Short thesis for the degree of Doctor of Philosophy (PhD)

SUPERVISED MACHINE LEARNING FOR GULLY MAPPING AND MODELING USING LOW-COST, HIGH-RESOLUTION SENSORS AND OPEN-SOURCE GEOSPATIAL DATA IN A SEMI-ARID ENVIRONMENT

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1. Introduction

Gully erosion has been a research topic for over a century (Liu et al. 2021; Castillo and Gómez 2016), but compared to rill and sheet erosion, gully modeling is still in its early stages (Roberts et al. 2022). Current gully models have limited global use due to their geographic specificity, physical mechanisms, and difficulties in obtaining observational data (Roberts et al. 2022). In addition, traditional field measurements and surveys are expensive and restricted to accessible locations, making it challenging to obtain a precise understanding and quantification of gullies, whereas the manual digitization and interpretation of gullies based on aerial or satellite images are time-consuming and subjective. In contrast, utilizing machine learning (ML)-based techniques to extract and model gullies from satellite images and related geospatial data has gained popularity due to advancements in computer processing and free geospatial data such as digital elevation models (DEMs) and satellite images.

High-resolution images (1.5-3m) such as Systeme Pour l'Observation de la Terre (SPOT-7) and PlanetScope are beneficial for mapping gullies with sufficient detail, but their application in severely gullied semi-arid regions such as South Africa is limited. Besides mapping gullies, ML algorithms have been increasingly utilized in predicting gully susceptibility at the catchment level. However, since many studies rely on a fixed set of predictor variables (Lana, Castro, and Lana 2022; Huang et al. 2022; Dewitte et al. 2015; Pourghasemi et al. 2017; Arabameri et al. 2019; Kulimushi et al. 2023), further investigation is necessary to assess the impact of different sets of predictor variables on the effectiveness of ML algorithms in gully susceptibility modeling. Besides, in order to recommend and execute effective preventive measures for reducing the risk of new gullies and reversing the growth of existing ones, it is imperative to have a comprehensive understanding of the susceptibility of different areas to gully formation.

2. Research objectives

1. determine if low-cost, high-resolution sensors improve gully mapping in semi-arid regions,
2. quantify gully classification accuracy and analyze factors biasing model performance on a class level,
3. examine how different gully morphological characteristics affect the precise mapping of gullies using high-resolution satellite data,
4. select geo-environmental variables with the greatest predictive power to model gully susceptibility, and
5. analyze algorithms' performance when using small, medium, and large input feature sets.

3. Materials and methods

The dissertation utilized remote sensing data acquired at no cost, including cloud-free satellite imagery and elevation data. The SPOT multispectral and visual range images were obtained from the South African National Space Agency (SANSA), while the geometrically and radiometrically corrected PlanetScope multispectral images were obtained from the Planet explorer website. The SPOT multispectral images were converted to top-of-atmosphere reflectance and enhanced using the Gram-Schmidt pan-sharpening method. Additionally, a digital elevation model was obtained from the Earth Explorer website.

Various geo-environmental predictors or covariates that influence gully erosion were used. These predictors include topographic factors such as elevation, slope, aspect, curvature, and soil physical and chemical properties like organic matter content, CEC, and pH. The K-factor, which represents soil erodibility, was computed using the empirical relation of Williams (1995). Other predictors included the NDVI, land use/land cover (LULC) map, land type map, distance from roads, and geology. Long-term annual gridded rainfall data from CHIRPS were also used. The data was collected from various sources, including the FAO, USGS, South African National Land Cover dataset, South African Land Type Survey database, and the Climate Hazards Group Infrared Precipitation (CHIRPS).

The study used the recursive feature elimination algorithm to identify and remove uninformative predictors and checked for multicollinearity using a correlation matrix, tolerance, and variance inflation factor (VIF). Three feature sets were generated: a large set with 16 predictors, a medium set with 12 predictors, and a small set with six predictors. These sets were used to examine the performance of the ML models with varying numbers of predictors. The terms “large,” “medium,” and “small” sets were used throughout the study for convenience.

