remote sensing

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Using Annual Landsat Time Series for the Detection of Dry Forest Degradation Processes in South-Central Angola

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Abstract: Dry tropical forests undergo massive conversion and degradation processes. This also holds true for the extensive Miombo forests that cover large parts of Southern Africa. While the largest proportional area can be found in Angola, the country still struggles with food shortages, insufficient medical and educational supplies, as well as the ongoing reconstruction of infrastructure after 27 years of civil war. Especially in rural areas, the local population is therefore still heavily dependent on the consumption of natural resources, as well as subsistence agriculture. This leads, on one hand, to large areas of Miombo forests being converted for cultivation purposes, but on the other hand, to degradation processes due to the selective use of forest resources. While forest conversion in south-central rural Angola has already been quantitatively described, information about forest degradation is not yet available. This is due to the history of conflicts and the therewith connected research difficulties, as well as the remote location of this area. We apply an annual time series approach using Landsat data in south-central Angola not only to assess the current degradation status of the Miombo forests, but also to derive past developments reaching back to times of armed conflicts. We use the Disturbance Index based on tasseled cap transformation to exclude external influences like inter-annual variation of rainfall. Based on this time series, linear regression is calculated for forest areas unaffected by conversion, but also for the pre-conversion period of those areas that were used for cultivation purposes during the observation time. Metrics derived from linear regression are used to classify the study area according to their dominant modification processes. We compare our results to MODIS latent integral trends and to further products to derive information on underlying drivers. Around 13% of the Miombo forests are affected by degradation processes, especially along streets, in villages, and close to existing agriculture. However, areas in presumably remote and dense forest areas are also affected to a significant extent. A comparison with MODIS derived fire ignition data shows that they are most likely affected by recurring fires and less by selective timber extraction. We confirm that areas that are used for agriculture are more heavily disturbed by selective use beforehand than those that remain unaffected by conversion. The results can be substantiated by the MODIS latent integral trends and we also show that due to extent and location, the assessment of forest conversion is most likely not sufficient to provide good estimates for the loss of natural resources.

Keywords: Landsat; time series analysis; Disturbance Index; dry tropical forest; Angola

1. Introduction

Miombo forests are one of the most extensive, yet compact, dry tropical forest units of the world [1]. They stretch from Tanzania at the east coast to Angola at the west coast of Southern Africa, covering an area of 2.57 million km^2 [2,3]. They are a source for the commodification of products for the local population, but also have an indirect value such as sustaining biodiversity by providing floristic and faunal habitats or acting as a carbon sink [2,4]. The largest proportional area of Miombo forest is located in Angola. Notwithstanding, there are still fundamental knowledge gaps due to the civil war (1975–2002) and the according research difficulties [5,6]. Currently, smallholder agriculture still dominates forest conversion processes. More recently, the Angolan government also invested in agro-industrial production and due to its natural settings, the area has been identified as one of the future hotspots for large scale agricultural production under foreign investments [7,8]. However, poor and corruptive governance, as well as the insufficient power of public forestry agencies, will pose challenges to sustainable forest management [9].

In contrast to the stand-replacing character of conversion processes, forest degradation in the tropics is attributed to the non-sustainable extraction of timber and other forest products, but also to over-hunting that leads to entry-logging and fires [10]. Wood products from Miombo forests are still mainly consumed by the private sector since these forests are as yet of no importance for industrial logging [11,12]. The various uses of plants within the Miombo forests in the Angolan highlands range from construction material, firewood, food, and medicine to spiritual purposes [13]. Furthermore, the production of charcoal and honey making are activities that generate direct cash income and are coupled to the construction and improvement of infrastructure [12].

The use of Miombo results in large areas of forest disturbance and only a small amount of old-growth forest being left [11]. Slash-and-burn agriculture is widespread and is further increasing due to population growth and the ongoing lack of food supply [14]. This has resulted in immense trade-off processes in south central Angola between wood products and food and an annual deforestation rate of 5.6% for all forested areas between 1989 and 2013 [15]. As a result, large gaps in the canopy of the surrounding forests can be observed, also because agricultural expansion is usually accompanied by selective felling for different purposes [1].

