Assessment of spatio-temporal changes of smallholder cultivation patterns in the Angolan Miombo belt using segmentation of Landsat time series.

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Abstract

Tropical dry forests provide globally important ecosystem services and host exceptionally high biodiversity. These biomes are currently under immense pressure, particularly for conversion to agriculture, and already experience high global deforestation rates. Miombo forests in Southern Angola are affected by deforestation, fragmentation and degradation, caused mainly by an increasing rural population who follows a traditional farming system of shifting cultivation with slash-and-burn agriculture. After the termination of the civil war in 2002, population growth and resettlements have accelerated the use of woody resources, selective logging and clearing for cultivation purposes and led to an exceedance of sustainability thresholds. Large scale projects are expected to put further pressure on the forests and increase the potential of conflicts regarding land resources and competition with local subsistence farming.

We use an existing time series segmentation tool (LandTrendr) with a time series of Normalized Burn Ratio (NBR) data in combination with adapted temporal metrics to provide information about the dynamics of different cultivation patterns, to gain insight into historical developments and to assess temporal cultivation characteristics. We define cleared areas and cultivation time on a pixel-by-pixel basis providing temporal and spatial information on current and past changes from 1989 to 2013 using data from Landsat 5-8. Overall accuracy for the disturbance detection is 72 %. We can follow the effect of armed conflicts on agricultural expansion with a drop in deforestation rate of more than 70 % from 12,000 to 4,000 ha per year (1994 – 1998) and subsequently tripling to 12,000 ha per year again after 2002. Deforestation patterns are in accordance with previous multi-temporal studies, although time series segmentation reveals more detailed information on deforestation and cultivation dynamics.

We successfully separate areas of different historic backgrounds and agricultural dynamics, e.g. areas that were severely affected during the civil war, which transition from shifting to semi-permanent and permanent systems. We provide recommendations for the assessment of agricultural dynamics in similar areas where ground data and basic information is missing.

Keywords: Landsat; time series analysis; LandTrendr; land use change; sub-Saharan Africa; shifting cultivation; Angolan civil war

Introduction

The conversion of natural land to agricultural areas has been identified as one of the main challenges of our time (MEA 2005b) and Southern Africa is expected to be one of the next agricultural intensification hotspots (Gasparri et al. 2015). Yet, in some Southern African areas, cultivation practices are still only rudimentarily developed with ineffective or even no fertilization techniques (Egoh et al. 2012; MEA 2005a). This is also the case in Angola and mainly due to the civil war, which intermittently lasted for 27 years (1975-2002). Beside the large number of casualties, the conflict led to the displacement of rural population, the break-down of the agricultural sector and many impacts on ecosystems and biodiversity, such as the virtual disappearance of most groups of large mammals (Kibble 2006). The impact and the consequences of the civil war cannot be quantified yet because ground data or reliable statistics on cultivation, socio-economic developments and biodiversity are almost absent especially for rural areas (Brinkman and Alessi 2009).

After the end of the civil war, the Angolan government invested in the reconstruction of infrastructure, the basic provision of food and currently also in large scale agro-industry (Muzima and Mendy 2015; World Bank 2013). Nevertheless, the supply of food, medicine and education is still insufficient especially in rural areas (BTI 2014). Due to low market access, the rural population relies on natural resources as important livelihood sources, which in some cases also serve as additional cash-income, e.g. by honey, charcoal or bushmeat (Domptail et al. 2013; Egoh et al. 2012). Subsistence agriculture is the main source of alimentary supply. The shifting cultivation system depends on regular forest clearing and fallowing, thus on forest availability to maintain its productivity. Due to ongoing population growth and the rise of competing land uses (urbanization, agro-industrial projects), the region is characterized by increasing land pressure and localized forest depletion, especially around urban centers. Miombo forests cover an area of 2.57 million km² stretching from east to west coast in Southern Africa and play an important role in the transport of

summer rainfall and humidity from northern rainforests to southern savannas(Leadley 2010; Timberlake et al. 2010). Due to their importance for global climate system and for local livelihoods and their biological integrity, the Miombo forests of the region have been identified to be one of the next socio-economic and ecological tipping points (Leadley 2010).

The sustainable management of natural resources requires the characterization of different farming systems (Jain et al. 2013). To capture the impact of cultivation on natural resources, especially regarding retrospective developments, both adequate spatial resolution and sufficient temporal resolution are needed. For areas where available information on land use or population dynamics is insufficient, remote sensing provides an objective view on past and current land cover and its change. This spatially explicit information about dynamics in the agricultural sector are of crucial importance to support decision makers regarding future management actions (Atzberger 2013).

We selected a study area in southern central Angola to analyze agricultural expansion and according cultivation patterns. The region covers the existing land cover diversity with rural and urban areas all being affected during the time of conflict, although to different extents. The Landsat mission data with its spectral setup, a pixel size of 30 m x 30 m, a repeat cycle of 16 days and its longtime legacy provides the appropriate database to retrospectively address the underlying land use dynamics.

