

Climate change and adaptive land management in southern Africa

Biodiversity & Ecology 6

Assessments
Changes
Challenges
and Solutions

Product of the first research portfolio of

SASSCAL 2012–2018

Southern African
Science Service Centre for
Climate Change and
Adaptive Land Management

SPONSORED BY THE



Federal Ministry
of Education
and Research

© University of Hamburg 2018
All rights reserved

Klaus Hess Publishers
Göttingen & Windhoek
www.k-hess-verlag.de

ISBN: 978-3-933117-95-3 (Germany), 978-99916-57-43-1 (Namibia)

Language editing: Will Simonson (Cambridge), and Proofreading Pal
Translation of abstracts to Portuguese: Ana Filipa Guerra Silva Gomes da Piedade
Page desing & layout: Marit Arnold, Klaus A. Hess, Ria Henning-Lohmann
Cover photographs:

front: Thunderstorm approaching a village on the Angolan Central Plateau (Rasmus Revermann)

back: Fire in the miombo woodlands, Zambia (David Parduhn)

Cover Design: Ria Henning-Lohmann

ISSN 1613-9801

Printed in Germany

Suggestion for citations:

Volume:

Revermann, R., Krewenka, K.M., Schmiedel, U., Olwoch, J.M., Helmschrot, J. & Jürgens, N. (eds.) (2018) Climate change and adaptive land management in southern Africa – assessments, changes, challenges, and solutions. *Biodiversity & Ecology*, **6**, Klaus Hess Publishers, Göttingen & Windhoek.

Articles (example):

Archer, E., Engelbrecht, F., Hänsler, A., Landman, W., Tadross, M. & Helmschrot, J. (2018) Seasonal prediction and regional climate projections for southern Africa. In: *Climate change and adaptive land management in southern Africa – assessments, changes, challenges, and solutions* (ed. by Revermann, R., Krewenka, K.M., Schmiedel, U., Olwoch, J.M., Helmschrot, J. & Jürgens, N.), pp. 14–21, *Biodiversity & Ecology*, **6**, Klaus Hess Publishers, Göttingen & Windhoek.

Corrections brought to our attention will be published at the following location:

http://www.biodiversity-plants.de/biodivers_ecol/biodivers_ecol.php

Biodiversity & Ecology

Journal of the Division Biodiversity, Evolution and Ecology of Plants,
Institute for Plant Science and Microbiology, University of Hamburg

Volume 6:

Climate change and adaptive land management in southern Africa

Assessments, changes, challenges, and solutions

Edited by

Rasmus Revermann¹, Kristin M. Krewenka¹, Ute Schmiedel¹,
Jane M. Olwoch², Jörg Helmschrot^{2,3}, Norbert Jürgens¹

¹ Institute for Plant Science and Microbiology, University of Hamburg

² Southern African Science Service Centre for Climate Change and Adaptive Land Management

³ Department of Soil Science, Faculty of AgriSciences, Stellenbosch University

Hamburg 2018

Please cite the article as follows:

de Blécourt, M., Röder, A., Groengroeft, A., Baumann, S., Frantz, D. & Eschenbach, A. (2018) Deforestation for agricultural expansion in SW Zambia and NE Namibia and the impacts on soil fertility, soil organic carbon- and nutrient levels. In: *Climate change and adaptive land management in southern Africa – assessments, changes, challenges, and solutions* (ed. by Revermann, R., Krewenka, K.M., Schmiedel, U., Olwoch, J.M., Helmschrot, J. & Jürgens, N.), pp. 242-250, *Biodiversity & Ecology*, **6**, Klaus Hess Publishers, Göttingen & Windhoek. doi:10.7809/b-e.00330

Deforestation for agricultural expansion in SW Zambia and NE Namibia and the impacts on soil fertility, soil organic carbon- and nutrient levels

Marleen de Blécourt¹, Achim Röder², Alexander Groengroeft^{1*}, Stephan Baumann¹, David Frantz², Annette Eschenbach¹

¹ Institute of Soil Science, CEN Center for Earth System Research and Sustainability, Universität Hamburg, Allende-Platz 2, 20146 Hamburg, Germany