Apart from slash-and-burn, fires are very common in the area but are generally considered as surface fires that mainly burn grass and litter [16]. While trees and woody plants can be regarded to be fire resistant, the herbaceous layer is highly flammable and fires are used in addition to clearcutting for the preparation of new fields [17,18].

While the detection of stand-replacing conversion of forest to agriculture has been studied most intensively in general, e.g., [19], and to a lesser degree in Angola [15,20], forest degradation is a subtle modification process [21] that is largely understudied [22,23]. Forest modification is more prevalent than conversion; however, the increased temporal and spatial complexity of measurements has resulted in a far lower number of case studies [24]. Forest degradation has been studied less for most tropical dry forests, especially for the Angolan Miombo [10,25]. Nevertheless, degradation via selective logging can be considered the most dominant disturbance of tropical forests, with a slow subsequent recovery [25].

The importance of carbon stocks in forests for the global climate was recognized by the United Nations framework convention on climate change in 2005. The program “Reducing Emissions from Deforestation and Forest Degradation and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries” (REDD+) aims at reducing the impact on climate change, conserving biology, and protecting ecosystem services by increasing carbon reductions [26]. However, one general method to measure carbon across the landscape does not yet exist and the aspect of forest degradation in this context has long been disregarded [26,27]. Remote sensing in combination with ground data has been identified as being one of the key methods to map and monitor forest dynamics [28], partially because historical trends (including deforestation, afforestation, forest degradation, and regeneration) can only be identified with space-based remote sensing time series due to the poor ground data availability in many developing countries [29].

We use a remote sensing approach that we adapt to study area specific characteristics to analyze the following objectives:

- Assess the extent and location of forest degradation areas and differentiate between modification processes;
- Identify the main underlying drivers of forest degradation;
- Assess the difference in degradation on later cultivated areas and on non-converted forest areas.

We assessed degradation processes within Miombo forests of different densities in a study area in south central Angola, characterized by highly dynamic land use changes and pressure on natural ecosystems. While the population is expected to grow rapidly, the use of natural resources is already beyond sustainability [12]. We used annual Landsat time series covering the period from 1989 to 2013 and the Disturbance Index to identify stable forest areas, as well as areas of forest degradation. We also assessed selective forest use before the conversion to agricultural areas. The results were compared to MODIS phenology and burned area products to substantiate our results and to identify the impact of fire on the local forest ecosystem.

2. Study Area

The study area is located in south-central Angola at a mean altitude of 1500 m a.s.l. and covers various land use types with an area of 48,600 km^2. Parts of the three provinces Bié, Cuando Cubango, and Moxico, and their corresponding municipality administrations, are covered by the extent of the study site. According to the census of 2014, Menongue is the largest city and the local center of the region (pop. of 306,622), followed by Chitembo (pop. of 68,581) and Cuchi (pop. of 42,899) [30]. Two paved roads cross the study area, one running from east to west, connecting Menongue and Cuchi and the other one, connects Chitembo and Menongue in the north-south direction (Figure 1). After these connections were destroyed during the civil war (1979–2002), the roads were reconstructed and paved between 2007 and 2010. In addition, a dense network of earth tracks covers the study area [31].

The climate of the study area is subhumid, with a mean annual temperature of 20.4 °C and a distinct rainy season from October to April (average amount of precipitation of about 900 mm) [32]. The soils are mainly deep, sandy Arenosols in the eastern part of the study area and shallow soils on granitic bedrock in the western part [33]. The landscape is traversed by large floodplains, mainly *Parinari capensis* grasslands on the sandy, leached soils in the eastern part and *Cryptosepalum maraviense* grasslands in the western part [34]. The floodplains are subject to frequent fires, generally man made [35]. On the slopes to the hilltops, there is a gradient from shrubland and open forests to dense Miombo [34].

The main land cover units are the Miombo forests, a dry tropical forest type, which are dominated by *Brachystegia*, *Julbernadia*, and *Cryptosepalum* species [6]. These forests mainly occur on soils with a medium nutrient content and are largely disturbed, forming woodlands of different densities and various species composition [33,36]. While woodland regeneration after slash-and-burn agriculture is fast in terms of species richness, species composition might not recover at all [37].

