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# Remote Sensing of Biomass in the Miombo Woodlands of Southern Africa: Opportunities and Limitations for Research

Natasha Ribeiro, Micas Cumbana,  
Faruk Mamugy and Aniceto Chaúque  
*Faculty of Agronomy and Forestry, Eduardo Mondlane University  
Mozambique*

## 1. Introduction

Biomass and Leaf Area Index (LAI) are two important biophysical properties of vegetation as they inform about vegetation production. LAI is directly related to the exchange of energy and mass between plant canopies and the atmosphere (Fassnacht *et al.*, 1997), while biomass reflects the amount of carbon converted through photosynthesis and accumulated in the different plant components. Thus, the two variables reflect much of the potential and actual production of plant ecosystems (Kasischke *et al.*, 2004).

Fire is ubiquitous in most terrestrial ecosystems causing spatial patterning at many scales (Chapin III *et al.*, 2003). In tropical savannas in general and, in the southern African savannas in particular, much of the ecosystem functioning is largely defined by the combination of climate, fires and herbivory. Andreae (1993) estimated that fires in the African and the world savannas account, respectively, for 22% and 42% of the biomass burned globally. Moreover, the amount of CO<sub>2</sub> exchanged with the atmosphere in southern Africa may represent up to 20% of the regional net primary production (Scholes & Andreae, 2000).

In spite of the elevated importance of disturbances in miombo woodlands, there still is a gap in the understanding of the interaction between them and vegetation. This, results partially from the short temporal and spatial scales of observation of much of the existing studies. For example, except for the long-term experimental study carried out in Zambia for 15 years (Trapnell, 1959), the other studies are all *points* in space and time, much of them lasted less than 5-years. Moreover, they address a specific aspect of miombo woodlands functioning, which is important but not sufficient for a complete understanding of this ecosystem. Thus, measurements of large spatial- and temporal-scale variations of vegetation production, disturbances and their interaction are crucial to fulfill the existing data gaps. This is particularly important to understanding the role of this crucial ecosystem in the global carbon budget.

Remote sensing of vegetation production and disturbances is a critical measurement needed to extend the field level understanding of ecological, hydrological and biogeochemical processes to broader spatial and temporal scales in terrestrial ecosystems (Asner, 2004) and the different scales of energy, CO<sub>2</sub> and mass exchange between ecosystems and atmosphere

(Carlson & Ripley, 1997; Goward *et al.*, 1985; Justice *et al.*, 1998; Running *et al.*, 1995; Schlesinger, 1996; Tucker *et al.* 1985). In areas where detailed and sufficient field data is scarce, as in much of the miombo context, the need for remote sensing data and techniques is even more important (Justice & Dowty, 1994; Malingreau & Gregoire 1996). Interpretation of the spaceborne data on land carbon stocks is needed, not only from the scientific point of view, but also within practical carbon management options mentioned in UNFCCC (Kyoto Protocol, REDD and REDD+).

To accurately measure objects on earth from the space several issues have to be considered including, the type and characteristics of remote sensing system, the spectral characteristics of the target objects, interactions between objects on earth, the statistical methods, among others. The advance of new generation of remote sensing such as IKONOS and QUICKBIRD optical sensors and, LiDAR and ALOS/PALSAR microwave sensors with high spatial resolution opens a new opportunity to improve understanding of miombo dynamics. These sensors, allow individual trees to be recognized and thus, large-scale biomass estimation in miombo woodlands. However, several constraints still exist and may limit the utilization of these data.

The aim of this chapter is to analyze the opportunities and constraints for the use of remote sensing techniques to estimate biomass (and carbon) in the miombo woodlands of southern Africa. The chapter also identifies research priorities for remote sensing of biomass in the miombo ecoregion.

## 2. Brief overview of miombo woodlands ecology

### 2.1 Geographic distribution

Miombo woodlands, herewith referred as Miombo, cover about 2.7 million km<sup>2</sup> within the southern sub-humid tropical zone of Africa from near the Equator to below the Tropic of Capricorn (Figure 1). They extend from Tanzania to the Democratic Republic of the Congo (DRC) in the north, through Angola, Zambia in the east to Malawi, Zimbabwe and Mozambique in the south (Desanker *et al.*, 1997; Frost, 1996).

Miombo occur within a mean annual precipitation range of 650 to 1,500 mm and more than 95% of annual rainfall occurs during a single 5-7 months wet season from October/November to March/April (Cauldwell & Zieger, 2000; Chidumayo, 1997; Desanker *et al.*, 1997; Frost, 1996). Few sites within the region receive more than 5% of their total mean annual rainfall during the dry months. Consequently, miombo is divided into dry and wet miombo according to the rainfall in the zone of occurrence (White, 1983). **Dry miombo woodlands** occur in the southern portion of the region in Malawi, Mozambique and Zimbabwe, in areas receiving less than 1,000 mm of rainfall annually. In contrast, **wet miombo woodlands** occur over much of eastern Angola, DRC, northern Zambia, south western Tanzania and central Malawi in areas receiving more than 1,000 mm rainfall per year. Variations to this pattern may occur within an area as a result of local variation in environmental factors such as altitude and precipitation.

This ecosystem occurs in geologically old and nutrient poor soils (Chidumayo, 1997; Frost, 1996). The dominant soils belong to the order Oxisol, which are highly weathered old soils with dominance of aluminum and iron oxides and low activity clays. The soils in miombo are typically acid (pH between 4.2 and 6.9), have a low Cation Exchange Capacity (CEC: 1.80-25.10 me100/g) and, are low in nitrogen (0.02-0.62%) and phosphorous (0.0-54 ppm) and Total Exchangeable Bases (TEB: 0.35-20.78 me100/g). The range of carbon content in

soils is 0.3-3.8% (Chidumayo, 1989; Ribeiro & Matos, *unpubl. Data*; Siteo *et al.*, *unpubl. Data*; Walker & Desanker, 2004). Miombo soils have low concentration of organic matter with an average in the topsoil of 1% and 2% for dry and wet miombo, respectively (Chidumayo, 1997). This is a consequence of the abundant termite activities and frequent fire incidence (Cauldwell & Zieger, 2000; Chidumayo, 1997).

