South African Journal of Geomatics, Vol. 8. No. 2, September 2019

Estimation of foliar nitrogen using remotely sensed data: A quantitative review

Rowan Naicker[1], * Onisimo Mutanga, Kabir Peerbhay

University of KwaZulu-Natal, Agricultural, Earth and Environmental Science, Department of
Geography, P/Bag X01, Scottsville, Pietermaritzburg, South Africa, 3209,
[1]rowannanicker@gmail.com

DOI: *http://dx.doi.org/10.4314/sajg.v8i2.6*

Abstract

Several ecosystems have been significantly altered by anthropogenic nitrogen inputs. The timely estimation of nitrogen concentration is essential for ensuring environmental sustainability. Academic publications between 1966 and 2016 were reviewed to assess the potential of remotely sensed information to estimate nitrogen concentrations for various applications. A discriminatory keyword search and a set of inclusion criteria was used to develop a representative sample (n = 100). Results revealed that the global distribution of academic publications is skewed towards the Northern Hemisphere with the largest research gap occurring within Africa. Moreover, prior to 2006, research into the remote estimation of nitrogen had a minor presence in literature, with the agricultural sector being the most extensively researched (56%). Freely available, high spatial and temporal resolution imagery has afforded research into the remote estimation of nitrogen in the African continent, particularly in the subject area of policy and management, the capacity to grow.

Keywords: *foliar nitrogen; hyperspectral; multispectral; radiative transfer models; remote sensing; the nitrogen cycle.*

1. Introduction

Nitrogen represents 78% of the atmosphere and is vital for all life on Earth (Socolow, 1999). The nitrogen cycle is highly intricate and involves multiple components (Templer *et al*., 2012). These components facilitate the conversion of biologically unreactive nitrogen to a reactive form which can be utilised by organisms (Cassman *et al*., 2002). At the turn of the century, anthropogenic activities such as the production of nitrogen-based fertilizers and the combustion of fossil fuels had radically transformed the natural nitrogen cycle (Hoegberg *et al*., 2006). This increase in anthropogenic activity has accelerated the introduction of nitrogen from long-term soil and organic matter storage (Pardo *et al*., 2011). This has impacted climate change significantly, as nitrogen-based trace gasses, such as nitrous oxide, when released into the atmosphere contributes considerably to the enhancement of the greenhouse effect (Templer *et al*., 2012). To safely sustain the global use of biologically reactive nitrogen, a safe operating space needs to be established (Templer *et al*., 2012).

Planetary boundaries was introduced as a framework to assist in defining a safe operating space for mankind (Rockström *et al*., 2009) and is based on essential biophysical processes which control the regulation of Earth's systems (Steffen *et al*., 2015). Several authors (Rockström et al., 2009, De Vries et al., 2013, Steffen et al., 2015) have stressed that the global planetary boundary for many of these processes, such as nutrient cycling, has been substantially exceeded. For instance, both Templer *et al*. (2012) and Pardo *et al*. (2011), highlight that with the continuous deposition of nitrogen, the available nitrogen pool will exceed that of both plant and microbial demand. This will result in ecosystems reaching a state of nitrogen saturation (Templer *et al*., 2012). Many regions have already experienced the effects of excess nitrogen, through changes in nitrogen cycling and biodiversity. The impacts of which are demonstrated by an increase in eutrophication, nitrate leaching rates, and elevated nitrogen concentrations within plant tissue (Pardo *et al*., 2011). Overall, anthropogenic activities emit approximately 140Tg of new nitrogen into terrestrial ecosystems each year, equalling the amount of naturally occurring fixed nitrogen (Cassman *et al*., 2002, Ling *et al*., 2014). As a result, the planetary boundary for nitrogen has been exceeded globally and this has brought about numerous consequences (Steffen *et al*., 2015).

An increase in anthropogenic nitrogen has several damaging consequences for the health and functioning of ecosystems. For example, grasslands occupy approximately 40% of the Earth's surface and provides vital ecosystem services (Dzerefos and Witkowski, 2001, Egoh *et al*., 2011). Apart from supporting biodiversity and grazing resources, grasslands provide essential services including soil retention, climate regulation, and the regulated flow of water (Naicker *et al*., 2016). In South Africa, the grassland biome sustains a high diversity of endemic flora and fauna and occupies roughly 339 240 km^2 of land (Mucina and Rutherford, 2006, Driver *et al*., 2005). These ecosystems are biologically adapted to function best under nitrogen constraints (Hoegberg *et al*., 2006). Increased nitrogen concentrations can result in nitrate leaching into soils reducing the pH of the soil, causing them to become acidic (Socolow, 1999, Hoegberg *et al*., 2006). Additionally, accumulation of nitrates will reduce soil fertility, as minerals and nutrients essential to plant growth will leach into ground water (Ling *et al*., 2014). This will result in nutrient imbalances, which can reduce photosynthetic ability and cause stunted growth (Cassman *et al*., 2002). Since ecosystems are designed to function best under nitrogen constraints, nitrogen enrichment can result in a shift in the dominant species and reduce overall species diversity and richness (Hoegberg *et al*., 2006). Grasslands provide critical roles within a landscape but are particularly vulnerable to nitrogen fluctuations. The quantification of nitrogen within these ecosystems are crucial to facilitate regional monitoring and maintain a safe operating space.

Over the decades, the determination of nitrogen compounds in agricultural, environmental, and geo-biochemical applications facilitated the development of several laboratory techniques (Kornexl *et al*., 1999). The Kjeldahl digestion method (Labconco, 1998) and the Duma's combustion method, described in Muñoz-Huerta *et al*. (2013), have emerged as reference methods for nitrogen content estimation (Kalra and Jood, 1998). Nonetheless these methods have several disadvantages, in addition to them being time consuming and labour intensive, they require noxious reagents that can be significantly destructive to samples (Labconco, 1998, Domini *et al*., 2009). The emergence of research into plant optics (Gates *et al*., 1965, Allen *et al*., 1969) and the advent of remote sensing has allowed for the non-invasive estimation of both biophysical and biochemical information from vegetation (Asner, 1998).

1.1. The Remote sensing of nitrogen

Several studies have demonstrated that the remote sensing of foliar biochemicals can be achieved through imaging spectroscopy (Gates *et al*., 1965, Curran, 1989, Martin and Aber, 1997, Lepine *et al*., 2016). The interaction of radiation with plant leaves is dependent on the chemical and physical characteristics of the plant (Gates *et al*., 1965). Photosynthetic pigments (i.e. Chlorophyll) absorb both red and blue wavelengths and facilitates visible leaf reflectance (Gates *et al*., 1965). Chlorophyll molecules are the primary plant components responsible for the absorption of electromagnetic energy at specific wavelengths in the electromagnetic spectrum (Ponzoni and De Gonçalves, 1999). These molecules can, however, be influenced by nitrogen (a compound linked to protein synthesis) concentrations (Mutanga *et al*., 2003). Fluctuations in nitrogen levels can disrupt the metabolic function of chlorophyll molecules and affect the photosynthetic process (Mutanga *et al*., 2003). Through this direct interaction, studies have highlighted the strong relationship between foliar nitrogen and chlorophyll (Oppelt, 2002, Mutanga *et al*., 2003). Following the identification of the visible and infrared region of the electromagnetic spectrum as the most characteristic wavelengths for vegetation (Allen *et al*., 1969), further investigations led to the discovery of distinctive spectral signatures for nitrogen and leaf constituents (Himmelsbach *et al*., 1988, Curran, 1989, Martin *et al*., 2008). For instance, Himmelsbach *et al*. (1988) and Curran (1989), documented the absorption features of several different biochemicals through laboratory and field studies (see table 1).

