ReForGenAI: A Generative AI Framework for Automated Micro-Site Reforestation Planning

Gopi Krishna D [1, a)], Ajay Kanth K [1, b)] and Dr Kiruthika M [1, c)]

Author Affiliations
[1] *Department of Computational Intelligence, School of Computing, SRM Institute of Science and Technology, Kattankulathur, Chengalpattu – 603203*

Author Emails
[a)] gd0002@srmist.edu.in
[b)] kk3916@srmist.edu.in
[c)] kiruthim4@srmist.edu.in

Abstract. Reforestation is the primary and crucial solution towards the unapologetic destruction made by humans towards the natural ecological structure. Yet, being the pivotal solution, its initial planning steps require manual site analysis and understanding suitable plants for reforestation. Current methods are time-consuming and lack accurate spatial analysis. This paper introduces ReForGenAI, a novel system with Generative AI principles to automate the preliminary planning process and provide an actionable plan in hand. ReForGenAI accepts the longitude and latitude of a location as inputs. It leverages Google Earth Engine (GEE) to acquire the environmental data such as temperature, elevation, soil ph, soil type and climate type. A neural network trained on 480 tree species suggests the top suitable trees with a suitability score. Parallelly, it acquires the satellite and roadmap maps through Google Maps Static API for visual site context. Using computer vision techniques, the plantable area mask is identified, which excludes roads, buildings, waterbodies, and already existing trees. Plantable points are generated in the visual map using the tree-dense algorithm and the 33-percentage algorithm. A structured output provides a list of trees suitable for the location and a map that covers a radius of 175 meters with plantable tree points. This approach offers a quick, actionable plan using generative AI to address complex ecological planning tasks.

INTRODUCTION

It is becoming increasingly alarming every day as the climate changes and biodiversity loss accelerates and creating a significant change when viewed in months and years. The need for large-scale ecological restoration is never-ending. Reforestation plays a pivotal role in it. When large-scale initiatives are taken, they mostly consume time and a lot of pre-planning. Effective planning should be carried out to maximize the current technologies and equipment usage.

Planning reforestation of a location demands the planner to understand the location and its existing coverage of entities. Space for planting trees must be analyzed; already occupied tree areas cannot be considered. The process also undergoes consideration of the location, temperature, elevation, soil and climate for suitable trees. To support the long-term ecological initiative, trees that can survive longer are identified and assigned as suitable trees for the location. Traditional methods of microsite analysis, where physical human efforts are put into determining the location and its ecological attributes, are labor-intensive. For a large coverage of land, it is hectic for any organization to carry out. Existing tools are excellent at the regional level but not at the micro-level to provide a comprehensive plan with plantable location of trees and specific, suitable recommendations of trees for that location.

This paper presents ReForGenAI, a system that can automate the planning process of the reforestation initiative and provide a detailed, actionable, structured output to start. With a simple input of location in the form of latitude and longitude, it fetches the details about the location, the visual map, and a list of suitable tree species based on the site-specific environmental parameters. The visual map with points and the list of trees are then provided as a structured output from the system.

ReForGenAI follows the principle of Generative AI. As it does not merely analyses with exciting conditions or predict a single output. It generates a novel output, a plan with a map locating plantable points and tree species that must be planted. The plan is synthesized from multiple modalities (environmental data layers, visual images, ecological species data) and AI models (CV for spatial masking, NN for species selection) to propose the actionable plan. This distinguishes it from purely analytics and predictive tools.

LITERATURE REVIEW

The process of enhancing forestry vulnerabilities through strategic reforestation depends on information that combines ecological expertise with forestry know-how and remote sensing technology, and computational analytics. The standard planning process depends on human field studies and expert judgment [1], yet shows limitations when monitoring various small locations and performing quick assessments. Spatial data management and decision support for forest management and restoration depend heavily on Geographic Information Systems, which allow analysts to merge various geographical elements, including topography and soil and land use data [2][3]. Membership of fine-grained site constraints that update in real-time with species suitability information poses a key challenge to most Modern Decision Support Systems (DSS) [4].

Google Earth Engine (GEE) serves as a remote sensing platform that has transformed how scientists access huge amounts of environmental data, which is necessary for reforestation planning [5]. The analysis system of Google Earth Engine enables quick access and processing of environmental data sources, including WorldClim climate elements and NASADEM elevation data and OpenLandMap soil properties, as well as land cover information to analyze site suitability [6][7]. These environmental data layers serve as the fundamental base from which suitability assessments can be developed.

The process of finding physically appropriate locations in complicated terrains requires site image evaluation. CV methods within satellite and aerial imagery have become popular for land cover classification applications while simultaneously detecting obstacles, including buildings and roads [8][9][10]. Such large-scale applications of these methods serve as the building blocks that enable ReForGenAI to identify potential planting areas that exclude built infrastructure and dense plants.