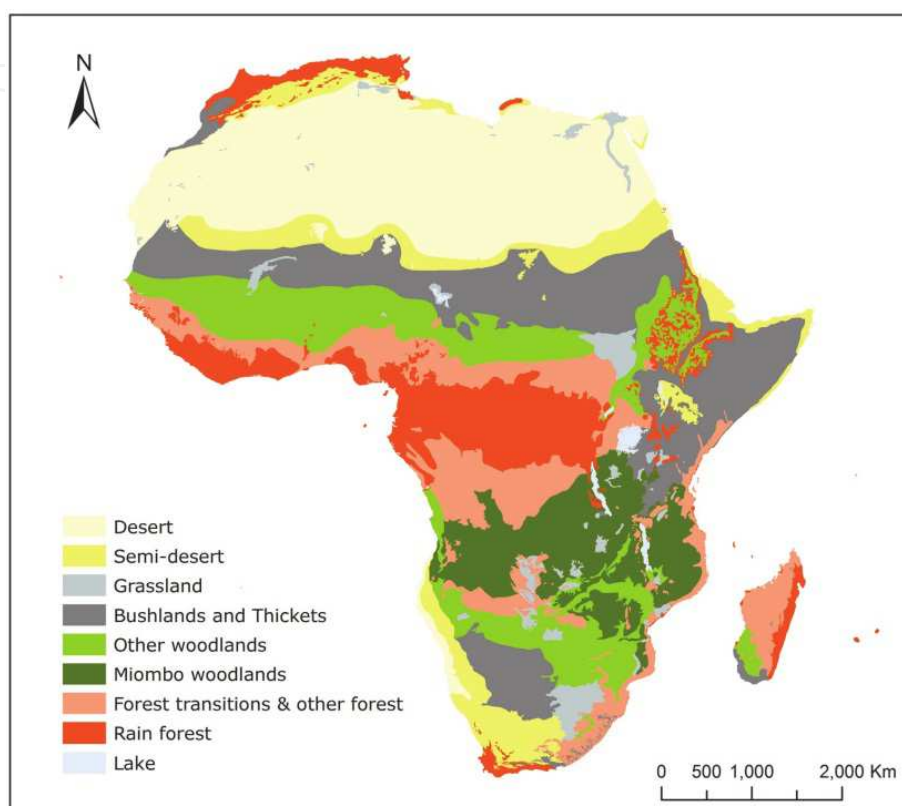


Fig. 1. Map of African vegetation, showing the miombo woodlands in dark green (Source: White, 1983).

## 2.2 Floristic composition and structure

Miombo have an estimated diversity of 8,500 species of higher plants, over 54% of which are endemic and 4% are tree species. Zambia is considered to be the centre of endemism for *Brachystegia* and has the highest diversity of tree species (Rodgers *et al.*, 1996). The diversity of canopy tree species is, however, low and characterized by the overwhelming dominance of trees in the genera *Brachystegia* (*miombo* in Swahili), *Julbernardia* and/or *Isoberlinia* (Campbell *et al.*, 1996). Other important tree species in miombo include *Pseudolachnostylis maprouneifolia*, *Burkea africana*, *Diplorhynchus condilocarpon* among others. In mature miombo these species comprise an upper canopy layer made of 10-20 m high trees and a scattered layer of sub-canopy trees. The understory is discontinuous and composed of broadleaved shrubs such as *Eriosema*, *Sphenostylis*, *Kotschyia*, *Dolichos* and *Indigofera* and suppressed saplings of canopy trees. A sparse but continuous herbaceous layer of grasses, forbs and sedges composed of *Hyparrhenia*, *Andropogon*, *Loudetia*, *Digitaria* and *Eragrostis* (Campbell *et al.*, 1996; Desanker *et al.*, 1997) dominate the ground-layer.

Species composition and structure of miombo vary along the rainfall gradient across the region. In the dry miombo, canopy height is less than 15 m and the vegetation is floristically

poor. *Brachystegia spiciformis*, *B. boehmii* and *Julbernardia globiflora* are the dominant canopy species. The herbaceous layer varies greatly in composition and biomass and contains grasses and suppressed saplings of canopy trees. The wet miombo in turn, presents canopy heights greater than 15 m. The vegetation is floristically rich and includes nearly all of the characteristic miombo species. *B. floribunda*, *B. glaberrima*, *B. longifolia*, *B. wangermeeana* and *Marquesia macroura* are widely distributed. The understory comprises a mixture of grasses, bracken (*Pteridium aquilinum*) and shrubs.

Biomass distribution is uniform across the ecoregion, with the woody component comprising 95-98% of the aboveground biomass in undisturbed stands (Figure 2); grasses and herbs make up the remainder (Chidumayo, 1997). However, biomass production is a function of rainfall and nutrients. For example, Chidumayo (1997) showed a variation of aboveground biomass of 53 t/ha in western dry miombo to 93 t/ha in wet miombo, in Zambia.

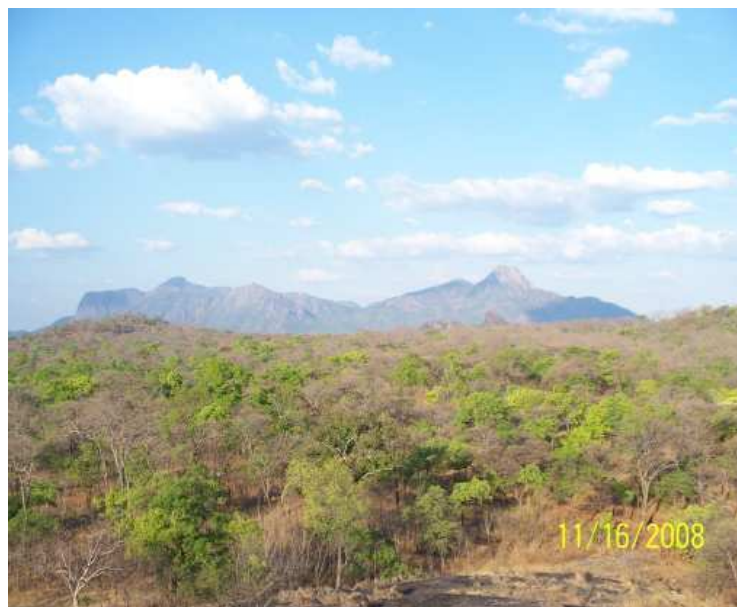


Fig. 2. Beginning of the wet season in mature miombo woodlands in Niassa National Reserve, northern Mozambique. A conserved stand where the homogeneous canopy layer is evident (Photo by: Ribeiro, N.).

The key indicator of the linkage between rainfall and miombo production is the observed structural and compositional variations following the rainfall gradient, from the drier fringes of the miombo to the wetter core area (Desanker *et al.*, 1997). The nutrient cycling seems to follow also the rainfall gradient across the region revealing that nutrients limitation is a function of moisture regime. Local variations are expected to be much higher and strongly affected by disturbances, especially fires and herbivory. The main structural characteristics of miombo woodlands are summarized in Table 1.

*Dambos* are distinctive features of the miombo and occupy seasonally waterlogged shallow valley depressions across the prominent catenas in the region (a regular alternation of two or more types of vegetation) (Campbel *et al.*, 1996; Scholes, 1997). *Dambos* are small *islands* of hygrophilous treeless grasslands emerged in the miombo landscape, which can make up to 40% of the landscape. They have a particular importance for the ecology of miombo, especially as habitat for animal species including some herbivores.

