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AI-Powered Afforestation Planner: Land Analysis For Tree Plantation

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Abstract: The AI-Powered Afforestation Planner project aims to address the growing issue of air pollution through strategic afforestation. By leveraging advanced remote sensing and machine learning techniques, the project identifies barren land areas suitable for tree planting to improve air quality. The study focuses on the Kanakapura Taluk in Ramanagara District, where land classification is performed using Google Earth Engine (GEE) with manually provided training samples. These samples were used to classify the region into urban areas, water bodies, vegetation, and barren lands using the Random Forest algorithm. The project fetches real-time Air Quality Index (AQI) data to assess pollution levels and recommends the optimal number and species of trees for planting. The final output is a web application that provides users with land classification results, barren land area calculations, and tree species recommendations tailored to improving air quality based on AQI levels. The web-based approach ensures accessibility for end users, offering an interactive tool for better environmental decision-making.

***Index Terms* -** Afforestation, Land Classification, Google Earth Engine (GEE), Random Forest, Air Quality Index (AQI)

I. INTRODUCTION

Afforestation—the planting of trees in barren or deforested areas—is a widely recognized method to combat environmental challenges such as air pollution, soil erosion, and climate change. Urban and industrial regions face increasing air pollution levels due to elevated concentrations of particulate matter (PM2.5), carbon dioxide (CO_2), and other harmful gases. Trees naturally mitigate these effects by absorbing pollutants and releasing oxygen. The primary challenge in afforestation lies in identifying suitable planting locations. Barren lands, often underutilized, offer high potential, but additional factors such as the Air Quality Index (AQI) must also be considered to guide species selection and ensure ecological impact.

To address this, the Afforestation Planner was developed—a web-based decision-support tool that integrates Google Earth Engine (GEE) for land classification and real-time AQI data to recommend suitable areas and species for tree planting. The system uses Random Forest, a machine learning algorithm, to classify land into four categories: urban, vegetation, water bodies, and barren land.

Kanakapura Taluk in Ramanagara District, Karnataka, was selected as the study region due to its diverse land cover and noticeable presence of barren patches. The identified barren areas are further analyzed to compute afforestation potential. A graphical bar chart visualizes the distribution of each land class to offer intuitive insights into the region's land cover. This paper outlines the methodology, implementation, and results of the Afforestation Planner, highlighting its potential in guiding afforestation strategies and supporting environmental restoration [6], [7].

II. Literature Review

A. Afforestation and Remote Sensing

Remote sensing and GIS enable large-scale land cover analysis for afforestation planning. Studies such as Lal et al. (2020) and Zhang et al. (2016) utilized satellite imagery to identify barren lands, improving decision-making through real-time, spatial insights [1], [2].

B. Land Classification and Machine Learning

Random Forest (RF) has proven effective in classifying urban, vegetation, water bodies, and barren lands due to its robustness and accuracy (Gislason et al., 2006; Pal & Mather, 2005). Cloud platforms like Google Earth Engine (GEE) support scalable RF implementation (Kumar et al., 2017) [3], [4], [5].

C. Air Quality and Tree Species Recommendations

Afforestation improves air quality by filtering pollutants like PM2.5 and NO_2. Research highlights the effectiveness of species such as Poplar, Oak, and Maple (Nowak et al., 2014; Gupta et al., 2018). Incorporating real-time AQI data enhances tree species selection based on pollution levels [6], [7].

D. GIS-Based Decision Support Systems

GIS tools facilitate afforestation site selection by combining environmental and socioeconomic criteria. Studies (Ahlqvist et al., 2012; Umar et al., 2015) demonstrate how such systems prioritize land suitability and restoration potential.

E. Visualization and User Engagement

Interactive maps and bar charts improve planning and accessibility. Web-GIS platforms like that of Santos et al. (2019) showcase the benefits of intuitive visual interfaces in afforestation mapping and community participation.

