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An Integrated MATLAB-ArcGIS Toolbox for Landfill Suitability Mapping Using Neural Networks

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Abstract: The Neural Network Toolbox for Landfill Suitability Mapping presents a novel approach to enhance solid waste management by automating landfill site selection using a combination of Python-ArcGIS and MATLAB environments. This study addresses the critical need for efficient landfill suitability mapping, which is essential for minimizing environmental risks and optimizing land use. We developed an automated toolbox that integrates the capabilities of MATLAB for neural network modeling with Python scripting in ArcGIS, facilitating a user-friendly workflow for decision-makers. Our methodology was tested in the northern region of Peninsular Malaysia, employing 14 specific criteria to generate training and testing datasets. The results of neural network model achieving an accuracy of 82%. This toolbox streamlines the process by automating various stages, from data preparation to suitability mapping, reducing the likelihood of human errors and minimizing processing time. The flexibility, interoperability, and user-friendly interface of the toolbox make it accessible to users with varying levels of GIS expertise, ensuring its adaptability to different geographic regions and environmental conditions. This research contributes to more efficient, accurate, and sustainable landfill site selection, benefiting decision-makers and supporting broader environmental protection efforts.

Key words: Landfill Suitability Mapping, Neural Networks, ArcGIS, Decision-Makers, Spatial Data.

Sinir Ağı Kullanarak Düzenli Depolama Alanı Uygunluk Haritalaması için Entegre MATLAB-ArcGIS Araç Kutusu

Öz: Atık depolama Sahası Uygunluk Haritalaması için Sinir Ağı Araç Kutusu, Python-ArcGIS ve MATLAB ortamlarının bir kombinasyonunu kullanarak depolama sahası seçimini otomatikleştirerek katı atık yönetimini geliştirmek için yeni bir yaklaşım sunar. Bu çalışma, çevresel risklerin en aza indirilmesi ve arazi kullanımının optimize edilmesi için gerekli olan verimli depolama sahası uygunluk haritalamasına yönelik kritik ihtiyacı ele almaktadır. Karar vericiler için kullanıcı dostu bir iş akışını kolaylaştıran, MATLAB'ın sinir ağı modelleme yeteneklerini ArcGIS'teki Python komut dosyası oluşturma ile birleştiren otomatik bir araç kutusu geliştirdik. Metodolojimiz Malezya Yarımadası'nın kuzey bölgesinde, eğitim ve test veri kümeleri oluşturmak için 14 spesifik kriter kullanılarak test edildi. Sinir ağı modelinin sonuçları %82 doğruluk oranına ulaşmıştır. Bu araç kutusu, veri hazırlamadan uygunluk haritalamasına kadar çeşitli aşamaları otomatikleştirerek, insan hatası olasılığını azaltarak ve işlem süresini en aza indirerek süreci kolaylaştırır. Araç kutusunun esnekliği, birlikte çalışabilirliği ve kullanıcı dostu arayüzü, onu farklı düzeylerde CBS uzmanlığına sahip kullanıcılar için erişilebilir hale getirerek farklı coğrafi bölgelere ve çevre koşullarına uyarlanabilirliğini sağlar. Bu araştırma, daha verimli, doğru ve sürdürülebilir depolama alanı seçimine katkıda bulunarak karar vericilere fayda sağlar ve daha geniş çevre koruma çabalarını destekler.

Anahtar kelimeler: Atık Depolama Sahasına Uygunluk Haritalaması, Sinir Ağı, ArcGIS, Karar Vericiler, Mekansal Veriler.

1. Introduction

Landfills stand as some of the most dangerous locations, posing a profound threat to environment, tourism, and property values [1–3]. The pursuit of suitability mapping has been an enduring concern within environmental planning endeavors, marked by the persistent need to address critical aspects. Aspects such as minimizing risks to public health, mitigating the adverse effects on the natural life, maximizing the services of landuse to communities, and minimizing the overall expenditure associated with the operation of facilities, underscoring the economic aspect of the challenge [4,5]. Numerous commendable efforts have been undertaken towards the enhancement of solid waste management, as underscored by several works [6,7]. Notably, among this research, a notable one transpired in Malaysia, led by [8]. Back in 2005, the Malaysian government took a significant step by publishing the National Strategic Plan (NSP) for Solid Waste Management under the Ministry of Housing and Local Government in Malaysia. Additionally, Japan International Cooperation Agency (JICA) embarked on an evaluation and baseline-setting initiative in 2005. This was supplemented by an array of research projects carried

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out by various researchers and organizations, including but not limited to [9–14]. These collective efforts saw the emergence of an array of methods for landfill suitability mapping [15–17].

The developed methods in the former works relayed on integration of vector and raster data, which proved the valuable aiding decision-makers operating within defined geographic regions. The integration empowered them to navigate the labyrinth of criteria selection and suitability mapping for landfill sites [18,19]. Such modules operated at the interconnection of Multi-criteria decision analysis (MCDA) and Geographic Information Systems (GIS), underpinned by the principles of these technologies. Additionally, they seamlessly merged diverse processing environments, primarily drawing upon the capabilities of Matlab and Python within the ArcGIS framework. Majumdar develops a Multi-criteria Decision Making (MCDM) tool using the Analytical Hierarchy Process to evaluate the suitability of three proposed landfill sites in Kolkata, considering various criteria such as environmental impact and economic viability. The analysis indicates that the sites are moderately suitable, with scores between 300 and 750 on both the Landfill Site Sensitivity Index (LSSI) and Economic Viability Index (EVI) [20]. Eldrandaly introduces a GIS-based multicriteria evaluation (MCE) tool in ArcGIS 9.3, designed for use by engineers and planners with varying GIS expertise, and demonstrates its application through a case study [21]. Daneshvar customizes ArcMap v8.2 using VBA to develop a user-friendly Landfill Site Selection (LSS) toolbar, aiding engineers of varying GIS expertise in evaluating landfill site suitability based on diverse criteria and scoring schemes [22]. The former studies include potential limitations in terms of scalability, adaptability to changing landscapes, and accessibility to users with varying levels of GIS expertise. Consequently, the development of a new tool is justified to address these limitations by offering a solution that is user-friendly, adaptable to evolving GIS technologies, and accessible to engineers and planners with varying levels of GIS expertise.