Structural characteristic	Range of values	Source
Woody density	1,500-4,100 stems/ha	Campbell <i>et al.</i> , 1995; Chidumayo 1997; Grundy 1995; Guy 1981; Ribeiro <i>et al.</i> , 2008a; Strang, 1974; Trapnell, 1959.
Tree density	380-1,400 trees/ha	Banda <i>et al.</i> , 2006; Campbell <i>et al.</i> , 1995; Chidumayo, 1985; Grundy, 1995; Guy, 1981; Strang, 1974; Trapnell, 1959.
Stand basal area	7-24 m <sup>2</sup> /ha	Banda <i>et al.</i> , 2006 ; Backéus <i>et al.</i> , 2006; Freson <i>et al.</i> , 1974 ; Lawore <i>et al.</i> , 1994;
Aboveground biomass	1.5 Mg/ha (3-6 years old coppice) - 144 Mg/ha (Mature wet miombo); 53-55 Mg/ha in dry and sub-humid miombo	Chidumayo, 1991; Chidumayo, 1997; Guy, 1981; Malaisse & Strand, 1973; Ribeiro <i>et al.</i> , 2008b; Siteo <i>et al.</i> ( <i>unpubl. Data</i> )
Aboveground herbaceous biomass	0.1-4.0 Mg/ha (2-5% of the total aboveground biomass)	Frost, 1996; Ribeiro and Matos ( <i>unpubl. Data</i> ); Siteo <i>et al.</i> ( <i>unpubl. Data</i> )

Table 1. Summary of structural characteristics of miombo woodlands.

### 2.3 Ecological role of disturbances in miombo woodlands

Changes in the landscape of many types of woodland in Africa have been attributed directly to the interactive effect of elephants and fire (Buechner & Dawkins, 1961; Guy, 1981, 1989; Laws, 1970; Mapaure & Campbell, 2002; Ribeiro *et al.*, 2008a; Sukumar, 2003; Walpole *et al.*, 2004). In general, the pattern of change is the same: as elephants over-browse the woodlands, laying waste to mature trees, there is an increase in the low woody vegetation and grass cover as well as a dramatic increase in fuel load. This allows fire to become progressively more intense. Fiercer and frequent fires affect both large trees and saplings lowering species diversity. Debarking of large trees by elephants may further expose inner tissues to fire damage and death (Laws, 1970; Sukumar, 2003).

Nearly 90% of fires in miombo are anthropogenic and associated with several human activities in the woodland including: hunting, honey collection and shifting agriculture (Figure 3). They occur every 1 to 3 years in the dry season from May to October/November with a peak in the late dry season (August-October). They are largely fuelled by grasses and take place in the understorey with flame heights generally low (Gambiza *et al.*, 2005; Trollope *et al.*, 2002). Thus fire intensity and frequency is linked through grass production to the previous season rainfall, the intensity of grazing and the extent of woody plant cover (Frost, 1996).

Fire frequency in miombo is expected to be locally highly variable according to fuel accumulation rates, the proximity to sources of ignition and interannual climatic variations (Chidumayo, 1997; Frost, 1996; Kikula, 1986; Ribeiro 2007; Trapnell, 1959). The impact of fire on plants depends on its intensity, frequency, seasonality and interaction with herbivory (Bond & Van Wilgen, 1996; Frost, 1984; Ribeiro, 2007; Trollope, 1978). The effect of seasonality was studied by Chidumayo (1989), indicating that stem mortality measured over

a two-year period in wet miombo was only 4-3% when both woodland and coppice plots were burned in early dry season but 18% and 40% respectively when burned in late dry season.



Fig. 3. Agriculture and associated fires in the Gorongosa Mountain, Central Mozambique (Photos by Ribeiro, N.)

The tolerance or susceptibility of miombo plants to frequent late dry season fire is a function of their growth form, developmental stage, physiological conditions and phenological state at the time of burning. For instance, grasses and many non-woody herbs tolerate intense, late dry season fires better than most woody plants. During this time of the year most tree species produce new leaves, which make them less tolerant to intense fires. Frequent late dry season fires also destroy young trees and shrubs, or their aboveground parts, preventing the development of taller, more fire resistant size classes (Brookman-Amisshah *et al.*, 1980; Hopkins, 1965).

Scientific accounts of elephant damage to vegetation in African savannas and woodlands emerged during the 1960s. Buechner & Dawkin (1961) analyzed the vegetation changes in the Murchinson Falls National Park, Uganda between 1932 and 1956 and found that tree populations had halved during that period. Thomson (1975) report that nearly 67% of the 500 original mature trees of *B. boehmii* in Chizarira National Park, Zimbabwe died, and another 20% were damaged, transforming relatively dense woodlands into more open wooded grasslands.

Guy (1981) studying miombo changes in the Sengwa Wildlife Research Area, Zimbabwe found that the biomass was reduced by 54% between 1972 and 1976. The decline was associated with the decreasing number of the dominant tree species, *B. boehmii*, a species markedly selected by elephants. In 1989 the area was dominated by *J. globiflora*, *P. maprouneifolia* and *Monotes glaber* but *B. boehmii* was rare (Guy, 1989). Comparing the woodlands inside the research area with those outside (where the elephants population and fires were excluded) the author found less tree density (267 stems/ha over 334 stems/ha), lower stem area (3.56 m<sup>2</sup>/ha compared to 9.52 m<sup>2</sup>/ha) and lower biomass (8.5 t/ha compared to 26.2 t/ha). Recently Mapaure & Campbell (2002) working in the same area report an overall rate of decrease in woody cover of 0.75% per year. Elephants (significantly high negative correlation coefficient,  $r=-0.90$ ,  $p<0.05$ ), and fire ( $r=-0.35$ ,  $p=0.61$ ) were pointed

out as the main cause of decline. The authors noticed that 82% reduction in the elephant population by culling between 1979 and 1982, result in a noticeable vegetation recovery. However, field observations indicate that some areas were not reverting to miombo, but to *Combretaceae*-dominated thickets. This behavior was also observed by Ribeiro *et al.* (2008a) in the Niassa National Reserve of northern Mozambique.

Dublin *et al.* (1990) studied the effects of elephants and fires in the Serengeti-Mara woodlands in Kenya and found that the combined effect of fire and elephants caused consistently decrease in the recruitment of tree species. Recently Walpole *et al.* (2004) assessed the status of the Mara woodlands (adjacent to the Serengeti National Park). They report that species diversity is relatively low, possibly because of decline in the density and extent of woodland and thickets originated by increasing elephant population within the area.

### 3. Remote sensing techniques for biomass estimation in the miombo woodlands

Remote Sensing refers to the acquisition and recording of information about objects on Earth without any physical contact between the sensor and the subject of analysis. It provides spatial coverage by measurement of reflected and emitted electromagnetic radiation, across a wide range of wavebands. Remotely sensed data provide in many ways an enhanced and very feasible alternative to manual observation with a very short time delay between data collection and transmission.

