Landfill Suitability Mapping using Satellite Imagery and Machine Learning Techniques: A Case Study for Delhi-NCR, India

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Abstract

The improper disposal of municipal waste is a worldwide problem that is dangerous to the environment. They are responsible for soil, water, and air pollution, resulting in ecological imbalance. Thus, effective landfill site selection reduces these adverse effects and supports sustainable urban development. However, it is difficult to identify suitable landfill sites, especially in fast-growing urban areas, because of the complexity of adjusting various environmental, infrastructural, and demographic factors. Moreover, the unavailability of comprehensive datasets and reliable predictive models worsens the problem, leading to frequent suboptimal site selection. This study overcomes these difficulties by combining satellite imagery and machine learning (ML) techniques to develop an integrated web-based framework for assessing landfill site suitability in the Delhi-NCR region. A comprehensive dataset comprising features such as spectral features captured using Landsat-9 satellite imagery, Digital Elevation Model (DEM), Land Use/Land Cover (LULC), proximity to roads, railways, rivers, industries, restricted zones, and settlements, along with Land Surface Temperature (LST), population density, Soil-Adjusted Vegetation Index (SAVI), Normalized Difference Vegetation Index (NDVI), and Modified Normalized Difference Water Index (MNDWI) was utilized for model development. The potential of ML techniques, such as random forest (RF) and extreme gradient boost (XGB), was assessed for landfill site classification. The experimental results show that RF outperforms XGB (F1-score:0.91, AUC:0.98). This study can help policymakers in sustainable waste management and provide a means for improved environmental sustainability with optimal landfill site selection in urbanizing areas.

1. Introduction

Waste disposal is a vital element of urban infrastructure, especially during this period of growth and expansion in cities, which continue to generate waste in increased quantities. Improperly managed dumping grounds contribute to extreme environmental pollution in air, water, and soil, and health hazards are usually risks to nearby communities **(Duan et al., 2022)**. In fast-growing urban areas, such as Delhi-NCR, with high population density and industrial activity, the choice of an optimal site for dumping is crucial in mitigating such adverse impacts while promoting sustainable urban development **(Zhou et al., 2023)**. Identifying the appropriate location for optimum dumping sites is important for ensuring sustainable urban waste management, especially in highly populated and industrially active regions where waste generation continues to increase daily **(Li et al., 2021)**. Site selection is traditionally performed through manual field surveys that require a lot of time and effort, which cannot meet the standards set to cover a larger area of a given urban area **(Giri et al., 2023)**. GIS and remote sensing technologies are available for waste management processes and are excellent platforms for efficient spatial data distribution and decision-making **(Wu & Zhang, 2022)**. Delhi-NCR is a highly complex area regarding the identification of waste disposal sites owing to the complicated structure of urban and mixed land use specimens and high population density. A combination of satellite images, population density, and environmental factors can help correctly predict a safe dumping site that could minimize the potential hazards to local communities and ecosystems **(Kumar et al., 2024)**. Advanced analytical approaches, such as machine learning models, support the systematic evaluation of multiple criteria while ensuring that the insights gained are accurate and actionable for informing urban waste management decisions **(Singh et al., 2022)**. Multidimensional datasets facilitating a deeper assessment of site suitability evaluation have considered a few parameters, such as soil attributes, distance to water bodies, land use, and population distribution. By using machine learning methods, we can increase the precision of site classification and provide urban planners and policymakers with better information **(Tan et al., 2023)**. However, hurdles such as data availability, urbanization, and changing environmental conditions make appraisal more difficult, so novel methodologies integrating spatial analysis with machine learning are even more essential **(Ahmed et al., 2022)**.

This study aims to provide a framework for identifying optimal dumping sites within the Delhi-NCR region, which recognizes the critical role of site selection in sustainable urban planning. The primary objectives of this study are as follows:

(1) To assess potential dumping sites in Delhi-NCR using GIS and remote sensing technologies.

(2) To analyse spatial relationships between environmental, demographic, and infrastructural factors influencing site suitability.

(3) To apply machine learning techniques to enhance the classification accuracy of suitable and unsuitable dumping sites.

(4) To recommend sustainable waste management practices and policies for the Delhi-NCR.