In our research, Matlab served as the primary programming environment for the implementation of neural networks (NN) models. The utilization of Matlab offers a multitude of advantages, essentially in its capacity to provide a robust foundation for the creation and refinement of NN models. However, it is worth noting that Matlab is not inherently a spatial software, which gives rise to certain challenges within the integrated model. These challenges manifest in the form of complex processing procedures, as identified by [23], demanding extensive and time-consuming efforts from decision-makers in the production of suitability maps. Consequently, end-users, particularly decision-makers, may cope with a host of difficulties and limitations when attempting to apply the developed model. These limitations encompass the intricacies of importing spatial data, the construction of training data sets from such data, spatial-related issues, the management of voluminous data, the potential for human errors, as well as the need for manual input variable assignment and implementation.

Manual analysis prone to consuming excessive time and possessing reduced accuracy. Furthermore, analysts must undertake the difficult task of assembling the model from scratch with every application. This often results in the dispersion of models due to the use of multiple functions, rendering them impractical and challenging to reproduce. Moreover, previous models lack adaptability to various geographical areas, each having distinct criteria, which necessitates repeated consultation with experts and deep understanding of variables. The earlier methods exhibit limitations in the implementation, prompting a demand to develop of these methods to streamlining landfill suitability mapping. This enhancement aimed at bolstering landfill suitability mapping systems and unifying all tasks into a singular, user-friendly workflow that provides to decision-makers requirements.

To overcome these limitations, an ArcGIS Toolbox has been developed using the Python scripting language. This toolbox provides a solution to improve integrality between the NN-Matlab environment, and ArcGIS-Python environment. Python is an open-source scripting language, offering a wide array of functionalities that facilitate geospatial data processing. This combination of Python and Matlab, realized through the NN toolbox we present in this paper, is specially tailored to accommodate non-specialist users. It provides to individuals with a basic understanding of Matlab and ArcGIS, enabling them to generate the suitability maps of different locations based on NN modeling. The toolbox simplifies and automates the various stages of processing, offering a user-friendly solution that holds the potential to revolutionize solid waste management systems.

2. Methods

1.1 Model Automation

The automated toolbox serve for conducting landfill suitability mapping. These toolboxes dynamically executed through a combination of the ArcGIS-Python and Matlab environment. They form an integral part of our workflow, seamlessly linking the ArcGIS Python toolbox with the sophisticated NN structure within the Matlab environment. Figure 1. illustrated the flowchart of our NN toolbox unfolds across nine distinct toolsets, each representing crucial stages for data preparation and analysis, as depicted in Figure 2. The toolbox carries several notable benifits as outlined below:

- User-Friendly Interface: It simplifies the end-users experience, particularly decision-makers, by automating various stages, reducing the likelihood of human errors, and minimizing time wastage.
- Flexible Functionality: Our toolbox empowers users to swiftly create both straightforward and complex workflows in a systematic and efficient manner.
- Interoperability: It seamlessly integrates Matlab environment, enhancing the range of functionalities for geospatial modeling.
- Streamlined Criteria Selection: The model facilitates the selection of criteria thus, streamlining the decision-making process.

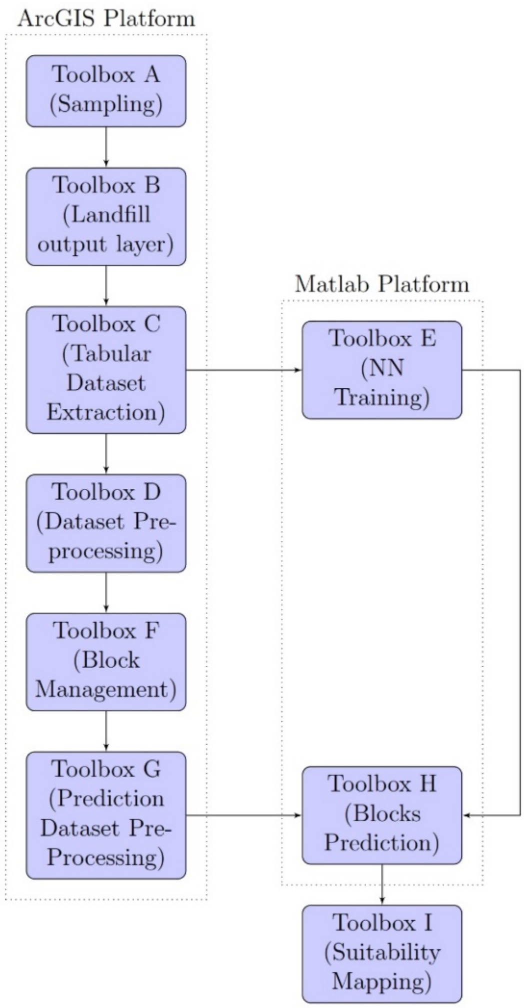

Figure 1. Presents the flowchart detailing the expansion of our Neural Network toolbox across nine distinct toolsets. Each toolset corresponds to essential stages in data preparation and analysis.

