Remote sensing patterns of net primary productivity in the Great Limpopo Transfrontier Conservation Area (GLTFCA) in relation to land use and land tenure

By

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(R049319P)

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AUGUST 2013
Dedication

To mum (Ms G. Rushwaya), my siblings (Patience, Nyasha, Tapiwa and Fungai) and my dearest friend (Virginia)

I owe this to you all.
Declaration 1: Originality

I hereby declare that this Thesis entitled “Remote sensing patterns of net primary productivity in the Great Limpopo Transfrontier Conservation Area (GLTFCA) in relation to land use and land tenure”, submitted for the Master of Philosophy at the University of Zimbabwe is my original work. This work has not been submitted to any other institution of higher learning in and outside Zimbabwe. Furthermore, I declare that all the sources cited or quoted are consistent with a comprehensive list of references provided.

Signature ................................................

Date ................................./................../.................

Godfrey Pachavo

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Declaration 2: Publication

Details that form part and/or include research presented in this thesis include publications in preparation, submitted, in press and published and give details of the contributions of each author to the experimental work and writing of each publication.

Publication 1
Pachavo, G.\textsuperscript{a} and Murwira, A.\textsuperscript{a} (Manuscript accepted for publication in the Geocarto International Journal) \textbf{Land use and Land tenure explain spatial and temporal patterns in terrestrial net primary productivity (NPP) in Southern Africa.}

This work was done by the first author under the guidance and supervision of the second author.

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Publication 2
Pachavo, G.\textsuperscript{a} and Murwira, A.\textsuperscript{a} (Manuscript submitted to International Journal of Applied Earth Observation and Geoinformation (JAG)) \textbf{Remote sensing Net Primary Productivity (NPP) estimation with the aid of GIS modelled Shortwave Radiation (SWR) in a Southern African Savanna.}

This work was done by the first author under the guidance and supervision of the second author.

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Certification by Supervisor: Professor Amon Murwira

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Abstract

Net Primary Productivity (NPP) is an important indicator of ecosystem health and its estimation and understanding of factors determining its spatial and temporal variations is critical. Previous studies have mainly attributed NPP variations to biophysical factors. However, the influence of these factors is particularly evident at large spatial/global scales. At small spatial/local/landscape scales, complexity is encountered as biophysical factors tend to account for no or less variance in NPP. In addition, it is difficult to consider some aspects of human management systems such as land-use/land tenure in relation to NPP variations on a global scale analysis than on a local scale analysis. To this end, it is predicted that land use and land tenure would dominate explanation of NPP variations at local scales. Thus, in this study, at the local scale, particularly in a high intensive system of a Southern African savanna—the Great Limpopo Transfrontier Conservation Area (GLTFCA), the hypothesis that land-use/land tenure types influence NPP variations was tested. However, it is important to quantify NPP in order to test the abovementioned hypothesis. Thus firstly, this study tested the extent to which a combination of remote sensing and geographic information system (GIS) modelled shortwave radiation (SWR) can be used to estimate NPP in a Southern African savanna. Results showed that NPP can successfully be mapped using a combination of Moderate Resolution Imaging Spectroradiometer (MODIS) data and GIS modelled SWR. One-way analysis of variance (ANOVA) statistical test was then used to test for group mean NPP differences among the different land-use/land tenure types of the GLTFCA. Results showed that land-use/land tenure types significantly (P=0.000, F(4:42056)=180.162, One-Way ANOVA, Tukey HSD Post Hoc Analysis) explain NPP variations at landscape scales even better than biophysical factors. Furthermore, results showed that biophysical factors remain essential in explaining NPP variations even at local scales. These results exhibited the intricacies that exist between the biophysical and human induced factors in explaining NPP
variations within ecological landscapes. Also, the findings of this study suggest the importance of human management systems, in this instance, land-use/land tenure factors, as an agent of environmental change through its effect on NPP variations in African savannas.
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<table>
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<th>Description</th>
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<tr>
<td>GLTFCA</td>
<td>Great Limpopo Transfrontier Conservation Area</td>
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<tr>
<td>NPP</td>
<td>Net Primary Productivity</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic Information Systems</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalised Difference Vegetation Index</td>
</tr>
<tr>
<td>MODIS</td>
<td>Moderate Resolution Imaging Spectroradiometer</td>
</tr>
<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
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<tr>
<td>SWR</td>
<td>Shortwave Radiation</td>
</tr>
<tr>
<td>LUE</td>
<td>Light Use Efficiency</td>
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<tr>
<td>APAR</td>
<td>Absorbed Photosynthetically Active Radiation</td>
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<tr>
<td>PAR</td>
<td>Photosynthetically Active Radiation</td>
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<tr>
<td>fPAR</td>
<td>Fraction of Photosynthetically Active Radiation</td>
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<tr>
<td>MOD PRI</td>
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<tr>
<td>MODNPP</td>
<td>MODIS-derived Net Primary Productivity</td>
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<tr>
<td>Lieth NPP</td>
<td>Lieth Model-derived Net Primary Productivity</td>
</tr>
<tr>
<td>DMP</td>
<td>Dry Matter Productivity</td>
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<tr>
<td>SPSS</td>
<td>Statistical Package for the Social Sciences</td>
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<tr>
<td>ILWIS</td>
<td>Integrated Land and Water Information System</td>
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<td>CLs</td>
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<td>SAs</td>
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<tr>
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<td>NPs</td>
<td>National Parks</td>
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<td>GNP</td>
<td>Gonarezhou National Park</td>
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<td>ZNP</td>
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Chapter 1: General introduction

1.1 Introduction

Savannas are one of the world’s predominant vegetation, contributing 30% to the global primary production of terrestrial systems (Grace et al., 2006). Fifty percent of Africa’s total land area is made up of the savannas (Menaut, 1983; Campbell, 1996). The levels of primary production are essentially estimated by net primary productivity (NPP), i.e., the amount of solar energy converted to biomass through photosynthesis by plants per unit area per unit time (expressed in weight or energy units, e.g. g m\(^{-2}\) yr\(^{-1}\) or kJ m\(^{-2}\) yr\(^{-1}\)) (Melillo et al., 1993; Clarke, 1994; Tao et al., 2003; Haberl et al., 2004; Imhoff, 2004). NPP is a fundamental ecological variable, not only because it measures the energy input to the biosphere and terrestrial carbon dioxide assimilation, but also because of its provision for food, fuel, timber and its significance in indicating the conditions of the land (Field et al., 1995; Scholes and Biggs, 2004; Kremen and Ostfield, 2005; Hendrickx et al., 2007). In fact, it is important to note that almost all life on Earth is directly or indirectly reliant on NPP. It is therefore invaluable to understand the spatial and temporal patterns in NPP, particularly in relation to factors that explain its variations in space and through time as a basis towards sustainable utilization and management of ecosystem services especially in savanna biomes. In this regard, it is important to map NPP accurately in order to explain its spatial and temporal distribution patterns.

1.2 Remote sensing of Net Primary Productivity (NPP)

In studies of ecosystem processes and environmental management, accurate net primary productivity (NPP) measurements are crucial as NPP represents an important energy flux in
ecosystems. Traditionally, NPP has been measured using biometric measurements, i.e., sample surveys and field measurements (Tao et al., 2003). Although these traditional field-based measurements have been used successfully with accurate NPP output for small scale observations (Ogawa, 1977; De Gier, 2003; Li et al., 2005), they are often time consuming and laborious (Lu, 2006). The methods are also hard to extend to larger spatial scales because of the sparse measurements network. In addition, the felling of sample trees at target research sites may lead to loss of habitat and biodiversity as well as carbon sequestration potential (Wang et al., 2007). Therefore, it is necessary to apply alternative methods of NPP estimation to replace or complement traditional methods.

The development of remote sensing has enhanced the ability to study and understand ecosystems with improved accuracy (Lu, 2006). Remote sensing provides an invaluable opportunity to improving the estimation of NPP at landscape and regional scales in a cost effective, efficient and accurate manner (Running et al., 1999; Running, 2000) at high temporal and spatial scales (Myneni et al., 1997; Myneni et al., 1998; Tucker et al., 2001; Zhou et al., 2001; Lu, 2006). Early applications of remote sensing have seen the use of the normalized difference vegetation index (NDVI), as a surrogate measure for NPP (Townshend and Justice, 1986). NDVI has been proven to provide an effective measure of photosynthetically active biomass and has been correlated to NPP at extensive spatial scales (Box et al., 1989; Prince, 1991; Oindo and Skidmore, 2002). However, NDVI is just an indicator so it does not give an estimate of the real quantity of biomass per unit area per unit time to determine the productivity patterns unless it is related to ground measurements.