Effective site selection will minimize the risk of environmental and health pollution caused by waste disposal while informing local governments about what decisions to make, given sustainability considerations. Available methods to find suitable sites for waste dumping and disposal are usually tedious and expensive in practice, whereas remote sensing and GIS methods easily provide scalable and efficient site mapping over vast expanses of city landscapes **(Wang et al., 2023)**. Urban planners can then watch all elements in real time and systematically overlay them all on one landscape when selecting a particular site **(Chen & Huang, 2023)**. With the aid of satellite technology, including Landsat 9, high-resolution spatial data can assess land coverage, environmental importance, and advancement towards sensitive areas. All these factors influence site selection. When amalgamated with machine learning techniques, such tools will enable researchers to create better predictions of sites that may be developed, thereby supporting the sustainability of urban waste management initiatives **(Jiang et al., 2023)**. Despite recent advances, issues remain in optimal site selection, such as urban sprawl, variability in data collection methods, and seasonal changes affecting land use. Because some environmental factors, such as proximity to water bodies, depend on local conditions and climate, modelling such complexity will require the adoption of a data processing scheme **(Sun et al., 2023)**. Another data processing technique is necessary, as the data gaps are sometimes due to urban infrastructure developments and cloud cover in the satellite image **(Liang et al., 2023)**.

2. Literature Review

Urbanization in Indian cities is a major issue, coupled with the ever-increasing need for effective waste management to keep pace with the population growth and sprawl **(Kumar & Rathi, 2022)**. This choice defines the method of identifying a suitable site based on a detailed assessment of land use, distance from residential areas, ecology, sensitivity, and the transport network. Most traditional landfill site selection methods are manual and heuristic-based, thus scale-bound with inherent inaccuracies. These operational conditions exclude incorporating into systems that could assist during city build-up phases. All the challenges are pronounced as cities grow. Machine learning design has become one of the most recently and frequently developed means of improving the effectiveness and efficiency of landfill site selection in recent years. ML techniques that utilize GIS and remote sensing data process large, multidimensional datasets and identify the most suitable locations for landfill sites. These techniques learn from historical data, identify patterns, and make predictions regarding other factors, including land cover, soil quality, proximity to sensitive areas, including water bodies and residential areas, and infrastructure networks **(Patel et al., 2021)**. Machine Learning, including Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN), has proven to have a high-performing ability for analysis in site suitability studies compared to other conventional techniques with utmost accuracy levels and robustness **(Ravindran et al., 2020)**. Machine learning with GIS has been successfully used for landfill site identification. **Kumar and Rathi (2022)** studied the application of machine-learning models, such as RF and SVM, for the suitability analysis of landfill site locations in an urban environment. They noted that RF performed better than other techniques, especially when spatial features such as land use, slope, or distance to water bodies were considered. In addition, SVM has been shown to have prominent performance in predicting the site suitability of different regions with varied land use patterns and complex environmental conditions. Moreover, remote sensing data are quite useful in updating information on changes in land use/land cover, which is vital in determining the landfill site **(Sahu et al., 2021)**. Satellite imaging technologies provide remote sensing with a broad view of urban and rural areas for monitoring factors such as vegetation, water bodies, and built-up areas. These datasets are coupled with machine learning models that identify landfill sites with the least environmental and community impact. In addition to proximal analysis and land utilization, other infrastructural and environmental factors should also be considered when selecting a site for a landfill. **Ravindran et al. (2020)** focused on adding factors such as seismic activity, groundwater vulnerability, and soil permeability that help maintain the long-term sustainability of landfill sites. The authors developed soil and ANN models for the various layers of data, and the results indicated a relationship between environmental factors, infrastructure, and ML models. Compared to traditional modeling methods, ML-based models may be more effective than ANN models for analyzing complex relationships between the two. ML methods can be of great assistance, especially in the case of a city and its surrounding regions. The rapid development of cities has also led to modifications in the policies of urban planners and waste management authorities regarding landfill site selection. **Sutton et al. (2021)** suggested that ML methods can better deal with such dynamic conditions by improving site suitability prediction through fitted data. ML-based approaches also have the upper hand in terms of scalability, as large amounts of data from different sources can be analyzed quickly by waste management planners using remote sensing, GIS, and demographic data. Therefore, this is even more applicable to India, where the scale of urbanization would make manual methods impracticable. This is especially true in India, where the scale of urbanization renders manual methods impractical. Machine learning enables the processing of vast datasets in real time with accuracy, thereby providing insights into potential landfill sites for decision-makers **(Kumar et al., 2019)**. This scalability ensures that the selection process can be applied over a large geographical area, supporting waste management in metropolitan areas and urban settlements. In addition, machine learning models can be beneficial in assessing the social and environmental consequences of proposed landfill sites. **Gupta and Sharma (2021)** emphasized that social aspects such as population density, land ownership, and local community issues must be considered. Incorporating these features into ML techniques may help reduce conflict and ensure that the landfill site is located in a place that causes minimal social disturbance. The integration of machine learning with GIS and remote sensing can revolutionize the premises of waste management practices in India, given the complexity involved in landfill site selection. More specifically, ML models tend to play an important role in improving the accuracy of site selection, identifying locations that reduce environmental and social impacts, while pursuing a more sustainable and efficient urban solid waste management system. In the long run, such innovations may result in less environmental degradation, better waste management practices, and more resilient urban systems **(Patel et al., 2021; Kumar et al., 2019).** The integration of machine learning with GIS and remote sensing offers a more accurate and scalable solution for landfill-site selection. This approach enhances urban waste management and promotes sustainable development in fast-growing cities.

