MODELLING NUTRIENT CONCENTRATION TO DETERMINE THE ENVIRONMENTAL FACTORS INFLUENCING GRASS QUALITY

N. Dudeni-Tlhone[1*], *A. Ramoelo*[2], *M. A. Cho*[2], *P. Debba*[1] *R. Mathieu*[2]

[1]Logistics and Quantitative Methods, Built Environment, CSIR, P O. Box 395, Preotria, 0001

[2]Ecosystems and Earth Observation, The Nautural Resources and the Environment, CSIR, P O. Box 395, Preotria, 0001

ABSTRACT

This paper uses the spatial and the least squares (Analysis of Covariance-ANCOVA) regression methods to evaluate the important environmental factors in estimating quality grass for grazing (based on the nitrogen (*N*) content in grass). The environmental variables such as those based on climate (temperature and precipitation), land-use, geology, slope, aspect and altitude were specifically evaluated in these models. Spatial regression accounted for higher variability (61%) when compared to the 41% variability explained by the ANCOVA model. The models indicate that some environmental variables are useful in assessing *N* variability. This provides an opportunity for the design of an intergraded system to incorporate both the environmental and remote sensing variables in the estimation and mapping of nitrogen content in grazing grass across the Kruger National Park (KNP) and the surrounding areas.

1. INTRODUCTION

According to South Africa's State of the Environment report published in 2005, about 80% of South Africa's land surface is classified as being dominated by agricultural productivity (Gibson et al., 2005). Approximately 69% of this land is used for extensive grazing since only 11% has arable potential. This report indicates that agricultural production has intensified since 1995 and crop varieties resulted in improved yields of maize and wheat. Even though the intensification of agricultural production yields desirable outputs, the environment on the other hand becomes under pressure. Animal production has also been reported to be on the increase since 1995. The main concern, however, is that the total stocking densities exceed the grazing capacity of the veld in many parts of South Africa. Meanwhile, the areas used for grazing had generally declined since the 1990s due to changes in land-use and the transformation of the land resulting from land degradation, crop cultivation, expansion of human settlements, conservation, forestry and mining. The Gauteng and Western Cape provinces were the most affected due to high rates of urbanization observed during this period (Gibson et al., 2005).

Land degradation, which refers to the reduction or loss of biological or economic productivity of the land caused mainly by human activities, is one of the critical environmental issues that results in moderate to severe levels of decline in the grazing potential of the agricultural land in South Africa (Gibson et al., 2005). Even though the extent of land degradation has not been updated since 1999, it is perceived that areas of severe degradation correspond to the distribution of communal grazing lands. For example, many communal areas in the Limpopo, Mpumalanga, Northern Cape and North West provinces are severely degraded. Generally, stocking rates differ between communal and commercial farming areas, and overstocking is more evident in areas with communal lands. The differences are largely due to poor management practices and land-use planning (Gibson et al., 2005).

Management practices often applied to cattle farming systems are rational and allow grass to recover (Sharpe, 2010). With wildlife, this is rather different as the most common control measure involves the positioning of water points and burning of sections of grassland to encourage grazing at specific points. Otherwise, control of wildlife grazing patterns is limited (Sharpe, 2010). For effective management and monitoring of grazing, it is important that the ecological value of grazing grass (Sharpe, 2010) be understood. Grass serves as the primary supplier of nourishment to livestock and wildlife in general. Grazing animals, however, have preferences over certain grass species due to factors such as grass structure, taste, texture and

[*]N. Dudeni-Tlhone is the corresponding and a presenting author. Thanks to the CSIR for funding.

accessibility (Sharpe, 2010). The nitrogen (*N*) content of grass is considered to be one of the indicators of grass quality (and or herbage in general) (Haferkamp et al., 2005). The quality of grass is an essential determinant of preferences of grazing animals (Cannon et al., 2004). Therefore, understanding the quality of grazing grass is essential in the strategic planning, monitoring and management of grazing areas or rangelands.