Table 1. Summarised Absorption features of specific biochemicals based on earlier research by Curran (1989), Himmelsbach *et al*. (1988), and Fourty *et al*. (1996).

Absorbing biochemical	**Wavelength (nm)**
Water	970, 1200, 1400, 1450, 1940
Nitrogen	1020, 1510, 1730, 1980, 2060, 2130, 2180, 2240, 2300
Lignin	1120, 1200, 1420, 1450, 1690, 1754, 1940, 2262, 2380

The use of imaging spectroscopy for assessing or estimating vegetation health has regularly been hindered through low spectral resolutions of previous generation sensors. The advancement of optical sensor capabilities has facilitated the improvement of foliar biochemical estimation (Asner, 2000).

1.2. Hyperspectral remote sensing

Early exploration by Card *et al*. (1988) using dried crushed leaves from deciduous and conifer trees demonstrated the utility of spectroscopy for estimating substances such as: chlorophyll, lignin, and nitrogen. The estimation of foliar biochemical properties using high spectral remote sensing has its origins within laboratory spectroscopy (Martin, 1992). This is apparent from studies such as Peterson *et al*. (1988) who replicated laboratory investigations by Card *et al*. (1988), using an airborne imaging spectrometer and a stepwise multiple linear regression to predict foliar biochemicals at a forest canopy level. Hyperspectral remote sensing, which comprises of numerous contiguous spectral bands that range from 350 nm to 2500 nm, can provide detailed spectral information from every pixel in an image (Goetz, 1985). It is an advanced tool that can deliver high spatial and spectral resolution data (Serrano *et al*., 2002). This subsequent data can facilitate the detection of absorption features based on the spectral characteristics of the investigated material (Goetz, 1985). For example, Wessman *et al*. (1988) and Johnston *et al*. (1994), both discovered positive relationships between wavelength segments for lignin and nitrogen and their absorption feature signals.

Several studies (Martin and Aber, 1997, Curran *et al*., 2001, Ollinger *et al*., 2002) have since documented the utility of the near-infrared and the shortwave-infrared regions of the electromagnetic spectrum for estimating foliar biochemicals, with the visible and red-edge sections showing the greatest potential for chlorophyll estimation (Curran *et al*., 2001). Nitrogen, a vital component to the photosynthetic process, has received significant attention (Card *et al*., 1988). Nitrogen has been documented to have absorption features between 1020 nm and 2300 nm of the spectrum (Table 1) (Curran, 1989). However, the spectral regions between 1355 nm – 1450 nm and 1800 nm – 1950 nm are known water absorption features and are usually excluded from analyses (Abdel-Rahman *et al*., 2010). The red-edge region of the electromagnetic spectrum is often used to estimate chlorophyll and nitrogen content (Ramoelo *et al*., 2015b). Furthermore, several studies have demonstrated that the usage of the red-edge part of the spectrum in ratio indices and normalised difference indices can aid in estimating chlorophyll and nitrogen content (Abdel-Rahman *et al*., 2010, Ramoelo *et al*., 2015b).

For instance, Martin and Aber (1997), successfully determined that AVIRIS (400 nm – 2500 nm) data and multiple linear regressions could be used to estimate forest canopy nitrogen and lignin at 20m spatial resolution. In addition, they successfully developed calibration equations linking nitrogen and lignin to selected first difference spectral bands with R^2 values of 0.87 and 0.77, respectively. Similarly, using AVIRIS data, Serrano *et al*. (2002) tested the possibility of estimating canopy nitrogen and lignin in chaparral vegetation with a multiple stepwise regression analysis. With Log transformed R indices based on known nitrogen and lignin absorption features, they demonstrated a significant correlation with canopy biochemical concentrations. Following this, Wang *et al*. (2013) in an unrelated study, compared two types of methods systematically to estimate the nitrogen concentration of rape seed. They discovered that with canopy hyperspectral reflectance data, an artificial neural network is better suited to predicting nitrogen concentrations in rape seed. In a different study, Ling *et al*. (2014) used various platforms to evaluate different methods for estimating canopy nitrogen from a tallgrass prairie with varying treatments. Their results demonstrated that the best method differed between *in situ* and aircraft data between seasons. Using controlled nitrogen addition and reference plots, O'Connell *et al*. (2014) demonstrated that the first order derivative normalised difference index (FDN) $_{1235,\ 549}$ bands were most strongly correlated with foliar nitrogen concentration. Building on this, Lepine *et al*. (2016) examined spectral signatures associated with foliar nitrogen in forests using partial least squares, simple and multiple regression calibration equations in tandem with hyperspectral data. The results produced indicated that most of the variability in canopy nitrogen percentage is linked to the broad reflectance properties in the near-infrared section of the spectrum. This indicates potential for nitrogen estimation at a broad canopy scale from an assortment of sensors.

Nitrogen concentrations within a landscape may vary across different plant species, the ability to remotely detect nitrogen deficiency in different species is extremely valuable. Ferwerda *et al*. (2005) attempted to detect nitrogen with hyperspectral normalised ratio indices for several vegetative types. They concluded that in a mixed-species scenario, the combined use of bands 693 nm and 1770 nm within normalised ratio indices will produce the best nitrogen correlation. Following this development, Martin *et al*. (2008) tested a generalisable technique to assess canopy nitrogen within diverse forest systems. After conducting a partial least squares regression analysis (R^2 values extending from 0.69 to 0.85), they concluded that additional research that contains a broader variety of ecosystems is needed. These and other studies have proved the utility of hyperspectral data to estimate foliar nitrogen and other biochemicals at varying spatial scales (Mutanga *et al*., 2003).

Hyperspectral data, however, is expensive, particularly over large spatial areas and is often difficult to obtain in many regions (Sibanda *et al*., 2015). In addition to these problems, the foliar water content of fresh leaves is often a factor that can mask absorption features of many biochemicals, such as nitrogen (Gao and Goetz, 1994). To address this, the water removal method was derived (Gao and Goetz, 1994). The procedure utilises a nonlinear least squares spectral method that analyses a fresh leaf spectrum as a nonlinear grouping of a fresh leaf water spectrum and a dry-matter spectrum (Schlerf *et al*., 2010). This technique was initially proposed by Gao and Goetz (1994), prior to being revised by Schlerf *et al*. (2010). Thereafter, utilising hyperspectral data, Ramoelo *et al*. (2011) in their study of estimating savanna grass nitrogen, incorporated a similar technique to successfully reduce the effects of foliar moisture on the estimation of biochemicals.

1.3. Multispectral remote sensing

Spatial and spectral monitoring from space was realised through the LANDSAT programme (Serrano *et al*., 2002). Multispectral sensors use a small number of broad spectral bands across the electromagnetic spectrum to obtain spectral data. The data produced by these sensors encompass high temporal and moderately high spatial resolutions, and are often freely available to resource constrained areas (Lu, 2006). Regardless of this, a large portion of the available research has critiqued the low spectral resolutions and large swath widths as hindering the ability to adequately discriminate the differences in plant characteristics (Hansen and Schjoerring, 2003).

However, advancements in multispectral sensors which include improved spectral resolutions and improved bandwidths has provided a greater potential for vegetation mapping applications (Oumar and Mutanga, 2013). Thus, a growing body of literature has emerged which document the capabilities of new generation multispectral remote sensing sensors in estimating biochemical properties (Serrano et al., 2002, Perry et al., 2012). For instance, Ramoelo *et al*. (2012) used the RapidEye multispectral sensor, which has a 440nm – 850nm spectral resolution and a 5m spatial resolution, to successfully regionally map foliar and canopy nitrogen. They established the potential of mapping grass nutrients at a regional scale using a non-linear spatial least squares regression. Similarly, Perry et al. (2012) used multispectral RapidEye imagery to rapidly estimate canopy nitrogen of cereal crops at a paddock scale. The results produced by the canopy chlorophyll content index, however, were indecisive, as R^2 values for individual datasets ranged from 0 to 0.70. Ramoelo *et al*. (2015b), achieved more definitive results in their study of monitoring foliar nitrogen and above ground biomass using higher resolution Worldview-2 (3m spatial resolution) satellite images. Their results indicated that foliar nitrogen concentrations for grass and trees species were explained by over 89% by the random forest algorithm and vegetation indices, with red-edge derived vegetation indices identified as crucial for estimating foliar nitrogen.

