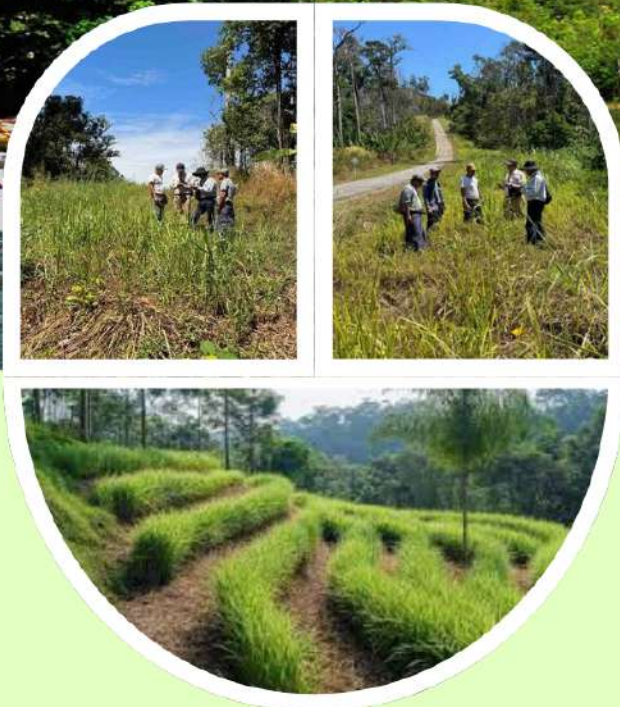




TANINTHAYI NATURE RESERVE PROJECT



တနင်္သာရီသဘာဝ ကြိုးဝိုင်းလုပ်ငန်းစီမံကိန်း



Monitoring on Planted Vetiver Grass in Taninthayi Nature Reserve (TNR) Using Remote Sensing and GIS Approach

Funded By The Taninthayi Nature Reserve Project

*RS and GIS Section
Planning and Statistics Division
Forest Department*

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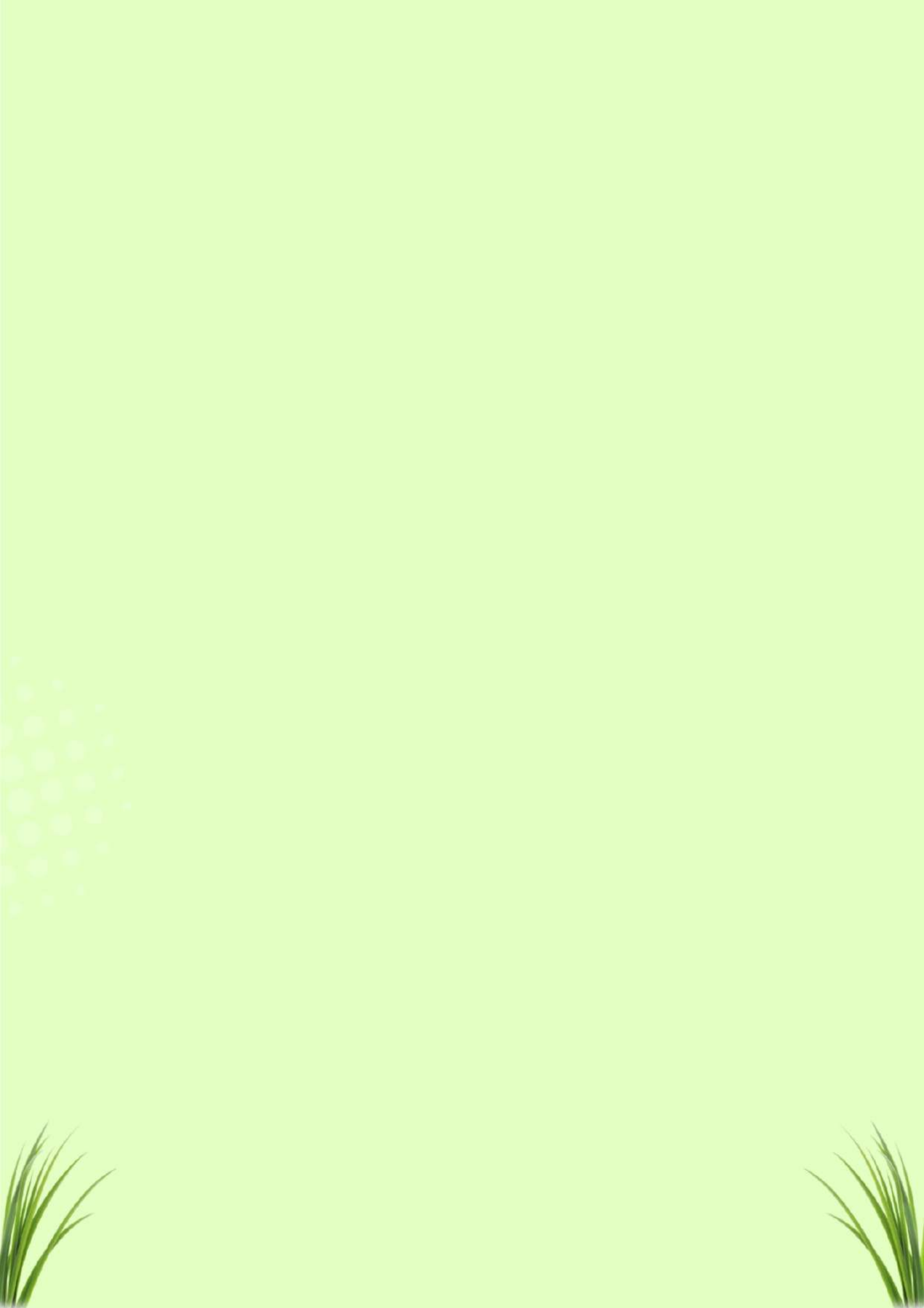


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ABSTRACT

Monitoring on Planted Vetiver Grass in Taninthayi Nature Reserve (TNR) Using Remote Sensing and GIS Approach

Land degradation caused by large-scale linear infrastructure is a substantial worldwide issue, affecting ecological services. Bioengineering, including nature-based solutions such as vetiver grass (*Chrysopogon zizanioides*), is a useful approach for land stabilization. Nonetheless, the introduction of non-native species needs continuous monitoring to ensure their ecological safety. This study addresses this gap in Myanmar's Taninthayi Nature Reserve (TNR), where sterile vetiver cultivars were planted in 2009 for erosion control along a gas pipeline. The recent significant soil degradation caused by illegal mining (about 1,315 acres) in TNR necessitates plans for further vetiver use, making the empirical verification of its non-invasive status essential. This research aimed to evaluate whether vetiver grass has spread beyond its intended pipeline corridor using an integrated remote sensing and GIS approach. We employed two predictive models, Binary Logistic Regression (BLR) and Random Forest (RF), to analyze the probability of vetiver occurrence. The models were developed using 1,028 field-collected presence (456) and absence (572) points and seven biophysical independent variables, including elevation, slope, aspect, distance from streams, distance from roads, and distance from gas pipelines and the Normalized Difference Vegetation Index (NDVI) obtained from Kompsat-3 remote sensing imagery. Both models demonstrated good predictive accuracy (BLR AUC = 0.938; RF AUC = 0.954). The results from both analyses unequivocally identified distance from gas pipelines as the most significant predictor of vetiver occurrence. The probability of vetiver presence was highest along the pipeline and adjacent roads, decreasing sharply with distance. The RF model also highlighted NDVI as a key factor, indicating vetiver is confined to open-canopy, high-sunlight areas, consistent with its known shade intolerance. The results provide substantial statistical evidence that the sterile vetiver cultivar has remained confined to its designated planting sites and has not exhibited invasive behavior in the TNR. This study confirms the ecological safety of vetiver grass as a bioengineering tool, supporting its continued use for future land rehabilitation initiatives, particularly for the stabilization of degraded mining sites within the reserve.

Keywords: Vetiver grass (*Chrysopogon zizanioides*), GIS-based Modeling, Remote Sensing, Land Rehabilitation, Taninthayi Nature Reserve (TNR)

1. Introduction

The rapid increase in anthropogenic landscape modification has triggered a global crisis of land degradation, fundamentally compromising the provision of essential ecosystem services vital for human society. This degradation of land capital, which is defined as the long-term loss of ecosystem function and productivity [1], directly threatens critical ecosystem services, such as food production, water regulation, and carbon sequestration, thereby affecting human well-being and biodiversity [2]. The drivers of land degradation are complex and interrelated, including agricultural expansion, deforestation, urbanization, and industrial pollution etc. Among these, large-scale linear infrastructure projects and unregulated mineral extraction have emerged as particularly severe contributors. Linear infrastructure projects, including pipelines, highways, and railways, require extensive earthworks, resulting in large areas of disturbed land. These corridors, characterized by steep embankments, cut slopes, and compacted soils, exhibit significant susceptibility to accelerated soil erosion, which not only threaten the integrity of the infrastructure itself but also lead to the sedimentation of downstream water bodies and the fragmentation of natural habitats. Addressing the severe ecological consequences of large-scale disturbances caused by these engineering activities has become a critical priority.