Recent developments in remote sensing are now focusing on estimating NPP quantities usually in grams of carbon per square metre per year (gC m$^{-2}$ yr$^{-1}$) or tonnes of carbon per
hectare per year (ton C ha\(^{-1}\) yr\(^{-1}\)). As a result, various NPP models that use remote sensing data have been developed (Goetz et al., 2000). Recently, the moderate resolution imaging spectroradiometer (MODIS) NPP model, based on a micrometeorological approach was developed by Rahman et al., (2004) to provide a consistent, continuous estimate of NPP (Heinsh et al., 2006) hereinafter referred to as the MODNPP model. This model is derived from the Monteith Model (Monteith, 1977) which estimates NPP as a product of light-use efficiency (LUE) and absorbed photosynthetically active radiation (APAR). However, the model’s limitation has been its demands for densely measured shortwave radiation (SWR) flux for APAR estimation, as well as LUE values. The LUE and SWR flux measurements have mainly been obtained from coarse resolution satellite-based weather data, making NPP studies difficult in cases where intensively measured LUE and SWR information is required (Turner et al., 2003; Rahman et al., 2004; Running et al., 2004). Scientists have therefore depended on calibrated LUE (Rahman et al., 2004) and SWR (Kumar et al., 1997) values whose accuracy is still largely unknown. Thus, the development of efficient and accurate methods for estimating LUE and SWR is critical.

1.3 Variations of NPP by land use and land tenure
Several studies have identified biophysical factors (i.e., soil conditions, vegetation types, herbivory, and climate) (Lieth and Whittaker, 1975; Burke et al., 1997a; Burke et al., 1997b; Tao et al., 2003; Piao et al., 2006) as key in explaining spatial and temporal NPP variations particularly at global scales. Thus, biophysical factors have become the most common way of explaining NPP distribution with climate being considered the best predictor of NPP variations across different biomes (Turner et al., 2006). The result of such a focus is the advancement in our understanding of potential NPP over the surface of the Earth at large spatial scales, i.e., among different biomes. While knowledge on potential NPP distribution is
vital at large spatial scales, it is also important to understand factors influencing NPP at small spatial scales. In addition, it is at the local scale that human activities particularly agricultural practices are evident. Thus, understanding factors affecting NPP variations at the local scale, in addition to larger scale biophysical factors is critical for the sustainable management of ecosystems.

To this end, land use/land tenure is hypothesised to be the most important local factor affecting the spatial and temporal variation of NPP (Vitousek, 1992; Burke, 2000; Guersehman et al., 2003; Haberl et al., 2004). In fact, land use change has emerged as one of the most important factors driving global environmental change (Turner et al., 1996; Zhiqiang et al., 2004). Protected areas have been to a large extent a result of the efforts to maintain ecosystem productivity in the face of human induced land use changes (Brandon, 1995; Mas, 2005; DeFries et al., 2007; Schmidt-Soltau and Brockington, 2007). In addition, there has been a long held view that protected areas contribute towards high NPP (Bruner et al., 2001) relative to other land-use/land tenure types. Work in temperate systems suggest that land ownership patterns create significant spatial and temporal variations in NPP (Crow et al., 1999; Fang et al., 2002). While variations of NPP in relation to land use/land tenure have been tested in the temperate regions, such work has barely been done in the tropical savannas such as those found in Africa. This focus raises the need to test the effect of human induced factors on NPP in tropical savannas particularly in a complex landscape dominated by humans.

In this thesis, the small spatial scale refers to the local or landscape scale which according to Ahern and Cole (2012) is an area resulting from the complex interaction of natural factors (e.g. biodiversity, soils), cultural factors (e.g. land-use/land tenure, settlement) and aesthetic
qualities. Thus this thesis investigates the effect of this complexity between the biophysical and human induced factors in a savanna landscape in influencing NPP variations, particularly the effect of human induced factors on NPP patterns.

1.4 Thesis Objectives

In this thesis we tested whether and in what way land use and land tenure practices, in a savanna landscape of the Great Limpopo Transfrontier Conservation Area (GLTFCA), influence both the spatial and temporal variations in NPP. To achieve this objective, it is important that NPP be accurately estimated. Thus, this thesis tested the extent to which MODIS remotely sensed data and GIS modelled SWR can be used to estimate NPP in the study area.

1.5 Organisation of the thesis

This thesis is divided into five chapters: Chapter 1 gives a detailed outline on the importance of NPP, the problems in estimating NPP, and the role of remote sensing in NPP estimation. The chapter also provides a background to the importance of biophysical factors in explaining NPP variations. It further explores the role of human induced factors in explaining NPP variations particularly in localised landscapes dominated by humans. Finally, the chapter details the objectives and hypothesis of the thesis.

Chapter 2 outlines the materials and methods used to answer our objectives and hypotheses in this study. The chapter explains the methods we used to estimate NPP in this study and how we tested for accuracy of our modelled NPP estimates using regression and correlation analysis. The chapter also explains how we used a One-Way Analysis of Variance (ANOVA) to test for differences in NPP, and how we used a Fourier Transform to determine rates of
NPP change among different land-use/land tenure types at different vegetation phenological stages.

Chapter 3 presents the results and discussion of the NPP estimation model used in this thesis in comparison with NPP results of other models within the same ecological landscape. A detailed discussion of the results concludes the chapter.

Chapter 4 presents results and discussion on the effect of different land-use/land tenure types on NPP spatial and temporal distribution patterns in addition to biophysical factors’ effect. A discussion of results in this chapter is also provided.

Chapter 5 synthesises the findings of this thesis presented in Chapter 3 and 4. In particular the chapter discusses the importance of using a combination of remote sensing and GIS modelled SWR to successfully estimate NPP in African savannas as well as the importance of human factors in explaining NPP variations at smaller scales better than biophysical factors. The chapter ends by discussing how future studies can improve this thesis.
Chapter 2: Materials and methods

2.1 Study area

This study was carried out in the GLTFCA (Figure 1) which lies across Zimbabwe, South Africa and Mozambique, specifically between 30.70°E and 35.00°E, and 25.50°S and 20.30°S. The GLTFCA is a union of the Limpopo National Park (LNP), Banhine National Park (BNP), and Zinave National Park (ZNP) of Mozambique, Kruger National Park (KNP) of South Africa, Gonarezhou National Park (GNP), Manjinji Pan Sanctuary (MPS) and Malipati Safari Area (MSA) of Zimbabwe, as well as Sengwe communal land of Zimbabwe and the Makuleke region of South Africa. Bordering the core Transfrontier Park are other land areas in each of the three countries, managed in various forms for conservation or natural resource use.

2.1.1 Climate, Soils and Vegetation

The GLTFCA landscape experiences mean annual temperature averaging between 25 and 32 degrees Celsius and rarely do temperatures drop below freezing point even in winter (Food and Agricultural Organization of the United Nations (FAO), 2004). The landscape is generally dry with a short rainy season spanning from November to March and mean annual rainfall being about 500mm per annum.

The soils are varied depending on the parent materials and age. However, the major soil types include haplic solonetz (SNh), eutric regosols (RGe), eutric vertisols (VRe), eutric leptosols (LPe), leptosols (LP), chromic luvisols (LVx), and arenosols (ARb). The vegetation varies from a tree savanna on deep fertile soils to shrub savanna on shallower soils. The *Colophospermum mopane* (mupane) is the dominant tree species in the woodlands and is
prevalent on the sodic soils. Other common tree species include the Baobab (*Adonsonia digitata*), Marula (*Sclerocarya birrea*), and various *Combretum* and *Acacia* species.

### 2.1.2 Land use and land tenure

The GLTCA is a multiple land use area approximately 100,000 km² in area and was therefore considered suitable for this study. Different land-use/land tenure types that include state protected national parks (NPs), safari areas (SAs), small scale commercial farming areas (SSCFAs), large scale commercial farming areas (LSCFAs) as well as surrounding communal lands (CLs) constitute the study area. The GLTFCA’s protected areas which include the NPs as well as SAs are under the control of the state and were primarily established for biological diversity conservation, i.e. the conservation of species of wild flora and fauna. In the SAs, hunting of wild animals is permitted but under the control of the state. On the Zimbabwe and South Africa sides, most LSCFAs are owned by farmers who have freehold title to land (Gambiza and Nyama, 2006) while in Mozambique farms are state owned. Farming in LSCFAs is highly mechanised and fully commercialised and it is the same across the landscape (Chenje and Johnson, 1994; Chenje *et al.*, 1998). In the CLs, land is owned communally and it is also known as smallholder sector, farming system is labour intensive and farmers mainly use ox-drawn implements. The size of farmson average, is 2200 ha/farmer for the LSCFAs, 123 ha/farmer for the SSCFAs and 16.3 ha/farmer for the CLs (Chaonwa and Mukwereza, 1997). Since the GLTFCA landscape receives erratic rainfall, the area has primarily been used for extensive livestock production and game ranching. Cropping practices are limited by the little and unreliable rainfall, thus most of the cropping practices are supplemented by irrigation especially in LSCFAs.
In CLs, crop farming is mainly subsistence and is affected by climate variability which is normally associated with drought. Thus, the mixed crops/livestock farming system is the main land use in areas outside nature conservation. However, the low rainfall in the GLTFCA makes livestock production more viable than cropping (Gambiza and Nyama, 2006). Cattle, goats and sheep are the common livestock with cattle being the most important (Sandford, 1982; Cousins, 1990; Food and Agricultural Organization of the United Nations (FAO), 2004). The GLTFCA is generally characterised by freehold commercial livestock production and mixed crops or livestock systems under communal management as well as small scale sector (Government of Mozambique (GOM)-MAF, 1997).

