Assessing the effects of subtropical forest fragmentation on leaf nitrogen distribution using remote sensing data

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28/01/2013
6408 words

Abstract Tropical forest loss resulting from conversion of forest to other land-cover types such as grassland, secondary forest, subsistence crop farms and small forest patches affects leaf nitrogen (N) stocks in the landscape. This study explores the utility of new remote sensing tools to model the spatial distribution of leaf N in a forested landscape undergoing deforestation, in KwaZulu-Natal, South Africa. Leaf N was mapped using models developed from a relatively new space-borne sensor, RapidEye (5 m spatial resolution). A detailed land-cover map derived from another new space-borne sensor, WorldView-2 (2 resolution) was used to assess differences in leaf N between land-cover types. The results showed that indigenous forest fragmentation leads to significant losses in leaf N as most of the land-cover types (e.g. pasture and subsistence farmlands) resulting from forest degradation showed lower leaf N when compared to the original indigenous forest. Further analysis of the spatial variation of leaf N revealed an autocorrelation distance of about 50 m for leaf N in the fragmented landscape, a scale corresponding to the average dimension of subsistence fields. The availability of new multispectral sensors such as RapidEye and WorldView-2 thus, moves remote sensing closer to widespread monitoring of the effect of tropical forest degradation on nutrient (e.g. N) cycle.

Keywords: subtropical forest fragmentation, leaf nitrogen, remote sensing

Introduction

Tropical forest ecosystems play a major role in nutrient and carbon cycling (Vitousek, and Sanford 1986; Van der Werf et al. 2009). For example, tropical forests constitute a major sink of atmospheric carbon dioxide and several studies have shown that tropical forest deforestation and degradation were major sources of global greenhouse emission in the 1990s (Malhi and Grace 2000; Achard et al. 2004, Fearnside and Laurance 2004; Gibbs et al. 2007; DeFries et al. 2002). Gibbs et al (2007) put the estimates at about 15-25% of annual global greenhouse gas emissions. Whereas, the effects of forest disturbance on carbon stocks at the broad landscape level have been widely studied, few studies have modelled the effects of forest degradation on nutrient stocks (e.g. Nitrogen (N) and phosphorus (P)) (e.g. Billings and Gaydess 2008).

Tropical forest degradation in many parts of Africa is characterised by the clearing of the forest for pasture, agriculture or urban development (van Wyk et al., 1996; Coops et al. 2004). In most cases, the forest is fragmented into patches of various sizes and shapes. The forest patches in most degraded landscape are surrounded by a matrix of different vegetation and/or land use types (e.g. mono-crop plantations, small subsistence farms, pasture lands) (Saunders et al. 1991; Harrera et al. 2011). The immediate environmental consequences of forest fragmentation include soil erosion, loss of biodiversity, invasion by alien species, loss of soil fertility, changes in litter and canopy nutrient stocks and vegetation productivity (Saunders et al. 1991; Gibbs 1998; McDonald et al., 2002; Vasconcelos, and Luizão, 2004; Giertz et al., 2005; Lauga and Joachim, 1992; Duguay et al. 2007; Lizee et al. 2011). Spatially explicit information on the above factors is rare, let alone on changes in foliar nutrient stocks, following forest fragmentation. Saunders et al. (1991) asserted that forest fragmentation affects nutrient cycling processes by increased soil heating and its effect on soil microorganism and invertebrate numbers and activity, on litter decomposition and soil moisture retention. The resulting loss of soil fertility might translate into low foliar nutrient stocks.