Since the first launch of an earth observatory satellite, in July 1972 by the US called Earth Resources Technology Satellite (ERTS, later renamed Landsat), remote sensing has been increasingly used to acquire information about environmental processes and over the last three decades this use has had a substantial increase with the development of modern remote sensing technology as radar sensors (ERS, RADARSAT, etc), LiDAR systems and the new generation of optical sensors (IKONOS, SPOT-5, GeoEye, etc.). Thus, remote sensing techniques are a time-and-cost-efficient method of observing forest ecosystems.

The capabilities of remote sensing techniques have been lately expanded to serve monitoring efforts as well as to provide valuable information on degradation in specific areas. Remote sensing, due to its potential to estimate biophysical parameters with detention of temporal and spatial variability, becomes a powerful technique. These, in combination with field sampling methods may provide detailed estimations of forestry parameters. In forest ecosystems, estimation of biophysical parameters has been made by a succession of methods. However, the extension of these estimations in space and time has obvious limitations especially in highly variable ecosystems such as miombo. Moreover, the network of field plots across the miombo ecoregion is not sufficient enough to cover it, which imposes further limitations in the use of remote sensing for biomass estimation.

In this section we highlight the uses of remote sensing techniques to derive biomass information in miombo. Emphasis is given to optical remote sensing techniques because the majority of measurements have been concentrated on these techniques. Radar and microwave remote sensing in miombo have, in the last decade, become a useful source of information for biomass estimation, but has been barely applied in the region. Therefore, radar and microwave remote sensing are also briefly discussed in this section.



### 3.1 Remote sensing of biomass using optical sensors

Passive optical remote sensing, the process of imaging or sampling the interactions between electromagnetic energy and matter at selected wavelengths, has the ability to monitor terrestrial ecosystems at various temporal and spatial scales and has been widely tested for land cover mapping and various forestry applications (Patenaude *et al.*, 2004).

Remote sensing of vegetation depends on the optical properties of plant tissues (foliage, wood, litter, etc.) that determine the landscape-scale reflectance of ecosystems (Asner, 2004; Jensen, 1996). Thus, plant species composition, stand structures and associated canopy shadows and vegetation vigor (leaves, branches and bark) are important factors affecting vegetation reflectance (Lu, 2001). Figure 4 is an example of the spectral signatures of two different types of vegetation in comparison with sand and water. In this example is clear the discrepant reflectance of vegetation and other targets. The shape of the curves of the two vegetation types is similar, but they have dissimilar percent of reflectance, which is due to differences in vegetation structure and composition.

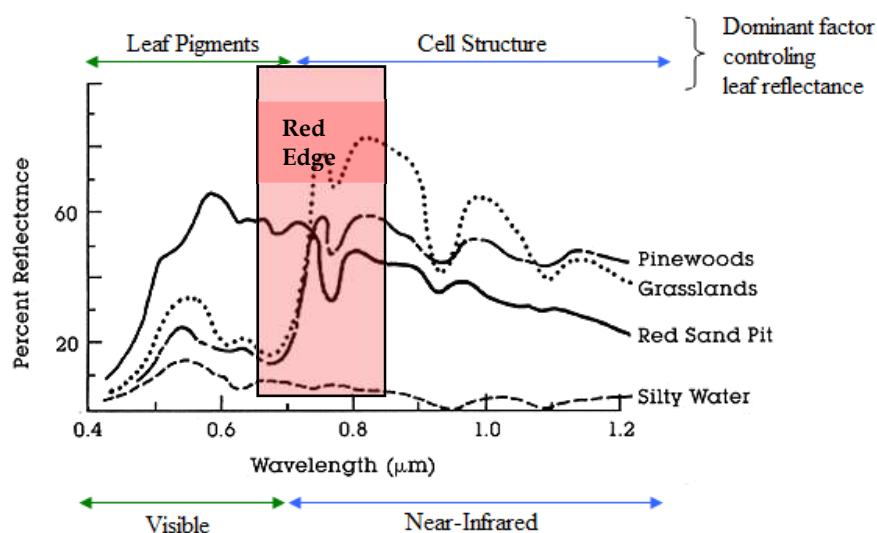


Fig. 4. Differential spectral signatures of vegetation, sand and water (adapted from <http://rst.gsfc.nasa.gov/Intro/Part25.html>). The Red Edge represents the basis for optical remote sensing of vegetation.

The basis for satellite measurements of vegetation from optical sensors is the differential reflection of light in the visible (0.4 to 0.7  $\mu\text{m}$ ) and Near-Infrared (NIR~0.8  $\mu\text{m}$ ) regions of the electromagnetic spectrum originated by the various leaf components (chlorophylls and  $\beta$ -carotene) and structure. For instance, chlorophyll strongly absorbs light in the red (~0.6  $\mu\text{m}$ ) while leaf's structural components highly reflect in the NIR (Jensen, 1996). In the visible part of the spectrum (Figure 4) the dominant signal detected by the sensor is the direct scattering. Multiple bounces of photons from the forest back to the sensor are small in comparison to direct scattering because the chlorophyll and other leaf pigments within the forest foliage are highly absorbing at visible wavelengths. At NIR wavelengths, however, the foliage is more transparent and multiple scattering becomes more important. Hence, this striking difference in light reflectance, known as the *red edge* (Figure 4), is sensitive to vegetation changes over a wider range of vegetation densities (Jensen, 1996; Shugart, *et al.*, 2010).

Within the same forest stand the sensor measures the aggregate reflectance as a function of the wavelength of the tree canopies and understory within a pixel. The reflectance changes

seasonally with phenological changes in vegetation. For example in the dry and sub-humid miombo most species lose their leaves for 4-5 months of the year in response to the dry season. The associated spectral reflectance spectrum within a year is exploited to extract information on woodland structure, type, age, condition, biomass, leaf area, and even photosynthetic rate (Shugart *et al.*, 2010).

Differential vegetation reflectance has resulted in the development of numerous vegetation indices and biomass estimation techniques that utilize multiple measurements in the visible and NIR. Vegetation indices (VIs) are dimensionless metrics that function as indicators of relative abundance and activity of green vegetation, often including LAI [most VIs saturate at around LAI = 4, Huete *et al.* (2002)], percentage green cover, chlorophyll content, green biomass, and Absorbed Photosynthetically Active Radiation (APAR) (Jensen, 1996). The first true VI was the Simple Ratio (eq. 1.) described by Birth & McVey (1968).

$$SR = \frac{\rho_{NIR}}{\rho_{Red}} \quad (1)$$

Where  $\rho_{NIR}$  is the reflectance in the NIR wavelength and  $\rho_{Red}$  is the reflectance in the red wavelength.