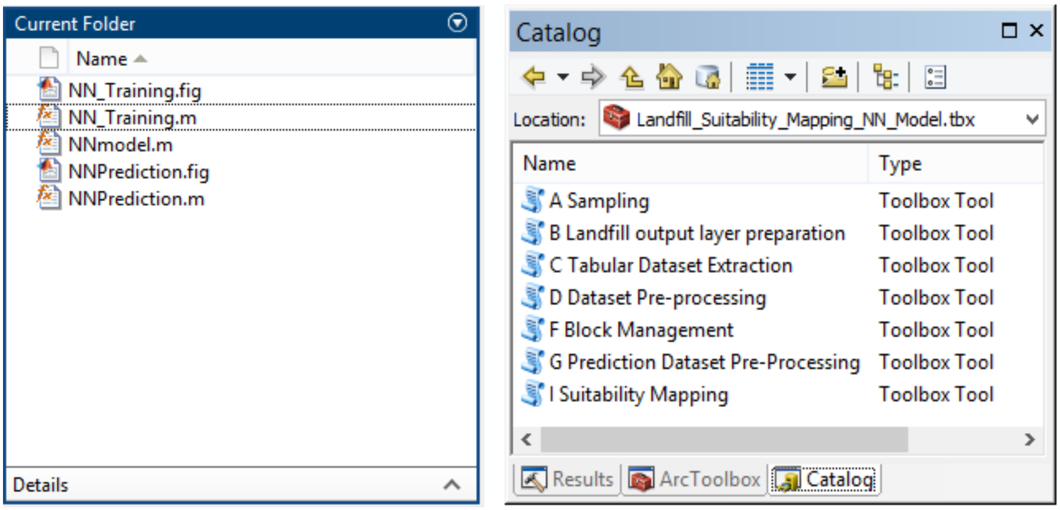

Figure 2. Developed Toolbox in ArcGIS and Matlab Environment.

The developed model designed to import ESRI layers and tabular data in Matlab. The toolboxes descried as the following:

The Python script named (A: Sampling) serves the purpose of generating a spatial sampling framework within a given study area, particularly focusing on areas designated as landfills (see Figure 3. and Annex 1.). It employs ArcPy, the Python site package for ArcGIS, to execute geospatial operations. Initially, it imports necessary modules and sets up the environment, including setting overwrite output to true and checking out the spatial extension license. The script then receives input parameters such as landfill polygons, study area polygons, and coordinate system information. It proceeds to create a fishnet grid within the boundaries of the landfill polygons, using the CreateFishnet function. Subsequently, the grid is clipped to the landfill extents, resulting in a refined grid. This clipped grid is further processed: converted to lines, then to points, and duplicates are removed. Another aspect of the script involves creating random sample points within areas excluding the landfills, achieved by erasing landfill areas from the study area and generating random points constrained within the resulting non-landfill areas. Finally, the script merges the refined grid points with the random sample points to produce a comprehensive set of sampling points for further analysis, facilitating spatial data collection and analysis within the specified study area.

The Python script named (B: Landfill output layer preparation) is designed to prepare an output layer that distinguishes between landfill areas and the rest of the study area (see Figure 3. and Annex 2.). Utilizing ArcPy and ArcGIS Spatial Analyst tools, the script initially imports necessary modules and sets up the environment. It then acquires input parameters such as landfill and study area polygon layers, coordinate system information, and cell size. Following this, the script defines field attributes for indicating landfill presence and absence, and it adds and calculates these fields accordingly to the study area layer. Subsequently, it merges the landfill and study area layers into a single vector layer and converts this merged layer into a raster format. The raster values are then reclassified to assign a value of 1 to landfill areas and 0 to non-landfill areas, resulting in the final output raster layer. Finally, the script refreshes the Table of Contents (TOC) and the Active View in the ArcGIS environment to reflect the updated layers. This process enables the creation of a spatially explicit representation of landfill areas within the study area for further analysis and visualization.

The Python script named (C: Tabular Dataset Extraction) is developed to extract values from raster layers to corresponding sample points and perform data cleanup operations (see Figure 3. and Annex 3.). The script acquires input parameters such as point features and raster layers. The script identifies and drops unnecessary fields from the input point features to streamline the dataset. Following this, it utilizes the ExtractMultiValuesToPoints function to extract values from target raster layers to the points. Additionally, the script extracts values from additional raster layers to the same set of points. This process ensures that the points possess relevant raster values, facilitating subsequent spatial analysis.

The Python script named (D: Dataset Pre-processing) is designed to prepare a dataset for training machine learning models (see Figure 3. and Annex 4.). The script begins by defines the workspace based on the input dataset and creates a feature layer. The script iterates through selected fields to remove rows with missing data, ensuring data integrity. Subsequently, it constructs the dataset by extracting samples and shuffling them to prevent biases during training. The dataset is divided into input features and target variables, reshaped as necessary. Finally, the script outputs the prepared input and target datasets to specified paths.

