Assessing woody biomass in African tropical savannahs by multiscale remote sensing

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Woody biomass production is a critical indicator in evaluation of land use management and the dynamics of the global carbon cycle (sequestration/emission) in terrestrial ecosystems. The objective of the present study was to develop, through a case study in Sudan, an operational multiscale remote-sensing-based methodology for large-scale estimation of woody biomass in tropical savannahs. Woody biomass estimation models obtained by different authors from destructive field measurements in different tropical savannah ecosystems were expressed as functions of tree canopy cover (CC). The field-measured CC data were used for developing regression equations with atmospherically corrected and reflectance-based vegetation indices derived from Landsat ETM+ (Enhanced Thematic Mapper Plus) imagery. Among a set of vegetation indices, the normalized difference vegetation index (NDVI) provided the best correlation with CC ($R^2 = 0.91$) and was hence selected for woodland woody biomass estimation. After validation of the CC-NDVI model and its applicability to Moderate Resolution Imaging Spectroradiometer (MODIS) data, time-series MODIS NDVI data (MOD13Q1) were used to partition the woody component from the herbaceous component for sparse woodlands, woodlands and forests defined by the Food and Agriculture Organization (FAO) of the United Nations Land Cover Map. Following the weighting of the estimation models based on the dominant woody species in each vegetation community, NDVI-based woody biomass models were applied according to their weighted ratios to the decomposed summer and autumn woody NDVI images in all vegetation communities in the whole of Sudan taking the year 2007, for example. The results were found to be in good agreement with those from other authors obtained by either field measurements or other remote sensing methods using MODIS and lidar data. It is concluded that the proposed approach is operational and can be applied for a reliable large-scale assessment of woody biomass at a ground resolution of 250 m in tropical savannah woodlands of any month or season.

1. Introduction

Woody biomass (WB) is a measure of cumulative above-ground net primary production (NPP) of trees or shrubs over a certain period of time and is expressed as weight of dry matter per unit area (e.g. t ha$^{-1}$). Information about WB is critical because it is closely related to land use practice and management in savannahs and forest ecosystems – for example, deforestation and slash-and-burn agriculture activities. The Intergovernmental Panel on Climate Change (IPCC) reported that 68.6–75.9% of total annual NPP is concentrated in the biomes
of boreal and temperate forests, tropical rainforests, and, particularly, in tropical savannah woodlands, the latter accounting for 23.8–29.5% of total annual NPP (IPCC 2001). Therefore, tropical savannah woodlands constitute an essential part of the global terrestrial ecosystem and play an important role in agroforestry and socio-economic development in tropical regions, not only for their energy, food, wood, and wood-based industrial applications, but also for their critical multi-function role in controlling the equilibrium between carbon emission and sequestration and climate change, and in protecting the soil against desertification and land degradation (Hall et al. 1985; Dixon et al. 1994; Campbell 1996; Frost 1996; Foley et al. 2005; UNEP 2006). Monitoring and assessment of WB production of savannah ecosystems at the regional scale are hence of major importance for the assessment of global carbon status, particularly in the context of climate change and land degradation and towards making sustainable land management decisions in the countries and regions involved.

Savannah woodlands are land cover types transitional between closed forests and open grasslands, with tree canopy cover (CC) less dense than forests but more so than grasslands. Savannah biomes are very common in tropical Africa, where they occupy a large region that is conventionally subdivided into southern Saharan/Sahelian Woodlands and Sudanian Woodlands north of the equator and Miombo Woodlands to the south. Given the continuum in CC within this large ecosystem, different subdivisions have been proposed for savannah woodlands based on CC (White 1983; Helldén 1987b; FAO 2000). Since, we had intended to use the land cover map produced by the Food and Agriculture Organization (FAO) Africover Project (FAO 2003) to identify woodland and forest areas, we followed the class terms of the FAO Land Cover Classification System (Di Gregorio and Jansen 2000): sparse woodland including wooded grassland and open woodland (tree/shrub CC: 1–20%), woodland/shrubland (CC: 20–60%), and forest (CC: >60%). However, this classification cannot fully demonstrate the spatial variability and mixture of woody species in tropical savannah woodlands. For this reason, it is better to take into account further information on vegetation communities (Harrison and Jackson 1958) in order to understand not only the diversity of woody species across different savannahs, but also their dominance in each community of each savannah eco-region (Table 1) in tropical Africa.

The extensive assessment of WB is based on models that extrapolate actual measurement of tree biomass, obtained at sampling sites, to large areas by establishing statistical relationships with indirect indicators of vegetation biomass, usually obtained by remote sensing. For boreal and tropical forests, a significant number of WB assessments have been undertaken either using allometric equations (e.g. Baskerville 1972; Brown, Gillespie, and Lugo 1989; Iverson et al. 1994; Brown and Gaston 1995; FAO 1997; Sawadogo et al. 2010) or by optical and radar remote sensing (Debson et al. 1992; Foody, Boyd, and Cutler 2003; Popescu, Wynne, and Nelson 2003; Zheng et al. 2004; Lu, Batistella, and Moran 2005; Rauste 2005; Heiskanen 2006; Baccini et al. 2008). Given the differences between biomes in species, CC, and environmental conditions, WB models developed for specific biomes for boreal forests and tropical rainforests are not applicable in savannah woodlands.

For tropical savannah woodlands, some studies have attempted to establish CC-based WB models. Helldén and Olsson (1982), Olsson (1985), and Helldén (1987a, 1987b; 1991) conducted biomass assessment in *acacia*-dominated Saharan/Sahelian Woodlands in Sudan and Ethiopia, where they obtained a linear WB-CC model and established a relationship between CC and NDVI (Rouse et al. 1973; Tucker 1979). These studies confirmed the feasibility of assessing WB by remote sensing. While investigating carbon stocks in the Sahelian Savannah in Senegal, Woomer, Touré, and Sall (2004) also reported a linear model between total carbon and CC. Due to certain shortcomings, these models cannot be directly
Table 1. Woody vegetation diversity and communities in tropical savannahs, taking Sudan as an example.