**Figure 1**: The Great Limpopo Transfrontier Conservation Area (GLTFCA) with map coordinates in Universal Transverse Mercator (UTM), Zone 36 south of the equator, WGS 1984 reference spheroid. A, B, C and D are the LSCFAs study sites.
2.2 Estimating NPP from remote sensing in the GLFTCA

In this thesis, MODIS level 1B Terra 1km (MOD021KM) satellite data acquired for the period January 2000 to December 2009 was used, freely available from http://ladsweb.nascom.nasa.gov. The MOD021KM data are available on daily basis with a spatial resolution of 1 kilometre at nadir. By visual inspection, we selected the days that were cloud-free over the study region. Cloud-free images were considered since clouds compromise the accuracy of the indices used in the NPP model used in this study. The multiple cloud-free images obtained were averaged for each month. The downloaded images were already geometrically and radiometrically corrected thus we only re-projected them from the native Sinusoidal projection to universal transverse mercator (UTM) Zone 36 South based on the WGS84 global spheroid. These MOD021KM products were of land reflectance bands 1 (620-670 nm) and 2 (841-876 nm) and ocean bands 11 (526-536 nm) and 12 (546-556 nm). The stated bands 1 and 2 as well as 11 and 12 were necessary for the estimation of two important vegetation indices used in NPP modelling in this thesis namely; the normalised difference vegetation index (NDVI) and the photochemical reflectance index (PRI).

2.2.1 The NPP estimation Model

We used a modified remote sensing micrometeorological model for estimating NPP after Rahman et al., (2004). The model which we hereinafter refer to as the MODNPP utilizes the visible (band 1: 620-670 nm) and the near infra-red (band 2: 841-876 nm) as well as the “ocean” bands (band 11: 526-536 nm and band 12: 546-556 nm) for estimating carbon dioxide (CO2) flux from terrestrial vegetation. The MODNPP model (Equation 2) is derived from the Monteith equation (Equation 1) (Monteith, 1977) which is given as follows:
\[ NPP = LUE \times APAR \]  

(1)

where, APAR refers to absorbed photosynthetically active radiation and LUE is the light use efficiency.

\[ MODNPP = 0.5139 \times MODPRI \times APAR - 1.9818 \]  

(2)

where, MOD PRI is MODIS-derived photochemical reflectance index which is used as proxy for LUE and 0.5139 and 1.9818 are constants.

In order to estimate APAR there is need to estimate the incoming solar radiation (shortwave radiation (SWR)) and the fraction of photosynthetically active radiation (fPAR). The fPAR is the fraction of the SWR in the photosynthetically active radiation spectral region that is absorbed by vegetation. This biophysical variable is directly related to photosynthesis and some models use it to estimate the assimilation of carbon dioxide in vegetation. Thus the daily APAR (Equation 3) is given by the relationship:

\[ APAR = fPAR \times \sum_{\text{sunrise}}^{\text{sunset}} PAR \]  

(3)

where, PAR is photosynthetically active radiation estimated from sunrise to sunset and is given by the formula (Equation 4):

\[ PAR = 0.5 \times SWR \]  

(4)

In this study, a modified approach of measuring SWR was used. SWR was modelled using a GIS and DEM based SWR model after Kumar et al., (1997) as opposed to weather station SWR data. This model uses solar altitude angle (\( \alpha \)), solar azimuth angle (\( \theta \)), angle of latitude (L), and solar declination angle (\( \partial_s \)), as well as hour angle (\( \phi_h \)) to calculate the amount of radiation received at a given surface per month given the location’s slope and aspect (Kumar et al., 1997). The ability of the model to integrate radiation over long time periods in a
computationally inexpensive manner enables it to be used for modelling radiation by itself, or input into other ecological, hydrological, or climatological models.

A DEM covering approximately 100000 km² of the study area with a pixel size of 110 metres for modelling the SWR in a GIS (http://gdex.cr.usgs.gov/gdex), was used. A DEM is particularly useful for the computation of aspect and slope values. Firstly we had to subdivide the study area DEM into separate latitude blocks (latitude 20 to 25 south of the Equator) as per algorithm’s specifications. Thus, SWR was calculated by latitude for each month (January to December) to produce 72 SWR maps altogether (6 per every month). Thus, the 6 latitude blocks of SWR covering the study site were then merged to give monthly GLTFCA SWR maps. The output SWR maps were converted to mega joules per square metre per day (MJ m⁻² day⁻¹), see Figure 2. The DEM derived SWR was then used for the estimation of PAR in Equation 4 of this study.
To calculate fPAR, NDVI values are needed (Equation 5). MODIS bands 1 and 2 were used to calculate NDVI as follows:

\[
NDVI = \frac{(\rho_{\text{NIR}} - \rho_{\text{R}})}{(\rho_{\text{NIR}} + \rho_{\text{R}})}
\]  

(5)

where, \( \rho_{\text{NIR}} \) is reflectance in the Near Infrared and \( \rho_{\text{R}} \) is reflectance in the visible Red of MODIS data and NDVI values range from -1 for water up to 1 for healthy vegetation. fPAR was then calculated as:

\[
fPAR = 1.24 \times NDVI - 0.168
\]  

(6)

To estimate MOD PRI, MODIS ocean bands 11 and 12 were used. MOD PRI is a recently developed remote sensing spectral index used as surrogate for LUE values (Rahman et al.,
2004). The concept of light-use efficiency (LUE) is the underlying basis for estimating carbon exchange in ecosystem models, especially in models that utilize remote sensing to constrain estimates of canopy photosynthesis. MOD PRI is sensitive to changes in carotenoid pigments (e.g. xanthophyll pigments) in live foliage. Carotenoid pigments are indicative of photosynthetic LUE, or the rate of carbon dioxide (CO\textsubscript{2}) uptake by foliage per unit energy absorbed. This MODIS satellite-based PRI is able to track changes in landscape-level photosynthesis activity (Rahman et al., 2004). Thus, in this study, we used a scaled MODIS-derived PRI (MOD PRI) calculated as:

\[
\text{MODPRI} = \left[ \frac{\rho_{\text{band}11} - \rho_{\text{band}12}}{\rho_{\text{band}11} + \rho_{\text{band}12}} \right] + 1 \div 2
\]

where, \(\rho_{\text{band}11}\) and \(\rho_{\text{band}12}\) represent reflectance in the band 11 (531nm) and band 12 (570nm) of MODIS, respectively. The values of MOD PRI range from 0 to 1.

Finally, in the MODNPP model, NPP was estimated using the regression equation developed by Rahman et al., (2004) (Equation 2). The units of our MODNPP have been converted from grams of carbon per square metre per month (g C m\textsuperscript{-2} mon\textsuperscript{-1}) to tonnes of carbon per hectare per year (ton C ha\textsuperscript{-1} year\textsuperscript{-1}) in this study.

2.2.2 Evaluation of remotely sensed NPP

In order to test the effectiveness of the MODNPP model, MODNPP results were compared with NPP results from an established empirical model for the savannas developed by Leith and Whitaker (1975). MODNPP estimates were also compared with satellite based dry matter productivity (DMP) estimates from “vision on technology” (VITO) (http://www.geoland2.eu/) as well as with NPP estimates from African savannas in refereed literature.
The Lieth NPP model predicts NPP from annual precipitation (Lieth and Whittaker, 1975) and it is given by:

\[ y = 3000 \left( 1 - e^{-0.000644x} \right) \]  

(8)

where, \( y \) is the NPP in g C m\(^{-2}\) year\(^{-1}\), \( x \) is the precipitation in millimetres (mm) and \( e \) is the natural log base. Conversion to ton C ha\(^{-1}\) year\(^{-1}\) was carried out by dividing the value in g C m\(^{-2}\) year\(^{-1}\) by 100, and rescaling by dividing the results by a factor of 2. The rainfall data for input into the Lieth model was downloaded as decadal rainfall from African Data Dissemination Service (http://earlywarning.usgs.gov/fews/africa/index.php) for the years 2000 to 2009 at a spatial resolution of 8 km by 8 km. All decadal rainfall maps were layer stacked and averaged in a GIS to produce rainfall maps per year and spatial references were corrected to suit the GLTFCA study site landscape (UTM WGS 1984 Zone 36 South). The annual rainfall maps were computed for the 10 years and their mean computed to give the long term mean rainfall (mm). Thus, the Lieth NPP model was used to calculate NPP for the same period as the MODNPP from 2000 to 2009.