In response, the scientific and policy communities have shifted their focus from traditional, resource-intensive civil engineering interventions to more sustainable, nature-based solutions [3]. This has enhanced the significance of ecological engineering, a field focused on designing and restorative system that harmoniously integrate human society with its natural environment [4]. The strategic utilization of vegetation to stabilize landscapes and remediate environmental damage, a practice referred to as bioengineering, is at the fundamental of this approach [5].

The operational success of bioengineering depends on the careful selection of suitable plant species, determined by two fundamental principles: functional efficacy and ecological safety [6]. The efficacy of a plant is primarily determined by its capacity to perform the desired engineering task, for instance, in the case of slope stabilization is primarily a function of tensile strength and root system architecture [5]. Therefore, the most appropriate species should develop a deep, dense root system that provides significant shear resistance to the soil layer. Simultaneously, it should demonstrate extensive physiological tolerance to the frequently severe edaphic and climatic conditions of degraded sites. The principle of ecological safety is also essential, especially when a species is introduced to a new environment. A fundamental requirement is that the candidate species must be non-invasive, ensuring the intervention remediates the initial problem without creating a subsequent, potentially more challenging ecological risk.

In this regard, Vetiver grass (*Chrysopogon zizanioides*), a perennial C4 grass, has emerged as a notable bioengineering tool [7]. The effectiveness of this species is based on its distinct morphological and physiological traits. Vetiver is a non-woody, clump-forming grass (family Poaceae) [8] that is native to tropical and subtropical India [9], reaching heights of 0.5 to 1.5 meters in dense tufts [10, 11]. Its distinctive feature is an extensive fibrous root system that penetrates down to depths of 3 - 4 m, rather than spreading laterally [10, 11]. The deep vertical root network significantly enhances slope stability by reinforcing the soil profile and augmenting its shear strength, making vetiver very useful for erosion management, slope stabilization, and soil moisture conservation [12]. The root system of Vetiver grass is capable of thriving in extreme environments, including temperatures ranging from -14°C to +55°C [14],

extended periods of drought and flooding, which are common on riverbanks, and saline soils that are contaminated with heavy metals or have a low fertility or high pH [17-21]. Although vetiver is tolerant to extreme soil and climatic conditions, it is intolerant to heavy shade and shading will reduce growth and, in extreme cases, may result in plant failure [13]. Simultaneously, vetiver fulfills the criteria for ecological safety: the cultivars used for soil conservation are sterile, reproducing only by clump division [14].

Therefore, Vetiver grass (*Chrysopogon zizanioides*) was regarded as species for bioengineering applications globally. Adapted to a variety of altitudes and climatic conditions, this species grows in the most diverse climates, most notably tropical and subtropical [15]. The Vetiver system was established in 1985 by the World Bank to protect India's soil and water resources [16]. The system aids in agricultural land management [17], environmental protection [18], soil and water conservation [19], infrastructure balancing [20], contamination management [21], and water and wastewater treatment [22].

The Tanintharyi Nature Reserve (TNR), a protected area in southern Myanmar, is a biodiversity hotspot and home to many native plant and animal species. The TNR reserve was established in 2005 to conserve natural resources, promote scientific research, and aid local communities. The reserve, a significant biodiversity hotspot, serves as a habitat for a variety of flora and fauna, including several threatened species: the endangered Asian elephant (*Elephas maximus*) and Indochinese tiger (*Panthera tigris corbetti*), and the vulnerable Malayan tapir (*Tapirus indicus*). Forests in TNR provide ecosystem services, regulating regional climate patterns, safeguarding watersheds that supply fresh water to local communities etc.

However, anthropogenic activities occurred within the TNR reserve area. Therefore, this study focuses on a specific issue resulting from a past conservation initiative. A major gas pipeline was built in the early 2000s for transporting offshore natural gas to Thailand, across the Tanintharyi Nature Reserve (TNR). In 2009, non-native vetiver grass (*Chrysopogon zizanioides*) were introduced along a newly established gas pipeline route inside the Tanintharyi Nature Reserve (TNR) to reduce soil erosion. Although the substantial scientific literature mostly supports the non-invasive nature of these cultivars, from a conservation standpoint, it is essential to empirically verify over the long term that this introduced grass has neither spread beyond its designated area inside the reserve. Currently, TNR is now facing land degradation from illegal gold mining in some parts of the reserve. Recent reports and satellite data revealed that a significant increase in illegal mining that has degraded extensive areas inside TNR in 2023 [23]. An estimated 1,315 acres (~532 ha) of land have been heavily degraded by mining activities [23]. In response, park authorities and conservation partners are considering replanting Vetiver grass as restorative approach on these mining sites to stabilize the ground and initiate biological recovery. Prior to continuing the restoration initiative, they are evaluating the results of the previous vetiver planting to confirm that its introduction did not result in any unintended invasive spread. The findings will support whether this non-native vetiver can be reliably recommended as a bioengineering tool for large scale restoration inside the reserve or not.

Remote sensing has emerged as a necessary technique for ecological monitoring and species distribution research, since it offers comprehensive, reliable, and geographically broad observations of vegetation in areas often inaccessible by continuous field surveys. Satellite imagery facilitates the acquisition of vegetation indices, structural characteristics, and environmental gradients that are essential for distinguishing vegetation types and their spatial

extent. When combined with GIS and field data, these data enable species-specific occurrence analysis, enabling researchers to examine both the distribution of target species and the environmental factors affecting their establishment.

2. Objective of the Study

The main objective of this study is to evaluate whether vetiver grass (*Chrysopogon zizanioides*) introduced along the Tanintharyi pipeline corridor has been maintained within established planting sites or spread beyond its intended area using integrated remote sensing and GIS approach. The specific objectives are as follows.

- (1) to evaluate the probability of vetiver occurrence beyond gas pipeline route (preliminary planted area) using statistical and machine learning models (binary logistic regression and random forest)
- (2) to identify the biophysical factors influencing occurrence status of vetiver grass (*Chrysopogon zizanioides*) in the TNR area

3. Materials and Methods

3.1. Study Area

Taninthayi Nature Reserve (TNR) is situated in Dawei District, Taninthayi Division, between the Dawei River and Myanmar-Thailand border, between latitudes 14° 20' 50" and 14° 57' 55" North and between longitudes 98° 5' 10" and 98° 31' 32" East as shown in figure 1. Taninthayi Nature Reserve includes two forest reserves: the eastern parts of Heinze / Kaleinaung Reserve Forest (85,725 ha or 211,836 acres) and Luwaing Reserve Forest (84,273 ha or 208,240 acres). Notably, gas pipelines to Thailand pass through the northern part of TNR. The Total-operated Motamma Gas Transportation Company (MGTC), The Taninthayi Pipeline Company (TPC), Andaman Transportation Limited -ATL company, which transports natural gas, crosses the reserve. The onshore pipeline extends around 63 kilometers inside Myanmar, of which approximately 55 km are within the reserve. Our study focuses on probability distribution of Vetiver grass beyond the planted area using remote sensing and GIS in assisting the machine learning algorithms.

The topography is characterized by significant variations in elevation, ranging from around 25 meters to 1,399 meters, resulting in distinct vegetation zones defined by altitude and landform. Giant evergreen forest occupied elevations between 500 ft (~152 m) and 1,000 ft (~305 m), whereas sub-evergreen and moist deciduous forests covered areas below 500 ft (~152 m) [24]. Furthermore, dry deciduous forests were located on low slopes and ridges along the Tavoy (Dawei) River, while riverine forests were set to narrow stream banks [24]. Slope gradients within the site vary significantly, ranging from 0° to 71°.

