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A Comparison of the Efficacy of Fuzzy Overlay and Random Forest Classification for Mapping and Shaping Perceptions of the Post-Mining Landscape of Gauteng, South Africa

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Abstract: Post-mining landscapes are multifaceted, comprising multiple characteristics, more so in big metropolitan regions such as Gauteng, South Africa. This paper evaluates the efficacy of Fuzzy overlay and Random Forest classification for integrating and representing post-mining landscapes and how this influences the perception of these landscapes. To this end, this paper uses GISs, MCDA, Fuzzy overlay, and Random Forest classification models to integrate post-mining landscape characteristics derived from the literature. It assesses the results using an accuracy assessment, area statistics, and correlation analysis. The findings from this study indicate that both Fuzzy overlay and Random Forest classification are applicable for integrating multiple landscape characteristics at varying degrees. The resultant maps show some similarity in highlighting mine waste cutting across the province. However, the Fuzzy overlay map has higher accuracy and extends over a larger footprint owing to the model's use of a range of 0 to 1. This shows both areas of low and high memberships, as well as partial membership as intermediate values. This model also demonstrates strong relationships with regions characterised by landscape transformation and waste and weak relationships with areas of economic decline and inaccessibility. In contrast, the Random Forrest classification model, though also useful for classification purposes, presents a lower accuracy score and smaller footprint. Moreover, it uses discrete values and does not highlight some areas of interaction between landscape characteristics. The Fuzzy overlay model was found to be more favourable for integrating post-mining landscape characteristics in this study as it captures the nuances in the composition of this landscape. These findings highlight the importance of mapping methods such as Fuzzy overlay for an integrated representation and shaping the perception and understanding of the locality and extent of complex landscapes such as post-mining landscapes. Methods such as Fuzzy overlay can support research, planning, and decision-making by providing a nuanced representation of how multiple landscape characteristics are integrated and interact in space and how this influences public perception and policy outcomes.

Keywords: GISs; MCDM; post-mining; landscape characteristics; integration; fuzzy overlay; random forest classification

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1. Introduction

Most of the literature on post-mining landscapes relates to their technical aspects, such as rehabilitation through water retention, biomass plant testing, soil reclamation, and geothermal conversion [1–3]. However, focus on these technical aspects may also influence their perception by the public and stakeholders [4]. Berger [5] also notes that post-extractive landscapes, including areas of post-mining and industrialisation, may be stigmatised. In agreement, Svoboda et al. [4] note that this is attributable to their perception as sustainability and socio-economic risks. This, therefore, leads to their neglect and development tends to move away from them, leading to their permanent exclusion from further use [6]. Some studies [7–9] argue that a more holistic view of post-mining landscapes and the opportunities arising from abandoned mining sites and their potential future uses is required. These studies posit that these landscapes present several new opportunities for the regeneration of the surrounding landscape and a better understanding of the spatial and cultural development of the surrounding landscape. The mapping and visualisation of these spaces can potentially benefit them by influencing their perception [4,10–12]. Thus, some studies, such as Liu and Nijhaus [13], posit that understanding landscape complexity is crucial for numerous scientific disciplines and practical applications by researchers, planners, and policy and decision-makers. Moreover, the effective visualisation and mapping of landscape characteristics gives decision-makers some insight into how landscapes function, while the representation and symbology of various landscape features may shape the perception of the landscape [4,6,10,11] and could potentially enable better communication of the landscape.

In response, there have been fundamental advances in the mapping of landscapes over the years, going from traditional empirical cartographic foundations to Geographic Information Systems (GISs). These advances potentially improve the perception of landscapes by incorporating geographically referenced information into conceptual frameworks also used in the social sciences [14]. Most of these frameworks have investigated the integration of a particular landscape's characteristics, such as the environment, society, culture, and heritage [15–23], improving the perception of landscapes by showing that they can be multifaceted. These integration frameworks are especially beneficial in regions with a rich and complex spatial history, such as the post-mining landscapes characterising mineralised urbanisations, such as Johannesburg, Gauteng, where development has continued despite the ceasing of mining activity, resulting in landscapes marred by active mining and mining remnants and urban processes [24]. In such landscapes, the characteristics and spatial patterns of such spaces can be analysed in a unified manner [25], deepening the perception of these landscapes as it provides insight into how their various spatial and societal features interact.

Spatial analysis, including Multicriteria Decision Making or Multicriteria Decision Analysis (MCDM or MCDA), is an important component in the integration of various components and multicriteria analysis. In recent years, MCDA has also expanded to include spatial elements (GIS-MCDA) [26]. MCDA is a widely used approach in GISs for evaluating alternatives based on multiple criteria [27–29], addressing complex spatial problems, and supporting sustainable development efforts [30]. In these situations, MCDA provides a structured decision-making method to combine different criteria and provides support for the evaluation and selection of alternatives and the interrelationships between criteria [27,28]. This synthesis of criteria also influences how the interaction of various landscape criteria or characteristics is perceived and how stakeholders using maps and involved in decision-making understand the landscape [28]. Some of the common MCDA methodologies include Geographically Weighted Regression (GWR), Analytic Hierarchy Process (AHP) [31,32], Fuzzy Logic, and Weighted Overlay—one of the most popular. MCDA is also used as a basis for constructing decision models in predictive machine learning algorithms, such as Random Forest classification [33,34].

However, despite the advances in the representation and mapping of landscapes, mapping landscapes with contrasting characteristics is challenging. Nevertheless, Roy [28] argues that MCDA is also useful in situations with contrasting characteristics for combining all characteristics. MCDA is used in land-use planning, particularly in suitability studies [13,35] and has also been applied in various stages of mining, including mine closure and post-mining landscape characteristics studies. It has also been used in the development of conceptual frameworks which combine spatial and socio-technical data to support decision-making in mining contexts [22,36–39].

Several studies [7,40–42] have mapped various aspects of Gauteng's mining and post-mining landscape, yet studies such as Watson and Olalde [43] and Crous et al. [44] also note that these efforts are hindered by data inaccessibility. These maps are mostly generated using land-use and -cover data or point and areal data, representing these landscapes in raster or vector formats and oversimplifying them in the process. The resultant maps, therefore, do not adequately capture or represent the complex interaction among multiple landscape characteristics in the same space [45–48].

This paper leverages GIS-MCDA, particularly Fuzzy overlay and Random Forest classification, to assess the performance of both models in integrating and representing post-mining landscape characteristics in Gauteng. The main objective of this study is to evaluate the efficacy of Fuzzy overlay and Random Forest classification, not only for the representation of post-mining landscapes but also for how they may influence the perception of these landscapes. In doing so, the paper seeks not only to identify technical challenges and ascertain how these mapping techniques may affect the perception and understanding of these landscapes but also to identify the best model for more nuanced landscape representation. The paper is divided into five sections. The first section above introduces post-mining landscapes, challenges mapping multiple characteristics, and the applications of GISs using MCDA. The study area and context section are introduced next. The third section specifies the data, methods, and analysis employed in this study. The fourth section discusses the findings of the study. The last section discusses the results and implications of Fuzzy overlay and Random Forest classification applications in the representation of Gauteng's post-mining landscapes and how this may influence perceptions of this landscape.

2. Materials and Methods

This section elaborates upon the datasets used, the methodological approach followed in the analysis, and the validation approach adopted for this study. The analysis utilised and combined various novel remote sensing, GIS point, and areal datasets available for the Gauteng province, which will be outlined next.

2.1. Study Area and Context

Gauteng province (Figure 1) is the smallest province in South Africa at just over 18,000 square kilometres (km^2), although it contributes to over a third of the country's gross economy [49]. The province is historically known for the Witwatersrand gold discovery and mining boom in 1886 [50]. Since then, the mining sector has declined, starting in the 1970s, leading to a diversification of economic activities in the region to secondary and tertiary industries [24,51–53]. Mining has, over the years, fuelled rapid urbanisation and infrastructural development [54]. Presently, the province is characterised by rapid and dense urbanisation at the core—an agglomeration of towns and cities—and surrounded by a less developed urban periphery [53], characterised mainly by natural land, small holdings, and agricultural activities. However, the urban landscape of Gauteng is characterised by prominent remnants of mining, specifically a post-mining physical landscape characterised by mine waste, which has significantly influenced urban development trajectories [42,52,53]. Moreover, the province faces population growth challenges and economic pressures driving excessive land transformation in this post-mining landscape [55].

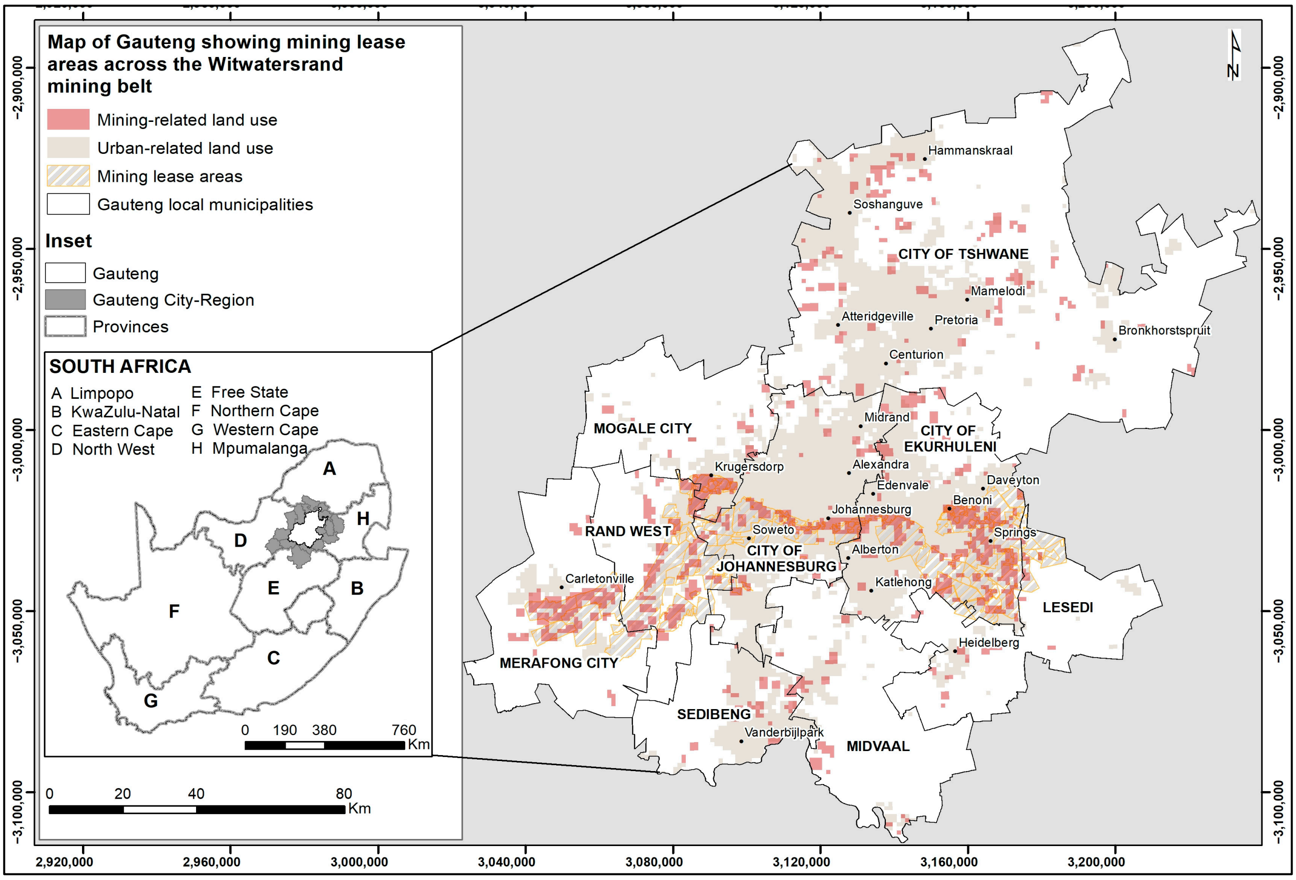

Figure 1. Map of Gauteng, South Africa, the study area. Data sources: [56–58]. Mapped by: Author.