² Department of Environmental Remote Sensing and Geoinformatics, Faculty of Regional and Environmental Sciences, Trier University, Campus II, 54286 Trier

* Corresponding author: alexander.groengroeft@uni-hamburg.de

Abstract: In southern African drylands, an important driver of deforestation is the ongoing conversion of woodland to smallholder agriculture. Our study in NE Namibia and SW Zambia evaluated the potential of operational earth observation satellites to characterize land-use change processes and quantified their impact on soil organic carbon (SOC) and nutrient concentrations. We found that the area under agricultural use increased by 24% from 2002 to 2013, mainly at the expense of natural vegetation (i.e., woodland). This conversion caused a decline in SOC and total N and tended to increase plant-available P in the soils of old agricultural fields. The effects were most pronounced in NE Namibia, where the total SOC stocks were 19.6% (± 18.4 SD) lower in agricultural land compared to woodland. Moreover, the losses in SOC and total N tended to result in a decline of predicted maize yields calculated with the QUEFTS model by $\sim 15\%$ when comparing soils of old agricultural fields and woodland. Overall, our results indicate that long-term continuation of low-input arable farming can reduce soil fertility.

Resumo: Nas terras áridas da África Austral, a conversão contínua de floresta para agricultura de subsistência é um factor importante de desflorestação. O nosso estudo no Nordeste da Namíbia e Sudoeste da Zâmbia avaliou o potencial dos satélites operacionais de observação da Terra na caracterização dos processos de alteração do uso das terras e na quantificação dos seus impactos nas concentrações de nutrientes e de carbono orgânico no solo (SOC). Descobrimos que a área de uso agrícola aumentou em 24% entre 2002 e 2013, sobretudo à custa da vegetação natural (i.e. floresta). Esta conversão causou um declínio em SOC e N total, havendo uma tendência de aumento do P disponível para plantas nos solos de antigos campos agrícolas. Os efeitos foram mais pronunciados no Nordeste da Namíbia, onde as reservas de SOC totais eram 19,6% (± 18.4 SD) mais baixas em terras agrícolas que em florestas. Além disso, as perdas de SOC e N total tenderam a resultar no declínio dos rendimentos previstos do milho calculados com o modelo QUEFTS em $\sim 15\%$, quando comparados com solos de antigos campos agrícolas e florestas. No geral, os nossos resultados indicam que a continuação a longo prazo da agricultura arável de subsistência pode reduzir a fertilidade do solo.

Introduction

Agricultural expansion is among the main drivers of deforestation in southern Africa (Chomba et al., 2012; Kim et al., 2016). The demand for agricultural land is related to population growth in combination with diminishing soil nutrient levels and low-input arable cropping (Chomba et al., 2012). The majority of the rural population depends on agriculture for their food supplies and financial

income (Pröpper et al., 2015). In these subsistence-farming systems, most farmers use little or no inputs of fertilizers or organic material, and crop yields strongly depend on the amounts of soil organic matter and soil nutrients. Farmers implement fallow periods when crop yields decline in order to restore soil fertility. Agricultural expansion is another way how farmers deal with declining yields or increasing food demand (Jayne et al., 2014; Stephenne & Lambin, 2001).

Remote sensing techniques can assist in monitoring agricultural expansion over long periods, as they provide an objective, repetitive, and consistent perspective across large areas. As such, time series of satellite images (for instance the Landsat mission that started in 1984) may contribute detailed information on land use, land cover, and corresponding changes and help to evaluate the impacts of human-driven processes on the environment (DeFries et al., 2004; Wulder

et al., 2012). However, remote sensing-based analyses in the area at appropriate spatial resolutions are rare and partially outdated (e.g., Petit et al., 2001; Yang & Prince, 2000). The recent global analysis by Hansen et al. (2013) partially fills this gap, but it remains confined to forest/non-forest classes and operates on a definition of forests (>25% cover of trees taller than 5m) that fails to pick up many southern African woodlands.

