Estimation of Forage Biomass and Nitrogen using MERIS Data

Saleem Ullah
March, 2009

Estimation of Forage Biomass and Nitrogen using MERIS Data

by

Saleem Ullah

Thesis submitted to the International Institute for Geo-information Science and Earth Observation in partial fulfilment of the requirements for the Master of Science Degree in Geo-information Science and Earth Observation - Natural Resources Management

Thesis Assessment Board

Chairman: Prof. Dr. A.K. (Andrew) Skidmore (Department of Natural Resources, ITC)

External examiner: Dr. Ir. J.G.P.W. Clevers (Wageningen University)

Supervisor: Dr. Martin Schlerf (Department of Natural Resources, ITC)

Supervisors:

Dr. Martin Schlerf

Prof. Dr. A.K. (Andrew) Skidmore

INTERNATIONAL INSTITUTE FOR GEO-INFORMATION SCIENCE AND EARTH OBSERVATION
ENSCHEDE, THE NETHERLANDS

Disclaimer

This document describes work undertaken as part of a programme of study at the International Institute for Geo-information Science and Earth Observation. All views and opinions expressed therein remain the sole responsibility of the author, and do not necessarily represent those of the institute.

Abstract

The quantification of biophysical and biochemical parameters of grassland is vital as they act as indicators of the productivity, stress, growth and nutrient status. The two main objectives of this study were to (a) evaluate the predictive performance of vegetation indices (NDVI, SAVI and TSAVI) and band depth analysis parameters (BD, BDR, BNA and NBDI) for green biomass estimation and (b) to evaluate the predictive performance of MTCI, REP and band depth analysis parameters for foliar nitrogen (nitrogen concentration and nitrogen density) using MERIS data. Simple linear regression was used to relate vegetation indices (NDVI, SAVI and TSAVI) with green biomass and stepwise multiple linear regression was used to predict green biomass from band depth analysis parameters (BD, BDR, BNA and NBDI). For estimating foliar nitrogen from MTCI and REP, simple linear regression was used while for estimating foliar nitrogen from band depth analysis parameters stepwise multiple linear regressions was used. Using calibration dataset, all band depth analysis parameters except BD resulted in higher coefficient of determination ($R^2 = 0.73$) compared to vegetation indices ($R^2 = 0.54$ for SAVI, $R^2 = 0.52$ for TSAVI and $R^2 = 0.51$ for NDVI). Using independent validation dataset, band depth analysis (NBDI) predicted green biomass with a higher accuracy (135 g/m^2, 47 % of the mean) compared to SAVI (159.6 g/m^2, 55 % of the mean). For the estimation of nitrogen concentration, band depth showed very low coefficient of determination ($R^2 = 0.21$) and the results of MTCI and REP were statistically non-significant ($P > 0.05$). Using calibration dataset for the estimation of nitrogen density, band depth analysis parameters resulted in a moderate coefficient of determination ($R^2 = 0.51$ for NBDI, $R^2 = 0.52$ for BNA, $R^2 = 0.52$ for BDR and $R^2 = 0.30$ for BD) compared to MTCI ($R^2 = 0.29$) and REP ($R^2 = 0.24$). Using independent validation dataset, band depth analysis (NBDI) predicted nitrogen density with a higher accuracy (404.8 g/m^2, 37 % of the mean) compared to MTCI (473.0 g/m^2, 43 % of the mean). Band depth analysis parameters predicted biomass more accurately than vegetation indices (SAVI, TSAVI, and NDVI). The prediction performance of band depth analysis parameters for nitrogen density was more accurate than MTCI and REP. The models failed ($R^2 < 0.25$) to predict nitrogen concentration.

Keywords: Biomass, Nitrogen density, Nitrogen concentration, Vegetation indices, Band depth analysis parameters

Acknowledgements

I am very grateful to the higher education commission (HEC) of Pakistan for granting me scholarship to study in ITC, without their financial support I would not be able to continue my studies.

I am extending sincere gratitude to my first supervisor Dr. Martin Schlerf, for his continuous support, guidance, encouragement and valuable comments from the development of research proposal till the accomplishment of this task. I am greatly indebted to Prof. Dr. Andrew Skidmore, my second supervisor, for accepting me as research student and his valuable comments during the design of research proposal.

I am also obliged to Dr. Micheal Weir, Programme Director, NRM, for his cooperation throughout MSc. I am grateful to Mr. Bos Wesselman, Student Advisor, NRM, for guidance regarding the selection of research topic. I am extending special thanks to all staff and faculty members of NRM department for their help throughout my MSc at ITC.

I would like to thanks Ms Si Yali, a PhD student at ITC, for her keen guidance and supervision during field work in Friesland and providing additional information. I am greatly indebted to Wageningen university for providing laboratory facilities to analyse foliar nitrogen in the field samples. I am greatly obliged to Mr. Gerard Reinink for his help in downloading MERIS images. I am also indebted to European Space Agency (ESA) for providing me access to their Images archive.

I am thankful to all NRM students (2007) for making student life memorable. My cordial appreciation to my cluster mates; Amjad Ali, Irwan Assad, M. Barmawi, Lelyana Medora, Claudia Hienze, Joki, Bharat Babu and Sigit for creating friendly environment and their supports.

Thanks to all Pakistani friends at ITC for providing moral and material support. Special thanks to M. Shafiq, M. Jahanzeb Malik, Zahir Ali, Amir Khan, Mubasher Riaz, M. Yaseen, Abdul Sattar Khatri, Saba and Zia for their continuous encouragement and moral support.

At the end, I am cordially thankful to my family members' especially my loving grandmother, parents, brothers and sister for their affection, support and prayers.

Table of contents

List of figures

List of tables

List of Abbreviations

MERIS	Medium Resolution Imaging Spectrometer
BD	Band Depth
BDR	Band Depth Ratio
BNA	Band Depth Normalized to Band Area
NBDI	Normalized Band Depth Index
NDVI	Normalized Difference Vegetation Index
SAVI	Soil Adjusted Vegetation Index
TSAVI	Transformed Soil Adjusted Vegetation Index
REP	Red Edge Position
MTCI	MERIS Terrestrial Chlorophyll Index
SMLR	Stepwise Multiple Linear Regression
AVHRR	Advanced Very High Resolution Radiometer
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
ESA	European Space Agency

1. Introduction

1.1. Remote sensing of vegetation biophysical and biochemical parameters

The quantification and monitoring of biophysical and biochemical parameters of vegetation play a vital role in the terrestrial ecosystem (Asner, 1998). Biophysical parameters such as biomass and leaf area index (LAI) are the indicators of the productivity and functioning of grassland (Moreau et al., 2003; Mutanga & Skidmore, 2004). Assessment of foliar bio-chemicals such as nitrogen and chlorophyll are important because they are providing information about the pasture growth, reproduction, stress and nutrient status (Curran, 1989; Lamb et al., 2002).

Space born remote sensing is an important technology for mapping and monitoring vegetation. Remote sensing images are covering large areas and provide repetitive observations at low costs. Contrary, field measurement techniques for the estimation of vegetation parameters are more time consuming, labour intensive, require more cost and difficult to perform (Curran, 1989).

1.2. Broadband sensors and vegetation parameters

Remote sensing has been used for the last three decades to characterise vegetation parameters. Broadband sensors like Landsat 5/7 TM/ETM+, SPOT HRVIR/HRG and Terra/ASTER are commonly used to estimate vegetation parameters (Richardson et al., 1983; Duchemin, 1999). Mostly an empirical relationship is established between ground-measured vegetation parameters and spectral transformations (Rasmussen, 1992; Kawamura et al., 2005; Zhao et al., 2007).

So far, vegetation indices (VIs) are the most common techniques to extract information from the spectral measurement. Spectral vegetation indices like normalised difference vegetation index (NDVI), ratio vegetation index (RVI), perpendicular vegetation index (PVI), soil adjusted vegetation index (SAVI), transformed soil adjusted vegetation index (TSAVI) etc. are mathematical conversions of vegetation reflectance into a dimensionless measure which are then used as predictors of vegetation parameters (Carlson & Ripley, 1997; Thenkabail et al., 2000; Zhao et al., 2007). Among these, the most widely used index is NDVI for biomass estimation (Todd et al., 1998). NDVI is calculated by equation (1):

$$NDVI = (R_{NIR} - R_{Red}) / (R_{NIR} + R_{Red}) \quad (1)$$

However, NDVI reaches saturation at a certain range of biomass or LAI and is also affected by background reflectance which may cause poor biomass estimations (Hurcom & Harrison, 1998; Todd et al., 1998; Gao et al., 2000; Van der Meer et al., 2001). SAVI, TSAVI (which are an advanced form of NDVI) have been developed to minimise the effects of atmosphere and background reflectance. The empirical relationships developed between vegetation indices and field measurements are naturally highly localised and sensor specific and not suitable for large area (Curran, 1994; Gobron et al., 1999).

1.3. Narrow band sensors and vegetation parameters

Narrow band sensors are assumed to contain more spectral information than broadband sensors (Schlerf et al., 2005; Zhao et al., 2007). In broadband sensors the spectral information is averaged over a large band width resulting in a loss of information while in narrow band sensors this is not the case (Thenkabail et al., 2000; Blackburn & Ferwerda, 2008). With the advent of hyperspectral remote sensing or imaging spectrometry, extra bands are make available in the visible, near infrared (NIR) and shortwave infrared (SWIR). This makes imaging spectrometry a powerful tool for assessing vegetation biophysical and biochemical parameters (Curran, 1989; Asner, 1998).

1.3.1. Biophysical parameters

Comparisons have been made between broadband and narrow band vegetation indices for estimating biophysical parameters (Elvidge & Chen, 1995; Broge & Leblanc, 2001; Broge & Mortensen, 2002; Hansen & Schjoerring, 2003). Most of them reported narrow band indices more accurate predictor than broadband indices (Elvidge & Chen, 1995; Thenkabail et al., 2000; Hansen & Schjoerring, 2003; Schlerf et al., 2005) while some found no difference (Broge & Leblanc, 2001; Broge & Mortensen, 2002).

As the amount of biomass increases, the reflectance in the red portion of the spectrum decreases and reflectance in NIR region increases as a result red absorption pit of vegetation spectrum also increase in depth and width (Todd et al., 1998). The band depth analysis parameters calculated from narrow band sensors were found to be more accurate predictors of biomass than NDVI (Mutanga & Skidmore, 2004). The previous study (Mutanga & Skidmore, 2004) regarding biomass estimation using band depth analysis was restricted to laboratory level.

1.3.2. Biochemical parameters

Estimating biochemical parameters compared to biophysical parameters is more difficult using broadband sensors. In broadband sensors a narrow absorption feature which is related to the chemical composition of the object under investigation is masked due to the averaging effect of the broadband width which makes it impossible to predict the biochemical characteristic of vegetation (Curran,

1989). With the introduction of imaging spectrometry various foliar biochemical parameters such as nitrogen, phosphorous, chlorophyll etc. have been successfully estimated (Curran, 1994; Ferwerda et al., 2005; Cho & Skidmore, 2006; Mutanga & Skidmore, 2007).

Red edge position (REP) is the wavelength of maximum slope between 670nm-780nm of vegetation spectrum (Clevers et al., 2002; Cho & Skidmore, 2006; Mutanga & Skidmore, 2007). As the amount of chlorophyll and nitrogen increases, the REP shift toward the longer wavelength in near infrared region (Munden et al., 1994; Dawson & Curran, 1998). This shift in REP has been successfully used as a predictor of chlorophyll/nitrogen content in different studies (Curran, 1994; Curran et al., 2001; Clevers et al., 2002; Lamb et al., 2002; Mutanga & Skidmore, 2007).

MERIS terrestrial chlorophyll index (Dash & Curran, 2004) has been recently introduced for the estimation of vegetation chlorophyll content (Dash & Curran, 2004; Curran et al., 2007; Dash & Curran, 2007). Up to the best of my knowledge, MERIS terrestrial chlorophyll index (MTCI) has not been used so far for grassland nitrogen estimation from MERIS data.

1.4. Need of the present study

Most of previous research using band depth analysis and red edge position (Curran, 1994; Munden et al., 1994; Dawson & Curran, 1998; Curran et al., 2001; Lamb et al., 2002; Mutanga & Skidmore, 2004; Cho & Skidmore, 2006; Mutanga & Skidmore, 2007) as a predictor of biophysical and biophysical parameters of vegetation were restricted either to laboratory level or highly localised. The potential of these techniques has been seldom explored at regional scale. This study investigates the potential of these techniques at regional scale.