A few studies have investigated the effectiveness of Sentinel-2 imagery in detecting leaf nitrogen content at a broader landscape scale (Sibanda *et al*., 2015). For example, Ramoelo *et al*. (2015a) tested the potential of Sentinel-2 to estimate leaf nitrogen concentrations within the African savanna by resampling field hyperspectral data to the spectral bands of Sentinel-2. They were able to explain 90% of leaf nitrogen variation using a random forest algorithm. Similarly, Sibanda *et al*. (2015) resampled hyperspectral data to the spectral resolutions of Sentinel-2 and Landsat OLI. They concluded that with the use of a sparse partial least squares regression, both Sentinel-2 ($R^2 = 0.81$) and Landsat OLI ($R^2 = 0.76$) are promising multispectral sensors for regional scale application in resource constrained regions.

1.4. Radiative transfer models.

Several studies have demonstrated the versatility of remote sensing for the estimation of vegetation properties at both leaf and canopy level (Feret et al., 2008, Gitelson et al., 2005, Asner and Martin, 2015). Historically, two main approaches have been utilised by the remote sensing community to derive plant biochemical information from remotely sensed data, namely: statistical methods, and physical methods (Ali *et al.*, 2016). Statistical methods, which includes both univariate and multivariate models (such as Partial least squares regressions and machine learning algorithms) usually combined with spectral vegetation indices, are used to obtain a relationship between vegetation properties and its spectral reflectance (Féret *et al.*, 2017, Asner and Martin, 2009, Le Maire *et al.*, 2011). These methods allow for the uncomplicated and timely assessment of vegetation attributes. However, due to the empirical nature of these methods, these models depend on the quality and variability of the data used (Le Maire *et al.*, 2011). Thus, their use can be limited to the representativeness of the calibration dataset (Féret *et al.*, 2017). Physical model approaches, such as the inversion of Radiative Transfer Models (RTM), provides an alternative (Ali *et al.*, 2016).

Radiative Transfer Model (RTM) approaches have been derived to characterise the interaction of diverse vegetation properties with incoming solar radiation (Koetz *et al.*, 2007). These models offer a clear connection between plant variables and the resultant spectral signature (Koetz *et al.*, 2007). RTM approaches have been established and revised since the early 1990s (Vilfan *et al.*, 2016). Initial research on leaf reflectance modelling was founded upon the “Kubelka-Munk” radiative transfer theory (Allen and Richardson, 1968), which is a dual approximation to the radiative transfer equation. Thereafter, Allen *et al.* (1969), developed the multiple “Plate” model that formed the basis of the “PROSPECT” model, derived by Jacquemoud and Baret (1990). The PROSPECT model is one of several leaf optical models designed to simulate the radiative transfer of light and biochemical properties (Dawson et al., 1998, Le Maire et al., 2011). It also describes the optical properties of plant leaves from 400 nm to 2500 nm with minimal parameters to support model inversion (Jacquemoud and Baret, 1990). Several studies have utilised the PROSPECT model to derive biochemical properties (Fourty *et al.*, 1996, Jacquemoud *et al.*, 1996, Jay *et al.*, 2016). For example, Feret *et al.* (2008), used PROSPECT-4 and 5 models to separate photosynthetic pigments. Their testing revealed that their new chlorophyll (RMSE = 9 $\mu g/cm^2$) and carotenoid (RMSE=3 $\mu g/cm^2$) specific absorption coefficients correlated with available *in vitro* absorption spectra. Whilst in a different study, Ali *et al.* (2016), successfully inverted the PROSPECT model to estimate leaf dry matter content (R^2 = 0.83) and specific leaf area (R^2 = 0.89). Although few studies have successfully utilised RTM approaches to indirectly estimate foliar nitrogen, RTM approaches can be considered robust and could be utilised for the large-scale estimation of foliar N, in addition to allowing nitrogen estimation models to be transferrable from one site to another.

Nonetheless, several studies (Martin *et al.*, 2008, Lepine *et al.*, 2016) have also shown the capacity of remote nitrogen estimation in regional monitoring. In particular, Martin and Aber (1997), concluded that remote sensing is central in monitoring and understanding how changes in forest ecosystem function can influence global biogeochemical cycles. As a result, the remote estimation of nitrogen is a field which can facilitate the creation of a safe operating space for biogeochemical cycles (Ling *et al.*, 2014).

This review delivers a systematic account of published literature directly associated with the use of remote sensing data in quantifying foliar nitrogen concentrations. Here, we exhibit examples from the available literature that summarise; a) the trends and number of studies published, b) types of applications and challenges associated with the research, and c) recommendations for future research, highlighting gaps and opportunities. In order to accomplish this, the relevant literature was methodically searched for explicit information concerning the remote sensing sensor used, the application of the research, and its geographical distribution.

2. Methods

This review paper, systematically focused on academic publications that investigated the estimation of foliar nitrogen levels for application in different sectors (e.g. agriculture, policy and management, academic research), between the years of 1966 and 2016. The method used to query relevant literature undertook a discriminatory keyword search within specific scientific platforms (i.e. Scopus and Web of Science) (de Araujo Barbosa *et al.*, 2015). A combined word search for “Remote Sensing” and “Nitrogen” was used in each academic platform to produce an extensive list of articles. A set of fixed inclusion criteria was applied using the Scopus and Web of Science platforms to obtain a more representative body of literature. These criteria included:

1) Literature should have “Remote sensing” or “Nitrogen” as the main or secondary subject area.
2) The keywords should exist as a whole in either the: title, keywords, or abstract.
3) The paper should be published in a scientific peer-reviewed journal.
4) The paper should be written in English (de Araujo Barbosa *et al.*, 2015).

Figure 1 demonstrates a simplified flow of the literature selection process. Preliminary search results produced a vast body of literature (*n* = 4345). The use of the inclusion criteria drastically reduced this list (*n* = 3069). Furthermore, only papers that met the criteria of peer-reviewed publication were included, this meant that books, grey literature, extended abstracts and presentations were excluded (*n* = 2994) (de Araujo Barbosa *et al.*, 2015). The DOI numbers of literature that were not excluded during the data extraction process were recorded in an Endnote database. This allowed for duplicate papers to be removed from the relevant literature (*n* = 2527). Thereafter, due to the large consortium of literature, the papers were sorted by their DOI numbers within and excel database and a random sample was used for closer analysis (*n* = 100).