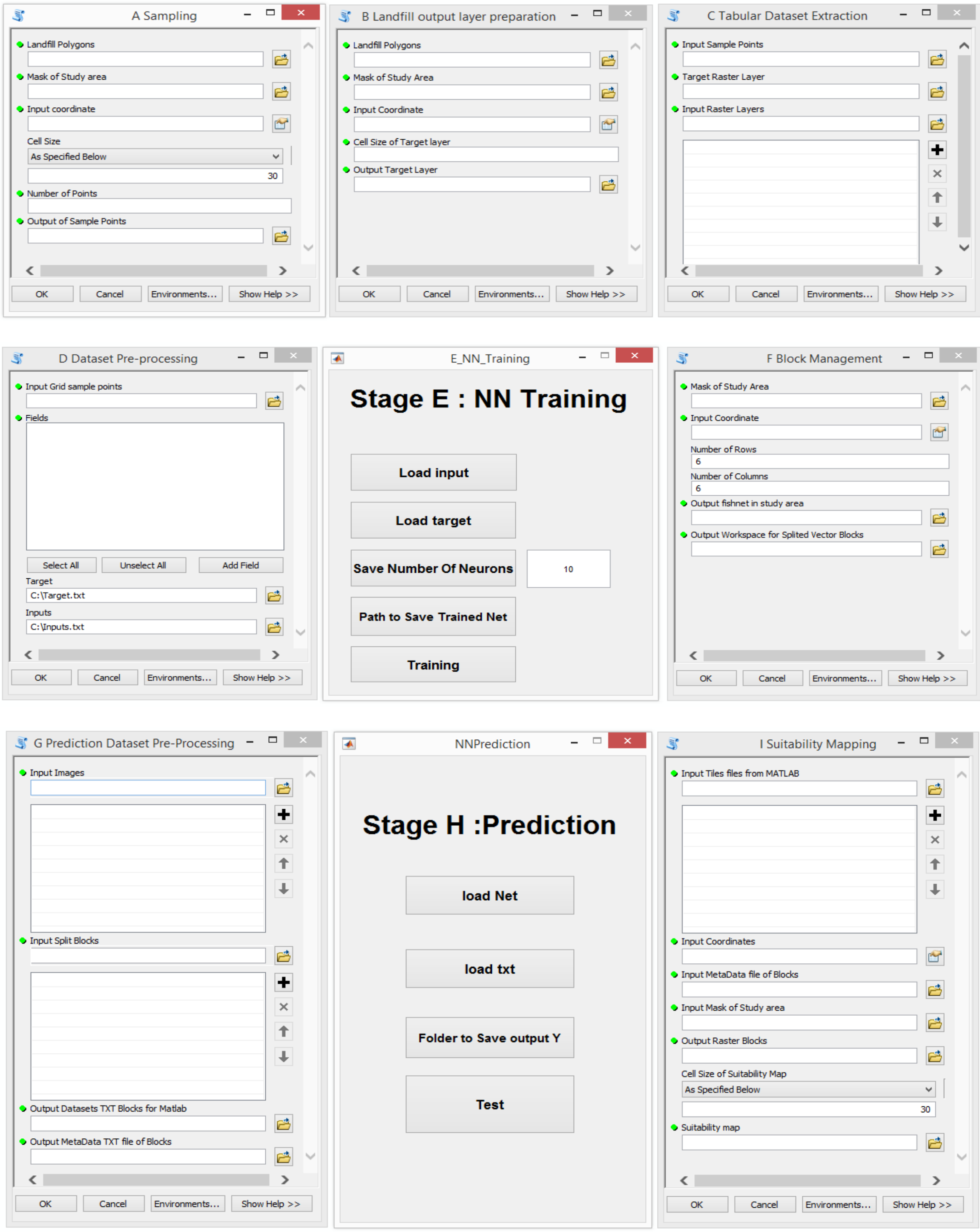

Figure 3. Toolbox Suite for Landfill Site Selection using Neural Networks. This comprehensive toolbox suite comprises nine interconnected Python and MATLAB scripts (A-I) designed for landfill site selection employing neural networks. From spatial sampling, dataset extraction, to neural network training and prediction, these scripts utilize Python, and MATLAB, to streamline processes like block management, dataset preparation, and suitability mapping.

The MATLAB script named (E: NN_Training) serves the purpose of training a neural network model using graphical user interface (GUI) interaction (see Figure 3. and Annex 5.). The script initializes the GUI parameters and handles user interactions, such as loading input and target data files, specifying the path to save the trained network, and setting the number of neurons for the model. Upon user inputs, the script executes the neural network training function "NNmodel" with the provided input, target data, and specified number of neurons. The trained model is then saved to the specified output network path. The trained NN model is encapsulate in (*.m) format for further stages. The MATLAB function "NNmodel" is developed to create and train a neural network model based on provided input and target data. The function utilizes the scaled conjugate gradient backpropagation algorithm for training, denoted by the variable "trainFcn". It initializes a neural network using the "patternnet" function with a specified number of neurons. The data is divided into training, validation, and testing sets using predefined ratios. This methodology streamlines the process of neural network model creation and training, enabling efficient experimentation and analysis with different datasets and model configurations.

1.2 Study area

The Python script named (F: Block Management) aims to generate blocks from a given shapefile and subsequently split them based on a provided mask (see Figure 3. and Annex 6.). The script creates a describe object from the input shapefile to extract its extent, which is used to define the boundary points for block generation. Blocks are generated using the CreateFishnet function, creating a grid within the extent of the shapefile. The script then selects blocks intersecting with the mask shapefile and copies them to an output feature class. Subsequently, it splits the selected blocks based on a specified field, assigning unique identifiers to each split block.

The Python script named (G: Prediction Dataset Pre-Processing) is designed to generate metadata and datasets for each block defined by vector polygons (see Figure 3. and Annex 7.). It retrieves input raster maps and vector polygons along with output folders for metadata and datasets. For each vector polygon, the script extracts its extent and iterates through the raster maps to clip them to the polygon extent. It then converts the clipped raster maps to NumPy arrays and saves them as text files. The script also computes metadata such as minimum x-coordinate (xmin), minimum y-coordinate (ymin), mean cell width, mean cell height, row count, and column count for each block and saves them to a metadata file. This methodology enables the creation of datasets and metadata tailored to each block within the study area, facilitating subsequent analysis and modeling tasks.

The MATLAB script named (H: Block NNPrediction) implements a graphical user interface (GUI) for conducting neural network predictions (see Figure 3. and Annex 8.). It initializes the GUI parameters and handles user interactions such as loading trained network models and input data files. Upon user inputs, specifically loading the trained model and input data files, the script executes the neural network prediction function. For each input data file, the script loads the trained model, performs prediction using the input data, and saves the predicted output (Y) as text files. The predicted values between 0 and 1 as the foundation for predictions. This methodology provides a user-friendly interface for conducting neural network predictions, allowing users to conveniently load models and input data, perform predictions, and save the results for further analysis.

The Python script named (I: Suitability Mapping) is representing the conclusive phase, this stage marks the step in generating the tentative suitability map (see Figure 3. and Annex 9.). The script retrieves input prediction files along with metadata and other parameters such as the study area mask and output folder. For each predicted (Y) text file, the script reshapes the data and saves it as an ASCII file, then converts it to a raster format. The raster paths are collected and used to mosaic them into a single raster image. Additionally, the script clips the mosaic raster based on the study area mask. Finally, the clipped raster is saved as the output suitability map. This methodology enables the conversion, aggregation, and clipping of prediction files to generate a comprehensive raster output tailored to the study area.