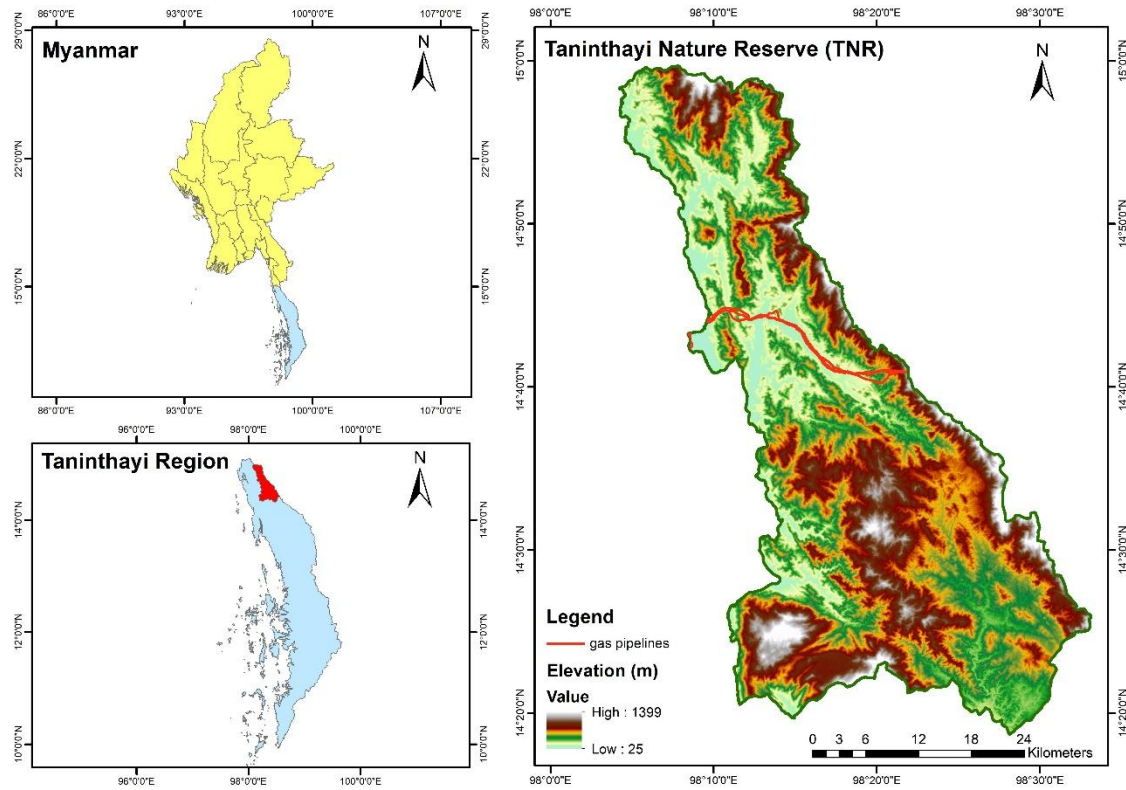


Figure 1: Location of Study Area

3.2. Research framework

The framework of this study is shown in figure 2.

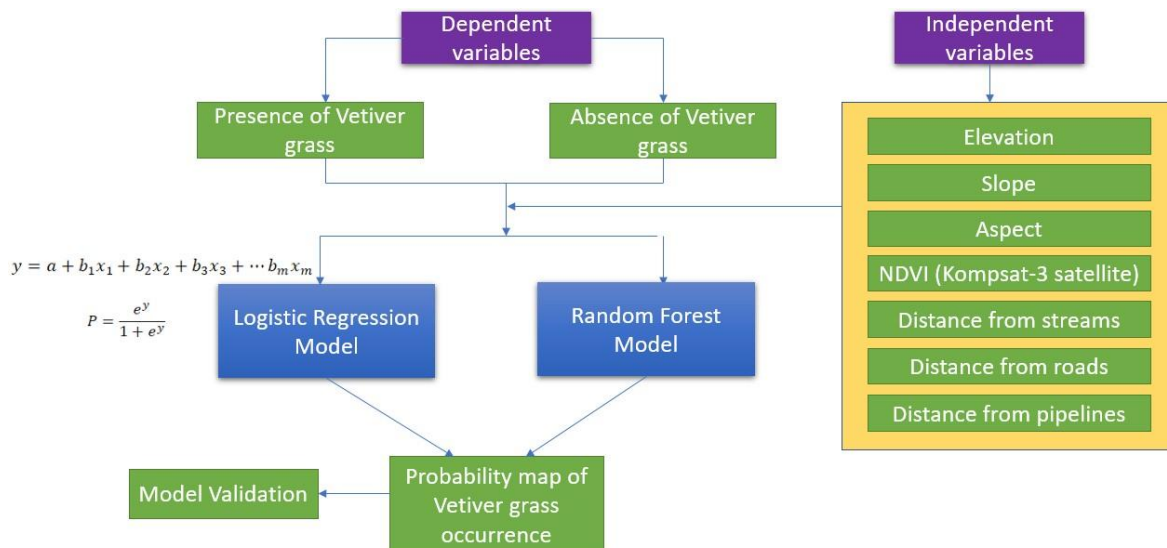


Figure 2: Framework of the Study

3.3. Data Acquisition

This study applied binary logistic regression (BLR) and random forest (RF) to evaluate the probability of vetiver occurrence beyond its intended planting sites and to identify the biophysical factors influencing its occurrence status. The sources of data are mentioned in Table 1.

Table 1: Descriptions of Variables

Variables	Data Format	Source of Data
(1) Altitude	Raster grid	Digital Elevation Model from USGS https://earthexplorer.usgs.gov/
(2) Slope	Raster grid	Digital Elevation Model from USGS https://earthexplorer.usgs.gov/
(3) Aspect	Raster grid	Digital Elevation Model from USGS https://earthexplorer.usgs.gov/
(4) NDVI	Raster grid	Derived from Kompsat 3 Satellite imagery
(5) Distance from roads (Euclidean distance)	Polyline	Digitized from topographic maps of compiled from 1:50,000 aerial photographs (Survey Department, Myanmar) and downloaded from https://www.openstreetmap.org/ (https://download.geofabrik.de/asia/myanmar.html)
(6) Distance from streams (Euclidean distance)	Polyline	Digitized from topographic maps of compiled from 1:50,000 aerial photographs (Survey Department, Myanmar)
(7) Distance from pipelines (Euclidean distance)	Polyline	Sourced from TNRP project

3.4. Assessing Probability of Vetiver Occurrence Through Binary Logistic Regression

The binary logistic regression model (BLR) is widely used across various fields, including the detection of probable deforestation zones, landslide susceptibility mapping, groundwater potential assessment, hazard zonation, and species distribution modeling etc. [25]. Binary logistic regression is a technique for analyzing problems where one or more independent variables influence an outcome, and the outcome is measured with a dichotomous variable [26,27]. In this study, binary logistic regression was employed to model the relationship between the occurrence status of Vetiver grass (presence vs non-detection), environmental variables, and remote sensing data.

Field data on Vetiver occurrence were collected in February 2025 throughout a 2-kilometer area of the gas pipeline route where this grass species was intentionally cultivated along pipeline infrastructure to reduce soil erosion, especially in locations with exposed slopes or disturbed terrain. However, field data collection did not conduct the whole reserve area due to logical and accessibility constraints. Each sample location was recorded with a handheld GPS device and assigned an occurrence state and is used as independent variable. A site was designated as an occurrence point if at least one mature vetiver clump was observed within a five-meter radius. Field observations revealed that Vetiver grass was primarily established in open clearings or disturbed sites similar to forest gaps, especially where canopy cover was minimal and sunlight exposure was abundant. Conversely, non-detection points were recorded in areas where no individuals were detected in forest gap environment. A total of 456 presence points and 572 absence points were recorded.

Seven biophysical factors, including elevation, slope, aspect, distance from streams, distance from roads, and distance from gas pipelines and the Normalized Difference Vegetation Index (NDVI) obtained from Kompsat-3 remote sensing imagery, were selected as independent variables for the logistic regression model. From a topographic map produced by the Survey Department of Myanmar using 1:50,000 aerial photographs, the roads and streams were digitized. Euclidean distance assessments were conducted using digitized road and stream

levels to create GIS layers representing 'distance from roads and streams.' Elevation and slope data were extracted from a Digital Elevation Model (DEM) provided from the USGS website. Distance from streams, distance from roads and distance from gas pipelines maps were generated using the Euclidean distance algorithm. The Euclidean distance measures the proximity of each raster cell to the nearest source; thus, it is common to construct raster layers from vector layers. Furthermore, it can be used when data representing the distance from a certain object is needed.

The 0.5 m spatial-resolution pansharpened Kompsat-3 satellite imagery was used to calculate the Normalized Difference Vegetation Index (NDVI), a critical indicator of the health and density of vegetation. NDVI was calculated using the standard formula.

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (1)$$

The raster layer was then added into the set of independent variables for the logistic regression model. The data format and sources of data for each independent variables are described in table 1 and the raster dataset for each independent variable is shown in figure 3.