MERIS terrestrial chlorophyll index (MTCI), devised by Dash and Curren, (2004), has been used for the estimation of vegetation chlorophyll content at regional scale (Dash & Curran, 2004; Curran et al., 2007; Dash & Curran, 2007). A strong positive correlation relation is often observed between chlorophyll and nitrogen content (Devlin, 1969; Vickery, 1981; Donahue et al., 1983; Lamb et al., 2002). In the present study, MTCI was used to predict foliar nitrogen.

1.5. Research objectives and research questions

1.5.1. General objective

The aim of this study was to estimate the quantity (biomass) and quality (nitrogen) of forage using MERIS data.

1.5.2. Specific objectives

1. To assess the accuracy of NDVI, SAVI, TSAVI and band depth analysis parameters for biomass estimation.

2. To assess the accuracy of red edge position (REP), MERIS terrestrial chlorophyll index (MTCI) and band depth analysis parameters for the estimation of nitrogen concentration/density from MERIS data.

3. To validate the predictive equations (models) using an independent dataset of different time.

1.5.3. Research questions

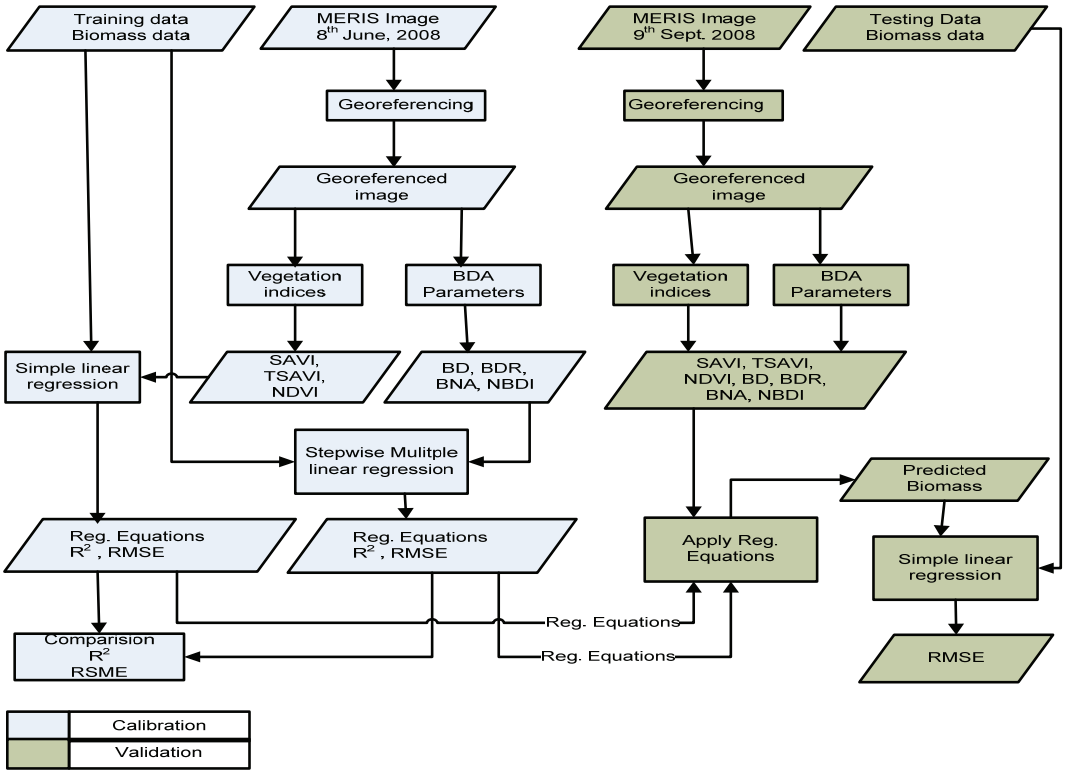
1. Which one estimates biomass more accurate, vegetation indices (NDVI, SAVI and TSAVI) or band depth analysis parameters derived from MERIS data?

2. What are the optimal band / bands combination for estimating biomass using band depth analysis parameters?

3. Can nitrogen concentration and density be estimated from MERIS data using REP, MTCI and band depth analysis parameters? If yes, which one performs more accurate?

1.6. Research approach

(a) Flow diagram for green biomass estimation



(b)Flow diagram for nitrogen estimation

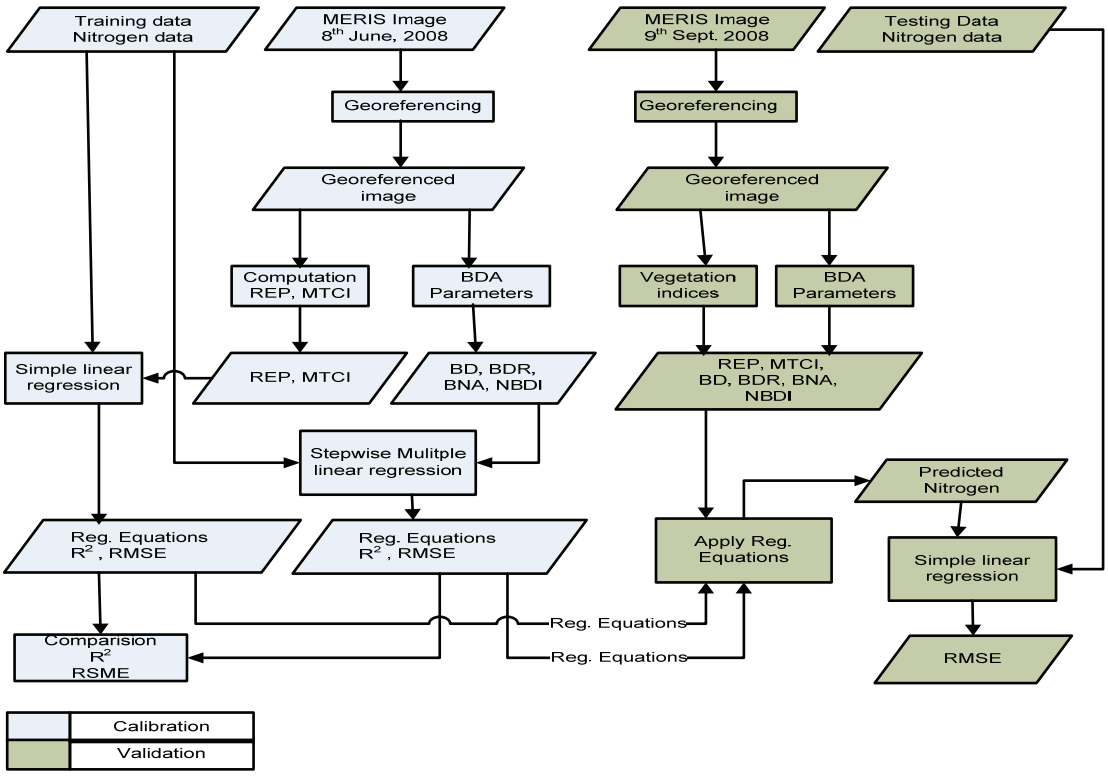


Figure 1-1. Flow diagrams for (a) green biomass estimation and (b) nitrogen estimation

2. Methods and Materials

2.1. Study area

The study area is located in the north of the Netherlands (Friesland). Friesland is located in temperate region with cool and wet climate. Friesland is mainly an agricultural province with a fertile land drained by numerous canals and small rivers and has many picturesque lakes. This area is an important stopover site of migratory birds like Barnacle goose *(Branta leucopsis),* Brent goose (*Branta bernicla*), Eurasian wigeon (*Anas Penelope),* Common shelduck *(Tadorna tadorna)* etc. along their flyway (western Palaearctic continental flyway).

Two study sites were selected; Site-1 (Anjumerkolken) is situated at Notheast Friesland (53° 21' N, 6° 7' E). Site-2 (Donlaburen-Ferwoude) is located in West Friesland (53° 1' N, 5°27' E). Most of the study area consists of agricultural land, interspersed with agriculture and natural sites. The most common vegetation in this area is perennial ryegrass (*Lollium perenne).*

Figure 2-1. A map and MERIS false colour composite images of the study area

2.2. Image data acquisition and pre-processing

Medium Resolution Imaging Spectrometer (MERIS) images (Level 2 product) of 8th June 2008 and 9th September 2008 were acquired from European Space Agency (ESA). MERIS Level 2 products are both geometrically and radiometrically corrected products in the form of surface radiance and surface reflectance (Van der Meer et al., 2001). MERIS is an advanced optical pushbroom sensor designed to acquire images at regional to global scales (Dawson, 2000). MERIS is acquiring images in 15 bands, within a spectral range of 390 nm –1040 nm (Table 1). The imaging spectrometer is programmable and the band width and position can be adjusted according to the user needs. The spectral band width is variable between 2.5 nm - 20 nm. The full spatial resolution is 300 m and reduced spatial resolution is 1200 m. The instrument has a 68.5° field of view providing a swath of 1150 km on the ground and a revisit time of 3 days. MERIS is radiometrically the most accurate imaging spectrometer in space (Rast et al., 1999; Van der Meer et al., 2001).

MERIS level 2 product (geometrically and radiometrically corrected to canopy reflectance) was used. When the field points were overlaid upon the image, there was slight shift. In order to overcome this problem, the MERIS image was georeferenced against a Landsat ETM^+ image.

Table 1. Standard band setting of MERIS and their potential applications (Rast et al., 1999)

Band number	Band centre (nm)	Band width (nm)	Potential applications
1	412.5	10	Yellow substances, turbidity
2	442.5	10	Chlorophyll absorption maximum
3	490	10	Chlorophyll, other pigments
4	510	10	Turbidity, suspended sediments, red tides
5	560	10	Suspended sediments, Chlorophyll reference
6	620	10	Suspended sediments
7	665	10	Chlorophyll absorption
8	681.25	7.5	Chlorophyll florescence
9	708.75	10	Atmospheric correction, red edge
10	753.75	7.5	Oxygen absorption reference
11	760	2.5	Oxygen absorption R-branch
12	778.4	15	Aerosol, vegetation
13	865	20	Aerosol corrections over ocean
14	890	10	Water vapour absorption reference
15	900	10	Water vapour absorption, vegetation

2.3. Field data collection

2.3.1. Sampling design

Stratified random sampling was used. The area was stratified into agricultural and semi-natural grassland using land cover map obtained from Dutch National Land Use Mapping and Monitoring (LGN5). The area occupied by agricultural land was more than semi-natural land. Coordinates (x, y) were generated randomly in the agricultural and semi-natural grassland to select parcels. 30 parcels were selected, out of which 23 parcels were distributed in agricultural land and 7 parcels were located in semi-natural land. The parcel size was set to be 300 m * 300 m, coinciding with the size of a MERIS pixel. Within each parcel, 5 plots (1 m * 1 m) were established (Fig. 2-2) in which the vegetation parameters were measured. Above ground grass was clipped from an area of 10 cm * 10 cm for biomass measurement. For nitrogen analysis a minimum of 30 grass leaves were picked from the rest of the plot.

Two season field data were collected: summer data (June 2008) was used for training purpose (building predictive models) and autumn data (September 2008) was used for the testing (validation) of the predictive models.

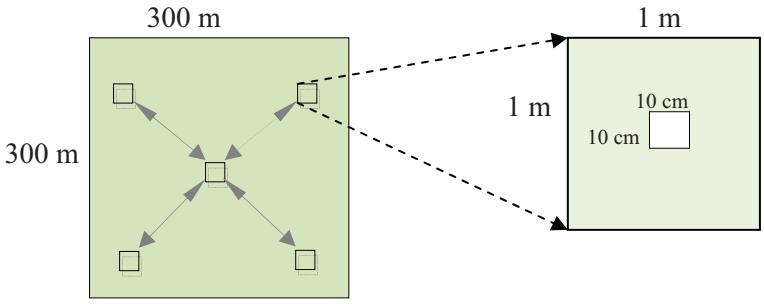


Figure 2-2. Schematic representation of the sampling within an idealized quadratic parcel of 300 m side length

2.3.2. Biomass measurement

All dry material was separated from the clipped grass before measuring green biomass. The green grass clipped at each plot was put in paper bags, labelled with parcel number and plot number and taken to the laboratory. There, the green material was dried in a microwave oven for 48 hours at 70 C°. The green grass was then measured using a digital weighing balance. The weight of the green grass was divided by the area of 100 cm^2 to obtain green biomass in g/cm^2, which was then converted to g/m^2 (Hurcom & Harrison, 1998). The plot biomass was then averaged per parcel.

2.3.3. Nitrogen analysis (measurement)

The laboratory analysis for foliar nitrogen was carried out in Wageningen University. The samples were dried in a microwave oven at 70 C° for 48 hours; each sample was ground to a particle size of 1 mm.