A fundamental requirement for reforestation success involves selecting suitable species based on site environmental conditions. SDMs utilize machine learning algorithms, especially Neural Networks (NNs) with environmental predictors to predict habitat suitability [11][12]. ReForGenAI incorporates AI models that predict species success by applying ecological principles to establish its species recommendation mechanism.

A workflow that combines established technologies into a system for generating micro-site reforestation plans, which determine specific species choices and exact planting locations, is less developed. The use of generative AI systems would enable the creation of new ecological planning solutions according to research [13] in unrelated domains. ReForGenAI uses proven methods of remote sensing alongside CV technology and AI-based species modelling as its foundation, but differs through an automated combination of elements to produce site-specific design options and customised species recommendations for reforestation plans.

SYSTEM ARCHITECTURE

The ReForGenAI system is designed as a modular pipeline that processes and separates each functionality, and also follows a linear progression in processing the output. It processes the geographical point to a structured micro-site reforestation plan. The overall system can be conceptualized as a sequence of distinct modules that process data from input to final output. The diagram below illustrates the flow of data through these modules.

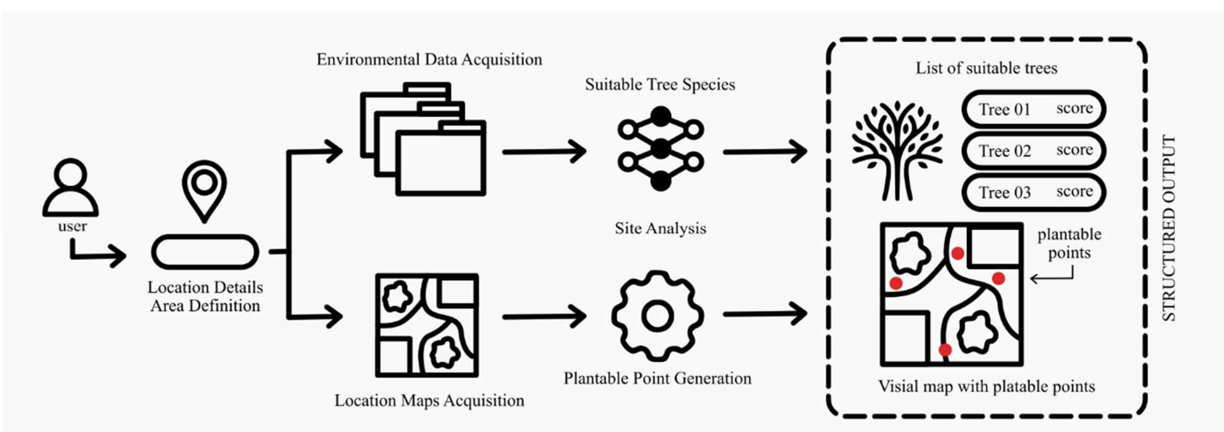


FIGURE 1. System Architecture of ReForGenAI

The key stages of the architecture are Location Details, Area Definition, Location Map Acquisition, Environmental Data Acquisition, Predict Suitable Tree Species, Site Analysis, Plantable Point Generation, and Structured Output.

- **Location Details and Area Definition:** When a user provides the location information in the form of two inputs, latitude and longitude, it defines a square area with the location point as the centre, and the sides that stretch approximately 370 metres. This area is considered for the analysis, defining the extent of boundaries for all the data that will be acquired for the location.
- **Location Maps Acquisition:** To understand the location's visual point of view, it needs aerial maps of the location are needed. The physical layout and ground cover within the analysis area are fetched using the Google Maps Static API. Images of 1200x1200 pixels with the zoom value of 17, both a roadmap and a satellite map.
- **Environmental Data Acquisition:** The system queries Google Earth Engine (GEE) using the defined Analysis Area boundaries. It retrieves specific geospatial datasets relevant to vegetation growth, including elevation (e.g., NASADEM), climate variables (e.g., WorldClim for temperature), soil properties (e.g., OpenLandMap for ph, soil components allowing inference of soil type and drainage), surface water (e.g., JRC Global Surface Water), and potentially land cover context (e.g., WorldCover).
- **Suitable Tree Species:** The NN model is trained to predict the suitable tree species for the location attributes such as temperature, elevation, soil ph, soil type and climate type. The recommended trees are also given a suitability score (ranging from 0.0 to 1.0), indicating how suitable the tree species is for the location.
- **Site Analysis:** For site analysis, the system employs computer vision techniques (using OpenCV) to analyse the satellite and roadmap images. It identifies and segments the pixels into non-plantable and plantable areas. Entities that are considered in non-plantable areas are infrastructure, water bodies and vegetation areas.
- **Plantable Point Generation:** The less dense area of the tree coverage is focused on more using the tree-dense algorithm, marking the plantable point effectively in the areas it needs to be and creating a uniform vegetation plan. The 33-percentage algorithm is used to record a cache system that will compensate for the coverage of trees; this algorithm is explained further in the methodology section. The generated points are ensured to fall under the plantable area.
- **Structured Output Generation:** Finally, the output is gathered together from the suitability prediction model and the plan map creation. Visually defining a map with plantable area and the plantable points along with the trees that can be planted in these areas is displayed with their suitability score. The output consists of various mask area maps and the final map with plantable points, with a list of tree species.