Rouse *et al.* (1974) developed what is now known as the Normalized Vegetation Index the Normalized Differentiated Vegetation Index (NDVI), a satellite metric used to detect changes in pixel-scale vegetation greenness (Asner, 2004).

$$NDVI = \frac{(\rho_{NIR} - \rho_{Red})}{(\rho_{NIR} + \rho_{Red})} \quad (2)$$

(eq. 2. 17 Symbol definitions are the same as in eq. 1.) NDVI is broadly correlated with both chlorophyll and water content of canopies and consequently is linked both theoretically and experimentally to LAI, the Fraction of Photosynthetically Active Radiation (fPAR) and the biomass of plant canopies (Gamon *et al.*, 1995; Sellers, 1985). SR and NDVI have been further developed and improved in other related vegetation indices such as the Soil Adjusted Vegetation Index (SAVI, Huete, 1988; Huete & Liu, 1994) and Enhanced Vegetation Index presented in eq. 3 (EVI, Huete *et al.*, 2002).

$$EVI = G \left[ \frac{\rho_{NIR} - \rho_{Red}}{(\rho_{NIR} + C1\rho_{Red} - C2\rho_{Blue} + L)} \right] \quad (3)$$

Where  $C1 = 6.0$ , atmosphere resistance red correction coefficient;  $C2 = 7.5$ , atmosphere resistance blue correction coefficient;  $L = 1.0$ , canopy background brightness correction factor;  $G = 2.5$ , gain factor. Given that EVI considers the canopy background (L) and reflectance in the blue it is more sensible to variability of canopy structure.

These indexes might be calculated with any sensor [ETM+, MODerate Resolution Imaging Spectroradiometer (MODIS)], except for EVI, which is calibrated exclusively for MODIS data.

Most optical remote sensing techniques for biomass estimation essentially explore the relationship between field measurements of vegetation parameters with spectral VIs to estimate large-scale distribution of biomass. The results vary according to the woodland structure and diversity derived from site-specific conditions such as the disturbance regime

and seasonality. Thus, we do not attempt to generalize the relationships between field measurements and VIs for miombo, but give some examples that reflect this variation.

Ribeiro *et al.* (2008)b worked in northern Mozambique in an area where fires occur annually during the dry season with higher incidence in the eastern side, where elephant density is also higher. In this area, the combination of fires and elephants imposes high variability of miombo structure (Ribeiro *et al.*, 2008a). Under these conditions, the authors found relatively low but significant relationships between woody biomass, Leaf Area Index (LAI) measured in the field and, NDVI and SR derived from Landsat ETM+ [NDVI ( $r_{\text{biomass}} = 0.30$ ,  $r_{\text{LAI}} = 0.35$ ;  $p < 0.0001$ ) and SR ( $r_{\text{biomass}} = 0.36$ ,  $r_{\text{LAI}} = 0.40$ ,  $p < 0.0001$ )].

Huete *et al.* (2002) found that the NDVI saturated in high biomass regions like the Amazon (150 Mg/ha or over 15 years of age) while the EVI was sensitive to canopy variations. NDVI ( $r = 0.15-0.25$ ) and SR (0.12-0.24) showed to be weakly correlated with biomass in dense stands, while the correlation coefficients were considerable ( $r_{\text{NDVI}} = 0.46$  and  $r_{\text{SR}} = 0.50$ ) for the less dense site. Recently a study conducted in the savannas and woodlands of the Amazon Basin detected quite good relationships between field biomass and MODIS derived NDVI with an  $r^2 = 0.45$  (Saatchi *et al.*, 2007).

A major constraint on the use of spectral VIs in dry and sub-humid ecosystems for vegetation studies, is that VIs are likely to underestimate live biomass due to their insensitivity to nonphotosynthetic vegetation (NPV) and sensitivity to low organic matter content in soils (Okin & Roberts, 2004). The effect of NPV is particularly important in the dry miombo where tree density is low (sometimes less than 10%) and disturbances may create several open patches in which NPV (such as litter, dry woody material, dry grass in the dry season) and soils are a significant component of the surface. In these areas, the effect of the exposed soil may be pronounced, while the low organic matter content on soils makes them bright and mineralogically heterogeneous.

The combination of those factors, creates vertical and horizontal structural differences that may not be depicted using VIs techniques, especially when using low to medium resolution sensors (e.g. 30-m Landsat, 250-m and greater MODIS, etc). In this situation, high spatial resolution optical sensors such as 1-4 m IKONOS, 2.5-10 m SPOT-5, among others, can detect variations in the spatial distribution of biomass density. This new generation of sensors also offer systematic observations at scales ranging from local to global and improves the monitoring of inaccessible areas (Rosenqvist *et al.*, 2003). However, these high spatial resolution instruments are only available for small geographic areas in the miombo ecoregion and thus they are not suitable for large-scale high-resolution ecological assessments in this ecosystem.

The use of Spectral Mixture Analysis (SMA) has become an important technique to overcome the spatial and temporal heterogeneity in miombo. SMA uses a linear mixture technique to estimate the proportion of each ground's pixel area that belongs to different cover type (Okin & Roberts, 2004). SMA is based on the assumption that spectra of materials in a pixel combine linearly with proportion given by their relative abundance. For example, an NPV value of 0.50 from SMA indicates that woody tissues, surface litter and other dead vegetation occupy 50% of the surface area of the pixel. A combined spectrum can thus be decomposed in a linear mixture of its spectral endmembers, spectra of distinct material within the pixel. The weighting coefficients of each spectral endmember, which must sum up to 1, are then interpreted as the relative area occupied by each material in a pixel.

Fractional cover of photosynthetic vegetation (PV), NPV and bare substrate are the principal determinants of ecosystem composition, physiology, structure, biomass and biogeochemical stocks. These also capture the biophysical impact of disturbances caused by both natural and human drivers (Asner *et al.*, 2005). In this case, SMA provides the fraction of per-pixel reflectance that is accounted for by the selected target. Results from SMA can be directly evaluated in field campaigns, including endmember abundance change over time. The temporal or spatial change in the NPV fraction can provide a quantitative measure of disturbance (Chambers *et al.*, 2007).

Up to date SMA has not been applied to miombo but due to its capacity to proportionally decompose several endmembers in a pixel it is a promising remote sensing technique in this ecosystem given the spatial heterogeneity referred previously. Asner *et al.* (2005) applied SMA for the Brazilian Amazon and bordering Cerrado (an ecosystem structurally similar to miombo) to estimate vegetation attributes for a large-scale and multi-temporal Landsat ETM+ scene spanning the years 1999-2001. Their results showed that PV fractional covers for the cerrado range from 74% to 85% depending on the degree of woody cover, while the NPV cover varied from ~9% and 12% and bare soil between 2% and 10%. The study was able to demonstrate the capacity of this technique to separate vegetation types (forests from savannas) as well as different kinds of disturbances (logging, grazing, etc).

In a particular interesting application Asner *et al.* (1998) applied SMA to invert a geometrical-optical model to estimate overstory stand-density and crown dimensions. The study applied SMA to a Landsat image to provide estimates of woody cover, herbaceous, bare soil and shade fractions. The estimated cover was then used to unmix the contribution of woody cover and herbaceous canopies to AVHRR multiangle reflectance data. The angular reflectance was used with the radiative transfer (RT) model inversions to estimate LAI, PAR and carbon uptake.