3. Materials and Methods

3.1 Study Area

The Delhi metropolitan area is in the north, which includes areas of Noida, Delhi, and Faridabad in India's National Capital Region (NCR), covering approximately 1484 square kilometres and largely urbanized, with extensive agricultural land. Therefore, this area is a hotspot for landfill suitability research. In addition, the capital city of Delhi has a mixed topography with varied land use patterns, including residential, commercial, and industrial. Semi-arid climatic conditions influence both land use and environmental factors in landfill site selection. Moreover, the newly sprawling urban landscape and increasing population have given rise to a significant waste management problem. Connected to Delhi, Noida is known for its planned development and green spaces, characterized by alluvial and sandy soils that affect agriculture and landfill suitability. Faridabad, to the south, is a mix of agriculture and industry, adding additional demand for landfill infrastructure. The industrialization in Noida also complements agriculture currently under production, while the topography and land use pattern in Faridabad are core factors on which landfill suitability assessment is based. This study utilized high-spatial-resolution satellite imagery and machine learning models to evaluate landfill suitability within these three interconnected regions. In assessing factors concerning geology, land use, proximity to sensitive areas, and physical infrastructure, this study will eventually outline methods for selecting landfill sites, incorporating data from remote sensing and geospatial analysis to improve the certainty with which sites for landfilling will ultimately be assessed and hence committed to sustainable waste management schemes within this densely populated region. The findings aim to inform policymakers, urban planners, and landfill authorities to establish the best practices for corresponding landfilling in the metropolis.

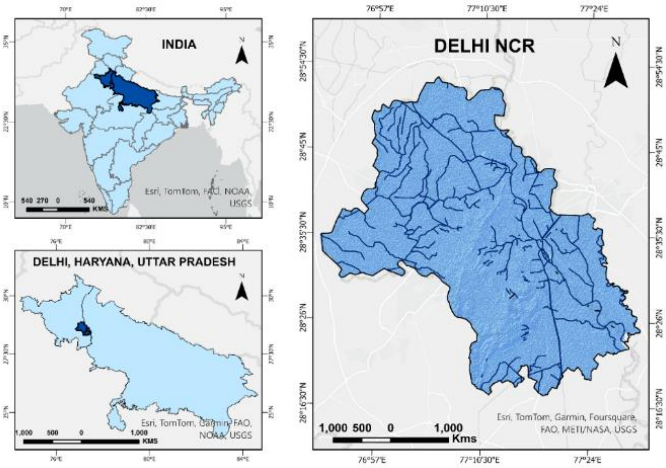

Figure 1. The Location Map of the Study Area

3.2 Data Collection

3.2.1 Satellite Imagery

The integration of Landsat 9, launched by NASA **(USGS, 2021)**, provides high-resolution multispectral imagery crucial for land use assessment and environmental monitoring. It offers 11 spectral bands with resolutions ranging from 30 m for the most commonly used in this study to 15 m for the panchromatic band. This study used bands most relevant to land-use classification and environmental assessment, particularly for identifying suitable dumping sites. The data necessary for the optimal dumping site location analysis were gathered from multiple sources, including satellite imagery, governmental databases, and field surveys (Table 1).

Data Required for Dumping Site Location	Source
Landsat 9 Satellite Data	USGS Earth Explorer
Digital Elevation Model (DEM)	Bhoonidhi
Land Use/Land Cover (LULC)	GIS software
Lithology	Bhukosh
LST Raster Layer	MODIS
River	
Population Density	
Road Network	
Railway	OpenStreetMap
Settlements	
Industrial Zones	
Restricted Zones	

Table 1. Dataset Details

3.3 Dataset Generation

Figure 2 outlines the process followed in this study for data preparation and analysis.