| Eco-regions        | Vegetation communities                                                                 | Model 1 | Model 2 |
|--------------------|----------------------------------------------------------------------------------------|---------|---------|
| Saharan            | Desert                                                                                  | 0.00    | 0.00    |
|                    | Montane vegetation in the state of Red Sea (northeast)                                  | 1.00    | 0.00    |
|                    | Semi-desert (e) *Acacia glaucophylla/Acacia etbaica* scrub                              | 1.00    | 0.00    |
|                    | Semi-desert (d) *Acacia mellifera/Commiphora* desert scrub                              | 1.00    | 0.00    |
|                    | Semi-desert (c) Semi-desert grassland on sand                                           | 1.00    | 0.00    |
|                    | Semi-desert (a) *Acacia tortilis/Maerua crassifolia* desert scrub                       | 1.00    | 0.00    |
|                    | Semi-desert (b) Semi-desert grassland on clay                                           | 1.00    | 0.00    |
| Sahelian            | Low-rainfall woodland savanna, on sand (b) *Combretum cordofaum/Dalbergia/Albizia sericephela* savannah woodland | 1.00    | 0.00    |
|                    | Montane vegetation in Jabal Marra Mountains (west)                                      | 0.60    | 0.40    |
|                    | Special areas of low-rainfall woodland savanna (d) Raqaba repeating pattern             | 1.00    | 0.00    |
|                    | Low-rainfall woodland savanna, on clay (c) *Anogeissus/Combretum hartmannianum* savannah woodland | 0.20    | 0.80    |
|                    | Low-rainfall woodland savanna, on clay (Acacia mellifera thornland) (i) on dark cracking clay, alternating with grass areas | 1.00    | 0.00    |
|                    | Low-rainfall woodland savanna, on sand (a) *Acacia senegal* savannah                    | 1.00    | 0.00    |
|                    | Low-rainfall woodland savanna, on clay (b) *Acacia seyal*/*Balanites* savannah, alternating with grass areas | 0.90    | 0.10    |
|                    | Low-rainfall woodland savanna, on sand (c) *Terminalia*/Sclerocaryea*/Anogeissus*/Prosopis* savannah woodland | 0.20    | 0.80    |
|                    | Special areas of low-rainfall woodland savanna (b) Hill Catena in Darfur (west)         | 0.80    | 0.20    |
|                    | Special areas of low-rainfall woodland savanna (c) Baggara Repeating Pattern           | 0.90    | 0.10    |
|                    | Low-rainfall woodland savanna, on clay (Acacia mellifera thornland) (ii) on hill soils formed in situ, associated with Commiphora africana, Boscia senegalensis | 1.00    | 0.00    |
| Sudanian            | Special areas of low-rainfall woodland savanna (b) Hill Catena Nuba (centre, around Kadugli) | 0.70    | 0.30    |
|                    | High rainfall woodland savanna, laterite catena (a) *Anogeissus*/Isoberrina* deciduous woodland | 0.00    | 1.00    |
|                    | Montane vegetation in Imatong and Didinga Mountains (south)                             | 0.00    | 1.00    |
|                    | Special areas of low-rainfall woodland savanna in Toposa Area                           | 1.00    | 0.00    |
|                    | Flood region                                                                           | 0.50    | 0.50    |
|                    | Special areas of low-rainfall woodland savanna (b) Hill Catena South (east of Juba)     | 0.20    | 0.80    |
|                    | Low-rainfall woodland savanna, on clay (b) *Acacia seyal*/Balanites* savannah, alternating with grass areas | 0.90    | 0.10    |
|                    | Special areas of low-rainfall woodland savanna (b) Hill Catena East (north of Kurmuk)    | 0.60    | 0.40    |
| Congolian            | High-rainfall woodland savanna, laterite catena (b) woodland recently derived from rainforest | 0.00    | 1.00    |
applied to larger regions of interest. In the CC-NDVI model of Helldén, NDVI was derived from Landsat MSS (Multispectral Scanner System) and TM (Thematic Mapper) images without atmospheric correction, and the radiance values were not converted to reflectance. The model of Woomer, Touré, and Sall (2004) was focused only on sparse woodlands (CC < 28%) and is therefore not applicable to Sudanian Woodlands.

Orthmann (2005) measured WB and CC in the field in Benin, allowing us to establish a power WB-CC model for Sudanian Savannah. Other authors (Malimbwi, Solberg, and Luoga 1994; Campbell 1996; Frost 1996) studied WB in Miombo Woodlands but did not report any relevant model coupling between WB and CC. Suganuma et al. (2006) constructed WB-CC models in western Australian Savannah, but their models cannot be directly applied to the tropical African savannahs due to endemic differences in woody species and environment.

From the above brief review, it is clear that due to its particular limitations, no regional-scale WB assessment can be undertaken in tropical Africa based on a single WB-CC model, because none is sufficiently spatially representative to cover all savannah biomes and the diversity of vegetation communities.

The main objective of this study was therefore to develop a regionally valid and year-round operational WB assessment methodology for the African tropical savannah ecosystems north of the equator by remote sensing based on existing studies. Sudan, the largest African country,1 encompassing a very representative cross-section of tropical savannah woodlands including the southern Saharan, Sahelian, and Sudanian Savannahs (World Wildlife Fund (WWF) 2010, Figure 1), was selected as a basis for developing and testing the methodology.

2. Methods

Based on an understanding of the background of the study area (subsection 2.1), large-scale WB assessment in tropical savannahs requires a multiscale remote sensing approach that includes five major steps: calibration of the relevant WB-CC models for different savannah woodlands (subsection 2.2); development of generally valid CC-VI (vegetation index) models by coupling field-measured CC with remote sensing VIs derived from high-resolution imagery (subsection 2.3); region- or country-scale biomass modelling using relevant WB-VI models based on extraction of the woody component by time-series analysis (subsection 2.4); model weighting and application to vegetation communities for biomass estimation (subsection 2.5); and biomass map evaluation (subsection 2.6). For this purpose, a multi-resolution satellite dataset, comprising very-high-resolution satellite images, such as QuickBird (partly GeoEye) images (0.5–2.5 m) that are available on Google Earth, 27 Landsat ETM+ images (15–30 m) that are sensitive to local-scale phenological change in land cover, and time-series moderate-resolution data, namely MOD13Q1 and MOD09Q1 (250 m) products, were prepared (Table 2), and the global procedure is demonstrated in the flowchart (Figure 2).

2.1. The study area

A typical tropical savannah country and located in East Africa, Sudan covers a territory of 2.51 million km², where the average temperature does not vary greatly throughout the year (e.g. 25–35°C in Khartoum) but the annual rainfall has a strong variation in space from north (0 mm in the Saharan Desert) to south (1400 mm in the Congolian Forest Savannah). The annual rainfall is mainly concentrated between June and September (88–93% of total
Figure 1. Distribution of CC sampling plots and coverage of Landsat scenes.

Notes: (1) The division of eco-regions or different savannahs was based on the annual rainfall of the period 1980–1999 according to WWF (2010). (2) Light blue and red image frames indicate, respectively, the 16 Landsat ETM+ scenes used for CC-VI model development and the 11 scenes for CC-VI model evaluation in this study. (3) Two sets of sampling plots: one includes 177 plots (in light blue) for development of CC-VI models and the other contains 72 plots (in red) for CC-VI model evaluation.

rainfall) in the Saharan and Sahelian Savannas (dry season starts from October), and between May and October (82–91% of the total rainfall) in the Sudanian and Congolian Savannas, where the dry season starts from November.