2.2. Datasets Used

The post-mining landscape of Gauteng is not only characterised by remnants of mining, in the form of mine waste, voids, and abandoned infrastructure but also some active mining activities [3,9,10,42,44]. Additionally, this mining landscape is intertwined with urban processes and land uses. Moreover, the literature on post-mining landscapes also generally posits that post-mining landscapes are unnatural and inaccessible [59], are characterised by declining economies and populations [60,61], are a sustainability and societal challenge [7,59,61], are in need of rehabilitation [4,59,62,63], and are constantly evolving spatially over time [42,53,64]. Proxy spatial data representing elements of these characteristics were identified and acquired using a web and manual search from the relevant data custodians (Table 1). All data used for this purpose were publicly available data. These datasets were used due to ease of access but also so that the exercises carried out within this research study could be replicable.

The analysis used a combination of raster and vector datasets. Specifically, the analysis exploited three raster layers, namely, the South African Land Cover (SANLC) 1990, SANLC 2020, and SANLC 1990–2020 class change data. All three land-use land-cover datasets had a resolution of 30 metres (m) per pixel. The SANLC 1990 dataset was derived from Landsat 5 Enhanced Thematic Mapper, and the 2020 dataset was derived from Sentinel 2 Multi-spectral Instrument. The datasets used span from 1990 to 2020, representing both historical and current landscape characteristics, noting that the historical characteristics are especially important as the focus of this paper is the post-mining landscape. The spatial data representing abandoned and active mines and shafts, employment, population, roads and railways, mine residue areas, and pollution buffers were in a vector format.

Table 1. Spatial data used in this study. The table has a column for the spatial layer description, format, and data source. Created by: Author.

Spatial Layer	Format	Resolution/Scale/Areal Extent	Data Sources
Abandoned mines and shafts	Point/ Vector	Point per mine/shaft—across Gauteng	[65,66]
Active mines	Point/ Vector	Point per mine/shaft—across Gauteng	[67]
Employment data	Polygon/ Vector	Per small area—across Gauteng	[68]
SANLC 2020	Raster	30 m—across Gauteng	[69]
SANLC 1990	Raster	30 m—across Gauteng	[70]
SANLC 1990–2020 Class change	Raster	30 m—across Gauteng	[71]
Hexagon summary area-based land cover	Raster	Per 400 m × 400 m hexagon—across Gauteng	[72]
Population data	Polygon/ Vector	Per small area—across Gauteng	[73]
Roads	Line/Vector	Line per road—across Gauteng	[74]
Railway	Line/Vector	Line per railway—across Gauteng	[75]
Mine residue areas	Polygon/ Vector	Polygon per mine residue area—across Gauteng	[76]
Pollution buffers	Polygon/ Vector	Polygon per buffer—across Gauteng	[77]

2.3. Methods

This study uses secondary data (Table 1) and multicriteria spatial modelling, specifically Fuzzy overlay and Random Forest classification to try and integrate post-mining landscape characteristics in Gauteng. This paper compares these two models to ascertain their efficacy for representing Gauteng's post-mining landscape, with the intention of establishing their impact on the perception of this landscape and determining the model that captures the nuances and complexity of this landscape. A total of eight input layers were used, representing economic decline and lack of diversity (using commercial areas, industry counts, and abandoned mines); population decline (population density); integrative rehabilitation and management (post-mining land uses and buffer zones); social impact (population near waste, demographics, and employment counts); inaccessibility (road and rail accessibility); abandoned infrastructure (mining-related buildings near abandoned mines); land transformation (historical and present-day mining-related land cover); and natural resource use and waste (waste, slimes, low vegetation, and barren and eroded land), for the final Fuzzy overlay and Random Forest classification.

The Fuzzy overlay analysis was conducted in Environmental Systems Research Institute (ESRI, Redlands, California, United States of America) ArcMap (version 10.8), using the 'Fuzzy membership' and 'Fuzzy overlay' Spatial analyst tools. Random Forest classification was conducted on R (a programming language for statistical computing and graphics, developed in Auckland, New Zealand), version 4.4.1 and RStudio Desktop version 1.2.5042 (an integrated development environment (IDE) for R). Both results were mapped in ArcMap. All data were projected to the World Geodetic System 1984 Universal Transverse Mercator Zone 35 South. Subsequently, the data format and scale were converted to ensure comparability and fit for integration. Non-spatial tabular data were joined to shapefiles using a common field and the 'Join field' Geoprocessing tool. A 1 km^2 grid (comprising 18851 rows) covering the study area was created using the 'Create Fishnet' Geoprocessing tool. Data were reclassified for scaling using the 'Reclassify' (Spatial analyst tool) and a scale of 1 (least important) to 9 (most important) guided by the literature on post-mining landscapes. For example, post-mining landscapes are not generally associated with accessibility; thus, those areas furthest from the road were reclassified to values closer to 9. While data were used in their layer form for the Fuzzy overlay analysis, they were extracted into Excel for Random Forest classification and later joined back to a grid for mapping

2.3.1. Fuzzy Overlay

A Fuzzy overlay, based on fuzzy set theory [78], is a generalisation of classical set theory, by using weighted membership with more than two elements, allowing a continuum of possible choices that can be used to describe imprecise terms [79–82]. Fuzzy overlay converts criteria into fuzzy membership values ranging from zero (non-membership) to one (indicating full membership, while infinite values in between indicate partial membership [83]. Thus, a Fuzzy overlay combines multiple spatial data layers by assigning fuzzy membership values based on relevance to decision-making criteria and represents the degree of suitability or membership of each spatial unit (for example, per grid cell or polygon) in the layers. A total Fuzzy overlay output is generated by overlaying and aggregating fuzzy membership values, representing the overall suitability or decision surface [27,48].

It originates from Ian McHarg's overlay map theory in GISs and is the most widely used function multicriteria analysis technique incorporating fuzzy logic principles into GIS operations [13]. It is helpful as it considers that some spatial features (such as buildings) have hard physical boundaries, although some have attributes varying according to location and definition. O'Sullivan and Unwin [84] posit that the latter would be termed as having fuzzy boundaries, where fuzziness is a way of representing a gradational property of spatial phenomena, such as soil, which varies across its boundaries and/or transitions from one type or category to another over a distance. This method applies to this study as it interrogates data that do not fit binary logic. A fuzzy methodology approach has been successfully used in studies such as [37,38,85,86] mapping complex landscapes such as post-mining landscapes.

This study uses a linear fuzzy membership function (Equation (1)), which is used when full membership is assigned to large or small observed values and the rate of change to non-membership is consistent. The smallest or largest observed values in the linear function can be altered to create thresholds called minimums and maximums. These thresholds are helpful for completely excluding large or small observed values, where there should be linearly increasing or decreasing membership between inputs, and results in a sigmoid-shaped graph [80].

$$\mu(x) = \frac{(x - min)}{(max - min)} \tag{1}$$

The fuzzy membership layers were combined using the AND and OR Fuzzy overlay operators to combine the characteristics. This resulted in seven fuzzy overlays showing the following characteristics: natural resource degradation, integrated natural resource rehabilitation, mining land transformation, social impact, low accessibility, and economic decline. These fuzzy overlays were combined using the OR fuzzy operator for a final Fuzzy overlay of post-mining landscapes (Figure 2). The method of operations determines the degree to which each membership layer contributes to the result, often referred to as the weight of its contribution [80]. The AND operator returns the minimum value of the factors at the cell's location, and the OR operator does the opposite and returns the maximum value of the factors at the cell's location [87].

2.3.2. Random Forest Classification

The other analysis used in this study is Random Forest classification, an ensemble classification and regression learning method by Friedman [88]. Compared to other ensemble classifiers, Random Forest is computationally simple and fast and efficiently handles large numbers of variables [34]. It does not overfit data and is robust to outliers, missing values and noise [34,89]. Random Forest generates several classifiers and aggregates the results, unlike traditional classifiers [89–91]. Each node is divided using the best score between a subset of the random predictors, generating an ensemble of decision trees from training data and features and aggregating individual trees to make a final classification decision [89,92,93].

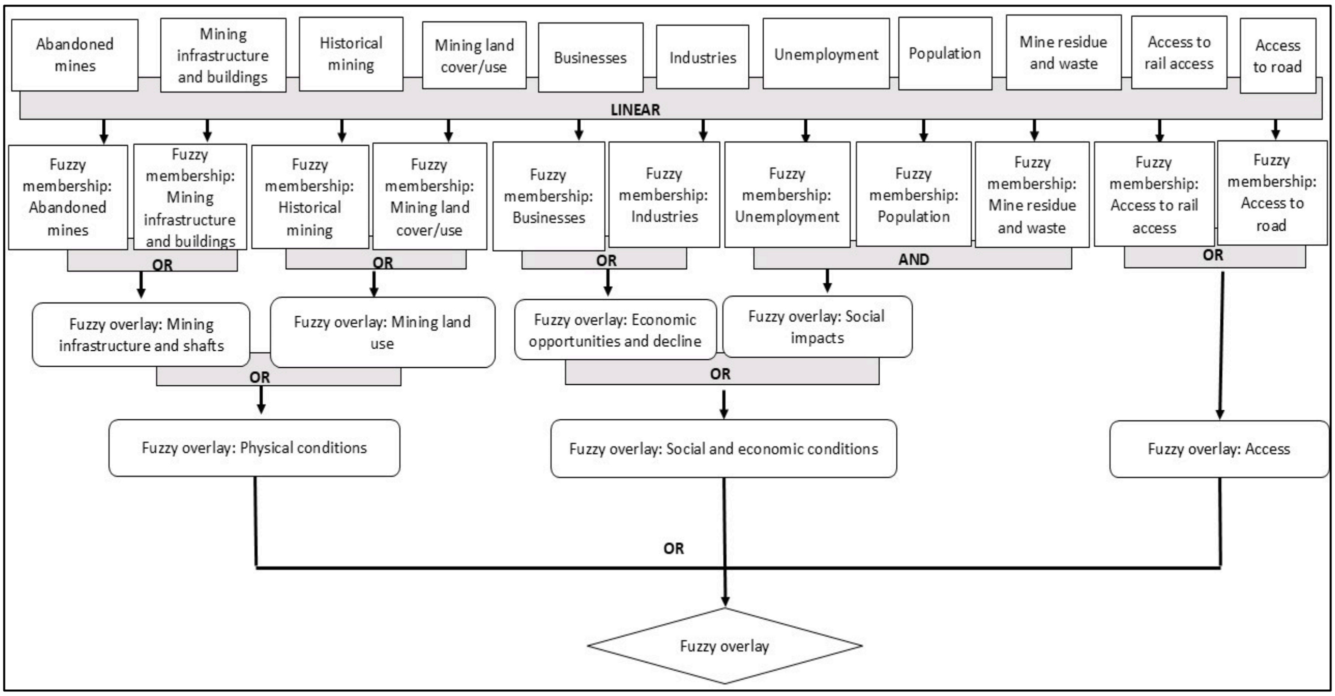

Figure 2. Diagram of the Fuzzy overlay process undertaken in this study. The diagram begins after the data had been converted into a grid format, showing the presence of the landscape characteristic per km^2. Created by: Author.