We expand on an established time series segmentation tool (Landtrendr, Kennedy et al. (2010)) and apply specific temporal metrics to characterize Landsat time series regarding deforestation and cultivation dynamics. Deforestation detection using LandTrendr has already been successfully applied in predominantly temperate regions (e.g. Anderson et al. (2012); Hudak et al. (2013); Kennedy et al. (2010); Main-Knorn et al. (2013)), and to a lesser extent in tropical forests (e.g. Fragal et al. (2016)). Regional studies to map dry forest dynamics, particularly in the Miombo belt still restrict to multi temporal Landsat data (e.g. Cabral et al. 2011; Kamusoko et al. 2014; Mayes et al. 2015; Prins and Kikula 1996). Regarding agricultural developments in sub-Saharan Africa, a limited number of studies concentrate on the medium resolution characterization (e.g. Kiage et al. 2007; Tappan et al.

2000; Thenkabail and Nolte 1996). Specifically for Angola, spatially explicit studies are almost absent (e.g. Cabral et al. 2011; Schneibel et al. 2016).

Our previous studies using multi-temporal Landsat datasets showed that the rate of annual agricultural expansion doubled between 1989 and 2013 and proved a clear connection to the quality and the location of transportation infrastructure (Schneibel et al. 2013; Schneibel et al. 2016). The analyses also indicated that people generally cut down undisturbed forest instead of reusing fallows. Forest regeneration on fallows is slow and biomass was observed not to recover to the pre-disturbance state after 25 years (Schneibel et al. 2016). However, to determine potential areas of land conflicts due to rising population numbers and the resulting expansion of cultivated land, it is crucial to specifically analyze the annual dynamics in the related smallholder systems and develop conceptual models and methods.

We investigate how the Landsat archive from 1989 to 2014 can contribute to the identification of different smallholder cultivation patterns in dry tropical forest systems. We use a test site in south-central Angola to interpret these related to driving factors between armed conflict to population growth and food security. Specific objectives are to:

- Derive metrics and parameters that are suitable to identify temporal characteristics of rainfed smallholder farming systems.
- Determine the length of cultivation periods according to the farming system.
- Analyze changes in field expansion patterns that reveal different historic and socio-economic backgrounds.
- Provide general recommendations for the assessment of cultivation patterns in similar natural and socio-economic settings with Landsat time series.

Study area

The study area is located in south-central Angola and mainly covers parts of the three provinces Cuando Cubango, Bié and Moxico. It includes the municipal administrations Menongue (population of 306,622), Chitembo (pop. 68,581) and Cuchi (pop. 42 899) (INE 2014). The roads that connect the cities were largely destroyed between 1975 and 2002. Road and bridge reconstruction started after the ceasefire in 2002, whereas continuous pavement of the two main roads started in 2007/2008 and was finished in 2010 for the whole study area (Fig 1).

Only sparse information about population development, economy or livelihoods is generally available, which is due to the civil war that ravaged in the area, making field work impossible, and to the location in the marginal region of south-east Angola (Brinkman and Alessi 2009).

Figure 1: Location of the study area including an overview of Southern Africa and paved roads connecting the municipality centers. Background image is a true color image of Landsat long term average reflectance.

We analyzed two subsets in more detail which differ in their historical development and in their current farming systems, i.e. Chitembo and Menongue. While both cities are well connected by one or two paved roads and both are important trading centers for the surrounding population, Menongue has also been an important military center of the People's Movement for the Liberation of Angola (MPLA) during the civil war (Brinkman and Alessi 2009). Fields in the surroundings were regularly destroyed by the opposing National Union for the Total Independence of Angola (UNITA) forces and people suffered from hunger and insufficient medical supply (Brinkman and Alessi 2009). Chitembo is located in an area more distant from the former frontlines (Brinkman and Alessi 2009), where land pressure on forested areas due to agricultural expansion has significantly increased.

Natural settings

Wet and dry season are highly distinct and the majority of the rainfalls (mean annual rainfall 990 mm) occur during the wet season, i.e. from November to April (Weber 2013). The study area was chosen because it provides a large urban-wildland interface with intact Miombo forests facing rapidly growing cities with recently improved infrastructure that cross natural woodlands. Large wetlands stretch from north to south with lateral valleys fragmenting the woodlands. These are situated on higher slopes and hilltops. In the wetlands, thick peat layers occur due to the constant interflow from the slopes (Gröngroft et al. 2013).

On the slopes and hilltops of the eastern part, deep sandy Arenosols dominate the soil layer whereas in the west shallow soils on granitic bedrock are found (Gröngroft et al. 2013). The main vegetation unit of the study area is the Miombo forest dominated by *Brachystegia*, *Julbernardia* or *Cryptosepalum* species. Floodplains are mainly covered by grassland, in the west dominated by *Cryptosepalum maraviense* and in the east on sandy soils by *Parinari capensis* (Revermann et al. 2013).