There are two drawbacks of biomass estimation using optical remote sensing techniques: (i) field plots are rarely designed to be related to spaceborne data and (ii) saturation at dense leaf canopies restricts estimates to low biomass levels when passive sensor data is used (Gibbs *et al.*, 2007). Also, biomass is a three-dimension feature of vegetation. However, the ability of optical sensors is limited to two dimensions only, i.e. the upper layers of vegetation (Anaya *et al.*, 2009). Remote-sensing systems relying on optical data (visible and infrared light) are further limited in the tropics by cloud cover. In view of these drawbacks microwave data has become an attractive technique to estimate biomass worldwide and in miombo in particular.

### 3.2 Radar remote sensing of biomass

The term radar remote sensing is used to denote the active remote sensing where microwave or radio frequency radiation is transmitted to the surface. Microwaves have higher wavelengths (3 to 75 cm for vegetation studies) than solar radiation (400 to 2,500 nm) that is used by optical remote sensing techniques. Unlike optical sensors, the microwave energy penetrates clouds, rain, dust, or fog and allows collection of images, regardless of solar illumination, so that the radar images can be generated at any time under the most varied weather conditions. The microwaves penetrate into the forest canopy and scatter from large woody components (stems and branches) that constitute the bulk of biomass and carbon pool in the forested ecosystems.

The microwaves in a specific wavelength and polarization is emitted from the sensor to the Earth, where it interacts with vegetation (and other objects) and is then backscattered to the sensor. Three different bands are commonly used in radar remote sensing of vegetation: P-band (30 cm) L-band ( $\lambda=23.5$  cm), C-band ( $\lambda=5.8$  cm) and X-band ( $\lambda=3.1$  cm). The sensitivity of backscatter measurements at different wavelengths and polarization (horizontal and/or vertical) to the size and orientation of woody components and their density makes the radar sensors suitable for direct measurements of aboveground woody biomass (carbon stock) and structural attributes such as volume and basal area.

Radar remote sensing has been widely used to map vegetation worldwide, but it is not commonly used in miombo. But, given the spatial variability of vegetation in this ecosystem, radar is a promising technique to estimate biomass. Another advantage of the radar system for miombo is its insensitivity to weather conditions, making wet season measurements possible. During that time of the year some areas are inaccessible. The constraint though is that radar imagery does not cover large areas in the miombo region nor it is being collected frequently, causing difficulties for large-scale frequent monitoring of biomass.

Pierce *et al.* (2003) refer that Synthetic Aperture Radar (SAR) is known to have a response directly related to the amount of living material that it interacts with. The strong relationship between field biomass and radar image intensity and the development of approaches to estimate aboveground biomass represents one of the unique applications of SAR data in ecology (Kasischke *et al.*, 2004). SAR sensor offers the potential of rapid, accurate, high resolution and low cost mapping of the lower biomass density vegetation of Africa. Moreover, the 46-day repeat cycle of ALOS/PALSAR allow sufficient images to be captured during the year to negate any effects of seasonality and soil moisture, and allow the monitoring of landscapes for any changes in aboveground biomass (Mitchard *et al.*, 2009).

Interferometric SAR (InSAR), which uses the phase information in signals received taken at multiple times to derive very precise measurements of movements on Earth, has been widely used. Recent innovations in orbital designs for repeat pass radar interferometry (InSAR) will allow the sensor to measure height of forest and provide a vertical dimension for accurately resolving the vegetation biomass of forests globally (Chambers *et al.*, 2007).

The most basic approach to estimating aboveground biomass in forests is to develop a multiple-linear regression equation that estimates total biomass as a function of a combination of SAR channels or ratio of different channels (Kasischke *et al.*, 2004). For example Pierce *et al.* (2003) studied the relationship between radar L-band (25 cm wavelength) and C-band (5.2 cm wavelength) combined and separately, in the regrowth forest of the Amazon Basin. The study found that L- and C-band together improve the accuracy compared to using only one frequency channel. In a recent study Saatchi *et al.* (2007) found high correlation between radar L-band and field biomass ( $r^2=0.68$ ) in woodlands and savannas of the Amazon Basin. The authors were able to produce a multiple linear regression model that includes microwave and optical data to estimate the biomass of this vegetation type.

Ribeiro *et al.* (2008)b correlated contemporary 30-m C-band (5.8 cm) RADARSAT backscatter and field woody biomass and LAI data ( $r_{\text{biomass}}=0.65$  and  $r_{\text{LAI}}=0.57$ ,  $p<0.0001$ ) to, in combination with optical data (30-m Landsat ETM+), produce the aboveground biomass map for the Niassa National Reserve (NNR) in northern Mozambique. The results were satisfactory but expected to underestimate biomass in dense woodlands due to radar

saturation at high biomass levels. The relationship between radar and field biomass in this area was further explored by Mitchard *et al.* (2009) by using ALOS PALSAR, an L-band sensor. The authors also studied other forested areas in Africa (Cameroon and Uganda). For all sites they found an improved relationship between field biomass and HV-backscatter ( $r^2_{\text{biomass}}=0.61-0.76$ ,  $p<0.0001$ ), but with a clear saturation between 150-200 Mg/ha of biomass. Biomass prediction was done with fairly good accuracy of  $\pm 20\%$  for plots with less than 150 Mg/ha. According to the authors these are partly because L-band SAR does not respond directly to aboveground biomass, but to aspects of vegetation structure, partially due to spatial variability in structure and partially due to radar calibration, orthorectification and field estimation errors propagating through the analysis. Also, backscatter responds differently to differing soil and vegetation moisture conditions, and the surface topography, adding to observed prediction errors. Despite these factors the analysis was able to predict, with fairly good accuracy, aboveground biomass from radar data for very different vegetation types. This finding suggests that utilization of L-band data should be essential for projects involving the mapping and monitoring of woodland and savanna biomass, thus having important implications for carbon-credit projects, such as those under proposed REDD schemes (Mitchard *et al.*, 2009). The comparison of Ribeiro *et al.* (2008)b and Mitchard *et al.* (2009) study for Niassa National Reserve in northern Mozambique indicate clearly that L-band is an improvement over C-band for biomass prediction in the low biomass miombo in this area.

Light Detection and Ranging (LiDAR) measurements provide the most direct estimates of canopy height and the vertical structure of canopy foliage. Together, these measurements enable ecologists to quantify the 3D distribution of vegetation at a landscape scale, to understand processes of carbon accumulation and forest succession and to improve the state of ecosystem models (Chambers *et al.*, 2007). LiDAR systems incorporate a laser altimeter to measure accurately the distance from the sensor to the canopy top and bottom elevations. The energy returned from distances between the canopy and ground provides evidence of the vertical distribution of sub-canopy strata. One application of LiDAR technology has been to map variations in canopy height with meter-level accuracy. Canopy heights can then be translated into estimates of aboveground biomass based on the allometric relationships between height, basal area and biomass (Shugart *et al.*, 2010). This airborne system has not been used in Miombo woodlands (Shugart *et al.*, 2010).