III. Study Area And Data Set

A. Study Area

The study area is Kanakapura Taluk, situated in Ramanagara District, Karnataka, India. Selected for its diverse land cover—urban zones, water bodies, vegetation, and barren lands—it serves as an ideal region for land classification and afforestation planning. As shown in Fig. 1, remote sensing techniques were employed to analyze and classify the land cover. This selection supports a focused evaluation of afforestation potential and enables strategic tree plantation planning.

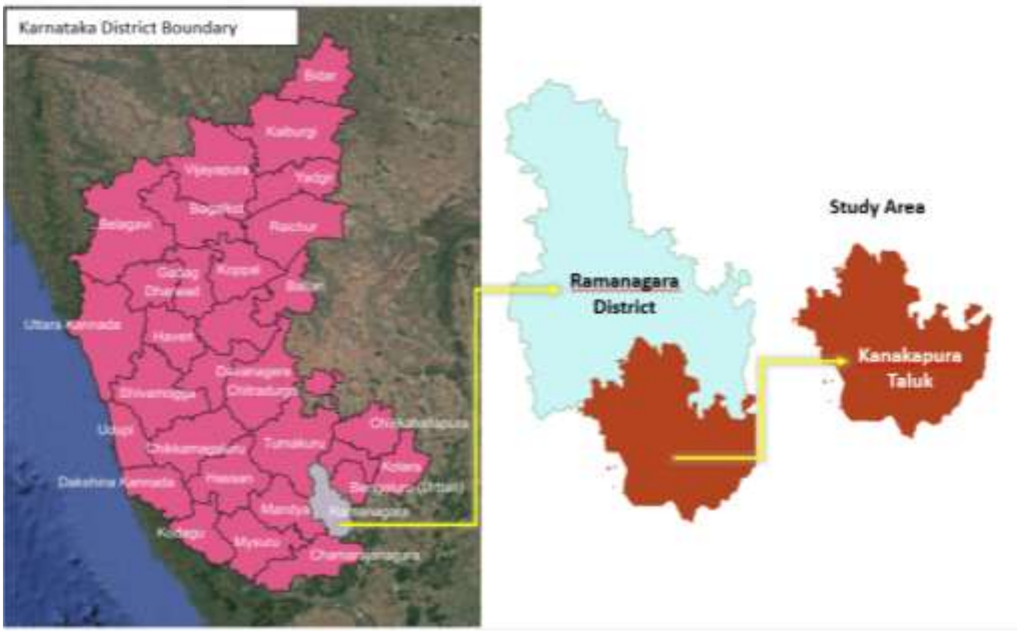

Fig. 1. Study area

B. Satellite Imagery and Data Sources

For land classification, we utilized Google Earth Engine (GEE) with satellite imagery from the Sentinel-2 datasets. Sentinel-2 provides a high-resolution 10m– 20m spatial resolution, making it suitable for distinguishing land cover features. The classification process was conducted using the Random Forest (RF) algorithm, trained with manually labeled samples to categorize land into four classes: urban, vegetation, water bodies, and barren land.

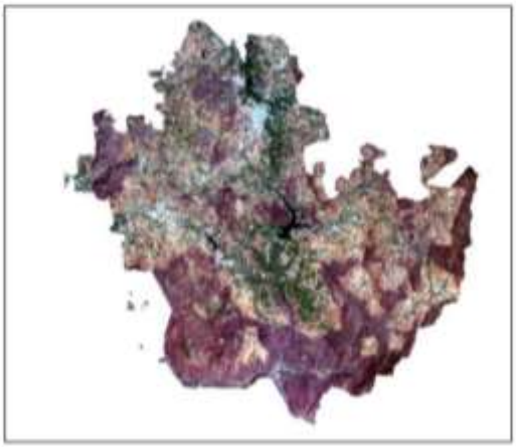

Fig. 2. Satellite image of study area

IV. METHODS

A. Research Structure

The methodology comprises five stages: land classification using Google Earth Engine (GEE), barren land identification, area calculation, tree species recommendation based on Air Quality Index (AQI), and final web-based visualization. This workflow ensures accurate, data-driven afforestation planning that is accessible to end users [5].