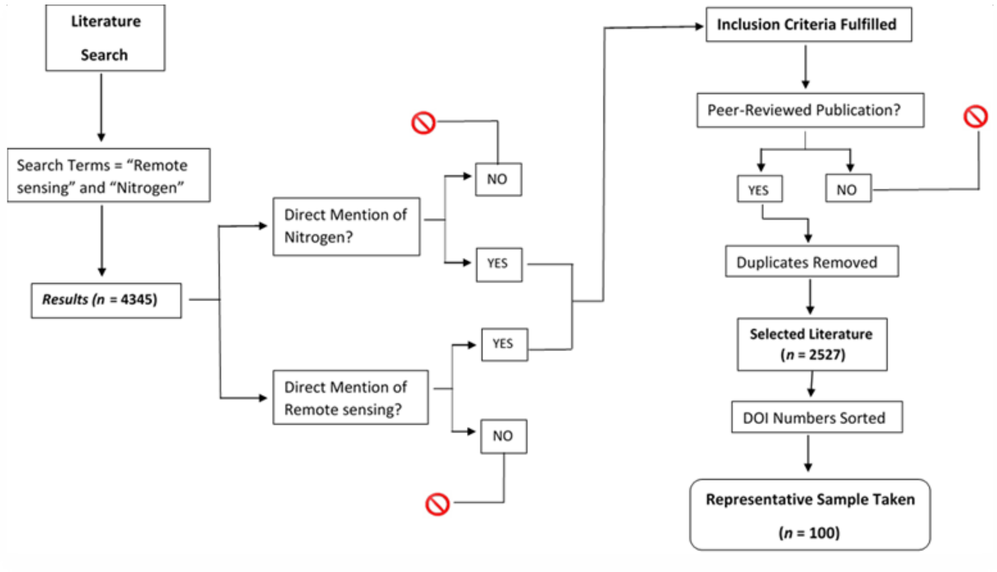

Figure 1. Flow diagram demonstrating the literature search process (modified from de Araujo Barbosa *et al*. (2015)).

3. Results

3.1. Numbers and spatial distribution of Research

Upon conclusion of the literature search, it was discovered that the amount of academic publications directly related to the subject of remote sensing and nitrogen grew from 1 published paper in 1966 to a collection of 2527 papers in 2016 (Figure 2). This exponential increase within a 50-year period denotes a rapid development of interest within this research space. However, on closer examination, it is evident that the global distribution of the research undertaken is heavily populated within the Northern Hemisphere, with the largest research gap prevalent within the African Continent (Figure 3). Other geographical regions that lack research into the remote estimation of nitrogen include Central America, Eastern Europe, and the Middle East. This gap in geographical focus persists due to a lack of availability and access to remote sensing resources in these regions.

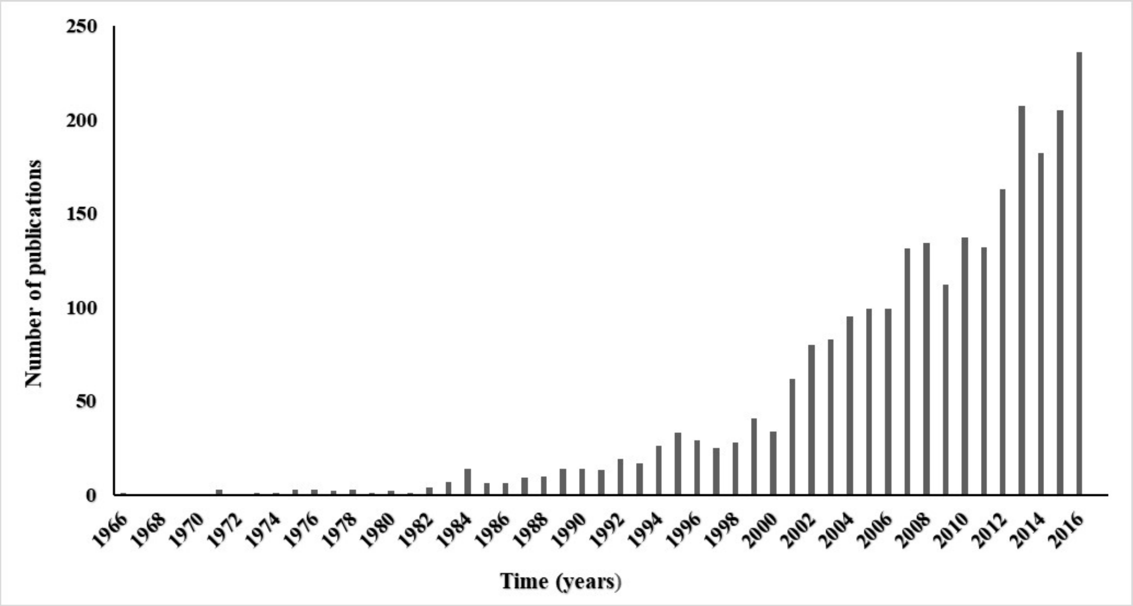

Figure 2. Number of remote sensing and nitrogen papers published annually between 1966 and 2016.

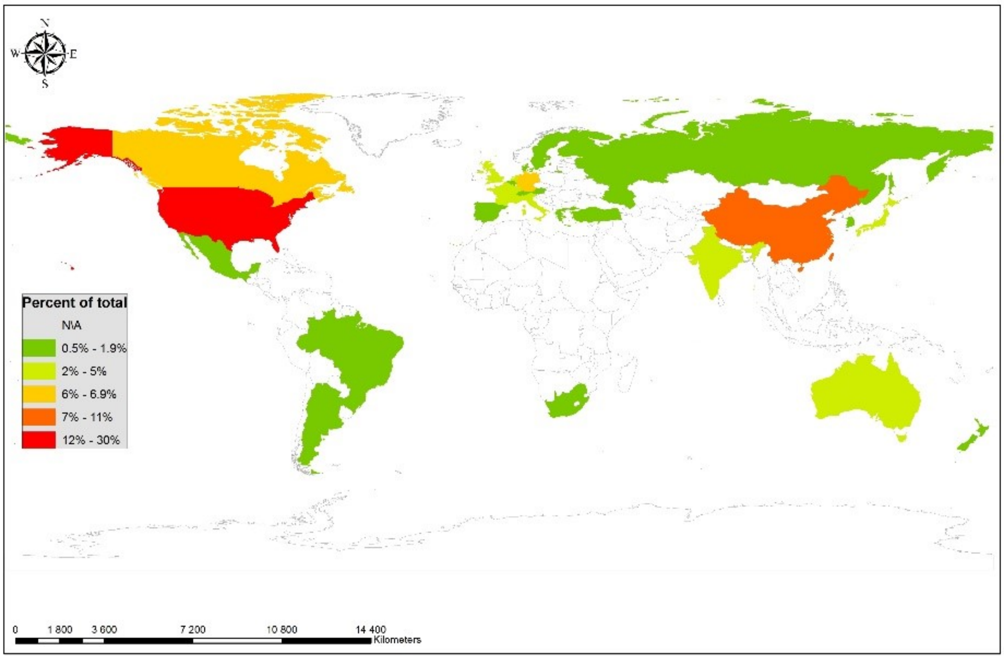

Figure 3. Global distribution of all published remote sensing and nitrogen estimation papers published between 1966 and 2016.

Figure 4 demonstrates the application focus of publications within the field of remote sensing and nitrogen estimation. A large consortium (56%) of the published work exists under the confines of agricultural research. Research into precision agriculture for cultivation purposes is the most investigated. For example, Fitzgerald *et al*. (2010), acquired field hyperspectral measurements and used both a canopy chlorophyll context index and a canopy nitrogen index to adequately manage nitrogen fertiliser application in wheat crops. In a similar study, Perry et al. (2012) combined multispectral data with a canopy chlorophyll context index to rapidly estimate canopy nitrogen and provide optimal support for nitrogen fertiliser management in cereal crops. Research into the remote nitrogen estimation for rangeland and forestry applications has not been as extensive as the investigation into precision agriculture. Several studies have demonstrated that the ability to remotely detect nitrogen concentrations is invaluable for rangeland and forestry applications. For example, Ramoelo *et al.* (2012) demonstrated that the red-edge band of the RapidEye sensor can assist in mapping grass nutrients at a regional scale. Figure 4 further highlights that limited research incorporates remote sensing with the intention to influence nitrogen management, with only 8% of publish work referring directly to policy and nitrogen management.