This paper seeks to determine the environmental factors that are important in predicting grass quality based on the nitrogen concentration in grass canopies. This will in turn inform the design of an integrated remote sensing system to predict and map the quality of grazing grass and rangelands in the Kruger National Park (KNP) and the surrounding areas. Previous studies have shown that forage nutrient content, which is largely determined by foliar nitrogen concentration, is essential for the health of grazing animals (Plummer, 1988). Integrated modelling of nutrient concentration through remote sensing technologies will improve understanding of both livestock and wildlife feeding patterns in the park and neighbouring areas. There are limited scientific tools to assist the park's management with these tasks. Therefore, the development of a system to predict nutrient content based on various factors including the remote sensing variables such as the Normalized Difference Vegetation Index (NDVI) and red-edge (Mutanga & Skidmore, 2007), and environmental variables such as those related to climate and land-use, might enable effective management and monitoring of rangelands and grazing pastures. This paper particularly focuses on assessing the potential of environmental factors such as those based on climate (temperature and precipitation), land use, slope, aspect, altitude and geology in predicting grass quality based on total nitrogen in grass canopies.

2. METHODOLOGY AND DATA

In order to determine significant relationships between nitrogen content as a measure of grass quality and the environmental factors; ordinary least squares regression and spatial regression models are designed. This section also provides details of the data used and the procedure by which data were collected.

2.1. Ordinary Least squares regression

The regression model based on the Analysis of Covariance (ANCOVA) method is adopted since both continuous and nominal explanatory variables are used to model these relationships. This model was expanded to include significant interactions as the preliminary analysis showed that the effects of some of the environmental variables in the prediction of nitrogen content in grass was not the same for all land-use activities and main geological materials in the soil. The generic form of the model used is given by:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon_i, \tag{1}$$

where β_0 is the intercept, $\beta_1, \ldots, \beta_n$ are parameter estimates corresponding to each of the explanatory variables $x_1, \ldots, x_n$, and ε_i are normally distributed error terms.

2.2. Spatial regression analysis

Spatial regression, often referred to as Geographically Weighted Regression is a method that is used to model spatially varying relationships (Fotheringham et al., 2002). This method does not assume that the regression parameters are constant across the study area, hence geographic variation does not have to be confined to the error term; instead, it is accounted for in the modelling. We apply spatial regression because we expect the influence of environmental factors on *N* concentration in grass canopies to vary spatially, and that points close to each other are more similar than points further away. A multivariate case of spatial regression, can be represented as follows:

$$y(u, v) = \beta_0(u, v) + \beta_1(u, v)x_1 + \cdots + \beta_n(u, v)x_n + \varepsilon(u, v), \tag{2}$$

where (u, v) are geographic locations (spatial coordinates) at which data are collected (Propastin et al., 2008; Cressie, 1991; Diggle & Jnr., 2007). This allows for separate estimates of parameters to be obtained at each location. In terms of capturing spatial dependencies, spatial relationships among the variables involved are quantified in various ways. For instance, a geographical weighting scheme where higher weight is given to data closer to (u, v) than those further away, can be used. Each data point can also be weighted by its distance from the regression point; where the closer the data point is to the regression point, the higher the weight it receives (Propastin et al., 2008). The parameters of a spatial regression model can then be estimated by solving the matrix equation given by:

$$\hat{\beta}(u,v) = [X^T W(u,v) X)]^{-1} X^T W(u,v) Y \tag{3}$$

where $\hat{\beta}$ are intercept and slope parameters in location (u, v) and $W(u, v)$ is a weighting matrix that represents the spatial weighting of observations around any point (Propastin et al., 2008). This is where points around a particular regression point of interest will be assigned bigger weights than those far apart. A number of spatial weighting functions can be used, in this case, a Gaussian function was applied since a fixed kernel bandwidth size was used. The weight of each point was computed from the Gaussian function as follows:

$$w_{i,j} = \exp\left[-\frac{1}{2}\left(\frac{d_{i,j}}{b}\right)\right]^2 \tag{4}$$

where $d_{i,j}$ is the distance between regression point i and data point j and b is a bandwidth.