Nitrogen is an important nutrient for plant growth (Groffman and Turner 1995). Nitrogen taken up by plants in the form of nitrates is used in the synthesis of components such as chlorophyll, the carbon fixing enzyme ribulose biphosphate carboxylase (Rubisco) and inert structural components in cell tissue (Mooney 1986). Leaf N concentration has been used as a proxy to assess ecosystem productivity (Mooney 1986; Smith et al. 2002). Nitrogen inputs into an ecosystem include lightning and bacteria fixation of atmospheric N, and decomposition and nitrification of dead organic matter (e.g. litter). Outputs from the system include plant uptake, denitrification, leaching and surface runoff. Thus, forest N pools consist of soil N (ammonium, nitrate, and some dissolved organic N compounds), N in litter and that retained in living plant parts (roots, stems and leaves) (Vitousek 1982). Rates of organic matter decomposition are high in lowland moist tropical forest than in temperate forest (Nye 1960). Greenland and Kowal (1960) argued that standing biomass is as important as the soil as a storehouse of plant nutrients, particularly in moist tropical forest where vegetation growth is so high and where the reserves of nutrients in the soil may be quite rapidly depleted by leaching or absorbed by plants. Vitousek and Sanford (1986) asserted that foliar chemistry represents a useful indicator of overall nutrient status of a plant, where nutrient concentrations in leaves are correlated with nutrient concentrations in other plant parts. Leaching and surface runoff of nutrients from moist tropical forest patches in a degraded landscape might serve as important nutrient sources for surrounding vegetation, including grasslands and subsistence farms.

The question is, how does the conversion of indigenous tropical forest into other land-cover types e.g. grassland, secondary forest, subsistence crop farms and small forest patches affect foliage N stock in the fragmented landscape? Another question of interest is, at what scale does leaf N vary in fragmented or disturbed landscape. The ability to adequately tackle the above questions may rely on our capability to accurately map land-cover types and leaf N concentration at the broad landscape level, a procedure that was rarely achieved before the advent of high spectral resolution (hyperspectral) remote sensing (Iverson et al. 1989; Groom et al. 2006). Most hyperspectral sensors acquire radiance information in less than 10 nm bandwidths from the visible to the shortwave infrared (400 – 2500 nm) (Curran 2001). The narrow bandwidth of hyperspectral data allows for the detection of the subtle absorption features of N in green vegetation (Curran et al, 2001; Cho et al. 2009). However, the high cost and limited availability of space-borne hyperspectral imagery has stymied the routine application of this sort of remote sensing for leaf N analysis at the regional scale. Many hyperspectral studies highlighted the region of the red-edge in the electromagnetic spectrum (700-760 nm) as having a high potential for accurate estimation of leaf chlorophyll and N at peak productivity (Horler 1983; Matson et al. 1994; Kokaly and Clark 1999; Cho and Skidmore 2006). More recently, new space-borne sensors such as RapidEye (Ramoelo et al. 2012) and Worldview-2 have been launched with new wavebands in the red-edge region, for example at 710 nm for Rapideye and at 725 nm for Worldview-2 (Mutanga et al. 2012). These sensors provide us with new opportunities to assess leaf N stock at the regional scale. Ramoelo et al. (2012) have successfully mapped leaf N concentration over a large area in the Kruger National Park, South Africa using the red-edge band of RapidEye images.

The aims of this study were to (i) ascertain the ability to assess leaf N concentration using RapidEye imagery in a fragmented landscape following indigenous forest degradation and (ii) assess the effects of forest fragmentation on leaf N distribution? The above aims were achieved through a detailed land-cover classification from WorldView-2 images, mapping of leaf N using RapidEye images, an analysis of the differences in the predicted leaf N among land-cover types and an analysis of the spatial heterogeneity of leaf N.

#Fig. 1 approximatetly here#

Material and methods

Study site

The study site is situated in the northern part of KwaZulu-Natal, South Africa between Mtubatuba town and the Indian Ocean, north of Richard’s Bay (Fig. 1). It consists of three main ecosystem types; intact closed canopy forest (inland coastal forest and dune forest), swamp forest and fragmented landscape. The inland coastal forest is known as the Dukuduku forest (28^{o}25’S, 32^{o}17’E). The Dukuduku forest is the largest patch (6500 ha) of coastal lowland forest along the eastern coastline in KwaZulu-Natal. A total of 29 % of the Dukuduku forest was lost to settlement and subsistence farming activities between 1992 and 2005 (Ndlovu 2011). The area forms part of the iSimangaliso Wetland Park which is the largest estuary in South Africa (Van Heerden, 2011). The study area as demarcated by the Map in Fig. 1 is surrounded by large commercial Eucalyptus (to the North) and Sugarcane (to the South) plantations. Thus, the study area consists of varying land uses including protected areas, commercial farms, communal areas and towns.