According to the FAO Africover Land Cover Map (FAO 2003), there are 23 main land use and cover types that can be further integrated into the following major classes: bare soil (mainly Saharan Desert, 36.33%), grasslands (in Saharan and Sahelian eco-regions, 8.19%), croplands (5.83%), sparse woodlands (including sparse shrublands and wooded
Table 2. Satellite dataset used in this study.

| Landsat ETM+ (30 m) | 16 Scenes for CC-VI model development | 11 Scenes for CC-VI model evaluation |
|---------------------|---------------------------------------|-------------------------------------|
| Scene               | Acquisition date | Total mean haze (DN) | Scene               | Acquisition date | Total mean haze (DN) |
| 173-50              | 06 Nov 2000      | 7.27                  | 171-49              | 30 Nov 2002      | 0                    |
| 173-51              | 06 Nov 2000      | 7.80                  | 171-50              | 30 Nov 2002      | 3.04                 |
| 173-52              | 04 Nov 1999      | 17.17                 | 171-57              | 30 Nov 2002      | 4.16                 |
| 173-53              | 04 Nov 1999      | 18.16                 | 172-53              | 05 Nov 2002      | 12.74                |
| 173-57              | 25 Nov 2001      | 17.46                 | 172-57              | 21 Nov 2002      | 12.88                |
| 174-51              | 27 Nov 1999      | 2.22                  | 173-55              | 09 Nov 2001      | 12.75                |
| 175-50              | 07 Nov 2001      | 0                     | 176-52              | 17 Nov 2002      | 2.40                 |
| 175-51              | 18 Nov 1999      | 0.99                  | 176-53              | 17 Nov 2002      | 5.06                 |
| 175-54              | 20 Nov 2000      | 17.56                 | 177-49              | 08 Nov 2002      | 0                    |
| 175-55              | 20 Nov 2000      | 18.34                 | 177-50              | 08 Nov 2002      | 1.36                 |
| 176-53              | 17 Nov 2002      | 10.33                 | 179-52              | 06 Nov 2002      | 5.97                 |
| 176-54              | 17 Nov 2002      | 12.81                 |                      |                    |                      |
| 178-50              | 12 Nov 2001      | 0                     |                      |                    |                      |
| 178-51              | 12 Nov 2001      | 1.43                  |                      |                    |                      |
| 178-53              | 07 Nov 1999      | 15.01                 |                      |                    |                      |
| 179-51              | 06 Nov 2002      | 3.66                  |                      |                    |                      |

**Time-series MODIS (250 m)**

| Frames | MOD13Q1 Acquisition period | MOD09Q1 Acquisition period |
|--------|----------------------------|----------------------------|
| H20V06 | 01 Jan 2002 to 31 Dec 2009 | H20V06 01 July 2007 to 03 Dec 2007 |
| H20V07 | H20V07                     |                            |
| H20V08 | H20V08                     |                            |
| H21V06 | H21V06                     |                            |
| H21V07 | H21V07                     |                            |
| H21V08 | H21V08                     |                            |

**QuickBird/GeoEye (0.5–2.5 m)**

Available on Google Earth Feb 2002 to Dec 2009

Grasslands, 16.88%), woodlands (including shrublands, 31.59%), forests (0.29%), water bodies (lakes and rivers, 0.56%), swamp (0.22%), and artificial (urban areas, villages, and road infrastructure, 0.11%). Therefore, woodlands (including sparse woodlands) crossing different savannah belts represent the most important land cover in Sudan (48.47%). About 1.2 million km² of woodlands crossing the Saharan, Sahelian, Sudanian, and Congolian Savannahs are included in our study.

2.2. Calibration of WB-CC models

To assess WB in the tropical savannahs, the first need was to calibrate reliable WB-CC models, which are usually obtained from field measurement. Whereas in situ measurements of WB and CC in different savannah ecosystems were planned at the beginning of the study, we were not recommended to travel due to security reasons and we had to use models developed by other authors, if relevant and applicable to our study.
As mentioned earlier, Helldén and others conducted field measurements for the species Acacia albida, Acacia mellifera, Acacia senegal, Acacia seyal, Acacia tortilis, Albizia amara, and Balanites aegyptiaca in the Saharan/Sahelian Savannahs in the 1980s. Helldén (1991) incorporated all of the field measurements from Kassala, Gedaref, and North Kordofan in Sudan, and Gojam and Shewa in Ethiopia to develop the Acacia-dominated WB-CC model (Equation (1)) and to obtain the relationship between CC and NDVI (Equation (2)), which can be, respectively, expressed as follows:

\[ B_W = 0.4644 \, CC - 0.6286 \quad (R^2 = 0.96), \]

\[ CC = -366 + 6.01 \, \text{NDVI}_{dc} \quad (R^2 = 0.90), \]

where \( B_W \) = dry weight WB (t ha\(^{-1}\)), CC in percentage (%), and NDVI\(_{dc}\) = NDVI digital count.

Despite the limitations of Equation (2), as recognized earlier, the CC measurement in the above studies covered a range of 3–47%, which is much wider than those of Woomer, Touré, and Sall (2004) and Franklin and Hiernaux (1991) in their assessment in Western Sahelian/Sudanian Savannahs in Mali, confirming that the model of Helldén (1987a, 1987b) produced better results than those of Olsson (1985) and Bille (1977). Thus, for the Acacia-dominated Sahelian/Saharan Woodlands, the model of Helldén (Equation (1)), was considered representative.

For the Sudanian Woodlands, Equation (1) is clearly not relevant due to differences from the Sahelian Woodlands in regard to dominant woody species and environmental conditions. Fortunately, Orthmann (2005) measured WB of 51 species in 35 plots (30 m × 30 m) in the western Sudanian Savannah in Benin, which floristically resemble those in the eastern Sudanian Savannah eco-region, where Anogeissus–Isoberlinia–Uapaca–Terminalia is the dominant combination. From her measured data, the following power WB-CC relationship, taking all measured trees into account, was obtained:
This WB-CC model is regarded as representative for the Sudanian Woodlands as it covers most dominant woody species in the Sudanian eco-region.

These two models, in spite of their representativeness for individual biomes, do not cover all woody species in all woodland savannas. As shown in Table 1, the dominant species show much spatial variation and are often present in different savannah biomes. For example, certain dominant species in Saharan-Sahelian savannahs (e.g. *Acacia seyal*, *Balanites*) also occur in the Sudanian eco-region, and vice versa. To avoid overestimation or underestimation, a combination usage of the two models based on the dominance of woody vegetation in each community seems essential. More detail will be provided in Section 2.5.