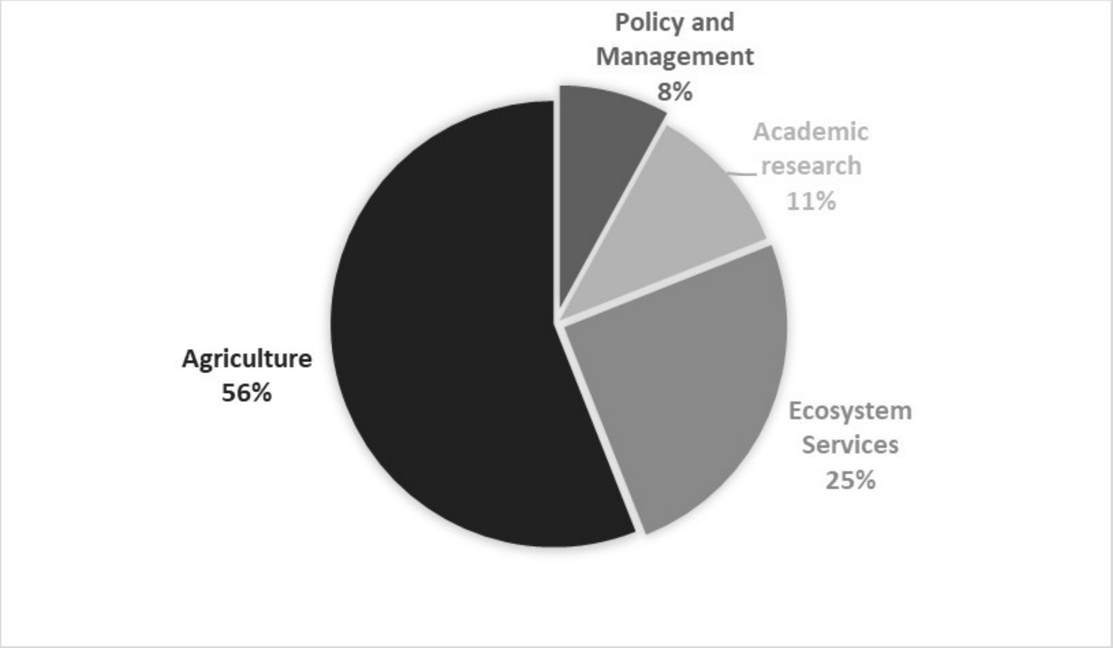

Figure 4. Application focus of Remote sensing and nitrogen publications.

4. Discussion

4.1. Challenges

The number of publications that incorporated remote sensing and the estimation of nitrogen concentrations has been limited. However, since 2006, the number of publications has grown exponentially indicating that more applications are integrating remote sensing for nitrogen determination in various disciplines. Despite the successes of the investigations reported, the growing rate of publications integrating remote sensing has alluded to regions for further development, particularly regarding practical applications. Here we contemplate some of the challenges identified within the literature reviewed and present viable solutions.

The use of hyperspectral and multispectral imagery still faces several challenges. For instance, many hyperspectral studies of foliar biochemistry founded on foliar reflectance were recorded under laboratory conditions (Gates *et al.*, 1965, Curran *et al.*, 2001). Inconsistencies regarding inadequate signal spread from the leaf to canopy level because of leaf morphology (i.e. leaf area, leaf angle, and canopy closure) plague the identification of biochemical absorption features at a canopy scale (Asner, 2000). To account for these complications, predictors which are independent to vegetation structure are required (Majeke *et al.*, 2008).

Furthermore, foliar water content of fresh leaves is often a factor that can disguise absorption features in the near-infrared and shortwave-infrared regions of the spectrum for many biochemicals, principally nitrogen (Gao and Goetz, 1994). An investigation by Curran (1989), revealed several biochemical absorption features (including nitrogen) exists within regions of the spectrum synonymous with water absorption. To reduce the effect of foliar moisture on the approximation of biochemicals, Gao and Goetz (1994) developed a technique to eliminate the impacts of water absorption centres on biochemical estimation in fresh foliage. This technique was modified and applied successfully by Schlerf *et al.* (2010) to predict nitrogen concentrations in Norwegian spruce needle. Building on this, Ramoelo *et al.* (2011) in their study of estimating savanna grass nitrogen and phosphorus concentrations, deduced that the water removed spectra technique produced a greater nitrogen estimation accuracy as opposed to conventional first derivative transformations with an R^2 of 0.84 and an RMSE of 0.28 compared to 0.59 and 0.45 respectively.

Lastly, accurate biochemical estimations can be hampered by a high supply of nitrogen. With an elevated supply of nitrogen, chlorophyll molecules can reach a stage of saturation, which may prevent the detection of excessive nitrogen in plants (Muñoz-Huerta *et al.*, 2013). Nevertheless, this can be corrected with relative chlorophyll concentration values, which can be derived from reference nitrogen plots (Serrano *et al.*, 2002).

4.2. The development of new technology and future opportunities

A large proportion of the research into nitrogen estimation utilised hyperspectral sensors as opposed to multispectral sensors. Several studies (Curran *et al.*, 2001, Hansen and Schjoerring, 2003, Mutanga *et al.*, 2003) have cited the low spectral resolutions and large swath widths of the previous generation of multispectral sensors as hindering the ability to adequately discriminate differences in plant characteristics. The development of new generation satellites such as high-resolution Worldview-3 (31 cm) and freely available 13 band Sentinel-2 offer high spatio-temporal resolutions to previously resource restricted regions (Kruse *et al.*, 2015). The unique spectral and spatial characteristics provide greater opportunities to rapidly detect and monitor environmental changes, such as mapping changes in nitrogen concentrations over larger areas of interest. WorldView-3 was introduced as a super-spectral, high resolution commercial satellite by DigitalGlobe (Wang *et al.*, 2016b). It has an average revisit time of < 1 day and boasts a 31-cm panchromatic resolution, 1.24 m multispectral resolution, and a 3.7 m short-wave infrared resolution (Kruse *et al.* 2015). WorldView-3 images can be used for a wide-range of applications, such as the monitoring of vegetation, however, the cost of purchasing these images are exorbitant (Wang *et al.*, 2016b).

Sentinel-2, which offers a high-spatio-temporal resolution and is freely accessible, offers a cost-effective option. Sentinel-2 is part of the Copernicus programme introduced by the European Space Agency (ESA) designed for the operational needs of the “Global Monitoring for Environment and Security” program (Clevers and Gitelson, 2013). The satellite is equipped with a Multi-spectral instrument (MSI) that will provide high spectral, temporal and spatial resolution imagery. It will cover the visible, near-infrared and the shortwave infrared parts of the electromagnetic spectrum (Gitelson *et al*., 2005). This is expected to further improve remote sensing capabilities for mapping Leaf Area Index (LAI), Chlorophyll Content, and Foliar Nitrogen (Ollinger, 2011). In addition, this will ensure that research into policy and management applications within the Southern Hemisphere will not be inhibited by a lack of high spatial and temporal resolution satellite imagery.

Furthermore, in recent years many studies have combined Light Detection and Ranging (LiDAR) with other remotely sensed datasets to facilitate the estimation of foliar nutrients (Gokkaya *et al*., 2015). For example, during an investigation of foliar nitrogen estimation in rice using hyperspectral LiDAR, Du *et al*. (2016), concluded that characteristic wavelengths of hyperspectral lidar systems can be flexibly selected according to different requirements and can be applied in other research applications (such as environmental monitoring). Moreover, the capabilities of Synthetic Aperture Radar (SAR) imagery in facilitating the remote estimation of nitrogen concentrations should be investigated. It has been highly effective in other areas of environmental research (e.g. studies of mangrove forests) due to its cost effectiveness and large-scale coverage (Wang *et al*., 2016a).

