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Aboveground physiological response and yield prediction of *Chloris gayana* and *Digitaria eriantha* grown in rehabilitated coal mined soils using random forest algorithm

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Abstract

A recent study demonstrated that a blend of amendments improved both the physical and hydraulic properties of reclaimed mine soils more effectively than standard mine treatments, suggesting further research on its impact on plant growth. Additionally, there is currently no published research that has examined the potential of the random forest (RF) algorithm for predicting the aboveground yield of *Chloris gayana* (Rhodes grass) and *Digitaria eriantha* (Smutsfinger grass) grown in reclaimed mine soils. To address this, a field trial of 36 bins consisting of nine treatments and four replications each was conducted in a randomized block design at the experimental farm of the University of Pretoria. The results showed that the dry matter yield, leaf area index, and leaf water potential were all significantly ($p < 0.05$) affected by the treatment. The blend of amendments increased aboveground dry matter yield by 70%–150% and leaf area index by 60%–95%. These improvements significantly enhanced productivity and, consequently, the carrying capacity of the rehabilitated land compared to the standard mine treatment of liming and fertilization. The most important wavelengths for predicting aboveground yield were located in the visible (400–700 nm) region of the electromagnetic spectrum, yielding an r^2 of 0.90, mean absolute error of 0.183 t ha^{-1} and root mean square error of 0.255 t ha^{-1}. These findings demonstrate that a blend of amendments can enhance the production potential of these grasses by improving soil nutrient availability. However, the longevity of these effects needs to be verified through long-term studies. The results also indicate that RF algorithm can accurately predict aboveground yield of *C. gayana* and *D. eriantha* accurately based on changes in the plant canopy spectral signature.

Abbreviations: ASD, analytical spectral devices; CART, classification and regression tree; DM, dry matter; LAI, leaf area index; LWP, leaf water potential; NDVI, normalized difference vegetation index; NIR, near-infrared; PAW, plant available water; RF, random forest; RMSE, root mean square error.

1 | INTRODUCTION

Mining activities significantly exacerbate issues related to soil degradation. The poor physical properties of soil contribute to land degradation (Muñoz-Rojas et al., 2016), primarily due to the removal of substantial amounts of topsoil and subsoil in open cast coal mining operations. This method entails the stripping and repositioning of large volumes of topsoil and subsoil using heavy machinery, which subsequently raises the likelihood of soil compaction (Chamber of Mines of South Africa, 2007). Over stripping of topsoil can lead to the mixing of topsoil and subsoil, resulting in complications for vegetation establishment during rehabilitation (Visser et al., 1984) due to the complex nature of the combined soil properties.

During active mining, stripped soil is typically stored in high stockpiles (Strohmayer, 1999). This phase is critical, as the duration of storage can significantly impact soil quality (Paterson et al., 2018). Once mining operations cease, the stockpiled soil is relocated back to the mined area and placed over coal spoils (Strohmayer, 1999) to facilitate plant establishment. Generally, these soils exhibit high bulk density, low water-holding capacity, low nutrient and organic matter content (Basta et al., 2016; Byrne et al., 2017; Ram & Masto, 2014). Consequently, they limit rainfall percolation and root penetration, adversely affecting plant establishment (Bindraban et al., 2012).

Coal mining companies are obligated to rehabilitate areas affected by mining activities, with the goal of achieving sustainable land use (Government Gazette, Republic of South Africa, 2002). The natural restoration of soil takes several decades before acceptable vegetation cover can be established (Steed et al., 2018). Therefore, it is essential to incorporate soil amendments to facilitate plant growth and reduce the time required to restore degraded soils. The application of these amendments within the zone of incorporation typically improves the physical, chemical, and microbial soil functions, making conditions more favorable for sustainable plant growth (Motavalli et al., 2003).

Numerous studies have investigated the effectiveness of various amendments on the physical properties of soil and the growth of vegetation in reclaimed coal mine soils. Notable amendments studied include manure (Bateman & Chanasyk, 2001; Shrestha et al., 2009), straw (Shrestha et al., 2009), hay (Chen et al., 2025), and compost (Spargo & Doley, 2016; Zafar, 2025). However, the improvements in soil physical properties and vegetation growth resulting from these amendments were found to be temporary. A more recent study by Abraha et al. (2019) demonstrated that a combination of amendments could enhance the physical and hydraulic properties of reclaimed coal mine soils. Nevertheless, this study did not evaluate the amendments' impact on plant growth and development, indicating a need for further research in this area to understand their potential for promoting sustainable plant growth.

Core Ideas

- Restoration of mine soils is a lengthy and expensive process.
- Easily accessible organic materials could be effective for mine soil amendments.
- Blend amendments are better than standard lime and fertilization of mine soils.
- Random forest could accurately forecast grass biomass yield in mine rehabilitation.

Organic amendments play a crucial role in restoring degraded soils, particularly those found in mined areas, due to their high carbon (C) and nitrogen (N) content (Cogliastro et al., 2001). Increasing soil organic matter through the application of organic amendments is a desirable goal because it is linked to improved soil physical properties. These enhancements include greater aggregate stability, reduced bulk density, increased water holding capacity, and enhanced porosity (Moreno et al., 2006). Such improvements significantly support the production potential of plants growing under these conditions (Mas-Carrió et al., 2018; Ryals et al., 2016). Furthermore, organic amendments help resist soil degradation and alleviate soil compaction, thereby reducing soil strength (Carter, 2002) and creating a conducive environment for crop growth.

Monitoring vegetation growth in reclaimed coal mine areas is crucial for timely intervention and accurate biomass estimation. While field measurements are precise, they are costly and time-consuming, especially in large or inaccessible areas (Adam et al., 2014; Nordh & Verwijst, 2004). Remote sensing offers a more efficient alternative, with strong correlations between spectral data and aboveground biomass (Lu, 2006; Mutanga & Skidmore, 2004). The advent of high-resolution satellite data, along with its availability for research purposes free of charge, has revolutionized the widespread use of remote sensing for mapping vegetation at the species level. This includes the application of common vegetation indices and classification algorithms like random forest (RF). For instance, Newete et al. (2024) utilized the Sentinel-2 normalized difference vegetation index (NDVI) series and the *K*-means unsupervised clustering of NDVI values extracted at different stages of the wheat growth period to monitor crop growth based on crop phenology. Gurdak et al. (2021) used 8-day accumulated NDVI (MOD09Q1) and the 8-day accumulated differences between land surface temperature (MOD11A2) and air temperature (Ta) from meteorological data to develop a model for effective maize yield prediction in

Poland. Hyperspectral techniques overcome the limitations of traditional methods by capturing detailed spectral signatures across narrow bands, enabling the detection of subtle vegetation variations. They identify specific wavelengths related to chlorophyll, leaf water potential (LWP), and nitrogen, enhancing biomass estimation accuracy, particularly in dense canopies (Adam et al., 2014; Mutanga & Skidmore, 2004). While NDVI uses red and near-infrared (NIR) bands to assess vegetation health, hyperspectral data provide finer spectral resolution, revealing more detailed plant characteristics. This enables better differentiation between vegetation types and improves biomass predictions by identifying factors such as pigment concentrations and water content (Newete et al., 2014). Combined with NDVI, hyperspectral data enhance the accuracy and precision of biomass estimates, making it a valuable tool for monitoring vegetation in rehabilitated coal mine soils. Recent studies have utilized advanced statistical techniques to improve the accuracy of predictive models, including the RF regression model, which effectively captures data variability (Liaw & Wiener, 2002). Unlike traditional regression trees that rely on a single model, the RF regression algorithm is a tree-based approach that optimizes predictive performance by averaging results across multiple trees (Breiman, 2001).

In machine learning and statistics, several predictive models are commonly used for making predictions or forecasts. These include linear regression, support vector regression, gradient boosting machines, K-nearest neighbors, neural networks, and RF, each with its own strengths and weaknesses.

While interpreting the outputs of RF can be more challenging and its computation requires more memory, particularly with large datasets, it excels in nonlinear regression problems. This is because the relationship between input and output is often nonlinear but can be transformed into a higher dimensional space. RF is particularly effective at capturing these complex relationships and is less prone to overfitting compared to individual decision trees. Additionally, it handles missing values and noisy data relatively well (Ao et al., 2019; Aria et al., 2021).

Recently, this approach has been successfully implemented not only as a classification algorithm (Ismail & Mutanga, 2011) but also for estimating aboveground biomass (Adam et al., 2014).

It was hypothesized that (a) the application of a blend of amendments would enhance the aboveground biomass yield of a mixture of *Chloris gayana* and *Digitaria eriantha* planted in reclaimed coal mine soil, compared to using single amendment, due to improvements in soil physical and hydraulic properties, and (b) the aboveground biomass yield of this mixture could be accurately predicted using the RF algorithm based on changes observed in the plant canopy's spectral signature. The primary objectives of this study were to (a) quantify the impact of a blend of amendments added to reclaimed coal mine soil on the aboveground biomass yield of a mixture of *C. gayana* and *D. eriantha* and (b) assess the reliability of the RF regression model as a robust predictor of aboveground biomass yield for C. *gayana* and *D. eriantha* cultivated in rehabilitated coal mined soil. The specific aims were to (i) quantify the effect of single and a blend of amendments on dry matter (DM) yield, leaf area index (LAI), and LWP of a mixture of *C. gayana* and *D. eriantha* grown in rehabilitated coal mined soils; (ii) identify specific narrow-band spectral indices for developing a reliable aboveground yield estimation model; and (iii) determine the effectiveness of the RF regression algorithm in predicting the aboveground yield of the *C. gayana* and *D. eriantha* mixture in rehabilitated coal mined soils.