The clearing of woodland for low-input arable cropping often leads to a decline in soil organic matter or soil organic carbon (SOC) and soil nutrient levels, as has been shown in pan-tropical reviews (Kleinman et al., 1995; Ribeiro Filho et al., 2015). The negative impacts on SOC levels were confirmed by the few published studies from semi-arid regions in sub-Saharan Africa (Demessie et al., 2013; Luther-Mosebach, 2017; Touré et al., 2013; Walker & Desanker, 2004). To our knowledge, there are no published studies for this region on the impacts of this land-use conversion on soil nutrient levels. Soil organic matter is important for crop productivity, as it improves the soil's cation exchange capacity, structure, and water-holding capacity. The negative impact of the woodland-to-agriculture conversion on soil organic matter and its primary component, SOC, may be related to various processes including the reduced input of organic material, soil erosion, and the accelerated decomposition of soil organic matter. The decline in soil nutrient levels is caused by loss in soil organic matter and by nutrient removal through crop harvesting (Kleinman et al., 1995). Additionally, burning of the plant biomass for woodland clearing affects soil nutrient levels. Although part of the nutrients in the plant biomass will be volatilized, burning causes an input of nutrients to the soil from ash and fire residues (Juo & Manu, 1996). The ash produced is strongly alkaline and increases soil pH (Ribeiro Filho et al., 2015), which in turn accelerates microbial activity and increases soil nutrient availability (Giardina et al., 2000a). However, this effect may only be short term, as highly soluble nutrients such as K, Mg, and Ca may be lost by leaching (Juo & Manu, 1996).

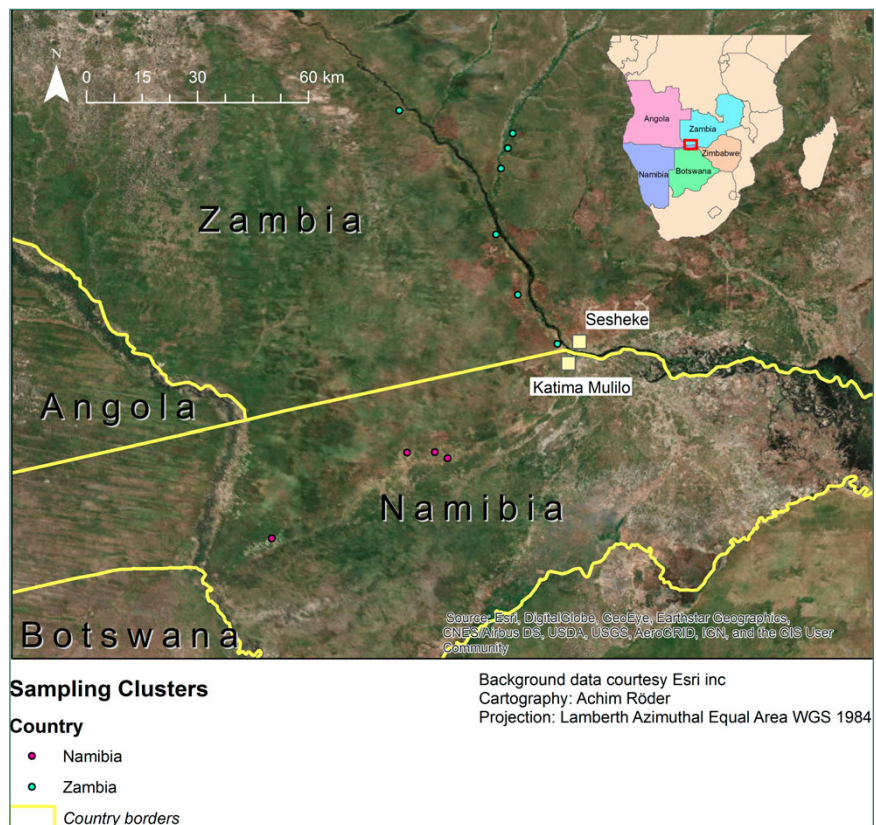


Figure 1: Overview of the study area and location of the sampling clusters. Note that within each cluster we sampled one to three agricultural fields and one plot in woodland.