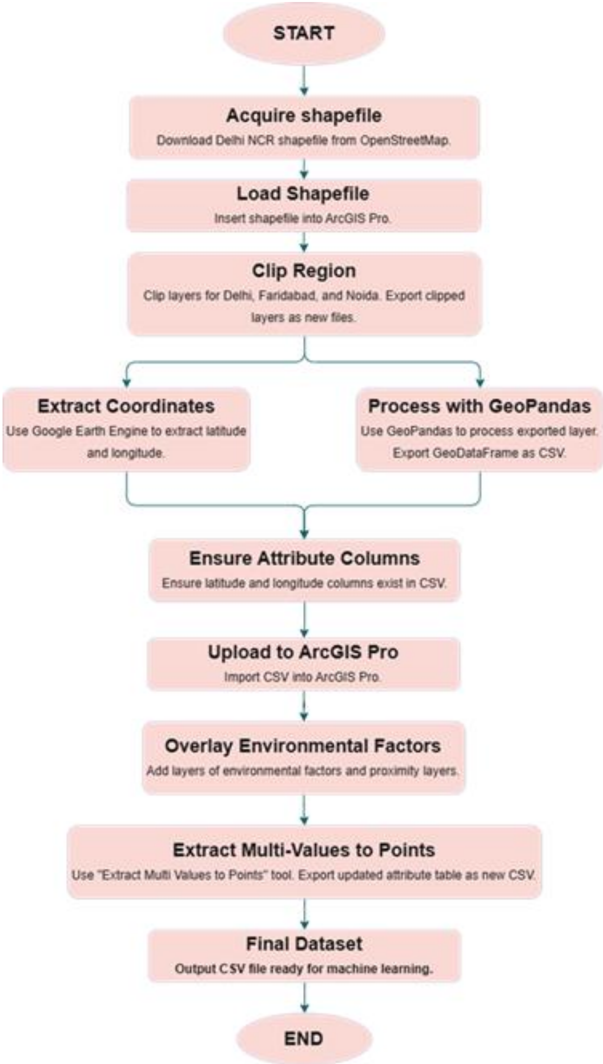

Figure 2. Methodological Flow for Dataset Generation

Using ArcGIS Pro, Google Earth Pro, and Google Earth Engine(GEE), a comprehensive dataset with more than 600 samples and 23 distinct features was generated. Features such as terrain elevation, land cover, lithology, proximity to water sources and roads, population density, industrial zones, NDVI, SAVI, and MNDI were identified as the features for model training.

3.4 Data Preprocessing

The collected datasets were pre-processed using GIS software, such as ArcGIS Pro, to ensure that spatial analysis was performed accurately to find the optimal dumping site. All environmental variables were converted into raster or vector layers for easy analysis. The DEM was processed to extract slope and aspect imagery and distinguish between urban, agricultural, and natural land to establish the area's suitability for the dumping site selection. Through preprocessing, variable lithology and variables of proximity to infrastructure were depicted correctly to conduct further analysis, which are important for determining the stability of a potential dumping site. LULC data were extracted from satellite images, distinguishing between urban, agricultural, and natural land to establish the area suitability for the dumping site selection. Through preprocessing, variable lithology and variables of proximity to infrastructure were depicted correctly to conduct further analysis.

3.5 Methodological Flow

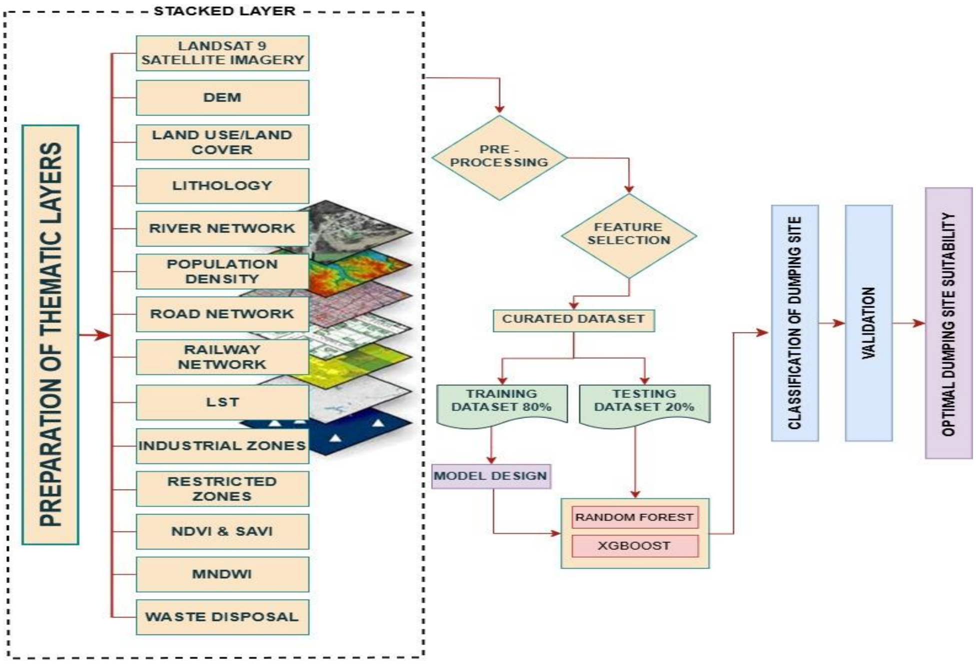

Figure 3: Methodological Workflow for Optimal Dumping Site Selection in Delhi-NCR

Figure 3 shows the methodological workflow used in the experiments. The curated dataset was split into training and testing datasets using a split ratio of 80:20. The ML models, RF and XGBoost, were trained using the training dataset, followed by model evaluation.