Random Forest aggregates values using boosting and bagging of classification trees [89,92]. The random selection of features, introduced by Ho [90,93] and Amit and Geman [94], constructs decision trees with controlled variation. Using boosting, weights are added to points incorrectly predicted, using a weighted vote for prediction, while bagging constructs each tree independently with different bootstrap samples [88,91,92]. The trained model is applied to new data, combining predictions of individual trees using majority voting or averaging to generate the final output (which can be spatial) [92,95]. It generates probability maps for each class indicating classification uncertainty. This classifier ranks variables with the greatest ability to discriminate between the target classes. Nevertheless, while handling large datasets, non-linear relationships, and interactions among criteria [95], it remains unstable with small disturbances in training data.

Random Forest classification was used to predict whether an area is a post-mining landscape based on the simultaneous occurrence of landscape characteristics (Figure 3). This study supports multicriteria analysis by training on a labelled dataset including spatial and attribute data. The training involved selecting relevant fields, dividing the dataset into training and validation subsets, and constructing multiple decision trees based on random subsets of the training data. The training data, created in Microsoft Excel, comprised 400 rows for each landscape characteristic. Variables representing post-mining landscape characteristics were recorded in columns, and cumulative and percentage values of post-mining characteristics per cell were calculated by summing reclassification values. Cells were classified as 'post-mining' if over 50% of the respective characteristics comprised the cell and indicated as 1 or 0 if less than 40%—as it comprised most characteristics. The test data were created in Excel by extracting variable values representing post-mining landscape characteristics. Random Forest classification was undertaken using R and RStudio, with libraries such as 'randomForest' and 'caret'. Thereafter, a Random Forest classifier was created, specifying the training data and predictor variables, trees, and split node features.

The classifier made predictions on the test data. The results were copied to Excel and joined to the grid in ArcMap using the 'Join to table' geoprocessing tool.

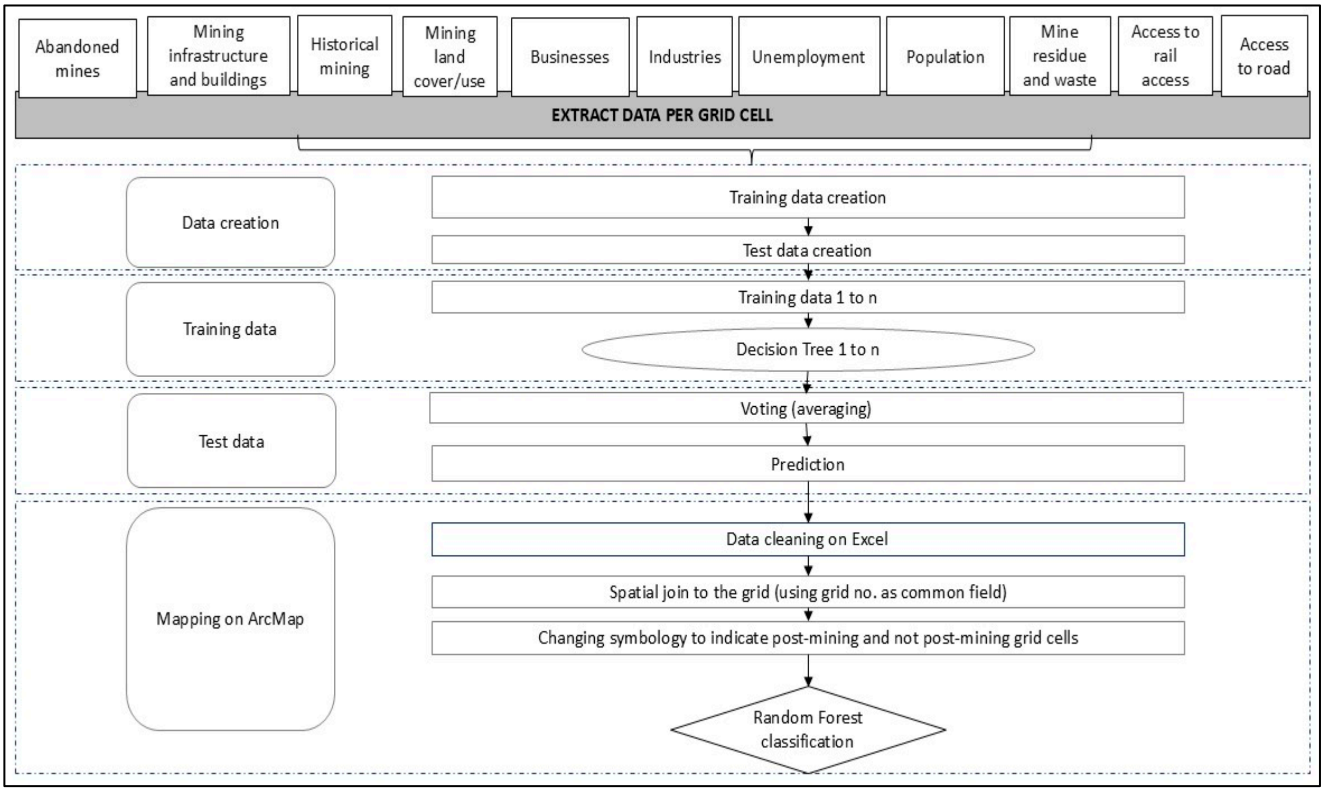

Figure 3. Diagram of the Random Forest classification process undertaken in this study. The diagram begins after the data had been converted into grid format. Created by: Author.

2.3.3. Validation

The results of the Fuzzy overlay and Random Forest classification of Gauteng's post-mining landscape were assessed in three ways. First, using an accuracy assessment commonly used in assessing classification accuracy [96], this accuracy assessment focused on assessing the two resultant maps' accuracy, specifically the users (errors of commission), producer (errors of omission), and percent accuracy (correctly identified classified and reference data). The reference data used for this purpose were the mining classes in the GTI hexagonal land-use dataset (2021), from which 50 reference points were created using the '*Create random points*' Spatial analyst tool (distribution of random points shown in Figure 4). The '*Extract values to points*' tool in Spatial analyst was used to extract cell values at each point. The resultant attribute tables were exported to Excel, where the labels of the column containing the reference values were changed to 'True values' and the extracted values column was relabelled to 'Predicted values'. The Random Forest predicted values used a binary of 0 or 1, while the Fuzzy overlay values ranged from 0.2 to 1.00. Thus, the Fuzzy overlay values were rounded off, where the values were either 0 or 1. Thereafter, a confusion matrix was conducted in RStudio, using the '*caret*' and 'pheatmap' libraries.

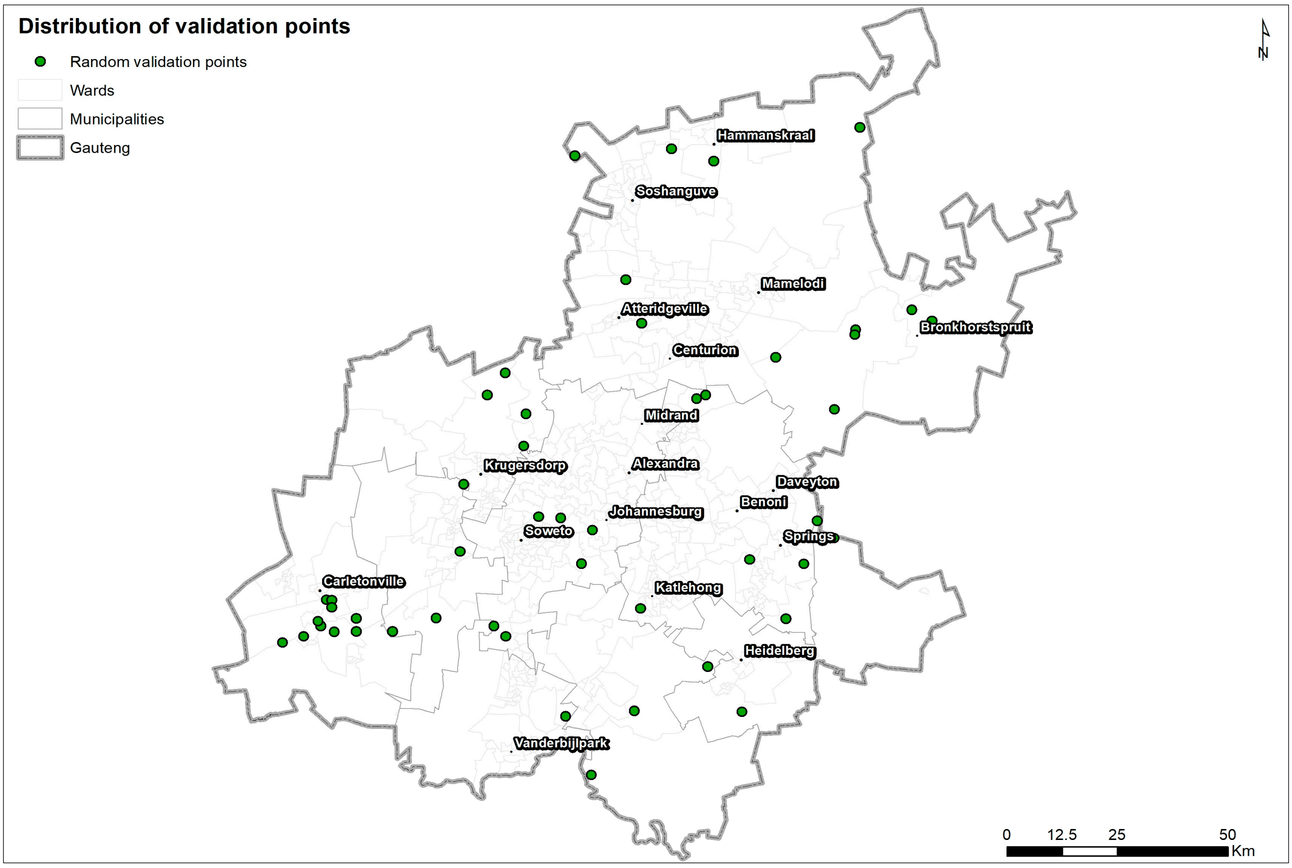

Figure 4. Map showing the spatial distribution of the validation points. Data Sources: [56,57,97]. Mapped by Author.

Second, the areal extent of post-mining and urban landscape characteristics was evaluated using the 'Extract by Attribute' Spatial analyst tool to extract and calculate the areal extent of post-mining landscape characteristics on the two resultant maps. The proportion of model values that were more than 25%, 50%, and 75% were evaluated.

Third, a comparative analysis between the Fuzzy overlay and fuzzy membership layers representing the different landscape characteristics was conducted. This was performed to ascertain the influence of individual landscape characteristic fuzzy membership layers on the Fuzzy overlay. Studies such as Brown et al. [98] have conducted correlation analysis to ascertain the relationship between input layers and the final output. This analysis was conducted by running a correlation analysis on ArcMap, using the 'Band Collection' Statistics Spatial analyst (multivariate) tool, which returned standard statistics as well as covariance and correlation matrices. A correlation heatmap was generated in RStudio (using the 'pheatmap' library) to visualise the correlation between the Fuzzy overlay and landscape characteristic fuzzy membership layers.