2 | MATERIALS AND METHODS

2.1 | Experimental site

Field trial was conducted at the experimental farm of the University of Pretoria, Pretoria, South Africa (25°45′ S, 28°16′ E), 1327 m above sea level, in 2014–2015 and 2015–2016 growing seasons. The trial involved 36 constructed bins, all of which were 1 m long by 1 m wide by 1.2 m high, equivalent to 1 m^3 rehabilitated mine soil profile (Figure 1).

The research bins were first filled with a 10 cm layer of gravel (to allow for free water drainage), followed by 50 cm layer of coal spoil, followed by 30 cm layer of subsoil (Figure 1), and lastly 30 cm layer of mine topsoil, which was treated with different soil amendments. The mine spoil, subsoil and topsoil were all acquired from a surface coal mine in Mpumalanga, South Africa. The topsoil (77% sand, 6% silt, and 17% clay) was a Hutton sandy clay loam (Soil Classification Working Group, 1991) (loamy, kaolinitic, mesic, Typic Eutrustox) with a pH in KCl of 4.76 and %C of 0.96.

The treatments include soil mixed with cattle manure (F1), standard prescribed local mine soil amelioration treatment of lime and fertilizer (standard mine treatment [SMT]) (F2), composted wood chips (F3), chopped Lucerne hay (F4), chopped pasture grass (F5), a blend of chopped pasture grass and cattle manure (F6), a blend of chopped pasture grass and composted wood chips (F7), and a blend of chopped Lucerne hay, cattle manure, and composted wood chips (F8). An additional unamended soil (F9) was included as a benchmark. The selected treatments, manure (Bateman & Chanasyk, 2001; Shrestha et al., 2009), straw (Shrestha et al., 2009), hay (Chen et al., 2025), and compost (Spargo & Doley, 2016; Zafar, 2025), are commonly utilized due to their effectiveness in enhancing soil quality and promoting vegetation recovery in

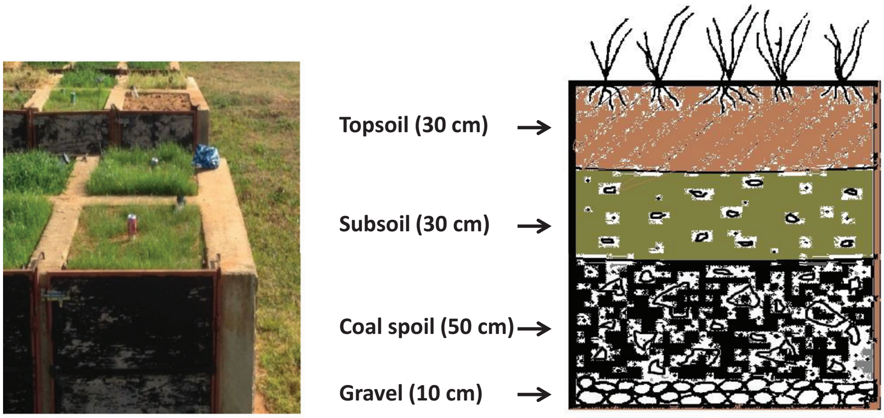

FIGURE 1 Soil research bin illustrating the different substrate layers.

TABLE 1 Chemical composition of ameliorants and soil substrate.

Treatments	pH (KCl)	P (mg kg^{-1})	K (mg kg^{-1})	Na (mg kg^{-1})	Ca (mg kg^{-1})	Mg (mg kg^{-1})
Manure (F1)	5.37	128	352	11	386	116
Standard mine treatment (F2)	6.87	109	124	12	1090	100
Compost (F3)	5.94	257	149	20	492	128
Lucerne (F4)	5.98	37	253	9	352	83
Grass (F5)	4.95	261	122	8	396	118
Grass + manure (F6)	5.09	138	212	8	385	113
Grass + compost (F7)	5.02	232	154	13	434	101
Lucerne + manure + compost (F8)	5.42	44	215	24	387	100
Soil only (F9)	4.76	142	161	10	348	126

disturbed coal mining sites. The SMT is composed of a mixture of fertilizer applied at a rate of 65 kg N ha^{-1} (in the form of limestone ammonium nitrate), 203 kg P ha^{-1} (in the form of super phosphate), and 134 kg K ha^{-1} (in the form of potassium chloride) and dolomitic lime (4 t ha^{-1}). The various soil amendments were thoroughly mixed with the soil in advance using an automated concrete mixer. This process ensured a uniform distribution of the amendments throughout the topsoil layer, applied at a rate of 40 t ha^{-1} across all treatments, in accordance with the South African mine rehabilitation strategy procedures (W. F. Truter, personal communication, May 12, 2013). The soil research bins were designed to simulate and represent a rehabilitated soil/substrate profile, which is commonly created through rehabilitation practices on surface coal mines in South Africa to support grazing land capability class. Prior to treatment applications, the topsoil and the different amendments were analyzed for pH and total nutrient content (Table 1).

2.2 | Experimental layout and treatment application

The research bins were arranged in a complete randomized block design and consisted of eight different topsoil treatments applied at 40 tons ha^{-1} with four replicates per treatment plus a control containing no soil ameliorant. A bird's eye view of the trial layout is shown in Figure 2. To ensure that the topsoil was thoroughly mixed with the amendment material, a concrete mixer was used. The treated soil was then offloaded into the research bins to make a 30 cm amended topsoil layer. The filled bins were given time to settle. To help with this, *Lolium multiflorum* (annual ryegrass) was planted in April 2014 at an application rate of 20 kg ha^{-1}, as a winter cover crop, to allow for the treatments and soil to settle (no data were collected for this cover crop). After settling, a mixture of *C. gayana* and *D. eriantha* were planted in the first week of October 2014 at an application rate of 40 kg

FIGURE 2 Panoramic view of a field experiment at Innovation Africa, University of Pretoria, Pretoria, South Africa.

ha^{-1} (Mine Rehabilitation Specifications). These were chosen as they are commonly used in mine rehabilitation in South Africa (Tanner, 2007). The grass was irrigated 10 mm every third day for 3 weeks until it was established and from there on no irrigation water was applied until the harvest date. After each harvest, the bins were irrigated 5 mm every other day for the first week if there was no rainfall in that period.

2.3 | Yield and growth measurement procedure

In each growing season the pasture was harvested four times (every 42 days to allow sufficient time for re-growth). In the first season (2014–2015), the first growth cycle was harvested on December 11, the second growth cycle on January 22, the third growth cycle on March 5, and the fourth growth cycle on April 16. In the second season (2015–2016), the first growth cycle was harvested on November 16, the second growth cycle on December 28, the third growth cycle on February 8, and the fourth growth cycle on March 21. Yield was measured by sampling plant material to a height of 50 mm above the soil surface from a 0.09 m^2 area and the values were converted to t ha^{-1}. For DM yield determination, the samples were oven-dried for 72 h at 65°C to a constant mass. Plant samples were collected every 3 weeks for LAI measurement from an area of 0.09 m^2. The samples were partitioned into stem and leaves for LAI determination. LAI was measured using an LI 3100 belt driven leaf area meter (Lincoln Corporation). The first sampling date, Day 21 (D21), was taken 3 weeks after the harvest date, and the second sampling date, Day 42 (D42), was taken 3 weeks later.

2.4 | Leaf water potential measurements

At the end of each growth season, midday LWP was measured on the young, fully expanded leaves with a WP4-T Dewpoint PotentiaMeter (Decagon Devices, Inc.) between 12:00 and 14:00 h. The size of one leaf was too small to cover the entire surface of the sample holder, therefore, three to four leaves were used at a time to get results that are more accurate. A delay from the time of cutting the leaf to making the LWP measurement could cause a significant error, so the WP4-T Dewpoint PotentiaMeter was taken to a lab as close as possible to the field site. As soon as the leaves were cut, they were placed in a reflective, sealable bag to minimize the loss of water from the leaves and were taken to the lab within 2–3 min and LWP measurements were taken.

2.5 | Spectral data collection and analysis

The surface area of the land under mine rehabilitation is vast and conducting field assessment of aboveground biomass production is impractical. The variation in the depth of soil across the rehabilitated lands, the topography, and other geomorphological conditions also contribute to the variation in biomass production across the field. Hence, spectral reflectance measurement methods could play significant role in providing timely estimation of aboveground biomass data across large areas. In the current study, the use of remotely sensed data was used to show correlations between spectral bands and aboveground biomass. Spectral measurements were collected at a height of 50 cm above the canopy cover between 11:00 and 13:00 h under sunny and cloudless conditions using a handheld FieldSpec3 spectrometer (Analytical Spectral Devices [ASD]), with a 25° field of view (FOV) through a permanent fibre optic cable. This device measures wavelengths ranging from 350 to 2500 nm with a resolution of 1.4 nm for the 350–1000 nm spectral region and a resolution of 2 nm for the 1000–2500 nm spectral regions. Measurements were then interpolated to 1 nm spectral resolution across the spectrum (ASD; Analytical Spectral Devices, Inc., 2005). Spectral measurements on each of the four replicates from the nine treatments (n = 36) were repeated 10 times. To offset any changes in the atmospheric condition and irradiance of the sun as affected by the zenith angle, spectral measurements were calibrated against a white reference Spectralon calibration panel (barium sulphate coating) every 5 to 10 measurements and were recorded as percentage reflectance. Narrow-band NDVI was calculated from all possible two-band combinations involving 1747 narrow bands located between 350 and

2500 nm (Cho et al., 2007; Mutanga & Skidmore, 2004) using the principle of NDVI equation calculated as follows:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}},$$

where NIR and red stand for the spectral reflectance measurements acquired in the near-infrared (NIR) and red (visible) regions of the spectrum, respectively (Tucker, 1979). The selection of bands was based on the correlation between the calculated NDVI values and aboveground biomass. Bands with a correlation coefficient (r) of 0.75 or higher were chosen, as this threshold ensures a strong relationship between the spectral indices and biomass, providing a solid foundation for model development. This approach ensures that the selected wavelengths are both statistically significant and biologically relevant, leading to more accurate biomass estimation.