2.3. Data and Study area

The Analytical Spectral Device (ASD) was used to collect 198 grass reflectance samples during April 2009. These samples were taken across a line transect along major sites in the Kruger National Park. This location is shown in Figure 1. Plot sizes of $30\ \mathrm{m} \times 30\ \mathrm{m}$ were randomly selected. Each of these plots were then subdivided into 4 subplots of about $0.5\ \mathrm{m} \times 0.5\ \mathrm{m}$. Samples were taken to the Agricultural Research Council (ARC) in Nelspruit for chemical analysis for Nitrogen (*N*) concentration.

The environmental data including variables such as precipitation, temperature, aspect, slope, geology and land-use, were sourced from various sources like the WorldClim (the Global Climate data) and the Council for Geosciences. The land-use classes include the Kruger National Park, the SABI sands and communal areas, while the main geological material found in the sampled area were the granite and gabbro classes. The land-use and geological classes were coded into dummy variables for modelling purposes.

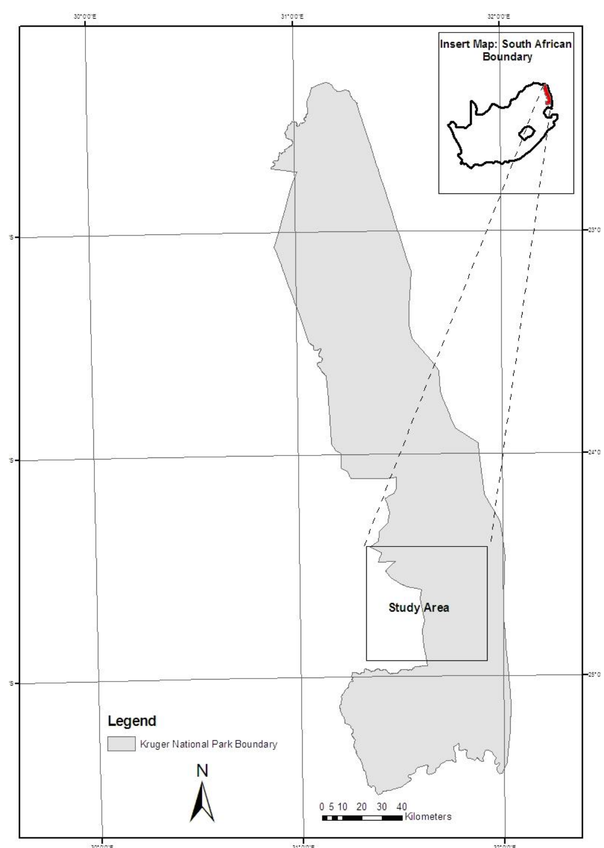


Fig. 1. Study area

3. RESULTS

This section presents the results obtained from both the least squares (specifically ANCOVA) and the spatial regression techniques. The preliminary analysis showed sufficient evidence that the effects of some of the environmental factors on the nitrogen content in grass canopies depend on the land-use activities and geological material on the land surface. The final models (based on the two techniques) were then expanded to include the significant interaction terms (two-way interactions). The other interactions such as the three-way and four-way, were not statistically significant. Also, statistically insignificant variables such as the temperature and aspect were eliminated from the final models.

3.1. Least Squares Regression (ANCOVA)

The analysis of covariance regression model with interactions indicates that environmental factors such as the altitude, slope and precipitation, land-use activities (particularly in communal areas) and geology can potentially be used to predict nutrient content in grass canopies. Table 1 shows the model fit. Approximately 41% of variation (R-square) in nitrogen content of grass can be explained by the environmental factors.

Table 1. Summary of fit of the ANCOVA model

Regression model	R-square	Adjusted R-square
ANCOVA	0.41	0.38

Table 2 shows the parameter estimates and significant interactions of all the variables included in the final model. All the variables included in the final model have significant (from at least 0.001 level of significance) relationships with the observed nitrogen content on grass canopies.

Regarding the relationships between the land-use activities, a negative change on grass quality (nutrient concentration) where there are communal areas is observed. This can be attributed to poor management of the land and its effect on the reduction of biological activity and land degradation, amongst other factors. The model indicates a positive relationship between grass quality and the SABI sands land-use activities. There is no significant influence on grass nutrients in the KNP land-use category.