Digestion of each sample was performed in tubes using concentrated sulphuric acid (H_2SO_4). Hydrogen peroxide (H_2O_2) was used to oxidize organic matter at relatively low temperature. In order to prevent loss of nitrate, salicylic acid ($C_7H_6O_3$) was added. When excess of H_2O_2 decomposed, the digestion was completed using concentrated sulphuric acid (H_2SO_4) at elevated temperature in the presence of selenium powder (Se) as catalyst. The nitrogen concentration (as a percentage of dry weight) was then measured using Skalar San-Plus auto analyser (Novozamsky et al., 1983). The nitrogen concentration at plot level was then averaged to nitrogen concentration at parcel level.

Nitrogen density of each plot was calculated by multiplying percentage nitrogen of a particular plot with the green biomass of that particular plot (Hansen & Schjoerring, 2003). The nitrogen density was expressed in the unit of (g/m^2). The nitrogen density at plot level was then averaged to nitrogen density at parcel level.

2.4. Estimation of green biomass using MERIS data

2.4.1. Calculating band depth analysis parameters

For calculating band depth analysis parameters, the red absorption pit (559.7 nm - 778.4 nm) was isolated through continuum removal technique. Continuum removal enhances the differences in absorption feature by applying a convex hull to the spectra and connecting regions of maximum reflectance points (Kokaly & Clark, 1999). The continuum-removed spectrum R' is obtained by dividing the reflectance value R for each point in the absorption pit by the reflectance level of the continuum line (hull) R_c at the corresponding wavelength (Table 3) and the output value range from 0 - 1 (Mutanga & Skidmore, 2004). The continuum removal procedure minimizes the influence of factors such as atmospheric absorptions, water absorptions, soil background and Bidirectional Reflectance Distribution Function (BRDF) (Kokaly & Clark, 1999).

Band depths (BD), normalized band depth ratio (BDR), normalized band depth index (NBDI) and band depth normalized to band area (BNA) were calculated from the continuum removed spectra using equations shown in table 2.

A number of previous studies (Kokaly & Clark, 1999; Curran et al., 2001; Mutanga & Skidmore, 2004; Mutanga et al., 2005) have successfully used band depth indices to estimate vegetation biophysical and biochemical parameters at laboratory level or local scale.

Table 2. Equations used for the calculation of band depth analysis parameters

Method	Equation
Continuum removed spectra R'	$R' = R / R_c$
Band depth (BD)	$BD = 1 - R'$
Normalised band depth ratio(BDR)	$BDR = BD / D_c$
Normalised band depth Index(NBDI)	$NBDI = BD - D_c / BD + D_c$
Band depth normalized to band area (BNA)	$BNA = BD / D_a$

where R = original reflectance value, R_c = reflectance value of continuum line, D_c = band depth at the band centre with maximum depth, and D_a = area of the absorption pit under the convex hull.

2.4.2. Calculating vegetation Indices (NDVI, SAVI and TSAVI)

Vegetation indices (VIs) are the most common techniques to extract information from the spectral measurement .Vegetation indices like normalised difference vegetation index (NDVI), soil adjusted vegetation index (SAVI), transformed soil adjusted vegetation index (TSAVI) were calculated from MERIS images using mathematical formulas shown in table 3.

Table 3. Equations used for the calculation of vegetation indices

Index	Equation	Reference
NDVI	$(R_{band12} - R_{band7}) / (R_{band12} + R_{band7}) = (R_{778.4} - R_{665}) / (R_{778.4} + R_{665})$	(Rouse et al., 1974)
SAVI	$[(R_{778.4} - R_{665}) / (R_{778.4} + R_{665} + L)] (1 + L)$	(Huete, 1988)
TSAVI	$\alpha (R_{778.4} - \alpha * R_{665} - b) / (\alpha * R_{778.4} + R_{665} - \alpha * b)$	(Baret et al., 1989)

where R_{665} and $R_{778.4}$ are reflectance in the centre wavelengths of band 7 and band 12 in the MERIS standard band setting, L (soil adjustment factor) = 0.5, b (intercept) = 0.1 and α (slope) = 0.9.

2.5. Estimation of nitrogen concentartion and nitrogen density from MERIS data

In order to estimate nitrogen concentration and nitrogen density from MERIS data, band depth analysis parameters, red edge position and MERIS terrestrial chlorophyll index were used. Band depth analysis parameters have already been discussed in section 2.4.1.

2.5.1. Red edge position (REP)

Red edge position (REP) or red edge inflection point is the point of maximum slope between red and near infrared region (670 nm - 780 nm) on vegetation spectra (Dawson & Curran, 1998). REP is strongly correlated with foliar biochemicals and is a sensitive indicator of vegetation stress. When the amount of chlorophyll and nitrogen in vegetation increases the red absorption pit gets deeper and wider. As a result REP shifts toward the longer wavelengths and when the amount of these

biochemical decreases the REP shifts towards shorter wavelengths (Dawson & Curran, 1998; Lamb et al., 2002; Cho & Skidmore, 2006; Darvishzadeh et al., 2008).

The linear interpolation technique (Guyot et al., 1988) was used to calculate REP. Linear Extrapolation (Cho & Skidmore, 2006) was not used because linear extrapolation technique requires four points (wavebands), two points on far-red (680 nm to 700 nm) and two points on NIR (725 nm to 760 nm) flanks of the first derivative reflectance spectrum (*D*) of the red edge region. In MERIS standard band setting, bands positioned at 681.25 nm, 708 nm and 753 nm. There is no band in-betweens 708 nm and 753 nm that could be used as two points for extending straight line on NIR flanks. Therefore this technique was not used in the present study.

Linear Interpolation Technique

Linear interpolation technique is based on the assumption that reflectance at the REP could be estimated by half of the reflectance between 670 nm and 780 nm. There are two steps involved to calculate REP by linear interpolation technique; first, calculation of reflectance at the inflection point and then calculation of the wavelength of the inflection point (Guyot et al., 1988).

Calculation of REP is formally stated in equation (2) & (3).

$$R_i = (R_{670} + R_{780}) / 2 \quad (2)$$

where R_i is the reflectance at the inflection point.

$$REP = 700 + 40(R_i - R_{700}) / (R_{740} - R_{700}) \quad (3)$$

where REP is the red edge position.

For MERIS band setting, wavebands 7 (centre at 665 nm) and 12 (centre at 778.75 nm) were used to calculate REP (Dash & Curran, 2004).

$$R_i\,(MERIS) = (R_{band7} + R_{band12}) / 2 \quad (4)$$

where R_i (MERIS) represent reflectance at the inflection point using MERIS data

$$REP\ (MERIS) = 708.75 + 45(R_i\,(MERIS) - R_{band9}) / (R_{band10} - R_{band9}) \quad (5)$$

where REP (MERIS) is red edge position calculated from MERIS data.

2.5.2. MERIS terrestrial chlorophyll index (MTCI)

MERIS Terrestrial Chlorophyll Index (MTCI) was for the first time introduced by Dash & Curran, (2001), to estimate chlorophyll content from MERIS data. MTCI is the ratio of the difference in

reflectance between band 10 and band 9 and the difference in reflectance between band 9 and band 8 of the MERIS standard band setting (Dash & Curran, 2004, 2007).

$$MTCI = (R_{band10} - R_{band9}) / (R_{band9} - R_{band8})$$

Or

$$MTCI = (R_{753.75} - R_{708.75}) / (R_{708.75} - R_{681.25}) \quad (6)$$

where $R_{753.75}$, $R_{708.75}$, and $R_{681.25}$ are reflectance in the centre wavelengths of band 8, 9 and 10 in the MERIS standard band setting.

MTCI has certain advantages; (a) it is single step process and easy to calculate from MERIS standard band setting and (b) it is sensitive to a wide range of chlorophyll contents (Dash & Curran, 2004, 2007).

MERIS Terrestrial Chlorophyll Index (MTCI) was used to estimating nitrogen concentration and nitrogen density from MERIS data.

2.6. Data analysis

Field data collected in June 2008 was used for training purpose (building predictive models) and data collected in September 2008 was used for the testing (validation) of the predictive models.

2.6.1. Calibration analysis

Two regression techniques were used to model the relationships between ground measurements (green biomass and foliar nitrogen) and the spectral transformations.

2.6.1.1. Simple linear regression

Simple linear regression is a widely used technique for establishing the empirical relationship between vegetation indices (NDVI, SAVI, TSAVI, REP, and MTCI) and vegetation parameters (biophysical and biochemical). The performance of various regression models were assessed by comparing the coefficient of determination (R^2) and standard error of estimate (SEE). Standard error of estimate is also called root mean square error (RMSE) and it is the equal to the square root of the mean square residual. Formally it can be calculated by (Equation 7)

$$SEE = \sqrt{\frac{\sum_{i=1}^{n}(y - y')}{n}} \quad (7)$$

where y = measured variable and y' = estimated variable and n = number of observation. The lower the value of standard error of estimate the better is the accuracy.

2.6.1.2. Stepwise multiple linear regression

To determine the relation of green biomass, nitrogen concentration and nitrogen density with spectral transformations (BD, BDR, NBDI and BNA) in each wavelength of the red absorption pit, stepwise multiple linear regression (SMLR) was used. The four wavebands (predictors) were used to predict the green biomass, nitrogen concentration and nitrogen density.

SMLR selects spectral bands (predictors) that are highly correlated with dependent variable (in this case green biomass, nitrogen concentration and nitrogen density). SLMR initiates with no predictors (wavebands of band depth analysis parameters) in the regression equation and at each step it adds statistically the most significant waveband (highest *F*-value and lowest *P*-value). Simultaneously, it removes the predictors (wavebands) with lowest *F*-value and highest *P*-values. This process ends when no entry or removal can be carried out (Darvishzadeh et al., 2008). The criteria for *P*-value (probability of F-value) to enter and remove from model were set to $P <= 0.05$ and $P >= 0.1$ respectively. SMLR regresses the dependent variable (biomass, nitrogen concentration and nitrogen density) against the independent variables (values of band depth parameters at four wavelength) using linear combination (Kokaly & Clark, 1999; Mutanga et al., 2005).

Adjusted R^2 and standard error of estimate (SEE) were used to assess the predictive performance of band depth analysis parameters. The adjusted R^2 is used instead of simple coefficient of determination R^2 due to the reason that adjusted R^2 is more robust for multivariate regression. The adjusted R^2 can be computed by using formula:

$$\text{Adjusted } R^2 = 1 - (1 - R^2)\,[(n - 1) / (n - k - 1)] \quad (8)$$

where R^2 is the coefficient of determination, n is the number of observations and k is the number of predictors.

2.6.2. Validation analysis

An independent test data of vegetation parameters (biomass and nitrogen) collected in September 2008 were used for validation purpose. The regression models developed from the calibration dataset were applied to the September image to predict response variables (biomass and nitrogen) which in turn were compared to the test data. Empirical relationships were established between the measured and predicted variables. The predictive performances of various models were judged by comparing standard error of prediction (SE_P).

2.7. Software used

ENVI 4.4

ArcGIS 9.3

ERDAS Imagine 9.2

SPSS 16.2

Microsoft Excel

3. Results

3.1. Green biomass estimation

For green biomass estimation vegetation indices (NDVI, SAVI and TSAVI) and band depth analysis parameters (BD, BDR, BNA and NBDI) were compared. Simple linear regression was used to predict green biomass from vegetation indices like NDVI, SAVI and TSAVI and stepwise multiple linear regression was used to predict biomass from band depth analysis parameters (BD, BDR, BNA and NBDI).

The summary statistics of training dataset of green biomass (Table 4) shows that green biomass varied between 75.0 g/m^2 and 669.5 g/m^2 with an average of 317.5 g/m^2. The green biomass in testing dataset falls between 143.0 g/m^2 and 512.0 g/m^2 with an average of 289.0 g/m^2.

Table 4. Summary statistics of measured green biomass for training and testing data sets

Variables	Training data, June 2008 (n = 30)						Testing data, September 2008 (n = 30)					
	Min	Max	Mean	SD	Range	CV	Min	Max	Mean	SD	Range	CV
Green-biomass (g/m^2)	75.0	669.5	317.5	179.4	589.0	0.57	143.0	512.0	289.0	106.7	369.0	0.37

where SD = standard deviation, CV = coefficient of variation and n = number of observations

3.1.1. Relationship between green biomass and vegetation indices (NDVI, SAVI and TSAVI)

Vegetation indices (NDVI, SAVI and TSAVI) were computed to estimate green biomass from MERIS data. Vegetation indices were related to field measured green biomass (training dataset) using simple linear regression. The results obtained from the regression of green biomass and vegetation indices are shown in table 5.