3.6 Factors for Optimal Landfill Site Selection

The spatial distribution of the key parameters affecting landfill site suitability, as shown in Figure 4, represents the critical element in finding the best possible landfill locations in the Delhi-NCR. These maps facilitate the examination of environmental, infrastructural, and socio-demographic factors necessary for choosing suitable landfill locations. Parameters mapped

These factors include terrain elevation, land cover, lithology, proximity to water sources and roads, population density, and industrial zones. Visualizing these factors clarifies their roles in landfill suitability, as the criteria used in machine learning models are now known. Therefore, the models learned herein can better predict more suitable landfill sites in the study area by integrating these spatial insights.

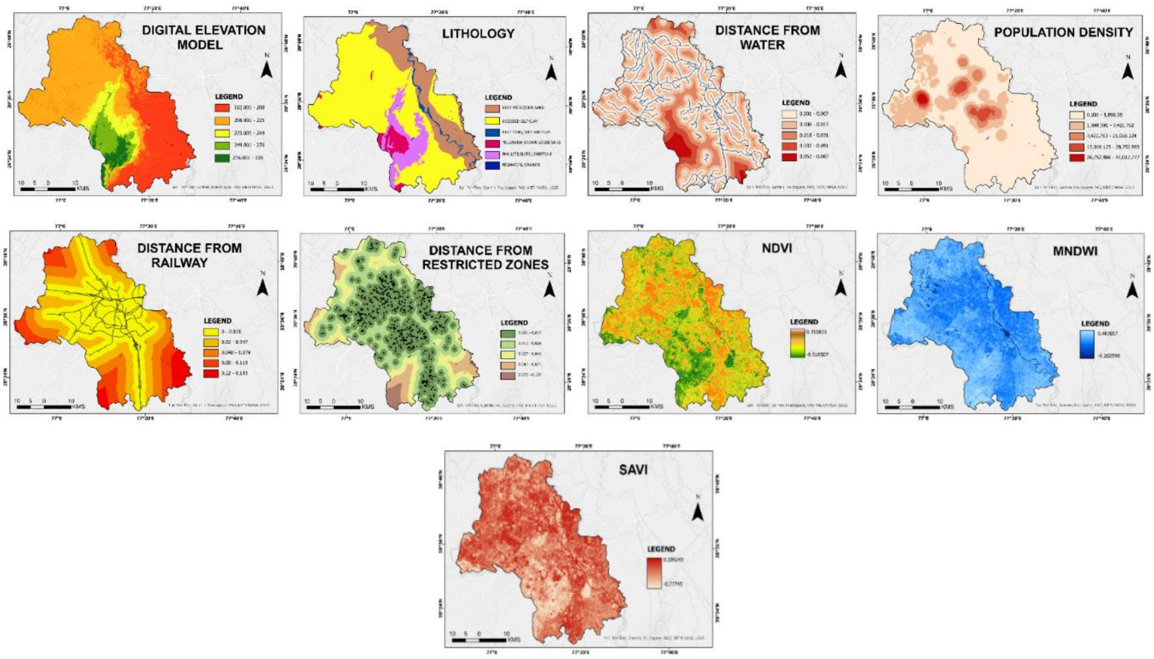

Figure 4. Analysis of Identified Factors for Optimal Landfill Site Selection

3.7 Spatial Distribution and Correlation Analysis

Digital Elevation Model (DEM): Landfills preferably choose a place with lower elevation values for better stability and accessibility; however, it must not be flood-prone. It is also avoided to have a steep slope that will create a problem for maintaining stability and the possibility of waste containment.

Land Use/Land Cover (LULC): This map identifies human land utilization patterns in barren or less productive areas as the ideal locations for landfills. Urban and agricultural zones were also excluded to minimize the impact of landfills on human activities and food production, including sparsely populated regions.

Lithology Map: It is ideal for any landfill site as this lithology contains stable rock formations and soil types to reduce the possibilities of environmental degradation or groundwater pollution. Loose or porous geological formations are avoided because they can affect landfill stability.

River Proximity: Maintaining a safe distance from rivers is crucial to prevent leachate and groundwater contamination and protect nearby water resources. Sites with a distance >1 km from rivers were considered.

Population Density: Densely populated areas are unsuitable for landfills because of the potential health and environmental risks. Landfills are strategically located in low-density areas to minimize human exposure.

