DERIVATION OF INDICES OF LANDSCAPE FUNCTION ANALYSIS (LFA) FROM HYPER-SPECTRAL REFLECTANCE DATA: A CASE STUDY ON FOUR TYPES OF GRASSLAND IN THE WITWATERSRAND BASIN GOLD MINING REGION OF SOUTH AFRICA

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1. ABSTRACT

The Minerals and Petroleum Resources Act (MRPDA) no 28 of 2002 of South Africa states that the holder of a mining permit remains liable for environmental damage until a closure certificate has been issued, but does not stipulate the environmental standards required to obtain such a certificate. Monitoring of surface mining environments requires a consistent, repeatable and efficient method that is applicable to heterogeneous landscapes on large properties. To this end, we describe the first stages in the testing of a remote-sensing method to assess the condition of gold mine land in a highly seasonal, summer rainfall region of the Grassland biome in South Africa.

Landscape Function Analysis (LFA) is a widely used field monitoring technique to rapidly determine the broad biogeochemical processes occurring at the soil surface. However, LFA is still time consuming. Hyper-spectral remote sensing (HSRS) is an alternative technique for monitoring large landscapes and is sensitive to both plant response to stress and soil mineral condition. The aim of this study was to derive LFA indices from surface reflectance data acquired with a hand-held analytical spectral device (ASD) in order to predict the condition of four grassland categories, representative of increasing physiognomic complexity. The first objective was to test the potential for using Vegetation Indices (VI), calculated from hyper-spectral data, to predict LFA indices. Twenty-three VIs for plant pigments (i.e. chlorophyll, carotenoids and anthocyanins), plant structural components (cellulose and lignin) and plant liquid water content, were tested. The second objective was to test the potential of Partial Least Squares Regression (PLSR) modelling to predict LFA indices from the spectral data.

The study was repeated in two seasons (winter 2007 and summer 2008) on the identical quadrats situated at two AngloGold Ashanti Ltd gold mining operations in the Highveld grassland biome: Vaal River Operations near Klerksdorp (North West Province) and West Wits Operations near Carltonville (Gauteng Province). Data was collected from three replicate 10 x 10m to 20 x 20m plots situated in low and high disturbance sites in each of the four grassland categories: wet grasslands, non-rocky grasslands, rocky dolomitic grasslands and wooded dolomitic grassland sites. Twenty five circular quadrats of 50 cm diameter were evenly distributed on five gradsects within each plot (total quadrats = 750). The study was conducted in winter (dry season) 2007 when seasonal herbaceous growth was not present to mask soil features and disturbance was most visible, and repeated on the identical plots in summer (wet season) 2008, when herbaceous vegetation did mask the soils, but biogenic crusts were active and alluvial fans subsequent to rain events were most visible. In winter 2007, paired data for reflectance (44 cm FoV) and for LFA soil surface condition indicators were acquired from a sub-sample of 105 quadrats (5 per plot), with high resolution photographs of the quadrats used to derive some LFA data. In summer 2008, paired data for reflectance and for all eleven LFA soil surface condition indicators was acquired directly from 525 quadrats, without reliance on photographs.

The results of ranking the three LFA indices for winter data showed that stability was above the threshold value for sustainability, while infiltration was below threshold and nutrient cycling was close to threshold for all grassland types and disturbance levels combined. These results suggest that soils are crusted and promoting run-off, and that disturbance is mainly impacting the vegetation component, rather than the soil component of the landscape. All three LFA indices: stability, infiltration and nutrient cycling, differed between grassland types (one-way ANOVA, $P < 0.05$, $df = 3, 101$) with wet

grasslands having consistently higher LFA indices than the other three grassland types. Disturbance levels, for all grassland types and mining regions combined, also differed (t-tests, $P < 0.01$, DF = 81.8, 102.3 and 100.08 for stability, infiltration and nutrient cycling respectively), with high disturbance quadrats having lower LFA indices than low disturbance quadrats. When comparing LFA indices between disturbance levels within each grassland type, low disturbance sites generally still had higher LFA indices than high disturbance sites ($P < 0.05$). These findings support the initial selection of distinct grassland types and disturbance levels.

The twenty-three VIs were not found to be useful for predicting LFA indices from reflectance data. For winter, all the VIs had generally low indices as expected (in the case of chlorophyll and plant water-based VIs) for senesced Highveld grasses, and linear regressions between LFA indices and VIs had very weak coefficients of determination ($r^2 < 26\%$). The lignin index (NDLI) had the strongest coefficient of determination with both the stability ($r^2 = 25\%$, $P < 0.01$) and the nutrient cycling indices ($r^2 = 25\%$, $P < 0.01$). The infiltration index had the strongest coefficient of determination with the standard normalised difference vegetation index (NDVI) ($r^2 = 16\%$, $P < 0.01$). PLSR modelling produced much stronger regression coefficients of determination than did the VIs. For winter data, the best PLSR model was that derived for predicting nutrient cycling with 15 components ($r^2 = 54\%$, $P < 0.01$). A 13-component model predicting stability had $r^2 = 38\ \%$ ($P < 0.01$), while a 17-component model was derived for infiltration ($r^2 = 32\%$, $P < 0.01$). In all three cases, these models were able to account for more than 90% of the spectral variability within the first two components. However, more than 16 components were required to account for 90% of the variability in the LFA measurements, and this was considered to be due to multiple observer bias, combined with inadequate replication in winter 2007.

PLSR models using the summer 2008 data, collected from a greater number of quadrats (525) by only two LFA observers, had much improved predictive results, with R^2 values of 62% for the stability model, 61% for Infiltration models and 54% for Nutrient Cycling models. This compares favourably to a previous study on tussock grassland in a semi-arid region of northern Australia (Ong *et al.*, 2008) which obtained R^2 values of 68%, 40% and 62% respectively. In this study, the best predictive models were derived from data for the single grassland types within each region. Predictive ability was reduced with increasing complexity of the grassland types, and when combining mining regions and/or grassland types into the modelling.

In conclusion, the derivation of LFA indices from reflectance data using PLSR models is achievable for simple grassland formations in the Highveld, but becomes progressively less reliable with increasing physiognomic complexity, such as the addition of rocky or woody layers. Future work will focus on incorporating soil chemical indices associated with landscape resource retention, such as clays and organic matter.

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