SAVI has the highest coefficient of determination (R^2 = 0.54) and the least standard error of estimate of calibration (SEE_c = 124.0 g/m^2). Compared to SAVI, TSAVI has a slightly lower coefficient of determination (R^2 = 0.52) and slightly higher standard error of estimate of calibration (SEE_c = 126.2 g/m^2). NDVI has the lowest coefficient of determination (R^2 = 0.51) and the highest standard error of estimate of calibration (SEE_c = 128.3 g/m^2) compared to SAVI and TSAVI (Table 5).

The coefficient of determination for SAVI (R^2 = 0.54) means that 54 % of the variance present in green biomass data is explained by SAVI, whereas NDVI (R^2 = 0.51) and TSAVI (R^2 = 0.52) explained 51 % and 52 % of the variance present in green biomass data respectively.

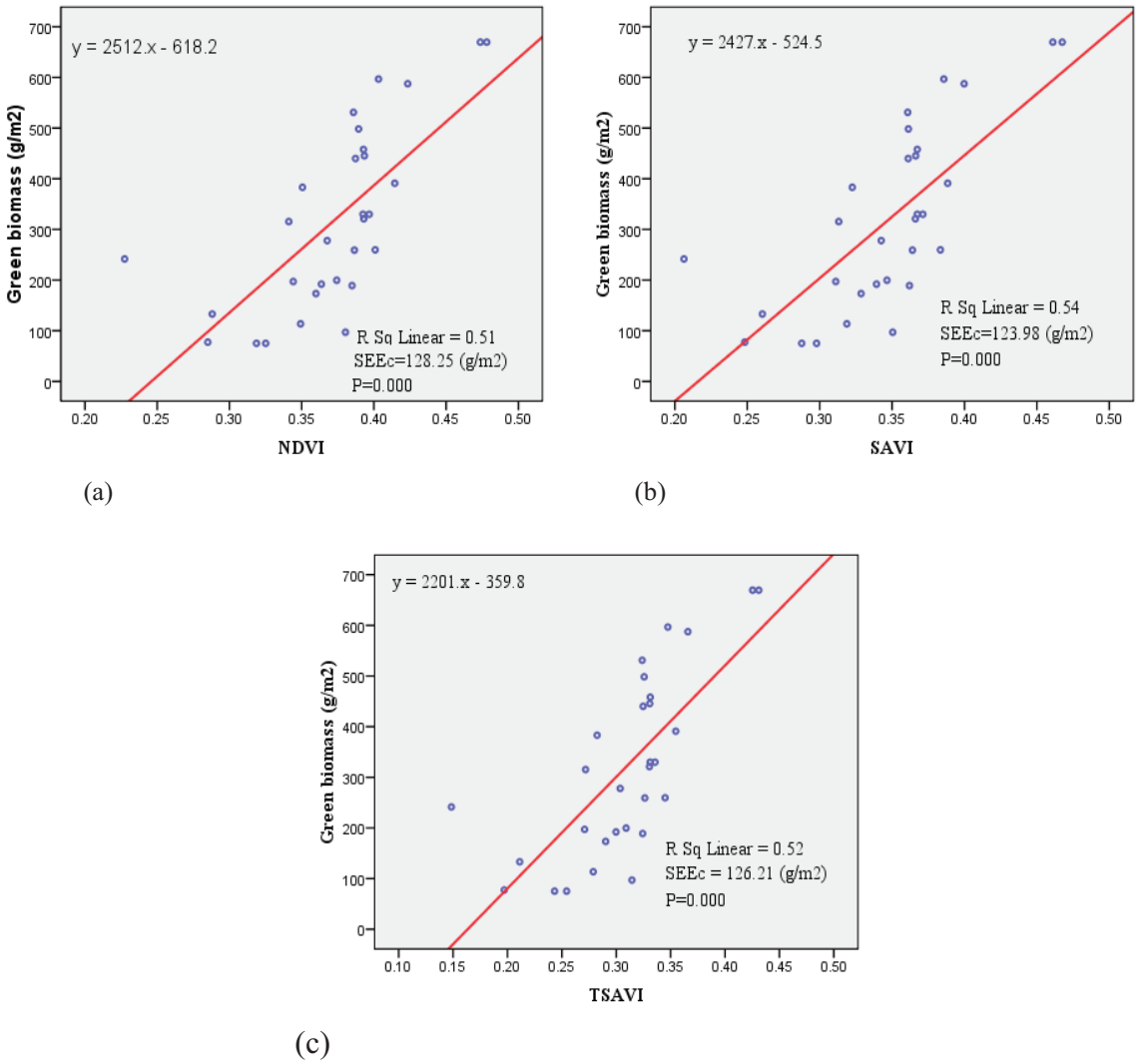


Figure 3-1. Scatter plots between green biomass and (a) NDVI, (b) SAVI and (c) TSAVI

Table 5. Results of correlation analysis between vegetation indices (NDVI, SAVI and TSAVI) and green biomass

Index	n	R	R^2	SEE_c (g/m^2)	$rSEE_c$ (% the of mean)	Sig (P)
SAVI	30	0.73	0.54	124.0	39.0	0.000
TSAVI	30	0.72	0.52	126.2	39.8	0.000
NDVI	30	0.71	0.51	128.3	40.4	0.000

where n = number of observation, and Sig (P) = significance limit at (P <= 0.05)

3.1.2. Relationship between green biomass and band depth analysis parameters

The band depth analysis parameters (BD, BDR, BNA and NBDI) values in the red absorption pit (between wavelengths 560 nm – 778.4 nm) were subjected to stepwise multiple linear regressions with green biomass as dependent variable. Table 6 shows the results of the regression models for BD, BDR, BNA and NBDI.

Four predictors (wavebands at 665 nm, 681.25 nm, 708 nm and 753 nm) were used to predict target variable (green biomass). The wavebands selected by the models of BDR, BNA and NBDI were similar (681.25 nm and 665 nm) at significance limit of ($P <= 0.05$) while DB selected a different waveband (708 nm) at significance of ($P <= 0.05$).

NBDI, BDR and BNA have an equal coefficient of determination (adjusted R^2) but with slight differences in the standard error of estimate of calibration (SEE_c) (Table 6). NBDI has slightly lower standard error of estimate of calibration ($SEE_c = 93.4$ g/m^2) compared to BNA ($SEE_c = 93.9$ g/m^2) and BDR ($SEE_c = 94.0$ g/m^2). Among band depth analysis parameters, Band depth (BD) has the lowest coefficient of determination ($R^2 = 0.53$) and the highest standard error of estimate of calibration ($SEE_c = 123.6$ g/m^2).

Band depth analysis parameters like BDR, BNA and NBDI have higher coefficients of determination (adjusted R^2) than vegetation indices such as NDVI, SAVI, and TSAVI as shown in the table 5. BDR, BNA and NBDI have lower standard error of estimate (SEE_c) of calibration compared to vegetation indices (NDVI, SAVI and TSAVI). The only band depth analysis parameter that has less coefficient of determination (R^2) than SAVI ($R^2 = 0.54$) was BD ($R^2 = 0.53$) but the standard error of estimate of BD ($SEE_c = 123.6$ g/m^2) was slightly less than SAVI (124.0 g/m^2). This indicates that vegetation indices are less accurate in the estimation of biomass than band depth analysis parameters.

The regression coefficients (β) of predictors (wavebands) selected by the stepwise multiple regressions shows the importance of each band in the regression equation to predict target variable (green biomass). In case of BDR, BNA and NBDI, the waveband at 681.25 nm has higher regression coefficient (β) value in absolute term then waveband at 665 nm (Table 6). The only single predictor selected by stepwise regression in band depth (BD) was waveband 708 nm having regression coefficient 0.73 at significance ($P = 0.000$).

Table 6. Results of the stepwise multiple linear regression applied to band depth (BD), band depth ratio (BDR), band depth normalised to band area (BNA) and normalised band depth index (NBDI) for green biomass estimation.

Index	Wavelength	R^2 (adjusted)	SEE_c (g/m2)	$rSEE_c$ (% of the mean)	Regression coefficients (β)	Sig (P <= 0.05)
BD		0.53	123.6	38.9		0.000
	Constant				-598.8	0.000
	708 nm				0.73	0.000
BDR		0.73	94.0	29.6		0.000
	Constant				1007.2	0.000
	681.25 nm				-4.63	0.000
	665 nm				4.21	0.000
BNA		0.73	93.9	29.6		0.000
	Constant				1008.0	0.000
	681.25 nm				-4.63	0.000
	665 nm				4.22	0.000
NBDI		0.73	93.4	29.4		0.000
	Constant				1671.1	0.000
	681.25 nm				-4.65	0.000
	665 nm				4.23	0.000

where SEE_c = standard error of estimates of calibration, $rSEE_c$ = relative standard error of estimates of calibration and Sig (P) = significance limit at (P <= 0.05)

3.2. Nitrongen estimation

For the estimation of nitrogen concentration and nitrogen density, red edge position (REP), MERIS terrestrial chlorophyll index (MTCI) and band depth analysis parameters (BD, BDR, BNA, and NBDI) were compared.

Simple linear regression was used to predict nitrogen concentration and nitrogen density from REP and MTCI. Stepwise multiple linear regressions were used to predict nitrogen concentration and nitrogen density from band depth analysis parameters.

Descriptive statistic of training dataset (Table 7) shows that nitrogen concentration varied between 1.9 (%) and 4.9 (%) with an average of 3.5 (%). Nitrogen density range between 236.7 g/m^2 and 2220.9 g/m^2 with an average of 1068.5 g/m^2.

Table 7. Descriptive statistic of measured nitrogen concentration and nitrogen density

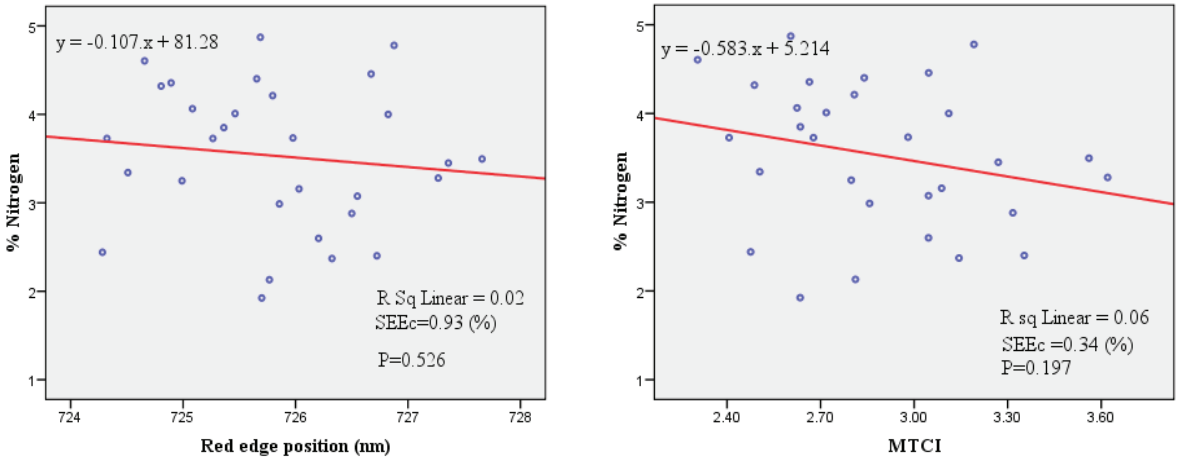
Variables	Training data, June 2008 (n = 30)						Testing data, September 2008 (n = 30)					
	Min	Max	Mean	SD	Range	CV	Min	Max	Mean	SD	Range	CV
Nitrogen conc. (%)	1.9	4.9	3.5	0.82	3.0	0.23	2.26	5.2	3.7	0.71	2.94	0.19
Nitrogen density (g/m^2)	236.7	2220.9	1068.5	560.0	1984.2	0.52	324.5	2230.4	1089.6	464.6	1906.4	0.43

where SD = standard deviation, CV = coefficient of variation and n = number of observations

3.2.1. Estimation of nitrogen concentration

Nitrogen concentration (%) were estimated from red edge position (REP), MERIS terrestrial chlorophyll index (MTCI) and band depth analysis parameters (BD, BDR, BNA, NBDI).

Linear regression was used to develop the relation between independent variables (REP, MTCI) and dependent variable (nitrogen concentration). The results (Fig. 3-2) shows that the relation between nitrogen concentrations was very weak and hardly any relationship exist between nitrogen concentration and REP and MTCI. The relations were also statistically insignificant at (P <= 0.05).