Cultivation settings

Traditional smallholder agriculture in the region follows a shifting cultivation system with slash-and-burn clearing, followed by decade long fallow periods to allow regeneration of soil fertility (Domptail et al. 2013). In the first year, forest is cut and burned and the ash is incorporated into the soil by creating earthen ridges. The main crop is maize, secondary crops are beans and manioc and a variety of tertiary crops include vegetables and tubers (Domptail et al. 2013). Every four to ten years (depending on soil fertility), these areas are abandoned and the household moves deeper into the forest to clear a new patch for the establishment of its next cultivation area (Domptail et al. 2013).

While cereals, legumes and tubers are harvested on an annual basis, the manioc plants need a few years to mature before they can be harvested. Manioc can even be left in the soil after the field is abandoned to serve as an emergency reserve for times of food shortage (Domptail et al. 2013). There is a second emerging farming system, which can be found in areas of increasing land pressure and which resembles characteristics of semi-permanent and permanent forms of smallholder agriculture (Finckh 2015).

Due to a low access to regional cash-based markets, rural livelihoods have been dominated by traditional livelihood sources such as crop production and hunter-gatherer activities (Domptail et al. 2013). Population growth, rising aspirations for cash income and increasing access to regional markets have recently resulted in commercializing these products (mainly charcoal), with concurrent intensification of natural resource use and possibly their overuse (Domptail et al. 2013; Finckh 2015; Kutsch et al. 2011). It is therefore essential to develop sustainable farming and natural resource use practices that allow the coverage of food and cash needs of rising population numbers without complete replacement of the forest.

Data& pre-processing

Landsat data

We processed all available Level 1T data from the Thematic Mapper (TM), Enhanced Thematic Mapper plus (ETM+) and the Operational Land Imager (OLI) to surface reflectance using an integrated multi-sensor preprocessing system (Frantz et al. 2016). Only TM-equivalent bands were processed. Level 1G data was not processed as a reliable co-registration amongst images was considered of prime importance. An overview of available images according to sensor is given in Figure 2.

A detailed description of the derivation of these inputs can be found in Frantz et al. (2016) and only a brief summary will be given here. The employed radiometric preprocessing chain is based on radiative transfer theory (Tanré et al. 1979), featuring integrated corrections for atmospheric and topographic effects. The atmospheric correction accounted for multiple atmospheric scatterings with variable illumination/view geometry, a combined image-, database- and object-based estimation of aerosol optical depth over temporally persistent dark targets. Adjacency effect correction and a spatio-temporally variable water vapor correction with the MODIS precipitable water product (Gao and Kaufman 2003) are also included. Topographic normalization was achieved with a modified image-based C-correction with 1-arc-Second SRTM data (USGS 2015, Sept.). Clouds and cloud shadows were identified with a modified version of the Fmask algorithm (Frantz et al. 2016; Frantz et al. 2015; Zhu et al. 2015; Zhu and Woodcock 2012).

All data were prepared in a regular grid (30 km x 30 km tiles), and share a single projection (Lambert Azimuthal Equal Area), allowing the usage of the full archive depth without any need for projection or co-registration considerations. 54 tiles were needed to fully cover the study area (i.e. 180 km * 270 km = 48,600 km²). The tasseled cap transformation was applied to all radiometrically normalized surface reflectance images (TM-equivalent bands) using the Crist (1985) reflectance data coefficients.

We compiled a reliable time series by choosing available images that are supposed to cover similar phenological stages. To avoid excessive cloud cover as well as burned areas and active fires disturbing the imagery (Stellmes et al. 2013), images from May and June (early dry season) were utilized, with data availability ranging from 65 observations up to 115 observations in overlap areas between neighboring acquisition orbits.

Figure 2: Data availability for all tiles in the study area per sensor and year for the study period of 1989-2014.

Previous studies allowed the stratification of the study area to those areas that were under cultivation and we thus avoided misinterpretation of regularly disturbed natural vegetation (e.g. by fires or flooding), especially in the eastern wetlands (Schneibel et al. 2016).

Field data

A farming system analysis was carried out in Cusseque, Angola. It was based on a quantitative household survey (N=60, covering 63% of the population), a yield assessment (N=30) as well as qualitative semi-structured interviews (N=10) and two focus group discussions. Together, these methods allowed for data triangulation. Especially the use of focus groups as a last step of data gathering allowed the confirmation of conclusions from previous survey analyses and to determine new explanatory categories (Wolff et al. 1993).

Field observations were analyzed according to the theoretical frameworks of Boserup (2005), Ruthenberg et al. (1971) and Jayne et al. (2014) that describe the typical evolutionary steps of

agrarian societies and present a continuum of typical tropical smallholder farming systems. Mean cultivation time of a field has been defined to vary between 4 to 10 years followed by a fallow period of many decades. Mean field size is usually below 3 ha and yet, smallholders perceive land scarcity to be low. All indicator values and characteristics of the analyzed farming system are typical for long-term forest fallow in African Savannas (Ruthenberg et al. 1971).

The identified management practices hold as long as land availability allows for long-term fallow periods and as long as market access is low, smallholders rely largely on subsistence production.

Methods

We used a combination of a time series analysis tool (LandTrendr, Kennedy et al. (2010)) with an adapted interpretation tool and field information about spatial drivers to analyze patterns and dynamics in the smallholder-driven agricultural systems.