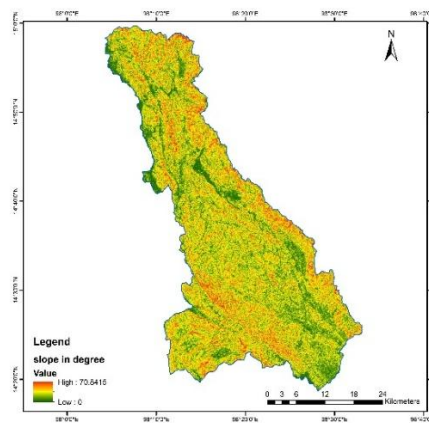
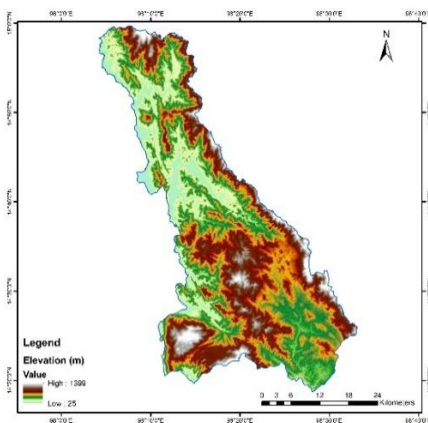
The attribute values of dependent and independent variables were extracted by using the 'extract values to points' tool of ArcGIS Pro. To determine the model's robustness, multicollinearity among the independent variables was measured using Variance Inflation Factor (VIF) and Tolerance statistics. Then, randomly 70% of the points have been taken for the training dataset and the remaining 30% have been kept for validating the model. The logistic regression model predicts the probability of Vetiver occurrence by combining the influence of several independent variables. The binary logistic regression analysis was done by using R software version 2022.02.0. Binary logistic regression model is as follows.

$$y = a + b_1x_1 + b_2x_2 + b_3x_3 + \dots b_mx_m \quad (2)$$

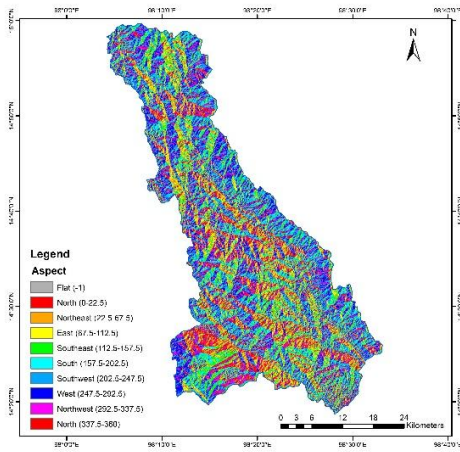
$$y = \log_e \left[\frac{P}{1-P} \right] = \text{logit}(P) \quad (3)$$

$$P = \frac{e^y}{1+e^y} \quad (4)$$

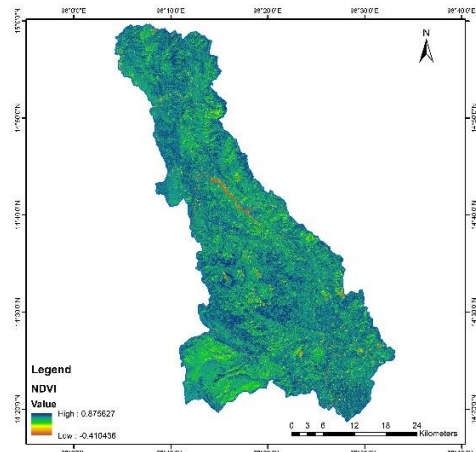
x_1, x_2 and x_3 are independent variables, b_1, b_2 and b_3 are coefficients, and a stand for constant value, and P means Probability. Y describes $\text{logit}(P)$. The model has been validated by receiver operating characteristics (ROC) curve, efficiency, true skill statistics (TSS) and Kappa.



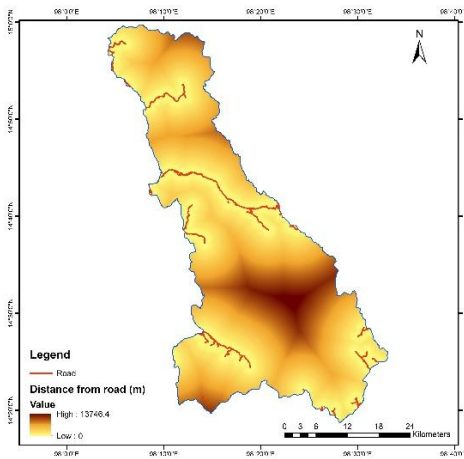
Altitude Map



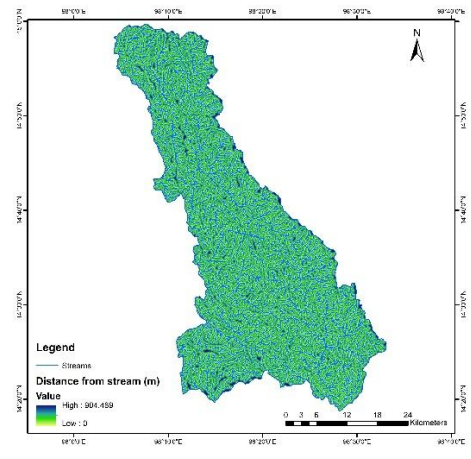
Slope Map



Aspect Map

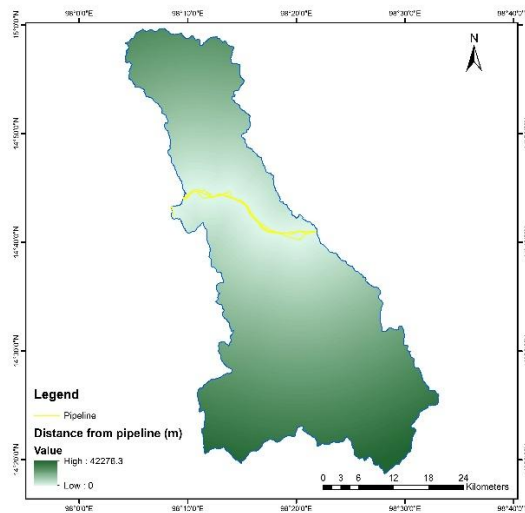


NDVI Map



Map showing Distance from Roads

Map showing Distance from Stream



Distance from pipelines

Figure 3: Raster Datasets of Independent Variables

3.5. Assessing Probability of Vetiver Occurrence Through Random Forest Algorithm

Random forest (RF) is a machine learning ensemble method widely used in classification and regression problems [28]. Random forest can successfully manage not only numerical and categorical variables but also high data dimensionality and multicollinearity, and is insensitive to overfitting [29]. It is an ensemble learning method that needs two parameters for implementation based on the number of trees and variables. In order to build a random forest, the number of trees (n) and predictive variables' split nodes (m) are required. Random forest is a method that constructs multiple decision trees on different samples during training phase and takes their majority voting for classification and average in case of regression as the final decision. In essence, RF is an extension of the bagging technique [30].

In this study, random forest has been carried out using the “Randomforest” package in R software to model the probability of vetiver occurrence within the study area. For the modeling of Vetiver grass occurrence, the dependent factor has been expressed as the binary variable as (occurrence vs non-detection of Vetiver). A total of 456 presence points and 572 absence points were (1028 total points that were used in BLR model). Biophysical variables include elevation, slope, aspect, distance from streams, distance from roads, distance from gas pipelines and NDVI. 70% of total random points were randomly selected for training dataset and the remaining 30% were used for model validation. Based on the default for RF, RF has been set to 500 numbers of trees, and the number of variables at each split denoted by the best mtry value has been set to be 3 with the minimum out of bag (OOB) error. The mean decrease in Gini error have been computed, and the results are validated with ROC curve, efficiency, true skill statistics (TSS) and Kappa.

3.6. Validation Methods on Probability Distribution of Vetiver Grass Occurrence

The receiver operating characteristics (ROC) is a well-accepted method of validation and it is the graphical representation of the true positive rate (TPR) or sensitivity values against the false positive rate (FPR). The TPR and FPR have been calculated using following equations:

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (5)$$

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} \quad (6)$$

Where, TN stands True negative, TP presents True positive, FN means False negative and FP stands False positive. The area under a receiver operating characteristics (ROC) abbreviated as AUC, is a single scalar value that measures the overall performance of a binary classifier [31]. The value of AUC ranges from 0 to 1, where 0.5-0.6 (weak), 0.6-0.7 (moderate), 0.7-0.8 (good), 0.8-0.9 (substantial or very good), and 0.9-1 (excellent) [32].

Moreover, in order to identify the robustness of the model, efficiency (E) and true skill statistics (TSS) were used. Efficiency is the proportion of true results (both true positives and true negatives) among the total number of cases examined. Efficiency is calculated as following equations:

$$E = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (7)$$

True skill statistics (TSS) is largely immune to prevalence [33] and TSS is calculated as follows:

$$\text{TSS} = \text{TPR} - \text{FPR} \quad (8)$$

Cohen's kappa index is the most popular statistical measure of accuracy, consistency and efficiency of the predictive models. The kappa statistic ranges from -1 to $+1$, where $+1$ indicates perfect agreement and values of zero or less indicate a performance no better than random [34]. Kappa index is calculated as follows:

$$k = \frac{P_{obs} - P_{exp}}{1 - P_{exp}} \quad (9)$$

P_{obs} and P_{exp} can be calculated using following equations –

$$P_{obs} = \frac{\text{TP} + \text{TN}}{N} \quad (10)$$

$$P_{exp} = \frac{(\text{TP} + \text{FN})(\text{TP} + \text{FP}) + (\text{FP} + \text{TN})(\text{FN} + \text{TN})}{N^2} \quad (11)$$

Where, “N” is the total number of pixels. The kappa index can be classified as 0-0.2 (low), 0.21-0.4 (moderate), 0.41-0.6 (good), 0.61-0.8 (substantial or very good) and >0.81 (excellent) accuracy [35].

