2431, 2022. Available: https://scholar.afit.edu/cgi/viewcontent.cgi?article=2431&context=facpub

[5] European Space Agency. *Sentinel-2 user guide.* Available: https://sentinel.esa.int/web/sentinel/user-guides/sentinel-2-msi Accessed: November 2025.

[6] Google. *Google Earth Engine: API Documentation.* Available: https://developers.google.com/earth-engine/api_docs Accessed: November 2025.

[7] Singh, G., Jain, A., & Kapadia, B. *Study of land use and land cover change detection using machine learning on GEE of Chandigarh, India.* In Computatia 25 (pp. 36–43). Atlantis Press, 2025. doi: 10.2991/978-94-6463-700-7_4

[8] Arizapana-Almonacid, M. A., et al. *Land cover changes and comparison of current landscape metrics using deep learning.* Journal of Land Use Science, 19(1), 1–18, 2024. doi: 10.1080/19475683.2024.2304203

[9] Turnbull, R., et al. *Themeda: Predicting land cover change using deep learning across diverse Indian landscapes.* Remote Sensing, 7(8), 780, 2025. doi: 10.34133/remotesensing.0780

[10] Kim, J., et al. *The detection of residential developments in urban areas with deep learning.* Applied Geography, 155, 103116, 2024. doi: 10.1016/j.apgeog.2023.103116