### 2.3. Development of CC-VI models

To develop CC-VI models, it is necessary to derive the most relevant VIs from high-resolution satellite images, in our case from Landsat ETM+ images (Section 2.3.1), then to measure CC in the field or in very-high-resolution images/air photos of different savannah woodlands (Section 2.3.2), followed by a calibration of CC-VI models by regression analysis (Section 2.3.3), and finally, to evaluate the applicability of the models developed in different savannahs (Section 2.3.4).

#### 2.3.1. Conversion of VIs from Landsat ETM+ images

Phenologically, herbaceous vegetation in tropical savannahs is affected by senescing but *Acacia*, coniferous, and broadleaved deciduous trees are still green in November, whereas in the dry months from December to February not only do woodland fires frequently occur but also the deciduous species lose their leaves. For this reason, November images are most pertinent for CC-VI calibration study, as the contrast between woody and herbaceous vegetation is maximized.

Sixteen November Landsat ETM+ images acquired in the period 1999–2002, the only available satellite imagery source prior to February 2009 we could find at no charge, were obtained (see Figure 1 and Table 2 for spatial coverage) and employed for CC-VI modelling. From February 2009, since the United States Geological Survey (USGS) made all Landsat data publicly available at no charge, we acquired another set of 11 Landsat ETM+ images of November for the same period 1999–2002 (see Figure 1 and Table 2). These images were used for evaluation rather than development of CC-VI models. The image processing of all Landsat imagery includes the following steps.

**Atmospheric correction:** The Landsat images obtained were radiometrically normalized and atmospherically corrected using the COST model developed by Chavez (1996), in which Chavez used cosine of the solar zenith angle (theta) was used to approximate the downwelling transmittance of the solar radiation to conduct atmospheric correction and hence termed the approach as COST model. Application of this approach was intended to remove both additive scattering and multiplicative path transmission effects. The haze values of images in digital number (DN) shown in Table 2, an important input for the COST model, were estimated using the 4th feature of Tasseled Cap Transformation (Crist and Cicone 1984a, 1984b). Haze removal was performed in terms of the multiplication factor for each band proposed by Chavez (1988). The correction procedure was described by Wu (2003).
Transformation of multispectral reflectance to relevant VIs: In addition to NDVI, we considered that other VIs might be also useful for biomass estimation in terms of their development theories, such as the enhanced vegetation index (EVI, Huete et al. 1997) and the soil adjusted and atmospherically resistant vegetation index (SARVI) proposed by Kaufman and Tanré (1992). These vegetation indices introduce the blue band to apply self-correction and remove not only soil influence but also atmospheric effects. In addition, the visible atmospherically resistant index (VARI) and the wide dynamic range vegetation index (WDRVI) developed by Gitelson et al. (2002) and Gitelson (2004), respectively, were considered in view of their reportedly higher sensitivity than NDVI to vegetation with a moderate-to-high Leaf Area Index (LAI = 2–6). For calibration of CC-VI models, reflectance-based NDVI, EVI, SARVI, VARI, and WDRVI were derived. However, in any ETM+ image, VARI and WDRVI values are negative in most pixels, except for some tracts of cropland. For this reason, only NDVI, SARVI, and EVI were selected for further calibration.

2.3.2. CC measurement
Canopy cover measurement is the key to developing CC-VI models and their evaluation, and requires a rational and representative selection of plots for sampling. Based on the FAO Land Cover Map, the ratio of surface area among sparse woodlands, woodlands, and forests was obtained (i.e. 58:109:1). In consideration of the available time investment and the requirement that sampling must be spatially representative, we decided to assign randomly 500 points in total to these woodlands where there was coverage of QuickBird imagery as per the ratio above, so that 172 points were allocated to sparse woodlands, 324 to woodlands, and 3 to forests. By removing those located in cloud-covered and burnt areas according to QuickBird images (where replacement was not possible due to the absence of trees or shrubs in adjacent areas), 287 points remained; then using 16 Landsat frames to clip, 177 points (of which 6, 86, 75, and 10, were respectively distributed in southern Saharan, Sahelian, Sudanian, and Congolian eco-regions and in which the distribution was considered spatially representative) were finally retained for CC sampling. The plot selection was hence half-stratified, half-random, or stratified-random, covering all savannah woodlands within the range of available QuickBird imagery and Landsat frames.

Using Google Earth, we conducted CC sampling plot-by-plot at the location of each of the above points. Each plot, taking one of the above points as centre, covered an area of 100 × 100 m² (1 ha), and the plot size was a compromise between the resolutions of Landsat (30 m) and Moderate Resolution Imaging Spectroradiometer (MODIS) (250 m) data in order that CC sampling results could be applied to imagery from both satellites’ imagery. In each plot, we counted the number of trees, measured canopy diameter, and calculated CC as follows:

\[ \text{CC} = \frac{\pi}{4} \sum_{i=1}^{n} d_i^2, \]

where \( n \) is the number of trees in the 1 ha plot and \( d_i \) is the canopy diameter of tree \( i \). Trees or shrubs of canopy diameter \( (d_i) < 2 \) m were not counted because, first, these are difficult to measure due to the resolution degradation inherent in QuickBird (including very locally GeoEye) images on Google Earth (their resolution is not 0.6–1.0 m but about 1.5–2.0 m in rural areas); and second, their biomass is negligible (about 1.6–3.0% of total
WB) according to measurements taken by Orthmann (2005) in tree savannah and savannah woodland. Manual counting all trees and measuring their crown diameter is tedious and very time consuming, especially when the number of trees exceeds 40–50. In its favour, the method is simple and easy to apply, especially in case of crown shading due to a low sun-elevation angle and low heterogeneity among tree canopy sizes.

Another approach to measuring CC is the copying of 1 ha plot sampling areas from Google Earth using the Print-Screen function of the keyboard and pasting it into Photoshop. After discarding the colour information, the plot was turned into a black-and-white image. By enhancing the contrast between the crown area (dark) and background soil (white), the number of black pixels can easily be read to obtain crown area percentage. The main limitation of this method is that it can be applied only in the plots where there is an apparent difference in reflectance between CC and background soil, and when the sun-elevation angle is sufficiently large not to produce much crown shadow.

Both methods were compared for accuracy and reliability in five plots (four in Sahelian and one in Sudanian), where QuickBird images were acquired in late spring and summer and both approaches were applied to CC sampling. It was noted that the difference between the two approaches varied between 3% and 7%; and, when images were obtained in summer without much canopy shadow, the second approach proved more accurate and time-effective.