Large areas in the eastern part are covered by undisturbed forests, whereas the current deforestation frontier is located in the western part [38]. Since the study site has been severely affected by the civil war, by population movements, and by a subsequent strong population growth, it is likely that the pressure on forests has changed over time and that degradation is spatially and temporally connected to population dynamics. During the civil war, people affiliated with UNITA ("União Nacional para a Independência Total de Angola") were settled deep in the forests and were moved close to roads and existing settlements by the MPLA ("Movimento Popular de Libertação de Angola") shortly after the ceasefire [39]. It is assumed that deforestation and forest degradation rates are unprecedentedly high, especially close to cities and infrastructures due to easy access and market opportunities [12]. While deforestation for agriculture has already been quantified [15], more subtle forest dynamics, like degradation processes in the study area, remain unstudied [37].

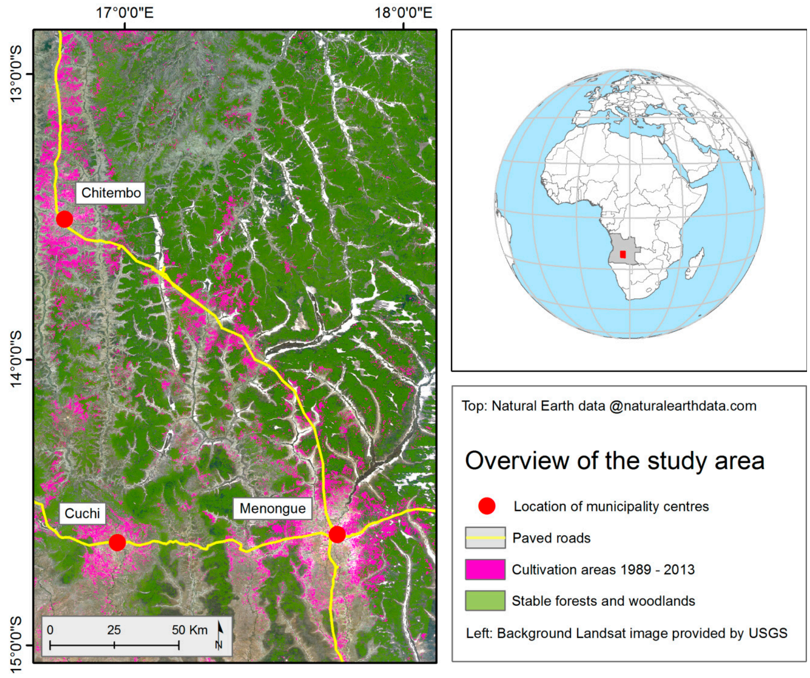


Figure 1. Location of the study area (top right) and distribution of stable forests/woodlands (green), as well as the location of cultivation areas (pink) that were established between 1989 and 2013 [15]. Furthermore, the municipality centres and the connecting paved roads are shown.

3. Data

Annual Landsat time series were generated for the period from 1989 to 2013. For this purpose, all available Level 1T data from the Thematic Mapper (TM) and Enhanced Thematic Mapper plus (ETM+) were processed to Bottom-of-Atmosphere (BOA) reflectance using the Framework for Operational Correction for Environmental Modelling (FORCE) software [40].

A detailed description of the derivation of these inputs can be found in [40] and only a brief summary will be given here. The employed radiometric preprocessing chain is based on radiative transfer theory [41], featuring integrated corrections for atmospheric, topographic, and adjacency effects. The atmospheric correction accounted for multiple atmospheric scatterings with variable illumination/view geometry, and produced a combined image-, database-, and object-based estimation of aerosol optical depth over temporally persistent dark targets. Water vapor correction was performed using the MODIS precipitable water product [42]. Topographic normalization was achieved with a modified image-based C-correction with 1-arc-Second SRTM data [43]. Clouds and cloud shadows were identified with a modified version of the Fmask algorithm [40,44–46]. All data were prepared in a regular grid (30 km × 30 km tiles), and share a single projection (Lambert Azimuthal Equal Area), allowing the immediate usage of the full archive depth. Overall, 54 tiles were needed to fully cover the study area (i.e., 180 km × 270 km = 48,600 km^2). The tasseled cap transformation [47] was applied to all radiometrically normalized BOA reflectance images using the Crist [48] reflectance data coefficients.