3. Results

3.1. Fuzzy Overlay of Gauteng's Post-Mining Landscape Characteristics

Figure 5 presents the Fuzzy overlay (combination of fuzzy membership layers) of the identified post-mining landscape characteristics. The highest fuzzy membership (closer to 1, from 0.75) is indicated in shades of red, the lowest values (below 0.25) in shades of blue, and intermediate values (0.26 and 0.74) in green to orange. High fuzzy membership means many post-mining characteristics in that cell or grid, and low fuzzy membership is the inverse of this. The map shows that the highest fuzzy values are most visible and clustered in areas traversing the central parts of the province, especially in areas such as Johannesburg, Krugersdorp, and Benoni. However, other areas have high values, such as areas in the western, eastern, and southern parts of the province, such as Carletonville, Khutsong, Sebokeng, and Vanderbijlpark. A splattering of medium values can also be seen across the province in areas other than the central, western, and southern parts of the province. By contrast, this map shows the lowest values concentrated at the core of the province, falling on either side of the high values traversing the mining belt, although mostly predominant in areas such as Randburg, Midrand, Centurion, and Pretoria.

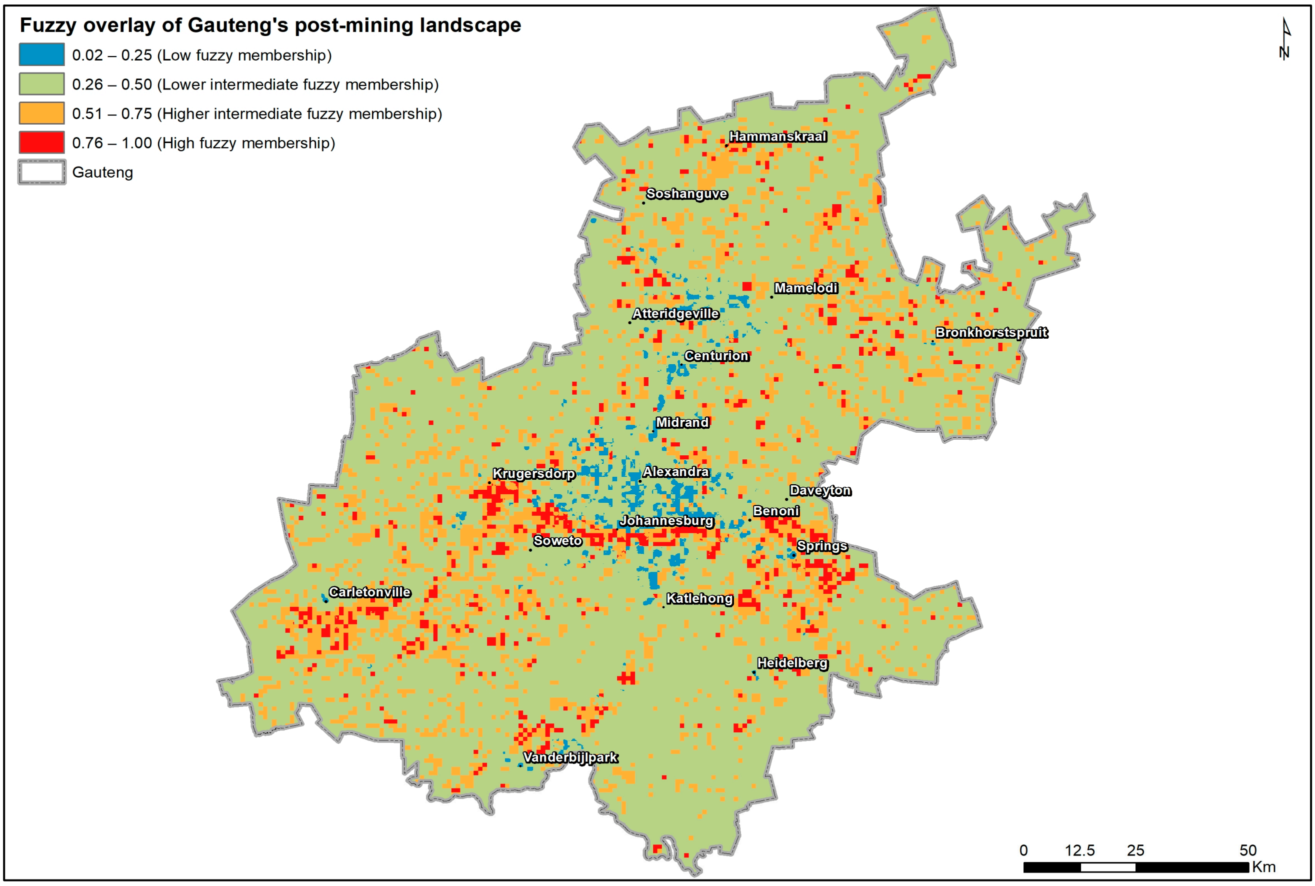

Figure 5. Fuzzy overlay of Gauteng's post-mining landscape characteristics. Mapped by: Author.

3.2. Random Forest Classification of Gauteng's Post-Mining Landscape Characteristics

The map (Figure 6) from the Random Forest classification shows the positive prediction of post-mining landscape characteristics in cells in values of 1 (in blue). In contrast, negative prediction is represented as 0 (in red). The positive classification of post-mining landscape characteristics is seen traversing the central parts of the province in an east–west direction in areas such as Johannesburg, Krugersdorp, Benoni, Carletonville, Khutsong, Sebokeng, and Vanderbijlpark. However, the map also shows positive classification as post-mining landscape for randomly placed areas across the province, for example, in areas such as east of Mamelodi in the north-eastern-most part of the province and the north-western-most part of the province around Hammanskraal. By contrast, most of the province is classified as not post-mining.

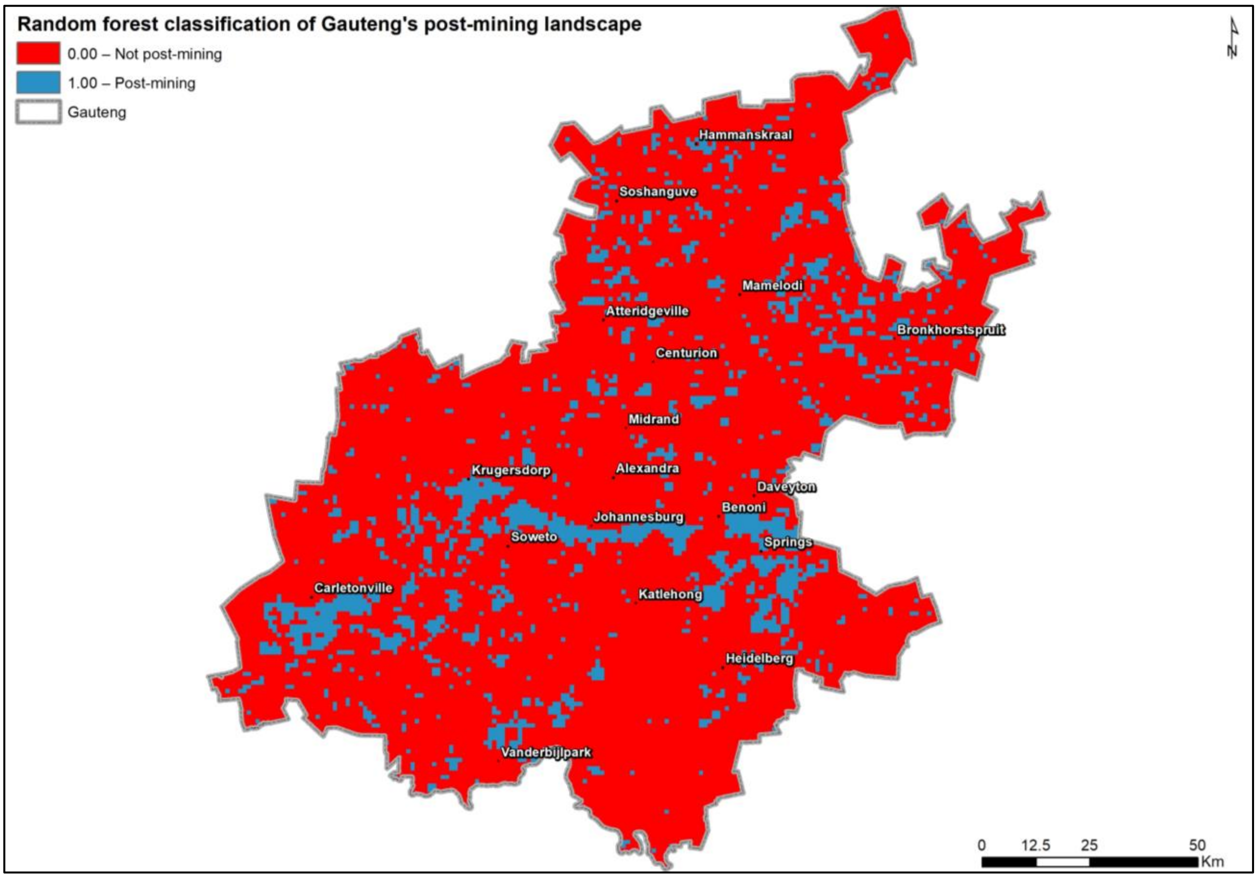

Figure 6. Random Forest classification of Gauteng's post-mining landscape characteristics. Mapped by: Author.

3.3. Accuracy Assessment, Area Statistics, and Correlation Analysis Results of the Fuzzy Overlay and Random Forest Classification of Gauteng's Post-Mining Landscape Characteristics

By way of comparing the results from the two resultant maps, the accuracy assessment, area statistics, and correlation analysis results are outlined in Table 2, Figures 7 and 8, and Tables 3 and 4. On the one hand, Table 2 presents the accuracy assessment results of the Fuzzy overlay and Random Forest classification analysis and mapping of post-mining landscape characteristics in Gauteng. The table shows that the Fuzzy overlay model accurately predicted 18 instances of both class 0 (true negatives) and 1 (true positives), while there were seven inaccurate predictions for both. The Fuzzy overlay model has an overall accuracy result of 72% and a Kappa score of 0.44. The Fuzzy overlay also resulted in sensitivity, specificity, positive predictive values (PPVs), and negative predictive values (NPVs) of 72%. Additionally, Mcnemar's test returned a *p*-value of 1.000. By contrast, the Random Forest classification model accurately predicted 14 instances of class 1 (true positives) and 20 instances of class 0 (true negatives, while inaccurately predicting 11 cases of class 0 and 5 cases of class 1. The model had an overall accuracy result of 68% and a Kappa score of 0.36. The model also demonstrated strong sensitivity (80%). However, the specificity values were lower at 56%, indicating inaccuracies in predicting positive cases (class 1). These results are further reflected in the PPV of 64.52% and the NPV of 73.68%. In addition, a Mcnemar's test of the Random Forest classification model prediction resulted in a *p*-value of 0.2113.

Table 2. Comparison of the accuracy assessments of the Fuzzy overlay and Random Forest classification of the post-mining landscape. Created by: Author.