There are a number of existing tools that provide good results when used with Landsat time series (e.g. LandTrendr, Kennedy et al. (2010); DBEST, Jamali et al. (2015) or BFAST, Verbesselt et al. (2010)).

We use LandTrendr to build and fit the provided temporal information to simplified segmentation trajectories. LandTrendr automatically builds time series based on certain criteria and using Tasseled Cap Indices (Crist 1985) for the interpretation of changes to ensure consistent data space regardless of sensor (Kennedy et al. 2010). Although the control parameters might be more complex than in other approaches (Jamali et al. 2015), we found the approach to be suitable for the examination of our objectives. Important parameters that characterize and describe smallholder cultivation patterns were derived on the basis of the fitted time series generated by LandTrendr. We tested several parameters and extracted those that reveal important information on deforestation but also on agricultural dynamics.

The overall work flow including all methodological steps from preprocessing to final products is shown in Fig. 3 and the steps are explained in the following sections.

Figure 3: Overall method work flow from pre-processing to the final product. Information about segmentation, stratification, accuracy assessment, temporal and spatial interpretation are given in the next subchapters.

Segmentation

LandTrendr provides pixel-based automatic selection of best observations according to the optimal phenological season via the day of year and the absence of cloud cover. This accelerates the construction of time series since a large number of Landsat scenes are available for the study area. Input data for this approach were the radiometrically corrected images, the thereof derived tasseled cap transformation images and the corresponding cloud masks. The preprocessed Landsat data were converted and renamed to mimic the LEDAPS data structure (Masek et al. 2006), which also enabled

Landsat-8 usage. LandTrendr offers the option of cloud mask calculation. Nevertheless, we use a cloud detection method specifically tuned for spectral conditions in drylands (Frantz et al. 2015) and provide these data ourselves. In areas of path overlap up to 25 years are available, while the minimum of years per pixel is 22.

LandTrendr uses the concept of time series segmentation by placing breakpoints within the source time series, i.e. the annual composite time series. It has been developed to detect long-term changes (trend) as well as short-term changes (disturbance) and to be robust against intra-annual variations. This is approximated by fitting a simplified model, yet covering the necessary temporal details by using statistical and geometrical criteria, like outlier detection, angle criteria and successive simplification of models (Kennedy et al. 2010). It is supposed to be robust in detecting disturbance and recovery without strong modification of parameters as long as the time series is dense enough and recoveries are not too fast (Kennedy et al. 2010). We thus adapted the index as well as the cover model while the other parameters were applied with standard values. For a detailed description of the segmentation algorithm see Kennedy et al. (2010). We tested several indices for the disturbance detection within the LandTrendr approach for a subset pilot area, among them established indices like Enhanced Vegetation Index (EVI), Normalized Difference Vegetation Index (NDVI) or tasseled cap greenness. We assessed the results according to visible temporal and spatial dynamics of agricultural expansion and found that the Normalized Burn Ratio (NBR) was most precise in detecting disturbances by Miombo forest clear cutting which might be due to Miombo forests having high water content and water stress resilience (Eq. 1).

$$NBR = \frac{\rho_{NIR} - \rho_{MIR}}{\rho_{NIR} + \rho_{MIR}} \quad (1)$$

Where ρ_{NIR} is the reflectance in the near infrared (Landsat band 4) and ρ_{MIR} is the reflectance in the shortwave infrared (Landsat band 7).

Temporal metrics

Temporal metrics, like disturbances or recovery processes are based on the Landtrendr fitting output but have been derived from an additional routine. Since we focus on cultivation patterns and their dynamics, we masked the study site to known agricultural areas mapped with an accuracy of 95% (Schneibel et al. 2016).

Regarding the subsets for Menongue and Chitembo, circular buffers were applied around the city centers, according to settlement structures and agricultural spatial patterns. Considering the number of inhabitants and the related settlement structures of both cities, we derived a buffer of 20 km around the city center of Chitembo and a buffer of 30 km for Menongue.

After masking the area, 5.7% of the whole study area was labelled as cultivated land. Based on this reduced data set, we extracted several characteristic parameters from the fitted time series (Fig. 4 top) that support interpretation of the agricultural cycle and fallow regeneration.

Figure 4 (middle) shows how different stages of cultivation can be attributed in a representative pixel's time series. After clearing and burning the available biomass ("slash and burn"), the NBR decreases to a minimum where cultivation is supposed to start ("Plantation of manioc, legumes and cereals"). Usually, fields show a rising NBR after the beginning of cultivation due to remaining trees, plants and the steady growth of perennial crops. The point where a field is abandoned is therefore not clearly detectable but relies on additional field information ("Abandonment of field and expansion of new cultivation areas"). Manioc can be harvested at a later time which might result in a second drop of NBR just like another cultivation period or selective logging ("Reuse of area, e.g. by cultivation or selective logging").

To describe these processes, we selected parameters that include the strength (magnitude) and time of clearing, but also duration of cultivation and general time series characteristics, like extreme values or trends (Table 1). Disturbances are defined as a strong and fast decrease of the NBR value.