2.6 | Random forest regression

RF, a classification and regression tree (CART) algorithm (Breiman, 2001), was used in the present study to predict the aboveground DM yield of *C. gayana* and *D. eriantha* biomass production (t ha^{-1}). To improve the CART, Breiman (2001) developed an RF algorithm to reduce the instability and variance of a single regression tree. In this study, the RF model was fine-tuned by testing different combinations of hyperparameters, including ntree (number of trees) and mtry (number of variables randomly sampled at each split). The optimal combination of these hyperparameters was determined by minimizing the root mean square error (RMSE) during the training phase. For validation, the dataset was split into a 70/30 ratio, with 70% used for training the model and 30% reserved for testing and validation. The model's performance was evaluated by calculating the coefficient of determination (r^2) between the predicted and observed values, as well as the RMSE. This approach ensures that the model is not overfitting and can be generalized to unseen datasets. For more information on how the RF algorithm works, refer to Breiman (2001).

2.7 | Weather

Weather data were collected from an automatic weather station located near the experimental site. The automatic weather station consisted of an LI 200X pyranometer (LiCor) for measuring solar radiation, an electronic relative humidity and temperature sensor installed in a Gill screen, an electronic cup anemometer (MET ONE, Inc.) to measure wind speed, an electronic rain gauge (RIMCO, R/TBR tipping bucket rain gauge, Rauchfuss instruments division, Australia) and a CR 10X data-logger (Campbell Scientific Inc.). All of the above data were monitored and recorded every 10 s with the CR 10X data logger. The logged data were downloaded once a month. Figure 3 shows a summary of the monthly rainfall and maximum and minimum temperatures during the experimental period for the site downloaded from the automatic weather station. The weather data were not included in the statistical analyses. It was, however, used in the interpretation of the results.

2.8 | Statistical analyses

Where applicable, restricted maximum likelihood or linear mixed model repeated measures analysis was used to examine DM yield, LAI, and LWP, testing for differences between the nine treatments, months, and the treatment-by-month interaction effects, while accounting for variation over time. Means were compared using the Tukey honestly significant difference test at the 5% significance level ($p < 0.05$), as the variances were heterogeneous (Snedecor & Cochran, 1980). A significance threshold of $p < 0.05$ was applied to all statistical analyses, as it is a widely accepted standard that balances Type I (false positive) and Type II (false negative) errors. This threshold ensures that only statistically significant differences are interpreted as meaningful, thereby strengthening the reliability of our findings regarding treatment effects on DM yield, LAI, and LWP.

Statistical analyses were performed using GenStat (Payne, 2015). For hyperspectral data analysis and the implementation of the RF algorithm, the RF library (Liaw & Wiener, 2002) within the R statistical package (R Core Team, 2018) was employed.

3 | RESULTS AND DISCUSSION

3.1 | Dry matter yield

The DM yield of the first season was significantly ($p < 0.05$) influenced by the soil amendments applied (Table 2). Within each harvest the treatments had significant differences in the DM yields. Treatments with a blend of amendments recorded higher ($p < 0.05$) DM yields when compared to the rest of the treatments. However, there was no significant ($p > 0.05$) yield difference within the blend of amendments. Among treatments, treatment F8 (lucerne + manure + compost) had the highest DM yield in each year; the DM yields for treatment F8 were 192%, 196%, 184%, and 227% higher than F9 (soil only) over the four harvests and 77%, 123%, 112%, and 89% higher than F2 (standard mine treatment). This clearly shows the benefits of blend of amendments over untreated and standard mine treatments of degraded mine soils. The other

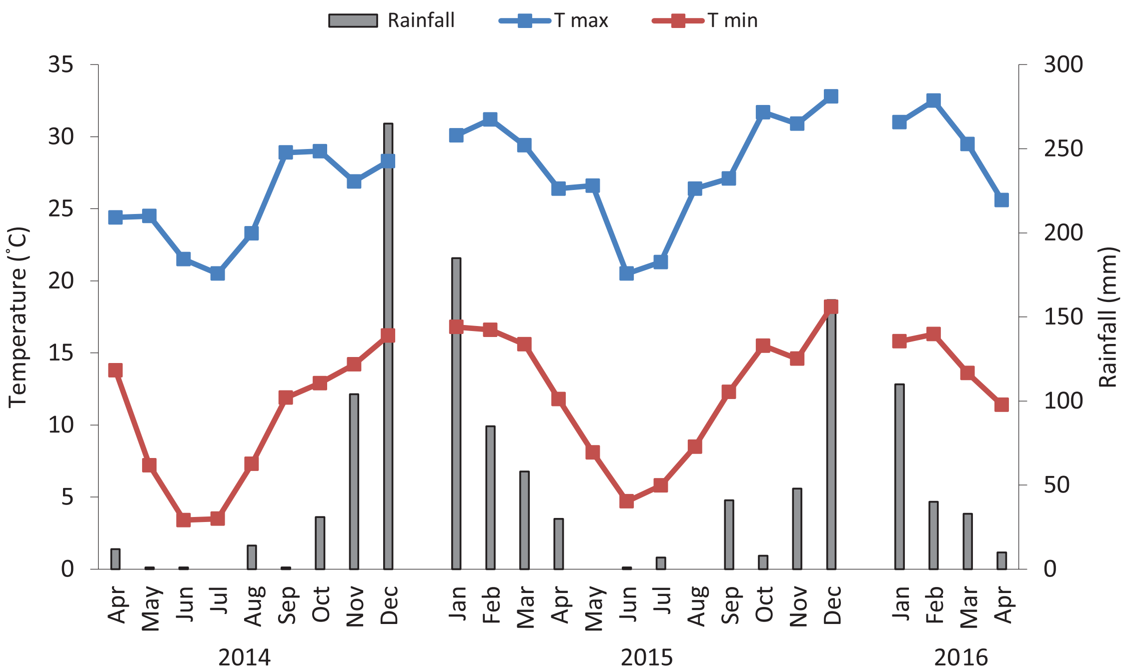

FIGURE 3 Monthly rainfall (mm) and maximum and minimum temperatures (˚C) at Innovation Africa, University of Pretoria, Pretoria, South Africa, during the experimental period.

TABLE 2 Dry matter yield (t ha^{-1}) of a mixture of *Chloris gayana* and *Digitaria eriantha* for the first growing season (2014–2015) at Innovation Africa, University of Pretoria, Pretoria, South Africa.

Treatment	Harvest 1 (t ha^{-1})	Harvest 2 (t ha^{-1})	Harvest 3 (t ha^{-1})	Harvest 4 (t ha^{-1})
Manure (F1)	2.10b	1.94b	2.17b	2.19b
Standard mine treatment (F2)	1.53c	1.25c	1.31c	1.47c
Compost (F3)	2.03b	1.87b	2.01b	2.01b
Lucerne (F4)	1.65c	1.84b	2.00b	2.04b
Grass (F5)	1.87bc	1.83b	1.93b	1.95b
Grass + manure (F6)	2.49a	2.55a	2.65a	2.66a
Grass + compost (F7)	2.48a	2.45a	2.57a	2.55a
Lucerne + manure + compost (F8)	2.72a	2.79a	2.79a	2.78a
Soil only (F9)	0.93d	0.94d	0.98d	0.85d
SEM	0.0789	0.0726	0.0625	0.0743

Note: Means with the same letter within a column are not significantly different. SEM denotes standard error of mean.

treatments that recorded higher ($p < 0.05$) DM yields compared with the single or no amendment treatments were F6 (grass + manure) and F7 (grass + compost). The reason for the high yields from the F6, F7, and F8 treatments could be attributed to the added advantage of increasing the chemical composition of the soil (Table 1) as well as the improvement in the physical characteristics of the soil (Abraha et al., 2019). Lucerne and manure produced an increase in nitrogen, while composted wood chips and manure provided phosphorus, potassium, and calcium. Additionally, as the lucerne and composted wood chips were chopped, it may have helped in improving the physical characteristics of the soil by reducing the bulk density, increasing porosity, pore size distribution and plant available water (PAW) (Abraha et al., 2019). Moreover, the blend of amendments consisted of diverse organic materials that decompose and release nutrients at different rates, some providing an immediate source, others releasing nutrients more gradually, and still others contributing slow-release benefits over time (Larney & Angers, 2012). The presence of organic material of varying composition with

TABLE 3 Dry matter yield (t ha^{-1}) of a mixture of *Chloris gayana* and *Digitaria eriantha* for the second growing season (2015–2016) at Innovation Africa, University of Pretoria, Pretoria, South Africa.