METHODOLOGY

The ReForGenAI system applies multiple sequential procedures that create micro-site reforestation plans through remote sensing data processing with computer vision and machine learning techniques. User-defined areas trigger the acquisition process, which leads toward the creation of both spatial planting maps and species selection lists.

Data Acquisition and Site Definition

When a user provides a target latitude and longitude point, the system creates an Analysis Area from a circular shape with a 175.15-meter radius positioned at this location. ReForGenAI combines two main data streams to acquire the physical ground conditions together with environmental parameters. The system accesses exact Satellite and Roadmap images with a 1200x1200 pixels resolution from the Google Maps Static API. Visual information from satellite imagery shows natural elements like vegetation and open areas, while roadmap imagery creates better displays of human-made features consisting of roads and buildings.

Through its Python API (ee), the system enables platform connectivity to Google Earth Engine (GEE). The system conducts point sampling operations at central points of the input coordinate location to access the required environmental information contained in GEE datasets. The system requests four main dataset types from NASADEM for elevation data and WorldClim V1 Bioclimatic variables (bio01, bio10, bio11, bio12, bio14) to understand climate patterns together with OpenLandMap supplying soil characteristics (texture class, organic carbon, and pH [User verify OLM or specify pH source]) and supplementary data from JRC Global Surface Water and HydroSHEDS along with ESA WorldCover to determine water features close by. There are two primary functions for gathering data, which include ee.Reducer.firstNonNull() together with ee.Reducer.mode(). These reduce functions operate at distinct spatial scales around the centroid position but require relative environmental consistency within the Analysis Area.

Environmental Feature Derivation and Classification

Features appropriate for the species prediction model and site characterisation are extracted from the raw environmental data obtained from GEE. This includes Python implementations of rule-based classification schemes. Features like temperature, elevation and soil ph are derived directly from the dataset, classification was not required.

A set of predetermined thresholds is applied to assign approximate climate classifications relevant to vegetation, such as "Tropical," "Subtropical," "Arid," "Temperate," "Mediterranean," or "Alpine," based on the retrieved WorldClim temperature and precipitation values (e.g., annual mean temperature, precipitation of driest month). For example, if the mean temperature of the coldest quarter stays above 18°C, tropical conditions may be assumed.

Similarly, descriptive site tags relevant to the target tree list are assigned to GEE and ph data using rules derived from ecological knowledge. Inferring texture classes ('Sandy', 'Loamy', 'Clay', etc.) from OpenLandMap texture codes, fertility status ('Poor') based on soil organic carbon levels (e.g., < 10 g/kg), acidity ('Acidic') based on pH values (e.g., < 5.5), drainage characteristics ('Well-drained', 'Poorly drained') from texture, and moisture or water-related tags ('Dry', 'Moist', 'Wet', 'Swampy') based on precipitation, JRC water occurrence, and WorldCover codes. Based on low slope (as determined by NASADEM) and proximity to HydroSHEDS rivers, a proxy class known as "Alluvial" is assigned. A list of relevant site descriptors for the location is the output.

Tree Suitability Prediction using Neural Network

A Neural Network (NN) model that predicts tree species suitability based on the derived environmental conditions is a fundamental part of ReForGenAI. The model's knowledge base is derived from a carefully selected dataset that describes the preferred categorical climate and soil types for 480 different tree species, as well as their ecological tolerance ranges (min/max temperature, min/max elevation, and ph range). These categorical preferences were encoded using sklearn.preprocessing.MultiLabelBinarizer.

Importantly, static range data was not used to directly train the NN. Rather, for each of the 480 trees, a synthetic training dataset was created by simulating a variety of possible site conditions (temperature, ele, ph, climate, and soil). While some simulations fall outside the tree's known tolerances, others do not. A deterministic, rule-based function (calculate_normalized_suitability) was used to determine a "ground truth" suitability score (normalised between 0.0 and 1.0) for each simulated site-tree pairing. This function merely verifies that the simulated conditions satisfy the tree's stated requirements.