The study area was conducted in the northern region of Peninsular Malaysia, specifically encompassing Penang, Perak, Perlis and Kedah, states as illustrated in Figure 4. The area of study area is covers 32,191 square kilometers, constituting roughly 9.75% of Peninsular Malaysia. As of the 2010 demographic data, the region inhabited by a population of 2,258,428 people. Meteorologically, the area is characterized by a warm and sunny climate, experiencing rainfall 3,218 millimeters per year. The topography of the area varies from flat terrain to hilly regions, with elevations spanning from 1 meter above sea level (m AMSL) to 3,978 meters AMSL.

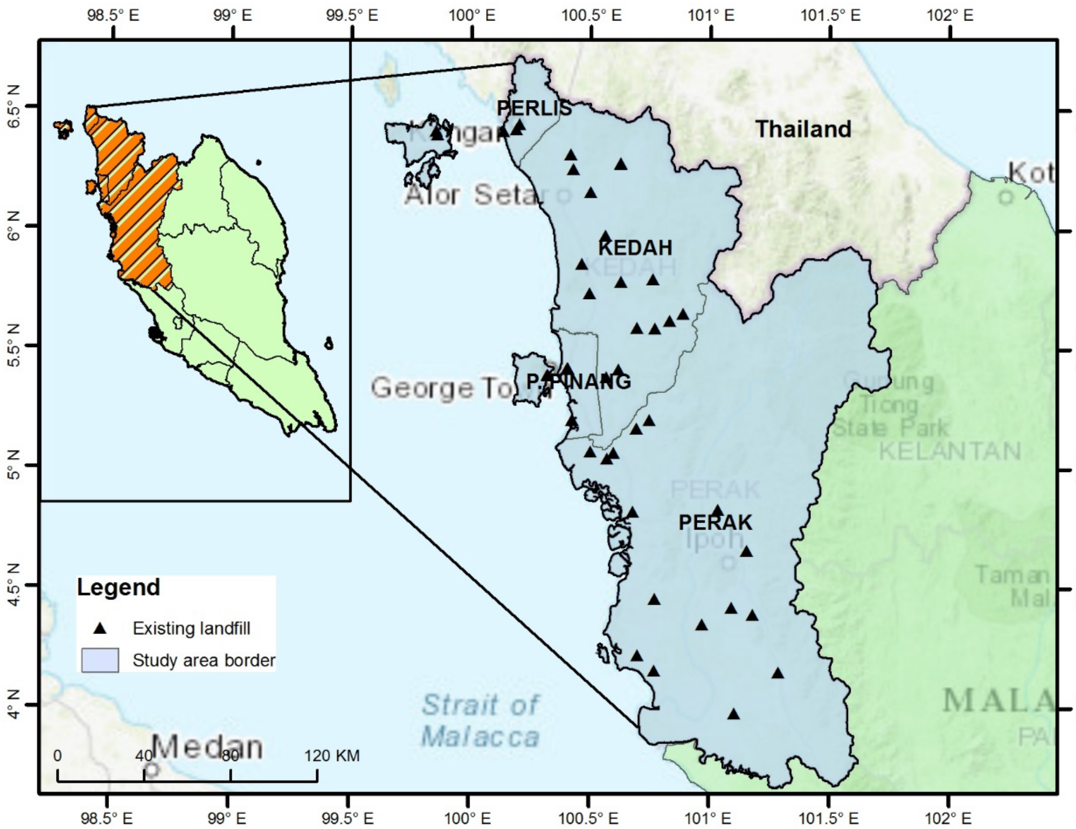

Figure 4. Study Region (Perak, Penang, Kedah, and Perlis).

Spatial data layers corresponding to the chosen criteria were prepared. The existing landfill sites depicted in Figures 4, while the sample points of non-landfill presented in Figure 5. The tabular data extracted using the developed toolbox. Figures 5 and 6 presenting the relevant explanatory 14 parameters, which are distance from district boundaries, secondary roads, federal roads, highways, hospitals, airports, dams, rivers, geological faults, caves, as well as precipitation, slope, elevation, and landuse.

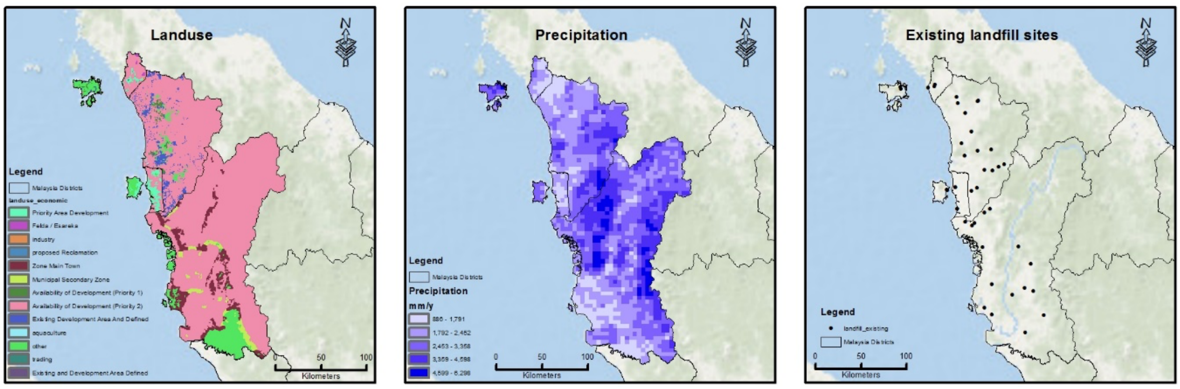

Figure 5. Precipitation, and Landuse, as well as the existing landfill sites.