Treatment	Harvest 1 (t ha^{-1})	Harvest 2 (t ha^{-1})	Harvest 3 (t ha^{-1})	Harvest 4 (t ha^{-1})
Manure (F1)	1.68cd	1.83cd	1.91c	1.58e
Standard mine treatment (F2)	1.16e	1.13f	1.14e	1.10f
Compost (F3)	1.89bc	1.48e	1.61d	1.67de
Lucerne (F4)	1.96b	1.87c	1.95c	1.90cd
Grass (F5)	1.56d	1.61de	1.63d	1.59e
Grass + manure (F6)	2.03b	2.14b	2.26b	2.16bc
Grass + compost (F7)	2.13b	2.18b	2.35b	2.41ab
Lucerne + manure + compost (F8)	2.65a	2.64a	2.75a	2.64a
Soil only (F9)	0.69f	0.57g	0.62f	0.71g
SEM	0.0562	0.0506	0.0573	0.0564

Note: Means with the same letter within a column are not significantly different. SEM denotes standard error of mean.

varying decomposition rates enhances the microbial diversity (Wang et al., 2025). These changes play an important role in creating a soil environment that improves plant growth and development (Zhang et al., 2015). Treatments treated with only one amendment recorded lower yields than those treated with a blend of amendments. Nevertheless, the single amendment treatments still had significantly ($p < 0.05$) higher DM yield than the untreated soil throughout the study period.

The DM yield of the second season was significantly ($p < 0.05$) influenced by the applied treatments (Table 3). The highest yield during the 2015–2016 growing season was recorded from the plot that was treated with a blend of lucerne + manure + compost (F8) treatments. The second highest yield was harvested from the blend of treatments F6 and F7. This is in contrast to the first growing season (2014–2015), during which there was no statistically significant ($p > 0.05$) difference between F6, F7, and F8 (Table 2). The higher yield from the F8 treatment could be ascribed to the higher fertility level (see Table 1) and improved soil physical properties of the treatment, resulting in creating more favorable conditions for plant growth. This highlights the advantage of the blend of amendments complementing one another, as some of them provide chemical advantages while others provide improved soil physical properties. Composted wood chips decompose at a slower rate, while manure decomposes at a faster rate (Gebhardt et al., 2017). As fresh wood products can tie up nitrogen and interfere with soil and water movement through the soil profile (Davis & Whiting, 2013) in the current study, the wood chips and manure were composted, having both short- and long-term effects in amending degraded mine soils. In all the plots, the yield from the fourth harvest was the lowest. This can be attributed to the reduced rainfall experienced during this period compared to previous harvests. During the fourth harvest, rainfall recorded was 68 mm in 2014–2015 and 63 mm in 2015–2016, which was 3.9 times (in 2014–2015) and 1.2 times (in 2015–2016) lower than the first harvest, four times (in 2014–2015) and 2.9 times (in 2015–2016) lower than the second harvest, and 2.2 times (in 2014–2015) and 1.9 times (in 2015–2016) lower than the third harvest, respectively (Figure 3). Peak production was attained in the second and third harvests. This coincided well with the 2 months (December and January), which recorded the highest rainfall and optimum temperature. Toward the end of the season, DM yield started to decrease as the rainfall and temperature decreased sharply. It is worthwhile noting that even though all the plots received the same amount of rainfall, the difference in the DM yield could be due to the treatment effect in utilization of the amount of water that was available in the soil.

TABLE 4 Summary of ANOVA on degrees of freedom, *F*-values, and *F* probabilities for the analysis of variance for dry matter yield (t ha^{-1}) (Tukey's studentized test) of a mixture of *Chloris gayana* and *Digitaria eriantha* for both seasons at Innovation Africa, University of Pretoria, Pretoria, South Africa.

Source of variation	*df*	*F*-value	$F > p$
Season	1	144.07	<0.001
Treatment	8	360.92	<0.001
Season × treatment	8	5.10	<0.001

Abbreviations: ANOVA, analysis of variance; *df*, degrees of freedom.

The cumulative seasonal DM yield of *C. gayana* and *D. eriantha* mixture for both seasons is shown in Figure 4. When data were combined for both years, there was a significant ($p < 0.001$) season × treatment interaction for DM yield (Table 4). The season × treatment interaction shows generally similar DM yield ranking of soil amendment treatments for each year. This shows that the interaction was primarily caused by a magnitude DM yield differences between years.

In both seasons, the highest yield was obtained from the plots treated with a blend of amendments (F6, F7, and F8).

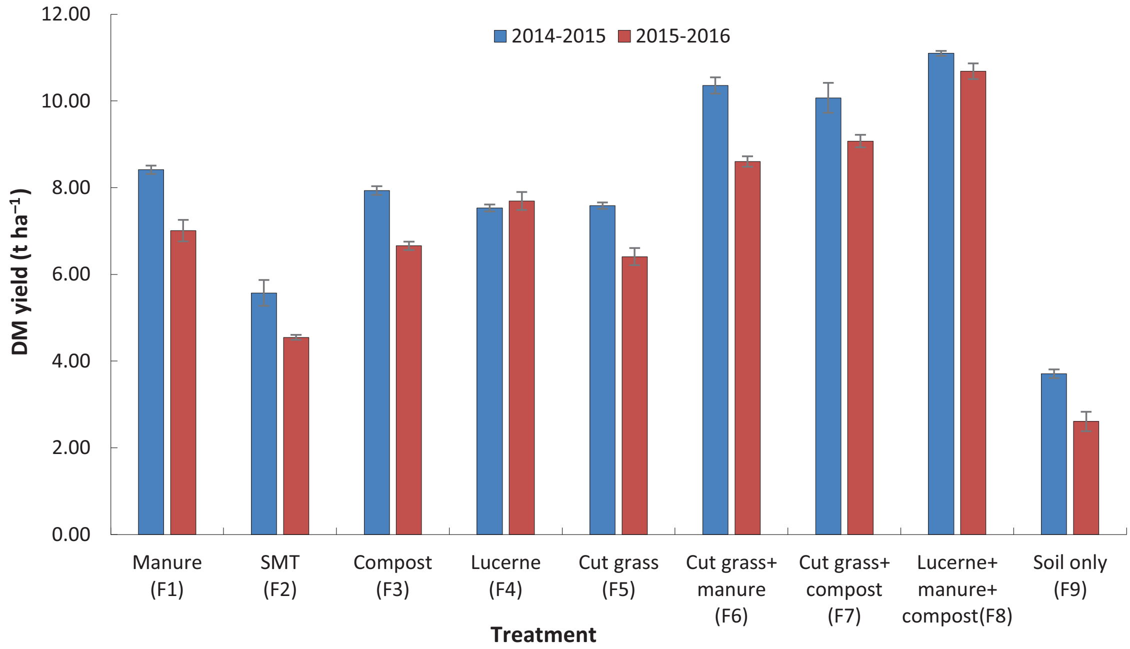

FIGURE 4 Cumulative dry matter yield (t ha^{-1}) of a mixture of *Chloris gayana* and *Digitaria eriantha* for both seasons at Innovation Africa, University of Pretoria, Pretoria, South Africa, SMT, standard mine treatment.

The plot that was not treated with any amendment (soil only) recorded the lowest cumulative DM yield (Figure 4). In the first season, a highest cumulative yield of 11.10 t ha^{-1} was obtained from the F8 treatment, while 10.69 t ha^{-1} was obtained from the same treatment in the second season (Figure 4). The blend of amendments played an important role in improving the chemical (Table 1) and physical (Abraha et al., 2019) properties of the soil, thus contributing to the maximum yield obtained from these treatments. Treatments F6 and F7 also recorded high yields. This was made possible due to the added benefits of chemical composition gained from the blend of amendments of the cut grass with manure and compost. Treatments treated with only one amendment recorded lower ($p > 0.05$) yields than those treated with a blend of amendments but had significantly ($p < 0.05$) higher yield than the unamended treatment. This decline in the yield of the treatments with a single amendment can be ascribed to reduced fertility of the soil. Overall, the DM yield was slightly lower in the second season than in the first season. This could be due to the lower amount of rainfall in the 2015 season (Figure 3). In addition, the slight increase in the soil bulk density due to soil settling and organic matter decomposition could have also played a role. Additionally, treatments F1 (manure) and F6 (grass + manure) experienced a sharp drop in the DM yield in the second season. Manure is known to improve soil nutrient status during the first year of application because of its rapid decomposition but both (chemical and physical) positive contribution to soil flora and fauna decreases as time progressed (Cooperband, 2002). The rapid decomposition of the manure in the F1 and F6 treatments could have played a role in decreasing the DM yield in the second season. Composted wood chips, on the other hand, decompose at a much slower rate due to the high lignin content, thereby releasing nutrients over a longer period of time (Palumbo et al., 2004). Taking these into consideration, the need for using a blend of amendments that have different decomposition rates would be more beneficial in rehabilitating degraded mine soils.

3.2 | Leaf area index

LAI is the leaf area of plants per unit surface area. It is one of the physical parameters that indicate the growth analysis that accounts for the ability of the plant to capture light energy, thus increased photosynthesis rate of the crop. Statistical analysis for LAI in both seasons (Table 5) shows that there was no interaction between treatment and harvest, so results will be presented separately for both seasons. This shows that the difference in the LAI was mainly due to the applied treatment effects.