(a) (b)

Figure 3-2. Scatter plots between nitrogen concentration and (a) red edge position (b) MTCI

Stepwise multiple linear regression was used to estimate nitrogen concentration (dependent variable) from band depth analysis parameters (BD, BDR, BNA and NBDI) as independent predictors. All band

depth analysis parameters except BD failed to develop any regression equation. The results of BD regression (Table 8) shows the coefficient of determination (R^2 = 0.21). The estimation of nitrogen concentration from band depth (BD) was poor but statistically significant (P = 0.006).

Table 8. Results of the stepwise linear regression applied to band depth (BD)

Index	Wavelength	R^2 (adjusted)	SEE_c (%)	$rSEE_c$ (% of the mean)	Regression coefficients (β)	Sig (P <= 0.05)
BD	Constant 665 nm	0.21	0.7	21.0	6.5 0.49	0.006 0.000 0.006

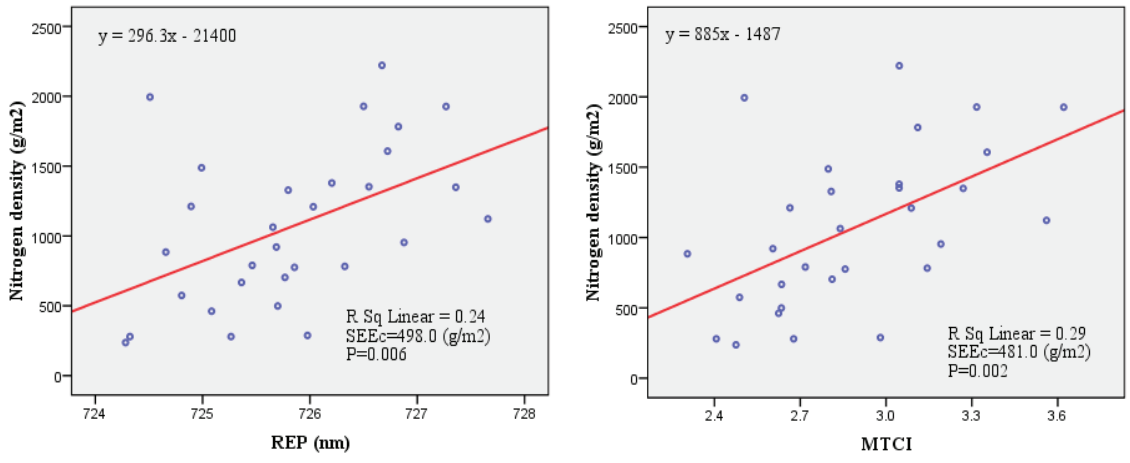
where SEE_c = standard error of estimates of calibration, $rSEE_c$ = relative standard error of estimates of calibration and Sig (P) = significance limit at (P <= 0.05)

3.2.2. Estimation of nitrogen density

Red edge position (REP), MERIS terrestrial chlorophyll index (MTCI) and band depth analysis parameters were used to estimate nitrogen density (g/m^2).

3.2.2.1. Relationship between nitrogen density, red edge position (REP) and MERIS terrestrial chlorophyll index (MTCI)

In order to predict nitrogen density, red edge position (REP) and MERIS terrestrial chlorophyll index (MTCI) was calculated from MERIS data. The REP and MTCI values of the sample points were regressed with nitrogen density through simple linear regression. The figure 3-3 shows the results of the linear regression between nitrogen density and (a) REP and (b) MTCI.



(a) (b)

Figure 3-3. Scatter plots between nitrogen density and (a) red edge position (b) MTCI

Table 9. Results of the simple linear regression between nitrogen density, red edge position and MTCI

Index	n	R^2 (adjusted)	SEE_c (g/m^2)	$rSEE_c$ (% of the mean)	Sig (P <= 0.05)
REP	30	0.24	498.0	47	0.006
MTCI	30	0.29	481.0	45	0.002

where SEE_c = standard error of estimates of calibration, $rSEE_c$ = relative standard error of estimates of calibration and Sig (P) = significance limit at (P <= 0.05)

The results (Table 9) shows the coefficient of determination of MTCI ($R^2 = 0.29$) was slightly higher than the coefficient of determination of REP ($R^2 = 0.24$). The standard error of estimate of calibration of MTCI (SEE_c = 481.0 g/m^2) was lower than the standard error of estimate of calibration of REP (SEE_c = 498.0 g/m^2).

3.2.2.2. Relationship between nitrogen density and band depth analysis parameters

Stepwise multiple linear regressions were used to estimate nitrogen density (dependent variable) from band depth analysis parameters (BD, BDR, BNA and NBDI) as independent predictors.

Table 10 shows the results of regression models for BD, BDR, BNA and NBDI. The wavebands selected by the model of BDR, BNA and NBDI were similar (681.25 nm and 665 nm) at significance level of (P <= 0.05) while the DB selected different waveband (708 nm) at significance of (P <= 0.05).

Band depth (BD) has the lower coefficients of determination R^2 (adjusted) and higher standard error of estimate (SEE_c) as compared to BDR, BNA and NBDI (Table 10). The coefficients of determination R^2 (adjusted) and standard error of estimate (SEE_c) of BDR and BNA and NBDI is almost equal.

All band depth analysis parameters (BD, BDR, BNA and NBDI) have higher coefficient of determination R^2 (adjusted) and lower standard error of estimate than REP and MTCI (Table 9). This indicates that REP and MTCI are less accurate in the estimation of nitrogen density than band depth analysis parameters.

Table 10. Results of the stepwise multiple linear regression applied to band depth (BD), band depth ratio (BDR), band depth normalised to band area (BNA) and normalised band depth index (NBDI) for the estimation of nitrogen density.

Index	Wavelength	R^2 (adjusted)	SEE_c (g/m^2)	$rSEE_c$ (% of the mean)	Regression coefficients (β)	Sig (P <= 0.05)
BD		0.30	467.4	43.7		0.001
	Constant				-1154.8	0.000
	708 nm				0.57	0.001
BDR		0.52	390.0	36.5		0.000
	Constant				3457.8	0.000
	681.25 nm				-3.87	0.000
	665 nm				3.47	0.000
BNA		0.52	389.8	36.5		0.000
	Constant				3459.3	0.000
	681.25 nm				-3.86	0.000
	665 nm				3.48	0.000
NBDI		0.51	391.0	36.6		0.000
	Constant				4490.9	0.000
	681.25 nm				-3.86	0.000
	665 nm				3.46	0.000

where SEE_c = standard error of estimates of calibration, $rSEE_c$ = relative standard error of estimates of calibration and Sig (P) = significance limit at (P <= 0.05)

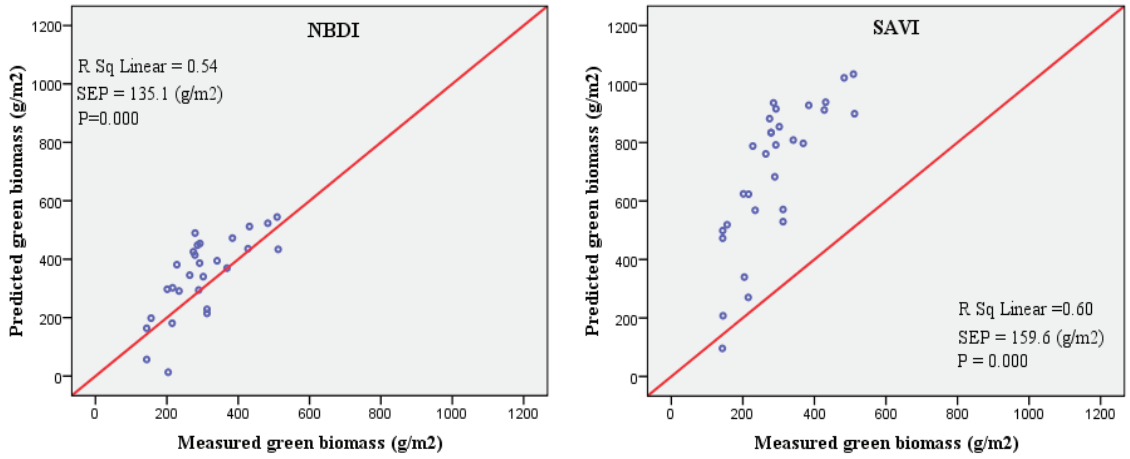
3.3. Validation of the regression equations

The regression equations of calibration (resulted from June 2008 dataset) were tested for their ability to predict green biomass and nitrogen density for independent testing dataset from September 2008. The calibration equations of SAVI and NBDI were applied to SAVI and NBDI calculated from September 2008 image to predicted green biomass. The predicted green biomass was regressed with field measured biomass in September 2008 (testing dataset). The calibration regression equation of SAVI and NBDI were used because of their higher predictive performance among vegetation indices and band depth analysis parameters respectively. The calibration equations of NBDI and MTCI were used to predict nitrogen density for testing dataset.

The predictive performance of validation for green biomass and nitrogen density was analysed by comparing their absolute standard error of prediction (SE_P g/m^2) and relative standard error of predictions (rSE_P % of the mean).

The scatter plots (Fig. 3-4) shows the results of measured against predicted biomass. The normalised band depth index (NBDI) has lower standard error of prediction (SE_P = 135.1 g/m^2, rSE_P = 47 % of the mean) compared to SAVI (SE_P = 159.6 g/m^2, rSE_P = 55 % of the mean).

In calibration dataset the NBDI (SEE_c = 93.4 g/m2, $rSEE_c$ = 29.4 % of the mean) estimates green biomass more accurately compared to SAVI (SEE_c = 124.0 g/m2, $rSEE_c$ = 39 % of the mean). The prediction based on validation dataset also shows that NBDI (SE_P = 135.1 g/m^2, rSE_P = 47% of the mean) has higher predictive performance compared to SAVI (SE_P = 159.6 g/m^2, rSE_P = 55% of the mean).



(a) (b)

Figure 3-4. Scatter plots between measured and predicted green biomass (a) prediction based on NBDI regression equation (b) prediction based on SAVI regression equation

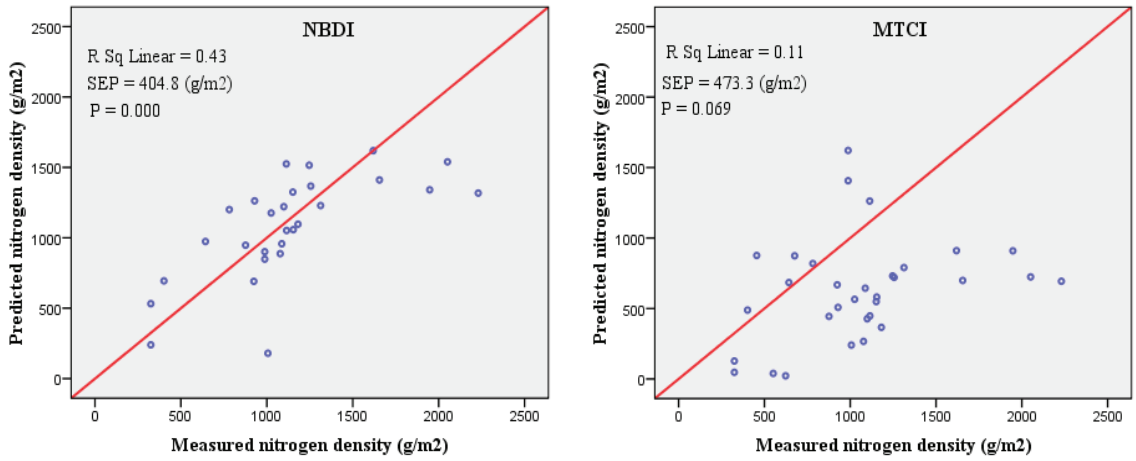
Table 11. Accuracy assessment for the estimation of green biomass and nitrogen density

Vegetation parameters	Spectral predictors	Calibration (n = 30)		Validation (n = 30)	
		SEE_c (g/m^2)	$rSEE_c$ (% of mean)	SE_P (g/m^2)	rSE_P (% of mean)
Green biomass (g/m^2)	NBDI	93.4	29.4	135.1	47.0
	SAVI	124.0	39.0	159.6	55.0
Nitrogen density (g/m^2)	NBDI	391.0	36.6	404.8	37.0
	MTCI	481.0	45.0	473.3	43.0

where SEE_c = standard error of estimate of calibration, $rSEE_c$ = relative standard error of estimates of calibration, SE_p = standard error of prediction and rSE_P = relative standard error of prediction

The scatter plots (Fig. 3-5) shows the results of measured against predicted nitrogen density. The normalised band depth index (NBDI) has lower standard error of prediction (SE_P = 404.8 g/m^2, rSE_P = 37% of the mean) compared to MTCI (SE_P = 473.3 g/m^2, rSE_P = 43% of the mean).

