THE APPLICATION OF REMOTE SENSING TECHNIQUES IN MAPPING ABANDONED TAILINGS STORAGE FACILITIES IN THE WEST RAND, GAUTENG, SOUTH AFRICA

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OVERVIEW OF THE PRESENTATION

- Introduction and background
- Challenges/problem statement
- Aim and objectives
- Study approach and methods
- Results (RF & SVM classifications, validation)
- Discussion of key findings
- Conclusion
- Recommendations
- References

INTRODUCTION

- Gold mining in the Witwatersrand has left a large legacy of abandoned tailings storage facilities (TSFs), especially in the West, Central, and East Rand. However, this study focuses on the West Rand.
- Sparse vegetation, erosion gullies, contaminated water, and toxic metal content characterise abandoned TSFs.
- These TSFs contribute to air pollution, acid mine drainage, and soil and water contamination, threatening ecosystems and human health.

INTRODUCTION (CONT…)

- Communities such as Krugersdorp report respiratory issues linked to dust from TSFs (e.g., Asthma, irritation to the eyes, and respiratory problems).
- The number of abandoned TSFs in Gauteng remain unclear, but in West Rand is approximately 29 abandoned TSFs.

EXAMPLES OF ABANDONED TSFS

CHALLENGES

- Unknown quantity and distribution of abandoned TSFs in Gauteng.
- Difficulty in assessing environmental hazards without accurate spatial inventories.
- TSFs are often misclassified due to vegetation cover or spectral similarity with other land cover types.
- Limited ground access due to safety risks, illegal mining, and unstable terrain.
- Need for scalable, accurate, and repeatable mapping methods.

AIM AND OBJECTIVES

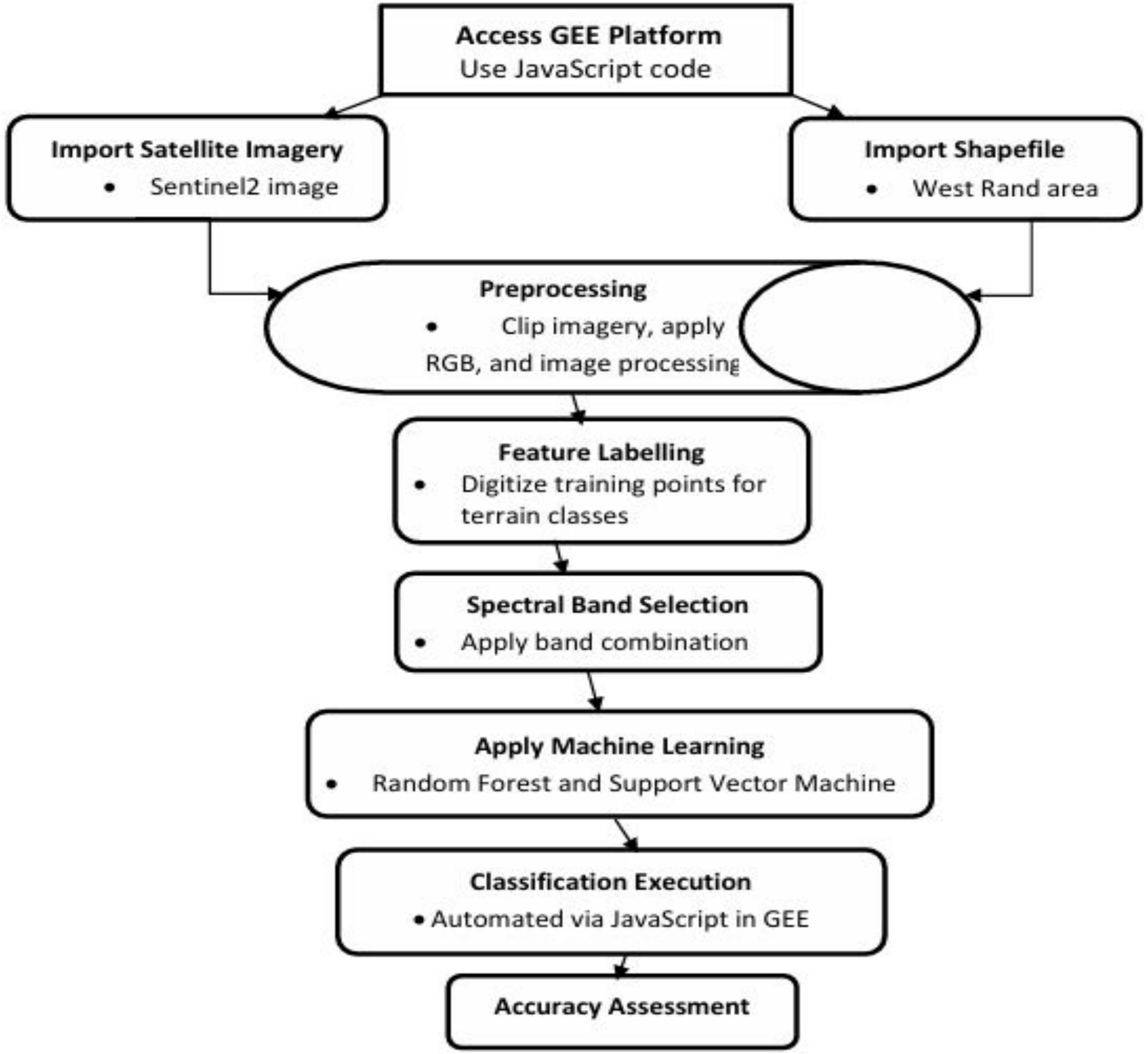
Aim:

- To identify and quantify abandoned TSFs in the West Rand using remote sensing and machine learning techniques.

Objectives:

- To classify active, dormant, and abandoned TSFs using Sentinel-2 imagery.
- To apply RF and SVM algorithms for LULC classification in Google Earth Engine.
- To validate classification outputs using DMPR field-verified TSF coordinates.
- To map the spatial distribution and extent of TSFs in the West Rand.

STUDY METHODS FLOW CHART



STUDY APPROACH

Data Collection

- Sentinel-2 MSI imagery (13 spectral bands) accessed via Google Earth Engine.
- Study period conducted from 1 April to 30 June 2025.
- Cloud cover limited to ≤5% for optimal visibility.

Pre-processing

- RGB composites (B4, B3, B2) for natural colour enhancement.
- Gamma correction and clipping to the West Rand boundary.

STUDY APPROACH (CONT..)

Training Data

- 548–586 digitised training points across classes: active TSF, dormant TSF, abandoned TSF, vegetation, water, bare land, built-up.

Model Training

- Random Forest (RF) and Support Vector Machine (SVM) classifiers.
- Key spectral bands: B2, B8, B11, B12 (visible, NIR, SWIR).

Analysis

- Exported classified maps to ArcGIS Pro for spatial analysis.

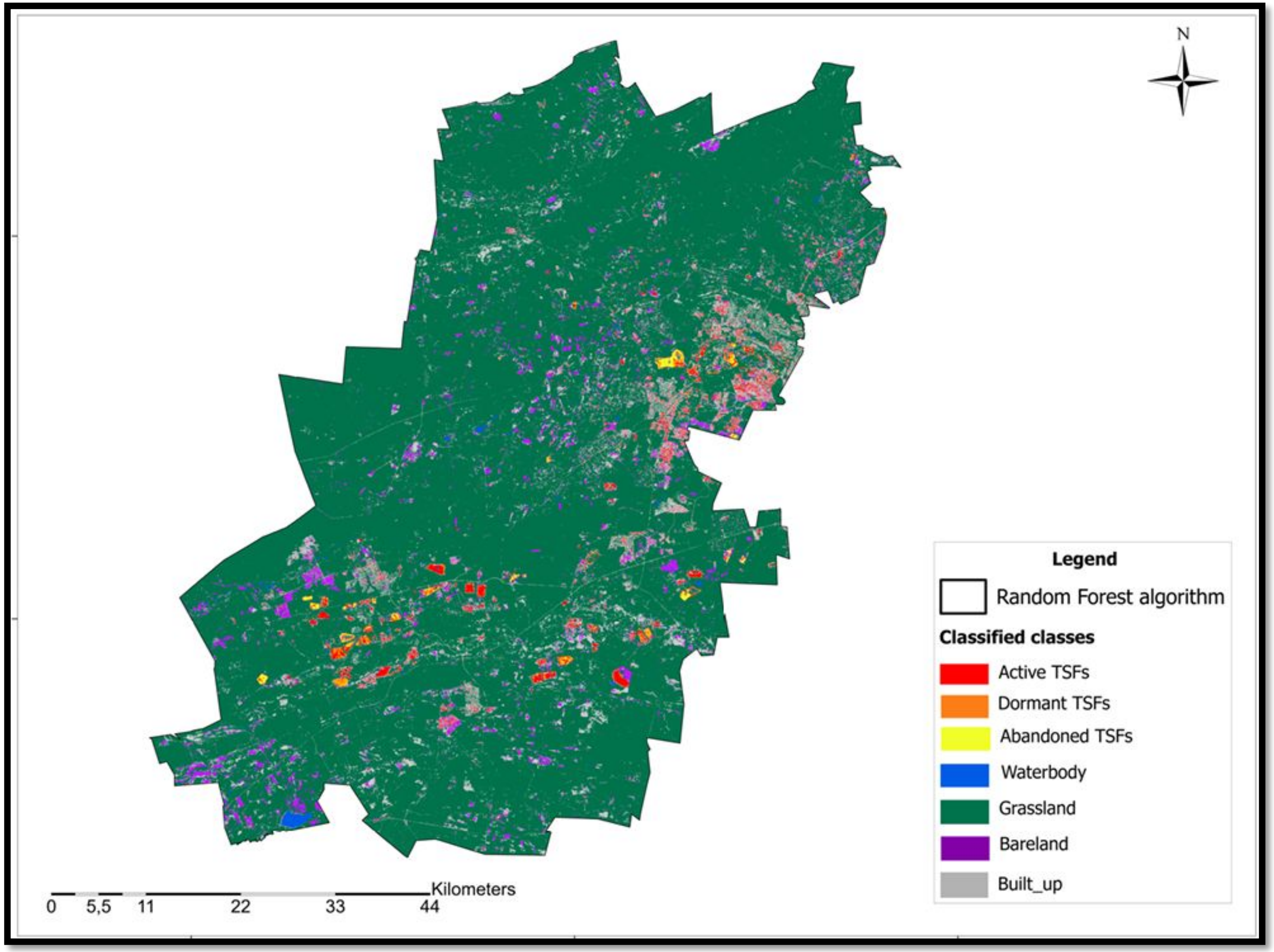
STUDY APPROACH (CONT..)

- Accuracy assessment using confusion matrices, overall accuracy, and kappa.