Using a dedicated function (create_nn_feature_vector), a unique feature vector is engineered for each tree about the input site conditions to provide rich input for the NN. In addition to the raw site values, this vector also includes binary flags that indicate whether the site conditions fall within the tree's ranges, the width of the tree's tolerance ranges (e.g., temp_range_width), the numerical distance of the site conditions from the tree's tolerance boundaries (e.g., temp_below_min), and binary flags that indicate matches between the site's classified climate/soil types and those that the tree prefers.

A Feedforward Neural Network (Multilayer Perceptron) constructed with tensorflow.keras is used in the system. To predict the suitability score between 0 and 1, the architecture consists of an input layer that is the same size as the engineered feature vector, three hidden Dense layers with ReLU activation functions (64, 32, and 16 neurons, respectively), and a single Dense output neuron with a Sigmoid activation function. Sklearn.preprocessing was used to scale the feature vectors before training.MinMaxScaler. The model learned to approximate the result of the rule-based calculate_normalized_suitability function based on the complex feature vector input by using the 'adam' optimizer and mean_squared_error loss function during training.

In practical application, ReForGenAI creates the scaled feature vector for every one of the 480 trees based on the site's conditions after receiving site input. A suitability score is then predicted for each tree by the trained Keras model (model.predict()). The species are ranked using these scores, and recommendations are given for the top trees.

Site Analysis and Masking via Computer Vision

The system uses the OpenCV (cv2) library in Python to apply computer vision techniques for identifying suitable areas for plantings through physical assessment. The system processes the Roadmap (BGR format) and the Satellite image (HSV format for illumination invariance improvement of vegetation areas).

The primary function in pixel segmentation, which identifies non-plantable features in the image, is colour thresholding (cv2.inRange). The BGR Roadmap image uses specific blue ranges to indicate water elements. The BGR Roadmap image contains buildings that appear as light grey and specific yellow tones. The system identifies road features through very light/white ranges in the inverted BGR Roadmap image by using cv2.bitwise_. A designated selection of green saturation and values within the HSV Satellite image identifies dense tree cover, along with possible green vegetation when combined with water mask exclusion.

A 9x9 rectangular morphological closing operation on the initial tree mask enhances the representation of contiguous canopy areas. The operation joins nearby patches together and completes small voids in the image. The separate feature masks created from water, buildings, roads, and refined trees merge into covered_mask through bitwise_or operation to generate a single binary image with white pixels representing unavailable planting areas.

The final plantable area map, known as result_mask, is generated through bitwise NOT inversion of covered_mask. The resulting white pixels in the result_mask point to areas of bare ground after clearing out native vegetation and water bodies, and built structures.

Planting Point Generation Algorithms

The two sophisticated algorithms within ReForGenAI refine basic random distribution by deciding where planting points should go in specific target areas (result_mask).

The Tree-Density Placement Algorithm distributes points into areas where new clusters have minimum proximity to already existing forest cover. The method produces a uniform canopy distribution as its main objective. Spatial analysis between result_mask and tree_mask allows the algorithm to find zones where tree planting is possible while maintaining minimal presence of existing trees. The random sample method receives directions towards locations where tree density is lower from this algorithm.

The Target Coverage Percentage Algorithm establishes 33% tree cover as per the India National Forest Policy, but can be modified within the Analysis Area. The program determines the combined area of the campaign along with the covered tree area through its designated data masks. The algorithm first evaluates deficit areas through calculations of selected planting density, and then generates required planting positions from these areas. The algorithm distributes points to the available planting space in the minimum essential numbers or maximum functional numbers. Simple random sampling and the Tree-Density Aware logic serve as options for point distribution. The method shows how to find planting shortages while failing to process direct cross-site compensation activities.

EVALUATION

The main purpose of the evaluation was to measure how well the ReForGenAI system performed and provided value across different environmental settings. The evaluation objectives consist of the following points.

The evaluation process must ensure the complete operation of the automated workflow from beginning to end. The evaluation checks the accuracy of the Computer Vision (CV) module to detect non-plantable regions, which include infrastructure along with water bodies and dense plant coverage. The evaluation analyses the ecological significance of species suggestions that which Neural Network (NN) generates. The evaluations assess if the planted tree points produced appropriate results according to the implemented Tree-Density Aware and Target Coverage Percentage (33%) rules.

Case Study Selection

Four distinct case study locations within India were selected to represent a range of common reforestation planning challenges:

- CS1: Urban Environment (Lat: 12.975215, Lon: 77.629372) – High infrastructure, minimal open space.
- CS2: Large Water Body (Lat: 12.945643, Lon: 80.15501) – Significant water feature constraint.
- CS3: High Vegetation Cover (Lat: 8.915714, Lon: 76.647475) – Dominated by existing forest canopy.
- CS4: Significant Open Space (Lat: 23.163968, Lon: 77.419374) – Mix of development and plantable plot.