Understanding the long-term impacts of low-input arable farming on the levels of soil nutrients and soil organic matter is necessary as a basis to develop strategies that may improve the crop yield of subsistence farmers. An approach that evaluates the combined impacts of soil pH and the levels of SOC and the macronutrients N, P, and K on yield is provided by the model Quantitative Evaluation of Fertility of Tropical Soils (QUEFTS) (Janssen et al., 1990; Sattari et al., 2014). QUEFTS is developed for tropical soils and applies a combination of empirical and theoretical relationships to calculate grain yields from chemical soil data. The predicted yields may serve as an indicator for soil fertility, and here soil fertility is defined as the soil's capacity to supply crops with N, P, and K (Janssen et al., 1990).

In this study, we focused on the conversion from woodland to low-input arable farming in the Zambezi region of NE Namibia and in the Sesheke District in SW Zambia. Our objectives were (1) to study the conversion from woodland to agriculture between 2002 and 2013 through a spatially explicit analysis using Landsat imagery, (2) to quantify the

conversion-induced changes in soil nutrient concentrations and SOC concentrations and stocks in agricultural fields with an age up to 26 years (including fallow periods), and (3) to evaluate the conversion-induced changes in soil fertility by assessing the combined effects of soil pH, SOC, and soil nutrient concentrations on predicted crop yields.

Methods

Study areas

The study was conducted in the Kalahari Basin in the Zambezi region of NE Namibia and in the Sesheke District in SW Zambia. The land-use change detection analysis was done for a test area of ~317,770 km² (Fig. 1). The soil survey was conducted in two study areas within this test area; one was in NW Namibia located west of Katima Mulilo, and the other area was in Zambia located NW of Shesheke on the upper slope of the Zambezi River valley and its tributary (Fig. 1). The selection of the two study areas was based on a priori stratification by soil type according to SOTERSAF

(Dijkshoorn, 2003) and the *Soil Atlas of Africa* (Jones et al., 2013), and on the results of a land-use change detection analysis from Landsat imagery (see the paragraph “Land-use change detection”); we selected those areas where we identified the largest areas of agricultural expansion within the studied time frame.

Our field observations and laboratory results showed that the soil properties of the two areas differ in soil texture. The soils of the Namibian study area have a soil texture ranging from sandy loam to sand, are characterized by clay illuviation in the subsoil, and are classified as Haplic Luvisols or Dystric/Eutric- and/or Protoargic- Arenosols (IUSS Working Group WRB, 2014). In the Zambian area, the soils have a sandy soil texture that is uniform with depth and are classified accordingly as Arenosols with one or more of the principal qualifiers Brunic, Rubic, Eutric/Dystric. Soils in both areas have a wide range in pH (H₂O) from 4.7 to 7.4, which is independent of soil type, soil texture, or land use (Tab. 1).

The climate is hot semi-arid with a mean annual temperature of 20–22°C and a median annual precipitation of 550–600 mm (Mendelsohn et al., 2002). The majority of the precipitation is received between October and March. The topography in both study areas is relatively flat with no pronounced differences in altitude. The predominant tree species in the woodlands of the Namibian study area are *Colophospermum mopane* and *Schinziophyton rautanenii* and *Acacia* species. In the Zambian study area, most common tree species are *Schinziophyton rautanenii*, *Baikiaea plurijuga*, *Burkea africana*, and *Pterocarpus angolensis*. The main crops grown on the agricultural fields are beans, groundnuts, pearl millet, maize, and sorghum. According to the farmers, manure or other fertilizer are not applied on any of the investigated sampling plots. Fields are ploughed with draught animals once a year before sowing. To establish new agricultural fields, farmers typically convert woodland by cutting and subsequently burning the trees (Pröpper et al., 2015).

Land-use change detection

To detect land-use changes we classified the land use in a test area of

Table 1: Soil properties (means ± SD) of woodland (WL), old agricultural fields (OA), and young agricultural fields (YA) in two study areas in NE Namibia (NAM) and SW Zambia (ZAM).