The DMP model predicts NPP by combining fraction of photosynthetically active radiation (fAPAR) estimated from satellite imagery, with solar radiation and temperature, as described by Monteith (1972). DMP is directly related to NPP and its computation is given as follows:

\[ DMP = SWR \times 0.48 \times fAPAR \times \varepsilon(T) \times 10000 \]  

(9)

where, SWR (J m\(^{-2}\) day\(^{-1}\)) is the incoming short wave radiation of the sun (200-3000 nm), which is composed of the average for 48% of PAR (Photosynthetically Active Radiation: 400-700nm), and fAPAR is the PAR-fraction absorbed by the green vegetation. The efficiency term \( \varepsilon(T) \) (kg DM JPAR\(^{-1}\)) accounts for the conversion of this absorbed energy into biomass (radiation use efficiency) and for the losses related to the transport of
photosynthetates, the maintenance of the standing phytomass, etc. DMP is derived from SPOT VGT S10 products and provided by VITO through (http://www.geoland2.eu/) as dekadal files in zip format with a spatial resolution of 1km x 1km. Thus, we downloaded a total of 360 DMP dekadal files for the GLTFCA from January 2000 to December 2009. A VGT Extract was used to extract the files into ILWIS raster format and conversion of units to kg ha\(^{-1}\) day\(^{-1}\) was done using the following formula (Equation 10):

\[
PV = 0.01 \times DN
\]

where, PV = pixel value or physical DMP value in kilograms per hectare per day (kg ha\(^{-1}\) day\(^{-1}\)) and DN = digitally stored number. The 10-day composite data were summed into annual totals for easier analysis. The long term mean DMP was computed by averaging the annual totals for period 2000 to 2009 and units converted to tonnes per hectare per year (ton C ha\(^{-1}\) year\(^{-1}\)).

To correlate MODNPP with Lieth NPP as well as MODNPP with DMP, sampling points were generated randomly in ArcView GIS 3.2 (ESRI, 1998) using the GLTFCA study area map. In ArcGIS, the hawth tools extension was activated and the random point generator was selected for the generation of sampling points. Minimum distance in the extraction of sampling points was 8km such that no pixel would have 2 or more sampling points within it given that pixel size for the MODNPP and DMP was 1km while it was 8km for the Lieth NPP. We then overlaid our sampling points with our MODNPP, Lieth NPP and DMP images to extract data for each sample plot. A correlation analysis of MODNPP with Lieth NPP as well as MODNPP with DMP was then performed. Specifically, the Pearson Product-Moment Correlation coefficient (R) was used since data followed a normal distribution. Since both correlations were significant at alpha=0.05, we further performed a regression analysis and the tests of statistical significance as well as the coefficients of determination (R\(^2\)) from the
resultant regression analysis were determined. Using a regression analysis, the intention was to find out whether the Lieth NPP as well as the DMP can significantly predict the spatial distribution of the MODNPP. The regression function with a higher coefficient of determination was regarded as the best regression function to predict the MODNPP. In Statistical Package for Social Scientists (SPSS) software, a One-Way ANOVA was performed to test the hypotheses of no significant difference among the NPP means estimated by the MODNPP, Lieth NPP and DMP models. However, due to its significantly higher values compared with MODNPP and Lieth NPP, the DMP was dropped from further analysis in this study.

The GLTFCA land cover map extracted from the GlobCover 2009 Land Cover Map created by the European Space Agency (http://ionia1.esrin.esa.int/) was also used to further investigate the strength of MODNPP model compared with the established Lieth NPP model. Thus, firstly the study area was stratified according to different land cover types mainly the grassland, water bodies, deciduous forest, mosaic vegetation and cropland and the shrubland. Next, sampling points were randomly selected in a GIS within the different strata. The mapvalue function in ILWIS GIS was then used to extract NPP values for both the MODNPP and Lieth NPP models. The Shapiro test and the Q-Q Plots were used in exploring and testing the normality of data and in this study data was found to be normally distributed. Since the objective was to compare means of a continuous random variable (NPP) over distinct populations (5 land cover types), One-Way ANOVA was used and a Fligner Killeen test of homogeneity of variance was run in R software (R Development Core Team, 2012). In the case where ANOVA tests for differences among the NPP means, a Tukey honestly significant difference (HSD) post hoc multiple comparison analysis was run to determine the specific means that differed. Next, the Paired T-Test was used to compare the two NPP models per
each individual land cover class. Specifically, the hypotheses that the difference between the MODNPP and Lieth NPP is zero across the individual land cover types, was tested.

### 2.3 Analysis of NPP as a function of land use and land tenure

For the purpose of statistical analysis of NPP in relation to land use and land tenure, the land-use/land tenure map of the GLTFCA was used. Thus, the GLTFCA study area was stratified into five major land-use/land tenure types namely the CLs, SAs, SSCFAs, LSCFAs and the NPs. Among the NPs were the GNP of Zimbabwe; KNP of South Africa; as well as LNP, BNP, and ZNP all of Mozambique. Samplings points were generated randomly per each stratum in ArcView GIS (ESRI, 1998). Next, we extracted our NPP values using the mapvalue function in ILWIS GIS. The Shapiro test and the Q-Q Plots were then used to explore and test the normality of data. Our data was found to be normally distributed hence One-Way ANOVA was used. Firstly, a Fligner Killeen test of homogeneity of variance was run in R software (R Development Core Team, 2012). In the case where ANOVA tests for differences among the means, a Tukey honestly significant difference (HSD) post hoc multiple comparison analysis was run to determine the specific means that differed.

Furthermore, we computed the rate of change in NPP values for each land-use/land tenure type by calculating the differences between successive month intervals of NPP data. A Fourier analysis, first developed by Joseph Fourier (1822), was then used to test whether and in what form the rate of change in mean NPP between successive month intervals for the 5 different land-use/land tenure types is a function of different phenological stages. In this study we had NPP seasonal profile data for seasons 2000/2001, 2001/2002, up to 2008/2009 and the following stages of the NPP phenological cycle: green-up, peak and senescence, were of particular interest. The Fourier transform is good for identifying a periodic component or
pattern in an image and it was proven to be useful in various applications including signal processing (Rahman, 2011) and it is given by the following formula;

\[ f(x) = a_0 + \sum_{n=1}^{\infty} \left( a_n \cos \frac{n\pi x}{L} + b_n \sin \frac{n\pi x}{L} \right) \]  

(11)

where, \( f(x) \) is a best-fit line of regression for changes in mean NPP between successive image dates, \( a_0 \) is the intercept of the mean change in NPP between successive image dates, \( a_n \) is the cosine of the coefficient of change in mean NPP between successive image dates, \( b_n \) is the sine coefficient of change in mean NPP between successive image dates, \( L \) is the number of image days throughout the year, \( \pi \) is PI and \( x \) is a particular image date. The algorithm was applied for all the 5 different land-use/land tenure types in this study.

2.4 Analysis of NPP as a function of biophysical factors

Firstly, the study tested the effect of rainfall on the distribution of NPP across the GLTFCA landscape. Rainfall estimate data was downloaded from African Data Dissemination Service for the years 2000 to 2009 made available at (http://earlywarning.usgs.gov/fews/africa/index.php). Using the sampling points generated for each land-use/land tenure stratum, we extracted rainfall profiles from the processed rainfall data. The mean monthly and mean annual rainfalls were calculated in millimetres (mm) for all the years. Rainfall data was then stratified according to the different land-use/land tenure zones within the GLTFCA and then correlated with the corresponding NPP data using the Pearson Product-Moment Correlation coefficient (R) since our data followed a normal distribution. Statistical comparisons of rainfall data among the different land-use/land tenure categories were also performed using One-Way ANOVA in R Statistical software (R Development Core Team, 2012).
Using the soil map of the GLTFCA, we used overlay analysis in a GIS to extract the different soils for each land-use/land tenure map and similar soil types cutting across the different land-use/land tenure types. The area of the different soil categories were used to determine the number of sampling points to be used in this study and random points were generated in a GIS which were then overlaid with our NPP data for the purpose of statistical analysis. Data was tested for normality using the Shapiro test and the Q-Q Plots and there was evidence that our data did not significantly deviate from a normal distribution hence the use of ANOVA.
Results and Discussion
3.1 Results

The range of NPP values for the MODNPP and Lieth NPP are almost similar with NPP ranging from 0 to 6 ton C ha$^{-1}$ year$^{-1}$ whilst NPP values range up to 30 ton C ha$^{-1}$ year$^{-1}$ for the DMP (Figure 3 (a), (b) and (c)).
Figure 3: NPP distribution in tonnes of carbon per hectare per year (ton C ha$^{-1}$ year$^{-1}$) across the GLTFCA as estimated by (a) the MODNPP model, (b) the Lieth NPP model, and (c) the
DMP. Points 1 and 2 demonstrate areas with low and high NPP respectively. Coordinates are in metres UTM Zone 36 South WGS 1984 reference spheroid.