5. Summary and Conclusion

This review has summarized the progression of research from the sole laboratory estimation of nitrogen, towards the use of remotely sensed data in estimating foliar nitrogen concentrations. A quantitative description showing the number of publications, both temporally and spatially, was achieved through a methodical assessment of the available literature. The capacity to remotely estimate nitrogen concentrations, particularly over large landscape regions has vastly improved over the last decade. Despite this, there are several factors that future research needs to consider. Moreover, there is a glaring gap within the research into the policy and management of nitrogen. Further investigation into the remote estimation of nitrogen to expressly influence policy is required to adhere to the confines of a safe operating space. The introduction of freely available, high spatial and temporal resolution imagery has opened the door for future investigation within the Southern Hemisphere.

6. Acknowledgements

This study was supported by eThekwini Municipality through the Durban Research Action Partnership, as a part of The Global Environmental Change Programme. The South African

Research Chairs Initiative of the Department of Science and Technology and the National Research Foundation of South Africa (grant no. 84157 and 114898) financially supported this research.

7. References

Abdel-Rahman, E. M., Ahmed, F. B., Van Den Berg, M. & Way, M. J. 2010, Potential Of Spectroscopic Data Sets For Sugarcane Thrips (Fulmekiola Serrata Kobus) Damage Detection. *International Journal Of Remote Sensing,* 31**,** 4199-4216.

Ali, A. M., Darvishzadeh, R., Skidmore, A. K., Van Duren, I., Heiden, U. & Heurich, M. 2016, Estimating Leaf Functional Traits By Inversion Of Prospect: Assessing Leaf Dry Matter Content And Specific Leaf Area In Mixed Mountainous Forest. *International Journal Of Applied Earth Observation And Geoinformation,* 45**,** 66-76.

Allen, W. A., Gausman, H. W., Richardson, A. J. & Thomas, J. R. 1969, Interaction Of Isotropic Light With A Compact Plant Leaf. *Josa,* 59**,** 1376-1379.

Allen, W. A. & Richardson, A. J. 1968, Interaction Of Light With A Plant Canopy. *Josa,* 58**,** 1023-1028.

Asner, G. P. 1998, Biophysical And Biochemical Sources Of Variability In Canopy Reflectance. *Remote Sensing Of Environment,* 64**,** 234-253.

Asner, G. P. 2000, Contributions Of Multi-View Angle Remote Sensing To Land-Surface And Biogeochemical Research. *Remote Sensing Reviews,* 18**,** 137-162.

Asner, G. P. & Martin, R. E. 2009, Airborne Spectranomics: Mapping Canopy Chemical And Taxonomic Diversity In Tropical Forests. *Frontiers In Ecology And The Environment,* 7**,** 269-276.

Asner, G. P. & Martin, R. E. 2015, Spectroscopic Remote Sensing Of Non-Structural Carbohydrates In Forest Canopies. *Remote Sensing,* 7**,** 3526-3547.

Card, D. H., Peterson, D. L., Matson, P. A. & Aber, J. D. 1988, Prediction Of Leaf Chemistry By The Use Of Visible And Near Infrared Reflectance Spectroscopy. *Remote Sensing Of Environment,* 26**,** 123-147.

Cassman, K. G., Dobermann, A. & Walters, D. T. 2002, Agroecosystems, Nitrogen-Use Efficiency, And Nitrogen Management. *Ambio: A Journal Of The Human Environment,* 31**,** 132-140.

Clevers, J. G. P. W. & Gitelson, A. A. 2013, Remote Estimation Of Crop And Grass Chlorophyll And Nitrogen Content Using Red-Edge Bands On Sentinel-2 And-3. *International Journal Of Applied Earth Observation And Geoinformation,* 23**,** 344-351.

Curran, P. J. 1989, Remote Sensing Of Foliar Chemistry. *Remote Sensing Of Environment,* 30**,** 271-278.

Curran, P. J., Dungan, J. L. & Peterson, D. L. 2001, Estimating The Foliar Biochemical Concentration Of Leaves With Reflectance Spectrometry: Testing The Kokaly And Clark Methodologies. *Remote Sensing Of Environment,* 76**,** 349-359.

Dawson, T. P., Curran, P. J. & Plummer, S. E. 1998, The Biochemical Decomposition Of Slash Pine Needles From Reflectance Spectra Using Neural Networks. *International Journal Of Remote Sensing,* 19**,** 1433-1438.

De Araujo Barbosa, C. C., Atkinson, P. M. & Dearing, J. A. 2015, Remote Sensing Of Ecosystem Services: A Systematic Review. *Ecological Indicators,* 52**,** 430-443.

De Vries, W., Kros, J., Kroeze, C. & Seitzinger, S. P. 2013, Assessing Planetary And Regional Nitrogen Boundaries Related To Food Security And Adverse Environmental Impacts. *Current Opinion In Environmental Sustainability,* 5**,** 392-402.

Domini, C., Vidal, L., Cravotto, G. & Canals, A. 2009, A Simultaneous, Direct Microwave/Ultrasound-Assisted Digestion Procedure For The Determination Of Total Kjeldahl Nitrogen. *Ultrasonics Sonochemistry,* 16**,** 564-569.

Driver, A., Maze, K., Rouget, M., Lombard, A. T., Nel, J., Turpie, J. K., Cowling, R. M., Desmet, P., Goodman, P. & Harris, J. 2005, National Spatial Biodiversity Assessment 2004: Priorities For Biodiversity Conservation In South Africa.

Du, L., Gong, W., Shi, S., Yang, J., Sun, J., Zhu, B. & Song, S. 2016, Estimation Of Rice Leaf Nitrogen Contents Based On Hyperspectral Lidar. *International Journal Of Applied Earth Observation And Geoinformation,* 44**,** 136-143.

Dzerefos, C. M. & Witkowski, E. 2001, Density And Potential Utilisation Of Medicinal Grassland Plants From Abe Bailey Nature Reserve, South Africa. *Biodiversity & Conservation,* 10**,** 1875-1896.

Egoh, B. N., Reyers, B., Rouget, M. & Richardson, D. M. 2011, Identifying Priority Areas For Ecosystem Service Management In South African Grasslands. *Journal Of Environmental Management,* 92**,** 1642-1650.

Feret, J.-B., François, C., Asner, G. P., Gitelson, A. A., Martin, R. E., Bidel, L. P., Ustin, S. L., Le Maire, G. & Jacquemoud, S. 2008, Prospect-4 And 5: Advances In The Leaf Optical Properties Model Separating Photosynthetic Pigments. *Remote Sensing Of Environment,* 112**,** 3030-3043.

Féret, J.-B., Gitelson, A., Noble, S. & Jacquemoud, S. 2017, Prospect-D: Towards Modeling Leaf Optical Properties Through A Complete Lifecycle. *Remote Sensing Of Environment,* 193**,** 204-215.

Ferwerda, J. G., Skidmore, A. K. & Mutanga, O. 2005, Nitrogen Detection With Hyperspectral Normalized Ratio Indices Across Multiple Plant Species. *International Journal Of Remote Sensing,* 26**,** 4083-4095.

Fitzgerald, G., Rodriguez, D. & O'leary, G. 2010, Measuring And Predicting Canopy Nitrogen Nutrition In Wheat Using A Spectral Index—The Canopy Chlorophyll Content Index (Ccci). *Field Crops Research,* 116**,** 318-324.

Fourty, T., Baret, F., Jacquemoud, S., Schmuck, G. & Verdebout, J. 1996, Leaf Optical Properties With Explicit Description Of Its Biochemical Composition: Direct And Inverse Problems. *Remote Sensing Of Environment,* 56**,** 104-117.