2.3.3. CC-VI model

While plotting the CC of these 177 sampling plots against the 16 November Landsat ETM+ images, the correlation between CC and vegetation indices, which are the weighted values of nine pixels within a kernel size of $3 \times 3$ (more or less equivalent to the plot size, 1 ha), was very low ($R^2 = 0.16$). Our first concern was whether this low level of correlation was a consequence of the difference in acquisition time between Landsat ETM+ and recent QuickBird imagery. To understand this phenomenon and to explore the applicability of the Landsat ETM+ imagery for CC-VI calibration, for each of the 177 plots the QuickBird was compared with the corresponding Landsat ETM+ image. Major discrepancies occurred in the following cases: (a) forest/woodland fire in November ETM+ images (1999–2002), but regrowth of trees or shrubs in the recent QuickBird images (low VIs vs. high CC case); (b) recent woodland fire–burning occurred 1–2 years before image acquisition but burnt scars still clearly distinguishable in the QuickBird images, with high VIs in the ETM+ images (high VIs vs. low CC case; measured CC cannot represent time of acquisition of Landsat images); and (c) very green herbaceous understorey (high VIs) in the November ETM+ images but low tree density (low CC) in the QuickBird images, particularly in the Sudanian Savannahs (again, high VIs vs. low CC). Plots within these three abnormal categories were excluded, thus reducing defects related to the occurrence of sudden events during the period of difference. To ascertain whether the 82 retained plots (6, 62, and 14 in Saharan, Sahelian, Sudanian savannahs, respectively) are pertinent for calibration, we need a further check on the tree/shrub canopy growth rate in its natural state without disturbance (e.g. fire). When growth rate is high, older images cannot represent the CC of 3–8 years hence. For this reason, we carefully selected both previous and new plots from which QuickBird image pairs acquired in the same month but in different years could be found on Google Earth, to investigate annual canopy growth rate. It was noted that the average annual growth rate of the five sites observed (perhaps still not sufficiently spatially representative enough) was about 1.55%. For a period of 3–8 years, the difference between measured CC may be around 4.7–12.4%, and such a difference should fall within the range of tolerable error in the
satellite remote sensing field, especially when we are dealing with moderate resolution data. We considered, therefore, that November Land ETM+ data can still be used for CC-VIs calibration despite the difference in date of acquisition.

The measured CC of the retained 82 plots was projected against VIs using least-square linear regression models, and we obtained a clear and strong correlation between CC and VIs ($R^2 = 0.83–0.91$) at a confidence level of 95% (Figure 3).

Although there were some concerns in regard to the use of NDVI to infer vegetation and soil properties, especially in drylands (Kaufman and Tanré 1992; Huete et al. 1997; Gitelson 2004), calibration revealed that among the three vegetation indices the atmospherically corrected, reflectance-based NDVI showed the best correlation with CC ($R^2 = 0.91$, Figure 3(a)). SARVI showed the same level of correlation with CC ($R^2 = 0.90$) as NDVI but at a lower dynamic range (0.1–0.2 units lower than that of NDVI and EVI). For this reason, we selected NDVI as the CC indicator for biomass estimation. Since, we had excluded the herbaceous influence, here NDVI represents woody NDVI, denoted as NDVI$^W$. The equation between CC and NDVI can be expressed as

$$CC = 153.09 \text{NDVI}^W - 10.12 \quad (R^2 = 0.91).$$

### 2.3.4. Evaluation of CC-NDVI model

To test the applicability and validity of the CC-NDVI model across different savannahs, we used the other series of 11 Landsat ETM+ images (Table 2), obtained after February 2009, to derive, or rather, to predict CC in the sparse woodland, woodland, and forest areas using Equation (5). Again, we used these 11 Landsat frames to intercept the same 500 points created in Section 2.3.2. By removing those in cloud-covered areas, bare land, and burnt scars in both QuickBird and Landsat ETM+ images, 72 points (18, 37, and 17 in Saharan, Sahelian, and Sudanian Savannahs, respectively) were retained for sampling. So a new set of CC samples was again measured on Google Earth (see Figure 1: Plots for validation). By coupling the predicted weighted CC from nine pixels derived from the 11 Landsat images using Equation (5) vs. measured CC using a linear least-square regression model at confidence level 95%, we obtained a very high $R^2$ value (0.95). If we remove the four outliers (two overestimated and one underestimated cases in rainforests, and the fourth in woodland but with green herbaceous vegetation on the November image) in the Sudanian Savannah, the $R^2$ value is increased to 0.99 (see Figure 4). Thus the predicted CC corresponds very well to the measured CC, and the CC-NDVI model can reliably predict CC across different savannah woodlands.

### 2.3.5. Upscaling analysis

Since, the CC-NDVI model was developed based on Landsat ETM+ images, a critical step was to evaluate whether they can be directly applied to MODIS data, because the sensed information between the two captors is not identical, even for the same targets or objects, due to the difference in spatial resolution and nadir viewing angle. For this purpose, three Landsat ETM+ images (176–53 and 176–54 dated 17 November 2002, and 179–51 dated 6 November 2002, Table 2) and two frames of MOD13Q1 (250 m) NDVI images (H20V07 and H20V08 of 16 November 2002) were selected for this upscaling test. To have comparability with MODIS data and to reduce the difference in spatial resolution, the three Landsat NDVI images were resampled to 250 m resolution. To ensure sufficient
Figure 3. Relationships between measured CC and VIs.
spatial check points to cover all land cover types, mainly sparse woodlands, woodlands, swamp, and croplands in each of the three Landsat images, and also a for rapid assessment, 2000 points in total were randomly generated, of which 1655 were finally retained for extraction of NDVI values from both Landsat and MODIS data, after removing those located in rivers and burnt areas. The NDVI of Landsat ETM+ images (NDVI_L) and that of MODIS (NDVI_M) for the same point in time or for approximately the same time period were found to be strongly correlated: (NDVI_M = 0.9786 NDVI_L + 0.0471, R^2 = 0.88).

A further approach to test applicability is to apply a differencing technique to ascertain agreement between MODIS and Landsat NDVI images. After subsetting the MODIS NDVI image to the same size as three Landsat NDVI images, the latter was subtracted from the former, followed by statistical analysis indicating normal leptokurtic distribution, where the mean (M) was found to be –0.041, standard deviation (σ) 0.060, and minimum (Min) and maximum (Max), respectively, –0.863 and 0.528. It was noted that pixels between M – σ (–0.101) and M + σ (0.018) represented 78.38%, and between M – 2σ (–0.161) and M + 2σ (0.078) 94.91%. The low percentage of abnormal pixels distributed in the two tail-ends of the histogram represented burning or burnt areas (2.79%) and herbaceous vegetation senescing (2.31%) along river courses in the 11-day observation period from 6 to 17 November 2002. Thus, if we do not consider abnormal pixels, MODIS and Landsat NDVIs are consistent with each other.

Both approaches confirmed the feasibility of transferring models developed from Landsat ETM+ images to MODIS data and to upscale from local-level studies to regional or nationwide assessments.