Table 1 shows mean NPP (ton C ha\(^{-1}\) year\(^{-1}\)) over a ten-year period (2000 to 2009) across the GLTFCA as estimated by the MODNPP model. It can be observed that the long-term mean NPP values in the GLTFCA vary spatially from as low as 3.758 ton C ha\(^{-1}\) year\(^{-1}\) in KNP to around 5.3 ton C ha\(^{-1}\) year\(^{-1}\) in ZNP. The mean and 95% confidence interval of the GLTFCA NPP are 4.366 ± 0.319, 5.962 ± 0.369, and 2.830 ± 0.34 ton C ha\(^{-1}\) year\(^{-1}\) for the overall long-term annual mean, wet season mean and dry season mean respectively.

**Table 1**: Long-term mean NPP distribution (ton C ha\(^{-1}\) year\(^{-1}\)) of the GLTFCA savanna.

<table>
<thead>
<tr>
<th>Land-use / Land tenure Type</th>
<th>Location</th>
<th>Method</th>
<th>Mean NPP (ton C ha(^{-1}) year(^{-1}))</th>
<th>Wet Season (ton C ha(^{-1}) year(^{-1}))</th>
<th>Dry Season (ton C ha(^{-1}) year(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>National Park</td>
<td>Gonarezhou, Zimbabwe</td>
<td>MODNPP</td>
<td>4.489</td>
<td>6.127</td>
<td>2.935</td>
</tr>
<tr>
<td>National Park</td>
<td>Kruger, South Africa</td>
<td>MODNPP</td>
<td>3.758</td>
<td>5.498</td>
<td>2.068</td>
</tr>
<tr>
<td>National Park</td>
<td>Limpopo, Mozambique</td>
<td>MODNPP</td>
<td>4.630</td>
<td>6.270</td>
<td>2.990</td>
</tr>
<tr>
<td>National Park</td>
<td>Zinave, Mozambique</td>
<td>MODNPP</td>
<td>5.248</td>
<td>6.815</td>
<td>3.941</td>
</tr>
<tr>
<td>National Park</td>
<td>Banhine, Mozambique</td>
<td>MODNPP</td>
<td>4.111</td>
<td>5.392</td>
<td>2.830</td>
</tr>
<tr>
<td>Safari Area</td>
<td>GLTFCA</td>
<td>MODNPP</td>
<td>4.150</td>
<td>5.632</td>
<td>2.661</td>
</tr>
<tr>
<td>SSCFA</td>
<td>GLTFCA</td>
<td>MODNPP</td>
<td>4.059</td>
<td>5.554</td>
<td>2.549</td>
</tr>
<tr>
<td>LSCFA</td>
<td>GLTFCA</td>
<td>MODNPP</td>
<td>4.906</td>
<td>6.814</td>
<td>3.057</td>
</tr>
<tr>
<td>Communal Land</td>
<td>GLTFCA</td>
<td>MODNPP</td>
<td>3.940</td>
<td>5.560</td>
<td>2.439</td>
</tr>
<tr>
<td><strong>Mean ± 95% CI</strong></td>
<td>GLTFCA</td>
<td></td>
<td><strong>4.366 ± 0.319</strong></td>
<td><strong>5.962 ± 0.369</strong></td>
<td><strong>2.830 ± 0.340</strong></td>
</tr>
</tbody>
</table>

Results show that the estimated long-term mean MODNPP and the Lieth NPP were significantly positively related (p<0.05) with an \(R^2\) of 0.66 (Figure 4 (a)). The MODNPP and DMP were also significantly (p< 0.05) positively related with an \(R^2\) of 0.82 (Figure 4 (b)). The correlation is also significantly (p<0.05) positive with strong Pearson Correlation Coefficient (R) of 0.812 and 0.911 for the relationship between MODNPP and Lieth NPP as
well as MODNPP and DMP, respectively. The relationship between MODNPP and DMP is actually stronger than that between MODNPP and Lieth NPP.

(a) 

Lieth NPP = 1.1131(MOD NPP) + 0.1937

\[ R^2 = 0.6586 \]

\[ R = 0.812 \]

\[ N = 366 \]

\[ P = 0.000 \]

(b) 

DMP = 4.4777(MOD NPP) - 2.3519

\[ R^2 = 0.8282 \]

\[ R = 0.910 \]

\[ N = 922 \]

\[ P = 0.000 \]
Figure 4: Relationship between (a) MODNPP and Lieth NPP, and (b) MODNPP and DMP, across the GLTFCA.

NPP (ton C ha\(^{-1}\) year\(^{-1}\)) estimated by DMP was significantly (p<0.05) higher compared with MODNPP and Lieth NPP respectively \([F(2, 2763) = 15374, p = 0.000, \text{ANOVA}, \text{Tukey HSD Post Hoc Comparison}]\) (Figure 5). However, the mean NPP estimated by the MODNPP model did not significantly (p>0.05) differ from the mean NPP estimated by the Lieth NPP model.

![Figure 5: Comparison in long-term mean NPP among 3 different models of NPP estimation.](image)

Means with different letters of the alphabet differ significantly at \(\alpha = 0.05\)

NPP estimated by the MODNPP model significantly differs \([F(4, 87)= 209.47, p=0.000, \text{ANOVA}]\) across the GLTFCA land cover types. There is however no significant difference \([F(4,87)=1.409, p=0.238, \text{ANOVA}]\) in NPP estimated using the Lieth NPP model across the different land cover types (Figure 6). For the MODNPP model, NPP for the grasslands is significantly (p<0.05) different from other land cover types while there are no significant (p>0.05, One-Way ANOVA, Tukey HSD Post Hoc Comparison) differences in NPP among
the deciduous forest, mosaic vegetation and cropland, and the shrubland. Nevertheless, our MODNPP is significantly (p<0.000, One-Way ANOVA, Tukey HSD Post Hoc comparison) lower in grasslands and zero in water bodies compared with other land cover types.

Further analysis show that the mean NPP estimated by the MODNPP model is not significantly (DF=35, p>0.05, Paired T-Test) different from mean NPP estimated by the Lieth NPP model for the deciduous forest, mosaic vegetation and cropland, and the shrubland land cover types. However, in grasslands the Lieth NPP is significantly (DF=35, t=-11.67, p=0.000, Paired T-Test) higher than the MODNPP. Actually, Lieth NPP model estimates a significantly higher value of NPP in water bodies contrary to a no NPP value by the MODNPP model.

Figure 6: Comparison of NPP estimated by the MODNPP and Lieth NPP models among different land cover types of the GLTFCA Savanna.
Significant variations in NPP as a function of land cover types can be noted as shown in the marked areas A and B (Figure 7). The land cover type for the area marked by A is grassland and the respective NPP for that area is lower compared with the area marked by B which is a deciduous forest.

Figure 7: MODNPP distribution in relation to land cover type across the GLTFCA Savanna. The areas marked by A and B represent a grassland and deciduous forest cover types as well as the corresponding NPP.

3.2 Discussion

Results of this study suggest that the modified MODNPP model can be used to successfully estimate NPP in savanna ecosystems. This fills an important knowledge gap as previous studies on the estimation of savanna NPP have mainly been using biometric measurements
(Miller et al., 2004). Most importantly, the results fall within the range established by a range of NPP studies in African savannas (Table 2). Specifically, results of the GLTFCA long-term annual MODNPP mean falls within 95% CI of 5.8 ± 1.9 ton C ha\(^{-1}\) year\(^{-1}\) for African savannas which as well is within the 7.2 ± 2.0 ton C ha\(^{-1}\) year\(^{-1}\) for Global savannas both estimated by the harvesting methods (Grace et al., 2006). Results of this thesis are also supported by several other studies including those conducted in tropical savanna ecosystems. For example, (Goetz et al., 2000) and (Running et al., 2004) estimated the global annual NPP range from 0 to 7.5 ton C ha\(^{-1}\) year\(^{-1}\) and 0.5 to 7.5 ton C ha\(^{-1}\) year\(^{-1}\) respectively.