Acquisition of satellite images and pre-processing

Rapideye imagery (5 m spatial resolution) of the study site was acquired on 21 March 2011. The sensor consists of five spectral bands (Blue: 440-510 nm; Green: 520-590 nm; Red: 630-685 nm; Red Edge: 690-730 nm; NIR: 760-850 nm). The level 1B RapidEye image (geometrically and radiometrically corrected) obtained from the image provider were atmospherically corrected using ATCOR-2, flat terrain model. ATCOR is based on MODTRAN radiative transfer code (Richter and Schlapfer 2002). Two archive geometrically corrected WorldView-2 images (2 m spatial resolution) acquired in April and December of 2010 were also used in the study to classify land-cover types. Worldview-2 consists of multispectral bands centred at 425 nm, 480 nm, 545 nm, 605 nm, 660 nm, 725 nm, 835 nm and 950 nm. We assessed the geometric accuracies of the two images using ground control points and found the WorldView-2 images more accurately corrected as compared to the RapidEye image. Using the WorldView-2 as the reference image, we re-projected the RapidEye image using image-image registration in ENVI software (ITT Visual Information Solution, Boulder Co USA). In this study, the WorldView-2 images were used only for the land-cover classification because of the huge time difference between the image acquisition (April and December 2010) and the field campaign to collect leaf N data (March 2011).

Field data acquisition and leaf nitrogen analysis

Fieldwork sampling of leaf specimens was conducted on the 29 and 30 March 2011. Sunlit leaves were collected from 69 randomly selected plots consisting of tree or grass canopies along paths in the intact and fragmented landscape. We ensured that each tree or grass canopy sampled consisted of a homogenous canopy (same species for the trees and similar set of species for the grasses) of about 15 m by 15 m. The sampled trees and grass plots were located between 10 m to about 100 m from the edges of intact forest and paths within the fragmented landscape. 44 and 25 of the plots were tree canopies and grassland areas, respectively. Five and two plots of the grassland plots were wetlands and sugarcane farms, respectively.

The leaf specimens were oven dried for 24 hours at $70^{o}C$ on the 31 April 2011. The dry leaf samples were sent to the Agricultural Research Council-Institute for Tropical and Subtropical Crops, South Africa for chemical analysis of leaf N. Leaf N concentration was analysed using acid digestion method (Novozamsky et al. 2003). Leaf N concentration was expressed as the percentage N to the leaf mass.

Additional data was collected for land cover classification in July 2011. The global positioning system (GPS) locations of different land cover (LC) types (intact forest, degraded forest, grassland/subsistence farms, eucalyptus farms, sugarcane farms) were recorded in the field. The points were only collected from homogenous areas (of at least 20 m by 20 m) of the land-cover types.

Land-cover (LC) classification

The WorldView-2 images were used for the LC classification. A mosaic of the April and December 2010 images were made prior to the classification using ENVI 4.8 software (ITT Visual Information Solution, Boulder Co USA). The classification was also conducted using ENVI 4.8. The GPS point data for the various land cover types (intact forest, degraded forest, grassland/subsistence farms, eucalyptus farms, wetlands and sugarcane farms) were overlaid on the image and a region of interest (ROI) consisting of an array of pixels was created for each point. Additional ROIs were created for the intact forest and wetland grasslands (mainly from the swamp forest) since these were clearly visible on the WorldView-2 image. The ROIs were randomly divided into the training and test datasets in the following ratio: intact forest (44/17), degraded forest (25/10), grassland/subsistence farms (11/6), eucalyptus farms (18/13), sugarcane farms (24/8), wetland grasslands (47/21), bare areas and settlements (22/11). The commonly used maximum likelihood classifier was used in this study. The overall, producer's and user's accuracies of classification were derived using the test data on a per pixel basis. The producer's accuracy is a measure of how accurately the analyst classified the image data for each cover-type, while the user's accuracy is a measure of how well the classification performed in the field on a per cover-type basis.