4. Results

4.1. Probability Distribution of Vetiver Grass by Binary Logistic Regression

Collinearity statistical test is conducted by linear regression in order to check variance inflation factor (VIF) and tolerance for the validation of independent variables to fit in logistic regression model. If tolerance value < 0.1 and VIF value > 5 also indicate multi-collinearity problem in the dataset [36]. There is no multicollinearity among the independent variables with the tolerance value > 0.1 and VIF < 5 (Table 2).

Table 2: Collinearity Statistics of Different Independent Variables

Variables	Collinearity Tolerance	Statistics VIF
Aspect	0.894	1.118
NDVI	0.770	1.298
Elevation	0.625	1.600
Slope	0.594	1.682
Distance from streams	0.856	1.167
Distance from roads	0.419	2.386
Distance from gas pipelines	0.387	2.581

Correlation matrix shows the correlation coefficients among the independent variables to identify the presence of multicollinearity (Table 3, Figure 4). If simple correlation coefficient is greater than 0.8 or 0.9 multicollinearity is a serious problem between datasets. There is no serious concern about multicollinearity between variables.

Table 3: Correlation matrix showing the relationship among independent variables using Pearson's correlation coefficient method

Variables	Aspect	NDVI	Elevation	Slope	Distance from streams	Distance from roads	Distance from gas pipelines
Aspect	1	0.0928	0.155	0.285	0.206	0.064	0.055
NDVI	0.093	1	0.199	0.328	-0.008	0.405	0.427
Elevation	0.155	0.199	1	0.516	0.309	0.132	0.336
Slope	0.285	0.328	0.515	1	0.227	0.354	0.390

Distance from streams	0.206	-0.008	0.309	0.227	1	-0.022	-0.006
Distance from roads	0.064	0.405	0.132	0.354	-0.023	1	0.734
Distance from gas pipelines	0.056	0.427	0.336	0.390	-0.006	0.734	1

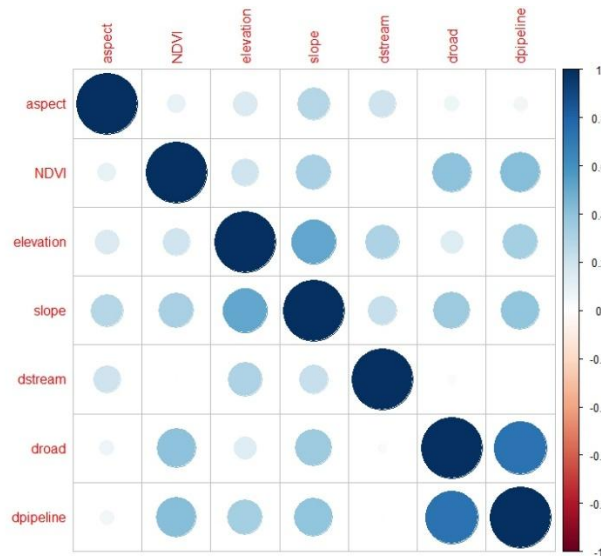


Figure 4: Correlation among the independent variables which reflect by a color matrix scale

The binary logistic regression (BLR) used in this study efficiently analyzed the relationship between the presence of Vetiver grass and selected environmental and remotely sensed variables in Taninthayi Nature Reserve (Table 4). The distance from gas pipelines showed a highly significant negative relationship ($B = -0.0250$, $\text{Exp}(B) = 0.975$, $p = 0.001$). This indicates that for each additional meter away from the pipeline, the odds of Vetiver occurrence are multiplied by 0.975. The natural logarithm of this odds ratio produces the regression coefficient: $\ln(0.975) = -0.025$, confirming the estimated slope. This equals to a 2.5% decrease in the probability of occurrence per meter. The effects fall with distance from the corridor: at 10 meters away, the odds decrease to $0.975^{10} = 0.78$ (approximately 22% lower); at 50 meters, they decline to $0.975^{50} = 0.28$ (approximately 72% lower); and at 100 meters, they reduce to $0.975^{100} = 0.08$, indicating a 92% decrease compared to the pipeline edge. This statistically significant trend indicates that Vetiver grass growth is limited to its designated planting corridor. It also offers statistical evidence that the species has not expanded uncontrollably outside the pipeline route. Elevation also showed a significant negative relationship with the presence of Vetiver ($B = -0.0068$, $\text{Exp}(B) = 0.993$, $p = 0.01826$). This is consistent with field observations that Vetiver grass were found lower altitudes within disturbed or cleared spaces along the gas pipeline route (Figure 5). The distance from roads also showed a statistically significant negative correlation ($B = -0.0019$, $\text{Exp}(B) = 0.998$, $p = 0.008$), suggesting that locations farther from roads had a lower probability of Vetiver occurrence. Vetiver grass was frequently observed in roadside environments, especially in areas where vegetation had been removed or the canopy was open. These zones often have increased sunlight exposure, exhibit less competition from trees. Distance from streams, NDVI, slope, and aspect were not significant predictors in the present study.



Figure 5: Field survey of Vetiver grass (*Chrysopogon zizanioides*) occurrences along the Tanintharyi pipeline corridor and adjacent roadside environment

Table 4: Binary logistic regression results

Independent Variables	B	S.E	Z value	Pr(> z)	Exp (B)	95% C.I for Exp(B)	
						Lower	Upper
Intercept	3.0373	0.8513	3.568	0.00036	20.849		
Aspect	-0.0002	0.0014	-0.175	0.86141	1.000	0.997	1.003
NDVI	-0.1034	1.4435	-0.072	0.94291	0.902	0.050	15.386
Elevation	-0.0068	0.0029	-2.360	0.01826*	0.993	0.987	0.998
Slope	-0.0099	0.0339	-0.295	0.76780	0.990	0.925	1.057
Distance from stream	0.0084	0.0044	1.916	0.05538	1.008	1.000	1.018
Distance from road	-0.0019	0.0007	-2.644	0.00820**	0.998	0.996	0.999
Distance from pipeline	-0.0250	0.0045	-5.537	3.08e-08***	0.975	0.966	0.983

Vetiver occurrence probability map was generated based on the computed value of the binary logistic regression model using the following equation.

$$P = \frac{e^y}{1 + e^y}$$

The probability map (Figure 6) shows that Vetiver is concentrated in pipeline and road corridors, with probabilities declining into the adjacent forest, signifying persistence within managed corridors rather than dispersion. The binary logistic regression value ranges from 0 to 1, where nearer to 0 means probability of Vetiver grass occurrence is very low and nearer to 1 is very high. Probability of Vetiver grass occurrence result has been subdivided with equal interval into four categories as very low, moderate, high and very high occupying 64.82%,

6.87%, 15.15 % and 13.15 % of the areas respectively (Table 5).

Table 5: Area distribution of Vetiver grass occurrence probability by Binary Logistic Regression

Vetiver grass occurrence probability zones	Binary Logistic Regression	
	Areas in acres	%
Very low	3762.62	64.82
Moderate	398.75	6.87
High	879.33	15.15
Very high	763.46	13.15