Gao, B.-C. & Goetz, A. F. 1994, Extraction Of Dry Leaf Spectral Features From Reflectance Spectra Of Green Vegetation. *Remote Sensing Of Environment,* 47**,** 369-374.

Gates, D. M., Keegan, H. J., Schleter, J. C. & Weidner, V. R. 1965, Spectral Properties Of Plants. *Applied Optics,* 4**,** 11-20.

Gitelson, A. A., Vina, A., Ciganda, V., Rundquist, D. C. & Arkebauer, T. J. 2005, Remote Estimation Of Canopy Chlorophyll Content In Crops. *Geophysical Research Letters,* 32.

Goetz, A. F. 1985, Portable Instant Display And Analysis Reflectance Spectrometer. Google Patents.

Gokkaya, K., Thomas, V., Noland, T., Mccaughey, H., Morrison, I. & Treitz, P. 2015, Mapping Continuous Forest Type Variation By Means Of Correlating Remotely Sensed Metrics To Canopy N:P Ratio In A Boreal Mixedwood Forest. *Applied Vegetation Science,* 18**,** 143-157.

Hansen, P. M. & Schjoerring, J. K. 2003, Reflectance Measurement Of Canopy Biomass And Nitrogen Status In Wheat Crops Using Normalized Difference Vegetation Indices And Partial Least Squares Regression. *Remote Sensing Of Environment,* 86**,** 542-553.

Himmelsbach, D., Boer, H., Akin, D. & Barton, F. 1988, Solid-State 13c Nmr, Ftir, And Nirs Spectroscopic Studies Of Ruminant Silage Digestion. *Analytical Applications Of Spectroscopy/Edited By Cs Creaser And Amc Davies*.

Hoegberg, P., Fan, H., Quist, M., Binkley, D. & Tamm, C. O. 2006, Tree Growth And Soil Acidification In Response To 30 Years Of Experimental Nitrogen Loading On Boreal Forest. *Global Change Biology,* 12**,** 489-499.

Jacquemoud, S. & Baret, F. 1990, Prospect: A Model Of Leaf Optical Properties Spectra. *Remote Sensing Of Environment,* 34**,** 75-91.

Jacquemoud, S., Ustin, S. L., Verdebout, J., Schmuck, G., Andreoli, G. & Hosgood, B. 1996, Estimating Leaf Biochemistry Using The Prospect Leaf Optical Properties Model. *Remote Sensing Of Environment,* 56**,** 194-202.

Jay, S., Bendoula, R., Hadoux, X., Feret, J. B. & Gorretta, N. 2016, A Physically-Based Model For Retrieving Foliar Biochemistry And Leaf Orientation Using Close-Range Imaging Spectroscopy. *Remote Sensing Of Environment,* 177**,** 220-236.

Johnston, A., Mcewen, J., Lane, P., Hewitt, M., Poulton, P. & Yeoman, D. 1994, Effects Of One To Six Year Old Ryegrass-Clover Leys On Soil Nitrogen And On The Subsequent Yields And Fertilizer Nitrogen Requirements Of The Arable Sequence Winter Wheat, Potatoes, Winter Wheat, Winter Beans (Vicia Faba) Grown On A Sandy Loam Soil. *The Journal Of Agricultural Science,* 122**,** 73-89.

Kalra, S. & Jood, S. 1998, Biological Evaluation Of Protein Quality Of Barley. *Food Chemistry,* 61**,** 35-39.

Koetz, B., Sun, G., Morsdorf, F., Ranson, K., Kneubühler, M., Itten, K. & Allgöwer, B. 2007, Fusion Of Imaging Spectrometer And Lidar Data Over Combined Radiative Transfer Models For Forest Canopy Characterization. *Remote Sensing Of Environment,* 106**,** 449-459.

Kornexl, B. E., Gehre, M., Höfling, R. & Werner, R. A. 1999, On-Line Δ18o Measurement Of Organic And Inorganic Substances. *Rapid Communications In Mass Spectrometry,* 13**,** 1685-1693.

Kruse, F. A., Baugh, W. M. & Perry, S. L. 2015, Validation Of Digitalglobe Worldview-3 Earth Imaging Satellite Shortwave Infrared Bands For Mineral Mapping. *Journal Of Applied Remote Sensing,* 9**,** 096044-096044.

Labconco, C. 1998, A Guide To Kjeldahl Nitrogen Determination Methods And Apparatus. *Labconco Corporation: Houston, Tx, Usa*.

Le Maire, G., Marsden, C., Verhoef, W., Ponzoni, F. J., Seen, D. L., Bégué, A., Stape, J.-L. & Nouvellon, Y. 2011, Leaf Area Index Estimation With Modis Reflectance Time Series And Model Inversion During Full Rotations Of Eucalyptus Plantations. *Remote Sensing Of Environment,* 115**,** 586-599.

Lepine, L. C., Ollinger, S. V., Ouimette, A. P. & Martin, M. E. 2016, Examining Spectral Reflectance Features Related To Foliar Nitrogen In Forests: Implications For Broad-Scale Nitrogen Mapping. *Remote Sensing Of Environment,* 173**,** 174-186.

Ling, B., Goodin, D. G., Mohler, R. L., Laws, A. N. & Joern, A. 2014, Estimating Canopy Nitrogen Content In A Heterogeneous Grassland With Varying Fire And Grazing Treatments: Konza Prairie, Kansas, Usa. *Remote Sensing,* 6**,** 4430-4453.

Lu, D. 2006, The Potential And Challenge Of Remote Sensing-Based Biomass Estimation. *International Journal Of Remote Sensing,* 27**,** 1297-1328.

Majeke, B., Van Aardt, J. A. N. & Cho, M. A. 2008, Imaging Spectroscopy Of Foliar Biochemistry In Forestry Environments. *Southern Forests,* 70**,** 275-285.

Martin, K. 1992, Recent Advances In Near-Infrared Reflectance Spectroscopy. *Applied Spectroscopy Reviews,* 27**,** 325-383.

Martin, M. E. & Aber, J. D. 1997, High Spectral Resolution Remote Sensing Of Forest Canopy Lignin, Nitrogen, And Ecosystem Processes. *Ecological Applications,* 7**,** 431-443.

Martin, M. E., Plourde, L., Ollinger, S., Smith, M.-L. & Mcneil, B. 2008, A Generalizable Method For Remote Sensing Of Canopy Nitrogen Across A Wide Range Of Forest Ecosystems. *Remote Sensing Of Environment,* 112**,** 3511-3519.

Mucina, L. & Rutherford, M. 2006, The Vegetation Of South Africa, Lesoto And Swaziland. Strelitzia 19. South African National Biodiversity Institute, Pretoria. *Memoirs Of The Botanical Survey Of South Africa*.

Muñoz-Huerta, R. F., Guevara-Gonzalez, R. G., Contreras-Medina, L. M., Torres-Pacheco, I., Prado-Olivarez, J. & Ocampo-Velazquez, R. V. 2013, A Review Of Methods For Sensing The Nitrogen Status In Plants: Advantages, Disadvantages And Recent Advances. *Sensors (Switzerland),* 13**,** 10823-10843.

Mutanga, O., Skidmore, A. K. & Van Wieren, S. 2003, Discriminating Tropical Grass (Cenchrus Ciliaris) Canopies Grown Under Different Nitrogen Treatments Using Spectroradiometry. *Isprs Journal Of Photogrammetry And Remote Sensing,* 57**,** 263-272.

Naicker, R., Rouget, M. & Mutanga, O. 2016, Assessing Habitat Fragmentation Of The Kwazulu-Natal Sandstone Sourveld, A Threatened Ecosystem. *Bothalia-African Biodiversity & Conservation,* 46**,** 1-10.