Transportation Proximity: Proximity to roads and railway networks ensures the efficient waste transportation to landfill sites. Locations with nearby road networks were chosen to balance accessibility while avoiding hazards to nearby residential or populated areas.

Industrial Zones: Landfill sites near industrial areas are considered because of synergistic waste management facilities. However, the distance is maintained within a safe limit due to the fear of increased pollution in industrialized zones.

Restricted Areas: Sensitive areas, such as protected heritage sites or other environmentally sensitive areas, are signposted as no-go zones to avoid legal and ecological conflicts.

NDVI and SAVI: These indices guide area selection towards areas with scant vegetation cover, thereby minimizing ecological disturbances. Densely vegetative areas are avoided to preserve the biodiversity.

MNDWI: This index depicts water bodies. Landfills should be located reasonably far from surface waters to avoid contamination risks.

Ground Control Points (GCPs): Because existing data were unavailable, GCPs were collected using GEE and Google Earth Pro to assess potential waste disposal sites based on capacity and suitability or to identify the need for additional landfill sites at a further distance.

3.8 Model Development

The process primarily involved the use of two supervised classification designs: Random Forest (RF) **(Breiman, 2001)** and XGBoost **(Chen & Guestrin, 2016), which** were applied to classify optimal dumping sites. These models incorporate climate and socioeconomic factors, such as slope, LULC, lithology, distance from rivers, population density, and infrastructure.

Random Forest (RF) Classification

Random Forest, an ensemble learning method, constructs multiple decision trees, with each tree trained on a different subset of data. The final classification is determined by majority voting among all trees. This study used RF to classify areas into suitable and unsuitable dumping sites based on input variables such as slope, LULC, and proximity to rivers **(Breiman, 2001)**.

Extreme Gradient Boosting (XGBoost)

XGBoost is a powerful and efficient boosting technique that iteratively corrects errors from previous models to improve the classification accuracy. In this study, XGBoost used variables such as population density and proximity to roads to predict the suitability of dumping sites **(Chen & Guestrin, 2016)**.

4. Results and Discussions

This study employed two machine learning techniques to classify and identify suitable landfill sites in the Delhi-NCR region. Suitability maps were developed to visualize the results of the model performance, and these models were evaluated using cross-validation results, accuracy scores, precision, F1-score, classification reports, and ROC-AUC metrics. Stratified cross-validation with five folds (CV=5) was used to evaluate the robustness and generalization performance of the models **(Kohavi, 1995)**. Between the two designs, the random forest estimated approximately 0.803 km² of the 7.007 km² of highly suitable land, showing a good capacity to model the complex interrelationship between variables within environmental and socio-economic spaces. XGBoost showed remarkable classification capabilities and outperformed all boosting accuracies on intricate variable interactions, but was slightly worse than the overall performance of RF. The generated suitability maps highlighted ideal landfill sites, emphasizing critical factors such as environmental safety, access, and the avoidance of densely populated areas. Such studies provide a robust basis for well-informed decisions in sustainable waste management and support the strategic planning needed for a rapidly urbanizing region like Delhi-NCR.

4.1 Model-Specific Analysis

Random Forest (RF):

The best technique was Random Forest, with an accuracy of 91.13% and an ROC-AUC score of 0.9827. The model correctly classified 185 of 203 samples and misclassified only 18 samples. RF showed better potential for capturing more complex interactions between variables, mainly environmental and infrastructural constraints. The RF suitability map estimated a highly suitable land for a landfill site at 0.803 sq. km.

XGBoost:

The model achieved an accuracy of 89.65% and an ROC-AUC score of 0.9616, which was nearly identical to that of the RF in terms of overall performance. There were 182 correct and 21 incorrect classifications out of 203 samples. It uses gradient boosting to train its models to minimize errors iteratively during classification. Although the model was powerful, it required hyperparameter tuning with the number of estimators set to 100, a learning rate tuned to 0.1, and a max_depth of 6.

Figure 5 presents the confusion matrices that correctly represent the classification performance of the dataset. The accuracy of the RF model was primarily based on the fact that it had higher true positive and accurate negative counts, measured with 86 correctly classified non-suitable and 99 suitable instances. At the same time, XGBoost closely followed with 87 non-suitable and 95 suitable classifications, respectively. Based on the cases mentioned, RF stood out as the more reliable method of data representation, as it exhibited fewer errors in classification by showing the skill in examining more complicated patterns in the dataset, similar to those shown in previous works on classification performance **(Smith et al., 2021)**.