Evaluation Procedure and Metrics

ReForGenAI operated through its designated coordinates to complete each assessment. The system produced environmental parameters together with recommended species and CV masks and generated a final planting plan map. Each case study employed a distinct planting point generation method (Such that Tree-Density served CS1 and CS3 because of tree preservation objectives, and 33% Target functioned for CS2 and CS4 to achieve maximum coverage).

An assessment of accuracy was conducted through a visual examination of overlaying generated masks against satellite imagery for both the Water, Tree, Building, Road, and Covered Area classifications. The ecological validity of the Top 10 species selection was evaluated according to identified site characteristics. A visual assessment verified that planting points stayed within suitable planting locations and the spatial distribution matched the expected algorithm behaviour, which included keeping away from the dense tree area in CS1/CS3 and focusing placement on CS2/CS4.

The analysis involved documenting the percentages obtained from calculations of Water, Tree, Building, Road coverage, as well as Total Covered and Plantable Area. The process included documenting the number of points where new plants should be planted.

TABLE 1. Case Study Examples and its results after execution

Metric	CS1 (Dense Urban)	CS2 (Urban + Water)	CS3 (High Vegetation)	CS4 (Urban + Space)
Climate Class	Tropical	Tropical	Tropical	Tropical
Soil Type (Main)	Alluvial, Loamy, Poor	Loamy, Moist, Poor	Loamy, Moist, Poor	Loamy, Moist, Poor
Soil pH	6.4	6.1	5.7	6.8
Water Cover	0.50%	36.07%	0.48%	0.00%
Existing Tree Cover	39.38%	22.28%	88.56%	8.26%
Building Cover	64.89%	22.39%	14.61%	40.96%
Road Cover	11.47%	11.54%	6.45%	19.71%
Total Covered Area	87.19%	83.61%	93.69%	65.58%
Plantable Area (%)	12.81%	16.39%	6.31%	34.42%
Points Generated	13	17	7	68
Top Species	Sausage Tree	Orange	Orange	Avocado
Score Range (Top 10)	>= 0.9996	>= 0.9996	>= 0.9996	>= 0.9996
CV Mask Accuracy	Good (High Infrastructure)	Excellent (Water Body)	Excellent (Tree Canopy)	Good (Open Area)
Species Plausibility	High	High	High	High
Point Placement	Correct (Limited Gaps)	Correct (Avoids Water)	Correct (Clearings Only)	Correct (Open Area Focus)

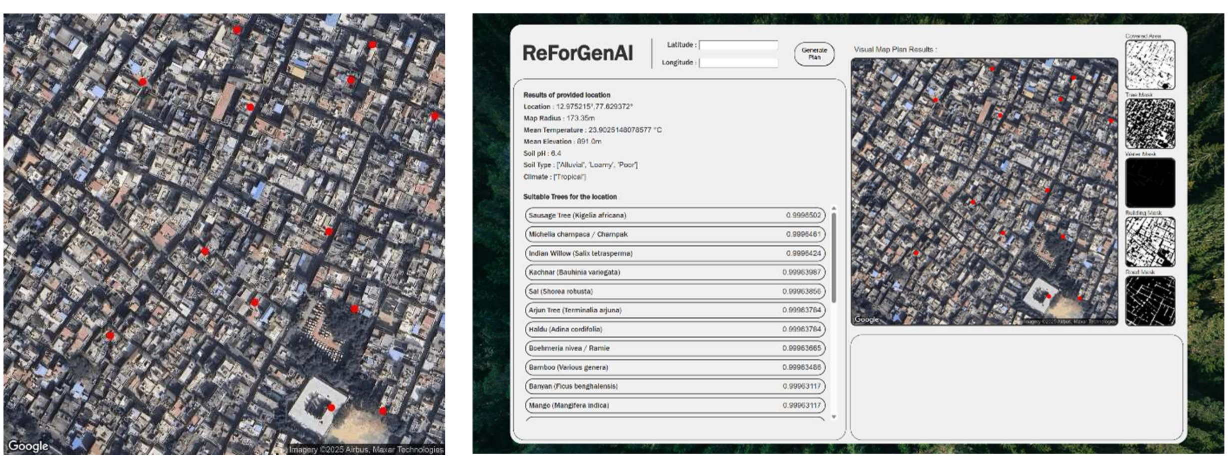
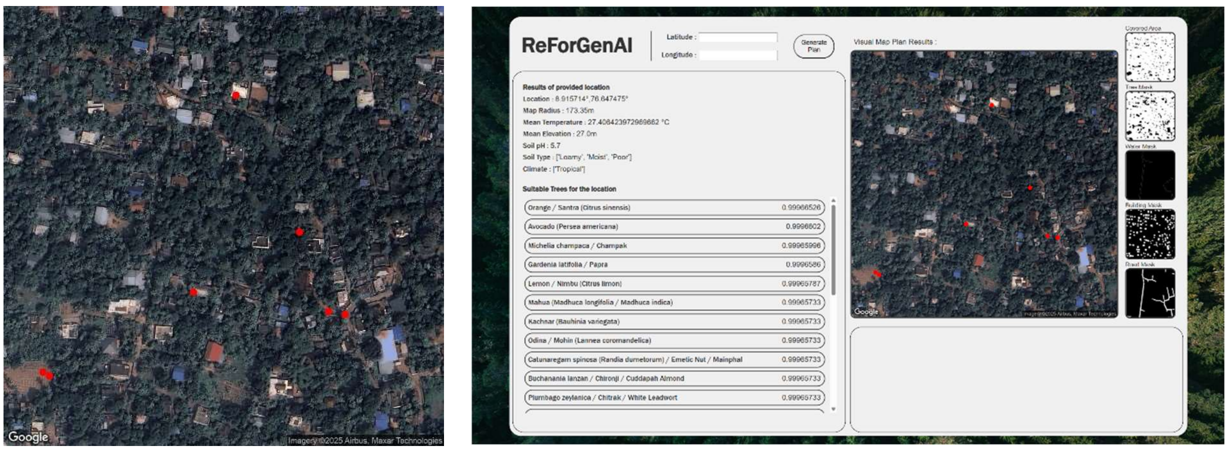