In D21 of the first season (Table 6), LAI was significantly ($p < 0.05$) affected by the treatment effect. There was no significant difference in the LAI between F1, F6, F7, and F8, as all recorded LAI of over 3.5 m^2 m^{-2} within the first 3 weeks of growth. The high LAI of these treatments could be attributed to the abundance of nutrients in the soil from the applied amendments. These treatments also recorded the highest DM yield, which is positively related to the LAI (Anwar et al., 2012). There was no significant ($p > 0.05$) difference in the

TABLE 5 Summary of ANOVA on degrees of freedom, *F*-values, and *F* probabilities for the analysis of variance for leaf area index (LAI) (m^2 m^{-2}) (Tukey's studentized test) of a mixture of *Chloris gayana* and *Digitaria eriantha* for both seasons at Innovation Africa, University of Pretoria, Pretoria, South Africa.

		2014–2015				2015–2016			
		LAI D21		LAI D42		LAI D21		LAI D42	
Source of variation	*df*	*F*-value	$p > F$	*F*-value	$p > F$	*F*-value	$p > F$	*F*-value	$p > F$
Harvest	3	17.51	0.0960	8.97	0.5711	12.03	0.5232	3.50	0.0537
Treatment	8	105.90	<0.001	116.08	<0.001	142.79	<0.001	280.78	<0.001
Harvest × treatment	24	12.22	0.0664	7.28	0.4645	11.90	0.6143	7.31	0.0604

Note: D21 and D42, sampling dates.
Abbreviations: ANOVA, analysis of variance; *df*, degrees of freedom.

TABLE 6 Leaf area index (LAI) (m^2 m^{-2}) of a mixture of *Chloris gayana* and *Digitaria eriantha* for both seasons at Innovation Africa, University of Pretoria, Pretoria, South Africa.

	2014–2015		2015–2016	
Treatment	LAI D21 (m^2 m^{-2})	LAI D42 (m^2 m^{-2})	LAI D21 (m^2 m^{-2})	LAI D42 (m^2 m^{-2})
Manure (F1)	3.59a	4.92b	3.16bc	4.77b
Standard mine treatment (F2)	2.36c	3.50e	1.98e	3.16e
Compost (F3)	3.17b	3.99d	2.84c	3.78d
Lucerne (F4)	3.21b	4.48c	2.86c	4.23c
Grass (F5)	2.93b	4.15cd	2.47d	3.81d
Grass + manure (F6)	3.57a	5.23ab	3.25ab	4.93b
Grass + compost (F7)	3.62a	5.19ab	3.31ab	4.95b
Lucerne + manure + compost (F8)	3.88a	5.51a	3.59a	5.38a
Soil only (F9)	1.97d	3.19e	1.12f	2.13f
SEM	0.0789	0.0755	0.0646	0.0613

Note: D21 and D42 = sampling dates. Means with the same letter within a column are not significantly different. SEM denotes standard error of mean.

LAI of treatments F3 (compost), F4 (lucerne), and F5 (grass) but these were significantly higher than F2 (SMT) and F9 (soil only), as low yields were obtained from the last two. At the end of the first season, the leaves of the treatments with a blend of amendments grew vigorously and retained the highest LAI on D42. There was no significant ($p > 0.05$) difference between F6 (grass + compost), F7 (grass + manure), and F8 (lucerne + manure + compost), and also between F6, F7, and F1 (manure). However, there was a significant ($p < 0.05$) difference between F8 and F1. This highlights the advantage of having a blend of amendments, as higher yields were recorded from treatment F8 (Table 2). The highest LAI of 5.52 m^2 m^{-2} was recorded from treatment F8, closely followed by F6 and F7 (Table 6). The higher LAI values may be due to the sufficient nutrients obtained from the mixture of amendments that induce rapid cell reproduction of plant leaves, better interception of photosynthetically active radiation, and thus increased DM production (Zhang et al., 2015). As expected, the lowest LAI value of 3.19 m^2 m^{-2} was recorded from the treatment that received no amendment (F9). The low values of LAI may be due to soil physical problems such as increased soil bulk density and low infiltration rate (Abraha et al., 2019) and the shortages of nutrients on the treatment, as analysis of the degraded mine soil showed deficiency in some of the critical nutrients needed for plant production (Table 1).

As in the first season, the same trend was shown in D21 and D42 LAI of the second season. The LAI of the second season was slightly lower than that of the first season (Table 6). The highest LAI of 5.38 m^2 m^{-2} was recorded from the F8 treatment, while the lowest was 2.13 m^2 m^{-2} recorded from the plot that received no amendment (F9). This is in agreement with the aboveground biomass, which was lower in the second season. Previous studies have shown a strong correlation between aboveground DM yield and LAI (Anwar et al., 2012). Scheffer et al. (2005) stated that LAI is strongly correlated to site water balance and nutrient status of the soil. As all the plots received equal amounts of rainfall, it can be said that the main difference in the LAI was associated with the applied amendment material, as most of them differed in their nutrient status. As the rainfall was lower in the second season, the DM

TABLE 7 Summary of ANOVA on degrees of freedom, *F*-values, and *F* probabilities for the analysis of variance for leaf water potential (MPa) (Tukey's studentized test) of a mixture of *Chloris gayana* and *Digitaria eriantha* for both seasons at Innovation Africa, University of Pretoria, Pretoria, South Africa.

Source of variation	*df*	*F*-value	$F > p$
Season	1	4.53	0.038
Treatment	8	101.14	<0.001
Season × treatment	8	4.57	0.065

TABLE 8 Leaf water potential (MPa) of a mixture of *Chloris gayana* and *Digitaria eriantha* for both seasons at Innovation Africa, University of Pretoria, Pretoria, South Africa.

	2014–2015	2015–2016
Treatment	MPa	
Manure (F1)	−1.468b	−1.960c
Standard mine treatment (F2)	−2.515c	−2.720d
Compost (F3)	−1.405ab	−2.402cd
Lucerne (F4)	−2.232c	−2.390cd
Grass (F5)	−2.252c	−2.102c
Grass + manure (F6)	−1.295ab	−1.212b
Grass + compost (F7)	−1.210ab	−1.110b
Lucerne + manure + compost (F8)	−0.782a	−0.542a
Soil only (F9)	−3.395d	−3.612e
SEM	0.1308	0.1102

Note: Means with the same letter within a column are not significantly different. SEM, standard error of mean.

yield decreased significantly (Table 2), thereby decreasing the LAI of all the plots.

The treatments with no amendment material and those with a single amendment material generally had lower DM yields, hence lower LAI. The low values of the DM yield and LAI may be due to the shortages of nutrients in the soil and increased soil bulk density, low water infiltration rate, and PAW. The plots that were not treated with any amendment had higher bulk density. This led to decreased plant growth, which greatly affects the LAI. On the other hand, larger LAIs are associated with greater yield. Higher LAI under sufficient supply of nutrients and water is usual due to turgid cells and rapid cell production of plant leaves (Lang et al., 2014). Canopy LAI increased with crop growth as the plots that received a blend of amendments produced higher DM productions. From these results, it can clearly be seen that the application of a blend of amendments significantly ($p < 0.05$) increased aboveground DM production, thus leading to an increase in the LAI.

3.3 | Leaf water potential

LWP is one of the most commonly measured parameters to assess plant responses to water stress. The statistical analysis for LWP (Table 7) indicates that there was no interaction between season and treatment. However, there was a highly significant treatment effect ($p < 0.001$) and a significant seasonal effect ($p < 0.05$) observed on LWP. Rainfall during the first season (758 mm) was 1.7 times greater than in the second season (440 mm), which contrasts with the mean seasonal temperatures (22.1˚C for the first season versus 23.5˚C for the second season). The LWP for treatments F1, F2, F3, F4, and F9 in the first season was generally lower than that in the second season. These treatments consist of single amendments and a compacted control. Conversely, the LWP for the blend of amendments (F6, F7, and F8) and the grass alone was lower during the first season compared to the second season.

Abbreviations: ANOVA, analysis of variance; *df*, degrees of freedom.

In the first season, LWP was highest ($p < 0.05$) in the F8 treatment (lucerne + manure + compost). However, no significant differences were observed among the F8, F3, F6, and F7 treatments (Table 8). The higher LWP in these treatments may be related to the favourable conditions created by the applied amendments, which enhanced PAW and improved soil water retention (Abraha et al., 2019). According to Curtis and Claassen (2005), the addition of compost can improve PAW in severely disturbed serpentine soils by reducing the soil bulk density. The F8, F6, and F7 treatments also yielded higher aboveground biomass (Figure 4), which likely contributed to increased belowground development, thereby enhancing water absorption. This, in return, facilitates better rehydration during the night and higher LWP during periods of peak evaporative demand. In contrast, treatment F9 exhibited the lowest LWP, possibly due to limited PAW in the root zone. Grasses often display wilting symptoms under moderate water stress, which can lead to decreased aboveground biomass production as a result of reduced photosynthesis (Baruch, 1994). Treatments F1, F6, F7, and F8 showed no signs of wilting, while the other treatments clearly displayed wilting symptoms.