We compiled a reliable annual time series using all available images within a narrow phenological window. For each year, we computed the average reflectance for the period May to June, which is the optimal point of year to avoid cloud cover and fires in the wet and dry seasons, respectively [32,35].

The study area was split into areas of presumably stable forest and those areas that were under cultivation during the observation time—based on data from Schneibel et al. (2016) [15]. This was conducted to assess long term trends of supposedly stable forests—potentially including forest degradation and regeneration, that are too subtle to be detected using methods tailored to deforestation—as well as to derive information about forest use before the stand-replacing slash-and-burn events.

The forest cover mask defines stable areas for the study area from 1989–2013. It has been created based on a spectral angle mapping approach and by defining areas that can be considered stable for the observation time. The process of how the mask was derived with an overall area-adjusted accuracy of 0.92 ± 0.06 can be found in Schneibel et al. (2016) [15]. This mask was applied to the study area imagery to identify areas of stable forest. A further mask was applied that incorporates agricultural areas and that is based on the same study. Cultivation areas for the time between 1989 and 2013 were reliably detected with an area-adjusted accuracy between 0.96 ± 0.04 and 0.99 ± 0.02. The time of disturbance was taken from Schneibel et al. (2017) [49], where time series segmentation allowed the derivation of the year of disturbance with an accuracy of 72% (±1 year of tolerance). For the derivation of the accuracy measures, please see [15,49,50]. The cultivation mask allowed us to analyze forest disturbance before the actual slash-and-burn, which is a likely scenario and has not yet been assessed [49].

We compare our results to results from the analysis of MODIS phenology and burned area products (ignition points). A description about the derivation of the MODIS phenology product can be found in Frantz et al. (2016) [51]. Ignition points were derived from the MODIS burned area product using the fire spread segmentation algorithm described in Frantz et al. (2016) [52].

4. Methods

We used an annual time series of the Disturbance Index to derive linear trends and time series parameters like error, trend significance, or variability measures. We used (1) the full time series of 25 years to analyze these patterns regarding the presumably stable forest and (2) the pre-slash and burn part of the time series to derive information about degradation processes that took place before agricultural usage. The workflow is shown in Figure 2 and the single sections are described in the following text.

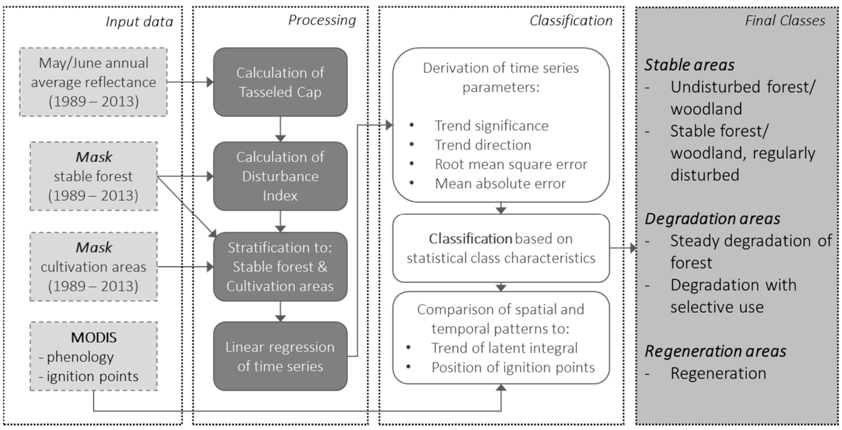


Figure 2. Flowchart of applied methodology from input data over processing and classification to the final set of classes.

We found that mean annual rainfall (African Rainfall Climatology 2" (ARC2), [53]) is correlated with tasseled cap wetness (r = 0.67), and to a certain extent, also to tasseled cap greenness (r = 0.46). As forest degradation is a subtle process that may be masked by climatic variability, we selected an index that reduces these influences using spatial benchmarking; a class of techniques that is commonly applied for monitoring subtle landscape modifications, e.g., [54,55]. Spatial benchmarking uses minimal disturbed reference areas, from which rescaling statistics are derived as it is assumed that influences like climatic variability occur on the regional scale (and vary between years), whereas management effects are superimposed onto that, and can thus only be extracted if separated from climate effects [54].