2.4. Modeling woody biomass

For regional WB assessment, it is essential to have representative biomass models corresponding to different savannahs based on the relationship between CC-NDVI (2.4.1) and relevant input such as regional-scale woody NDVI (2.4.2).

2.4.1. WB-NDVI models

As calibrated in Section 2.2, we have two WB-CC models relevant for Saharan/Sahelian and Sudanian Savannas, respectively. Through the CC-VI model development in
Section 2.3, we now have the CC-NDVI model, Equation (5), which is applicable to multiple tropical savannahs. We can combine Equations (1) and (5) to construct a WB-NDVI model for Acacia-dominated Saharan/Sahelian Savannahs (Model 1), and then merge Equations (3) and (5) to construct the WB-NDVI model for the Sudanian eco-region (Model 2):

\[
\text{Model 1: } B_W = 71.095 \text{NDVI}_W - 5.3283, \quad (6)
\]

\[
\text{Model 2: } B_W = 0.8868(153.09 \text{NDVI}_W - 10.12)^{1.1069}. \quad (7)
\]

These models allow regional WB assessment by direct application to the most popular remote sensing products such as NDVI, if the woody component (NDVI\textsubscript{W}) can be extracted.

2.4.2. Derivation of woody NDVI by time-series analysis

As already mentioned in Section 1, woodland represents the land cover between grassland and forest, and is itself a mixture of trees or shrubs and annual herbaceous vegetation. In savannahs, tree cover is generally low, especially in lower-rainfall zones, but may be dense locally, particularly in lowlands and valleys dominated by Acacia in the southern Saharan and Sahelian Woodlands. With higher rainfall, tree cover becomes generally denser, as is the case in the Anogeissus–Khaya–Isoborlinia- and Combretum–Terminalia-dominated Sudanian Savannahs (Harrison and Jackson 1958; White 1983; Franklin and Hiernaux 1991; Hiernaux and Le Houérou 2006). Hence, the NDVI value of a pixel is not completely contributed by the tree cover but also by the herbaceous vegetation. Normally, using autumn imagery (e.g. November), the confounding influence of herbaceous vegetation can be minimized but cannot be completely removed because in lowlands, valleys, and riparian plains, grasses are still green, favoured by available moisture, especially in the Sudanian and Congolian Savannahs.

It is evident that no matter in which season imagery is taken, herbaceous confusion is always a challenge for WB assessment by remote sensing, especially in the Sudanian and Congolian eco-regions. To achieve our objective in developing an approach to estimate year-round WB, it is essential to separate the woody component from the herbaceous in any image from any season; and time-series analysis provides a useful tool for this purpose.

Research by Roderick, Noble, and Cridland (1999), Lu et al. (2003), and Verbesselt et al. (2010) indicates that time-series NDVI data can be decomposed into a trend, a seasonal change, and a random or irregular change component. Verbesselt et al. (2010) used time-series trend analysis to detect abrupt changes, while Roderick, Noble, and Cridland (1999) and Lu et al. (2003) used this technique to partition the woody component from the herbaceous. In this study, we adopted the same concepts as the trend and baseline of Roderick, Noble, and Cridland (1999) and Lu et al. (2003), and applied these to 8 years of MODIS NDVI time-series data (MOD13Q1 product) from January 2002 to December 2009 (96 months and 184 acquisitions for each of the six frames) for decomposition.

Within the sparse woodlands, woodlands, and forests as defined by the FAO Land Cover Map, a number of polygons were, respectively, defined in the MODIS NDVI images across Sahelian and Sudanian Savannahs as having spatial representativeness: 795, 4048, and 5006 pixels for forest cover, woodlands, and sparse woodlands. The corresponding time-series monthly average NDVI datasets from January 2002 to December 2009 were extracted.
using these polygons. The time-series NDVI dataset for each type of woodland was then decomposed into trend and seasonal components, following the ‘locally weighted regression smoother’ approach proposed by Cleveland et al. (1990) using the R-Code developed by Wessa (2008). The decomposed results are shown in Figure 5. According to Roderick, Noble, and Cridland (1999) and Lu et al. (2003), the baseline (NDVI_{Bi}), which can be obtained by shifting the trend of NDVI (NDVI_{Ti}) by a constant $K$, is a good measure of the evergreen woody NDVI or woody component (NDVI_{Wi}) at a given time $i$ and can be expressed as

$$\text{NDVI}_{Wi} = \text{NDVI}_{Bi} = \text{NDVI}_{Ti} - K,$$

(8)

where $K$ is the absolute value of minimum seasonal component for two consecutive years. $K$ for forest, woodland, and sparse woodland was, respectively, measured as 0.1466, 0.2143, and 0.1982 for the entire period of 8 years. The baseline is shown in Figure 5. The percentage of the woody component, i.e. the ratio ($R\%$) between the woody component (NDVI_{W}) and observed NDVI (NDVI_{O}), in our case, the NDVI of MOD13Q1 product, of a given pixel at any time $i$, can be calculated by

$$R_i = 100 \left( \frac{\text{NDVI}_{Wi}}{\text{NDVI}_{Oi}} \right).$$

(9)

Woody NDVI percentage for different types of woodland is shown in Figure 5(d). In some winters the $R$ values exceeded 100%, due to an abnormally low NDVI of woodlands caused by an abrupt change, most likely woodland fire (Wu and De Pauw 2010), in which the estimated woody NDVI was higher than that observed. Based on such abnormality, time-series data can be used for change detection, but this is not the focus of our paper. The calculation results are illustrated in Table 3, taking the MODIS NDVI images of 2007 as an example. These $R$ values were determined for all pixels of the savannah woodlands selected.

2.5. Application of models

Application of the models to conduct region- or country-scale WB assessment comprises critical input, woody NDVI data (2.5.1), model weighting based on the dominance of vegetation species in each community, and community-scale model application (2.5.2).

2.5.1. Production of summer (peak) and autumn (trough) cloud-free woody NDVI images

Tropical savannahs are frequently covered with cloud in summer and autumn, especially in the Sudanian and Congolian eco-regions. In order to enhance the possibility of cloud-free NDVI for each pixel, we used 8-day interval MOD09Q1 reflectance data (Table 1) from 2007 in consideration of the fact that most QuickBird images on Google Earth used for CC sampling were dated 2004–2007. Reflectance data from 1 July to 30 September (12 acquisitions) and from 1 November to 3 December (5 acquisitions) were converted to NDVI. An algorithm was designed to extract the maximum value for each pixel of the 12 summer acquisitions, and the observed peak NDVI (or wet season cloud-free NDVI) image was thus produced; the same function was applied to the five November NDVI images to extract the autumn (or dry season cloud-free) NDVI for each pixel.