Other approaches for biomass estimation from radar sensors develop regression equations to use different channels of radar imagery for average height and basal diameter estimation and then use these parameters to estimate biomass (Kellndorfer *et al.*, 2004; Simard *et al.*, 2006). Kellndorfer *et al.* (2004) used the Shuttle Radar Topography Mission (SRTM) data in conjunction with a National Elevation Dataset (NED) to estimate pine canopy height in Southeast Georgia, USA. The study indicates that SRTM can be successfully correlated via linear regression modeling with ground-measured mean canopy height ( $r^2=0.79-0.86$ ). Mean canopy height can *a posteriori* be used in allometric equation to estimate landscape biomass. In a recent study Simard *et al.* (2006) calibrated the SRTM data using Light Detection and Range (LiDAR) data and high resolution Digital Elevation Model (DEM) for the mangrove forests in Everglades National Park. The resulting mangrove tree height map (error 2.0 m) was then used in combination field data to map the spatial distribution of biomass for the entire area. This kind of approach has not been used yet for the miombo or similar woodlands but the results above indicate that the technique can be applied to miombo with some caution, due to

its heterogeneity. This may imply for example that the canopy height estimation may only apply to canopy species, while the understory is not completely measured. This should be considered a topic of research for miombo, before any conclusion is raised.

Radar and LiDAR sensors provide complementary information about the forest structure. LiDAR is sensitive to leaf material and radar to structural features, which can be combined to increase accuracy of biomass and the forest structure estimates (Figure 5). However, the signatures have some level of commonality because of biophysical and structural nature of forest stands. The vertical distribution of reflective surfaces that can be inferred from LiDAR reveals the bole and branch structure supporting the leaves within a near vertical volume of the vegetation. LiDAR sensors measure this vertical profile by sampling the forest stand along its orbital tracks. Radar provides imaging capability to estimate forest height through InSAR configuration or forest volume and biomass through polarimetric backscatter power. However, the vegetation signature from radar measurements is from a slanted volume and is sensitive to both vertical and horizontal arrangement of vegetation components (leaves, branches, and stems). The combination of the two sensors has the capability of providing the vegetation three-dimensional structure at spatial resolutions suitable for ecological studies (25–100 m). However, there are limited studies to explore the fusion of the two measurements because of the lack of data over the same study areas as well as well-developed ground data (Shugart *et al.*, 2010). According to the authors this will be an ongoing research area for several years to come.

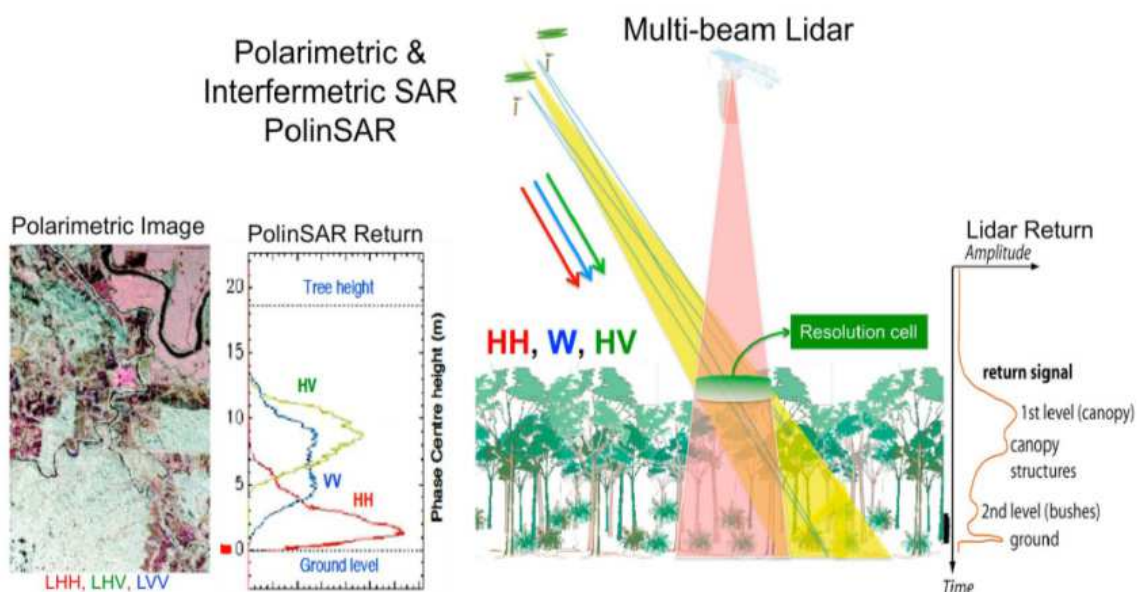


Fig. 5. Radar imager maps of observed radar energy returned at various polarization transmit-receive combinations (HH, HV, VV, where H is horizontal polarization and V is vertical polarization) which are related to the volume and biomass of forest components. The multibeam lidar sampler measures the vertical variation in the strength of the scattered laser signal, which is related to forest vertical structure profile and biomass. The two signals are combined using “fusion” algorithms to improve the accuracy of radar estimates of biomass and to extend lidar measurements of structure in both space and time (Source: Shugart *et al.*, 2010).

This technique is promising in estimating biomass and other parameters for miombo, due to its high spatial variability associated to disturbances across the region. Relatively to herbivory by elephants (tree debarking and debranching) and fires (killing of juvenile trees and natural regeneration, soil degradation, killing of adult debarked trees, etc.) data fusion from these instruments may have a significant contribution in addressing the impacts of these disturbances on biomass production in the region. The immediate result will be an improved and informed management of the woodlands in particular for conservation areas.

Future satellite missions plan to make frequent measuring of standing vegetation feasible. Houghton *et al.* (2009) laid out the required specifications for these and other future satellite missions to significantly reduce the nowadays existing uncertainties. They claimed, that in order to reduce the uncertainty in the land-atmosphere fluxes to those of the next uncertain term (which is the net carbon uptake of the ocean with an uncertainty of  $\pm 18\%$ ) a measurement error of less than 2 MgC (or an aboveground biomass uncertainty of about 4 Mg) per ha is required. It is furthermore argued, that disturbances (deforestation, fires and herbivory) are patchy on spatial scales of 100 m and less and only if remote sensing is operating on a similar scale, one can clearly identify changes in carbon storage over time and minimize sampling errors due to averaging (Kohler & Huth, 2010).