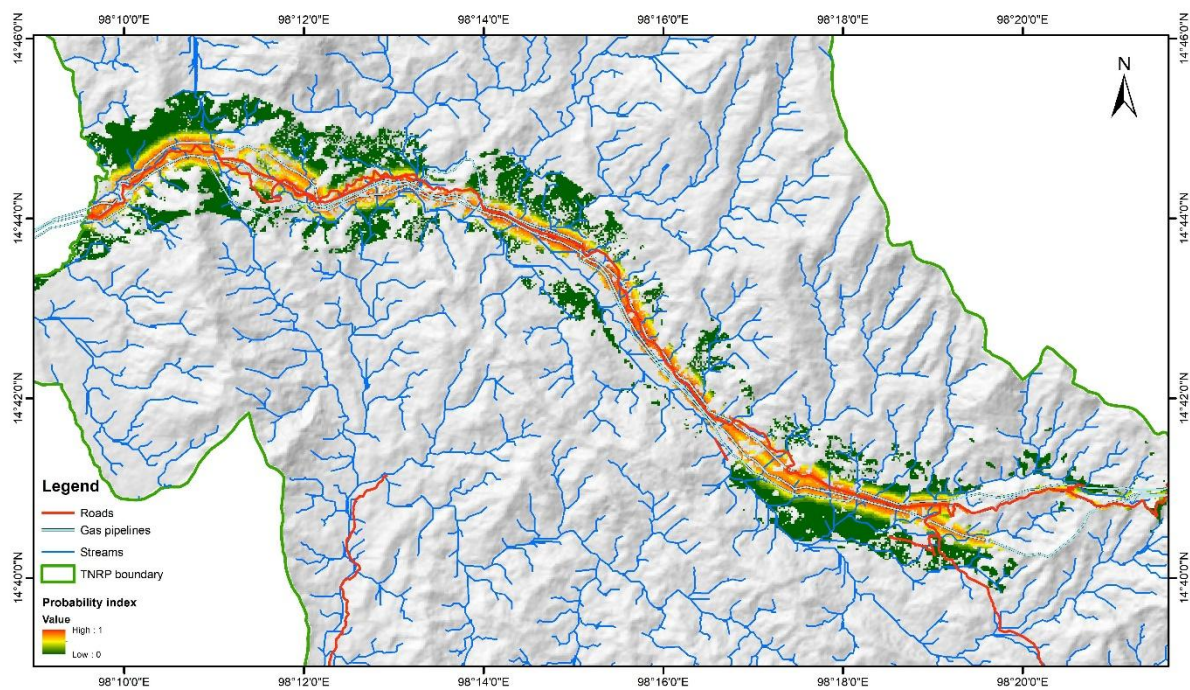


Figure 6: Predicted probability map of Vetiver grass occurrence based on the binary logistic regression model

4.2. Probability Distribution of Vetiver grass by Random Forest

An advantage of the RF model is that it offers variable importance measures that are based on the extent to which each predictor contributes to reducing classification error, which is frequently quantified by the Mean Decrease in Gini impurity (Table 6). The random forest's most important variable was distance from gas pipelines, with a Mean Decrease Gini value of approximately 133.65. This reveals that proximity to the pipeline is the primary factor impacting Vetiver presence: both the RF and logistic models show that the majority of Vetiver occurrences are clustered along the pipeline. The second most important variable was distance from roads (Mean Decrease Gini ≈ 77.65). This indicates that roadside areas provide open environments with enough light penetration for the persistence of Vetiver. The NDVI was identified as the third most significant variable in the RF model (Mean Decrease Gini = 65.51). Although NDVI was not a significant predictor in the logistic regression, the ecological relationship between NDVI and shade intolerant grass like vetiver is fundamentally non-linear. This indicates a low chance for vetiver occurrence at both high NDVI values, which suggest a closed canopy and light-limited understory, and low NDVI values with bare ground. The RF model effectively detected such patterns, but a basic linear model failed to reveal a significant overall trend with NDVI. Accordingly, in this study, NDVI should be interpreted not as a direct

driver of vetiver occurrence, but rather as a proxy for canopy openness. Subsequent to these three primary predictors, the significance values decrease substantially. Mean Decrease Gini value of elevation and slope are around 21.9 and 21.7 respectively, indicating they had minor influence on the predictions but much less than proximity to roads and pipelines. Mean Decrease Gini value of distance from stream is 13.43 and it is not a strong determinant of Vetiver occurrence in this data. With a mean decrease Gini of 9.5, aspect was the least significant predictor, indicating that the occurrence of vetiver is mostly unaffected by the slope direction.

Table 6: Relative importance of the factors calculated by Random Forest

Variables	Mean Decrease Gini
Distance from pipelines	133.647
Distance from roads	77.649
NDVI	65.511
Elevation	21.913
Slope	21.671
Distance from streams	13.430
Aspect	9.519

Probability of Vetiver grass occurrence by RF shows that 65.93 %, 7.23 %, 13.48 % and 13.36% of the areas under very low, moderate, high, and very high respectively (Table 7). The Vetiver grass occurrence probability map developed by the random forest model (Figure 7) indicates higher predicted values are observed along roads and pipelines.

Table 7: Area distribution of Vetiver grass occurrence probability by Random Forest

Vetiver grass occurrence probability zones	Random Forest	
	Areas in acres	%
Very low	3826.44	65.93
Moderate	419.43	7.23
High	782.59	13.48
Very high	775.70	13.36

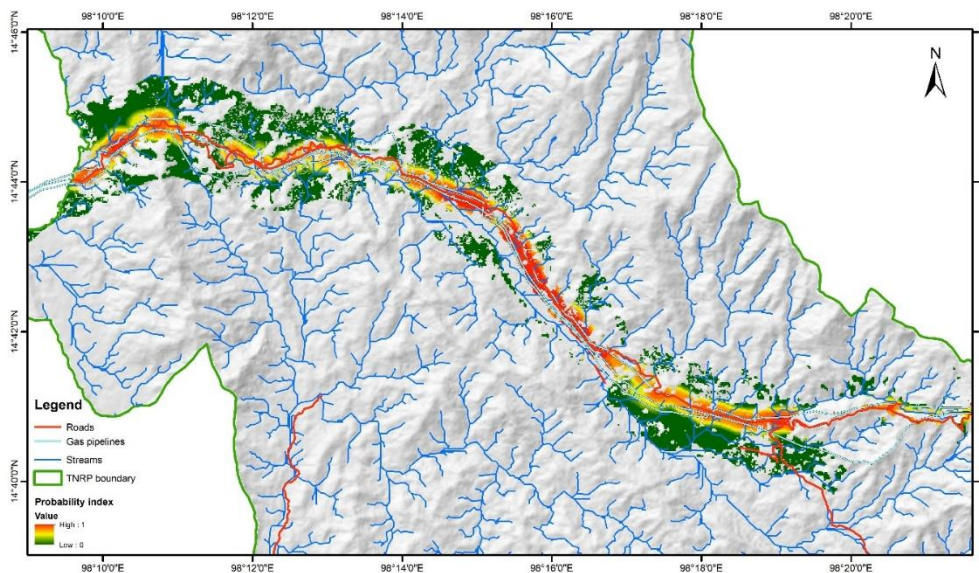


Figure 7: Predicted probability map of Vetiver grass occurrence based on the Random Forest model

4.3. Model Validation and Predictive Performance of Two Models

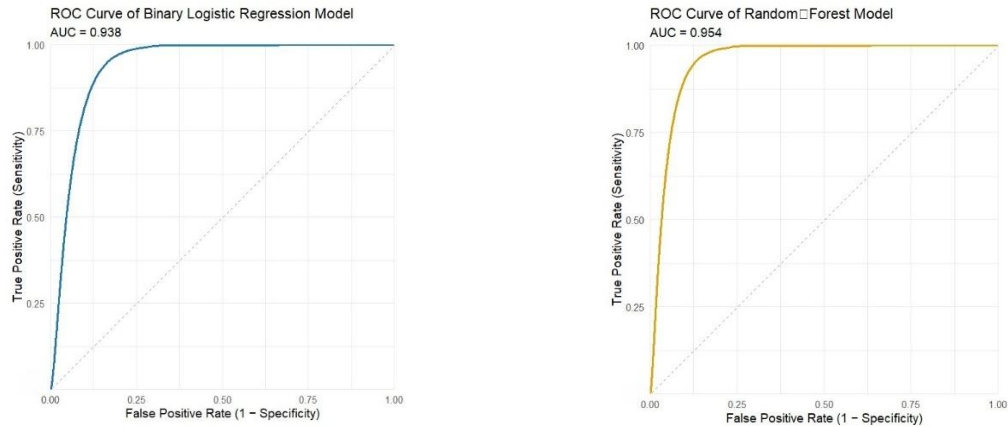


Figure 8: ROC curve for Binary Logistic Regression and Random Forest (RF) Models

The accuracy and reliability of binary logistic regression and random forest models have been evaluated based on 30% validation dataset. ROC curve (receiver operating characteristic curve) is represented graphically when True Positive Rate (TPR) or sensitivity values is in Y-axis, and the specificity values is in X-axis, which exhibits the performance of the classification model at all classification thresholds (Figure 8). Table 8 shows values of true positive rate (TPR), false positive rate (FPR), efficiency (E), true skill statistics (TSS) and Kappa co-efficient of binary logistic regression and random forest. The sensitivity (TPR) values measures the proportion of actual positive cases (Vetiver occurrence) that the model correctly identified. The false positive rate (FPR) value is 0.123 that also shows the ability of the model that indicates low commission error. True skill statistics (TSS) takes into account both omission and commission errors, and success as a result of random guessing, and ranges from -1 to $+1$, where $+1$ indicates perfect agreement with values below 0.4 indicate poor model discrimination [32] and values of zero or less indicate a performance no better than random. TSS values of binary logistic regression model is 0.8285, and efficiency is 0.8214. The kappa co-efficient of binary logistic regression is 0.813, which is also substantial or very good accuracy [34]. Area under the curve (AUC) can explain model validation. According to the generated AUC (Areas Under Curve) of the binary logistic regression model from this study, AUC value is 0.938 which indicates this model has 93.8% accuracy (Figure 13).