The Disturbance Index (DI) was specifically developed for forest-related disturbances [56] and was successfully used for detecting forest loss with Landsat data, e.g., [56–60]. The DI is designed to highlight bio-physical changes in forest stands in response to partial canopy loss [61]: i.e., higher reflectance of soil/litter compared to healthy canopies, as well as lower water absorption, and greater shadow fraction [62]. The DI is a linear transformation of the rescaled Tasseled Cap indices [47] and thus indicates increases of brightness with simultaneous decreases of greenness and wetness values [56] (Equation (1)).

$$DI = B_r - (G_r + W_r) \tag{1}$$

with B_r being the rescaled Tasseled Cap Brightness, G_r the rescaled Greenness, and W_r the rescaled Wetness.

By rescaling the values with the mean and standard deviation of a reference population, the DI measures the difference of a certain pixel to the mean state of this reference population (Equation (2)), as follows:

$$\begin{aligned} B_r &= \frac{(B - B_\mu)}{B_\sigma} \\ G_r &= \frac{(G - G_\mu)}{G_\sigma} \\ W_r &= \frac{(W - W_\mu)}{W_\sigma} \end{aligned} \tag{2}$$

where B_μ, G_μ, W_μ are mean values and B_σ, G_r, W_σ are the standard deviation of Brightness, Greenness, and Wetness of the reference population, respectively. It is assumed that the Miombo forest covered by the presumably stable forest mask is largely intact, and thus was used to obtain μ and σ. The DI was computed for the complete forest, including the areas that were cultivated sometime during this period.

This results in negative DI values for overperforming pixels (relative to the reference population) and positive DI values for underperforming pixels. Degradation processes would thus be expressed as an increase of DI values, while areas of regenerating biomass show a decrease in DI values.

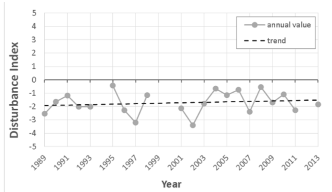
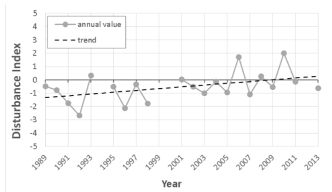
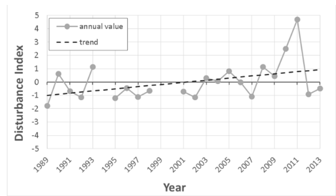
For each available and temporally suitable Landsat dataset, the DI values were calculated on a per pixel basis, which results in annual time series. Linear regressions were computed for each pixel's DI time series and the intercept, significance of trend, mean absolute error (MAE), and maximum residuum were obtained. They are expressed in DI values, i.e., in standard deviations. While areas without cultivation were assessed for the whole observation period, trends in areas that were used for cultivation purposes were only assessed until one year before the onset of cultivation. The parameters are connected to processes like previous usage or disturbance (intercept), strong, regular, or absent disturbances (mean absolute error and maximum residuum), and the general development of an area (significance and sign of trend) (Table 1). The thresholds are as follows:

Table 1. Thresholds & classes of statistical parameters of linear regression.

Significance		**Intercept**	
Insignificant		min–0	overperforming
Sign. negative		0–3	underperforming
Sign. positive		3–max	strongly underperforming
Mean Absolute Error		**Maximum Residuum**	
min–1	steady trend	−3–3	no disturbances
1–3	medium deviations	<−3 or >3	additional disturbances
3–max	strong deviations		

By using these thresholds, we described the dominant processes within the study area (Table 2). Dense, stable forests, for example, would show an insignificant trend, with a low intercept (high performance of DI), low mean absolute error (MAE), and no extreme residuum. We derive two stable forest classes, with and without regular disturbances. The same applies for the less dense stable woodland classes. Degradation is separated into steady degradation (low maximum residuum) and degradation with selective use (high maximum residuum). For regenerating areas, all pixels with a significant negative trend were grouped into one class.

Table 2. Exemplary description of how different processes are expressed by the Disturbance Index time series.