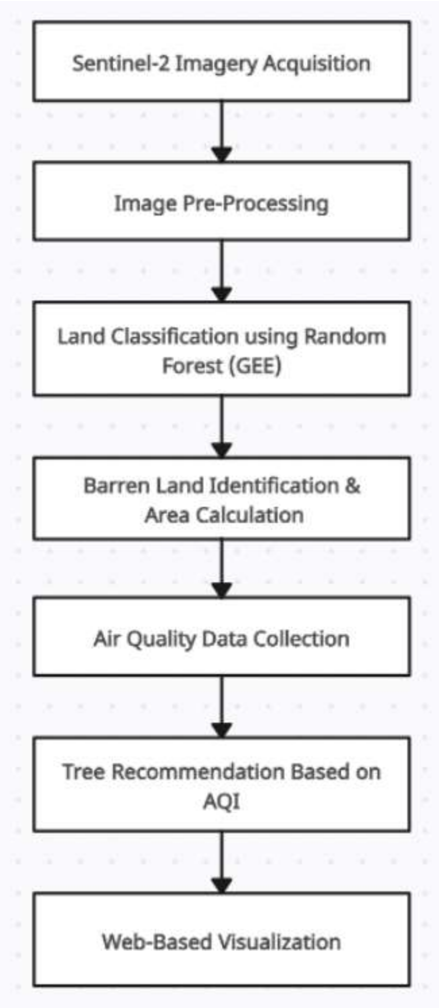

Fig. 3. Structure of research methodology

B. Land Classification Using Google Earth Engine

Sentinel-2 satellite imagery was classified using the Random Forest algorithm within GEE. The data was pre-processed to remove atmospheric distortions. Manually labeled training samples were used to classify land into urban areas, vegetation, water bodies, and barren lands, enabling targeted afforestation analysis.

C. Barren Land Identification and Area Calculation

Post-classification, barren land was extracted as a separate layer. GEE's geospatial functions were used to calculate the total area of these regions. The spatial coordinates of each barren patch were also retrieved to support precise plantation site selection and mapping.

D. Air Quality Data Collection and Tree Recommendation

Real-time AQI data was collected from publicly available APIs. Based on pollution levels, tree species with strong pollutant absorption capacity (e.g., Neem, Peepal, Banyan) were recommended. These suggestions were tailored to the AQI values of each area to enhance environmental impact.

E. Web-Based Visualization and User Interface

To ensure accessibility, the results were integrated into a web-based application. The interface allows users to interact with:

- A classified land cover map, highlighting urban areas, water bodies, vegetation, and barren lands.
- A graphical representation (bar chart) showing the proportion of each land cover type.
- Barren land details, including area, location, and recommended tree species.

V. Implementation

The implementation follows a structured pipeline consisting of satellite image acquisition, machine learning–based classification, and interactive web-based visualization to support afforestation planning.

A. Study Region and Data Collection

The selected study area is Kanakapura Taluk in Ramanagara District, Karnataka, a region witnessing rapid urbanization and forest loss. Sentinel-2 Level-2A imagery was sourced via Google Earth Engine (GEE) due to its high resolution and consistent revisit frequency. Cloud-free imagery was selected to improve classification accuracy.

B. Land Classification Using Google Earth Engine

The selected image was classified using the Random Forest classifier, a robust supervised machine learning algorithm. For training the model, we manually labeled training samples for four land categories:

- Urban Areas
- Vegetation
- Water Bodies
- Barren Lands
- Crop Lands

Training points were selected using visual inspection of high-resolution satellite imagery, supported by existing land use maps. At least 150–200 samples per class were chosen, and these were geographically distributed across the region to ensure variability in land features and spectral diversity. The classifier was trained within GEE, and the final output was exported for analysis and web display.

C. Data Quality and Training Validation

To ensure reliability:

- All imagery used was top-of-atmosphere corrected, cloud-masked, and pre-processed in GEE.
- A 70/30 train-test split was followed to ensure the classifier's performance was validated on unseen data.
- Misclassified areas were visually inspected, and training samples were refined accordingly to enhance accuracy.
- Data labeling was done with expert supervision, ensuring reliable class definitions and separation.