NBDI (SEE_c = 391.0 g/m^2, $rSEE_c$ = 36.6 % of the mean) has higher predictive performance for the estimation of nitrogen density compared to MTCI (SEE_c = 481.0 g/m^2, $rSEE_c$ = 45 % of the mean) in calibration data (Table 11). The prediction based on independent validation dataset also shows that NBDI (SE_P = 404.8 g/m^2, rSE_P = 37% of the mean) has higher predictive performance compared to MTCI (SE_P = 437.3 g/m^2, rSE_P = 43% of the mean).



(a) (b)

Figure 3-5. Scatter plots between measured and predicted nitrogen density (a) prediction based on NBDI regression equation (b) prediction based on MTCI regression equation

4. Discussion

4.1. Comparison of vegetation indices and band depth analysis parameters for the estimation of green biomass.

One aim of the study was to assess the accuracy of vegetation indices (NDVI, SAVI and TSAVI) and band depth analysis parameters (BD, BDR, BNA, and NBDI) for biomass estimation.

The results (Table 5) shows SAVI has slightly higher coefficient of determination (R^2 = 0.54) and slightly lower SEE_c (124.0 g/m^2) than TSAVI (R^2 = 0.52 & SEE_c = 126.2 g/m^2) and NDVI (R^2 = 0.51 & SEE_c = 128.3 g/m^2). This slightly higher predicting accuracy of SAVI and TSAVI compared NDVI is probably due to the fact that SAVI and TSAVI are less sensitive to background effect of soil (Thenkabail et al., 2000; Darvishzadeh et al., 2008). The study area is mostly agricultural land and had been regularly fertilized (manured) which turns the soil colour into dark brown.

The results for estimating biomass from BDR (adjusted R^2 = 0.73 & SEE_c = 94.0 g/m^2), BNA (adjusted R^2 = 0.73 & SEE_c = 93.9 g/m^2) and NBDI (adjusted R^2 = 0.73 & SEE_c = 93.4 g/m^2) were consistent while BD (adjusted R^2 = 0.53 & SEE_c = 123.6 g/m^2) has the lowest predictive performance for biomass among band depth analysis parameters. The biomass estimation ability of band depth analysis parameters was lower than the finding of Mutanga and Skidmore, (2004). The coefficient of determination reported by Mutanga and Skidmore (2004) were (R^2 = 0.81for BD, R^2 = 0.83 for BDR, R^2 = 0.85 for BNA and R^2 = 0.86 for NBDI). The sequence of predictive ability was the same in a sense that NBDI > BNA > BDR > BD. The lower performance of the band depth analysis parameters in this study can be attributed to the fact that MERIS data (used in this study) has lower spectral resolution than GER 3700 spectroradiometer used by Mutanga and Skidmore (2004). The spectral mixing effect (multiple scattering interactions between soil, water, and vegetation etc. within a single pixel of MERIS data) can also be considered one of the reasons of lower predictive performance.

The comparison of the prediction ability for green biomass between vegetation indices (NDVI, SAVI and TSAVI) and band depth analysis parameters shows that green biomass was estimated with higher accuracy using band depth analysis parameters like BDR, BNA and NBDI. Using band depth analysis (NBDI) based on an independent validation dataset it is shown, that green biomass can be estimated with an accuracy of 135 g/m^2, 47 % of the mean and an R^2 of 0.54 from medium resolution satellite data.

The higher accuracy of the band depth analysis parameters compared to vegetation indices can be attributed to the utilization of additional information available on bands other than the two bands (mostly in the red and NIR domains) used for the vegetation indices (Hansen & Schjoerring, 2003).

The previous research conducted by Mutanga and Skidmore (2004) under controlled laboratory condition has proven band depth analysis parameters an accurate predictor of grass biomass than NDVI. The finding of the present study also shows that band depth analysis parameters are more accurate predictor for grass biomass using MERIS data.

4.2. Optimal band/bands selection from band depth analysis parameters

One of the objectives of this study was to determine the optimal band/bands for the prediction of green biomass from band depth analysis parameters using stepwise multiple linear regressions. The results (Table 6) shows that BDR, BNA, and NBDI selected the same variables (681.25 nm & 665 nm) at the significance level of ($P <= 0.05$).

The negative value (Table 6) of regression coefficients (β) at 681.25 nm can be attributed to the fact that when amount of canopy chlorophyll increases (which may be due to increase in green biomass), the depth and area of the red absorption pit increases and a maximum depth is observed around 680 nm (Munden et al., 1994; Dawson & Curran, 1998) which reduce the values of BDR, BNA, and NBDI and this results in a negative correlation at 681.25 nm between green biomass and these band depth parameters. The positive correlation of band 665 nm is probably due to the fact that band 665 nm is situated in-between green peak (560 nm) and maximum depth (681.25 nm). As the amount of biomass increases, reflectance at green peak (560 nm) increases and reflectance at maximum depth (681.25 nm) decreases and the slope between green peak and maximum depth become steeper. When the slope becomes steeper the reflectance at 665 nm may also increase which results in a positive correlation with green biomass.

4.3. Comparison of REP, MTCI and band depth analysis parameters for the estimation of nitrogen concentration

The scatter plots (Fig. 3-2) shows that any relation could hardly be seen between nitrogen concentration and independent variables (REP, MTCI). The relation was also statistically insignificant ($P = 0.526$ and $P = 0.197$) for REP and MTCI respectively. The estimation of nitrogen concentration from calibration dataset using BD (adjusted $R^2 = 0.21$) was poor but statistically significant ($P = 0.006$).

4.4. Comparison of REP, MTCI and band depth analysis parameters for the estimation of nitrogen density

The result (Table 9) shows the relationships between (a) REP and nitrogen density and (b) MTCI and nitrogen density. The predictive performance of both MTCI and REP for estimating nitrogen density was poor.

MTCI has slightly higher coefficient of determination (R^2 = 0.29) and slightly lower SEE_c (481.0 g/m^2) than REP (R^2 = 0.24 & SEE_c = 498.0 g/m^2). MERIS terrestrial chlorophyll index (MTCI) was basically designed for estimating chlorophyll content from MERIS data (Dash & Curran, 2004). As a strong positive correlation is often observed between foliar chlorophyll and nitrogen content (Devlin, 1969; Vickery, 1981; Donahue et al., 1983; Lamb et al., 2002), this study tested MTCI for the estimation of nitrogen density in a grassland ecosystem. This slightly better predictive ability of MTCI can be attributed to the fact that MTCI was designed for the discontinuous reflectance spectra of MERIS while REP was designed for continuous spectrum (Dash & Curran, 2004).

The result (Table 10) shows that performance of band depth analysis parameters to predict nitrogen density of grassland. The BNA (R^2 = 0.52 & SEE_c = 389.8 g/m^2), BDR (R^2 = 0.52 & SEE_c = 390.0 g/m^2) and NBDI (R^2 = 0.51 & SEE_c = 391.0 g/m^2) have higher coefficients of determination and lower standard errors of estimate than BD (R^2 = 0.30 & SEE_c = 467.4 g/m^2). All of the band depth analysis parameters were found more accurate predictors than MTCI and REP. The validation based on independent testing dataset also confirmed the high predictive performance of NBDI compared to MTCI. The absolute standard error of prediction (SE_p g/m^2) and relative standard error of prediction (rSE_p % of the mean) of NBDI (SE_p = 404.8 g/m^2, rSE_p = 37.0 % of the mean) were lower than those of MTCI (SE_p = 473.3 g/m^2, rSE_p = 43.0 % of the mean).

The higher accuracy of band depth analysis parameters compared to MTCI and REP can be attributed to the multivariate information available at numerous bands (Hansen & Schjoerring, 2003). The previous studies (Kokaly & Clark, 1999; Curran et al., 2001; Mutanga et al., 2005) have reported band depth analysis parameters being more accurate predictor of foliar biochemicals using laboratory spectroscopy. The finding of the present study also confirms that band depth analysis parameters are more accurate predictor for nitrogen density using MERIS data than REP and MTCI.

The nitrogen density is an integrated variable of nitrogen concentration and green biomass (nitrogen density = green biomass x nitrogen concentration). The estimation of nitrogen concentration from MERIS data using MTCI, REP and BD was very poor. The better predictive performance of nitrogen density than nitrogen concentration shows that it was dominated by the effect of green biomass.

5. Conclusions

The quantification and monitoring of biophysical and biochemical parameters play a vital role in the terrestrial ecosystem. Biophysical and biochemical parameters such as biomass and foliar nitrogen are the indicators of the productivity and functioning of grassland and provide information about the pasture growth, reproduction, stress and nutrient status. There were two main objectives of this research (a) to evaluate the predictive performance of SAVI, NDVI, TSAVI and band depth analysis parameters for the estimation green biomass in Friesland (b) to evaluate the predictive performance of MTCI, REP and band depth analysis parameters for foliar nitrogen from MERIS data. The main conclusion of this research are summarised as follows.

- Band depth analysis parameters (BDR, BNA, and NBDI) provide more accurate prediction of green biomass compared to vegetation indices like SAVI, NDVI and TSAVI.
- Band depth analysis parameters (BDR, BNA and NBDI) at wavebands 681.25 nm and 665 nm prove the optimal waveband combination for estimating green biomass. For estimating green biomass from BD, the only optimal waveband was at 708 nm.
- Red edge position (REP) and MERIS terrestrial chlorophyll index MTCI failed to estimate foliar nitrogen concentration from MERIS data.
- Band depth (BD) poorly predicts foliar nitrogen concentration from MERIS data.
- Band depth analysis parameter were good predictor of nitrogen density compared to MTCI and REP position

6. Recomendations

This study shows that forage biomass and nitrogen density can be estimated from MERIS data with reasonable accuracy using band depth analysis parameters. The empirical models are considered more reliable if the field measurements are contemporaneous with image acquisition. The study area is located in the region which is mostly overcast and very few cloud free images were available.

Future research on this theme can be improved by considering the following recommendations:

1. It is recommended to focus this kind of research in the regions, where mostly clear sky prevails because there are more chances of getting cloud free images.

2. The number of samples (observation) should be increased (both at parcel and plot level) to calibrate and validate the model on the same season data. As different season's data could be affected by various factors like variation in humidity, azimuth and sun zenith angle, phenology of grass etc. that can led to discrepancies in modelling biophysical and biochemical parameters. One of the limitations of empirical relationships developed between vegetation indices and field measurements is their unsuitability for different seasons.

3. Comparing the predictive performance of biophysical and biochemical parameters from various sensors having different spatial and spectral resolution could be investigated. For this contemporary data from various sensors should be acquired.

4. This study incorporated only one biophysical parameter (green biomass), other biophysical parameters like LAI, grass height, percent cover etc. can be considered for future research.

5. In band depth analysis parameters, continuum removed reflectance was used in this study. Future study can investigate original reflectance and first derivative spectra from MERIS data for the estimation of biophysical and biochemical parameters.

6. As biomass and nitrogen density of grassland were estimated with reasonable accuracy using MERIS images, this technique could further be extended to time series images to explore the dynamics of forage biomass and nitrogen density.

References

Asner, G. P. (1998). Biophysical and biochemical sources of variability in canopy reflectance. Remote Sensing of Environment, 64(3), 234 - 253.

Baret, F., Guyot, G., & Major, D. J. (1989). TSAVI: a vegetation index which minimizes soil brightness effects on LAI and APAR estimation. Proceedings of the 12th Canadian Symposium on Remote Sensing, Vancouver, Canada, 10-14 July (pp. 1355 - 1359). Ottawa: Canadian Remote Sensing Society.

Blackburn, G. A., & Ferwerda, J. G. (2008). Retrieval of chlorophyll concentration from leaf reflectance spectra using wavelet analysis. Remote Sensing of Environment, 112(4), 1614 - 1632.

Broge, N. H., & Leblanc, E. (2001). Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density. Remote Sensing of Environment, 76(2), 156 - 172.

Broge, N. H., & Mortensen, J. V. (2002). Deriving green crop area index and canopy chlorophyll density of winter wheat from spectral reflectance data. Remote Sensing of Environment, 81(1), 45 - 57.

Carlson, T. N., & Ripley, D. A. (1997). On the relation between NDVI, fractional vegetation cover, and leaf area index. Remote Sensing of Environment, 62(3), 241 - 252.