Field surveys, satellite images, and Google Earth image interpretation were used to collect reference data in all four study areas. In Study Area #1, a multiclass and binary approach was investigated, with stratified random sampling applied to collect 20795, 31784, and 22512 datasets for sites 1A, 1B, and 1C, respectively. In Study Area #2, the reflectance values of gullies were compared during two different seasons by computing the Normalized Difference Vegetation Index (NDVI). In Study Area #3, four land cover classes were distinguished, and training data for each class was obtained by digitizing polygons. The gully density map was generated using an algorithm with the highest overall and class-level accuracies. Finally, in Study Area #4, the reference data consisted of 592 gully and non-gully points collected from Google Earth for gully susceptibility modeling.

Several algorithms, such as random forest (RF), support vector machines (SVM), partial least squares (PLS), maximum likelihood classifier (MLC), k-nearest neighbor (K-NN), regularized discriminant analysis (RDA), artificial neural network (ANN), stochastic gradient boosting (SGB), and minimum distance (MD), were used to identify gully features and model gully susceptibility in different study areas. The algorithms were executed using Python programming language in Study Area #1 and #2, and R programming language in Study Area #4. In Study Area #3, RF, ML, K-NN, and MD algorithms were implemented within the Sentinel Application Platform (SNAP) toolbox to extract gullies from a visual range SPOT-7 image.

The performance of these algorithms (RF, SVM, LDA, ML, K-NN, RDA, ANN, PLS, SGB, and MD) was evaluated using various statistical metrics. Study Area #1 employed repeated 10-fold CV with three sites and three algorithms to evaluate RF, SVM, and LDA. Study Area #2 used 5-fold CV and bootstrapping to assess RF and SVM. Study Area #3 used confusion matrix metrics, and Study Area #4 used six ML algorithms and a confusion matrix in R software. Additional metrics, such as PA, UA, F1-score, commission, and omission errors, were calculated, along with unbiased areal coverages and confidence intervals.

Statistical analyses were conducted using R software and WRS2, jamovi 1.2., and GAMLj modules. In Study Area #1, the normality assumption of the land cover data was checked using the Shapiro-Wilk test. Hypothesis testing was applied to determine if land cover classes had identical medians or differed in reflectance values. General Linear Modelling (GLM) was used to evaluate model performance. In Study Area #2, the NDVI values were compared using the robust Mann-Whitney test. The GLM was used to analyze the effects of spectral bands, seasons, and land cover classes. The Dunnett test determined if gullies differed significantly from other land cover types.

4. Scientific results

Thesis statement 1

Low-cost, high-resolution sensors such as SPOT-7 and PlanetScope improve gully mapping in semi-arid regions.

Although all SPOT-7 multispectral bands could discriminate gullies, the NIR band was the most effective, and a multiclass approach confirmed the significance of models for each combination of bands and study sites (Tables 1-2). However, in the case of the binary approach, the blue band was less effective in discriminating gullies when combined with study site 1A. Gullies were not significantly different from stressed vegetation and roads in the red, green, and blue bands but significantly differed from other categories regarding reflectance values across all study sites (Table 3).

Table 1. Results of robust independent samples t-test performed on SPOT-7 bands using the binary (gully—non-gully) approach (study sites: 1A–1C, t: the value of t-statistic, p: significance, ξ: effect size).

Bands	1A			1B			1C		
	t	p	ξ	t	p	ξ	t	p	ξ
Red	8.3	< 0.001	0.159	9.55	< 0.001	0.14	6.74	< 0.001	0.11
Green	2.99	0.003	0.062	28.21	< 0.001	0.38	15.98	< 0.001	0.28
Blue	1.07	0.286	0.02	14.42	< 0.001	0.2	9.56	< 0.001	0.17
NIR	86.1	< 0.001	0.964	171.7	< 0.001	0.98	113.3	< 0.001	0.98

Table 2. Results of robust ANOVA performed on SPOT-7 bands using the multiclass (7-classes) approach (study sites: 1A–1C, F: the value of F-statistic, p: significance).