D. Land Classification Accuracy Assessment

An independent set of test points was used to validate classification results. The confusion matrix was computed to evaluate performance, measuring how accurately each class was predicted. From this, we calculated:

- Overall Classification Accuracy
- User's and Producer's Accuracy for each class
- Kappa Coefficient, which adjusts for random chance classification

The confusion matrix revealed high accuracy for barren land and vegetation detection, which are crucial for afforestation recommendations. Minor confusion was observed between vegetation and cropland boundaries, which is expected in rural fringe zones.

VI. Results and Analysis

A. Land Classification Results

The land classification of the Kanakapura taluk in the Ramanagara district was successfully carried out using Google Earth Engine (GEE). The classification was performed using the Random Forest algorithm, with manually provided training samples to distinguish between different land cover types. The study region was classified into four major categories: urban areas, water bodies, vegetation, and barren lands. The classification results provide a foundational understanding of the land use distribution in the region, which is crucial for further analysis related to afforestation planning.

B. Visualization of Land Cover Classification

The output was visualized as a color-coded thematic map (Fig. 4), clearly illustrating the spatial distribution of land cover types. This aids in pinpointing barren land patches, serving as priority areas for afforestation efforts.

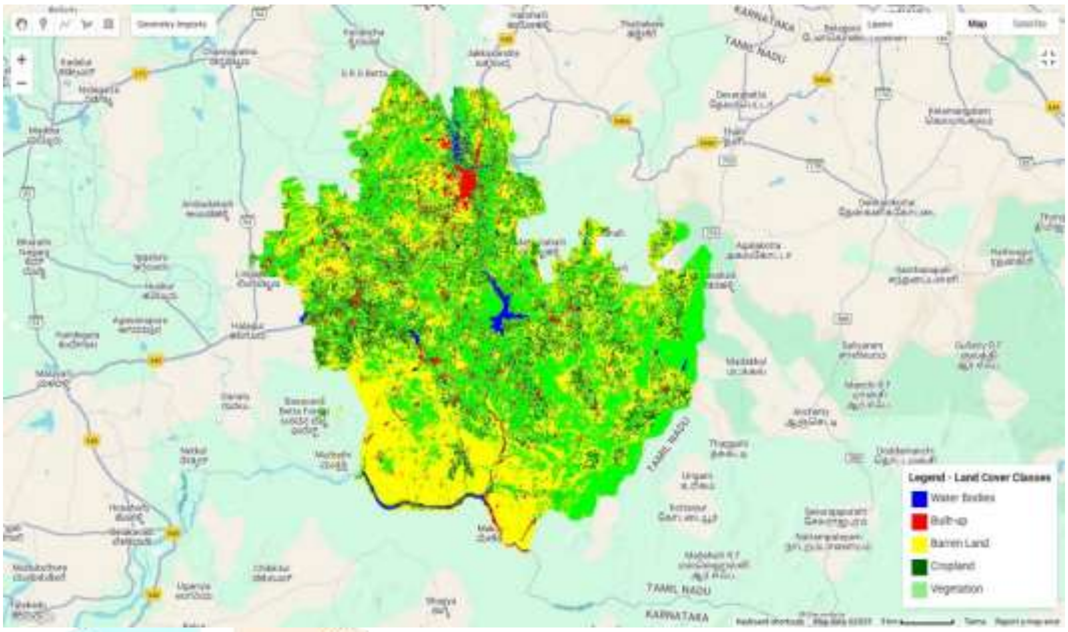

Fig. 4. Land Use and Land Cover map of study area.

C. Area Calculation of Land Cover Classes

Geospatial tools within GEE were used to calculate the area occupied by each land class. The results revealed a substantial share of barren land, highlighting its potential for large-scale plantation. These area metrics can further guide tree capacity estimation and impact modeling.