Results also indicate that by using PRI as a surrogate for LUE values as well as GIS and DEM modelled SWR rather than calibrated LUE and SWR values, we can successfully estimate NPP levels in the savannas. Previously, LUE and SWR data were obtained from sparse weather station based data thereby producing pseudo-dynamic LUE and SWR values to estimate NPP. Thus, the ability to model SWR continuously in a GIS has provided enhanced opportunities to model NPP in African savannas where SWR and LUE data may not be readily available. In fact, results also imply that DEM modelled SWR after Kumar et al., (1997) can be a useful input to the MODNPP model after Rahman et al., (2004). This finding is especially important because although interest on the use of MODNPP estimation model is rising, most of these studies have been using field-measured LUE values (Turner et al., 2003; Running et al., 2004) as well as field-measured SWR values (Rahman et al., 2004) which are expensive and sometimes simply non-existent in most areas where estimation of NPP has to be made. Thus, this study improves upon previous studies by demonstrating that GIS and DEM modelled SWR can be used as a substitute for weather station measured SWR.
Table 2: The NPP (ton C ha\(^{-1}\) year\(^{-1}\)) estimates for other African savannas as estimated by the harvesting method after Grace et al., (2006)

<table>
<thead>
<tr>
<th>Forest</th>
<th>Method</th>
<th>Location</th>
<th>NPP (ton C ha(^{-1}) year(^{-1}))</th>
<th>Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open Shrub Savanna</td>
<td>Harvesting</td>
<td>Lamto, Cote d'Ivoire</td>
<td>6.4</td>
<td>(Mordelet and Menaut, 1995)</td>
</tr>
<tr>
<td>Dense Shrub Savanna</td>
<td>Harvesting</td>
<td>Lamto, Cote d'Ivoire</td>
<td>8.1</td>
<td>(Mordelet and Menaut, 1995)</td>
</tr>
<tr>
<td>Grass Savanna</td>
<td>Harvesting</td>
<td>Nairobi, Kenya</td>
<td>6.1</td>
<td>(Kinyamario and Macharia, 1992)</td>
</tr>
<tr>
<td>Shrubs and grasses</td>
<td>HAPEX-Sahel flux measurements</td>
<td>Niger, West Africa</td>
<td>2.2</td>
<td>(Hanan, 1998)</td>
</tr>
<tr>
<td>Grass savanna</td>
<td>Harvesting</td>
<td>Nairobi National Park, Kenya</td>
<td>6.2</td>
<td>(Long et al., 1989)</td>
</tr>
<tr>
<td>Mean±95% CI</td>
<td></td>
<td>Africa Savannas</td>
<td>5.8±1.9</td>
<td>(Grace et al., 2006)</td>
</tr>
<tr>
<td>Mean±95% CI</td>
<td></td>
<td>Global Savannas</td>
<td>7.2±2.0</td>
<td>(Grace et al., 2006)</td>
</tr>
</tbody>
</table>
NPP estimates in this study also compare favourably with the NPP estimates for the tropical savannas obtained using NPP-Rainfall regression model developed by (Lieth and Whittaker, 1975). In fact results indicate that there is no significant difference in the mean NPP obtained with our MODNPP model and the mean obtained using the Leith regression model. However, when land cover type is considered our MODNPP model’s performance is superior as it is able to take into account differences in land cover. For example, unlike the MODNPP model, the Leith model does not return a zero NPP value over water. This is because the Leith model is rainfall based. Thus, we deduce that the mean NPP estimated using our MODNPP model is comparable to the Leith model estimated NPP especially over vegetated areas. We make a claim that this in effect improves confidence in our NPP estimates.

Furthermore, a comparison of MODNPP estimates with the NPP estimated from the DMP product (http://www.geoland2.eu/) indicate a strong and positive significant relationship between our NPP estimate and the DMP estimate. However, a comparison of the means indicate that the DMP product estimates significantly higher NPP than MODNPP estimates. Therefore, this thesis deduce that MODNPP estimates are correlated with the DMP product in terms of capturing the spatial variations in NPP but the DMP products estimates significantly higher values of NPP than MODNPP model.

This study differs from previous research in that it introduces the DEM and GIS modelled SWR flux in the estimation of NPP. To date, various NPP models that utilise MODIS data such as the MOD17 (Running et al., 1999; Running et al., 2004) and the MODNPP after (Rahman et al., 2004) relied mainly on coarse resolution weather station data for LUE as well as SWR flux measurements. Also the MODNPP model had been untested especially in African savanna landscapes, with research mainly concentrated in the broadleaf deciduous
forests of the United States of America (USA) (Rahman et al., 2004) and the temperate deciduous and tropical rain forests of Asia (Rasib et al., 2007; Rasib et al., 2010). However, the major limitation of the study is failure to use ground data to validate MODNPP. Thus, further research is needed to test MODNPP with results from biometric methods in an African savanna landscape. Nonetheless, results of this thesis are consistent with those obtained from NPP research in tropical savannas.
4.1 Results

Figure 8 shows the mean NPP (ton C ha\(^{-1}\) year\(^{-1}\)) for 10 years from 2000 to 2009. NPP varies spatially across the GLTFCA with significant (F(4:42056)=180.162, P=0.000; One-Way ANOVA) differences in the mean NPP among the different land-use/land tenure zones within the GLTFCA. In fact, the results show that the LSCFAs have significantly (P< 0.05) higher NPP compared with other land-use/land tenure types followed by NPs, while CLs have the lowest NPP. All the long-term NPP means for the different land-use/land tenure types are significantly (P<0.05, Tukey HSD Post Hoc Multiple comparisons analysis) different from each other except for the SAs and SSCFAs which show no significant (P=0.544, Tukey HSD Post Hoc comparison) differences in the long-term mean NPP.

**Figure 8**: Mean NPP differences among different land-use/land tenure types. Means with different letters of the alphabet differ significantly at \(\alpha = 0.05\).
Figure 9: (a) Seasonal NPP profiles for the long-term means among the different Land-use/land tenure zones and (b) Rate of change for the long-term mean NPP between successive months for the different Land-use/land tenure types across the GLTFCA (Fourier Transform).
Figure 9 shows the long-term mean NPP (ton C ha\(^{-1}\) year\(^{-1}\)) profiles for the different land-use land tenure types within the GLTFCA. All the NPP profiles exhibit a rising limb (green-up stage) from October to January, reaching the green peak in February after which it begins to fall gradually (senescence stage) to the lowest point in August. Statistical comparison of the rates of NPP change between successive months for the different land-use/land tenure types during the green-up stage shows that at least two of the means are significantly (\(p < 0.05\)) different. Furthermore, it can be observed that the rate of change in mean NPP for the CLs during the green-up stage is significantly (\(P < 0.05\)) higher than the rates of change in mean NPP for other land-use/land tenure types. In other words, the CLs’ NPP profile rise steeper than other land use/land tenure types at the green-up and also fall steeper at the senescence period compared with other land-use/land tenure types. The rate of change in the NPP of the LSCFAs falls much slower than any other land-use/land tenure type. All in all, the CLs have the lowest NPP associated with the highest rate of change in NPP while the LSCFA has the highest NPP associated with the lowest rate of change in NPP.
Figure 10: Cumulative mean monthly NPP for the different Land-use/land tenure zones within the GLTFCA landscape.

The cumulative mean monthly totals of NPP for the different land-use/land tenure zones are plotted in Figure 10. It is observed that the cumulative NPP total for the LSCFAs is the highest followed by the NPs with the CLs having the lowest value.

![Figure 10: Cumulative mean monthly NPP for the different Land-use/land tenure zones within the GLTFCA landscape.](image)

Figure 11: Long-term mean NPP comparisons among the protected areas of the GLTFCA (One-Way ANOVA, P=0.000, DF=5 between groups and 43222 for within groups, F=340.615, Tukey HSD Post Hoc Analysis)

Comparisons in the NPP long-term means among the specific protected areas of the GLTFCA shows that KNP has significantly (P<0.05) the least mean NPP (Figure 11). On the other hand ZNP has significantly (P<0.05) the highest long-term mean NPP compared with all the other protected areas followed by LNP, GNP and BNP respectively.
Further comparisons of the long-term means of NPP between the specific protected areas and the other different land-use/land tenure types show that the NPP for ZNP is significantly (One-Way ANOVA, $P=0.000$, Tukey HSD Post Hoc Analysis) the highest even when compared with the LSCFAs (Figure 12). On the other extreme, the NPP in KNP is significantly ($P<0.05$) the lowest even when compared with the CLs of the GLTFCA. The same can also be observed for BNP which has a mean NPP that is significantly ($P<0.05$) lower than all the other land-use/land tenure types.
Figure 13: Seasonal mean NPP (ton C m\(^{-1}\) year\(^{-1}\)) distribution across the GLTFCA landscape
Figure 14: Significant (P < 0.05) NPP differences among different Land-use/land tenure zones in good (a) and (b) bad NPP season. A good NPP season in this case has an average NPP greater than the long-term mean NPP of 4,366 ton C ha$^{-1}$ year$^{-1}$ and a bad NPP season has a value below long-term mean NPP.
Figure 13 shows the seasonal mean NPP distribution within the 2000 to 2009 period. Our results show that our mean seasonal NPP varied from as low as 2.39 ton C ha\(^{-1}\) year\(^{-1}\) to 5.16 ton C ha\(^{-1}\) year\(^{-1}\). The maximum and minimum mean seasonal NPP were in 2000/01 season and 2001/02 season respectively.