Class	Parameters	Example
Stable, dense forest/woodland	- No significant trend - Low Intercept - Low MAE - Low maximum residuum	
Steady forest degradation	- Significant positive trend - Low intercept - Low MAE - Low maximum residuum	
Steady forest degradation with selective use	- Significant positive trend - Low intercept - Low MAE - High maximum residuum	

For stable areas, we also identified those pixels without a significant trend, but where selective use is prevalent, which is either expressed in high MAE or high maximum residuum values. Additionally, those areas with a significantly negative trend were grouped into one "regeneration" class. We differentiated between dense forests and less dense woodlands by their intercept. Originally, underperforming pixels were considered as woodland, while overperforming pixels were labeled as forests.

5. Results and Discussion

Almost 74% of the Miombo forests did not show any significant trend and were thus considered as stable. The remainder of the forest either had significant positive trends (13.3%), thus being regarded as degrading, or negative trends (12.8%), which suggests accumulating biomass. We considered regenerating areas as currently undisturbed and since we had no information on previous use, we only included those areas in a more detailed analysis that showed no significant or a significant positive trend.

Figure 3 shows the spatial patterns of stable forest and of degradation areas. Along settlements and roads, there is a clear pattern of degrading forest with selective use (pink areas). This pattern follows the spatial arrangement of cultivation areas. These areas thus describe pixels that were converted for cultivation during the observation period and might indicate previous selective use before the actual slash-and-burn. In the southern part, woodlands are more open than in the north-eastern part of the study area, which is expressed in more abundant woodland areas in the southern part.

The deforestation frontier moves from north-west to east and is roughly located around Chitembo. To the east, more dense and undisturbed forest is retained. Large areas do not show a significant trend, but disturbances are prevalent. However, these areas are already highly fragmented by areas of regular disturbances or even degradation. Of most interest are those degrading areas that occur within closed forests without any spatial proximity to infrastructure or settlements. Since cultivation areas are usually established along streets or in close distance to already existing fields, these areas are less likely to be disturbed for cultivation purposes. We assume that these areas were either very early fields (before the observation period) or were selectively used and are thus more susceptible to recurring fires.

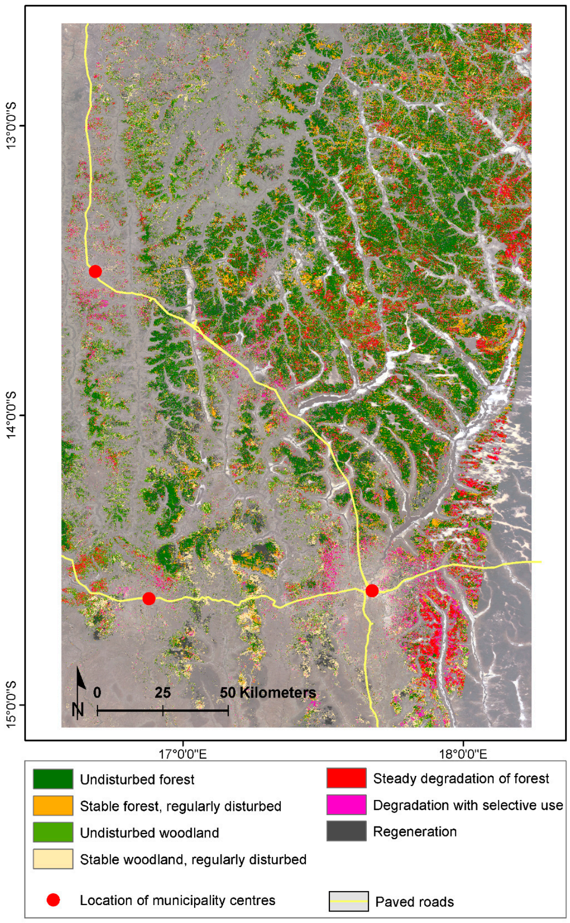


Figure 3. Classification result of the linear regression analysis. The classes have been grouped to stable areas, degradation areas, and regeneration areas. Furthermore, the municipality centers and the main roads are shown for orientation reasons. Background image is a true color image of Landsat long term average reflectance.

Ground truth data, especially for the past, is sparse in the study area. Furthermore, information on cultivation practices, timber use, or forest product use in general is hardly available. The plausibility of our results has thus to be estimated with a workaround and by indirect assessment methods. However, since the Disturbance Index is based on a well-established transformation and only the main processes are covered by statistical parameters, we assume that these main processes can be well separated.