In the FAO classification of sparse woodlands, woodlands, and forests, the decomposed woody NDVI percentages as shown in Table 3 were, respectively, applied to the
Figure 5. Seasonal components, trends, and baseline of NDVI series, and the ratio between the woody component and observed NDVI; (a) forest; (b) woodland; and (c) sparse woodland. (d) Ratio (r, %) between woody NDVI (NDVI_W) and observed NDVI (NDVI_O).

Note: Numbers on the x-axis represent monthly time steps, with 1 = January 2002 and 96 = December 2009; 67–68 and 71 indicate, respectively, the summer (July/August) and autumn (November) of 2007.
Table 3. Woody NDVI percentage in summer and autumn.

|                  | Forest (CC: >60%) | Woodland (CC: 20–60%) | Sparse woodland (CC: 1–20%) |
|------------------|-------------------|------------------------|----------------------------|
|                  | Summer | Autumn | Summer | Autumn | Summer | Autumn |
| Observed NDVI (NDVI_{Oj}) | 0.88   | 0.82   | 0.80   | 0.58   | 0.72   | 0.48   |
| Woody NDVI (NDVI_{Wj} or baseline) | 0.65   | 0.65   | 0.38   | 0.38   | 0.26   | 0.26   |
| R (%)            | 73.51  | 78.63  | 47.14  | 65.54  | 35.45  | 53.45  |
| Woody NDVI of pixel j (NDVI_{Wij}) | 0.7351 \times NDVI_{Oj} | 0.7863 \times NDVI_{Oj} | 0.4714 \times NDVI_{Oj} | 0.6554 \times NDVI_{Oj} | 0.3545 \times NDVI_{Oj} | 0.5345 \times NDVI_{Oj} |

summer/peak and autumn/trough cloud-free MODIS NDVI images to produce summer and autumn woody component (NDVI_{W}) images.

2.5.2. Vegetation community-based model weighting and application

As mentioned above, due to the strong variability and combination of dominant woody species across different savannahs, it is important to take account of the combined use of the two biomass models (Models 1 and 2). This can be achieved by adjusting the models to the woody species composition of each vegetation community or, more precisely, vegetation community-level model weighting.

In order to identify woody species communities in different savannahs, we used the Vegetation Map of Sudan of Harrison and Jackson (1958). To account for dominance and composition in woody species, a weight ratio between Model 1 (Equation (6)), and Model 2 (Equation (7)) was estimated for each vegetation community based on the description in the monograph by Harrison and Jackson (1958). Model weights were determined subjectively based on our expert knowledge. Taking the community, ‘Low rainfall woodland savannah, on sand (c) Terminalia–Sclerocaryea–Anogeissus–Prosopis Savannah Woodland’ in the Sahelian eco-region (see Table 1), for example, the dominant woody species are Terminalia, Sclerocaryea, Anogeissus, and Prosopis, which are mixed locally with Acacia senegal. We therefore gave a weighting of 0.2 and 0.8 for Models 1 and 2, respectively. If only the Acacia-dominated model (Model 1) were used, WB would be underestimated. Another example is the community, ‘Special areas of low rainfall woodland savannah (b) Hill Catena East (North of Kurmuk)’ in the Sudanian eco-region (see Table 1). This community is geomorphologically part of the west slope of the Ethiopian Highlands extending to Sudan, dominated by Acacia seyal and Balanites, but is at lower elevations mixed with more Anogeissus and Combretum spp. To account for this effect, a weight of 0.6 and 0.4 was applied to Models 1 and 2, respectively. The result after weighting should be closer to the actual value than that acquired by the simple application of Model 2.

One point to be noted here is that the Congolian eco-region in the southwest of Sudan (Figure 1), the former rainforests, can for practical purposes be considered part of the Sudanian Savannah, because the rainforests have degraded into woodlands (see Table 1) due to slash-and-burn agricultural activities over the past 200–300 years (Harrison and Jackson 1958).
In accordance with the weightings given in Table 1, Models 1 and 2, either singly or in combination, were applied to both the decomposed summer and autumn woody NDVI images in each vegetation community to produce the above-ground WB maps for both summer and autumn.

2.6. Evaluation of two biomass maps

To evaluate whether the two biomass maps (summer and autumn) produced in Section 2.5 are mutually consistent, a differencing procedure was again applied; more precisely, the summer biomass map was subtracted by the autumn one to check spatial variation and differences.

Given $M (0.232), \sigma (5.542), \text{Min} (-49.99), \text{and Max} (45.99)$ of this difference map, it follows that the pixels in the range $M - \sigma$ to $M + \sigma$ have an absolute percentage (84.12%). The positive difference ($M + \sigma$, Max), 7.98%, implying that the estimated summer biomass density is higher than that of autumn, is mainly distributed in the Saharan and, in particular, the Sahelian Savannas and northern Sudanian Savanna; whereas the negative difference (estimated autumn biomass higher than summer one, about 7.90%), is found mostly in the Sudanian Savanna. An investigation was conducted first in the Sahelian Savanna. If we can briefly consider one tree or large shrub containing 0.5 t of WB on average, and if the tree number in the 1 ha area is known, the WB can be estimated. We used the 249 (177 + 72) CC sampling plots and examined those falling within the Sahelian area, and found that autumn biomass is closer to the ‘real’ approximation and that summer biomass had been overstated. A similar check was undertaken in the Sudanian Savannah, assuming an average tree biomass density of about 2–5 t per tree depending on tree size. It was noted that WB in some plots was intermediate between the two maps, while in others it was closer to the summer one. Thus the summer map may provide a slightly better estimation in the Sudanian Savanna. One potential option is to combine the two maps to calculate the average for the Sudanian Savannah woodlands, and the autumn estimation for the Saharan/Sahelian Savannahs.

3. Results and discussion

Through the processing procedure described above, the results obtained are presented below for discussion.

3.1. CC-NDVI model

Our study found that among the vegetation indices observed, atmospherically corrected and reflectance-based NDVI showed the best correlation with CC ($R^2 = 0.91$). This validated CC-NDVI model can accurately predict CC in woodland savannahs – in particular the Saharan and Sahelian Savannas—and can be applied to MODIS data for regional and country-scale studies. However, care has to be taken while deriving CC using this model. As mentioned above, we checked the outliers, the plots where there was significant difference between measured and predicted CC, and noted that they were all located in the Sudanian eco-region (either in rainforests in the mountains or in the plain where there is green herbaceous vegetation even in the dry season). The difference between predicted and measured CC in these plots may have been caused by (a) difference in temporal acquisition between Landsat and QuickBird images; (b) the slope effect in mountains, implying that NDVI cannot fully reflect actual CC; and (c) unsuitability of the model itself for closed
rainforests (normally with CC more than 85–90%). In regard to the third point, a further
check was made in the Imatong Mountains in southern Sudan. Given that the top CC of the
closed rainforest is 100% (theoretically reasonable), we found that our model overestimated
CC (more than 100%) in about 39% of the pixels in the closed rainforests in this montane
area. Hence, adaption or modification is essential if one wants to apply this model for CC
characterization in closed rainforests.