Validation

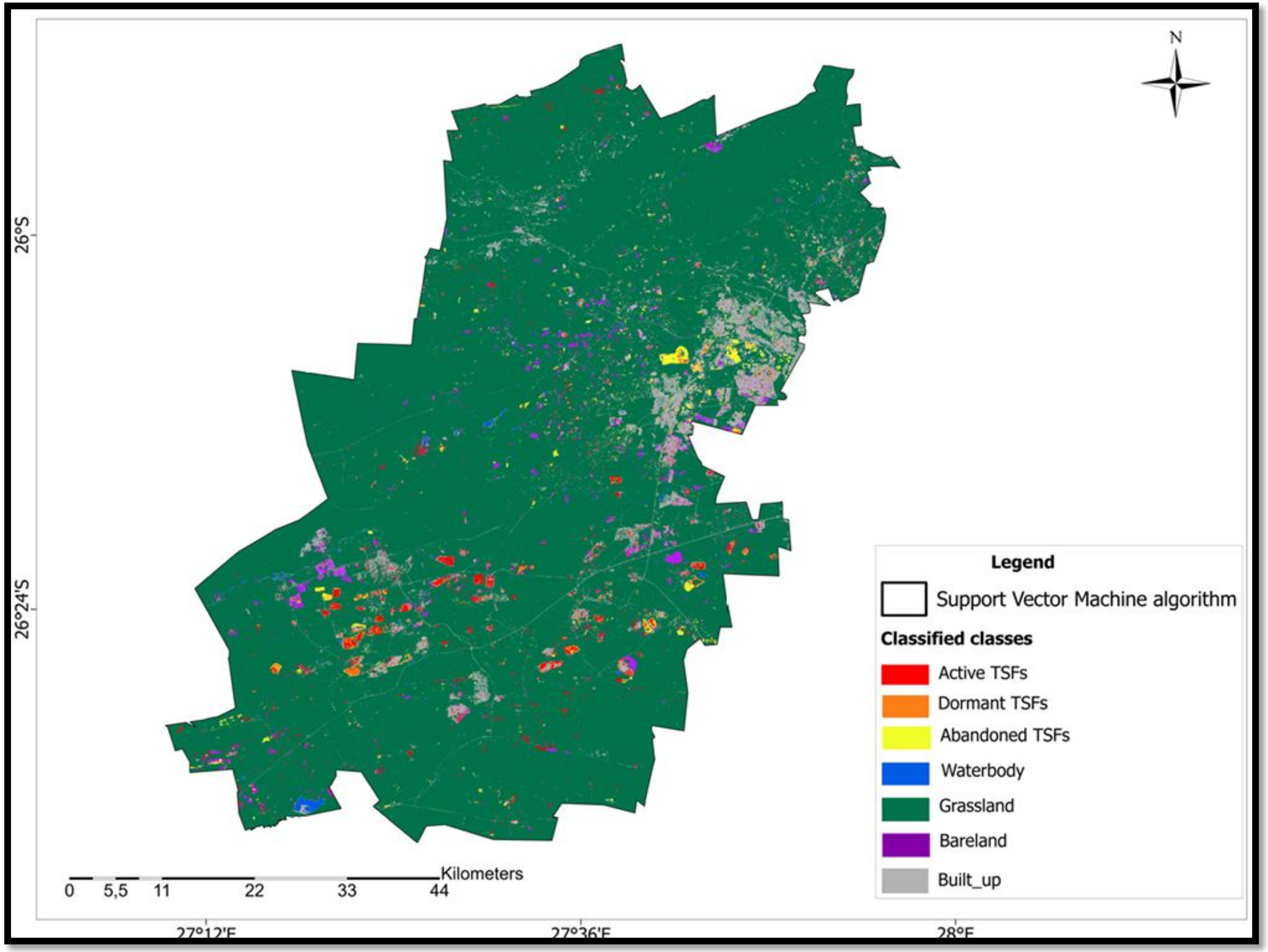
- Field-verified TSF coordinates from DMPR overlaid on aerial outputs.