311 We derived them by detecting minima in the time series and the according starting point when the
312 NBR changes substantially. The parameters that were derived from the fitted time series are shown in
313 Fig. 4 (bottom) and are described in the following table.

Figure 4: Source and fitted time series extracted by LandTrendr for a selected pixel (above), description of the traditional shifting cultivation system for the lifecycle of a field according to the example time series (middle) and the derived time series parameters (below). See table 1 for a description of parameters.

318 **Table 1: Parameters derived from the fitted time series. See position in time series in Fig. 4 (bottom)**

Description of Parameter	
a	Year and value of the strongest minimum to characterize time and intensity of clearing
b	Year and value of the second strongest minimum
c	The preceding maxima to the strongest disturbance to determine the onset of the clearing process and the end of cultivation
d	The preceding maxima to the second strongest disturbance
e	The date where the largest NBR difference between two consecutive years occurs. In case that the process of clearing starts with a decline over several years, we expect to define the year of greatest impact on natural vegetation.
f	The number of years between the greatest minimum and the following maximum to derive the time between two clearings.
g	The NBR from the years right before the strongest minimum to analyze if an area is slowly cleared/recovering or if changes are rather abrupt
h	The NBR from the years right after the strongest minimum
i	Year of the global maximum
	The number of uses per pixel and if no clearing is detected but rather a monotonous trend, this is also described to be either positive or negative.

319

320 The detection accuracy was assessed by manually interpreting the source and fitted NBR time series
321 that is part of the LandTrendr output (Fig. 4, top). This method allowed for the assessment of both,
322 the LandTrendr fitting procedure as well as the disturbance detection. Overall, 1000 points were
323 randomly selected within the study area with the only constraint that the distance between two
324 points was above 60m (= two Landsat pixels). For each point, the source (un-fitted) and fitted NBR
325 time series were extracted. Each time series was manually interpreted by detecting the start of the
326 strongest clearing and the related minimum, while in case of no clear disturbances, trends or other
327 characteristics were noted. We removed the first and the last year from the analysis. Without

information about the NBR in the year before and after a clearing, a correct detection of disturbances is not guaranteed.

We analyzed accuracies for exact accordance and to account for missing data (e.g. in 1999 or in SLC-off imagery) also for a tolerance of one year.

Cultivation time

Due to farming practices, the determination of the point where a field is expected to be abandoned and left in fallow for regeneration is not straightforward (Fig. 4, middle). We used the empirical data on field cultivation gathered in Cusque to identify parameters that can be applied to the time series.

We adapted a regrowth threshold to the average age of a field. The threshold was based on the difference between pre-disturbance value and the magnitude of the disturbance and expressed as a percentage threshold of this difference value (Eq. 2).

$$NBR_{cult. time} = NBR_{MIN_GD} + TH * (NBR_{MAX_PD} - NBR_{MIN_GD}) \quad (2)$$

where $NBR_{cult. time}$ is the NBR value that results from the according threshold (TH) and above which a field is expected to lie fallow. NBR_{MIN_GD} is the NBR value at the time of the greatest disturbance and NBR_{MAX_PD} is the related pre-disturbance maximum.

We excluded the last years from 2010 on from the analysis, since these fields fall below the minimum cultivation time. We apply a regrowth threshold of 50% to define cultivation length of a field. This results in a mean cultivation time of 6.8 years which is close to the field survey results that indicate an average cultivation time of 7 years.

This approach is not directly related to biomass regrowth due to the above mentioned likelihood of confusion with agricultural practices and results vary with the selected threshold. However, it

provides a systematic characterization of cultivation periods and their changes through time and can therefore be connected with regeneration processes.

Results&discussion

Outcome of the analysis are several parameters and results that can be either analyzed spatially but also expressed as statistical information about the development of the farming system.

The following figure shows a RGB map derived from time series parameters.

Figure 5: On the left, overall spatial patterns of different cultivation practices are shown by a combination of change rate (red) regrowth rate (green) and regrowth time (blue). On the right side, close up looks for the two cities, Chitembo and Menongue, are provided.

The map shows a color combination of the difference between strongest minimum and the preceding maximum (red), the NBR difference between the minimum and the following maximum (green) and the number of years from minimum to next maximum (blue). Purple areas were thus strongly disturbed for cultivation with low regrowth rates and a long period of regrowth. These areas are predominant all over the study area but especially around Chitembo and further north. They indicate that former cultivated areas are abandoned for a long time without strong regeneration and reuse is not likely. The more blueish an area the longer regeneration takes without strong recovery rates. These areas are mostly found close to cities or in the forests. Yellowish areas that are located around Menongue and some other settlements also show high disturbance but also high and fast recovery. This indicates that fields might have only been used for a short time and that selective use after fallowing is likely due to the short period until the next maximum. These results are confirmed and described in more detail by assessing further parameters in the two subset areas (Fig.8).