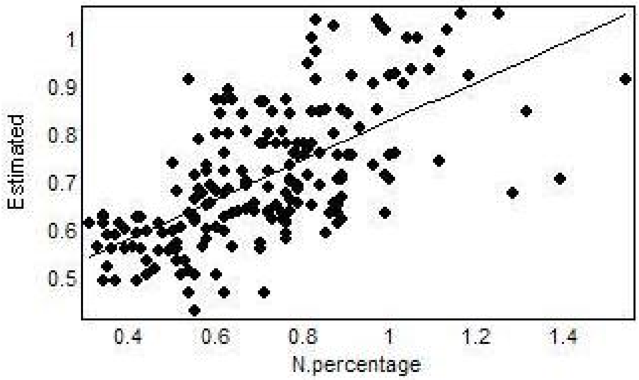
Precipitation and the gabbro geological class show positive relationships with nitrogen concentration in grass. Precipitation is generally understood to have a good effect on vegetation (including grass) as different vegetation types require varying amounts of water to survive and to maintain soil nutrients, explaining the positive relationship that is observed in this case.

Table 2. Results of the ANCOVA model and parameter estimates

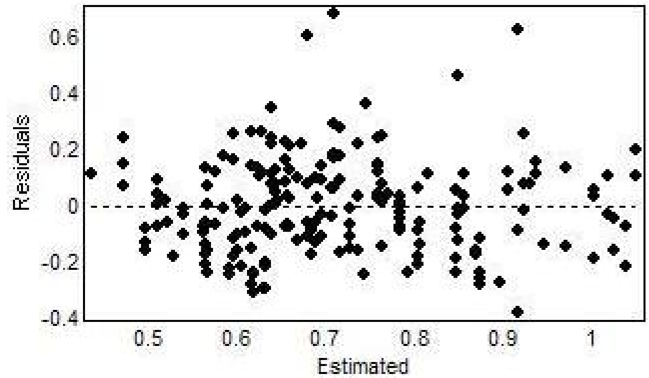
Parameter	Estimate	Std Error	t-value	$(P > t)$
Intercept	1.0376	0.2687	3.86	< 0.001
Altitude	-0.0038	0.0009	-4.41	< 0.001
Slope	-0.0732	0.0200	-3.68	< 0.001
Precipitation	0.0016	0.0004	4.05	< 0.001
Comm.Areas	-2.5719	0.4769	-5.39	< 0.001
Geology	2.2807	0.3566	6.40	< 0.001
Altitude*Comm.Areas	0.0075	0.0012	6.07	< 0.001
Altitude*Geology	-0.0060	0.0009	-6.844	< 0.001
Slope*Geology	0.1400	0.0282	4.96	< 0.001
Slope*Comm.Areas	-0.1000	0.0282	-3.55	< 0.001

The two main geology classes used in this analysis were the gabbro and granite. Both classes showed a positive influence on grass quality, +3.451 for gabbro (geology=1) and +1.037 for granite (geology=0). It is understood that soil patterns that develop from gabbro materials contain relatively higher nutrients than soil patterns originating from granite materials (Kruger, 2010). As a result, grazing is said to be more palatable in soils formed from gabbro. Thus a stronger positive relationship with grass quality is expected in areas where gabbro is a predominant geological material, than in granite covered areas.