FIGURE 2. CS1: Urban Environment (Lat: 12.975215, Lon: 77.629372) (a) Result map (b) ReForGenAI Interface

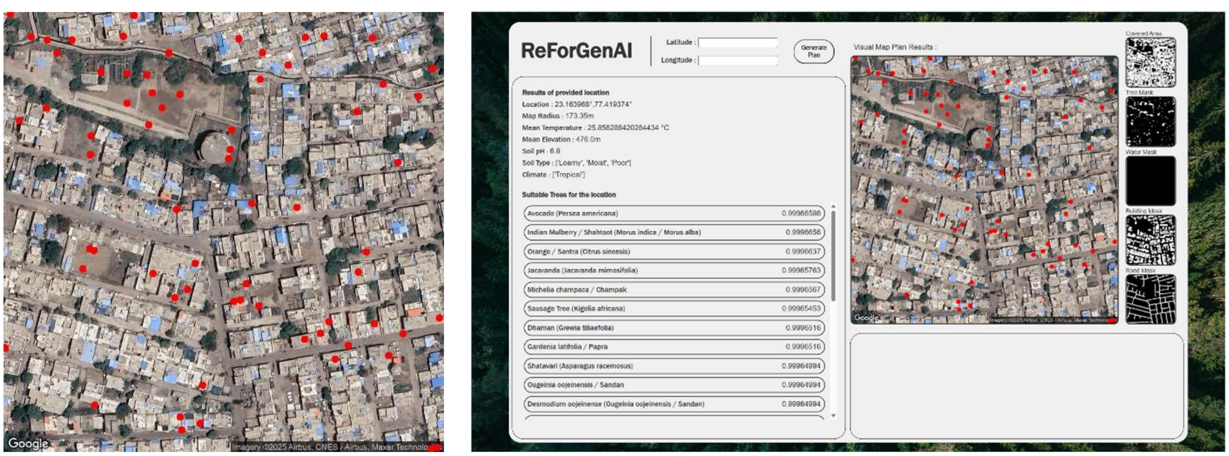
(a) (b)

FIGURE 3. CS2: Large Water Body (Lat: 12.945643, Lon: 80.15501) (a) Result map (b) ReForGenAI Interface



(a) (b)

FIGURE 4. CS3: High Vegetation Cover (Lat: 8.915714, Lon: 76.647475) (a) Result map (b) ReForGenAI Interface



(a) (b)

FIGURE 5. CS4: Significant Open Space (Lat: 23.163968, Lon: 77.419374) (a) Result map (b) ReForGenAI Interface

RESULTS

This section showcases outcomes achieved through ReForGenAI as the tool operates within the four diverse study sites for CV masking alongside NN species recommendation and planting point algorithm implementation. Table 1 shows the essential quantitative data that can be found in the Evaluation section.

Computer Vision Masking Performance

The CV module within all case studies achieved success in marking non-plantable land features through its evaluation of Google Maps Satellite and Roadmap images.