Confusion Matrix and Statistics				
Prediction	Fuzzy Overlay		Random Forest Classification	
	Reference		Reference	
	0	1	0	1
0	18	7	20	11
1	7	18	5	14
Accuracy	0.72		0.68	
95% CI	0.5751	0.8377	0.533	0.8048
No Information Rate	0.5		0.5	
p-value [Acc > NIR]	0.001301		0.007673	
Kappa	0.44		0.36	
Mcnemar's Test *p*-value	1.00		0.21	
Sensitivity	0.72		0.8	
Specificity	0.72		0.56	
Pos Pred Value	0.72		0.64	
Neg Pred Value	0.72		0.7368	
Prevalence	0.5		0.5	
Detection Rate	0.36		0.4	
Detection Prevalence	0.5		0.62	
Balanced Accuracy	0.72		0.68	

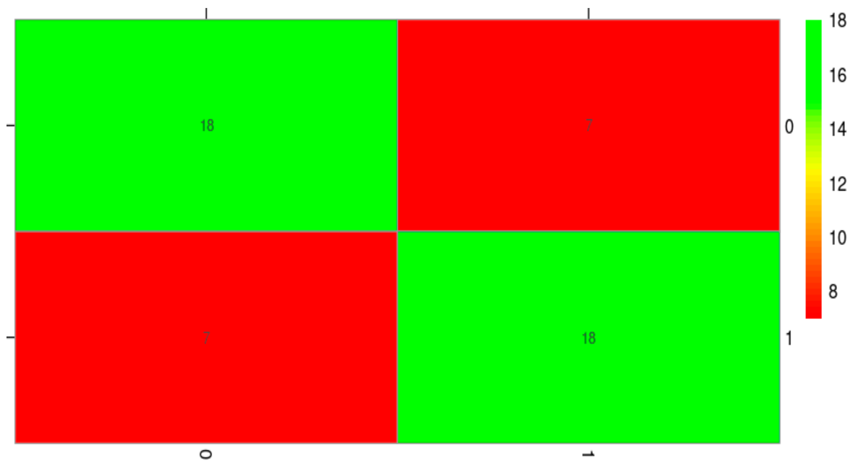

Figure 7. Fuzzy overlay confusion matrix heatmap. The actual (true) values are on the y-axis and the predicted values are on the x-axis). The y-axis represents the true values, where 0 represents false positives (no post-mining landscape characteristics), and 1 represents true positives (post-mining landscape characteristics), respectively. The x-axis represents values predicted as not post-mining as 0 and those predicted as post-mining as 1. The graduated shades of green to red show where the two axes intersect: the green on the top-left quadrant is where the model accurately predicted all 18 true negatives, red on the top-right quadrant represents 7 false positives, green on the bottom-left quadrant represents 7 false negatives, and the red quadrant in the bottom-right quadrant represents 18 true positives. Created by: Author.

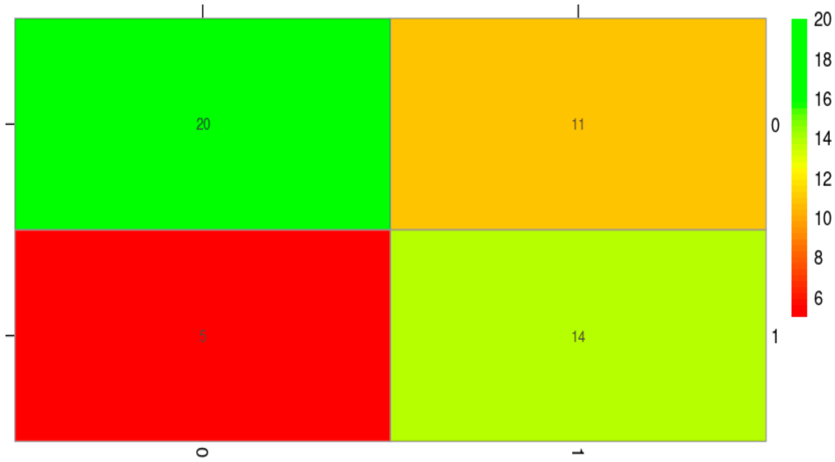

Figure 8. Random Forest classification confusion matrix heatmap. The y-axis represents the true values, where 0 represents false positives (no post-mining landscape characteristics), and 1 represents true positives (post-mining landscape characteristics), respectively. The x-axis represents values predicted as not post-mining as 0 and those predicted as post-mining as 1. The green is where the model accurately predicted 20 true negatives, orange represents 11 false positives, red represents 5 false negatives, and yellow represents 14 true positives. Created by: Author.

Table 3. Area statistics of the Fuzzy overlay and Random Forest classification of post-mining landscape characteristics. Created by: Author.

Areal Statistics	Fuzzy Overlay	Random Forest Classification
Total Area (km^2) > 25% Value	17,845.46	2258.24
Percentage Area > 25% Value	98.18	12.42
Total Area (km^2) > 50% Value	4029.15	2258.24
Percentage Area > 50% Value	22.16	12.424
Total Area (km^2) > 75% Value	772.36	2258.24
Percentage Area > 75% Value	4.24	12.42
Minimum Value	0.02	0.00
Maximum Value	1.00	1.00
Standard Deviation	0.24	0.25

The heatmaps in Figures 7 and 8 visually illustrate the performance of the Fuzzy overlay and Random Forest classification models for mapping post-mining landscape characteristics. In both heatmaps, darker colours on the diagonal axis indicate accurate characterisations or predictions for classes 0 and 1, and lighter colours on the diagonal indicate inaccurate predictions. On the one hand, Figure 7, showing the Fuzzy overlay confusion matrix heatmap, presents a balanced distribution of both darker and lighter colours, indicating that the model's performance was equal for both classes 0 (true negatives) and 1 (true positives) and had similar error inaccuracy rates for both the false-positive and false-negative predictions. On the other hand, Figure 8, showing the Random Forest classification confusion matrix, indicates that the model performed well in the prediction of class 0 (true negatives) and true positives (class 1); however, there are high inaccuracies in the prediction of class 0 as class 1.

Table 4. Statistics of Fuzzy overlay and landscape characteristic fuzzy membership layers. The minimum (Min), maximum (Max), mean and standard deviation (Std) values are presented in the table. Created by: Author.

Layer	Layer Name	Min	Max	Mean	Std
1	Fuzzy overlay	0.0271	1	0.3866	0.1506
2	Inaccessibility and isolation	0.0003	0.9497	0.8526	0.2199
3	Natural resource use and degradation	0	1	0.1505	0.305
4	Social impact	0	1	0.2803	0.324
5	Economic decline	0.0003	1	0.0849	0.27
6	Landscape transformation	0	1	0.1216	0.3111
7	Abandoned mines and infrastructure	0	0.7784	0.0172	0.1084
8	Population decline	0	1	0.9445	0.1414
9	Integrative management and rehabilitation	0	1	0.1085	0.239

The findings from the area statistics of the resultant Fuzzy overlay (Table 3) indicate that most of the province (98% or 17,845 km^2 of Gauteng's total land mass) is characterised by at least two (25%) post-mining landscape characteristics. The table also shows that at least 22% (4029 km^2) is characterised by at least half of the post-mining landscape characteristics identified, while only 4% is characterised by more than six. By contrast, the table shows that only 12% (2258 km^2) of the province's landmass is characterised by post-mining landscape characteristics based on the Random Forest classification. Noting the areal coverage of the Random Forest classification remains the same across the 25, 50, and 75% areal coverage ranges.

The findings from the correlation analysis between the Fuzzy overlay and landscape characteristic fuzzy membership are presented in Table 4 and Figure 9. Table 4 indicates that the Fuzzy overlay (layer 1) has a moderate mean value of 0.3866, while the maximum value is 1.00. The table shows that the Fuzzy overlay has low variation, indicated by the standard deviation of 0.1506. By contrast, the eight landscape characteristic fuzzy membership layers indicate that their fuzzy membership values vary across all layers. The inaccessibility and population decline fuzzy membership layers present high means (0.8526 and 0.9445, respectively), mainly indicating high membership across the region. In contrast, the natural resource use and degradation and the social impact fuzzy membership layers have lower means, 0.1505 and 0.2803, indicating low membership. The abandoned mines and infrastructure, economic decline, integrative management and rehabilitation, and landscape transformation fuzzy membership layers present even lower mean values, which range from 0.0172 to 0.1216, indicating low membership and varying spread as some of the layers have high standard deviation values.

The correlation findings are visually represented in Figure 9. The x-axis shows the correlation values of the fuzzy membership layers, and the y-axis shows the correlation with the Fuzzy overlay (layer 1). Darker shades of red indicate a strong correlation, while darker shades of green indicate a weak correlation. Figure 9 shows that the Fuzzy overlay has the strongest correlation (r = 0.695) with the landscape transformation fuzzy membership layer (layer 6), suggesting that high values in layer 1 may also be high in layer 6. Similarly, there is a strong correlation between the landscape transformation and integrative management and rehabilitation (layer 9) fuzzy membership layers (r = 0.652) as well as between layers 1 and natural resource use and degradation (layer 3) fuzzy membership layers (r = 0.576). By contrast, weak correlations are observed between layers 1 and economic decline (layer 5) (r = 0.031) and layers 2 (inaccessibility) and economic decline (5) (r = −0.296).

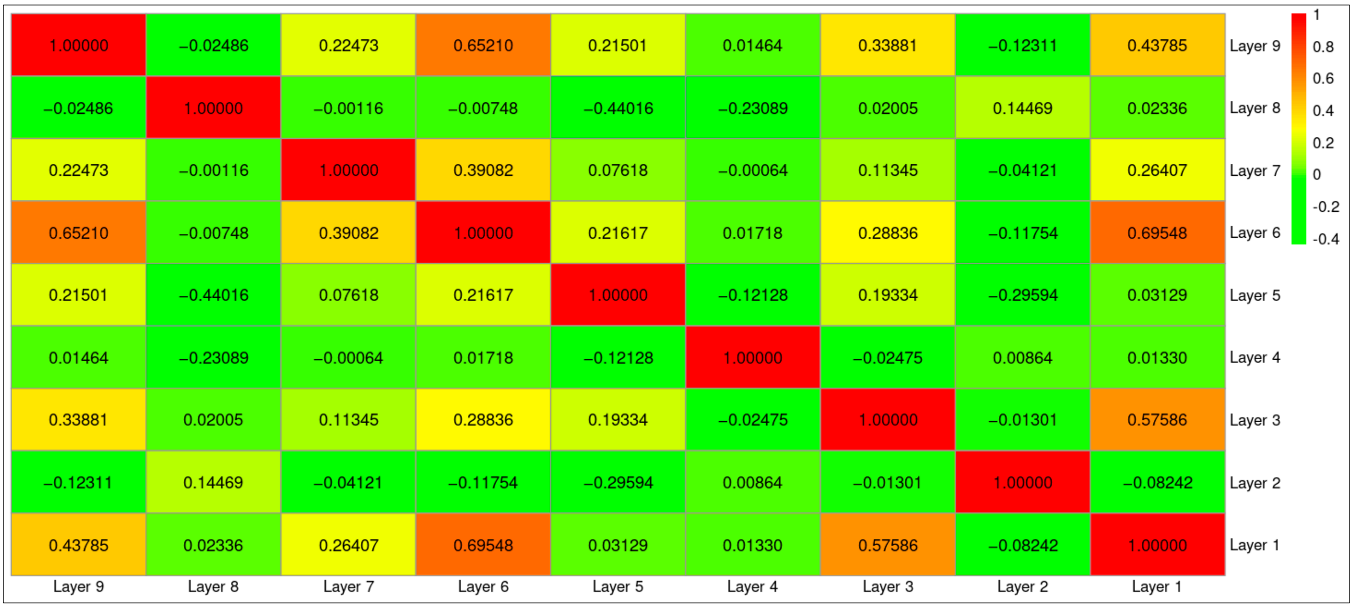

Figure 9. Correlation heatmap results between Fuzzy overlay and landscape characteristic fuzzy membership layers. Created by: Author.