The pattern of agricultural expansion is also connected to the historical characteristics of the study area (Fig.6). During the fragile ceasefire from 1994-1998 the rate of new fields is quite stable (about 12,000 ha per year) but subsequently decreases to a final minimum of 4,000 ha per year during the resumptions of fights from 1998-2002. After the termination of the civil war, expansion of cultivation areas rises to a second maximum and remains quite stable on a high level of around 10,000 ha per year again. A trend of slowly decreasing expansion can be seen since 2004 which might be due to the changes in cultivation patterns from shifting to semi-permanent cultivation. Fluctuations during the 2000s cannot be completely explained. They are likely connected to the improvement of infrastructure (railway but especially the roads) and resettlements. From 2008 to 2010, the two main roads running north-south and east-west were reconstructed and tarred. This enabled people to easily access new forest areas but also local markets and could thus have increased agricultural activities. After the end of the civil war, returns from former refugees, resettlement actions by governmental orders and increased safety to use forest areas might have impacted the first wave of

agricultural expansion. The according drops might be attributed to the natural life cycle of fields and follow increased agricultural activities.

Figure 6: Total area of natural land converted to agriculture (in hectare) on an annual basis (dotted line) and fitted with a moving average filter of 3 years.

Missing Landsat data in 1999 and the restricted availability in 2000 will result in false assignments to 2001 disturbances. The general dynamics are likely not affected since the number of new agricultural area is very small between 1997 and 2001 which can also be seen in the curve progression of the moving average.

Overall, 7.5% of the considered pixels do not show a distinct clearing pattern but are characterized by a negative trend. These pixels were excluded from further analysis. They can either be attributed to a clearing that is not distinct enough to be described by vertices during LandTrendr fitting or it is due to errors in the classification that was used to mask the study area to agricultural areas (Schneibel et al. 2016).

In a previous analysis of 5 time steps from 1989-2013, a constant increase of field expansion was found (Schneibel et al. 2016). This could generally be confirmed when summarizing the annual time

series to the according multitemporal time steps. Nevertheless, it is obvious that by choosing time steps covering several years, certain dynamics are missed due to averaging. Especially the weakening of the agricultural sector during the resumption of fights 1998-2002 is only visible with a dense time series.

Regarding the number of clearings, we only consider those fields where the time period between the two strongest disturbances is longer than 7 years which equals the average cultivation time of a field. As a result, about 51% of the fields in the whole study area are cleared only once, whereas about half of the areas are cleared twice (approx. 38%) or more often (approx. 10%).

The analysis revealed that the time between the onset of the clearing and the final minimum is more than 3 years for approx. half of the fields. This might be due to selective logging before the actual slash and burn or to inter-annual variations in biomass. The establishment of fields is furthermore often accompanied with previous charcoal production.

According to accuracy analysis, 60.3% of the pixels are correctly labeled for exact accordance. For one year of tolerance, accuracy increases to 71.9%. False detection of disturbances can either be due to multiple disturbances in the time series that are more or less similar in their magnitude. Furthermore, subtle disturbances that are visibly characterized by the user might not be detected by the LandTrendr approach as they are not distinct enough for vertex placement. Overall accuracy for the fitted time series is above 88% and shows that still about 11% of the fitted time series show disturbance patterns that are not covered by our approach.

We found that in our case, clearings in the second-to-last year (2013) were not always reliably detected because in these cases the segmentation algorithm places the last vertex in 2014. This led to the effect that fields which were established in 2013 were generally detected in 2014. We avoided this issue by differentiating the fields detected in 2013 and 2014 subsequently with a straightforward query routine. All pixels that were detected to be cleared in 2014 were selected and their NBR values for 2013 and 2014 were extracted. If the 2013 value was lower, we assigned this pixel to the 2013

clearingclass. If the value was higher, we assumed that the minimum was in 2014 or later and thus assigned the pixel to the 2014 class.

Cultivation pattern

Regarding the two different areas of interest, Menongue and Chitembo, the extracted parameters show distinct dynamics and cultivation patterns, e.g. regarding the time of clearing, the duration and also the number of clearings. Figure 7 shows the establishment of fields for the buffer zone around both cities. According to data availability, the results were grouped with a moving average of 3 years.

Figure 7: Proportion of converted area per year (greatest disturbance) within a 20 km buffer around Chitembo (straight line) and a 30 km buffer around Menongue (dotted line). The different background colours represent different stadiums of conflicts and ceasefire, respectively.

As a result of the civil war, land conversion decreased below 0.4% of the observation area until 2001. One year later the peace contract known as the Lusaka Protocol was signed and in both cases, the area that is converted to agriculture increases hereafter. The impact is visible earlier and more intensive in Menongue, which was an important military center and suffered from the outbreak of

440 open hostilities with UNITA regularly destroying cultivated areas at the beginning of the 1990s. For
441 both areas, rates recover even before the final ceasefire and constantly remain on a certain level,
442 where population movements or the pavement of the streets might have high impacts. The delay
443 effects (decrease of rate in period of ceasefire and increasing rate before 2002) cannot be fully
444 explained. This might be related to the resettlements of former displaced persons, with open fights
445 concentrating on other areas or shortage of food supply that required higher agricultural
446 activities. Proportionally, more areas are converted around Chitembo than around Menongue,
447 especially during conflict time and also most recently. It is likely that this high rate was and is caused
448 partly by post-war remigration of the displaced population, which was favoured by the
449 reconstruction of the road network, and the post-war economic boom of Angola. Although the
450 cultivation system around Chitembo is to a certain extent already semi-permanent, people still
451 expand further into the woodlands and strongly depend on subsistence agriculture.