Cho, M. A., & Skidmore, A. K. (2006). A new technique for extracting the red edge position from hyperspectral data: The linear extrapolation method. Remote Sensing of Environment, 101(2), 181 - 193.

Clevers, J., De Jong, S.M., Epema, G.F., Van der Meer, F.D., Bakker, W.H., Skidmore, A.K., & Scholte, K.H. (2002). Derivation of the red edge index using the MERIS standard band setting. International Journal of Remote Sensing, 23(16), 3169 - 3184.

Curran, P. J. (1989). Remote-sensing of foliar chemistry. Remote Sensing of Environment, 30(3), 271 - 278.

Curran, P. J. (1994). Imaging Spectrometry. Progress in Physical Geography, 18(2), 247 - 266.

Curran, P. J., Dash, J., & Llewellyn, G. M. (2007). Indian Ocean tsunami: The use of MERIS (MTCI) data to infer salt stress in coastal vegetation. International Journal of Remote Sensing, 28(3), 729 - 735.

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(3), 349 - 359.

Darvishzadeh, R., Skidmore, A. K., Schlerf, M., Atzberger, C. G., & Cho, M. A. (2008). LAI and chlorophyll estimation for a heterogeneous grassland using hyperspectral measurements. ISPRS Journal of Photogrammetry and Remote Sensing, 63(4), 409 - 426.

Dash, J., & Curran, P. J. (2004). The MERIS terrestrial chlorophyll index. International Journal of Remote Sensing, 25(23), 5403 - 5413.

Dash, J., & Curran, P. J. (2007). Evaluation of the MERIS terrestrial chlorophyll index (MTCI). Advances in Space Research, 39(1), 100 - 104.

Dawson, T. P. (2000). The potential for estimating chlorophyll content from a vegetation canopy using the Medium Resolution Imaging Spectrometer (MERIS). International Journal of Remote Sensing, 21(10), 2043 - 2051.

Dawson, T. P., & Curran, P. J. (1998). A new technique for interpolating the reflectance red edge position. International Journal of Remote Sensing, 19(11), 2133 - 2139.

Devlin, R. M. (1969). Plant Physiology (2 ed.). New York, Van Nostrand Reinhold.

Donahue, R. L., Miller, R. W., & Shickluna, J. C. (1983). Soils: an introduction to soils and plant growth (5 ed.). Englewood Cliffs, New Jersey, Prentice Hall.

Duchemin, B. (1999). NOAA/AVHRR bidirectional reflectance: modeling and application for the monitoring of a temperate forest. Remote Sensing of Environment, 67(1), 51 - 67.

Elvidge, C. D., & Chen, Z. (1995). Comparison of broad-band and narrow-band red and near-infrared vegetation indices. Remote Sensing of Environment, 54(1), 38 - 48.

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(18), 4083 - 4095.

Gao, X., Huete, A. R., Ni, W., & Miura, T. (2000). Optical-biophysical relationships of vegetation spectra without background contamination. Remote Sensing of Environment, 74(3), 609 - 620.

Gobron, N., Pinty, B., Verstraete, M., & Govaerts, Y. (1999). The MERIS global vegetation index (MGVI): description and preliminary application. International Journal of Remote Sensing, 20(9), 1917 - 1927.

Guyot, G., Baret, F., & Major, D. J. (1988). High spectral resolution: determination of spectral shifts between the red and the near infrared. International Archives of Photogrammetry and Remote Sensing, 11, 740 - 760.

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(4), 542 - 553.

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, 25(3), 295 - 309.

Hurcom, S. J., & Harrison, A. R. (1998). The NDVI and spectral decomposition for semi-arid vegetation abundance estimation. International Journal of Remote Sensing, 19(16), 3109 - 3125.

Kawamura, K., Akiyama, T., Yokota, H., Tsutsumi, M., Yasuda, T., Watanabe, O., Wang, G., & Wang, S. (2005). Monitoring of forage conditions with MODIS imagery in the Xilingol steppe, Inner Mongolia. International Journal of Remote Sensing, 26(7), 1423 - 1436.

Kokaly, R. F., & Clark, R. N. (1999). Spectroscopic determination of leaf biochemistry using band-depth analysis of absorption features and stepwise multiple linear regression. Remote Sensing of Environment, 67(3), 267 - 287.

Lamb, D. W., Steyn-Ross, M., Schaare, P., Hanna, M. M., Silvester, W., & Steyn-Ross, A. (2002). Estimating leaf nitrogen concentration in ryegrass (Lolium spp.) pasture using the chlorophyll red-edge: theoretical modelling and experimental observations. International Journal of Remote Sensing, 23(18), 3619 - 3648.

Moreau, S., Bosseno, R., Gu, X. F., & Baret, F. (2003). Assessing the biomass dynamics of Andean bofedal and totora high-protein wetland grasses from NOAA/AVHRR. Remote Sensing of Environment, 85(4), 516 - 529.

Munden, R., Curran, P. J., & Catt, J. A. (1994). The relationship between red edge and chlorophyll concentration in the Broadbalk winter wheat experiment at Rothamsted. International Journal of Remote Sensing, 15(3), 705 - 709.

Mutanga, O., & Skidmore, A. K. (2004). Hyperspectral band depth analysis for a better estimation of grass biomass (Cenchrus ciliaris) measured under controlled laboratory conditions. International Journal of Applied Earth Observation and Geoinformation, 5(2), 87 - 96.

Mutanga, O., & Skidmore, A. K. (2007). Red edge shift and biochemical content in grass canopies. ISPRS Journal of Photogrammetry and Remote Sensing, 62(1), 34 - 42.

Mutanga, O., Skidmore, A. K., Kumar, L., & Ferwerda, J. (2005). Estimating tropical pasture quality at canopy level using band depth analysis with continuum removal in the visible domain. International Journal of Remote Sensing, 26(6), 1093 - 1108.

Novozamsky, I., Houba, V. J. G., van Eck, R., & van Vark, W. (1983). A novel digestion technique for multi-element plant analysis. Communications in Soil Science and Plant Analysis, 14(3), 239 - 248.

Rasmussen, M. S. (1992). Assessment of millet yields and production in northern Burkina Faso using integrated NDVI from the AVHRR. International Journal of Remote Sensing, 13(18), 3431 - 3442.

Rast, M., Bezy, J. L., & Bruzzi, S. (1999). The ESA Medium Resolution Imaging Spectrometer MERIS a review of the instrument and its mission. International Journal of Remote Sensing, 20(9), 1681 - 1702.

Richardson, A. J., Everitt, J. H., & Gausman, H. W. (1983). Radiometric estimation of biomass and nitrogen content of Alicia grass. Remote Sensing of Environment, 13(2), 179 - 184.

Rouse, J. W., Hass, R. H., & Schell, J. A. (1974). Monitoring the vernal advancement of retrogradiation of natural vegetation (Type III. Final report). MD, USA: NASA / GSFC.

Schlerf, M., Atzberger, C., & Hill, J. (2005). Remote sensing of forest biophysical variables using HyMap imaging spectrometer data. Remote Sensing of Environment, 95(2), 177 - 194.

Thenkabail, P. S., Smith, R. B., & De Pauw, E. (2000). Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. Remote Sensing of Environment, 71(2), 158 - 182.

Todd, S. W., Hoffer, R. M., & Milchunas, D. G. (1998). Biomass estimation on grazed and ungrazed rangelands using spectral indices. International Journal of Remote Sensing, 19(3), 427 - 438.

Van der Meer, F., Bakker, W., Scholte, K., Skidmore, A., De Jong, S., Clevers, J., Addink, E., & Epema, G. (2001). Spatial scale variations in vegetation indices and above-ground biomass estimates: implications for MERIS. International Journal of Remote Sensing, 22(17), 3381 - 3396.

Vickery, P. J. (1981). Pasture growth under grazing. In F. H. W. Morley (Ed.), Grazing Animals (pp. 55–78). Amsterdam: Elsevier.

Zhao, D., Huang, L., Li, J., & Qi, J. (2007). A comparative analysis of broadband and narrowband derived vegetation indices in predicting LAI and CCD of a cotton canopy. ISPRS Journal of Photogrammetry and Remote Sensing, 62(1), 25 - 33.

Appendices

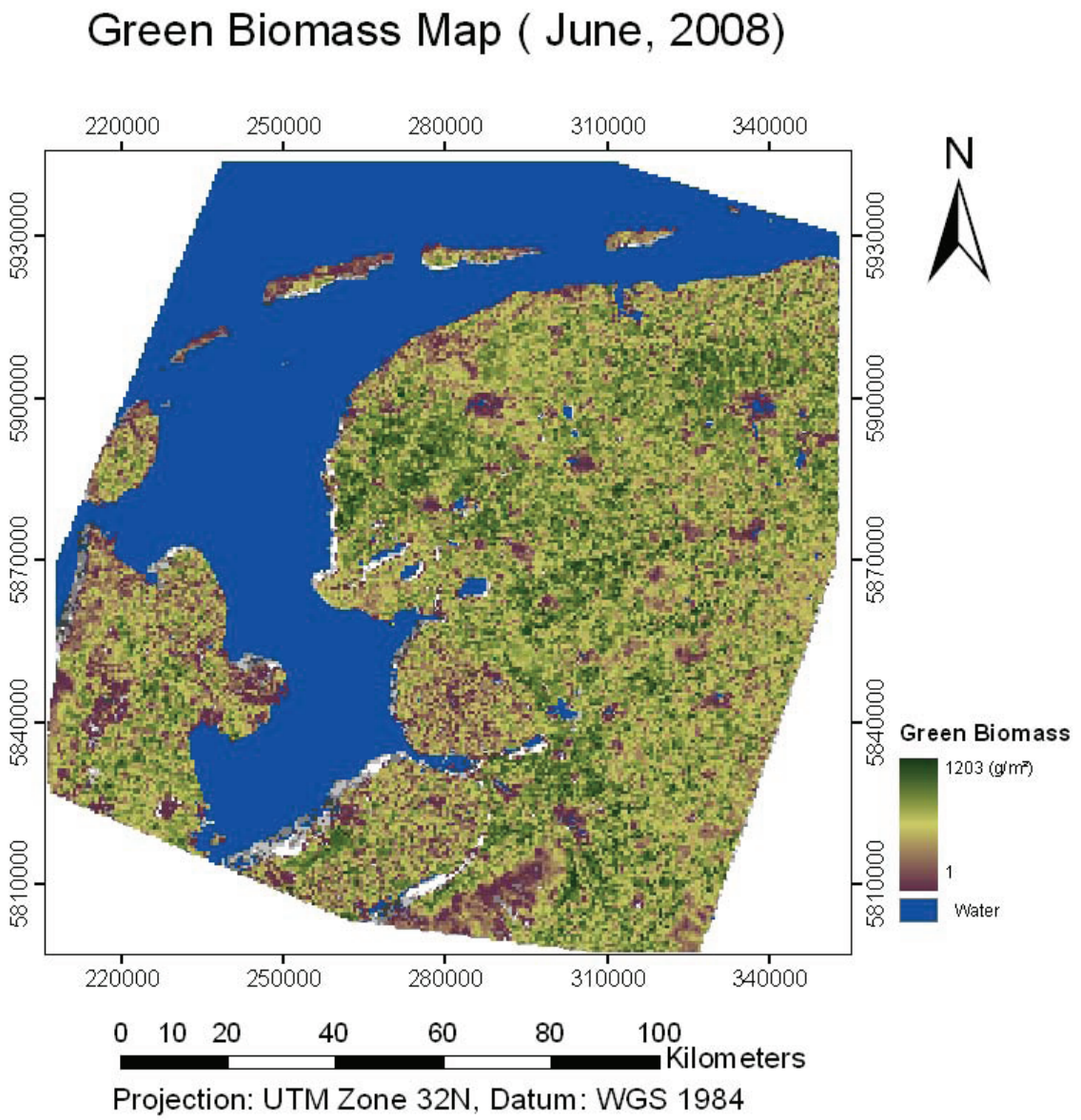
Appendix 1: Field data collected in June 2008