Regression analysis and mapping of leaf nitrogen

The GPS points of the field sample plots were overlaid on the atmospherically corrected RapidEye images and the tree or grass canopy spectral profiles were extracted using an array of 2-by-2 pixels. Several red-edge spectral indices that have shown great promise for leaf N or chlorophyll estimation in previous studies including normalised difference vegetation index (NDVI) (Rouse et al. 1974), Gitelson and Merzlyak index (Gitelson and Merzlyak, 1997), Datt index (Datt, 1998; Datt, 1999) and the MERIS terrestrial chlorophyll index (MTCI) (Dash and Curran) were computed from the spectral profile. After exploring the relationship between leaf N and the red-edge indices, the MTCI was chosen for the prediction of leaf N in the study area as it provided the highest coefficient of determination (R^2) with leaf N.

It should be noted that the MTCI was originally derived for leaf chlorophyll estimation. We have used this index to estimate leaf N because leaf chlorophyll is a good correlate of leaf N, particularly at peak productivity (Yoder and Pettigrew-Crosby 1995). The strength of the linear relationship between leaf N and the MTCI was assessed using a bootstrapped

(McGarigal et al. 2000) linear regression (Eq.1) because of the small number of sample points.

$$y = mx + c \tag{1}$$

where y is the leaf nitrogen concentration, x the vegetation index (i.e. MTCI), m the slope and c the intercept on the y-axis.

The regression coefficients were computed for 1000 iterative sampling with replacement, i.e. for each iteration, 2/3 of the data were randomly drawn and used for calibration of the regression model and the remaining 1/3 for validation. For each iteration, the root-mean-square error (RMSE, Eq.2) of calibration and validation (termed standard error of prediction (SEP, same as Eq.2)) were computed. The leaf N for each pixel of the vegetation index image was then predicted using Eq.1, whereby, m and c were the average values for the 1000 iterations in the bootstrapped linear regression.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y-y')}{n}} \tag{2}$$

An MTCI map was derived from the RapidEye image using the ENVI 4.8 bandmaths feature. Using the linear regression equation involving MTCI, a leaf N concentration map was computed from the MTCI map. To evaluate the effect of forest fragmentation on leaf N stock, the land-cover map derived from the WorldView-2 imagery was spatially re-sampled to a spatial resolution of RapidEye i.e. to 5 m. Lastly, differences in leaf N concentration between the different land-cover classes were assessed. First, ROIs for the different land cover classes were created and overlaid on the leaf N Map using ENVI software. Subsequently, leaf N values for the different land cover classes were extracted from the N map and saved as text files. Tables for the leaf N values were then created. The differences among the various land cover classes were assessed using descriptive statistics including a table of mean and inter-quartile ranges, and box plots.

Characterising spatial heterogeneity of leaf nitrogen concentration

The spatial variation or heterogeneity of leaf N in the intact and fragmented regions was analysed using semivariogram models (Garrigues et al. 2006; Murwira and Skidmore, 2006). Semivariogram modelling involves the hypothesis of statistical stationarity i.e. the characteristics of the underlying random function are invariant to the shifting of a group of pixels from one part of the image to another (Garrigues et al. 2006). In this study, we proposed to assess the spatial variation of leaf N from exponential models fitted to experimental semivariograms (Eq.3). The exponential model was adopted in this study as it provided the best fit when compared to the spherical and Gaussian models.

$$\gamma(h) = \frac{1}{2n} \sum_{n(h)} \left[z(u) - z(u+h) \right]^2 \qquad (3)$$

where *γ(h)* are the semivariances, *z(u)* is the pixel value at position *u* in the input map, *z(u+h)* is the pixel value at position *u+h* in the input map and *h* is the lag vector representing separation (distance) between two spatial points (pixels). We used a lag tolerance of 200 pixels (1000 m). Two parameters that describe a semivariogram are of particular importance in this study: (i) the sill represents the point (semivariance) at which a semivariogram levels off and (ii) the range represents the lag distance at which a semivariogram reaches the sill.

The range describes the size or scale of the dominant objects in an image that give rise to the semivariogram structure (Jupp et al., 1988). The semivariograms were modelled using the Integrated Land and Water Information System (ILWIS) software (ITC, Enchede, The Netherlands).