In the second season, LWP of treatment F8 (lucerne + manure + compost) was significantly ($p < 0.05$) higher than other treatments (Figure 5). This could mainly be due to the increase in PAW resulting in higher LWP during periods of peak evaporative demand. Abraha et al. (2019) stated that the addition of amendments had an effect on the PAW by altering the pore size distribution and PAW, which influences crop response to stress. There was no significant difference in the LWP between F6 and F7, and also between F1, F3, F4, and F5 treatments (Table 8). Even though soil moisture content was not measured directly, the higher aboveground production from the F8 treatment could be related to an improvement in the soil moisture regime caused by the blend of amendments. As a result, the soil physical properties improved, and thus,

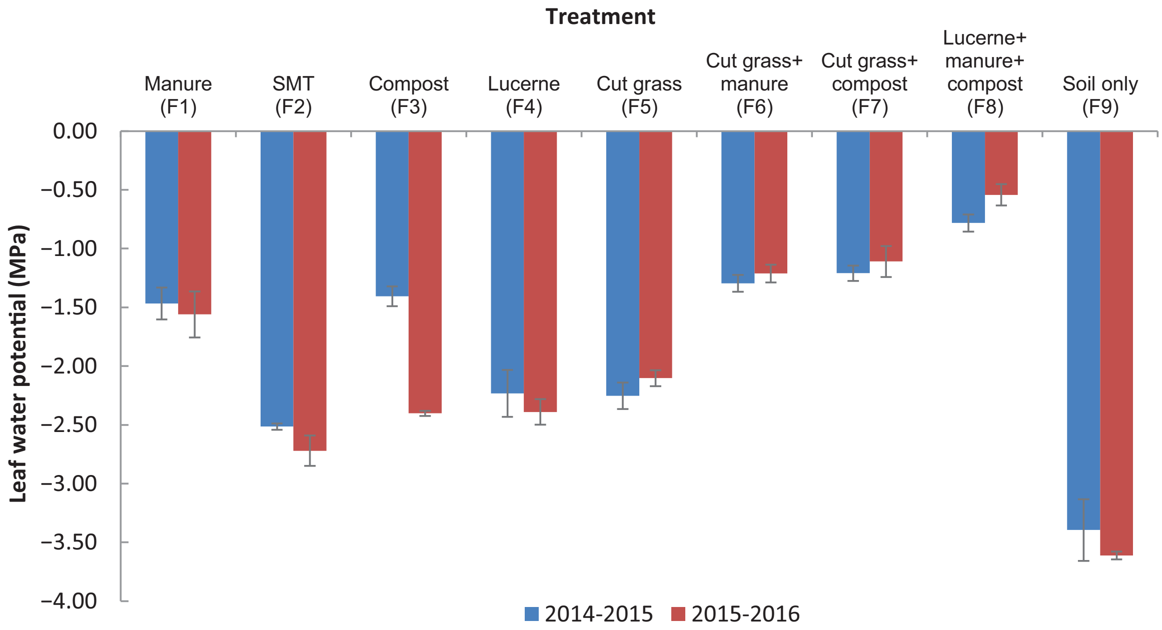

FIGURE 5 Leaf water potential (MPa) of a mixture of *Chloris gayana* and *Digitaria eriantha* for both seasons at Innovation Africa, University of Pretoria, Pretoria, South Africa. SMT, Standard mine treatment.

enhanced adequate root structure that helps in the absorption of higher amounts of moisture from the soil that increases the LWP.

3.4 | Variation in reflectance response

The spectral signature of *C. gayana* and *D. eriantha* across the full spectrum is shown in Figure 6. Due to the ultraviolet border, atmospheric water absorption, and short wave infra-red, and their resulting noise in the reflectance spectra, bands (n = 404) between 350–400 nm, 1350–1450 nm, and 1800–1950 nm, respectively, were excluded from the analyses. The spectrum in Figure 6 shows high reflectance in the NIR (700–1300 nm) range and low reflectance in the visible light spectrum (400–700 nm). The high reflectance response in the NIR is related to plant photosynthesis and the low response in the visible range is related to the leaf chlorophyll content. This is in line with previous studies that show high spectral signatures of green plant material in the NIR region of the spectrum (Mirik et al., 2007). Stress can cause a variation in the plant's response to NIR reflectance (Smith, 2012). In the present study, the treatments responded differently to the NIR reflectance. F2, F4, and F9 treatments had low spectral signatures in the NIR, indicating grasses in these treatments experienced stress. This is also confirmed in the present study as those treatments recorded low LWPs (Figure 5). Other studies (Bayat et al., 2016; Ollinger, 2011) stated that plants subjected to water stress will display differences in their reflectance response, especially in the visible and NIR regions of the spectrum. They concluded that the differences are associated with leaf (leaf pigments) and canopy properties (leaf structure and scattering), which change under variable water stresses.

3.5 | NDVI relationship with aboveground yield

Contour plot representing the correlation coefficient (r) values between the narrow band NDVI for each λ_1 (wavelength 1) (350–2500 nm) and λ_2 (wavelength 2) (350–2500 nm) pair with aboveground yield is shown in Figure 7. The results showed a wide variation in the strength of the relationship between the narrow band NDVI and aboveground yield, with values of r ranging from 0.00 to 0.73, indicating that the narrow band combinations respond differently to a variation in biomass. The strongest correlations were found in the red (600–690 nm) and red edge (690–730 nm) range of the spectra. This could be due to the presence of chlorophyll content of the leaves. Filella and Penuelas (1994) stated that the wavelengths of the red edge portion of the spectrum are sensitive to chlorophyll content and nitrogen status of plants. The shorter wavelengths recorded in the red and red edge regions are sensitive to changes in chlorophyll content (Filella & Penuelas, 1994). Kumar et al. (2001) stated that at longer wavelengths of the red edge region, multiple scattering from the leaf layers results in higher reflectance, confirming strong correlations between the red edge region and aboveground biomass. Spectral indices using narrow bands have been successfully used

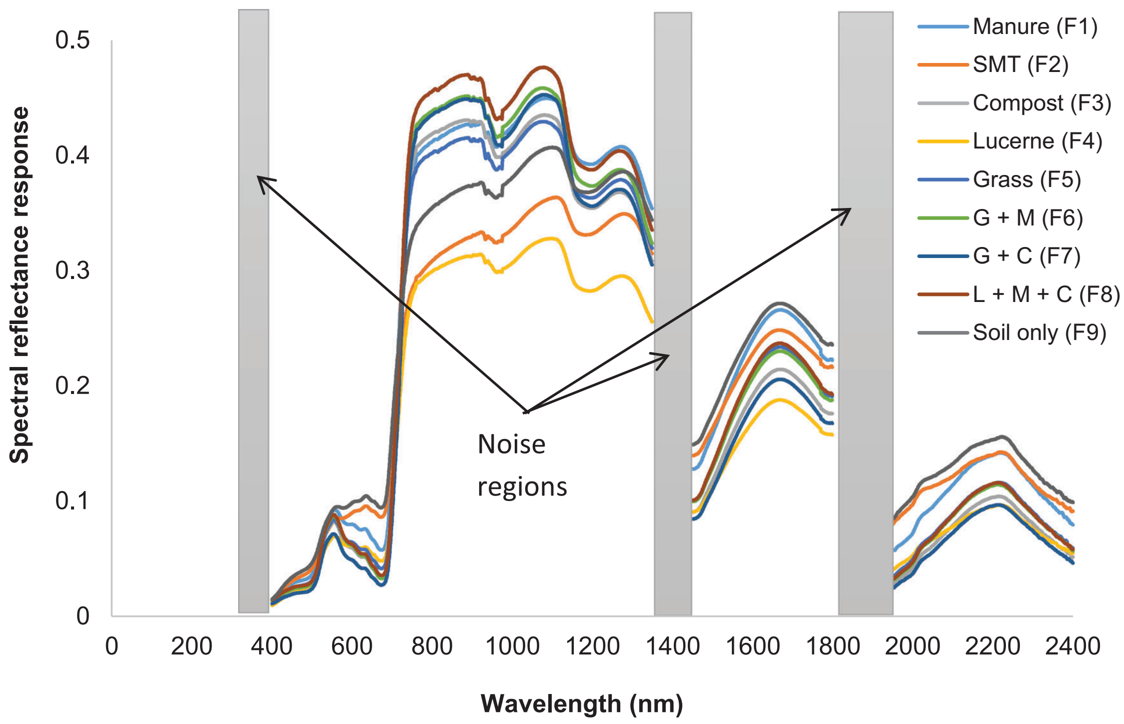

FIGURE 6 Canopy reflectance spectra of *Chloris gayana* and *Digitaria eriantha* mixture across the full spectrum. Highlighted regions show spectral regions excluded from analysis due to noise. G+C, a blend of pasture grass and compost; G + M, a blend of pasture grass and manure; L + M + C, a blend of lucerne, manure, and compost; SMT, standard mine treatment.

to determine chlorophyll content, nitrogen status, and subsequently green biomass of wheat (Li et al., 2022; Newete et al., 2024). These are in line with the results in the present study as strong correlation was found between the red edge bands and biomass.

From a total of 1749 spectral band measurements, bands that had an r^2 value of 0.75 and above were chosen. The reason for choosing a minimum r^2 value of 0.75 is that it is considered as a strong correlation between the variables (Henseler et al., 2009). Based on this criterion, the spectral bands that recorded an r^2 value of 0.75 and above in predicting the DM yield of *C. gayana* and *D. eriantha* are shown in Table 9. These wavelengths are located in the visible (400–700 nm) region of the electromagnetic spectrum, which is associated with chlorophyll content of plants.