Bands	1A		1B		1C	
	F	p	F	p	F	p
Red	10105	< 0.001	25193	< 0.001	12660	< 0.001
Green	9309	< 0.001	21188	< 0.001	10571	< 0.001
Blue	9718	< 0.001	25694	< 0.001	13036	< 0.001
NIR	3590	< 0.001	10905	< 0.001	4317	< 0.001

The results were consistent with post hoc tests, except for sites 1B where significant differences were found. Based on Dunnett's test statistics, confidence intervals indicated non-significance between gullies and roads (Figure 1).

Table 3. Results of robust ANOVA performed on SPOT-7 bands using the multiclass (7-classes) approach (LC: land cover, study sites: 1A–1C, G: gully, DV: dense vegetation, SV: stressed vegetation, S: settlement, BS: bare soil, MS: mixed soil, R: road).

LC	**1A**				**1B**				**1C**			
	Red	**Green**	**Blue**	**NIR**	**Red**	**Green**	**Blue**	**NIR**	**Red**	**Green**	**Blue**	**NIR**
G-DV	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
G-SV	<0.001	**0.275**	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	**0.281**	**0.275**	**0.883**	<0.001
G-S	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
G-BS	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
G-MS	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
G-R	<0.001	**0.528**	<0.001	<0.001	**0.614**	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

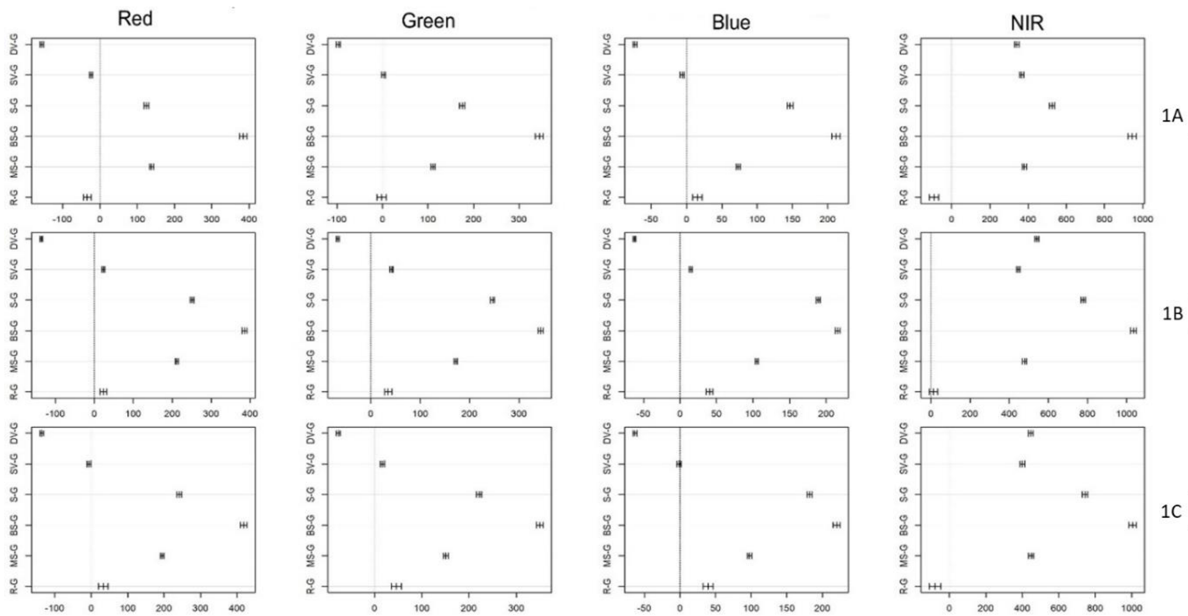

Figure 1. Mean differences between gullies (G) and other land cover categories (mean ± 95% confidence intervals; 95% confidence intervals coinciding with 0 are not significant differences, $p > 0.05$; DV: dense vegetation, SV: stressed vegetation, S: settlement, BS: bare soil, MS: mixed bare soil, R: roads) by SPOT 7 bands (columns) and study areas (rows).