The Random Forest's ROC curve (Figure 8) had an AUC of 0.954, which suggested that it had an overall accuracy of 95.4% in distinguishing between occurrences and non-occurrences in the validation data. The AUC value of this RF model is slightly higher than that of BLR model. The True Positive Rate for RF was 0.9559 (95.59% sensitivity), whereas the False Positive Rate was 0.1345. The overall accuracy of the RF was 90.55%, almost comparable to that of the binary logistic regression model at 90.61%. The True Skill Statistic for RF was calculated at 0.8214, nearly as high as the BLR's TSS of 0.8285. The Kappa coefficient for the RF was 0.811, almost similar to the BLR's Kappa of 0.813.

Table 8: Values of true positive rate (TPR), false positive rate (FPR), efficiency (E), true skill statistics (TSS) and Kappa co-efficient

Metrics	Binary Logistic Regression	Random Forest
TPR	0.9854	0.9559
FPR	0.1569	0.1345
Efficiency	0.9061	0.9055
TSS	0.8285	0.8214
Kappa	0.813	0.811

5. Discussion

The primary objective of determining whether the Vetiver grass remained confined was fulfilled due to the fact that vetiver did not extend beyond the areas where it was deliberately planted, as evidenced by the high predictive accuracies of these models ($AUC > 0.93$). This result aligns with global evidence, vetiver remains in its designated location; there is no record of this South Indian grass establishing as an invasive species outside of its intended sites [37]. For example, in Hawaii's, a 15 year monitoring of Vetiver was evaluated for invasiveness by the Hawaii-Pacific Weed Risk Assessment and Pacific Island Ecosystems at Risk and received a low risk score for the potential to become invasive and spread [38]. Similarly, in the southern United States, vetiver grass have provided no indication of spontaneous colonization into surrounding habitats [39]. The comparable results enhance the fact that, with appropriate management and the use of sterile cultivars, vetiver functions as a secure bioengineering species, aligning with both our TNR findings and the global experience.

Both the binary logistic regression and random forest models indicated that the probability of vetiver occurrence declines significantly outside the pipeline corridor of TNR, with no presence detected in the adjacent forests and thus verifies about the sterility and ecological safety of the approved vetiver cultivar. The analysis further identified the key biophysical factors that influence vetiver's occurrence status, revealing a strong dependence on human activity rather than natural landscape features. The models showed that biophysical factors such as topography (slope, aspect, elevation) and hydrology (distance to streams) were not significant limiting factors and its presence is overwhelmingly dictated by anthropogenic corridors (the pipeline and roads). This reflects vetiver's broad physiological tolerance to a variety of moisture [12] and terrain conditions - a characteristic that provides these variables secondary to its absolute need for sunlight [13]. These results are consistent with worldwide observations, indicating that vetiver has been extensively used for bioengineering purposes especially in roadway and transportation projects [40-42] without any indication of invasive spread. Countries such as Australia, Brazil, Fiji, Vietnam, Ethiopia, South Africa, Malaysia, China, and Bangladesh have also planted vetiver into infrastructure corridors for erosion management, slope stabilization, and hazard mitigation [14, 40, 43-48]. The similarities between its international applications and its implementation along the pipeline in TNR highlight the grass's dependability as a nature-based engineering solution - able to execute essential stabilizing tasks while ensuring ecological safety. Consequently, management strategies in TNR can be tailored to specific goals. For permanent infrastructure protection, maintaining open-canopy conditions through periodic clearing is crucial. This should be complemented by the regular trimming of vetiver clumps, as this practice promotes dense, vigorous growth and enhances their long-term effectiveness for erosion control.

This infrastructure-associated occurrence pattern has management implications for the

~1,315 acres (~532 ha) of mining-degraded land within TNR. Mined lands typically have soil compaction, nutrient depletion, heavy metal contamination, and altered hydrological regimes, which hinder natural regeneration [49]. Chen [49] reports that nature-based approaches using pioneer vegetation have proven more effective in initiating biological recovery. Previous rehabilitation programs in Asia and Africa have shown that vetiver effectively reduces erosion rates, immobilizes toxic elements, and creates microhabitats that accelerate secondary succession [11, 49]. For instance, in South Africa, vetiver played a crucial role in the regeneration of very acidic gold mine and diamond mining areas, thriving under exceptionally adverse soil conditions (pH extremes, heavy metals) and a climate characterized by minimal rainfall and significant temperature fluctuations [50]. In a comparative study intended for rehabilitating a degraded oil shale mine in Guangdong, China, vetiver grass emerged as the most effective species, exhibiting a remarkable survival rate of 99% along with the highest coverage and biomass after six months, compared to bahia grass (*Paspalum notatum*), St. Augustine grass (*Stenotaphrum secundatum*), and bana grass (*Pennisetum glaucum* x *P. purpureum*) [51]. In the case of TNR, the implementation of vetiver on mined areas may stabilize the substrate and serve as a pioneer species, promoting the eventual establishment of native plants. However, it is essential to acknowledge limitations. Vetiver alone does not restore full ecological function, and monoculture may provide limited habitat complexity. Therefore, Chen [49] points out that the success of restoration depends on the integration of soil amendments, and the gradual introduction of native species alongside structural bioengineering species like Vetiver. For TNR, it is recommended that vetiver should be utilized as an initial stabilizer, with subsequent enrichment planting of native tree species once soil conditions improve.

6. Actionable Recommendation

Based on the Random Forest analysis identifying 1,558.29 acres (26.84%) as High and Very High probability zones and these areas should be demarcated as Priority Action Zone (PAZ) to prevent distribution of the Vetiver grass by operating the following actions;

- Mandate twice-monthly **grid-based surveys** within PAZ during the growing season to ensure early detection.
- Overlay the PAZ maps onto field GPS units and official reserve management documentation to ensure all ground crews and decision-makers are operating with the same spatial data.
- Initiate an aggressive program of native reforestation and groundcover planting within PAZ in order to rapidly achieve 100% native vegetative cover to outcompete Vetiver seedlings for light and resources.
- Establish a dense, multi-tiered barrier using fast-growing, deep-rooting native shrub and canopy species along the boundary separating the pipeline corridor from the PAZ to act as a permanent, living containment mechanism.
- If the high-risk zones are correlated with canopy gaps, prioritize the planting of early successional native tree species to rapidly increase canopy cover and reduce light levels, making the habitat unsuitable for heliophilous invaders like Vetiver.

7. Conclusion

The TNR situation demonstrates that, when well managed and using the sterile cultivar, vetiver will provide erosion control and land restoration advantages without escaping cultivation or endangering natural ecosystems. In conclusion, our findings support the continuous use of vetiver grass as a dependable, non-invasive element of nature-based solutions, consistent with its proven efficacy in enhancing infrastructure sustainability and landscape resilience. The results of this study provide a solid foundation for the further use of vetiver in upcoming restoration initiatives, particularly in the rehabilitation of mining-affected areas inside TNR.

8. References

- [1] L. Montanarella, R. Scholes, and A. Brainich, "The assessment report on land degradation and restoration," *Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES): Bonn, Germany*, 2018.
- [2] M. Millennium ecosystem assessment, *Ecosystems and human well-being*. Island press Washington, DC, 2005.
- [3] E. Cohen-Shacham, G. Walters, C. Janzen, and S. Maginnis, "Nature-based solutions to address global societal challenges," *IUCN: Gland, Switzerland*, vol. 97, no. 2016, p. 2036, 2016.
- [4] W. J. Mitsch and S. E. Jørgensen, *Ecological engineering and ecosystem restoration*. John Wiley & Sons, 2003.
- [5] D. H. Gray and R. B. Sotir, *Biotechnical and soil bioengineering slope stabilization: a practical guide for erosion control*. John Wiley & Sons, 1996.
- [6] A. D. Bradshaw, "Restoration: an acid test for ecology," 1987.
- [7] P. Truong and D. Baker, *Vetiver grass system for environmental protection*. Pacific Rim Vetiver Network, Office of the Royal Development Projects Board, 1998.
- [8] K. Kim, S. Riley, E. Fischer, and S. Khan, "Greening roadway infrastructure with vetiver grass to support transportation resilience," *CivilEng*, vol. 3, no. 1, pp. 147-164, 2022.
- [9] S. Mickovski, L. v. Beek, and F. Salin, "Uprooting resistance of vetiver grass (*Vetiveria zizanioides*)," in *Eco-and Ground Bio-Engineering: The Use of Vegetation to Improve Slope Stability: Proceedings of the First International Conference on Eco-Engineering 13–17 September 2004*, 2007: Springer, pp. 53-60.
- [10] J. M. Erskine, "Vetiver grass: its potential use in soil and moisture conservation in southern Africa: news and views," *South African Journal of Science*, vol. 88, no. 6, pp. 298-299, 1992.
- [11] P. N. Truong, "Vetiver grass technology for land stabilization, erosion and sediment control in the Asia-Pacific Region," 2004.
- [12] D. Hengchaovanich, "Fifteen years of bioengineering in the wet tropics: from A (*Acacia auriculiformis*) to V (*Vetiveria zizanioides*)," 2004.
- [13] M. Pease, P. Truong, J. Rubio, R. Morgan, S. Asins, and V. Andreu, "Vetiver grass technology: a tool against environmental degradation in Southern Europe," in *Man and soil at the Third Millennium. Proceedings International Congress of the European Society for Soil Conservation, Valencia*, 2002.
- [14] P. Truong, T. T. Van, and E. Pinners, "Vetiver system applications technical reference manual," *The Vetiver Network International*, vol. 89, 2008.
- [15] P. Truong, *Vetiver grass technology for mine rehabilitation*. Office of the Royal Development Projects Board Bangkok, 1999.