3.6 | Optimization of the RF regression model

The RF algorithm was optimized using the default mtry value (one-third of the total variables) and ntree set to 1000, as these parameters yielded the lowest RMSE (Figure 8). The variable importance measurement (Figure 10) indicated that LAI and treatment had the highest influence on the model, followed by wavelengths in the red (655 and 651 nm) and red edge (693 nm) regions. These wavelengths are closely linked to chlorophyll content and plant biomass, further supporting the model's predictive capability.

To simplify the modeling process in the RF algorithm, it was necessary to identify the smallest number of indices in the dataset that would ultimately offer the best predictive performance for estimating aboveground yield of a mixture of *C. gayana* and *D. eriantha*. The value of *ntree* was chosen at 1000 as the RMSE did not change for *ntree* values greater than 500 (Figure 9). Adam et al. (2012) stated that highest accuracy and stability of RF can be achieved by using a large number of trees as a forest consisting of a high number of trees allows the use of more variables from the dataset.

The algorithm calculated and ranked all the variables; however, only a few variables responded noticeably to the estimation of the aboveground yield. The variable importance measurement determined by the RF algorithm with default settings of *mtry* and *ntree* values for prediction of aboveground yield is shown in Figure 10. The most important variables are those with the highest increase in mean square error. From the figure, it is clear that LAI and treatment had the highest increase in mean square error, followed by wavelengths located at the red (655 and 651 nm) and red edge (693 nm). These wavelengths are in the visible region (400–700 nm) of the spectrum, due to their sensitivity to chlorophyll content and biomass, which are critical for accurate prediction (Adam et al., 2014; Mutanga & Skidmore, 2004).

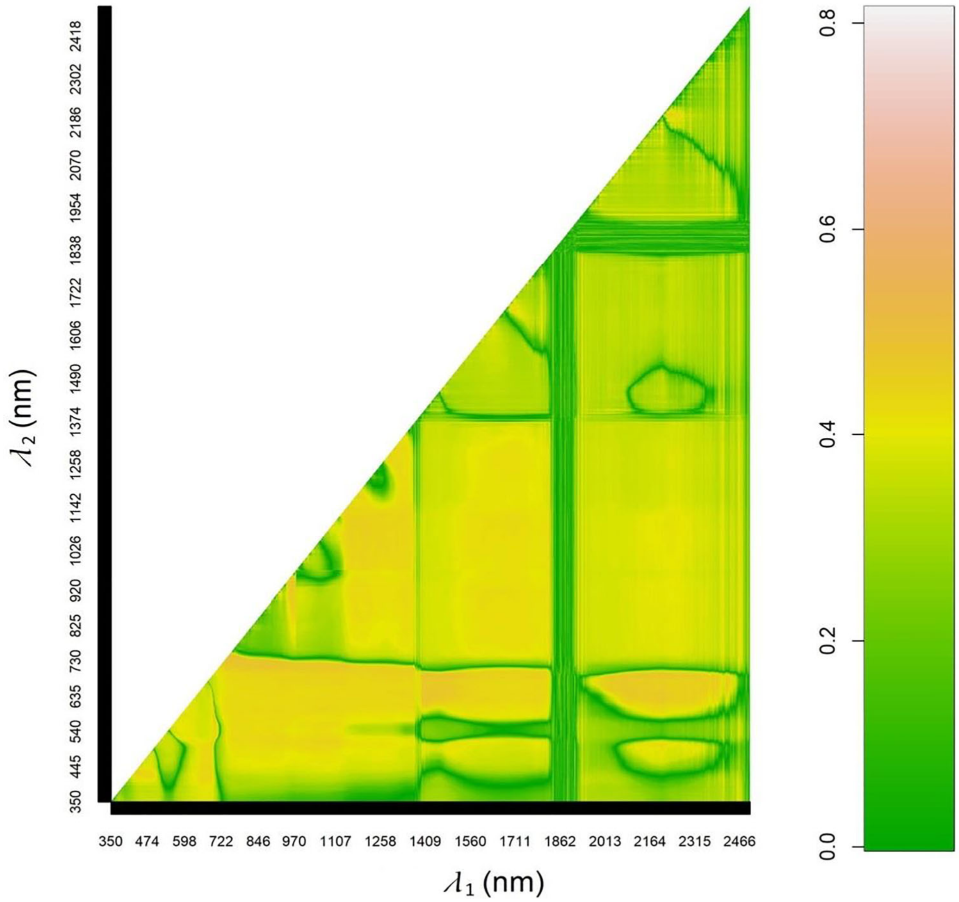

FIGURE 7 Contour plot representing the correlation coefficients (*r*) between the aboveground yield and narrow-band normalized difference vegetation index (NDVI) values calculated from all possible combinations spread across λ_1 (350–2500 nm) and λ_2 (350–2500 nm).

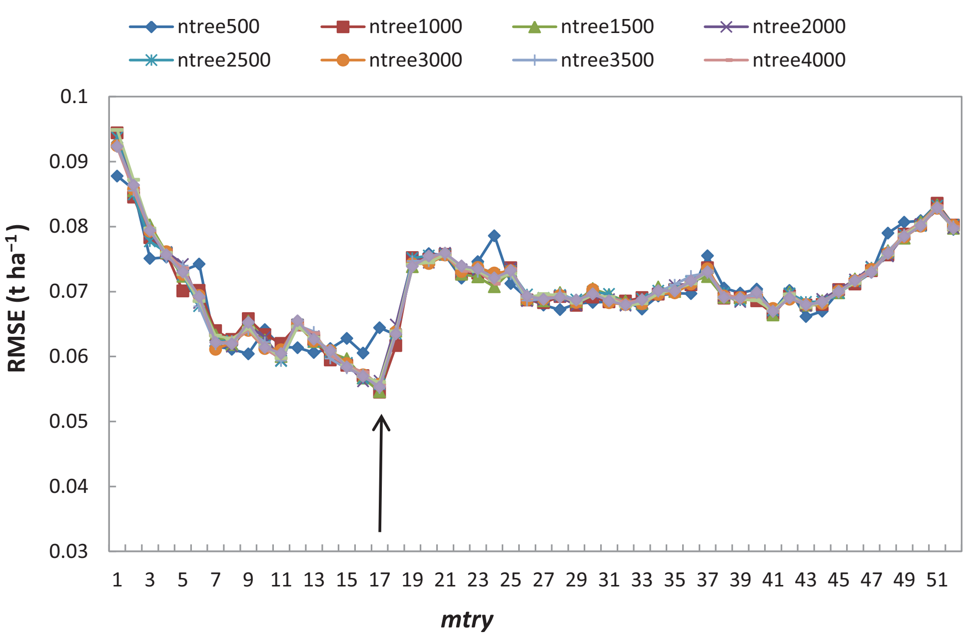

FIGURE 8 Determining the best random forest parameters (*ntree* and *mtry*) as determined by the root mean square error. The arrow shows the lowest root mean square error (RMSE) value.

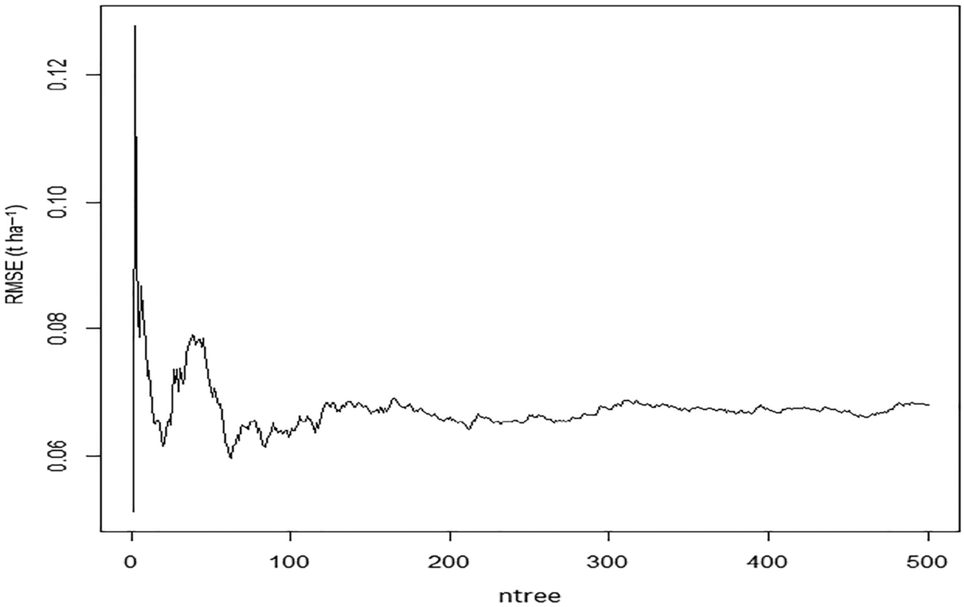

FIGURE 9 The effect of the number of trees (*ntree*) parameter on the performance of the random forest (RF) algorithm determined by the root mean square error (RMSE).