4. Discussion

The main objective of this study was to ascertain the efficacy of Fuzzy overlay and Random Forest classification in integrating and representing post-mining landscape characteristics and how they may influence the perception of Gauteng's post-mining landscape. Both the Fuzzy overlay and Random Forest classification were used as GIS-MCDA spatial models to combine multiple landscape characteristics related to post-mining landscapes. Either method is effective if each satisfies most of the input characteristics for the identification of post-mining landscapes in Gauteng. The discussions of the findings of the study centre around a comparative evaluation of the representation of post-mining landscapes based on these two models, followed by a statistical summary of the areal statistics and accuracy assessment.

First, the maps depicting post-mining landscapes show some similarities to traditional representations of the post-mining landscapes in Gauteng, such as the example provided in Figure 1, as they both pick up mining activities and waste along the central parts of the province. These findings demonstrate the influence of the existing literature and traditional mapping approaches in shaping how space is represented and, therefore, how different stakeholders and users perceive it. However, there are also some differences in the representation of Gauteng's post-mining landscape by these maps, owing to their different mapping approaches. On the one hand, the Fuzzy overlay map (Figure 5) shows more areas across the province as characterised by post-mining landscape characteristics. For example, this map shows a large part of the province as having intermediate fuzzy membership, especially at the periphery, despite the province not having a lot of mining activities in these areas. This is noted to be attributable to post-mining landscape characteristics such as inaccessibility, population, and economic decline as identified in the literature [53,59,61]. However, it should be noted that peripheral areas in Gauteng have not been used for mining or inhabited—and low populations and economic activities in those areas are due to most of the population inhabiting the core of the province [54,55]. This map, therefore, stands the risk of miscommunicating on-the-ground realities, which could influence perceptions of certain spaces. However, at the same time, the Fuzzy overlay map uses a gradual scale, allowing the representation of even the least post-mining landscape characteristics to be highlighted. On the other hand, the Random Forest classification (Figure 6) of the post-mining landscape primarily follows the traditional pattern of areas characterised by mine waste, suggesting a smaller footprint. The Random Forest classification highlights areas as either post-mining or not post-mining, with no in between. This is attributable to majority voting amongst its trees [92,95]. However, the resultant map is restrictive as it does not consider the unclear and imprecise boundaries [34,89,93,99] cutting across all the post-mining landscape characteristics. Therefore, this map might be perceived as highlighting areas in need of remediation, ignoring other potentially important landscape characteristics shaping public and stakeholder perceptions of this landscape. As such, the former's use of a range is a bit more inclusive and demonstrates how various landscape characteristics can be integrated.

Second, the accuracy assessment results of the mapping of post-mining landscape characteristics using Fuzzy overlay and Random Forest classification (Table 2 and Figures 7 and 8) suggest that the mapped accuracy results are generally higher than 50%. The Fuzzy overlay mapping of the post-mining landscape has a higher accuracy level (72%) and a Kappa score of 0.44, indicating moderate agreement between model characterisations or predictions and the true values. The sensitivity, specificity, PPV, and NPV also suggest that 72% of class 0 (true negatives) and class 1 (true positives) were characterised accurately. Additionally, Mcnemar's *p*-value of 1.000 indicates the lack of significant difference between false positives and false negatives and, therefore, a balanced distribution of prediction errors across both classes. These results are higher than those obtained for the Random Forest classification map (68%) and a Kappa score of 0.36, suggesting only fair agreement between the predicted and actual classes. While the model demonstrates a high prediction of negative instances (class 0), it had a lower specificity value, suggesting inaccuracies in predicting positive instances. In addition, Mcnemar's test, resulting in a *p*-value of 0.2113, indicates that there was no significant difference between false positives and false negatives, suggesting that the model's misclassification errors are relatively balanced between the two classes. These findings between the two models indicate that the Fuzzy overlay model performs better.

Third, the comparison of the total areal extent (in km^2) of post-mining landscape characteristics across the province (Table 3) shows a difference between the two resultant maps. More specifically, the Fuzzy overlay map showed the post-mining landscape as having a larger areal coverage. For example, when considering the areal coverage based on values over 0.25 (25%), these post-mining landscape characteristics cover 98% of the Gauteng landscape. This overestimation is discussed above as being attributable to the intermediate fuzzy membership in the periphery. When the same is performed for those values over 50% (0.5), the Fuzzy overlay of post-mining characteristics has an areal coverage of 22%, which is more realistic. By contrast, the Random Forest classification of the same characteristics shows that only 12% of Gauteng is covered by these characteristics.

Fourth, the results yielded from the correlation analysis (Table 4 and Figure 9) show that the Fuzzy overlay of post-mining landscape characteristics has a mean value of 0.3866, while the maximum value is 1.00. This, therefore, suggests that most values in the raster are below the midpoint of 0.5, which demonstrates its ability to capture both high and low values and nuances in landscape characteristics. Table 4 also shows that fuzzy membership values of post-mining landscape characteristics vary across Gauteng. Some post-mining landscape characteristics, such as inaccessibility and population decline, have high membership across the landscape. In contrast, natural resource use and degradation, social impact, economic decline, land transformation, abandoned mines and infrastructure, and integrative management and rehabilitation have lower means, indicating low membership in most areas. Figure 9 also shows that the Fuzzy overlay has the strongest correlation with the landscape transformation fuzzy membership layer, suggesting that high values in the Fuzzy overlay are also visible in the landscape transformation membership layer. Similarly, there is a strong correlation between the landscape transformation and integrative management and rehabilitation fuzzy membership layers as well as between the Fuzzy overlay and natural resource use and degradation. By contrast, weak correlations are observed between the Fuzzy overlay and economic decline and inaccessibility and economic decline [59–61]. These findings, therefore, suggest that the natural resource use and degradation and landscape transformation landscape characteristics strongly influence the Fuzzy overlay. This is aligned with most descriptions of post-mining landscapes, citing a change in the landscape and various types of waste [3,10,42]. The Fuzzy overlay also shows divergence with those areas, indicating economic decline and inaccessibility. This contrasts descriptions of post-mining landscapes as in isolation or with low populations, as this post-mining landscape is at the centre of a growing metropolitan region.

These maps also demonstrate how the characteristics of these two landscapes intersect on the same spatial unit, which is visible in those areas of high fuzzy membership or predictive values. This indicates that using an MCDA approach is useful for moving away from the simplistic representations of landscapes using simple raster and vector representations [45–47,100]. This is also useful for enabling a better representation and therefore perception of Gauteng's complex post-mining landscape, as not just mining waste. Additionally, the integration of these landscape characteristics in general and specific points across the Gauteng province also point towards the porosity of the boundaries between landscapes, such as post-mining landscape characteristics. This is especially demonstrated by the Fuzzy overlay results, which not only consider the mining characteristics but also other physical and social factors. The continuous surface of the Fuzzy overlay, compared to the discrete representation of landscapes by the Random Forest classification, further demonstrates the value of Fuzzy overlay in offering more detailed representations of space. Therefore, these results demonstrate the importance of interrogating the representation of space, as also posited in other studies such as Cattoor [18].

Nevertheless, mapping post-mining landscapes in Gauteng, as conducted in this study, also faces several challenges and limitations. These include data availability and quality, which hinder a better understanding of post-mining landscapes in several studies [7,43,44] and also affect their perception and decision-making related to them. The study also makes use of proxies to represent some landscape characteristics, which may not always capture all the complexities of landscape dynamics. Similarly, this research notes that the spatial data applied in this study are of secondary origins and are of varying resolutions. Additionally, this study does not include contextual descriptions of the post-mining landscape. Thus, the findings from previous studies investigating alternative methods of mapping the complexity of the landscape [13,20,36,48,85,101] and this current study present a starting point for future investigations into the integration and therefore communication of multiple landscape characteristics, particularly concerning how they may influence perceptions and decision making in landscapes with complex histories.

5. Conclusions

Landscapes are recognised as being multifaceted and complex, and as such, how they are perceived is significantly influenced by their representation. To this end, there has been an increasing body of work on the mapping and integration of landscape characteristics of complex landscapes, and post-mining landscapes invariably fall under this category. Mapping complex landscapes, including post-mining landscapes, is vital in rapidly urbanising developing contexts such as Gauteng, not only for insight into their spatial characteristics but also for influencing perceptions that have implications for decision-making.

Gauteng (and other mineralised urbanisations) faces the challenge of not only population growth and rapid urbanisation but also a host of socio-economic challenges, which may be compounded by the locality of these in a post-mining landscape. This places Gauteng in a unique situation, where improved mapping of its post-mining landscape characteristics could potentially influence a better understanding of its complex set of socio-economic challenges. Therefore, this paper focuses on how the various post-mining landscape characteristics of Gauteng can be integrated and uses the example of the applications of Fuzzy overlay and Random Forest classification.

The results from the study show that MCDA mapping using Fuzzy overlay and Random Forest classification is useful for integrating multiple post-mining landscape characteristics, although each has distinct implications for how these landscapes are perceived and, therefore, understood and communicated. The results show that post-mining landscapes in Gauteng are heterogeneous, regardless of the mapping method applied. Nevertheless, the mapping of Gauteng's post-mining landscape using Fuzzy overlay and Random Forest classification also shows some differences in their visualisation of this landscape, highlighting how the choice of mapping approach influences the representation and, therefore, perception and understanding of the same landscape and decisions. The map of post-mining landscapes generated using Fuzzy overlay tends to have a larger spatial footprint compared to the map generated using the Random Forest classification. This is attributable to the Fuzzy overlay's use of a range between 0 and 1 for assigning fuzzy membership and the literature's characterisation of post-mining landscapes as inaccessible, with declining populations and economies, amongst other characterisations. The findings from the correlation analysis also show a divergence from areas of inaccessibility and economic decline and varying interaction between areas marred by mine waste and landscape transformation with other landscape characteristics. Moreover, the map of Gauteng's post-mining landscape generated using Fuzzy overlay presents higher accuracy scores compared to the Random Forest classification model.

These findings suggest that the application of Fuzzy overlay for integrating landscape characteristics may be more favourable than the use of Random Forest classification, particularly enabling a broadening of the scope of the research into integrating landscape characteristics to consider general and contextual characterisations of landscape characteristics and thus indirectly their implications for mapping complex landscapes. Moreover, the results from this study demonstrate that different mapping methods have different implications for the integration of landscape characteristics and their representation. This is an important consideration when investigating the perception of landscapes as mapping is an important planning tool for researchers, planners, and other decision makers, where the inclusive mapping of landscape characteristics can provide information on how landscapes are comprised, how they function, and how their multiple characteristics interact with each other. Therefore, from a research perspective aimed at challenging the understanding of post-mining landscapes, it is important to highlight the application of methods such as Fuzzy overlay, more so in areas facing other socio-economic challenges and other pressures due to rapid development. Such methods not only offer a more nuanced representation of landscapes, but also inform how these landscapes may be perceived and, therefore, understood and managed.

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Data Availability Statement: Some data restrictions apply to some of the data utilised in this study, specifically mining-related data. These data can be requested directly from the data custodians referenced in the reference list. Land-cover data are available from the Department of Environmental Affairs' (DEA) website at https://egis.environment.gov.za/data_egis/accessed on 28 February 2022, and the administrative boundaries' data are openly available from the MDB's website at https://spatialhub-mdb-sa.opendata.arcgis.com/, accessed on 4 March 2022. Data created through the analysis conducted in this study may be requested from the author. It will be shared once approval has been received from the data custodians.