Concerning PlanetScope, results showed that NDVI values were generally higher during wet than dry seasons (Figure 2). The distribution of NDVI values was bimodal for the dry season and multimodal for the wet season, with non-vegetation pixels in the first mode and vegetation and forest pixels in the last two modes. Statistical analysis revealed that spectral bands, land cover classes, seasons, and their interactions significantly influenced reflectance, with the difference between dry and wet seasons having the most significant effect (Table 4). Reflectance varied across bands, land cover classes, and seasons, significantly affecting their interactions. The interaction between seasons and land cover classes had a smaller effect size but was still substantial.

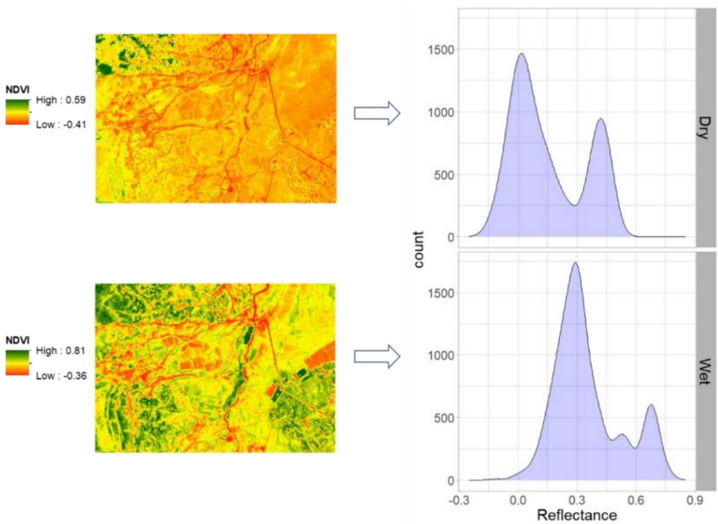

Figure 2. Distribution of NDVI reflectance values in the dry and wet seasons.

Table 4. Results of General Linear Modelling (GLM) performed with reflectance as an independent variable (SS: Sum of Squares, df: degree of freedom, F: F-statistic, p: significance, ω^2p: effect size; $p < 0.05$: significance level).

Variables	**SS**	**df**	**F**	**p**	**ω²p**
Model	6.99e0+9	55	860.4	< .001	0.923
Bands	1.00e0+9	3	2256.1	< .001	0.633
Season	3.80e0+9	1	25715.0	< .001	0.868
Class	9.79e0+8	6	1104.2	< .001	0.629
Bands × Season	4.48e0+8	3	1010.0	< .001	0.436
Bands × Class	5.30e0+8	18	199.3	< .001	0.477
Season × Class	9.62e0+7	6	108.5	< .001	0.141
Bands × Season × Class	1.34e0+8	18	50.3	< .001	0.185
Residuals	5.70e0+8	3860			
Total	2.96e+10	3916			

Gullies significantly differed from other land cover classes in the dry season but not in the wet season except for some cases (Figure 3). The NIR and red bands were the most influential in discriminating gullies, while the blue band had the most negligible impact. NDVI was less effective in differentiating gullies and did not perform well in the dry season. It performed better in the wet season but did not differ significantly from the built-up class values.

Despite limited spectral information, the high spatial resolution (1.3 m) of the visual range SPOT-7 image enabled effective discrimination of gullies from other land cover types (Figure 4), using the Normalized Green-Red Difference Index (NGRDI). In addition, the study sites' spectral profiles revealed the morphology of gullies, including Vshaped gullies in site 3C and dendritic networks in sites 3A and 3D, which were the most detectable in the study.