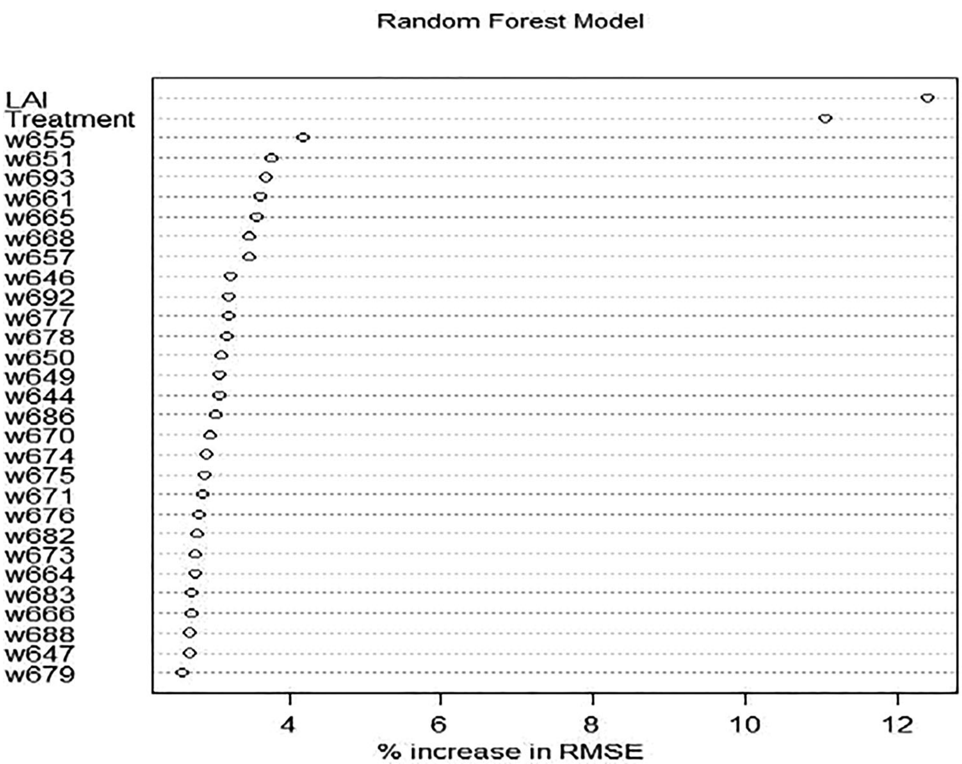

FIGURE 10 Variable importance measurement determined by the random forest algorithm with default settings of *ntree* values of 1000 and *mtry* ($n = 17$) for prediction of a mixture of *Chloris gayana* and *Digitaria eriantha* yield (t ha^{-1}). LAI, leaf area index; RMSE, root mean square error.

3.7 | Model validation and accuracy assessment

The predictive performance of the RF model was validated through a one-to-one comparison between measured and predicted aboveground biomass, as shown in Figure 11. The model achieved a high coefficient of determination ($r^2 = 0.90$), with a mean absolute error of 0.183 t ha^{-1} and an RMSE of 0.255 t ha^{-1}. These results demonstrate the model's accuracy in predicting aboveground biomass for *C. gayana*

TABLE 9 Rank of the spectral bands that recorded an r^2 of 0.75 and above for the aboveground biomass prediction of a mixture of *Chloris gayana* and *Digitaria eriantha* at Innovation Africa, University of Pretoria, Pretoria, South Africa.

Rank	Wavelength 1 (nm)	Wavelength 2 (nm)	r^2
1	644	688	0.870
2	644	689	0.869
3	645	688	0.866
4	646	688	0.852
5	645	690	0.846
6	645	689	0.846
7	646	689	0.844
8	644	690	0.844
9	647	688	0.837
10	648	688	0.833
11	646	687	0.816
12	644	687	0.806
13	646	690	0.803
14	647	687	0.802
15	654	655	0.795
16	648	687	0.789
17	645	687	0.789
18	647	689	0.786
19	654	656	0.781
20	647	649	0.780
21	655	656	0.779
22	654	657	0.777
23	653	657	0.776
24	653	658	0.775
25	650	687	0.773
26	648	689	0.773
27	649	650	0.773
28	649	688	0.772
29	649	687	0.770
30	653	655	0.769
31	652	659	0.769
32	649	658	0.769
33	655	658	0.767
34	647	648	0.766
35	648	649	0.766
36	650	688	0.766
37	651	658	0.765
38	651	688	0.764
39	648	650	0.763
40	655	657	0.762
41	653	659	0.761
42	647	650	0.761
43	653	656	0.761
44	653	654	0.760
45	652	658	0.760
46	647	663	0.760
47	652	656	0.759
48	646	663	0.759
49	652	657	0.758
50	653	662	0.758

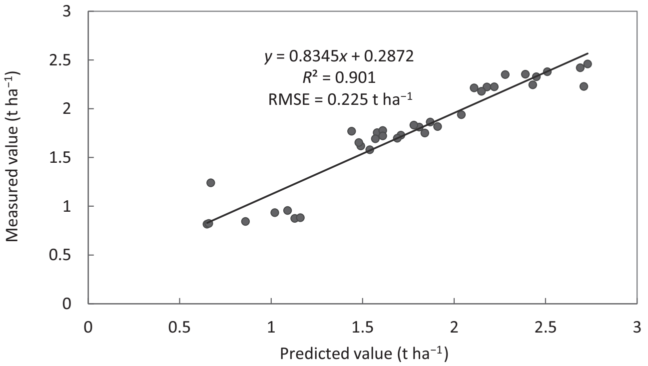

FIGURE 11 One-to-one relationship between the measured and predicted aboveground biomass prediction of a mixture of *Chloris gayana* and *Digitaria eriantha* at Innovation Africa, University of Pretoria, Pretoria, South Africa. RMSE, root mean square error.

and *D. eriantha*. The strong correlation between measured and predicted values further confirms the robustness of the RF algorithm in capturing the variability in biomass production. This validation emphasizes the effectiveness of using hyperspectral data and RF regression for precise biomass estimation in rehabilitated coal mine soils. Further studies are recommended to validate the model across diverse regions and conditions to ensure its broader applicability. Hyperspectral remote sensing offers significant potential for monitoring rehabilitated soils by providing detailed, spatially continuous data on soil composition, moisture, organic matter, and vegetation health. It allows for the detection of subtle soil variations and the assessment of rehabilitation progress over time. However, its complexity, high data processing demands, and limited ability to analyze deeper soil layers are notable drawbacks. Compared to traditional methods like soil sampling, which provide high accuracy but are labor-intensive, or multispectral sensors, which are simpler but less detailed, hyperspectral remote sensing strikes a balance by offering comprehensive insights. When combined with other techniques like LiDAR (light detection and ranging) or ground-based sensors, it can enhance soil monitoring efforts for large-scale and long-term rehabilitation projects.

Using hyperspectral data for scaling land rehabilitation efforts offers significant benefits by enabling large-scale, cost-effective, and efficient monitoring of soil and vegetation health. It provides detailed, real-time insights that help target resources, adapt strategies, and assess the effectiveness of rehabilitation projects over time. This data-driven approach supports better decision-making, fosters global collaboration, and contributes to long-term environmental benefits such as enhanced biodiversity, carbon sequestration, and improved water retention. Ultimately, hyperspectral data can accelerate the restoration of degraded lands and support sustainable environmental policies on a global scale.

4 | CONCLUSIONS

The effect of a single and a blend of amendments on the aboveground DM yield, LAI, and LWP of a mixture of *C. gayana* and *D. eriantha* was evaluated. Results from this study show that the application of a blend of amendments increased the aboveground DM yield and LAI of a mixture of *C. gayana* and *D. eriantha* by 70%–150% and 60%–95%, respectively, compared with the unamended control. This was mainly due to enhanced nutrient availability and improved soil physical properties, which improved both the plant availability of soil water and nutrients. The increase in plant-available soil water resulted in higher LWP in the blend of amendments, which was 120%–140% higher than the untreated control treatment. Hence, the study indicated that a blend of amendments could play significant role in rehabilitating degraded coal mined soils better than the existing standard treatments of liming and fertilization. However, this needs to be tested under various climatic and soil conditions. Additionally, further studies are required to assess the logistical and economic feasibility of its application at the field scale. Further research is also recommended to investigate the long-term impact of blended amendments on soil and plant systems.

It was also apparent from this study that the hyperspectral reflectance data could be successfully employed to predict aboveground yield of a mixture of *C. gayana* and *D. eriantha* accurately. This could solve the practical infeasibility of using the traditional methods to assess aboveground biomass and physiological response of plants. Hyperspectral remote sensing technique, which is a rapid, nondestructive, and cost-effective tool, can therefore be implemented as a useful tool in predicting the aboveground yield of *C. gayana* and *D. eriantha* in the coal mining industry via the detection of changes in the spectral signature of plant canopies. However, further study is recommended to validate the RF model in other regions.

AUTHOR CONTRIBUTIONS

Amanuel B. Abraha: Conceptualization; data curation; formal analysis; investigation; methodology; resources; software; validation; visualization; writing—original draft. **Eyob H. Tesfamariam**: Conceptualization; funding acquisition; investigation; methodology; supervision; validation; visualization; writing—review and editing. **Wayne F. Truter**: Conceptualization; funding acquisition; resources; supervision; visualization; writing—review and editing. **Khaled Abutaleb**: Data curation; formal analysis; investigation; methodology; software; validation. **Solomon W. Newete**: Data curation; formal analysis; investigation; methodology; resources; validation; writing—review and editing.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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