- A high percentage of building structures (64.89%) along with road infrastructure (11.47%) received successful masking while plantable areas constituted (12.81%) in the densely populated CS1 area. The tree identification algorithm revealed 39.38% of existing vegetation which may encompass rooftop vegetation along with trees or dense shrubs because the study area is in an urban setting.
- The large water body within CS2 (Urban + Water) received proper definition through system processing and represented 36.07% of total space. The plantable land occupation reached 16.39% because the surrounding buildings received a correct entry (22.39%) and roads (11.54%) as well as existing trees (22.28%).
- The software accurately established 88.56% as the extent of existing tree canopy within CS3 (High Vegetation). The system effectively masked buildings along with roads to determine a small plantable area of 6.31% in addition to successful clearance identification of 6.45% by roads and 14.61% by buildings.
- The large open area in CS4 (Urban + Open Space) became easily distinguishable because CV modules separated it from buildings by 40.96%, roads by 19.71% and existing trees by 8.26%.

Visual inspection confirmed that the generated masks generally aligned well with the input imagery, providing a reasonable basis for identifying plantable zones.

Planting Point Generation

Different site limitations influenced the number together with placement of planted points which varied significantly between case studies due to the utilization of specific planting algorithms.

The planting point generation in CS1 (Dense Urban) and CS3 (High Vegetation) resulted in only 13 and 7 points respectively because the available plantable space amounted to 12.81% and 6.31% and existing tree cover reached 39.38% and 88.56% of the total area. The assumed Tree-Density Aware algorithm selects placements of points in small available gaps while paying regard to existing vegetation and infrastructure constraints.

To achieve a 33% coverage target in CS2 (Urban + Water), the Target Coverage Percentage (33%) algorithm was used on the available 16.39% plantable area which had a 22.28% existing tree cover. Despite the confined lakeside area the algorithm released 17 planting points for purposes of reaching the 33% tree cover target.

The target coverage percentage algorithm in CS4 (Urban + Open Space) produced 68 points despite its 8.26% baseline tree coverage and 34.42% plantable area because this space had the largest area available for plantation. The generated points in the 33% Target Coverage algorithm represent the fundamental planting requirements together with previously unattainable deficits ("cached") derived from multiple scenarios like CS1 or CS3 due to restricted space. The extensive plantable space in CS4 enabled the system to utilize its extra capacity for compensating past coverage shortfalls while demonstrating the planned approach to obtain wider coverage objectives during long-term operations despite site-specific constraints.

Visual evaluation of output points showed that each point existed solely within plantable areas on the final map. The algorithm used the spacious open area in CS4 by concentrating generated points in that location while staying within its boundaries.

DISCUSSION

The results of investigated cases confirm ReForGenAI operates effectively as an automatic solution for data-centered micro-site reforestation plan production. ReForGenAI performs environmental data analysis and site observation with computer vision to combine with artificial intelligence-generated species selection in a comprehensive operational pipeline.

Interpretation of Findings

The CV module successfully recognize non-plantable features in multiple landscape types (dense urban, large water body, high vegetation and open plots) which exhibits excellent stability within the color thresholding identification method used for standard maps The system definitively identified plantable areas from obstacles including its efficient obstruction detection of the big water body in CS2 and the dense canopy in CS3.

The NN system always generated species lists which matched the feasible plants for each result environment (climate and soil type with variations in pH etc.). High suitability scores above 0.9996 in the model most likely derive from the training approach which forced it to produce results that matched the scoring system used for tolerance data.

The experimental results viewed through the dual algorithms of Tree-Density Aware and Target Coverage Percentage (33%) demonstrate how the system allows complicated planting procedures that go beyond random location placements. The point count data in CS1 and CS3 confirms proper management of spatial constraints along with respect for existing ground cover according to density-aware principles. The moderate point count recorded in CS2 demonstrates an appropriate approach for the 33% target when working with constrained land areas. The 68-point count in CS4 represents a distinct strength of the system because it allows advanced functionality that releases deficit requirements in restricted areas to meet broader ecological 33% cover targets through available sites. The system provides an operational aspect which extends traditional site-by-site optimization capabilities. This caching system serves as an important capability based on agreed user feedback.

Addressing Reforestation Planning Challenges with ReForGenAI

ReForGenAI addresses fundamental issues that standard micro-site reforestation planning presents according to the originally discussed issues. The system performs automated integration of diverse environmental and visual and ecological data sets in addition to delivering fine-grained site assessments that consider limitations while improving the process between site evaluation and species selection through its integrated approach.

The main power of ReForGenAI stems from its capability to combine several programs into a single system. The system utilizes Google Earth Engine environmental data together with Google Maps visual context and computer vision for fast obstacle identification to automate information collection and site examination activities that usually need substantial time and resources. The automated system enables fast assessments in the initial stage. The system combines spatial and environmental discovery outcomes with an AI species suitability model through one automated workflow to deliver species recommendations specified for individual micro-site conditions. The proposed method differs from traditional spatial planning methods that separate species selection from spatial planning procedures.