Parameter	Depth (cm)	Study Area in Namibia		Study Area in Zambia			
		WL (n = 4)	YA (n = 6)	OA (n = 4)	WL (n = 7)	YA (n = 6)	OA (n = 7)
Bulk Density (g cm ⁻³)	0–10	1.41 (0.13)	1.48 (0.05)	1.45 (0.02)	1.49 (0.09)	1.51 (0.06)	1.54 (0.08)
	70–100	1.49 (0.03)	1.54 (0.05)	1.55 (0.07)	1.55 (0.03)	1.53 (0.03)	1.54 (0.05)
pH (H ₂ O)	0–10	6.24 (0.43)	6.34 (0.31)	6.17 (0.38)	5.93 (0.43)	6.28 (0.51)	6.08 (0.39)
	70–100	5.79 (1.2)	5.8 (0.48)	6.15 (0.2)	5.75 (0.29)	6.11 (0.55)	5.94 (0.43)
Phosphorus (mg kg ⁻¹)	0–10	0.25 (0.06)	0.44 (0.34)	0.97 (1.33)	6.17 (2.19)	7.53 (3.19)	5.43 (1.82)
	70–100	0.06 (0.006)	0.04 (0.009)	0.03 (0.007)	0.06 (0.015)	0.06 (0.029)	0.04 (0.01)
Total N (%)	0–10	0.06 (0.006)	0.04 (0.009)	0.03 (0.007)	0.06 (0.015)	0.06 (0.029)	0.04 (0.01)
	70–100	0.02 (0.004)	0.02 (0.002)	0.02 (0.002)	0.02 (0.002)	0.01 (0.002)	0.02 (0.002)
SOC (%)	0–10	0.69 (0.1)	0.49 (0.14)	0.36 (0.08)	0.74 (0.25)	0.73 (0.34)	0.43 (0.13)
	70–100	0.21 (0.02)	0.19 (0.02)	0.18 (0.03)	0.12 (0.04)	0.12 (0.05)	0.11 (0.02)
SOC Stocks (Mg C ha ⁻¹)	0–100	47.9 (2.2)	40.1 (4.3)	39.3 (7.2)	37.2 (8.8)	39.1 (11.0)	31.4 (5.6)
Exchangeable K (mg kg ⁻¹)	0–10	110 (33.43)	130.43 (51.72)	101.58 (27.69)	41.89 (12.98)	34.67 (9.41)	48.84 (20.39)

~317,770 km² (one Landsat full frame, path 174/172) from Landsat images acquired in the 2002 period and in 2013 representing the recent state. We made use of a Landsat archive that provides all existing images until 2015 processed to surface reflectance (Frantz et al., 2016; Röder et al., 2018). By selecting multi-temporal datasets for each of the studied years (9/4/2002, 30/7/2002, 18/10/2002, and 15/4/2013, 20/7/2013, 8/10/2013), we incorporated the phenological variability of the different surfaces through a climatic season. All images were stacked to form 18-band layers for the 2002 and 2013 periods, respectively. Information on the most distinct land-use classes was based on a supervised classification using the maximum likelihood classifier, which assigns class membership based on the highest probability of class membership by comparing the respective pixel to a set of training pixels (Richards, 2013). Target classes were settlements, agricultural areas, bare areas, sparse vegetation, forests, water, and wetlands. In addition, areas recently affected by fires were differentiated. Using high-resolu-

tion imagery (e.g., Google Earth™ and Bing Maps™) and a visual analysis of the Landsat data, we selected an average of 60 reference points for each class to train the classifier. Since no corresponding high-resolution data were available to derive training data for the previous date, we propagated the training dataset to the historic dataset using band- and date-wise differences between corresponding recent and historic images (and bands). Since, independently of surface type, spectrally stable features can be assumed to have unchanged reflectance, we could identify these using thresholds and use the respective land use information derived for the recent date to parameterize the classifier for the earlier period. For both periods, the agricultural and settlement classes showed overlaps with vegetation classes; therefore, for these classes an unsupervised classification with manual attribution was additionally carried out. Furthermore, we calculated the tasselled cap coefficients for all images (Kauth & Thomas, 1976), which decompose images into “brightness”, “greenness” and “wetness” components

using a linear transformation based on predefined coefficients. Thus, the discrete vegetation classes could be replaced by continuous fields represented by the “greenness” fraction for different periods for maps, while discrete classes were used together with 591 independent points identified in Google Earth™ and Bing Maps™ for validation using a stratified random sampling. We used the results from the land-use change analysis to stratify the test area into areas that were largely affected by the woodland-to-agriculture conversion (i.e., agricultural expansion) and used this information to select our two study areas for the soil survey.