In good rainfall seasons (mean seasonal NPP greater than long-term mean NPP) such as 2000/01, 2003/04, and 2008/09, a lesser number of significant (P=0.000, One-Way ANOVA, Tukey Post Hoc Analysis) differences in mean NPP among the different land-use/land tenure types is observed especially between the NP and LSCFA (Figure 14). In bad rainfall seasons (mean seasonal NPP less than long-term mean NPP), LSCFAs tend to have significantly (P<0.05) higher NPP than the other land-use/land tenure types whereas the CLs significantly (P<0.05) record the least values.

The relationship between estimated NPP and long-term rainfall over the GLTFCA landscape for 12 months data summarised over all land uses show that the rainfall-NPP relationship is significant (R=0.911, P=0.00) (Figure 15).
**Figure 15:** Relationship between the long-term means of rainfall and NPP for the 12 month of the year.

Next, when each of the 5 land use types is considered, it can be observed that the relationship between rainfall and NPP is consistently positively significant ($P < 0.05$) (Table 3) in each of the land use/tenure type.

**Table 3:** Relationships between long-term mean NPP and long-term mean rainfall across the GLTFCA land-use/land tenure types

<table>
<thead>
<tr>
<th>Land-use/Land Tenure Type</th>
<th>Pearson Correlation (R)</th>
<th>Regression P-Value at 95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>CL</td>
<td>0.693</td>
<td>0.001</td>
</tr>
<tr>
<td>NP</td>
<td>0.699</td>
<td>0.001</td>
</tr>
<tr>
<td>SA</td>
<td>0.634</td>
<td>0.002</td>
</tr>
<tr>
<td>LSCFA</td>
<td>0.669</td>
<td>0.001</td>
</tr>
<tr>
<td>SSCFA</td>
<td>0.651</td>
<td>0.002</td>
</tr>
</tbody>
</table>
Comparisons among the different land-use/land tenure types show no significant (p=0.916, DF=4:1075, One-Way ANOVA) differences in the long-term means of rainfall across the GLTFCA landscape (Figure 16). However, mean rainfall is highest in the LSCFAs. Further investigations per each rainfall season from 2000/01 to 2008/09 also show no significant (P>0.05, One Way ANOVA) differences in the mean monthly rainfall among the different land-use/land tenure types.

Figure 16: Comparisons of the long-term mean monthly rainfall among the different land-use/land tenure types of the GLTFCA.
Figure 17: Significant (P<0.05) differences in the long-term mean monthly rainfall among the protected areas of the GLTFCA

When compared with other parks, the long-term mean rainfall for BNP is significantly (P=0.000, One-Way ANOVA, DF=4:595, Tukey HSD Post Hoc Analysis) the lowest (Figure 17) while rainfall among the rest of the parks is not significantly (P>0.05) different. In a further investigation, there are no significant (P>0.05) differences in the means of rainfall in the respective years between 2000 and 2009 among the GLTFCA protected areas (Figure 18). However, rainfall is slightly the highest in ZNP and lowest in BNP compared with the other protected areas. Between the same period of time we observe that mean monthly rainfall is significantly (P<0.05) different among the selected GLTFCA LSCFAs with the area marked C significantly receiving the highest rainfall over the years (Figure 19).
Figure 18: Mean monthly rainfall comparisons from 2000 to 2009 among the protected areas of the GLTFCA (KNP = Kruger National Park, LNP = Limpopo National Park, BNP = Banhine National Park, ZNP = Zinave National Park and GNP = Gonarezhou National Park).
Figure 19: Mean monthly rainfall comparisons from 2000 to 2009 among the LSCFAs of the GLTFCA (A, B, C and D are sample sites)
Different soil types significantly (P<0.05, One-Way ANOVA, Tukey Post Hoc Analysis) influenced NPP variations across the GLTFCA. Specifically, holding land-use/land tenure constant, it can be observed that at least one of the NPP means among the different soil types significantly differ (P=0.05, One-Way ANOVA) from the other (Figure 20). However, a post hoc analysis in the form of Tukey HSD shows that for all the respective land-use/land tenure categories, NPP does not significantly (P>0.05) differ among the different soil types except for very few categories.
Figure 20: NPP differences among different soil types within specific different land-use/land tenure categories (a) Communal land soils and (b) Large-scale commercial farming areas

When soil type is held constant, there are significant differences (P=0.05, One-Way ANOVA, Tukey Post Hoc Analysis) in NPP among different land-use/land tenure units of the same soil type (Figure 21). For most of the explored soil types, NPP is significantly (P<0.05) highest in ZNP followed by the LSCFA and least in KNP.

![Graph showing NPP comparisons among different land-use/land tenure types with similar soil types](Image)

Figure 21: Long-term mean NPP comparisons among different land-use/land tenure types with similar soil types

Overall, it can be observed that land-use/land tenure has a significant effect on NPP patterns. Specifically, we observe significant (P<0.05) differences in NPP among different land-use/land tenure types but no significant (P>0.05) differences in mean rainfall among different land-use/land tenure types of the GLTFCA (Figure 16). Also, there are significant (P<0.05) differences in NPP among different land-use/land tenure types of the same soil types.
4.2 Discussion

Results of this thesis indicate that different land-use/land tenure types explain differences in NPP across the GLTFCA at the local scale. In fact, when soil type and rainfall were held constant, results show that NPP significantly varied across land-use/land tenure types. Specifically, this thesis makes a claim that land-use and land tenure systems, significantly explain NPP patterns at a smaller scales even better than biophysical factors in the savanna landscapes of Southern Africa. Previous studies have largely attributed variations in NPP to biophysical factors particularly at larger scales. For example, studies by Lauenroth, (1979); Huntley and Walker, (1982); and Tothill and Mott, (1985) considered rainfall amount and its distribution, soil conditions, herbivory, and fire as the four principal factors explaining spatial and temporal NPP patterns in the savanna biomes whilst temperature is dominant in tropical deserts (Noy Meir, 1973; Turner et al., 2006). As a result, biophysical factors had become the most acceptable explanatory variable of NPP spatial and temporal patterns especially at larger scales. Thus this study improves on previous studies by directly showing that land-use/land tenure types explain spatial and temporal NPP patterns even better than biophysical factors at local scales.

It is apparent in the findings of this thesis that NPP is highest in LSCFAs followed by NPs while the CLs have the least NPP. This result is contrary to the expectation that NPP should be quite higher in protected areas (NPs) compared with other land-use/land tenure types (Wilshusen et al., 2002; Hayes, 2006). Instead, our results indicate that LSCFAs have the highest NPP compared with other land-use/land tenure types of the GLTFCA. This thesis makes a claim that the management hypothesis explains this phenomenon. This is because farmers in commercially managed ranches such as those found in the study area are likely to enhance NPP for increased beef production through practices such as managed stocking.
densities and use of farm inputs to reduce pressure on grazing land (Cousins, 1990; Food and Agricultural Organization of the United Nations (FAO), 2004). On the other hand, herd management in the CLs is characterised by low input methods and poor veld management practices such as open grazing systems (Cousins, 1990). Thus contrary to the expectation that NPP should be higher in protected areas; this study deduces that NPP is higher in LSCFAs compared with any other land-use/land tenure type.

Although NPP is higher in the LSCFAs on the whole, the rates of NPP change are not always higher for LSCFAs compared with other land-use/land tenure types during the different stages of the NPP phenological cycle. In fact, temporal patterns indicate that CLs have the highest NPP levels during the green-up stage of the NPP phenological cycle compared with protected areas and other land-use/land tenure types of the GLTFCA. The importance of overgrazing as a disturbance factor in influencing high NPP levels in certain ecological landscapes can come into play. This result is supported by Pickett and White (1985) who noted that NPP is usually highest in areas experiencing disturbance, a characteristic of CLs during the green-up stage. The CLs of the GLTFCA experience disturbance largely due to overgrazing than any other managed areas (Cousins, 1990). Hence, some species of tree can regenerate extensively by issuing new vegetative shoots, after damages caused by disturbance especially on the onset of the green-up stage. Moreover, disturbance can also play an important role by opening habitats and facilitating invasions (Burke and Grime, 1996). Hence the young-growth will promote high NPP in the CLs than it will be in other land-use/land tenure types. Tang et al., (2011) noted an increase in NPP in a subtropical forest in China from 1982 to 2004 in a young-growth forest with no significant change in NPP in an old-growth forest. Nevertheless, this thesis proposes that further studies may need to be
conducted to establish the reasons for higher rates of NPP change in CLs compared with other land-use/land tenure in the GLFTCA.