The analysis through a defined radius achieves site-specific results which broader regional planning tools fail to deliver. The output from ReForGenAI combines integrated data analysis through its vision of generating new solutions which manifest as planting maps with exact point locations and corresponding species recommendations. The planning solution directly fulfills the requirement for easily implementable solutions. The combination of adaptive planting strategies using the Target Coverage Percentage algorithm with deficit caching mechanism (clearly shown in CS4) addresses challenges of fulfilling large-scale ecological goals (such as 33% coverage) by strategically optimizing available site areas. It outperforms traditional fixed site planning techniques using adaptive functionality.

ReForGenAI provides an effective solution against identified problems through its quick processing and data-automation coupled with location-specific deployment and generative design features that generate usable reforestation plans adjusted for diverse site scenarios as well as broader ecological targets.

CONCLUSION

The research centres around ReForGenAI, which integrates Generative AI with geospatial analysis under a human-centred design to enhance reforestation planning. The system aims to provide time-sensitive, sustainable data-based reforestation planning because of present-day climate change and biodiversity reduction trends.

ReForGenAI utilizes geospatial data components together with neural networks for automated decision-making that focuses on reforestation. Environmental data training enables the model to provide predictions about future outcomes along with species recommendations that suit specific contexts. Visual presentations together with interactive features create a user-friendly interface that shows ecological plans using clear visual elements of heatmaps and satellite data and prediction time data. Users with no expertise in technology can effortlessly move through AI suggestions within the system. Engineers designed the system architecture to fulfil the operational requirements of environmental staff together with organizations and public governance agencies. ReForGenAI generates quick usability across different ground-based situations through its capacity to adapt to local settings and provide instant user feedback and straightforward user interfaces.

REFERENCES

1. Evans, J., & Turnbull, J. W. (2004). Plantation Forestry in the Tropics (3rd ed.). Oxford University Press. (Example: Classic text on practical forestry)
2. Franklin, S. E. (2001). Remote Sensing for Sustainable Forest Management. Lewis Publishers. (Example: GIS/RS application in forestry)
3. Pérez-Soba, M., & Elbersen, B. (2012). GIS-based decision support tools for sustainable forest management: A review. Forest Systems, 21(2), 178-188. (Example: Review of GIS/DSS)
4. Reynolds, K. M., Twery, M. J., Lexer, M. J., Vacik, H., Ray, D., Shao, G., & Borges, J. G. (2008). Decision support systems in forest management. In Handbook on Decision Support Systems 1 (pp. 499-534). Springer. (Example: DSS overview)
5. Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, 202, 18-27. (Canonical GEE paper)
6. Tamiminia, H., Gholizadeh, A., & Pour, A. B. (2020). Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. ISPRS Journal of Photogrammetry and Remote Sensing, 164, 152-171. (Example: Review of GEE applications)
7. Hengl, T., Mendes de Jesus, J., Heuvelink, G. B., Ruiperez Gonzalez, M., Kilibarda, M., Blagotić, A., ... & Guevara, M. A. (2017). SoilGrids250m: Global gridded soil information based on machine learning. PLoS One, 12(2), e0169748. (Example: Specific GEE dataset like OpenLandMap's basis)
8. Zhang, L., Zhang, L., & Du, B. (2016). Deep learning for remote sensing data: A technical tutorial on the state of the art. IEEE Geoscience and Remote Sensing Magazine, 4(2), 22-40. (Example: Deep learning for land cover)
9. Wegner, J. D., Branson, S., Hall, D., Schindler, K., & Perona, P. (2016). Cataloging wildlife images using deep learning. In ECCV 2016 Workshops (pp. 539-554). Springer. (Though wildlife, shows object detection principle from aerial-like views, adapt if a better building/road detection paper found)
10. Kaiser, P., Eppenhof, K. A., Topol, A., & Pluim, J. P. (2017). Building detection from satellite imagery using ensembles of convolutional neural networks. In MICCAI Satellite Events - DLMIA 2017 (pp. 153-160). Springer. (Example: Specific CV application for buildings)
11. Elith, J., & Leathwick, J. R. (2009). Species distribution models: ecological explanation and prediction across space and time. Annual Review of Ecology, Evolution, and Systematics, 40, 677-697. (Canonical SDM review)
12. Botella, C., Joly, A., Bonnet, P., Monestiez, P., & Munoz, F. (2018). A deep learning approach to species distribution modeling. Oikos, 127(8), 1151-1163. (Example: Deep learning specifically for SDMs)
13. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press. (Example: Foundational Deep Learning / Generative Models textbook/reference)