O'connell, J. L., Byrd, K. B. & Kelly, M. 2014, Remotely-Sensed Indicators Of N-Related Biomass Allocation In Schoenoplectus Acutus. *Plos One,* 9.

Ollinger, S. V. 2011, Sources Of Variability In Canopy Reflectance And The Convergent Properties Of Plants. *New Phytologist,* 189**,** 375-394.

Ollinger, S. V., Smith, M. L., Martin, M. E., Hallett, R. A., Goodale, C. L. & Aber, J. D. 2002, Regional Variation In Foliar Chemistry And N Cycling Among Forests Of Diverse History And Composition. *Ecology,* 83**,** 339-355.

Oppelt, N. 2002, *Monitoring Of Plant Chlorophyll And Nitrogen Status Using The Airborne Imaging Spectrometer Avis.* Lmu.

Oumar, Z. & Mutanga, O. 2013, Using Worldview-2 Bands And Indices To Predict Bronze Bug (Thaumastocoris Peregrinus) Damage In Plantation Forests. *International Journal Of Remote Sensing,* 34**,** 2236-2249.

Pardo, L. H., Fenn, M. E., Goodale, C. L., Geiser, L. H., Driscoll, C. T., Allen, E. B., Baron, J. S., Bobbink, R., Bowman, W. D. & Clark, C. M. 2011, Effects Of Nitrogen Deposition And Empirical Nitrogen Critical Loads For Ecoregions Of The United States. *Ecological Applications,* 21**,** 3049-3082.

Perry, E. M., Fitzgerald, G. J., Nuttall, J. G., O'leary, G. J., Schulthess, U. & Whitlock, A. 2012, Rapid Estimation Of Canopy Nitrogen Of Cereal Crops At Paddock Scale Using A Canopy Chlorophyll Content Index. *Field Crops Research,* 134**,** 158-164.

Peterson, D. L., Aber, J. D., Matson, P. A., Card, D. H., Swanberg, N., Wessman, C. & Spanner, M. 1988, Remote Sensing Of Forest Canopy And Leaf Biochemical Contents. *Remote Sensing Of Environment,* 24**,** 85-108.

Ponzoni, F. J. & De Gonçalves, J. L. M. 1999, Spectral Features Associated With Nitrogen, Phosphorus, And Potassium Deficiencies In Eucalyptus Saligna Seedling Leaves. *International Journal Of Remote Sensing,* 20**,** 2249-2264.

Ramoelo, A., Cho, M., Mathieu, R. & Skidmore, A. K. 2015a, Potential Of Sentinel-2 Spectral Configuration To Assess Rangeland Quality. *Journal Of Applied Remote Sensing,* 9**,** 094096.

Ramoelo, A., Cho, M. A., Mathieu, R., Madonsela, S., Van De Kerchove, R., Kaszta, Z. & Wolff, E. 2015b, Monitoring Grass Nutrients And Biomass As Indicators Of Rangeland Quality And Quantity Using Random Forest Modelling And Worldview-2 Data. *International Journal Of Applied Earth Observation And Geoinformation,* 43**,** 43-54.

Ramoelo, A., Skidmore, A. K., Cho, M. A., Schlerf, M., Mathieu, R. & Heitkönig, I. M. 2012, Regional Estimation Of Savanna Grass Nitrogen Using The Red-Edge Band Of The Spaceborne Rapideye Sensor. *International Journal Of Applied Earth Observation And Geoinformation,* 19**,** 151-162.

Ramoelo, A., Skidmore, A. K., Schlerf, M., Mathieu, R. & Heitkönig, I. M. A. 2011, Water-Removed Spectra Increase The Retrieval Accuracy When Estimating Savanna Grass Nitrogen And Phosphorus Concentrations. *Isprs Journal Of Photogrammetry And Remote Sensing,* 66**,** 408-417.

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin Iii, F. S., Lambin, E. F., Lenton, T. M., Scheffer, M., Folke, C. & Schellnhuber, H. J. 2009, A Safe Operating Space For Humanity. *Nature,* 461**,** 472.

Schlerf, M., Atzberger, C., Hill, J., Buddenbaum, H., Werner, W. & Schüler, G. 2010, Retrieval Of Chlorophyll And Nitrogen In Norway Spruce (Picea Abies L. Karst.) Using Imaging Spectroscopy. *International Journal Of Applied Earth Observation And Geoinformation,* 12**,** 17-26.

Serrano, L., Penuelas, J. & Ustin, S. L. 2002, Remote Sensing Of Nitrogen And Lignin In Mediterranean Vegetation From Aviris Data: Decomposing Biochemical From Structural Signals. *Remote Sensing Of Environment,* 81**,** 355-364.

Sibanda, M., Mutanga, O. & Rouget, M. 2015, Examining The Potential Of Sentinel-2 Msi Spectral Resolution In Quantifying Above Ground Biomass Across Different Fertilizer Treatments. *Isprs Journal Of Photogrammetry And Remote Sensing,* 110**,** 55-65.

Socolow, R. H. 1999, Nitrogen Management And The Future Of Food: Lessons From The Management Of Energy And Carbon. *Proceedings Of The National Academy Of Sciences,* 96**,** 6001-6008.

Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Biggs, R., Carpenter, S. R., De Vries, W. & De Wit, C. A. 2015, Planetary Boundaries: Guiding Human Development On A Changing Planet. *Science,* 347**,** 1259855.

Templer, P. H., Mack, M. C., Chaplin, F. S. I., Christenson, L. M., Compton, J. E., Crook, H. D., Currie, W. S., Curtis, C. J., Dail, D. B., D'antonio, C. M., Emmet, B. A., Epstein, H. E., Goodale, C. L., Gunderson, P., Hobbie, S. E., Holland, K., Hooper, D. U., Hungate, B. A., Lamonetagne, S., Nadelhoffer, K. J., Osenberg, C. W., Perakis, S. S., Schleppi, P., Schimel, J., Schmidt, I. K., Sommerkorn, M., Spoelstra, J., Tietema, A., Wessel, W. W. & Zak, D. R. 2012, Sinks For Nitrogen Inputs In Terrestrial Ecosystems: A Meta-Analysis Of 15n Tracer Field Studies. *Ecology,* 93**,** 1816-1829.

Vilfan, N., Van Der Tol, C., Muller, O., Rascher, U. & Verhoef, W. 2016, Fluspect-B: A Model For Leaf Fluorescence, Reflectance And Transmittance Spectra. *Remote Sensing Of Environment,* 186**,** 596-615.

Wang, F., Huang, J., Wang, Y., Liu, Z. & Zhang, F. 2013, Estimating Nitrogen Concentration In Rape From Hyperspectral Data At Canopy Level Using Support Vector Machines. *Precision Agriculture,* 14**,** 172-183.

Wang, G. L., Yu, M., Pal, J. S., Mei, R., Bonan, G. B., Levis, S. & Thornton, P. E. 2016a, On The Development Of A Coupled Regional Climate-Vegetation Model Rcm-Clm-Cn-Dv And Its Validation In Tropical Africa. *Climate Dynamics,* 46**,** 515-539.

Wang, T., Zhang, H., Lin, H. & Fang, C. 2016b, Textural–Spectral Feature-Based Species Classification Of Mangroves In Mai Po Nature Reserve From Worldview-3 Imagery. *Remote Sensing,* 8**,** 24.

Wessman, C. A., Aber, J. D., Peterson, D. L. & Melillo, J. M. 1988, Remote Sensing Of Canopy Chemistry And Nitrogen Cycling In Temperate Forest Ecosystems. *Nature,* 335**,** 154-156.