The results of this study also indicate the importance of biophysical factors in shaping the spatial and temporal NPP patterns within the GLTFCA. Specifically, rainfall and soil type are important biophysical factors explaining spatial and temporal NPP patterns within the GLTFCA with a strong correlation between NPP and rainfall. However, studies have mainly linked NPP variations to biophysical factors at large spatial scales. For example, on a national scale in China between 1981 and 1998, it was found that rainfall was a key factor controlling NPP patterns, with a slightly increasing trend in NPP during the study period linked to increasing rainfall (Tao et al., 2003). Goetz et al., (2000) indicated that NPP increased in boreal regions for the period 1982-1989 on a global scale as a result of increasing rainfall. Hulme and Murphree, (2001) also highlighted that water availability was one of the main limiting factors for higher NPP patterns within semi-arid landscapes of the world. This study therefore makes a claim that biophysical factors remain essential in explaining spatial and temporal NPP patterns even at localised scales other than human induced factors.

Contrary to the expectation that the same land-use/land tenure system should have the same effect on NPP patterns, results of this thesis showed significant differences in NPP among the NPs of the GLTFCA. In fact, NPP is highest in ZNP with the least in KNP which has NPP even lower than that of CLs. Thus, this thesis deduces that NPP disparities in these NPs can be attributed to differences in soil types, rainfall distribution, landscape composition and structure as well as other forms of management practices within these landscapes. However, it is important to note that rainfall did not significantly vary across the GLTFCA NPs which again make soils the main explanatory factor, land-use/land tenure type being constant. In a
related study in the southern Appalachians and Washington’s Olympic Peninsula, (Turner et al., 1996) discovered that the differences in the landscape NPP patterns of private lands, which are of course of the same land tenure system, were a result of landscape composition as well as differences in management structures.

This study is different from previous studies in that, besides testing whether biophysical factors explain NPP variation, it also tests the hypothesis that land use and land tenure explain NPP spatial and temporal patterns at smaller scales (Burke, 2000). To date, few studies have tested the NPP-land-use/land tenure hypothesis especially in savanna landscapes, with studies relating NPP patterns to land ownership mainly limited to the Tundra (Piao et al., 2006). Moreover, most previous studies have concentrated on the effect of biophysical factors on NPP variation particularly at larger scales. Thus, this thesis makes a claim that the findings of this research present an opportunity to monitor spatial and temporal NPP patterns on more localised scales of the savannas in relation to land-use and land tenure types.
Chapter 5: Estimating NPP and understanding its distribution by land use and land tenure: A synthesis

5.1 Introduction

The ecological and social value of NPP is immense (Luo et al., 2002) and in African savanna ecosystems NPP is particularly invaluable as an indicator of the availability of forage for wildlife and livestock, as well as fuel and food for humans (Groten, 1993). Thus, it is essential to accurately quantify NPP as a way of generating information for ecosystem rangeland management (e.g., estimating carrying capacity), precision farming activities, and evaluating the sustainable utilization, development and management of terrestrial ecosystems (Groten, 1993). Previous studies on the accurate quantification of NPP have mainly been done at localised scales using environmentally unfriendly destructive methods (Rasib et al., 2010). In this thesis, a remote sensing NPP model in which shortwave radiation (SWR), a key input, has been modelled from a GIS and DEM SWR model was used. To this end, we have not come across an NPP model in which the GIS and DEM modelled SWR was used.

The long term sustainability of ecosystem goods and services of African savannas will also depend on understanding factors (e.g., different land use and land tenure types) that explain the spatial and temporal variations in NPP particularly at localised scales. Previous studies have largely indicated the importance of biophysical factors in explaining NPP patterns particularly at larger scales (Lieth and Whittaker, 1975; Burke et al., 1997a; Burke et al., 1997b; Tao et al., 2003). Thus studies explaining spatial and temporal NPP patterns in relation to land use and land tenure are still rudimentary especially in African savannas. Therefore, it is important to gain knowledge on the factors, such as land use and land tenure types, related with NPP variations in African savannas particularly at smaller scale levels other than biophysical factors.
This thesis tested whether and in what way land use and land tenure practices in a Savanna landscape of the Great Limpopo Transfrontier Conservation Area (GLTFCA) influence both the spatial and temporal variations in NPP. However, as a preamble, the thesis tested whether and to what extent a remote sensing net primary productivity (NPP) estimation model based on the Moderate Resolution Imaging Spectroradiometer (MODIS) data and geographic information system (GIS) modelled short wave (SWR) radiation can be used to estimate NPP in a Southern African Savanna landscape.

5.2 Remote sensing NPP modelling in African Savanna

Traditionally, NPP has been measured using biometric measurements, i.e., sample surveys and field measurements (Tao et al., 2003). Although they are considered the most accurate way of estimating NPP (Ogawa, 1977; Li et al., 2005), the use of biometric measurements has remained largely on small spatial extents because of a series of methodological limitations which includes their destructive and expensive nature (Lu, 2006; Wang et al., 2007). However, model simulation in the quantification of NPP has since gained interest amongst ecologists particularly in the forests of developed world (Hazarika et al., 2005; Rasib et al., 2010). Thus, after realizing the potential of the remote sensing micrometeorological NPP model by Rahman et al. (2004) this thesis took a step further by modifying from its limitations. This thesis demonstrated that the remote sensing micrometeorological NPP model can successfully be used with the aid of GIS modelled SWR flux in African Savanna ecosystem. In fact, NPP estimates of this study fall within the mean and 95 % confidence intervals for both the African savannas and global savannas with NPP for African savannas having been quantified using biometric methods. In addition, remote sensing and GIS modelled NPP estimates of this study do not significantly (p>0.05) differ
with results from an established Lieth regression model. Nevertheless, the NPP model of this study performed better over the Lieth NPP model when land cover type was taken into consideration.

5.3 Land use and land tenure explain NPP variations in African savannas

Biophysical factors have often been used to explain the spatial and temporal variations in NPP (Lieth and Whittaker, 1975; Burke et al., 1997a; Burke et al., 1997b; Tao et al., 2003; Piao et al., 2006). It is generally known that biophysical factors operate at larger spatial scales (Vitousek, 1992) while having less relevance at smaller spatial scales in influencing NPP variations, yet in a complex landscape dominated by humans it is predicted that human factors explain spatial and temporal variations in NPP better (Burke, 2000; Guersehman et al., 2003; Haberl et al., 2004). Nonetheless, research on the effect of land use and land tenure on spatial and temporal variations of NPP has remained largely rudimentary. Therefore, in multiple use landscapes of Southern African savanna, the importance of different land-use/land tenure types in explaining NPP patterns was tested against the effect of biophysical factors. This thesis found out that at landscape scales, different land-use/land tenure types explain NPP differences better than biophysical factors. In fact, this thesis found significant (P<0.05) differences in NPP among different land-use/land tenure types whilst they were no significant (P>0.05) differences in rainfall among different land-use/land tenure types. Overall, this thesis deduces the importance of human induced factors in explaining spatial and temporal NPP patterns at smaller scales where the effect of biophysical factors is not so clear.
5.4 Summary of findings

This thesis has demonstrated that a combination of remote sensing and GIS modelled SWR flux can successfully be used to estimate NPP in African savanna ecosystems. Specifically, this thesis has shown that NPP estimates of this study are within the range of NPP estimates found in refereed literature (Grace et al., 2006). The thesis has also shown that MODNPP estimates are even superior over an established NPP model by Lieth and Whittaker (1975) when land cover type was taken into consideration. Thus, to investigate spatial and temporal NPP patterns within savanna landscapes, this thesis first makes a claim that the MODNPP model presented in this study can be used successfully to estimate NPP in African savannas.

This thesis has also demonstrated the importance of human induced factors in explaining NPP variations in African savannas particularly at small spatial scales while biophysical factors supersede at large spatial scales. Specifically in this thesis, it has been shown that land-use/land tenure type is an invaluable factor explaining NPP differences in African savannas at small spatial scales. Thus, this thesis draws the conclusion that while biophysical factors’ influence on spatial and temporal NPP patterns remain critical particularly at large spatial scales, human factors are also important particularly at small spatial scales.

5.5 The future

What emanates from this thesis is the importance of human induced factors in explaining NPP spatial and temporal variations in African savannas particularly at smaller spatial scales other than the biophysical factors. In order to investigate factors explaining NPP variations within landscapes, this thesis has successfully demonstrated the use of remote sensing and GIS modelled SWR to estimate NPP in African savanna landscapes. Reliable NPP estimates should therefore form the basis of future ecological research especially in African savanna
landscapes. Thus, this thesis caution that it may be important to validate the method used to estimate NPP in this thesis with biometric measurements of NPP obtained from other field of studies. In addition it would be also important to apply the methods used to estimate NPP in this thesis to other savanna study sites to check for consistency of results and provide room for improvements.
References