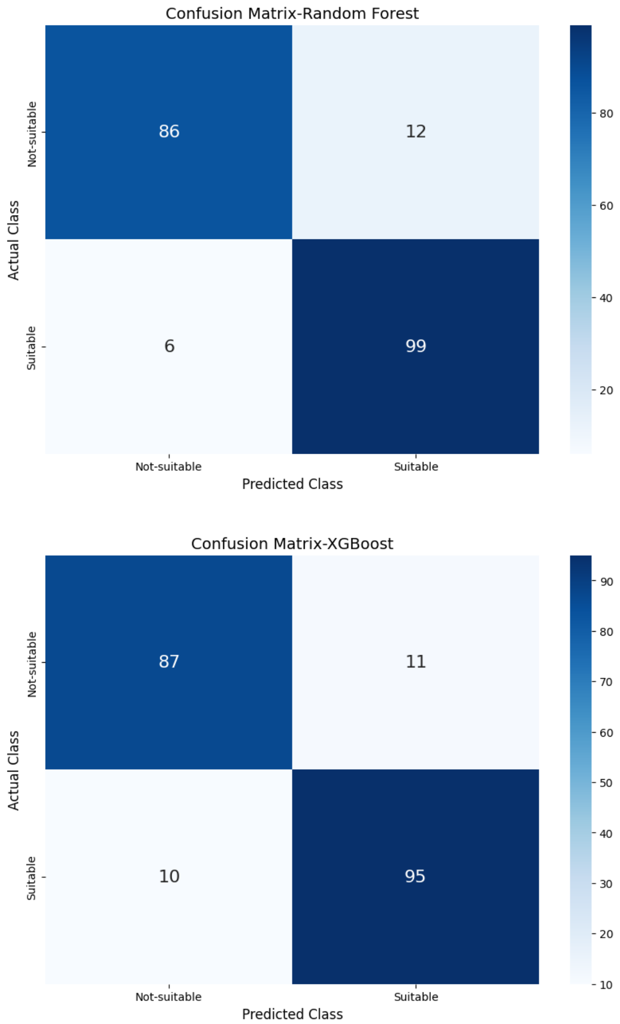

Figure 5. Confusion Matrix for Models

Table 2. Comparative Analysis of Models

Model	Test Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Random Forest	91.1	91.0	91.0	91.0
XGBoost	89.7	90.0	90.0	90.0

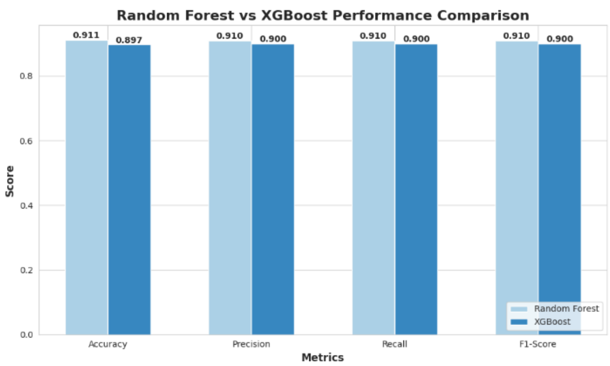

Figure 6. Comparative Analysis of Models

4.2 Predicted Suitability Map for Landfill Site Selection in Delhi NCR

The RF model outperformed XGBoost with an F1-score of 91% on the test dataset (Table 2 and Figure 6). Figure 7 shows the prediction results obtained using the RF.