RANDOM FOREST (RF) MAP



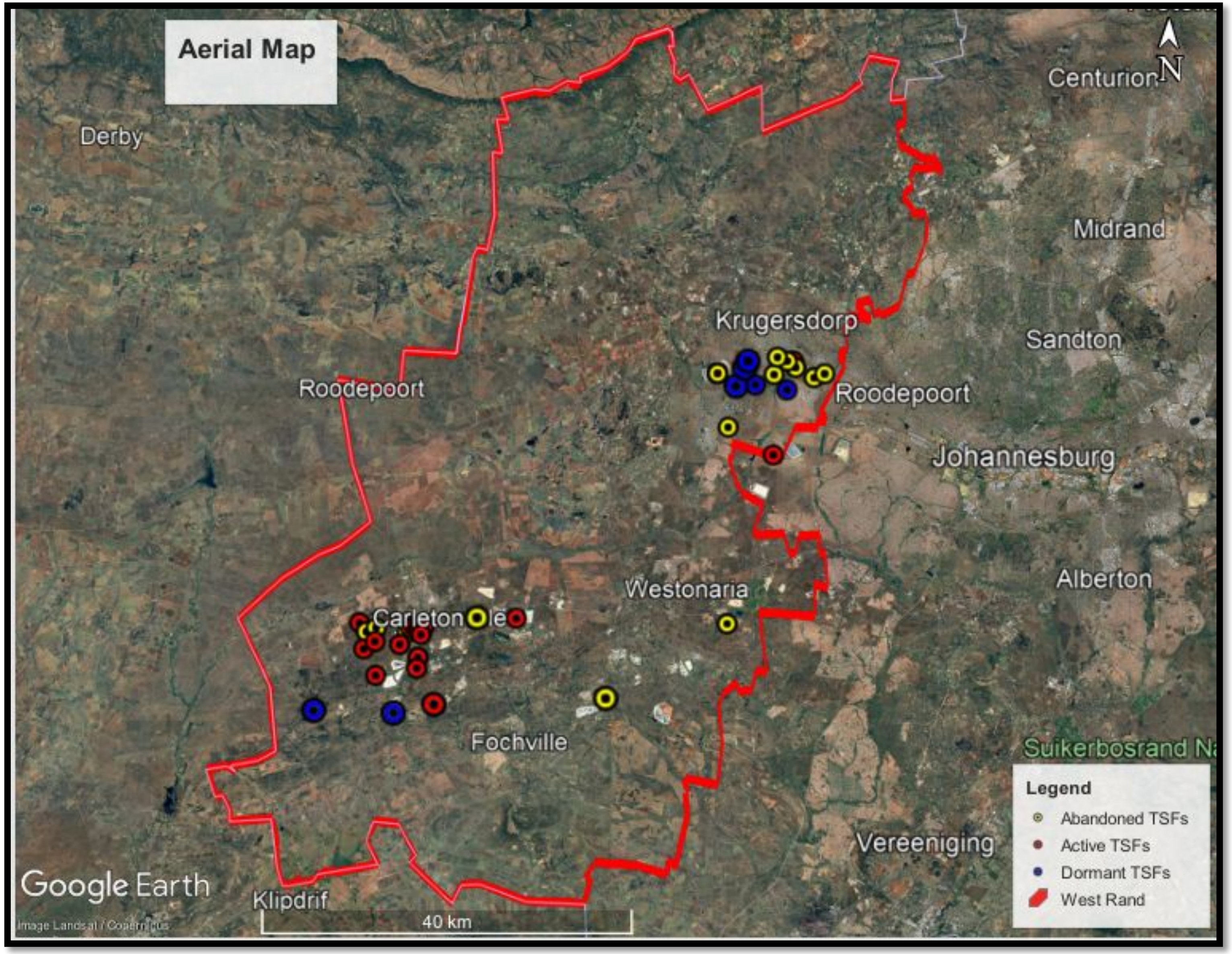
This map illustrates the spatial distribution of land-cover classes in the West Rand, with a specific emphasis on identifying active, dormant, and abandoned tailings storage facilities using the Random Forest classifier

SUPPORT VECTOR MACHINE (SVM) MAP



SVM-derived land-cover map highlighting the location and extent of active, dormant, and abandoned TSFs in the West Rand.

AERIAL MAP


Aerial Map
Centurion
N
Derby
Midrand
Krugersdorp
Sandton
Roodepoort
Roodepoort
Johannesburg
Westonaria
Alberton
Carleton
Fochville
Suikerbosrand N
Legend
Abandoned TSFs
Active TSFs
Dormant TSFs
West Rand
Vereeniging
Google Earth
Klipdrif
40 km

RESULTS – SLIDE 1 (RF CLASSIFICATION)

- RF produced high-accuracy TSF classification.
- Active TSFs are clearly mapped in the southern and eastern West Rand.
- Abandoned TSFs are dominant in western areas; some are partially obscured by vegetation.
- Dormant TSFs are few and occasionally confused with abandoned TSFs due to similar reflectance.
- RF achieved ~99.29% overall accuracy with minimal misclassification.