#Fig.2 approximately here#

#Table 1 approximately here#

Results

Land-cover classification from WorldView-2 imagery

An overall classification accuracy of 85% (kappa coefficient = 0.79) was obtained for the land-cover classification (Fig. 2). With the exception of the normal grassland class (pasture and farmlands), the producer's and user's accuracies were in general high (Table 1). The low user's accuracy (44%) for the grassland class was due to a miss-classification of wetland grassland pixels (16% of wetland pixels) into other grasslands (pasture and farmlands). Natural forest remains by far the largest (about 7500 ha) land-cover type in the study area followed by wetland grasslands (Table 2). The average patch size of natural forest, eucalyptus farm, grasslands (pasture and subsistence farms) and sugarcane farms in the fragmented landscape are 5900 m^2, 3100 m^2, 1500 m^2 and 625 m^2, respectively; yielding an overall patch size of 2781 m^2.

#Table 2 approximately here#

#Fig.3 approximately here#

Statistics of laboratory measured leaf nitrogen

The laboratory measured leaf N (Fig. 3) showed the following statistics; average = 2.19%, maximum = 4.76%, minimum = 0.70% and standard deviation (SD) = 0.94%. The grass leaf N concentration (mean = 1.38%) was significantly (p-value < 0.0001) lower than the tree leaf N (2.66%). Furthermore, a Shapiro-Wilk normality test conducted on the data showed that the leaf N data for grasses and trees were normally distributed; grass (W = 0.92, p-value > 0.05) and trees (W = 0.98, p-value > 0.05).

#Fig. 4 approximately here#

#Table 3 approximately here#

Mapping leaf nitrogen from RapidEye imagery

Amongst the four vegetation indices investigated, the MTCI yielded the highest linear regression with leaf N (R^2 = 0.52, SD = 0.05) and the lowest prediction error on the test data (SEP = 0.65% i.e. 29% of mean leaf N, SD = 0.08) (Table 3, Fig.4). The commonly used NDVI yielded the highest prediction error (SEP = 0.77, SD = 0.1) amongst the indices applied in this study.

The regression model based on the MTCI (Eq. 4) was used to predict leaf N concentration for every pixel on the RapidEye image (Fig. 5).

$$[N] = 0.8926 * MTCI - 0.6103 \qquad \text{Eq.4.}$$

where $[N]$ is the leaf N concentration (%). The slope of the line of best fit (0.8926) and the intercept (-0.6103) were the means for 1000 bootstrapped iterations.

#Fig. 5 approximately here#

#Table 4 approximately here#

Differences in predicted leaf nitrogen among land cover types

Table 4 shows the descriptive statistics of predicted leaf N for the large intact forest areas (intact inland coastal forest and dune forest) and leaf N of land-cover types in the degraded landscape including small natural forest patches, degraded forest patches, grasslands, eucalyptus and sugarcane farms. Among the cover types, eucalyptus farms showed the highest average leaf N concentration. The conversion of intact forest into grasslands significantly reduces the leaf N stock in the landscape. The Natural forest fragments in the disturbed area still showed leaf N concentrations comparable to those of the large intact forest areas.

Fig. 6 approximately here#

#Table 5 approximately here#

Scale of leaf nitrogen variability

Leaf N varies at a higher distance (50 m) in the fragmented landscape when compared to the intact forest (25 m) (Table 5 and Fig 6). The lower autocorrelation distance of leaf N variability in the intact forest probably corresponds to tree crown level variability while the autocorrelation distance in the fragmented landscape might depict spatial dependence at the scale of subsistence fields (e.g. crop and eucalyptus farms) in the region (i.e. 2500 m^2 for a rectangular field). It should be recalled that the land-cover classification yielded an average patch size of 2781 m^2 in the fragmented landscape.

Discussion

This study has demonstrated the utility of RapidEye imagery for mapping leaf N concentration at the broad landscape scale, corroborating the results obtained by Ramoelo et al. (2012). Leaf N concentration was mapped with a prediction error equal to 29% of mean N concentration. The accurate mapping of leaf N concentration with Rapideye imagery can be attributed to the presence of the red-edge band at 710 nm. MTCI, an index derived from the red-edge band at 710 nm provided the highest accuracy of estimation of leaf N in this study. Variations in the red-edge reflectance are mostly controlled by differences in leaf chlorophyll concentration. Therefore, the positive correlation between leaf N and MTCI depends on the positive correlation relationship between leaf N and leaf chlorophyll and this relationship has been shown to vary with leaf phenology (e.g. Huang et al. 2004). Low cost space-borne sensors with strategic bands in the shortwave infrared (SWIR) might improve on the spatial modelling of leaf N because most of the spectral absorption features of N are located in the shortwave infrared (Curran 1989). It is hoped that the Sentinel-2, an upcoming space-borne sensor to be launched by the European Space Agency (ESA) with strategically located bands in the visible to SWIR would provide new opportunities to routinely assess and monitor leaf N stocks in fragmented and subsistence farming landscapes.