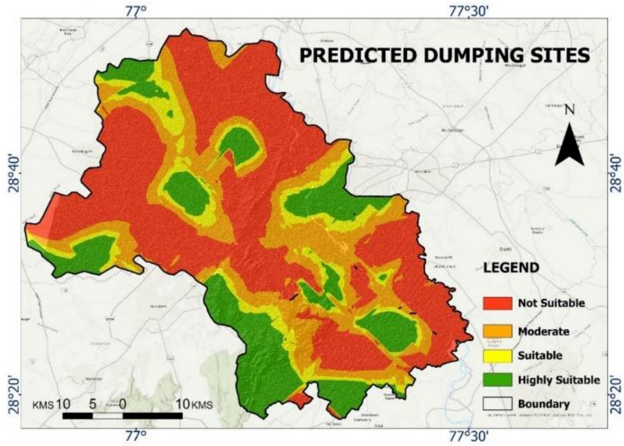

Figure 7. Predicted Optimal Dumping Sites using RF

The map presents a suitability analysis for potential dumping sites within a defined region, categorized into four classes based on their suitability for waste disposal activities. These classes, depicted with a color-coded legend, are Highly Suitable (green), Suitable (yellow), Moderate (orange), and Not Suitable (red). The analysis marked an important part of the region as "Not Suitable," indicating areas of high environmental sensitivity, densely populated zones, or locations close to critical infrastructure such as water bodies or protected ecosystems. These are unsuitable for waste disposal because of the potential adverse environmental and social impacts. Conversely, "Highly Suitable" zones are sparse, indicating limited areas where waste disposal would have minimal impact on the environment and surrounding communities. These regions are ideal for implementing sustainable waste management practices. There are intermediate categories, "Suitable," and "Moderate," with fewer restrictions. Nonetheless, such zones require further site-specific studies and mitigation measures before being used as dumping areas. The spatial framework of the map involves all key features, especially road networks, settlements, and natural landmarks, to help develop comprehensive guidance on strategic waste management planning. Table 3 shows the total area identified by the RF model as suitable and unsuitable for a dumping site in Delhi-NCR. This analysis is a critical tool for urban planners and policymakers, which suggests actionable insights in the attainment of decisions related to waste disposal, being environmentally conscious, socially acceptable, and sustainable for urban development. Categorization helps focus on priority areas for waste management while protecting ecological and human well-being.

Table 3. Machine Learning (RF) Based Dumping Site Suitability Classification in Delhi-NCR

Class	Suitability	Area (in Sq. Km)
0	Not Suitable	7.007
1	Suitable	0.803

The appropriate zones, colored green, were primarily located in the area's southern portion. These areas would most likely meet vital needs, such as low population density, stable soil characteristics, and a minimum distance from water sources, making them prime candidates for landfill construction. Using spatial analysis, the available map provides a data-driven approach to waste management, allowing policymakers to concentrate on areas where landfill construction would have the least ecological and social impact.

The ROC curve analysis is an important method for assessing the performance of classification models, particularly under distributed imbalanced datasets **(Hanley & McNeil, 1982; Fawcett, 2006)**. The ROC curves for each model are presented in Figure 8.

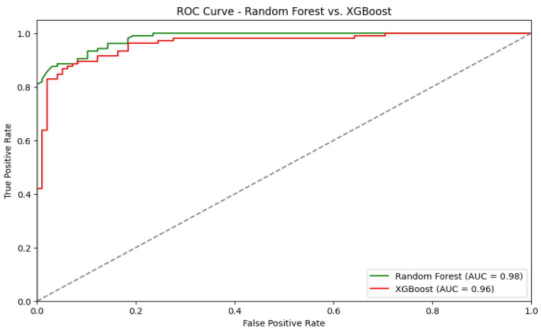

Figure 8: ROC Curve of Models for Dumping Site Suitability Predictions

In this study, the performances of the RF and XGBoost models in the classification of sites suitable for landfilling were compared using ROC curves. The AUC values indicated their effectiveness in correctly highlighting the specified sites. With an AUC value of 0.98, RF proves its capability of handling non-linear relations among the variables better than the others **(Breiman, 2001)**. These results make the RF model better than the others in predicting suitable landfill sites without losing precision compared to XGBoost.

Municipal bodies in the Delhi-NCR region can integrate the generated dumping site suitability maps into their existing waste management planning frameworks by adopting a GIS-enabled decision-support system. It can help planners to visualize feasible locations, conduct rapid scenario analyses, and cross-verify compliance with environmental norms and zoning regulations. This integration enables evidence-based site selection, reduces public opposition through transparent spatial justification, and supports the long-term goal of transitioning toward sustainable regional waste management.

5. Conclusion

This study illustrates the effectiveness of combining machine learning techniques and geospatial technologies to address the crucial issue of landfill site selection in Delhi-NCR. In light of this, using high-resolution spatial data and advanced algorithms such as Random Forest and XGBoost, this study highlights the contribution of machine learning through the improved classification of suitable and unsuitable landfill sites. Among all models considered, Random Forest achieved 91.13% accuracy, indicating its superiority in capturing complex spatial patterns and non-linear relationships among critical environmental, demographic, and infrastructural factors.

GIS and remote sensing integration has provided an overall framework that has been useful for assessing a vast range of variables such as population density, proximity to infrastructure, and environmental constraints. Therefore, it protects the identified landfill sites and minimizes ecological risks to sustain urban sustainability, particularly in a fast-developing region with dynamic land use. In addition, machine learning has simplified the decision-making process through scalable and data-driven methods that promote sustainable waste management. It is more accurate, scalable, and efficient than the previous methods. Such analytics can provide policymakers with actionable insights for informed decision-making in the pursuit of sustainability. There is scope for further robustness improvement in these methods with real-time data, the hybrid model, and incorporating socio-economic and cost-benefit analysis for optimizing landfill site selection.

Integrating machine learning and geospatial analysis lends a more forward-thinking approach to urban planning, incorporating both sustainability and the pressing needs of growing urban centers such as Delhi-NCR. Future studies can integrate real-time data input, such as live population density and environmental monitoring, to increase the model's adaptability. Further, the precision of the proposed approach can be enhanced with consideration of ensemble approaches.

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