#### **4. Remote sensing of biomass in miombo woodlands: Opportunities and limitations for research**

Miombo display complex vegetation patterns in which dense vegetation alternates with sparsely populated or bare soil in response to environmental and disturbance (deforestation, fires and herbivory) factors. Low vegetation cover, in some places, and small-scale variations in others, can produce unpredictable errors in the quantification of biophysical and ecological properties of the vegetation. Ignoring this spatial variation can produce inaccurate results, even in fairly homogeneous environments (Aubry & Debouzie, 2001 cited by Hufkens *et al.*, 2008; Haining, 1990).

The use of remote sensing for estimations of vegetation biomass has proved to be of great importance to fill up data gaps and to estimate large-scale variations, especially in low accessible places. The technique lacks of precision when compared to detailed forest inventories. But, for miombo the lack of detailed field data and uncertainty of biomass stocks associated to disturbances, make remote sensing one important technique to address temporal and spatial variations in biomass.

Although repeated satellite imaging has improved in resolution over the years, it is still limited in detecting fine patterns within savanna vegetation. Some forms of remote sensing, such as the sub-meter resolution IKONOS, GeoEye and QUICKBIRD satellite sensors, allow individual trees to be recognized. Other, such as microwave remote sensing from radar (RADARSAT, ALOS-PALSAR, JERS-1, etc.) and LiDAR provide a three dimensional representation of vegetation, which is an improvement over optical remote sensing. However, both low-resolution optical and microwave scenes are currently too expensive for large-scale or regional studies and they require a substantive amount of processing capacities. These represent some of the major limitations for its use in the southern Africa region.

Discriminating between subtypes of savanna vegetation, even simply looking at structural differences, has proved a taxing undertaking, especially in places where field data is limited.



Thus, there is a pressing need to intensify studies calibrating satellite with field measurements, albeit the low accessibility of some areas in the miombo ecoregion. In addition to spatial measurement, it has long been clear that temporal surveys at varied time intervals are required, particularly in biomes that are highly dynamic such as miombo (Furley, 2010).

The problem of biomass retrieval in miombo is compounded by the fact that senescent and dead material (also known as NPV) associated with phenology and disturbances can be a major component of the total surface cover. These three factors play a major role in both abiotic and biotic dynamics of the miombo as explored in Section 2 of this chapter. NPV can represent an important carbon pool in this ecosystem. Many common methods for estimating vegetation cover and biomass use VIs that are insensitive to the presence of NPV. Thus, SMA, data fusion among others may be more appropriate techniques to address spatial and temporal variations of biomass in miombo, but they still need to be adapted and calibrated for this ecosystem.

Addressing large-scale and temporal variations of biomass in the different compartments of miombo (PV, NPV, soils and underground) has to be enhanced in the near future due to their varied contribution to global emissions of greenhouse gases - Carbon dioxide in particular. For example, NPV is the main source of fuel-load for fires, which causes large amounts of carbon to be lost in the form of carbon dioxide to the atmosphere. Because of this, the contribution of miombo to global climate changes may be significant but not completely understood yet.

The southern African region is embarking in the carbon market under the Kyoto Protocol and REDD schemes of the UNFCCC. The ability to negotiate in this market and gain a better position is dependent on the capacity of a country (or region) to estimate carbon stocks with minimal errors. Thus, the advance of remote sensing measurements of biomass from space is an important step towards that achievement (Houghton, 2005 cited by Houghton, 2010). However, it is important to acknowledge that most remote sensing techniques for measurements of biomass usually miss belowground biomass and soil carbon in tropical and sub-tropical regions, which may hold a representative fraction of carbon in the whole system. Thus, future research should focus on the use of microwave radar remote sensing (P-Band and higher) or optical techniques such as SMA and data fusion, that are able to differentiate carbon pools.

## 5. Conclusions

Remote sensing of biomass in miombo faces the following constraints:

1. Biomass variations at scales of less than 25 m associated with season and disturbances (fires, herbivory and slash and burn agriculture);
2. Limited network of field plots due to low accessibility of some areas;
3. Lack of contemporary field and remote sensing data;
4. Limited accessibility to improved sensors (high resolution optical, microwave and LiDAR data).

However there are some opportunities that may be explored to improve data generation and analysis, thus a better understanding of this ecosystem:

1. Improved methods to estimate biomass in different compartments of the ecosystem (SMA, data fusion, etc.);

2. There exist few sites in the region with detailed data on biomass variations that can be used to test improved remote sensing techniques. For example, permanent sample plots exist in almost all miombo countries. These plots are being frequently evaluated for several parameters including biomass and carbon in different compartments;
3. There are a growing number of remote sensing specialists in the region. In addition, several networks (miombo network, safnet, saccnet, among others) are dedicated to improve remote sensing techniques and data sharing. These involve not only regional but also international senior specialists thus representing a good way of data sharing, improve techniques, establish a link between research and decision making, etc.

In face of the limitations and opportunities for the remote sensing of biomass in miombo, there are five research areas of interest in the region that can benefit from the advance of remote sensing techniques. The core areas presented below are general and can accommodate several research topics according to site particularities. The research themes are:

1. Land use and land cover changes and its effects on miombo biodiversity and biomass;
2. Improved techniques for spatial and temporal variations of biomass and biodiversity;
3. Contribution of miombo to the global changes. This may include several topics such as: carbon stock assessment for different ecosystem compartments (vegetation, soils, NPV, belowground); fire regimes and management; vulnerability and adaptation to climate change.
4. Biomass changes and effects on the availability of resources to human population;
5. Knowledge Management: from science to policy.

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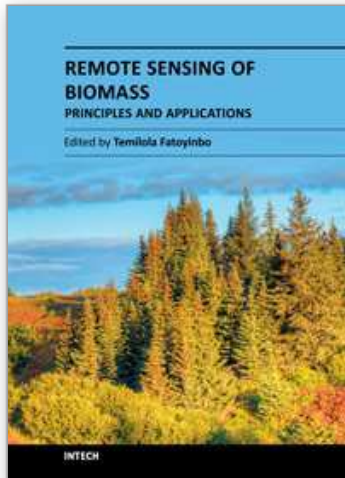
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## **Remote Sensing of Biomass - Principles and Applications**

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The accurate measurement of ecosystem biomass is of great importance in scientific, resource management and energy sectors. In particular, biomass is a direct measurement of carbon storage within an ecosystem and of great importance for carbon cycle science and carbon emission mitigation. Remote Sensing is the most accurate tool for global biomass measurements because of the ability to measure large areas. Current biomass estimates are derived primarily from ground-based samples, as compiled and reported in inventories and ecosystem samples. By using remote sensing technologies, we are able to scale up the sample values and supply wall to wall mapping of biomass. Three separate remote sensing technologies are available today to measure ecosystem biomass: passive optical, radar, and lidar. There are many measurement methodologies that range from the application driven to the most technologically cutting-edge. The goal of this book is to address the newest developments in biomass measurements, sensor development, field measurements and modeling. The chapters in this book are separated into five main sections.

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No.65, Yan An Road (West), Shanghai, 200040, China  
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元  
Phone: +86-21-62489820  
Fax: +86-21-62489821



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