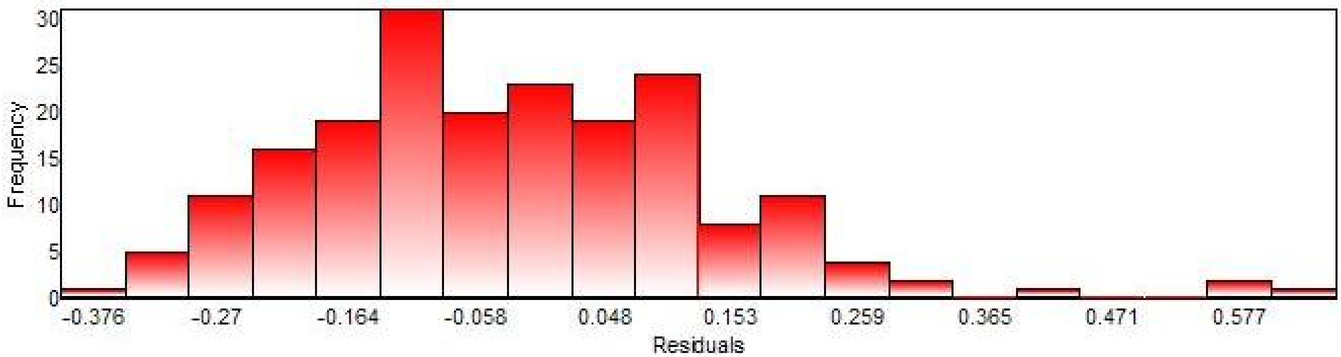
Figure 2 (a) shows how the environmental factors used in the final models predicted the nitrogen content in grass. Figures 2 (b) and (c) are used to examine whether or not it is sensible to assume that the random errors inherent in the process of estimating



(a) Plot of estimated nitrogen



(b) Residual plot



(c) Residual Histogram

Fig. 2. ANCOVA Regression Plots

grass quality (based on *N* concentration) come from a normal distribution. These figures show no major departures from normality.

3.2. Spatial Regression model

For the spatial regression model, the distance between regression points (fixed bandwidth $= 3661.136$ m distance units) was used as a weighting scheme. The Gaussian weighting function was applied. The spatial regression equation model in table 3 accounted for approximately 61% of variation in the percentage of *N*.

Table 3. Summary of fit of the spatial regression model

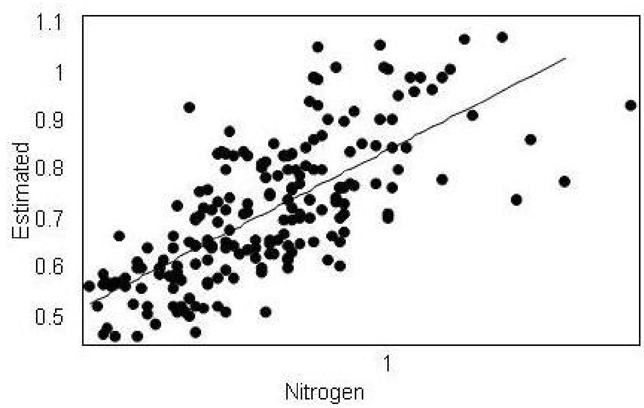
Regression model	R-square	Adjusted R-square
Spatial regression	0.61	0.53

Table 4 shows the descriptive statistics indicating variations in local parameter estimates for each of the predictor variable. The estimates based on the median values from the spatial regression model correspond (to a large extent) to the estimates produced by the ANCOVA regression model, while estimates of the maximum of the spatial regression model show positive relationships between nitrogen content and most of the predictor variables, with the exception of the altitude and geology interactions and the slope and communal land-use interaction. This indicates that even though the communal land-use activities generally have effect on grass quality, they do not have a negative effect in all communal locations included in this study. This is an important aspect that the spatial model is able to describe.

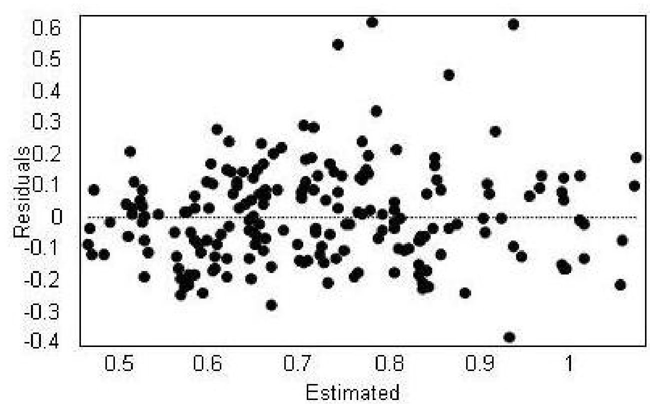
Table 4. Descriptive statistics of the local regression parameter estimates