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References

1. Bungart, R.; Hüttl, R.F. Production of biomass for energy in post-mining landscapes and nutrient dynamics. *Biomass Bioenergy* **2001**, *20*, 181–187. [CrossRef]
2. Gerwin, W.; Raab, T.; Birkhofer, K.; Hinz, C.; Letmathe, P.; Leuchner, M.; Roß-Nickoll, M.; Rüde, T.; Wätzold, F.; Lehmkuhl, F. Perspectives of lignite post-mining landscapes under changing environmental conditions: What can we learn from a comparison between the Rhenish and Lusatian region in Germany? *Environ. Sci. Eur.* **2023**, *35*, 36. [CrossRef]

3. Marot, N.; Harfst, J. Post-mining landscapes and their endogenous development potential for small-and medium-sized towns: Examples from Central Europe. *Extr. Ind. Soc.* **2021**, *8*, 168–175. [CrossRef]
4. Svobodova, K.; Barták, V.; Hendrychová, M. Visiting mine reclamation: How field experience shapes perceptions of mining. *Ambio* **2024**, 1–14. [CrossRef] [PubMed]
5. Berger, A. *Drosscape: Wasting Land in Urban American*; Princeton Architectural Press: New York, NY, USA, 2006; p. 10003.
6. Clifton, N.; Benneworth, P.; Doucet, B.; Goebel, C.; Hamm, R.; Schmitz, V. (Eds.) *The Regeneration of Image in Old Industrial Regions: Agents of Change and Changing Agents*; Cuvillier Verlag: Göttingen, Germany, 2010; p. 22.
7. Bobbins, K.; Trangos, G.; Mining landscapes of the GCR. Gauteng City-Region Observatory Occasional Paper, Johannesburg, Gauteng City-Region Observatory. 2018. Available online: https://cdn.gcro.ac.za/media/documents/Mining_Landscapes_of_the_GCR_final_web_FA.pdf. (accessed on 18 April 2024).
8. Esterhuysen, A.; Knight, J.; Tarquin, K. Mine waste: The unseen dead in a mining landscape. *Prog. Phys. Geogr.* **2018**, *42*, 650–666. [CrossRef]
9. Mhlongo, S.E.; Amponsah-Dacosta, F. A review of problems and solutions of abandoned mines in South Africa. *Int. J. Min. Reclam. Environ.* **2016**, *30*, 279–294. [CrossRef]
10. Sklenicka, P.; Molnarova, K. Visual perception of habitats adopted for postmining landscape rehabilitation. *Environ. Manag.* **2010**, *46*, 424–435. [CrossRef]
11. Svobodova, K.; Slenicka, P.; Molnarova, K.; Salek, M. Visual preferences for physical attributes of mining and post-mining landscapes with respect to the sociodemographic characteristics of respondents. *Ecol. Eng.* **2012**, *43*, 34–44. [CrossRef]
12. Vavrouchová, H.; Fukalová, P.; Svobodová, H.; Oulehla, J.; Pokorná, P. Mapping Landscape Values and Conflicts through the Optics of Different User Groups. *Land* **2021**, *10*, 1306. [CrossRef]
13. Liu, M.; Nijhaus, S. Mapping landscape spaces: Methods for understanding spatial-visual characteristics in landscape design. *Environ. Impact Assess. Rev.* **2020**, *82*, 106376. [CrossRef]
14. Goodchild, M.; Janelle, D.G. Toward critical spatial thinking in the social sciences and humanities. *GeoJournal* **2010**, *75*, 3–13. [CrossRef] [PubMed]
15. Brown, G.; Brabyn, L. An analysis of the relationships between multiple values and physical landscapes at a regional scale using public participation GIS and landscape character classification. *Landsc. Urban Plan.* **2012**, *107*, 317–331. [CrossRef]
16. Brown, G.; Hausner, V.H.; Lægreid, E. Physical landscape associations with mapped ecosystem values with implications for spatial value transfer: An empirical study from Norway. *Ecosyst. Serv.* **2015**, *15*, 19–34. [CrossRef]
17. Brown, D.G.; Riolo, R.; Robinson, D.T.; North, M.; Rand, W. Spatial process and data models: Toward integration of agent-based models and GIS. *J. Geogr. Syst.* **2005**, *7*, 25–47. [CrossRef]
18. Cattoor, B. Mapping and design as interrelated processes: Constructing space-time narratives. In *Mapping Landscapes in Transformation*; Leuven University Press: Leuven, Belgium, 2019. [CrossRef]
19. Fagerholm, N.; Käyhkö, N.; Ndumbaro, F.; Khamis, M. Community stakeholders' knowledge in landscape assessments—Mapping indicators for landscape services. *Ecol. Indic.* **2012**, *18*, 421–433. [CrossRef]
20. Klug, H. An integrated holistic transdisciplinary landscape planning concept after the Leitbild approach. *Ecol. Indic.* **2011**, *23*, 616–626. [CrossRef]
21. Mackenzie, K.; Siabato, W.; Reitsma, F.; Claramunt, C. Spatio-temporal visualisation and data exploration of traditional ecological knowledge/indigenous knowledge. *Conserv. Soc.* **2017**, *15*, 41–58. [CrossRef]
22. Soltanmohammadi, H.; Osanloo, M.; Bazzazi, A.A. An analytical approach with reliable logic and a ranking policy for post-mining land-use determination. *Land Use Policy* **2010**, *27*, 364–372. [CrossRef]
23. Wang, H.; Shen, Q.; Tang, B.-S. GIS-Based Framework for Supporting Land Use Planning in Urban Renewal: Case Study in Hong Kong. *J. Urban Plan. Dev.* **2015**, *141*, 05014015. [CrossRef]
24. Bryceson, D.; MacKinnon, D. Eureka and beyond: mining's impact on African urbanisation. *J. Contemp. Afr. Stud.* **2012**, *30*, 513–537. [CrossRef]
25. Tisma, A.; van der Velde, R.; Nijhuis, S.; Pouderoijen, M. A method for metropolitan landscape characterization; case study Rotterdam. *Spool* **2014**, *1*, 201–224. [CrossRef]
26. Chakhar, S.; Mousseau, V. Goal programming with multiple criteria: A new variance-based method. *Eur. J. Oper. Res.* **2007**, *180*, 509–521.
27. Malczewski, J. *GIS and Multi-Criteria Decision Analysis*; John Wiley & Sons: New York, NY, USA, 1999.
28. Roy, B. *Multicriteria Methodology for Decision Analysis*; Kluwer: Dordrecht, The Netherlands, 1996.
29. Sitorus, F.; Cilliers, J.J.; Brito-Parada, P.R. Multi-criteria decision making for the choice problem in mining and mineral processing: Applications and trends. *Expert Syst. Appl.* **2019**, *121*, 393–417. [CrossRef]
30. Malczewski, J. GIS-based multicriteria decision analysis: A survey of the literature. *Int. J. Geogr. Inf. Sci.* **2006**, *20*, 703–726. [CrossRef]
31. Saaty, T.L. Decision making with the analytic hierarchy process. *Int. J. Serv. Sci.* **2008**, *1*, 83–98. [CrossRef]
32. Ziemba, P.; Becker, J.; Becker, A.; Radomska-Zalas, A. Framework for multi-criteria assessment of classification models for the purposes of credit scoring. *J. Big Data* **2023**, *10*, 94. [CrossRef]
33. Belton, V.; Stewart, T.J. An integrated approach. In *Multiple Criteria Decision Analysis*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2002. [CrossRef]

34. Rodriguez-Galiano, V.F.; Ghimire, B.; Rogan, J.; Chica-Olmo, M.; Rigol-Sanchez, J.P. An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS J. Photogramm. Remote Sens.* **2012**, *67*, 93–104. [CrossRef]
35. Collins, M.G.; Steiner, F.R.; Rushman, M.J. Landuse suitability analysis in the United States: Historical development and promising technological achievements. *Environ. Manag.* **2001**, *28*, 611–621. [CrossRef]
36. Arratia-Solar, A.; Svobodova, K.; Lèbre, É.; Owen, J.R. Conceptual framework to assist in the decision-making process when planning for post-mining land-uses. *Extr. Ind. Soc.* **2022**, *10*, 101083. [CrossRef]
37. Bielecka, M.; Król-Korczak, J. Fuzzy decision support system for post-mining regions restoration designing. In *Artificial Intelligence and Soft Computing: Proceedings of the 10th International Conference, ICAISC 2010, Zakopane, Poland, 13–17 June 2010*; Part I 10; Springer: Berlin/Heidelberg, Germany, 2010; pp. 11–18. [CrossRef]
38. Król-Korczak, J.; Brzychczy, E. Fuzzy system for decision support of post-mining regions reclamation. *Arch. Min. Sci.* **2019**, *64*, 35–50. [CrossRef]
39. Sheoran, V.; Sheoran, A.S.; Poonia, P. Soil reclamation of abandoned mine land by revegetation: A review. *Int. J. Soil Sediment Water* **2010**, *3*, 13.
40. Fair, T.J.D.; Moolman, J.H.; Quass, F.W.; Winkle, F.F.; Gie, G.W.; Sevenster, F.H.; Willers, J.B. *A Planning Survey of the Southern Transvaal: The Pretoria-Witwatersrand-Vereeniging Area*; South Africa Natural Resources Development Council: Pretoria, South Africa, 1959.
41. Gauteng Department of Agriculture and Rural Development. *Feasibility Study on Reclamation and Rehabilitation of Mine Residue Areas for Development Purposes: Phase II (Strategy and Implementation Plan)*; Technical Report No. 788/06/01/2011; Gauteng Department of Agriculture and Rural Development, Gauteng Provincial Government: Johannesburg, South Africa, 2012.
42. Khanyile, S. Development of Mining and Settlements: 1956–2013, Map of the Month of the Gauteng City-Region Observatory. Johannesburg: Gauteng City-Region Observatory. 2016. Available online: http://www.gcro.ac.za/outputs/map-of-the-month/detail/development-of-human-settlements-and-mining-areas-1956-2013/ (accessed on 18 February 2023).
43. Watson, I.; Olalde, M. The state of mine closure in South Africa—What the numbers say. *J. South. Afr. Inst. Min. Metall.* **2019**, *11*, 639–645. [CrossRef]
44. Crous, C.; Owen, J.R.; Marais, L.; Khanyile, S.; Kemp, D. Public disclosure of mine closures by listed South African mining companies. *Corp. Soc. Responsib. Environ. Manag.* **2021**, *28*, 1032–1042. [CrossRef]
45. Kelso, C. Ideology of mapping in apartheid South Africa. *S. Afr. Geogr. J.* **1999**, *81*, 15–21. [CrossRef]
46. Kwan, M. Feminist Visualization: Re-envisioning GIS as a Method in Feminist Geographic Research. *Ann. Assoc. Am. Geogr.* **2002**, *92*, 645–661. [CrossRef]
47. Pickles, J. *Arguments, Debates, and Dialogues: The GIS-Social Theory Debate and the Concern for Alternatives, in Geographical Information Systems: Principles, Techniques, Management, and Applications*; Longley, P.A., Goodchild, M.F., Maguire, D.J., Rhind, D.W., Eds.; John Wiley and Sons: New York, NY, USA, 1999; pp. 49–60.
48. Simensen, T.; Halvorsen, R.; Erikstad, L. Methods for landscape characterisation and mapping: A systematic review. *Land Use Policy* **2018**, *75*, 557–569. [CrossRef]
49. South African Statistics South Africa (StatsSA). Stats SA Releases New Provincial GDP figures. South African Statistics South Africa. Republic of South Africa. Pretoria. 2023. Available online: https://www.statssa.gov.za/?p=16650 (accessed on 10 October 2023).
50. Phillips, G.N. Witwatersrand gold: Discovery matters. *Appl. Earth Sci.* **2013**, *122*, 122–127. [CrossRef]
51. Bredenkamp, G.; Brown, L.; Pfab, M. Conservation value of the Egoli Granite Grassland, an endemic grassland in Gauteng, South Africa. *Koedoe* **2006**, *49*, 59–66. [CrossRef]
52. Chakwizira, J.; Bikam, P.; Adeboyejo, T.A. Restructuring Gauteng City Region in South Africa: Is a transportation solution the answer. In *An Overview of Urban and Regional Planning*; IntechOpen: London, UK, 2018. [CrossRef]
53. Harrison, P.; Zack, T. The power of mining: The fall of gold and rise of Johannesburg. *J. Contemp. Afr. Stud.* **2012**, *30*, 551–570. [CrossRef]
54. Harrison, K.; International Land Banking Practices: Considerations for Gauteng Province. Gauteng Department of Housing and Urban LandMark. 2007. Available online: http://urbanlandmark.org.za/downloads/Land_Banking_Paper_Harrison-1.pdf (accessed on 9 July 2022).
55. Hamman, C.; Ballard, R. Gauteng's Urban Land Cover Growth: 1990–2020. Gauteng City-Region Observatory: Map of the Month. 2022. Available online: https://www.gcro.ac.za/outputs/map-of-the-month/detail/gautengs-urban-land-cover-growth-1990-2020/ (accessed on 18 June 2022).
56. Municipal Demarcation Board. Provincial Boundaries. 2011. Available online: https://csggis.drdlr.gov.za/server/rest/services/CSGSearch/MapServer (accessed on 4 March 2022).
57. Municipal Demarcation Board. Local Municipal Boundaries. 2018. Available online: https://dataportal-mdb-sa.opendata.arcgis.com/datasets/27bbdd5b041b4ba6b5707dfed5aa3923_0/explore (accessed on 4 March 2022).
58. Chief Surveyor General. Mining Licenses. 2023. Available online: https://csggis.drdlr.gov.za/server/rest/services/CSGSearch/MapServer (accessed on 15 March 2024).
59. Kivinen, S. Sustainable Post-Mining Land Use: Are Closed Metal Mines Abandoned or Re-Used Space? *Sustainability* **2017**, *9*, 2–18. [CrossRef]