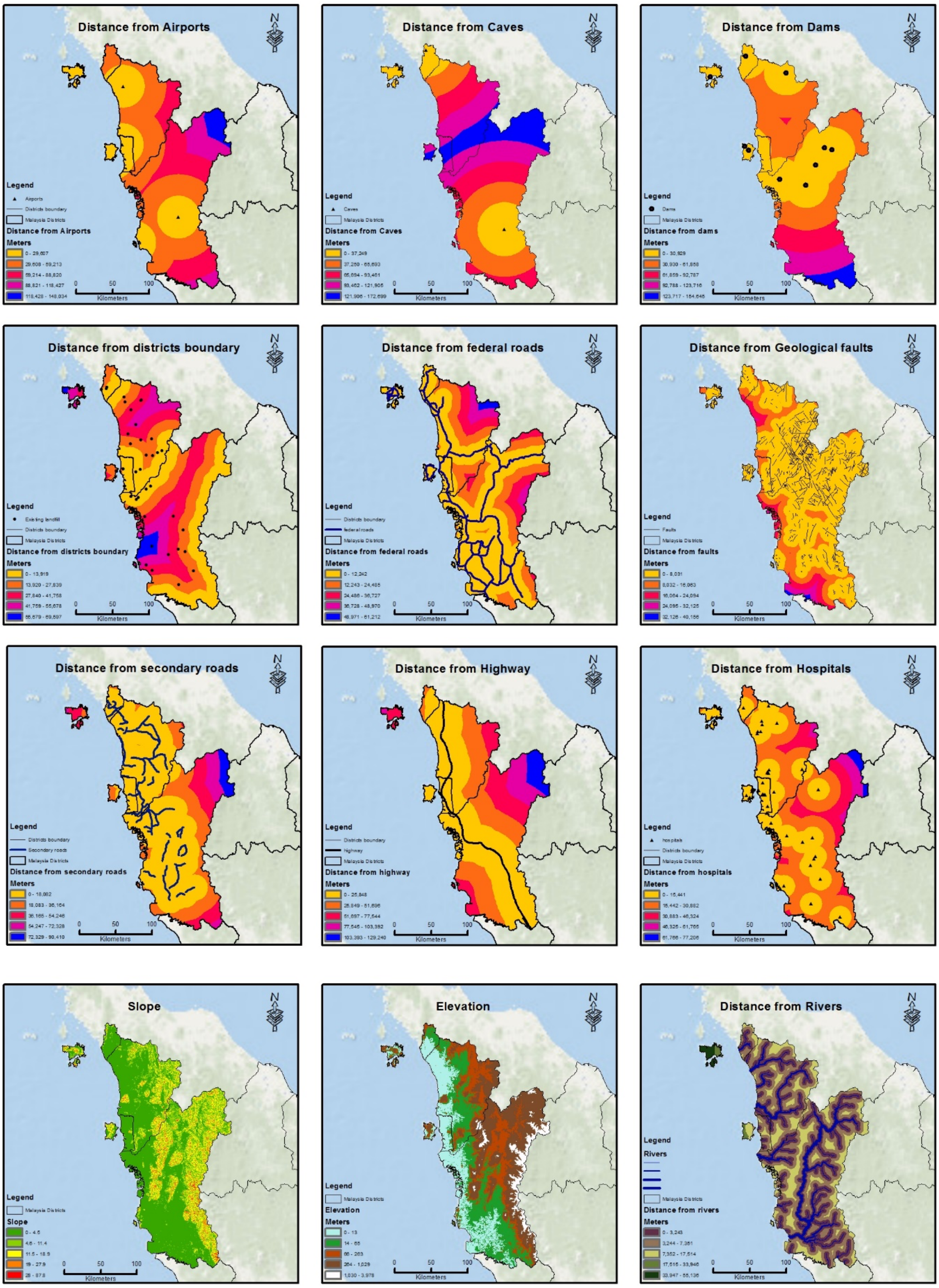

Figure 6. Distance from several variables such as Caves, dams, Geological faults, Secondary roads, federal road, Highway, local boundaries, Airports, Rivers, and hospitals as well as Slope, and Elevation.

3. Results

3.1.Tool implementation for Suitability Mapping

The utilization of the developed toolkit facilitated the systematic generation of a suitability map tailored to our designated study area. In phase A, samples established with spatial resolution of 30 meters, ultimately yielding a 7000 sample points. Moving to phase B, the landfill binary target map produced, drawing it from the pool of collected landfill polygons. Simultaneously, stage C generate the attributes through the 14 variables in conjunction with the binary output map of landfill and non-landfill categories. Phase D undertook the critical task of processing the tabular data associated with the generated points, which was then construct our training dataset. It is worth noting that this process resulted in a final processed dataset housing 5,902 records, after the removing of missing records and outliers. Phase E, the NN model generated and trained as well exhibited remarkable accuracy of 82% during testing. Phase F created of a grid of blocks that effectively partitioned our study area into manageable blocks. Stage G, assembled tabular dataset of blocks. In totality, 19 subsets generated (see figure 7). In stage H, we transitioned into the prediction stage, supported by the trained NN model. The trained NN model processing the 19 subsets, yielding Y values. Phase I, present of the suitability mapping of landfills.