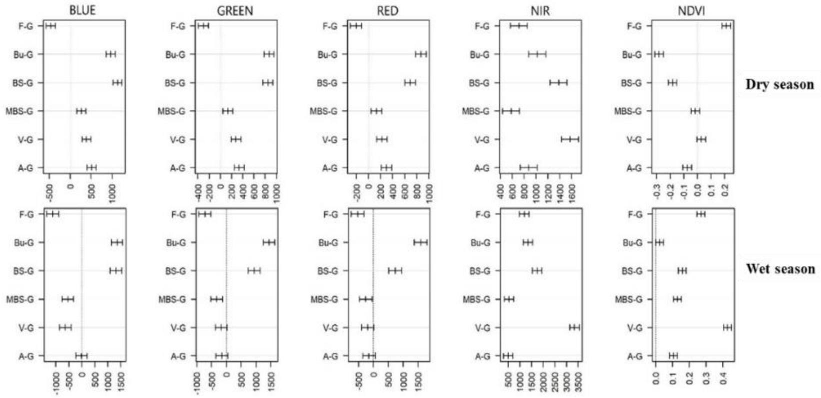

Figure 3. Differences of gullies and other land cover types' reflectance by bands and seasons (G: gully; F: forest; Bu: built-up; BS: bare soil; MBS: mixed bare soil; V: vegetation; A: agriculture; mean ± 95% confidence intervals; the difference was not significant if confidence range intersects the dashed line).

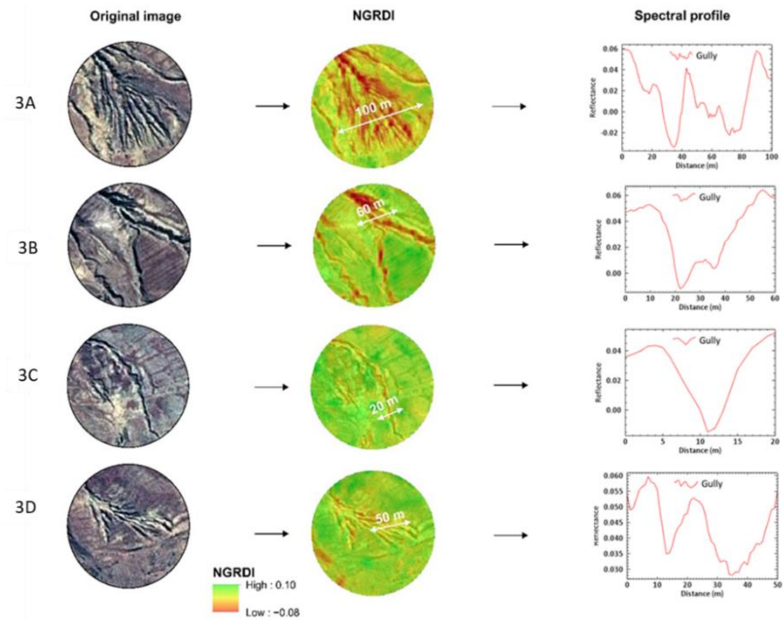

Figure 4. Gully transects (20–100 m) with Normalized Green Red Difference Index (NGRDI)-based spectral profiles of selected gullies.

Thesis statement 2

GLM indicated that both the study sites and the algorithms used could account for the differences in efficiency observed among the classification models.

The study site had a significant impact on both the PA and UA, while the applied algorithm significantly affected only the UA (Tables 5-6). The interaction between the algorithms and study sites did not have a significant effect on the PA. The effect size (ω^2) revealed a substantial influence of the study sites on PA and the algorithms on UA. Moreover, there was a significant interaction between the applied algorithms and the type of classification approach (binary or multiclass), indicating that these algorithms exhibit distinct performance based on the number of categories involved.