We thus evaluated degradation areas against a temporal trend derived from the MODIS phenology parameters. Among these, the latent integral describes the standing biomass that is not affected by seasonality, and is thus optimal to derive long-term forest degradation. For those areas that we assessed as degrading, the MODIS time series was in good agreement (85%). Mismatches might occur due to differences in spatial resolution (30 m Landsat vs. 250 m MODIS), the length of time series (1989–2013 for Landsat vs. 2000–2012 for MODIS), and different measures (Tasseled Cap-based DI vs. latent integral of EVI), but the general pattern is confirmed.

To assess the difference between the previous degradation of areas where fields are established during the observation time and other forest areas, we assessed the overall change in the DI magnitude. Although the DI cannot be quantitatively connected to true biomass values, qualitative comparisons between the classes are nonetheless possible. For this purpose, we separated the degrading forest into areas that were converted for agricultural use and into those where no conversion took place during the observation time. We consequently assessed the magnitude of change for the time from 1989–2013 (non-cultivated forest) and for a dynamic time range from 1989 until one year before a field was established (Figure 4).

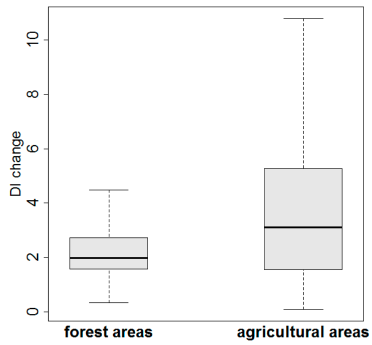


Figure 4. Magnitude of DI change for forest areas (left) from 1989–2013. The DI change for agricultural areas (right) has been estimated for the time from 1989 until one year before the disturbance, i.e., the time where forest was still prevalent.

Although disturbances in stable forests are present to a large extent, their severity is smaller than disturbances that took place in those forests that are cut and burnt for a later creation of fields. The difference in magnitude is highly significant and is supported by the boxplots (Figure 4). This also supports the hypothesis that forests are generally heavily used before they are converted to field areas. This effect has also been observed by Cabral et al. (2011) [20], who studied deforestation patterns in central Angola by using a multi-temporal supervised classification. They found that people would rather extract wood from already degraded forests than from intact Miombos, where the time and effort for wood extraction would be disproportionately higher. Furthermore, although the disturbances in stable forests are characterized by a significant trend, their magnitude is lower, which might indicate that the use of stable forests is less severe—if a future conversion is not planned. This might also support the hypothesis that many forest areas are affected by fires, but that these mainly affect the understory.

A once disturbed forest is more susceptible to recurring fires [63]. To evaluate the impact of fires, we used fire ignition points derived from the MODIS burned area product. Ignition points that were not in close distance to forest areas (>90 m), and that occurred in floodplains, were removed for visibility reasons (Figure 5).

Although the different observation times between the MODIS product (2000–2012) and the Landsat time series (1989–2013) do not allow a direct, quantitative comparison, two aspects become evident: (I) fires are highly prevalent in the study area, also within the forests. Although fires are generally not stand replacing, they can consume large parts of the understory and make forests more susceptible to recurring fire events [63]; (II) the spatial patterns of forest degradation are related to ignition points. Around 15% of the ignition points occur in close distance to degrading areas. Regarding that these degraded areas only account for roughly 5% of the study area, a relationship is likely but cannot be quantitatively stated due to the different observation times. In both subsets shown in Figure 5, the distribution of ignition points concentrates on those areas that were labelled as degradation. In those cases where no ignition points are in close distance to degradation pixels, the fire might have taken place before the MODIS observation time or degradation is caused by another reason. Fires in the study area are usually man made. So far, fires have been considered to mainly affect floodplains for hunting and visibility reasons [35]. The presented results suggest that Miombo forests might also be strongly affected, especially by recurring fires. Since the biomass in these forests is known to recover slowly [15], recurring fires might have a strong and long lasting effect on Miombo forest stands.