Variable	Minimum	Lwr Quartile	Median	Upr Quartile	Maximum
Constant	−0.0643	0.6381	0.9809	1.1929	1.9358
Altitude	−0.0059	−0.0046	−0.0035	−0.0003	0.0008
Slope	−0.1401	−0.0934	−0.0541	−0.0333	0.0065
Precipitation	−0.0007	−0.0001	0.0010	0.0020	0.0035
Geology	0.7139	1.6281	2.6675	3.5327	5.5620
Comm.Areas	−6.1667	−4.0564	−2.8399	−1.1658	0.1769
Altitude * Comm.Areas	0.0004	0.0036	0.0084	0.0113	0.0158
Altitude * Geology	−0.0129	−0.0091	−0.0069	−0.0047	−0.0027
Slope * Geology	−0.0188	0.1184	0.1553	0.1779	0.2562
Slope * Comm.Areas	−0.2283	−0.1595	−0.1202	−0.0926	0.0155

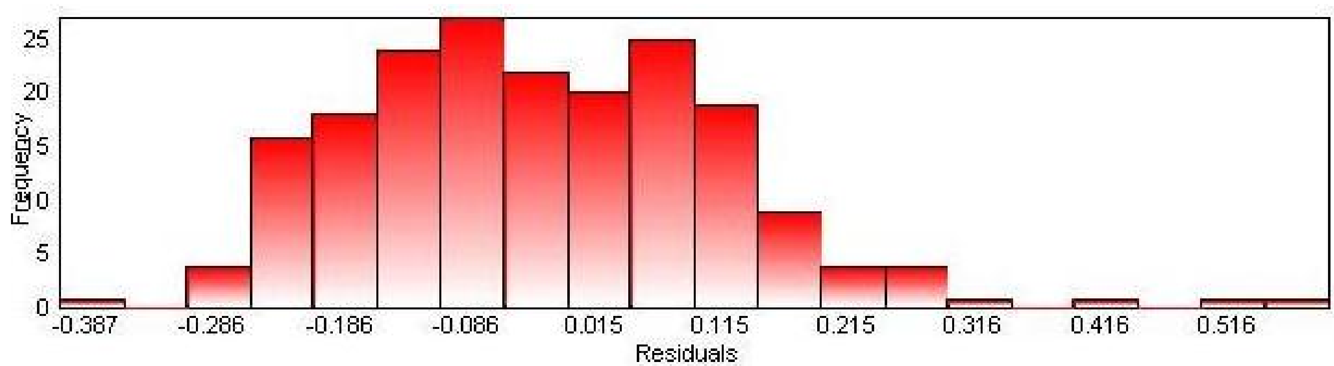
Figure 3 (a) shows the plot of estimated nitrogen using the environmental variables and observed nitrogen, while figures 3(b) and (c) show the residual plots. The fitted model is almost in line with the observed data and fits better than the ANCOVA model.



(a) Plot of estimated nitrogen



(b) Residual plot



(c) Residual Histogram

Fig. 3. Spatial Regression Plots

Temperature, aspect and the land-use activities in the Kruger Park did not show any significant relationships with *N* content and were excluded from the models. Altitude seems to have a slightly negative influence in grass quality.

4. CONCLUSION AND RECOMMENDATIONS

The objective of this study was to assess the potential of estimating nitrogen *N* content in grass using environmental factors such as precipitation, aspect, temperature, land-use, geology, altitude and slope. The analysis of covariance regression and the spatial regression models indicate that some environmental variables are useful in assessing *N* variability. Furthermore, the estimation and mapping of *N* across KNP and the surrounding areas, cannot only be done by using environmental variables. This is because of the strength of the predictions shown by both models. Between 41% to 61% variation is explained by the explanatory variables. There is evidence, however, that some of these variables can be used in the integrated system of modelling of the biochemical variability in the KNP. The results indicate that the spatial regression model predicted the nitrogen percentage on grass better than the least squares method and would be the best model. Incorporating the remote sensing vegetation indicators such as NDVI and red-edge in the integrated system could improve *N* estimation. With respect to the spatial regression model, ways of optimizing the bandwidth could be used in order to improve the model.

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