RANDOM FOREST CONFUSION MATRIX

Class Names	Active TSF 1	Abandoned TSF 2	Dormant TSF 3	Waterbody 4	Grasslands 5	Bare-land 6	Built-up 7	Row total	PA%
Active TSF	**92**	0	0	0	0	0	0	92	100
Abandoned TSF	1	**33**	1	0	0	0	0	35	94,3
Dormant TSF	0	0	**128**	0	0	0	0	128	100
Waterbody	0	0	0	13	0	0	0	13	100
Grasslands	0	0	0	0	36	0	0	36	100
Bare land	0	0	0	0	0	46	0	46	100
Built-up	0	0	0	0	1	0	69	70	98,6
Column Total	93	33	129	13	37	46	69		
UA%	98,92	100	99,2	100	97,3	100	100		

RESULTS – SLIDE 2 (SVM CLASSIFICATION & VALIDATION)

- SVM successfully mapped TSFs but with lower accuracy than RF.
- Active TSFs showed significant confusion with built-up areas (PA = 76.1%).
- Dormant TSFs had high recall but very low precision (UA = 53%) due to overprediction.
- Overall accuracy: ~95%.
- Field validation using DMPR coordinates showed strong spatial agreement between model outputs and actual TSF locations.

SVM CONFUSION MATRIX

Class Names	Active TSF 1	Abandoned TSF 2	Dormant TSF 3	Waterbody 4	Grasslands 5	Bare-land 6	Built-up 7	Row total	PA%
Active TSF	**70**	2	7	0	0	0	13	92	76,1
Abandoned TSF	3	**32**	0	0	0	0	0	35	91,4
Dormant TSF	4	0	**124**	0	0	0	0	128	96,9
Waterbody	0	0	0	**13**	0	0	0	13	100
Grasslands	0	0	0	0	**36**	0	0	36	100
Bare land	0	0	0	0	0	**46**	0	46	100
Built-up	10	0	0	0	0	0	**60**	70	85,7
Column Total	87	34	131	13	36	46	73		
UA%	80,5	94,1	53	100	100	100	82,2		

DISCUSSION

- RF outperformed SVM due to its robustness in handling spectral variability and mixed pixels.
- Abandoned TSFs were successfully identified despite vegetation cover and spectral similarity challenges.
- Spatial clustering of TSFs in Krugersdorp, Randfontein, Westonaria, Fochville, and Carletonville aligns with historical mining belts.
- Misclassification mainly occurred between dormant vs. abandoned TSFs and active TSFs vs. built-up areas.
- The integrated ML + remote sensing workflow provides a scalable, repeatable, and cost-effective method for TSF monitoring

CONCLUSION

- Remote sensing and ML techniques effectively mapped active, dormant, and abandoned TSFs in the West Rand.
- RF demonstrated superior performance, achieving near-perfect accuracy.
- The workflow supports environmental monitoring, regulatory compliance, and rehabilitation planning.
- The study contributes to a more transparent and proactive approach to managing South Africa’s mining legacy.

RECOMMENDATIONS

- Use higher-resolution imagery (e.g., PlanetScope, WorldView) to reduce misclassification.
- Incorporate object-based image analysis (OBIA) for improved boundary detection.
- Extend temporal analysis to monitor TSF evolution over time.
- Integrate additional indices (NDVI, NBR, moisture indices) to improve class separability.
- Conduct field surveys to update TSF inventories and confirm reclaimed sites.
- Apply deep learning models (e.g., CNNs, U-Net) for enhanced TSF detection.

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THANK YOU

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