Table 5. Summary of General Linear Modelling (GLM) performed with PA as an independent variable (Alg: algorithm, type: binary or multiclass approach, stud: Study site; SS: Sum of Squares, df: degree of freedom, F: F-statistic, p: significance, ω^2: effect size; $p < 0.05$ is highlighted with bold).

Source	SS	df	F	p	ω²
Model	3200.5	17	3.632	**0.005**	0.554
Alg	174.9	2	1.687	0.213	0.017
type	25.5	1	0.493	0.492	0.006
stud	1431.9	2	13.811	**< 0.001**	0.317
Alg × type	946.7	2	9.132	**0.002**	0.201
Alg × stud	323	4	1.558	0.228	0.028
type × stud	99.1	2	0.956	0.403	0.001
Alg × type × stud	199.4	4	0.962	0.452	0.002
Residuals	933.1	18			
Total	4133.6	35			

Table 6. Summary of GLM performed with UA as an independent variable (Alg: algorithm, type: binary or multiclass approach, stud: Study site; SS: Sum of Squares, df: degree of freedom, F: F-statistic, p: significance, ω2: effect size; $p < 0.05$ is highlighted with bold).

Source	SS	df	F	p	ω²
Model	20720.3	17	4.0014	**0.003**	0.586
Alg	17390.9	2	28.547	**< 0.001**	0.633
type	82.6	1	0.2711	0.609	0.008
stud	2413.4	2	3.9615	**0.038**	0.068
Alg × type	98.6	2	0.1618	0.852	0.019
Alg × stud	666.8	4	0.5473	0.703	0.021
type × stud	18.7	2	0.0307	0.97	0.022
Alg × type × stud	49.4	4	0.0405	0.997	0.044
Residuals	5482.8	18			
Total	26203.1	35			

Thesis statement 3

Gully morphological characteristics such as pattern, depth, and width influence the precise mapping of gullies and their density.

The classification of gullies was strongly influenced by their morphological characteristics, such as pattern, depth, and width. The detection efficiency varied across the study sites, with shallow and wide gullies more challenging to detect (Figure 5). There was a discrepancy between the actual digitized gullies and those derived by the algorithms, possibly due to differences in resolution or because the classifiers mainly detected gullies with steep-sided walls or shadows. Gully density was highest in areas with dendritic patterns and steep-sided walls (Figure 6).

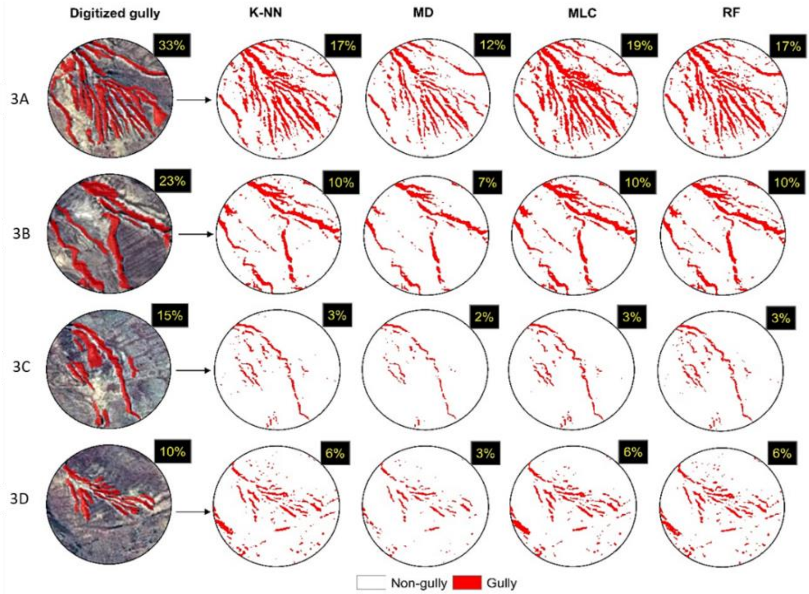

Figure 5. Selected gully sites (3A–3D) showing the spatial distribution of the classified gullies by different algorithms (KNN: k-nearest neighbor, MD: minimum distance, MLC: maximum likelihood, RF: random forest) and actual (digitized) gullies.