452 These patterns are also spatially visible, where early fields are established in the 1990s around
453 Chitembo (Fig. 8). In the surrounding of Menongue, expansion is rather delayed to the early 2000s,
454 when the civil war was terminated. Furthermore, forest clearing starting from the city centers is
455 visible, indicating that cultivated areas are growing in radial patterns.

Figure 8: Year of greatest disturbance for Chitembo (upper left) and Menongue (upper right). At the bottom duration of cultivation is shown in years for the two cities Chitembo (bottom left) and Menongue (bottom right).

More than half of the fields in the total study area are cleared once, however these general patterns vary throughout the study area. Around Chitembo, one third of the area is cleared once and more than half of the fields are cleared twice. Around Menongue on the other hand, more than 45% of the field area is still cleared only once.

Cultivation time

The defined threshold of 50% is applied to all pixels to define the recovery after the strongest detected minimum. Those areas that exceed the threshold during the observation time were assumed to be under shifting cultivation (Fig. 9). Areas that have been established before 2009 and did not recover were regarded as semi-permanent or permanent. We found that for the whole study area, 22% of the fields do not regenerate.

For the two subsets of Menongue and Chitembo different spatial patterns in cultivation length are visible (Fig.8). Around Chitembo, a constant number of cultivation areas never fell into fallow, and it is therefore likely that these turned into a system of semi-permanent agriculture. The proportion of fields that are probably under permanent or semi-permanent cultivation remains on a quite stable level of around 20%. Furthermore, this pattern has not changed significantly during the civil war. Areas close to the city that have been cultivated in the early 1990s even show a slow long-term regeneration, indicating that these areas are still in use but not for cultivation. On the contrary, the area surrounding Menongue was characterized by shorter cultivation periods. Since the year 2000, people appear to have switched to a system of semi-permanent farming where fallow periods become scarce. The value of fields not recovering decreases to almost 10% in the 90s and then increases steadily up to a value of above 50% in the final observation year 2010 (Fig. 9).

Figure 9: Proportion of cultivation areas that do not recover during the observation time in the urban sphere of Chitembo (straight line) and Menongue (dotted line).

The results for fields that were established after 2007 have to be cautiously interpreted regarding that the mean cultivation time of 7 years is not reached within our observation period. However, the

observed trend seems to continue, although overestimation of the number of fields that do not turn into fallow is likely.

Transferability

The focus of this study was to detect dynamics within a smallholder agricultural system in a rainfed cultivation system. Although the chosen method provides information where field data is scarce, certain ground information is necessary, e.g. information on average length of cultivation and cultivation practices. To transfer the approach to similar landscapes regarding climatic and cultivation settings, the following points have to be considered:

- Selection of an appropriate index for time series segmentation: We tested several indices to represent the temporal characteristics of the cultivation pattern from which subsequently the according parameters were derived from representative time series profiles. In our case, the NBR was found to reliably detect clearings and cultivation time. If agricultural systems are not characterized by clearcutting of natural vegetation, other indices might be more appropriate for characterization of cultivation dynamics, e.g. NDVI (DeVries et al. 2015), tasselled cap indices (Powell et al. 2010) or fractions resulting from spectral unmixing (Morton et al. 2011).
- Definition of a suitable observation period: We were constrained to a limited season of the year, i.e. to the early dry season after the cloudy rainy season and before the dry season where fires spread within the study area. Depending on different climatic and environmental conditions and agricultural systems, the season from which the imagery is selected will differ and has to be carefully selected with regard to temporal characteristics of cultivation, e.g. Edlinger et al. (2012) use Landsat data from the summer months to maximise the vegetation index in a study area of cotton cultivation in Uzbekistan. Qin et al. (2015) adapt the selection of Landsat imagery for rice detection in China to the growing season derived via MODIS products.

- The derivation of the time series parameters needs to be adapted to the agricultural system. We applied the approach to a shifting cultivation system with decades of fallows between two cultivation periods. In areas with intensive agriculture, other parameters might be more significant than the description of land clearing and cultivation duration.
- We define cultivation length based on field surveys. This approach requires reliable ground based surveys but is also data driven due to the subsequent connection to time series data for threshold definition. Thus, while it does represent systematic dynamics and changes during time it has to be adapted to local specification, if necessary.

Conclusion

We demonstrated that temporal analysis of remote sensing data delivers important information on the development and status of cultivation patterns especially for an area where general ground data is almost absent and where no statistics or information on past activities are available. Time series analysis has proven to be a useful tool for the retrospective analysis of cultivation dynamics in this area of former conflicts. We could show that the use of LandTrendr and the combination with a user adapted assessment can provide a differentiated view into agricultural dynamics in rural Angola.