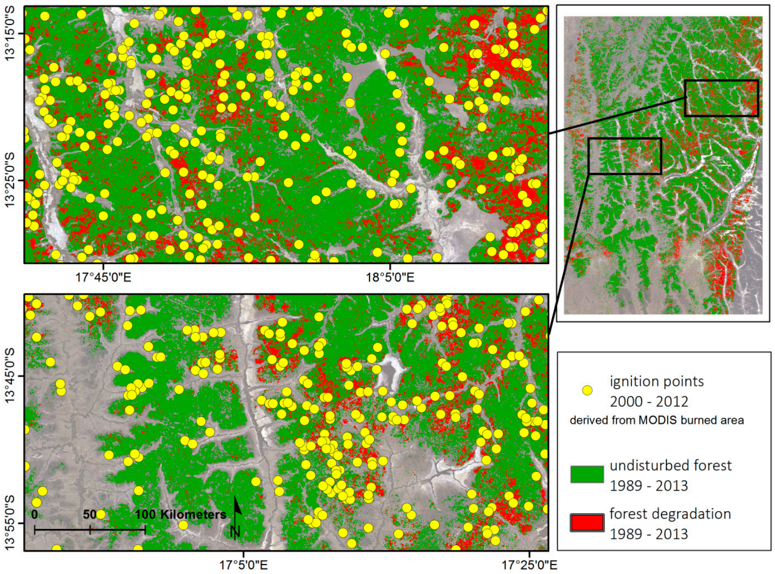


Figure 5. Comparison of forest degradation areas (1989–2013) with fire ignition points derived from the MODIS burned area product (2000–2012).

Although fires are used as a stand replacing management method, mapping only conversion is insufficient to holistically describe forest cover dynamics in tropical dry study areas. The degradation of dry tropical forests significantly contributes to the loss of natural resources and has a high impact on the functioning of ecosystems [64,65]. Furthermore, only reporting complete forest losses substantially underestimates the true carbon losses as areas affected by forest degradation are not less important than those used for land conversion. This has immediate implications for national to global budgeting programs like REDD+, and thus one cannot overemphasize the inclusion of forest degradation processes in the assessment of forest dynamics for tropical dry forests. The outcomes of this study might thus be connected to well-established global products like the forest cover map from [38] to provide estimations of carbon dynamics. In this regard, the next step would be to link remote sensing-based forest dynamics assessments with biomass measurements, either through extensive ground-based forest inventory or by using other remote sensing sources like data from the upcoming Earth Explorer Biomass Satellite.

6. Conclusions

The aim of this study was to spatially and temporally identify historical degradation processes for a study area in south central Angola that is poorly studied. We found that the forests are, to a large extent, undisturbed, mainly due to difficult accessibility and resettlement actions by the government. Nevertheless, large areas of Miombo forests are also exposed to degradation processes due to various reasons. The results of degradation extent and severity can contribute to understanding the status and dynamics of forest loss, especially in the context of the REDD+ incentive.

We found that a main driver of forest degradation in remote areas seems to be recurring fires. Fires in the Miombo forests have been expected to only be used for slash-and-burn conversion. Although this hypothesis might still hold true for the study area, there is evidence that once disturbed areas are prone to subsequent fires although they are hardly stand replacing.

We could furthermore show that already degraded forests are more likely to be affected by conversion processes. Additionally, we identify areas that are currently affected by selective use and show degradation dynamics and thus have a high chance of being converted for agriculture, especially if they are in close distance to existing fields.

Given the vast areas of degrading tropical dry forests, the isolated detection of forest conversion falls short of meeting budgeting requirements of all carbon stored in forest stands. Regarding the success of detecting forest loss with high certainty after decades of dedicated research, we conclude that future remote sensing efforts need to focus on our ability to monitor subtle modification processes with similar certainty. This study is a first step to accomplish this bold undertaking in an area characterized by data scarcity and political unrest. In this regard, it will be key to more closely integrate data from different sensor types (like optical, SAR, and LiDAR data), as well as to invest in the development of regular forest inventories that are currently hardly available for many countries covered by tropical dry forests.

Future projections of the development of the study area and especially its forest dynamics are vague, also due to the poor power of forestry management agencies. In addition, foreign investments are expected to rise, but their extent cannot yet be assessed. Further remote sensing studies can thus support the retrieval of the most basic information on land use change to support retrospective analysis, as well as future scenarios. Overcoming these challenges cannot only contribute to the REDD+ program, but also to a sustainable management of natural resources in the study area in general.

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