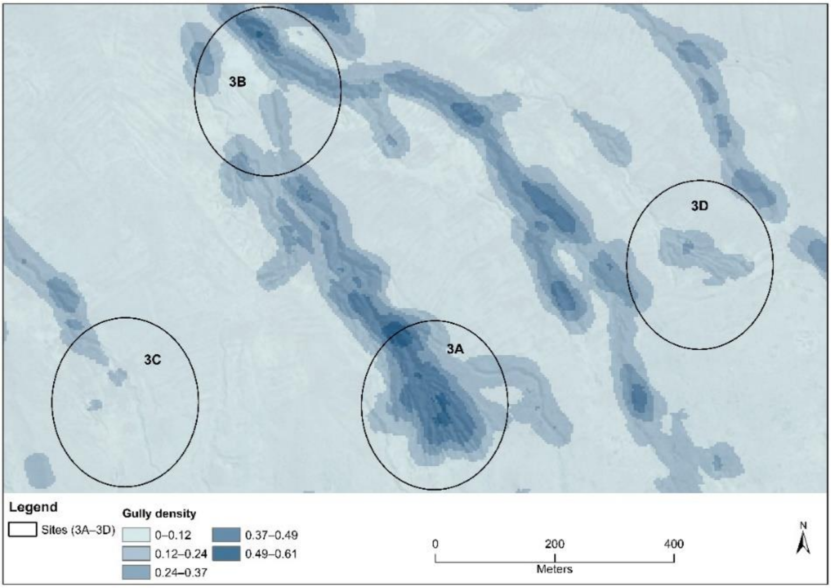

Figure 6. Gully density (m/m^2) map of the study area.

Thesis statement 4

Among geo-environmental covariates, NDVI, elevation, TWI, population density, SPI, and LULC, had the greatest predictive power for gully susceptibility modeling.

The study found that NDVI had the greatest predictive power for gully susceptibility modeling, followed by elevation, TWI, population density, SPI, and LULC (Table 7). Areas with low NDVI, low elevation, low TWI, and low SPI were found to be more vulnerable to gully erosion. Grassland and cultivated lands were the most susceptible LULC classes to gully erosion, and lower population densities were more prone to gullying than higher densities due to the rural nature of the catchment.

Table 7. Relationship between the six most critical geo-environmental predictors and gully erosion.

Gully factor	Class	Gully pixels	Gully pixels (%)
	-0.23-0.18	132725	18.068
	0.18-0.24	196895	26.803
NDVI	0.24-0.29	167825	22.846
	0.29-0.35	133145	18.125
	0.35-0.72	24277	3.305
	538-765	276441	37.625
	765-893	342962	46.679
Elevation (m)	893-1039	24540	3.340
	1039-1255	10286	1.400
	1255-1772	748	0.102
	<6.13	287932	39.189
	6.13-7.53	295262	40.187
TWI	7.53-9.36	62294	8.479
	9.36-11.89	9437	1.284
	11.89-24.99	52	0.007
	1	654515	89.143
Population density (people/km^2)	1-85	0	0.000
	<-6.25	156181	21.257
	-6.25- -1.56	117122	15.941
SPI	-1.56-0.36	166513	22.663
	0.36-3.23	169113	23.017
	3.23-13.35	46048	6.267
	Forested Land	8126	1.106
	Grassland	318769	43.389
	Waterbodies	2703	0.368
	Wetlands	1073	0.146
LULC	Barren Land	58494	7.962
	Cultivated	239029	32.535
	Built-up	26123	3.556
	Mines & Quarries	606	0.082

Thesis statement 5

Feature sets of varying sizes (small, medium, and large) considerably affect the accuracy and computation time of various algorithms.