60. Marais, L.; Cloete, J.; Denoon-Stevens, S. Informal settlements and mine development: Reflections from South Africa's periphery. *J. S. Afr. Inst. Min. Metall.* **2018**, *118*, 1103–1111. [CrossRef]
61. Marais, L.; Ndaguba, E.; Mmbadi, E.; Cloete, J.; Lenka, M. Mine closure, social disruption, and crime in South Africa. *Geogr. J.* **2022**, *188*, 383–400. [CrossRef]
62. Kretschmann, J. Post-mining excellence: Strategy and transfer. *J. S. Afr. Inst. Min. Metall.* **2018**, *118*, 853–859. [CrossRef]
63. Limpitlaw, D.; Briel, A. Post-mining land-use opportunities in developing countries-a review. *J. S. Afr. Inst. Min. Metall.* **2014**, *114*, 899–903.
64. Owen, S.M.; MacKenzie, A.R.; Bunce, R.G.H.; Stewart, H.E.; Donovan, R.G.; Stark, G.; Hewitt, C.N. Urban land classification and its uncertainties using principal component and cluster analyses: A case study for the UK West Midlands. *Landsc. Urban Plan.* **2006**, *78*, 311–321. [CrossRef]
65. Council for Geosciences. Abandoned, Active and Derelict and Ownerless Mines. South African Mineral Deposits Database (SAMINDABA). 2012. Available online: https://bgismaps.sanbi.org/server/rest/services/BGIS_Projects/2012ActiveAndAbandonedMines/MapServer (accessed on 25 November 2022).
66. Department of Mineral Resources, Republic of South Africa. *Abandoned Mines*; Department of Mineral Resources: Pretoria, South Africa, 2014.
67. Department of Mineral Resources, Republic of South Africa. *Active Mines*; Department of Mineral Resources: Pretoria, South Africa, 2014.
68. South African Statistics South Africa (StatsSA). Stats SA Census Release—Employment Data. South African Statistics South Africa. Republic of South Africa. Pretoria. 2011. Available online: https://microdata.worldbank.org/index.php/catalog/2772/data-dictionary/F1?file_name=ZAF2011-H-H (accessed on 25 November 2022).
69. GeoTerra Image (GTI). 1990 South African National Land Cover. *Department of Environmental Affairs.* 2020. Available online: https://environmentza-my.sharepoint.com/:u:/g/personal/gisdocs_environment_gov_za/ES-FzVtv8WRDkeP4VYdK_9MBon_GPbZhPt6egdAmq8hDQQ?e=vQvCGm (accessed on 28 February 2022).
70. GeoTerra Image (GTI). 2020 South African National Land Cover. Department of Environmental Affairs. 2020. Available online: https://environmentza-my.sharepoint.com/:u:/g/personal/gisdocs_environment_gov_za/ES4E0gweVd5AsgfyVJptT-0BjAJyY4EOIW5W3liJMBs8gw?e=RTgF6v (accessed on 28 February 2022).
71. GeoTerra image (GTI). 1990 to 2020 South African National Land Cover Class Change. *Department of Environmental Affairs.* 2020. Available online: https://environmentza-my.sharepoint.com/:u:/g/personal/gisdocs_environment_gov_za/EY6E2raiGptJuflMzZcnXh8BT3vhPR8aKVgWgTjw8yE5dw?e=aH1fik (accessed on 28 February 2022).
72. GeoTerra Image (GTI). *Hexagon Summary Area-Based Land Cover/Use*; GeoTerra Image (GTI): Pretoria, South Africa, 2020.
73. South African Statistics South Africa (StatsSA). Stats SA Census Release—Population Data. South African Statistics South Africa. Republic of South Africa. Pretoria. 2011. Available online: https://microdata.worldbank.org/index.php/catalog/2772/data-dictionary/F1?file_name=ZAF2011-H-H (accessed on 25 November 2022).
74. Chief Surveyor General. Roads. 2018. Available online: https://csggis.drdlr.gov.za/server/rest/services/CSGSearch/MapServer (accessed on 15 March 2024).
75. Chief Surveyor General. Railways. 2018. Available online: https://csggis.drdlr.gov.za/server/rest/services/CSGSearch/MapServer (accessed on 15 March 2024).
76. Gauteng Department of Agriculture and Rural Development. *Mine Residue Areas*; Gauteng Department of Agriculture and Rural Development, Gauteng Provincial Government: Johannesburg, South Africa, 2012.
77. Gauteng Department of Agriculture and Rural Development. *Gauteng Pollution Buffers*; Gauteng Department of Agriculture and Rural Development, Gauteng Provincial Government: Johannesburg, South Africa, 2017.
78. Zadeh, L.A. Fuzzy sets. *Inf. Control.* **1965**, *8*, 338–353. [CrossRef]
79. Mitchell, A. *The ESRI Guide to GIS Analysis*; ESRI Press: Redlands, CA, USA, 2012.
80. Raines, G.L.; Sawatzky, D.; Bonham-Carter, F. *Incorporating Expert Knowledge: New Fuzzy Logic Tools in ArcGIS 10. ArcUser*; Spring: Berlin/Heidelberg, Germany, 2010; Available online: https://www.esri.com/news/arcuser/0410/files/fuzzylogic.pdf (accessed on 10 October 2023).
81. Zimmermann, H.J. *Fuzzy Set Theory—And Its Applications*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 1992.
82. Zimmerman, H.-J. Fuzzy set theory. *WIREs Comp. Stat.* **2010**, *2*, 317–332. [CrossRef]
83. Mitchell, R.; Kim, Y.; El-Korchi, T. System identification of smart structures using a wavelet neuro-fuzzy model. *Smart Mater. Struct.* **2012**, *21*, 115009. [CrossRef]
84. O'Sullivan, D.; Unwin, D.J. Putting Maps Together–Map Overlay. In *Geographic Information Analysis*; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2010; pp. 315–340.
85. Gopal, S.; Tang, X.; Phillips, N.; Nomack, M.; Pasquarella, V.; Pitts, J. Characterizing Urban Landscapes Using Fuzzy Sets. *Comput. Environ. Urban Syst.* **2016**, *57*, 212–223. [CrossRef]
86. Van Eetvelde, V.; Antrop, M. A stepwise multi-scaled landscape typology and characterisation for trans-regional integration, applied on the federal state of Belgium. *Landsc. Urban Plan.* **2009**, *91*, 160–170. [CrossRef]
87. Environmental Systems Research Institute (ESRI). ArcGIS Desktop Help 10.2, How Fuzzy Membership Works. 2016. Available online: https://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/how-fuzzy-membership-works.htm (accessed on 3 November 2022).

88. Friedman, J.H. A recursive partitioning decision rule for nonparametric classification. *IEEE Trans. Comput.* **1976**, *26*, 404–408. [CrossRef]
89. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [CrossRef]
90. Ho, T.K. Random decision forests. In Proceedings of the 3rd International Conference on Document Analysis and Recognition, Montreal, QC, Canada, 14–16 August 1995; IEEE: New York, NY, USA, 1995; Volume 1, pp. 278–282.
91. Quinlan, J.R. Induction of decision trees. *Mach. Learn.* **1986**, *1*, 81–106. [CrossRef]
92. Breiman, L.; Friedman, J.; Olshen, R.; Stone, C. *Classification and Regression Trees*; Wadsworth: Belmont, CA, USA, 1984.
93. Ho, T.K. The random subspace method for constructing decision forests. *IEEE Trans. Pattern Anal. Mach. Intell.* **1998**, *20*, 832–844.
94. Amit, Y.; Geman, D. Shape quantization and recognition with randomized trees. *Neural Comput.* **1997**, *9*, 1545–1588. [CrossRef]
95. Fisher, A.; Rudin, C.; Dominici, F. All models are wrong, but many are useful: Learning a variable's importance by studying an entire class of prediction models simultaneously. *J. Mach. Learn. Res.* **2019**, *20*, 1–81.
96. Congalton, R.G. A review of assessing the accuracy of classification of remotely sensed data. *Remote Sens. Environ.* **1991**, *37*, 35–46. [CrossRef]
97. Municipal Demarcation Board. Ward Boundaries. 2020. Available online: https://dataportal-mdb-sa.opendata.arcgis.com/search?tags=ward (accessed on 8 February 2022).
98. Brown, W.; Groves, D.; Gedeon, T. Use of Fuzzy Membership Input Layers to Combine Subjective Geological Knowledge and Empirical Data in a Neural Network Method for Mineral-Potential Mapping. *Nat. Resour. Res.* **2003**, *12*, 183–200. [CrossRef]
99. Misra, S.; Li, H.; He, J. Non-invasive fracture characterization based on the classification of sonic wave travel times. *Mach. Learn. Subsurf. Charact.* **2020**, *4*, 243–287.
100. Sui, D.Z. GIS and Urban Studies: Positivism, post-positivism, and beyond. *Urban Geogr.* **1994**, *15*, 258–278. [CrossRef]
101. Alp, S.C.; Güçhan, N.S. Challenges in use of geographical information systems (GIS) in a research for understanding conservation of cultural heritage in Bursa. *J. Cult. Herit. Manag. Sustain. Dev.* **2017**, *7*, 328–344. [CrossRef]