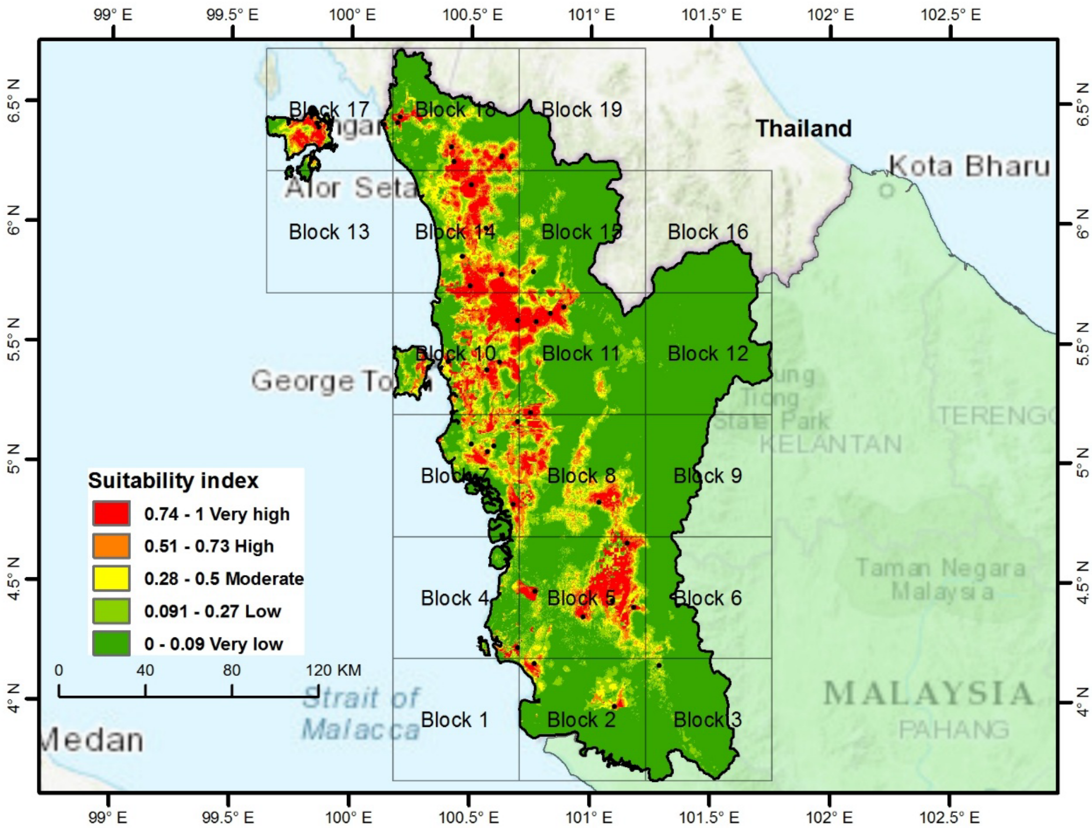

Figure 7. Suitability Map for Solid Waste Landfill Sites Generated Using the Automated and Integrated NN Model.

Figure 7 illustrates the suitability map for the solid waste landfills. This map highlights areas categorized as either suitable or unsuitable for landfill placement. To enhance the map's clarity, a legend provided with the suitability index. Notably, majority of area falls into the low suitability category, encompassing 57.84% of the total area. This distribution includes 26.56% in the low suitability category, 2.89% in the moderate suitability category, and 1.86% in high suitability category. A 10.82% exhibits a very high suitability category.

3.2.NN model performance

The Figure 8. shows a confusion matrix for a machine learning model classifying two classes. The confusion matrix is a table that compares the actual labels of the data with the labels predicted by the model. In this case, the rows represent the actual classes, and the columns represent the predicted classes. Each cell of the table shows the number of instances (5273 for class 0 and 3153 for class 1) and the corresponding percentage (51.3% and 30.7% respectively) of how many instances were correctly classified. For example, the top-left cell (5,273) shows that the model correctly predicted 89.4% of the instances that actually belong to class 0. The bottom right cell (3153) shows that the model incorrectly classified 27.9% of the instances that actually belong to class 1 as class 0. Overall, the model performs better at classifying class 0 with a higher accuracy (89.4%) and a lower error rate (10.6%) compared to class 1 (72.1% accuracy and 27.9% error rate). The overall accuracy metric is 82%.

In addition, the figure shows a Receiver Operating Characteristic (ROC) curve, which is a graph used to visualize the performance of a binary classification model. The ROC curve plots the true positive rate (TPR) on the y-axis against the false positive rate (FPR) on the x-axis. The TPR is the proportion of positive cases that were correctly identified by the model, while the FPR is the proportion of negative cases that were incorrectly classified as positive. A perfect classifier would have a ROC curve that follows the upper left corner of the graph, meaning it has a 100% TPR and a 0% FPR. In the ROC curve depicted in the figure, the AUC (Area Under the Curve) is difficult to determine visually due to the lack of gridlines and specific data points. However, a higher AUC generally indicates a better performing classifier. Overall, the ROC curve in the figure can be used to assess the trade-off between TPR and FPR for the binary classification model.

The F1 score, which balances precision and recall, was calculated as 77.2% for Class 1, indicating a strong but improvable model performance. This suggests that while the model effectively identifies landfill-suitable areas, some misclassification persists. Future improvements could focus on optimizing feature selection and refining classification thresholds to enhance predictive accuracy.