The performance of six algorithms was evaluated based on accuracy and processing time using three different feature subsets (small, medium, and large). Results showed that the algorithm's performance varied depending on the feature set size (Figure 7). SVM was found to be the most efficient algorithm with medium and small feature sets, while SGB performed well with larger feature sets but took more time to compute. RF was the most computationally expensive algorithm but yielded high accuracies with a large feature set. PLS and RDA were fast algorithms producing relatively high accuracy with a medium feature set. Finally, ANN's performance varied with the number of input features, taking longer to compute with a larger feature set but consistently achieving high accuracies with a small feature set.

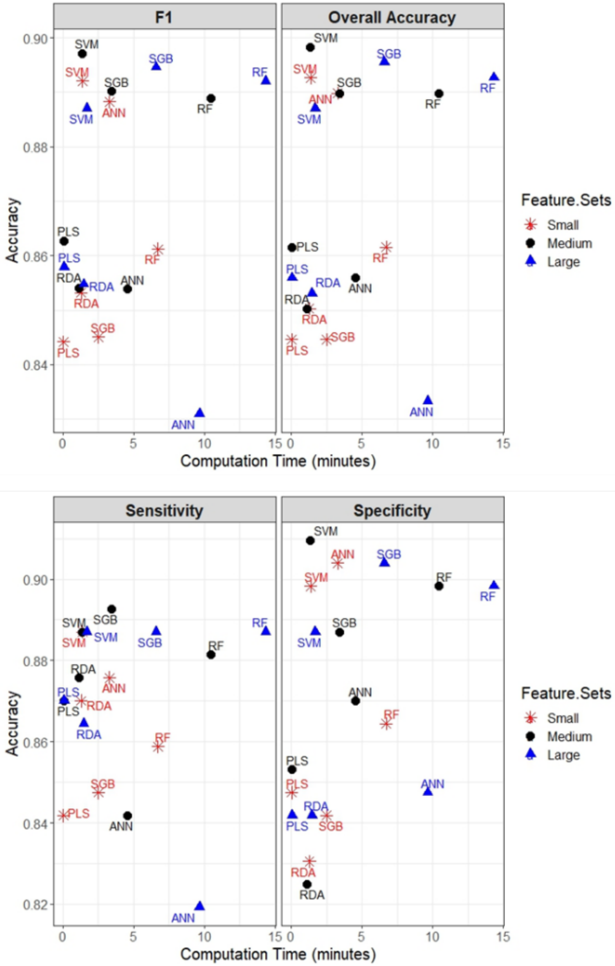

Figure 7. Predictive performance of ML models (ANN: artificial neural network, PLS: partial least squares, RDA: regularized discriminant analysis, RF: random forest, SGB: stochastic gradient boosting, SVM: support vector machines) using smaller, medium, and larger feature sets.

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Subject: PhD Publication List

Candidate: Kwanele Phinzi
Doctoral School: Doctoral School of Earth Sciences
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List of publications related to the dissertation

Foreign language scientific articles in international journals (3)

1. **Phinzi, K.**, Abriha, D., Szabó, S.: Classification Efficacy Using K-Fold Cross-Validation and Bootstrapping Resampling Techniques on the Example of Mapping Complex Gully Systems. *Remote Sens. 13* (15), 1-18, 2021. EISSN: 2072-4292.
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4. **Phinzi, K.**, Szabó, S.: NDVI-based land-use/cover change detection in a mountainous heterogeneous landscape.
   In: Az elmélet és a gyakorlat találkozása a térinformatikában XI. : theory meets practice in GIS. Szerk.: Molnár Vanda Éva, Debreceni Egyetemi Kiadó, Debrecen, 201-206, 2020. ISBN: 9789633188866

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6. Saidi, F. A., **Phinzi, K.**, Molnár, E.: Urbanization in Algeria: Toward a More Balanced and Sustainable Urban Network?
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Total IF of journals (all publications): 20,643
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