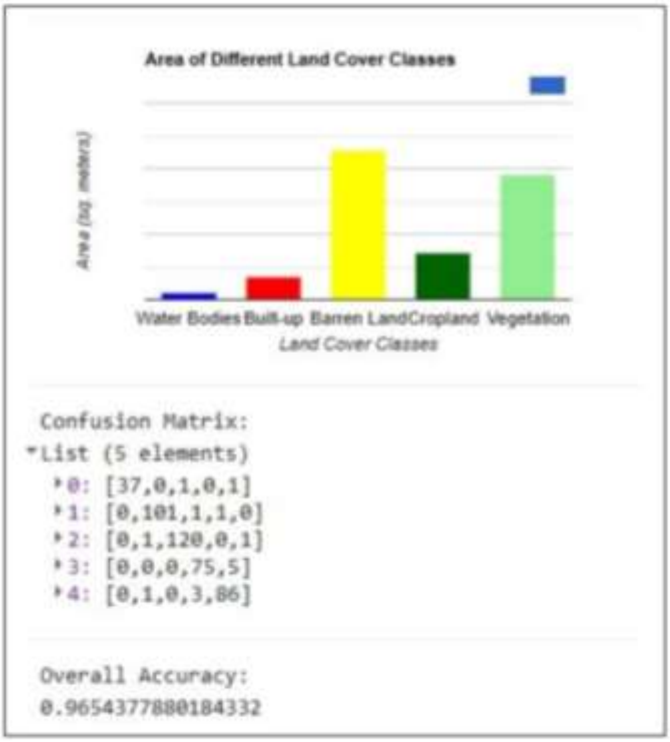

Fig. 5. Area of Different Land Cover Classes

D. Land Classification Accuracy Assessment

The classification was validated using a confusion matrix (Table I) based on five land classes: Water Bodies, Built-Up, Barren Land, Cropland, and Vegetation. High accuracy was achieved for Barren Land (120/122) and Built-Up (101/103). Some confusion occurred between Vegetation and Cropland, and between Water and Barren Land, likely due to similar spectral signatures. The overall accuracy and kappa coefficient confirm the robustness of the Random Forest classifier for land cover mapping.

Actual\Predicted	Water Bodies (0)	Built-Up (1)	Barren Land (2)	Cropland (3)	Vegetation
Water Bodies (0)	37	0	1	0	1
Built-Up (1)	0	101	1	1	0
Barren Land (2)	0	1	120	0	1
Cropland (3)	0	0	0	75	5
Vegetation	0	1	0	3	86

TABLE I: Confusion Matrix for Land Classification using Random Forest in GEE

VII. Future Scope

The Afforestation Planner has significant potential for expansion and enhancement through advanced technologies. Scaling the project from Kanakapura to a national level, integrating real-time environmental data like AQI, soil quality, and weather conditions, and implementing AI-driven species recommendations can improve afforestation accuracy and impact. A mobile application and crowdsourced data collection will allow users to identify barren lands and contribute realtime insights, making the system more dynamic. Additionally, drones for monitoring, IoT-based smart irrigation, and longterm climate impact assessments can ensure sustainable afforestation. Collaboration with government agencies and NGOs can support large-scale afforestation policies, urban greening initiatives, and carbon credit programs. Transforming the system into an open-source platform can further enhance research collaboration, making afforestation planning more accessible, automated, and globally scalable.

Conclusion

The Afforestation Planner provides a technology-driven approach to identifying barren lands and recommending suitable tree species for afforestation. By leveraging Google Earth Engine (GEE) for land classification, the project successfully differentiates urban areas, water bodies, vegetation, and barren lands in Kanakapura, Ramanagara district. The system also incorporates AQI data to enhance tree recommendations for reducing air pollution. This project has demonstrated the feasibility of remote sensing and machine learning techniques in afforestation planning. While the current implementation focuses on a specific region, future enhancements—such as AI-powered species recommendations, real-time environmental data integration, drone-based monitoring, and IoT-enabled irrigation systems— can significantly improve scalability and impact.

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