Parcel No.	X	Y	Lat	Lon	Green Biomass (g/m^2)	% N_2	Nitrogen Density (g/m^2)
1	313136.92	5906449.25	53.2743	6.197476	259.10	1.92	498.60
2	315536.92	5908249.25	53.2913	6.232379	189.00	4.87	920.76
3	312536.92	5908549.25	53.29295	6.18725	445.50	4.00	1782.21
4	307436.92	5910049.25	53.30458	6.109924	133.00	4.32	574.43
5	305336.92	5911549.25	53.31728	6.077531	315.33	4.21	1328.08
6	310436.92	5919349.25	53.38916	6.149319	241.50	4.40	1063.08
7	310436.92	5916949.25	53.36761	6.150759	113.50	4.06	461.17
8	308936.92	5916649.25	53.36438	6.128426	440.00	3.07	1352.71
9	308636.92	5913949.25	53.34003	6.125555	391.00	3.45	1348.96
10	308336.92	5915749.25	53.35608	6.119966	321.00	3.50	1122.03
11	303836.92	5915449.25	53.35174	6.052629	498.25	4.46	2220.93
12	305036.92	5914249.25	53.34141	6.071372	197.00	4.01	789.81
13	307436.92	5915449.25	53.35306	6.106643	173.25	3.85	666.89
14	308036.92	5915149.25	53.35059	6.115828	192.00	4.61	884.21
15	307136.92	5917549.25	53.3718	6.100861	330.00	2.13	702.90
16	310736.92	5920849.25	53.40273	6.152925	330.00	2.37	782.10
17	310136.92	5920249.25	53.39713	6.144273	259.67	2.99	775.55
18	310436.92	5914249.25	53.34337	6.152377	199.50	4.78	953.47
19	303536.92	5917249.25	53.36779	6.04701	75.00	3.73	279.58
20	315536.92	5917849.25	53.3775	6.22679	75.00	3.73	279.58
21	314336.92	5912149.25	53.3259	6.212116	97.00	2.44	236.72
22	259436.92	5882749.25	53.04005	5.411441	77.30	3.73	288.50
23	261236.92	5882749.25	53.04086	5.438235	278.00	4.36	1210.95
24	261536.92	5880649.25	53.02215	5.444253	596.67	3.34	1994.31
25	261836.92	5878549.25	53.00344	5.450265	458.00	3.25	1487.99
26	263336.92	5882749.25	53.04179	5.469497	669.50	2.88	1928.16
27	260636.92	5878249.25	53.00022	5.43264	669.50	2.40	1606.80
28	261836.92	5877949.25	52.99806	5.450707	383.00	3.16	1209.27
29	270536.92	5878849.25	53.00993	5.579465	531.00	2.60	1379.45
30	270236.92	5877649.25	52.99904	5.575855	587.50	3.28	1926.55

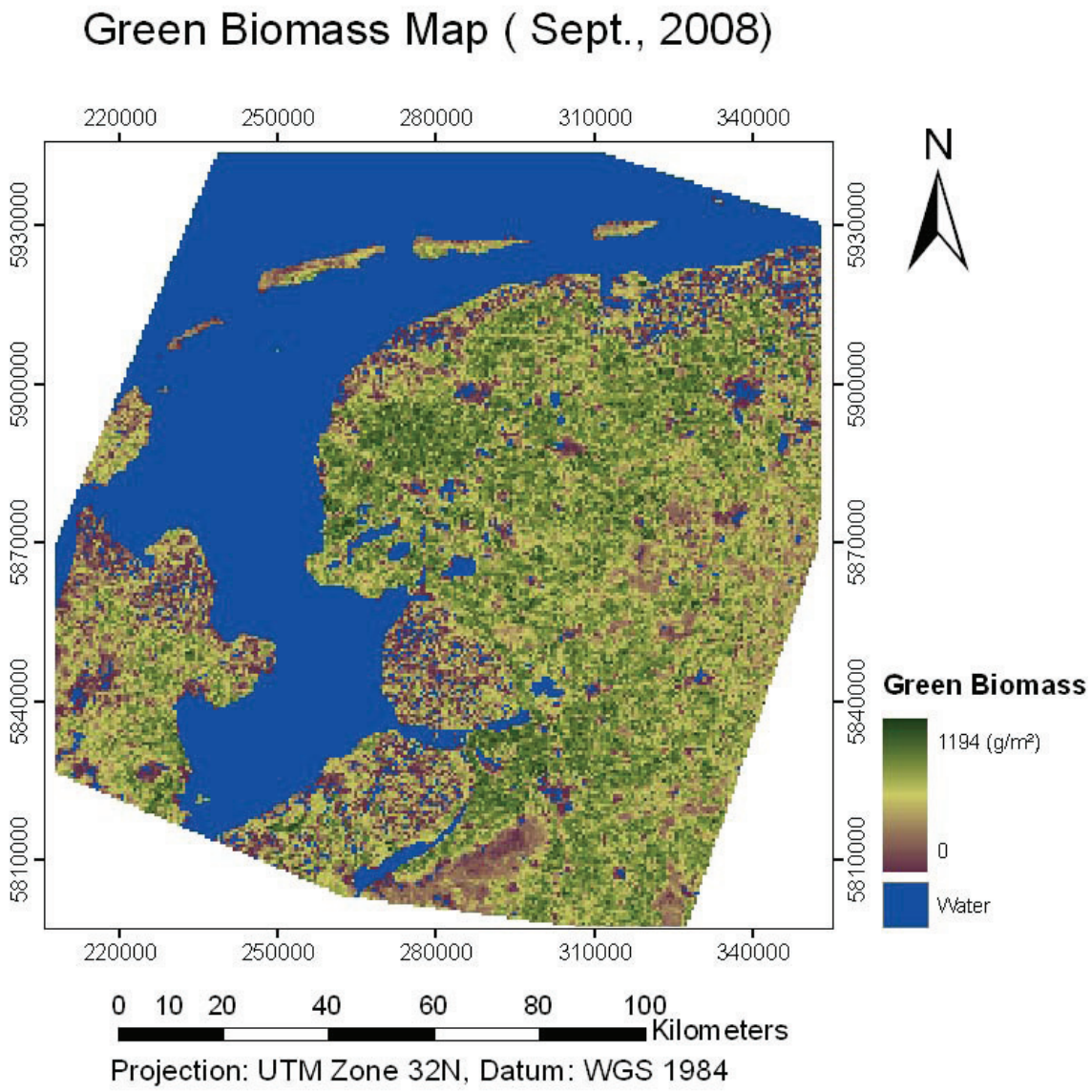
Appendix 2: Field data collected in September 2008

Parcel No.	X	Y	Lat	Lon	Green Biomass (g/m^2)	$\%N_2$	Nitrogen Density (g/m^2)
1	313136.9	5906449	53.2743	6.197476	215.00	4.30	924.36
2	315536.9	5908249	53.2913	6.232379	292.67	4.29	1255.87
3	312536.9	5908549	53.29295	6.18725	234.33	4.60	1077.49
4	307436.9	5910049	53.30458	6.109924	279.00	3.99	1113.36
5	305336.9	5911549	53.31728	6.077531	368.67	3.20	1181.46
6	310436.9	5919349	53.38916	6.149319	289.33	3.76	1087.16
7	310436.9	5916949	53.36761	6.150759	142.67	3.87	551.47
8	308936.9	5916649	53.36438	6.128426	431.33	2.89	1246.94
9	308636.9	5913949	53.34003	6.125555	274.50	3.38	929.02
10	308336.9	5915749	53.35608	6.119966	204.00	4.93	1006.47
11	303836.9	5915449	53.35174	6.052629	285.67	4.03	1151.19
12	305036.9	5914249	53.34141	6.071372	144.50	4.31	623.27
13	307436.9	5915449	53.35306	6.106643	292.00	3.51	1025.32
14	308036.9	5915149	53.35059	6.115828	509.00	3.18	1619.47
15	307136.9	5917549	53.3718	6.100861	143.67	2.26	324.55
16	310736.9	5920849	53.40273	6.152925	143.67	2.26	324.55
17	310136.9	5920249	53.39713	6.144273	201.33	3.19	642.78
18	310436.9	5914249	53.34337	6.152377	156.00	2.57	401.27
19	303536.9	5917249	53.36779	6.04701	312.50	3.16	987.90
20	315536.9	5917849	53.3775	6.22679	312.50	3.16	987.90
21	314336.9	5912149	53.3259	6.212116	278.75	3.94	1098.84
22	259436.9	5882749	53.04005	5.411441	384.00	4.31	1655.71
23	261236.9	5882749	53.04086	5.438235	264.00	4.22	1114.87
24	261536.9	5880649	53.02215	5.444253	228.00	3.43	782.16
25	261836.9	5878549	53.00344	5.450265	512.00	3.80	1947.88
26	263336.9	5882749	53.04179	5.469497	427.50	5.22	2230.37
27	260636.9	5878249	53.00022	5.43264	483.00	4.25	2051.47
28	261836.9	5877949	52.99806	5.450707	216.00	4.06	876.18
29	270536.9	5878849	53.00993	5.579465	302.00	3.82	1154.03
30	270236.9	5877649	52.99904	5.575855	341.00	3.85	1313.32

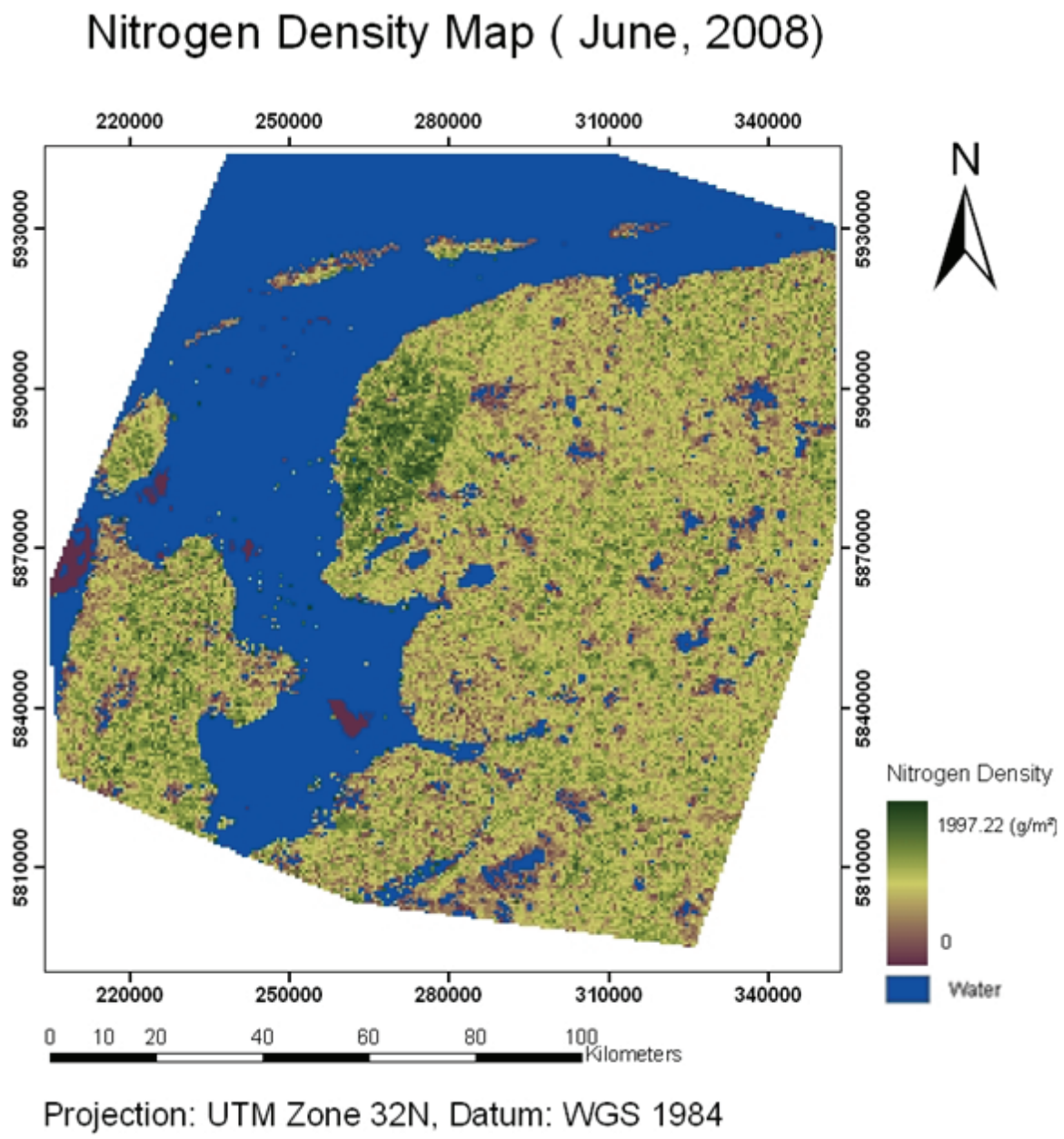
Appendix 3: Green biomass map of June 2008.



Appendix 4: Green biomass map of September 2008.



Appendix 5: Nitrogen density map of June 2008.



Appendix 6: Nitrogen density map of September 2008.