The loss of leaf N stock following forest degradation in the tropics is not an unknown phenomenon. However, the ability to map leaf N at the broad landscape facilitates the task of analysing the effect of forest degradation on the spatial distribution of leaf N on a plot-by-plot level, thus permitting a better understanding of different landscape patterns and processes. This is even more relevant in the tropical forest region of Africa, where more than 80% of the population depends on subsistence farming for their livelihoods. Mapping leaf N at the scale of the RapidEye images (5 m) in the tropical forest systems of Africa would allow for a farm-to-farm assessment of leaf N stocks because of the usual small sizes of subsistence fields. For example, this study shows that leaf N in the degraded landscape varies at a scale (50 m) that might corresponds to the size of a subsistence field in the region. Thus, the ability to map leaf N at the farm-size scale might provide a greater understanding of the different land management or farming practices at that scale. Leaf N maps could be used in participatory exercises with the farming communities to create awareness on the consequences of forest degradation on leaf N and hence productivity of subsistence farms.

The results of this study show that deforestation and the subsequent conversion of the degraded area into grasslands leads to loss of N from the system. However, patches of indigenous forest within the degraded areas still retain relatively high concentration of N in their foliage. This also applies to eucalyptus trees which are exotic species grown in the degraded area. The cleared areas in the study site are mostly used for farming of crops like sweet potato, maize and sugarcane. The sandy soils in the area are low in fertility. Thus, soil fertility in the area is highly dependent on the decomposition of the dead organic matter, reason for which crop production declines quickly after one to two years of farming on the cleared land. Furthermore, farming methods used in this area are not adequate to maintain soil fertility for long periods of time. Farmers often resort to clearing more forest area to acquire new fertile lands. The vicious cycle of forest clearance and poor farming methods leads to soil depletion and subsequent acquisition of new fertile forest land, resulting in a high rate of forest loss.

Indigenous forest patches in the degraded area can serve as nutrient sources for the surrounding farmlands. Leaching and surface runoff from the forest patches might feed adjacent grasslands and farmlands with nutrients. While both exotic and indigenous trees have the potential to provide N replenishment in degraded tropical systems, domestication of indigenous tree species has been considered in the past two decades as an alternative to subsistence commercial plantations and slash-and-burn operations associated with the destruction of tropical and sub-tropical indigenous forests (Leakey and Simons, 1998; Simons & Leakey, 2004). Although the commercial value of domesticated indigenous trees might not meet those of eucalyptus in the study area e.g. for the construction business, agroforestry and non-timber products of domesticated indigenous species offer a number of benefits to the poor rural communities in comparison to commercial plantation, which may include:

- Indigenous forest provide food resources, raw material for craft work and medicine to the poor rural communities
- indigenous species might sustain more diversity of plants and animals in the area when compared to the subsistence eucalyptus farms
- patches of indigenous trees may provide corridors of faunal and floral dispersion

Prasad (2003) has recommended that mixed farming practices with patches of indigenous tree species should be encouraged in fragmented landscapes to help sustain biodiversity in degraded tropical forest. On the other hand, allelochemicals in eucalyptus leaf litter may suppress growth of understorey vegetation (May and Ash 1990).

Conclusions

The following conclusions could be drawn from the study:

- Nitrogen can be mapped at peak productivity using RapidEye sensor
- Forest fragmentation significantly affects leaf nitrogen concentration
- Eucalyptus trees tend to accumulate as much leaf nitrogen as the natural forest in the Dukuduku region.

Acknowledgments The Council for Scientific and Industrial Research (CSIR) and the Department of Science and Technology (DST) provided the funding for this study. We wish to thank Oupa Malahlela for atmospherically correcting the RapdEye images used in the study. We also express gratitude to Mr Khanyile MM, the manager of the Dukuduku forest for his wonderful cooperation throughout the project.

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