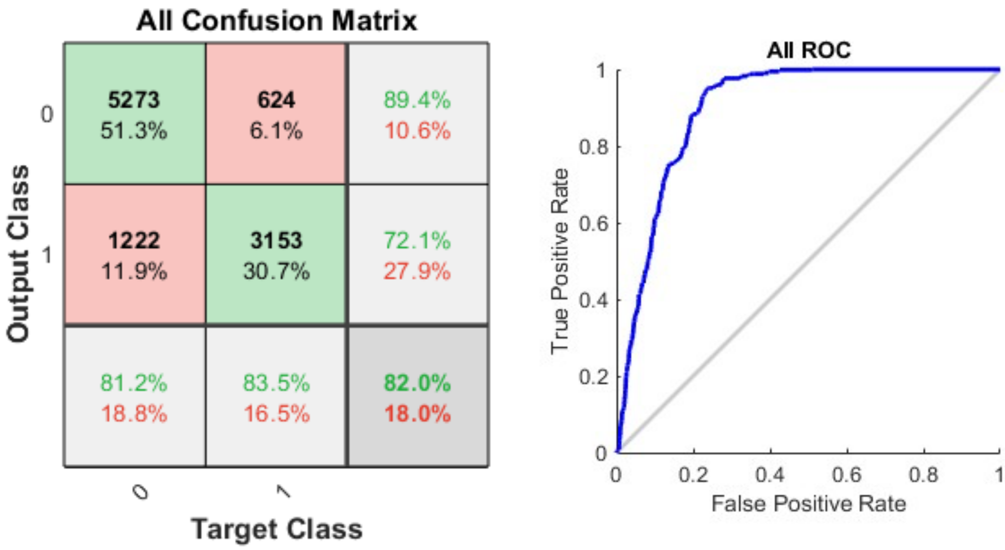

Figure 8. Evaluation Metrics for the Machine Learning Model

4. Discussion

The developed Neural Network Toolbox demonstrably improved the efficiency and accuracy of landfill suitability mapping by automating various stages of the process (See Table.1.). By automating tasks like spatial sampling, data preparation, and suitability map generation (previously completed manually), the toolbox minimizes human error and significantly reduces the time required to generate suitability maps, allowing decision-makers to focus on strategic planning and analysis. The integration of a neural network model within the toolbox facilitates highly accurate suitability assessments, as evidenced by the mentioned 82% accuracy, which surpasses traditional methods that may rely on subjective criteria or less sophisticated modeling techniques. Earlier methodologies, such as those developed by Majumdar, Eldrandaly, and Daneshvar, often struggled with scalability, adaptability, and accessibility, especially for users with varying levels of GIS expertise [20–22]. By contrast, our toolbox simplifies these challenges through its user-friendly interface, flexible functionality, and seamless interoperability between MATLAB and ArcGIS environments.

Table 1. Comparison of the Developed Toolbox with Existing Methods.

Feature/Criteria	Traditional GIS-Based Approaches	Machine Learning-Based Methods	Proposed Neural Network Toolbox
Automation Level	Manual or semi-automated	Semi-automated	Fully automated
Integration	GIS-based only	Standalone ML models	Seamless integration with GIS & MATLAB
Ease of Use	Requires expert knowledge	Requires coding experience	User-friendly GUI, minimal coding required
Flexibility	Limited to rule-based models	Requires extensive parameter tuning	Adaptive learning with minimal manual intervention
Computational Efficiency	Moderate (depends on GIS software)	High computational cost	Optimized for efficiency with parallel processing
Interpretability	High (rule-based models)	Moderate to low (black-box nature)	Moderate (provides decision layers)
Scalability	Limited to small datasets	Works with large datasets	Optimized for large-scale analysis
Accuracy & Performance	Relies on predefined rules	Performance varies based on training data	High accuracy (82% with F1 score of 77.2%)
Strengths	Simple and interpretable	Can capture complex patterns	Combines GIS & ML for robust, automated decision-making
Weaknesses	Limited adaptability	Requires extensive tuning	Initial setup requires MATLAB & ArcGIS

The utilization of Python scripting within the ArcGIS toolbox creates a user-friendly interface, eliminating the need for in-depth GIS expertise and making the tool accessible to a wider range of decision-makers involved in waste management. The toolbox streamlines the entire workflow by automating various stages and provides flexibility by allowing users to create both simple and complex workflows, tailored to their specific needs and data requirements. The seamless integration of Python and MATLAB environments within the toolbox expands the range of functionalities available for geospatial modeling, leveraging the strengths of both platforms for a more comprehensive approach to landfill suitability mapping. This innovative toolbox, integrating Python-ArcGIS and MATLAB environments, automates the complex process of landfill site selection, addressing several limitations observed in previous models that struggled with scalability, adaptability, and accessibility, especially for users with varying levels of GIS expertise.

The highly promising results, highlighted by a testing accuracy of 82%, underscore the robustness and reliability of our model. The automation of the neural network model not only minimizes human errors but also significantly reduces the time required for data processing and suitability mapping. Moreover, the toolbox's ability to dynamically execute processes across nine distinct stages ensures efficient data handling and streamlined workflows, optimizing internal memory usage and allowing for the integration of diverse datasets, making the model adaptable to various geographic regions and environmental conditions.

Our case study in northern Peninsular Malaysia demonstrates the practical application and effectiveness of the toolbox, with the suitability map generated through our automated process providing a clear and accurate identification of potential landfill sites, crucial for informed decision-making. By overcoming the limitations of previous models and offering a robust, automated solution, our research contributes to more efficient, accurate, and sustainable landfill site selection, benefiting decision-makers and supporting broader environmental protection efforts by optimizing the management of solid waste.

5.Conclusion

In this research, we introduced an innovative approach that addresses the challenges of developing a robust method for landfill suitability mapping through automating a NN model. Through a case study in the northern region of Peninsular Malaysia, we demonstrated effectiveness of our methodology by employing 14 specific criteria to create training and testing datasets.

The results of our study were highly promising, with a remarkable testing dataset accuracy of 82% achieved. This automated toolbox has laid a durable foundation for decision making process of landfill suitability mapping. It has shown great potential for optimizing processes within this critical domain, contributing to enhanced solid waste management systems and unifying tasks into a user-friendly workflow tailored to the needs of decision-makers.

The significance of our research lies in the simplification and automation of the landfill suitability mapping process, offering a user-friendly interface that minimizes human errors and accelerates decision-making. The flexibility and interoperability of our model enable users to create both simple and complex workflows while integrating various environments. We streamlined criteria selection and facilitated the decision-making process, making it more accessible to a broader audience.

Our research has overcome the limitations of previous models, such as data integration challenges, manual input requirements, and lack of adaptability to different geographical areas. By developing an ArcGIS Toolbox using Python scripting, we have successfully enhanced the performance of the streamlining Landfill suitability mapping workflow, which ultimately benefits solid waste management systems.

The suitability mapping in the study area exemplifies practical application of our model. By automating the entire process, from data preparation to suitability mapping, we achieved an impressive level of accuracy in identifying potential landfill sites. The division of the workflow into nine distinct stages optimizes internal memory usage and ensures efficiency throughout the process.

Future studies should expand the geographic scope of the toolbox, validating its use in diverse regional and global settings. Incorporating additional criteria, such as detailed soil characteristics, groundwater flow, and climate change projections, could improve model accuracy. Enhancing the user interface and automating more processes would simplify decision-making for non-experts. Integrating the toolbox with other decision-making tools and incorporating policy and economic analysis could provide a more comprehensive support system. Real-time data integration and updating capabilities, along with performance optimizations like advanced neural network architectures and parallel processing, can improve efficiency. Validating the model against existing ones and conducting longitudinal studies to assess temporal changes and long-term impacts will ensure the model's reliability and sustainability in landfill suitability mapping and broader environmental planning applications.

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