3.2. Woody biomass maps

Using the multiscale remote sensing methodology described, the WB maps obtained and
evaluated are presented in Figure 6, and total biomass of forests, woodlands, sparse wood-
lands, and a combination of these three three classes were calculated for both summer
and autumn. Table 4 indicates the total WB estimated in Sudan in 2007 in the range
733–751 million t. Though some variation was found between the two maps (e.g. slight
overestimation of the summer map in the Sahelian savannah – green in Figure 7 – and
overestimation of the autumn map in the Sudanian eco-region – brown in Figure 7), largely
speaking, total woodland biomass was almost identical between summer and autumn with
a difference of only 2.4%. Furthermore, the estimates for specific states are also in good
agreement with WB ground data and the results obtained by other authors. The field-
measured values from Helldén and Olsson (1982, 1989) and Helldén (1987b, 1991) in
the northern Kordofan and Kassala states (Acacia-dominated savannahs with a woody CC
range 3–47%) were in the range 0.14–18.63 t ha$^{-1}$. The values predicted from our remote
sensing-based approach were in the range 0–23 t ha$^{-1}$ for northern Kordofan and 0–21.19 t
ha$^{-1}$ for Kassala, with a CC range for Acacia trees and shrubs of 0–50%. Our results for
mountain forests (12–161 t ha$^{-1}$) also agree with those of Baccini et al. (2008), who con-
ducted a rainforest biomass assessment in Central Africa using MODIS and lidar data, and
estimated a forest WB for southern Sudan in the range 11–166 t ha$^{-1}$.

3.3. Applicability of the method

Consistency between the summer and autumn biomass maps, and agreement between our
results and those of other authors, indicate that although we could not conduct field work for
security reasons, the methodology developed can produce reliable WB assessments and can
therefore be considered for operational use in tropical Africa north of the equator. However,
two points are worthy of attention.

First, in our estimation approach, the decomposed results of the forests, woodlands, and
sparse woodlands sampled were used for countrywide biomass assessment. Inevitably for
some pixels, biomass will be underestimated and for others overestimated due to spatial
variability – for example, overestimation in the Saharan/Sahelian eco-region on the sum-
mer map. Therefore, the biomass quantity modelled for each pixel should be regarded as
a relative value, rather than an absolute indication of stand volume for commercial usage.
In the next stage, we can try eco-region-level or even vegetation community-level decom-
position to take spatial variability into consideration in order to achieve an estimation as
close as possible to reality.

Second, the model coupling CC with woody NDVI may lose its sensitivity when CC
is below 5%, due to the influence of soil, or over 75%, especially in closed rainforests due
to overestimation; and hence, estimated results may be less accurate at the extremes of CC
than in the mid-range 10–60%.
Figure 6. Woody biomass for Sudan in the summer (left) and autumn (right) of 2007.
Table 4. Estimated summer and autumn woody biomass in Sudan.

| Forest (CC: >60%) | Woodland (CC: 20–60%) | Sparse woodland (CC: 1–20%) |
|-----------------|------------------------|-----------------------------|
| 2007            |                        |                             |
| Summer          |                        |                             |
| Mean density    | 107.69 t ha\(^{-1}\)  | 44.28 t ha\(^{-1}\)        | 8.49 t ha\(^{-1}\)         |
| Sub-total       | 10,604,688 t           | 595,649,470 t               | 145,053,140 t              |
| Total           | 751,307,298 t          |                             |                             |
| Autumn          |                        |                             |
| Mean density    | 98.95 t ha\(^{-1}\)   | 44.55 t ha\(^{-1}\)        | 7.31 t ha\(^{-1}\)         |
| Sub-total       | 9,746,618 t            | 599,183,420 t               | 124,855,450 t              |
| Total           | 733,785,488 t          |                             |                             |

Figure 7. Difference between summer and autumn biomass maps.
Note: Green indicates (1) the estimated summer biomass higher than autumn; and (2) overestimation of summer biomass in comparison with the ‘real’ approximation (see Section 2.6); brown indicates (1) that autumn biomass obtained is higher than summer; and (2) slight overestimation of autumn biomass compared with the ‘real’ approximation.
In regard to other tropical savannahs in Africa (e.g. Miombo Woodland, south of the equator), the methodology developed may be extendable – with some slight adaption of the WB-CC model – since many woody species (*Isoberlinia*, *Terminalia*, *Combretum*, *Burkea africana*, *Mopane*, etc.) are the same as those found in the Sudanian eco-region. Nevertheless, while disseminating this method to other non-tropical savannahs, further adaption and calibration of the CC-VI and WB-CC models are necessary due to variation in woody species and the endemic environment from our study area. Theoretically, the method should be repeatable if land cover map and vegetation community information are available. Time-series decomposition for derivation of the woody component is applicable in any savannah.

4. Conclusions
Through a case study in Sudan, this paper describes the development and large-scale operational use of a methodology for WB estimation in tropical savannahs. The biomass calculation method based on the combination of several procedures involving CC–VI calibration and evaluation, upscaling from high-resolution (Landsat) to moderate-resolution (MODIS) data, time-series NDVI decomposition to extract the woody component, biomass model weighting in line with the dominant woody species, and application of models to vegetation communities, is scientifically sound and can provide reliable biomass assessment. The results obtained from Sudan are compatible with available ground-truth data and those presented by other authors, suggesting that our methodology and its principles are operational and can be applied for WB assessment in both wet and dry seasons in other tropical African countries where woodland savannahs are dominant. Another important outcome of this research is an innovative approach to derive tree CC by time-series decomposition analysis superimposed on the CC-NDVI model. Applied to a multi-resolution, multi-sensor, time-series dataset, this new technique allows not only the estimation of CC at any time in each year observed, but also the assessment of year-round WB if cloud-free NDVI images are available.

In conclusion, the developed methodology offers a promising approach for year-round WB assessment and monitoring in tropical savannah woodlands, and can contribute to low-cost, large-scale assessment and monitoring of carbon balances in savannah woodland ecosystems in Africa at both local and regional scales. Future work will be focused on testing this methodology for WB assessment, first in Miombo Woodland and then in other non-tropical woodlands.

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Notes
1. In this paper, we are talking about the Sudan prior to 9 July 2011, when South Sudan became independent.
2. Method developed based on a personal communication with Dr Rolf Sommer (ICARDA), October 2008.
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