- [16] R. Banerjee, P. Goswami, S. Lavania, A. Mukherjee, and U. C. Lavania, "Vetiver grass is a potential candidate for phytoremediation of iron ore mine spoil dumps," *Ecological Engineering*, vol. 132, pp. 120-136, 2019.
- [17] J. K. Raman and E. Gnansounou, "A review on bioremediation potential of vetiver grass," *Waste bioremediation*, pp. 127-140, 2017.
- [18] N. Darajeh, A. Idris, H. R. F. Masoumi, A. Nourani, P. Truong, and N. A. Sairi, "Modeling BOD and COD removal from Palm Oil Mill Secondary Effluent in floating wetland by *Chrysopogon zizanioides* (L.) using response surface methodology," *Journal of environmental management*, vol. 181, pp. 343-352, 2016.
- [19] B. O. Otunola *et al.*, "Influence of clay mineral amendments characteristics on heavy metals uptake in vetiver grass (*Chrysopogon zizanioides* L. Roberty) and Indian mustard (*Brassica juncea* L. Czern)," *Sustainability*, vol. 14, no. 10, p. 5856, 2022.
- [20] R. Mahadevan, "The high price of sweetness: The twin challenges of efficiency and soil erosion in Fiji's sugar industry," *Ecological Economics*, vol. 66, no. 2-3, pp. 468-477, 2008.
- [21] A. Worku, N. Tefera, H. Kloos, and S. Benor, "Bioremediation of brewery wastewater using hydroponics planted with vetiver grass in Addis Ababa, Ethiopia," *Bioresources and Bioprocessing*, vol. 5, no. 1, p. 39, 2018.
- [22] S. Panja, D. Sarkar, and R. Datta, "Vetiver grass (*Chrysopogon zizanioides*) is capable of removing insensitive high explosives from munition industry wastewater," *Chemosphere*, vol. 209, pp. 920-927, 2018.
- [23] F. D. Remote Sensing and GIS Section, "Land Use Land Cover Assessment of Tanintharyi Nature Reserve and Its Surroundings in the Year 2023," 2024.
- [24] S. W. M. M. Pyone, "Final Evaluation Report - Taninthayi Nature Reserve," 2013.
- [25] A. Ozdemir, "Using a binary logistic regression method and GIS for evaluating and mapping the groundwater spring potential in the Sultan Mountains (Aksehir, Turkey)," *Journal of Hydrology*, vol. 405, no. 1-2, pp. 123-136, 2011.
- [26] S. Menard, *Applied logistic regression analysis*. SAGE publications, 2001.
- [27] F. C. Pampel, *Logistic regression: A primer* (no. 132). Sage publications, 2020.
- [28] L. Breiman, "Random forests, vol. 45, no. 1," *Doi*, vol. 10, p. 10, 2001.
- [29] M. Belgiu and L. Drăguț, "Random forest in remote sensing: A review of applications and future directions," *ISPRS journal of photogrammetry and remote sensing*, vol. 114, pp. 24-31, 2016.
- [30] L. J. M. I. Breiman, *Bagging predictors*. 1996, pp. 123-140.
- [31] J. A. Hanley and B. J. McNeil, "The meaning and use of the area under a receiver operating characteristic (ROC) curve," *Radiology*, vol. 143, no. 1, pp. 29-36, 1982.
- [32] E. Yesilnacar and T. Topal, "Landslide susceptibility mapping: a comparison of logistic regression and neural networks methods in a medium scale study, Hendek region (Turkey)," *Engineering Geology*, vol. 79, no. 3-4, pp. 251-266, 2005.
- [33] O. Allouche, A. Tsoar, and R. Kadmon, "Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS)," *Journal of applied ecology*, vol. 43, no. 6, pp. 1223-1232, 2006.
- [34] J. Cohen, "A coefficient of agreement for nominal scales," *Educational and psychological measurement*, vol. 20, no. 1, pp. 37-46, 1960.
- [35] J. R. Landis and G. G. Koch, "The measurement of observer agreement for categorical data," *biometrics*, pp. 159-174, 1977.
- [36] R. Johnston, K. Jones, and D. Manley, "Confounding and collinearity in regression analysis: a cautionary tale and an alternative procedure, illustrated by studies of British voting behaviour," *Quality & quantity*, vol. 52, no. 4, pp. 1957-1976, 2018.

- [37] R. Grimshaw, "Ecological impact of Vetiver in foreign environments," in *Proceedings of workshop on Potential Applications of Vetiver Plant in the Arabian Gulf Region, Kuwait*, 2006, pp. 131-138.
- [38] R. Joy, "Sunshine vetivergrass *Chrysopogon zizanioides* (L.) Roberty," *USDA-NRCS Pacific Island Area Plant Materials Program, Hoolehuam HI*, 2009.
- [39] P. Truong, "Vetiver grass system: Potential applications for soil and water conservation in northern California," in *Invited paper presented at the STIFF GRASS TECHNOLOGY Seminar; sponsored by the Yolo County Flood Control & Water Conservation District and Family Water Alliance at Woodland on*, 2000, vol. 9.
- [40] C. Ghosh and S. Bhattacharya, "Landslides and erosion control measures by vetiver system," in *Disaster risk governance in India and cross cutting issues*: Springer, 2017, pp. 387-413.
- [41] C. Chong and L. Chu, "Growth of vetivergrass for cutslope landscaping: effects of container size and watering rate," *Urban Forestry & Urban Greening*, vol. 6, no. 3, pp. 135-141, 2007.
- [42] S. Sanguankao, S. Chaisintarakul, and E. Veerapunth, "The application of the vetiver system in erosion control and stabilization for highways construction and maintenance in Thailand," in *Proceedings of the Third International Conference on Vetiver and Exhibition*, 2003, pp. 1-6.
- [43] P. Truong and R. Loch, "Vetiver system for erosion and sediment control," in *Proceeding of 13th international soil conservation organization conference*, 2004, pp. 1-6.
- [44] P. Bobrowsky and L. Highland, "The Landslide Handbook-A Guide to Understanding Landslides: A landmark publication for landslide education and preparedness," in *Landslides: Global Risk Preparedness*: Springer, 2012, pp. 75-84.
- [45] R. G. Grimshaw and A. Faiz, "Vetiver grass: Application for stabilization of structures," in *Proceedings of the Sixth International Conference on Low-Volume Roads*, 1995, pp. 74-81.
- [46] N. Bracken and P. Truong, "Application of Vetiver Grass Technology in the stabilization of road infrastructure in the wet tropical region of Australia," in *Proc. Second International vetiver Conf. Thailand*, 2000.
- [47] M. S. Islam, "Application of Vetiver (*Vetiveria zizanioides*) as a bio-technical slope protection measure—some success stories in Bangladesh," in *Proceedings of the 6th International Conference on Vetiver*, 2015, pp. 5-8.
- [48] H. Abate, "Multiple benefits of the Vetiver System and its environmental application in Ethiopia," 2014.
- [49] X. W. Chen, J. T. F. Wong, J.-J. Wang, and M. H. Wong, "Vetiver grass-microbe interactions for soil remediation," *Critical Reviews in Environmental Science and Technology*, vol. 51, no. 9, pp. 897-938, 2021.
- [50] P. Truong, "An overview of research, development and application of the vetiver grass system (VGS) overseas and in Queensland," *Annual report of the vetiver Network*, pp. 5-17, 1996.
- [51] H. Xia, "Ecological rehabilitation and phytoremediation with four grasses in oil shale mined land," *Chemosphere*, vol. 54, no. 3, pp. 345-353, 2004.