The LandTrendr approach has proven to be suitable for the assessment of changes and to differentiate between long-term trends and short-term disturbances (Kennedy et al. 2010). While requiring relatively few preprocessing steps, the pixel-by-pixel based analysis, the automatic derivation of best observations and the LandTrendr fitting process provided a product that could directly be interpreted and analyzed without any further processing. We integrated Landsat 5 - 8 data and provided a study area adapted interpretation of the time series until 2014. Regarding different parameters derived from the fitted time series, most important were the characterization of minima and maxima (year and value) also including the number of disturbances. But also the parameters from which regeneration and the duration of cultivation can be derived are important measures providing information about changes in cultivation pattern. The time of maximum difference is closely related to the strongest minimum and can hence be neglected as well as the NBR

values in the years before and after the strongest minimum, because this information is more conveniently represented by the cultivation time. We could not yet characterize previous use of cultivation areas (e.g. charcoal or honey production, selective extraction of woody biomass), which needs to be further analyzed because it influences the detection of the onset of the clearing. Nevertheless, we found indication that for half of all agricultural areas previous use is likely according to the stepwise, multi-year disturbances. The analysis of former uses requires field data and information that can be temporally connected to the earth observation time series, which would then rather need to be analyzed with respect to apparent trends.

The temporally detailed analysis reveals important land use details compared to previous multi-temporal results. Pixel based time series analysis provides essential details that can be connected to historic or socio-economic land change patterns. Although the general trend of the multi-temporal analysis was confirmed, information about length of cultivation and number of disturbances, about different cultivation pattern and the consecutive regeneration is only possible with higher temporal resolution. This is especially confirmed by the contrast of the two subset characteristics. The cultivation patterns of both study areas are distinct, although showing similarities in the drivers of the observed spatial and temporal changes. In our case, dynamics are associated with the armed conflicts, resettlement of people and reconstruction of infrastructure.

Regarding transferability to other regions showing distinct conversion processes from forests or woodlands to agriculture, we would suggest to use this approach for similar ecosystems and socio-ecological backgrounds. In many cases, higher-level temporal information, e.g. on cropping cycle, is hardly available due to the very distinct wet season on one hand and on the other hand due to annual fires occurring in the dry season. These study results can also form the basis for scenario building which will support the identification of future deforestation and forest degradation hotspots. While possible future developments have already been highlighted ranging from slow growth to exploitative activities (Finckh 2015), specific consequences on ecosystems and their

resources have not yet been considered. Models that assess future ecosystem service dynamics (e.g. INVEST; Sharp et al. (2014)) can profit from the spatially accurate input of land use change.

Our results indicate that shifting cultivation is widespread in the research area. It can be considered an ecologically sustainable farming system that balances periodic soil utilization during cultivation periods with soil regeneration during decade-long fallow periods. In and near urban areas, with improved market access and higher population pressure, shifting cultivation appears to be replaced by more permanent forms of cultivation. This change occurred only over the last decades, and farmers expressed that lack of seeds, field input and knowledge keeps them from adopting new (e.g. horticultural) production practices. This development follows a typical transition of tropical smallholder farming systems described by Ruthenberg (1971): from shifting cultivation to semi-permanent cultivation or permanent rain-fed cultivation. Gradually, this may result in decreased yields and degraded soils, with negative impacts on rural livelihoods. It is therefore an undesired form of intensification. By assessing land use dynamics which indicate a rise of permanent forms of smallholder agriculture, our research identifies hot-spots where increased soil exploitation is a likely phenomenon and where specific management concepts are required to prevent further fragmentation of Miombo forests. Ultimately, this can help in the design of pro-smallholder policies which are able to better target regions of accelerated change, like the increase in agro-industrial developments (Frolking et al. 2009). Especially studies on the provision and changes of ecosystem services rely on quantitative information about cultivation systems, clearing of natural vegetation and the related temporal dynamics.

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740

741 **List of figure captions**

742

743 Figure 1: Location of the study area including an overview of Southern Africa and paved roads
744 connecting the municipality centers. Background image is a true color image of Landsat long term
745 average reflectance.

746 Figure 2: Data availability for all tiles in the study area per sensor and year for the study period of
747 1989-2014.

748 Figure 3: Overall method work flow from pre-processing to the final product. Information about
749 segmentation, stratification, accuracy assessment, temporal and spatial interpretation are given in
750 the next subchapters.

751 Figure 4: Source and fitted time series extracted by LandTrendr for a selected pixel (above),
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754 description of parameters.

755 Figure 5: Spatial patterns of different cultivation practices are shown by a combination of change rate
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760 Chitembo (straight line) and a 30 km buffer around Menongue (dotted line). The different
761 background colours represent different stadiums of conflicts and ceasefire, respectively.

762 Figure 8: Year of greatest disturbance for Chitembo (upper left) and Menongue (upper right). At the
763 bottom duration of cultivation is shown in years for the two cities Chitembo (bottom left) and
764 Menongue (bottom right).

765 Figure 9: Proportion of cultivation areas that do not recover during the observation time in the urban
766 sphere of Chitembo (straight line) and Menongue (dotted line).