Sampling design

In the two study areas we selected a total of 11 sampling clusters, four in Namibia and seven in Zambia. Each sampling cluster had a 1 km radius in which we selected up to three sampling plots in agriculture and one plot in woodland. We selected the clusters by stratified random sampling as follows: First, based on the results from the discrete change detection, we stratified the two study areas into woodland (classified as natural vegetation), young (classified as agriculture since 2013) and old agricultural fields (classified as agriculture from both 2002 and 2013 imagery), and others. Second, within each study area, we randomly selected clusters within a 5 km distance from a road in from areas that contained both woodland and agriculture. Finally, in the field, the sampling plots within a cluster were carefully selected to have similar topographic and soil characteristics. To verify the age of the selected agricultural fields, we used the information from farmers and a time series from 1987 to 2014 of the Enhanced Vegetation Index (EVI) derived from Landsat satellite images. By visual comparison of EVI time series of agricultural and woodland plots, we were able to determine the first year of agricultural usage. Moreover, the EVI data showed that most sampling plots after original conversion have rested for some growing seasons. Thus, the ages of the agricultural fields used in this study are based on the first year of agricultural usage and should be interpreted

as total agricultural duration that may include a sequence of cropping and fallow periods. The agricultural plots classified as young fields ranged in age from 2 to 12 years and the old fields from 13 to 26 years. In the Namibian study area, we sampled four plots in woodlands, six in young agricultural fields, and four in old agricultural fields, and in the Zambian study area seven in woodlands, six in young agricultural fields, and seven in old agricultural fields.

Soil sampling and laboratory analysis

Sampling plots had a size of 30 m x 30 m. A soil pit was dug in the plot centre. We took soil samples for chemical and physical property analyses from five depth intervals down to 100 cm: 0–10 cm, 10–20 cm, 20–40 cm, 40–70 cm and 70–100 cm. Additionally, soil samples of the upper three depths were taken with an Edlmann auger from 12 points that were situated at a distance of 5 m, 10 m, and 15 m from the plot centre in each of the four cardinal directions. We mixed these samples in the field to form one pooled sample per depth and plot. All soil samples were collected in November 2015. Sieved soil samples (<2 mm) were analysed for pH (H₂O), bulk density, SOC, total N, exchangeable K, and plant-available P. Soil pH (H₂O) was measured with a pH electrode in soil suspensions with a 1:2.5 soil-to-water ratio. Soil bulk density was measured using the core method (Blake & Hartge, 1986). The bulk density samples did not contain stones or coarse fragments >2 mm, so we did not correct for gravel content. Soil carbon and nitrogen concentrations were measured on ground samples by dry combustion using an elemental analyzer (varioMAX, elemental analyzer). As soil pH was below pH 7, carbonates were not expected and total carbon was assumed to equal SOC. Exchangeable potassium was extracted with ammonium acetate. The extracted cations were quantified by atomic absorption and atomic emission spectroscopy (Helmke & Sparks, 1996). We extracted plant-available P (P-Olsen) with a buffered alkaline solution according to Kuo (1996).

Calculations and statistical analysis

SOC stocks in each depth interval were calculated by:

$$SOC \text{ (Mg C ha}^{-1}\text{)} = \frac{\% C}{100} \times BD \text{ (Mg m}^{-3}\text{)} \times \Delta D \text{ (m)} \times 10,000 \text{ m}^2\text{ha}^{-1}$$

where BD is the soil bulk density and ΔD is the thickness of the sampling depth. Total SOC stocks to a 100 cm depth were calculated as the sum over all depths. The comparisons of SOC stocks among the studied land-use types were based on equivalent soil masses (Ellert & Bettany, 1995) to account for possible alterations in soil bulk density with land-use change. In our calculations of SOC stocks, it was not necessary to correct for the proportion of rocks in the soil profile, since the profiles were free of rocks and the BD samples did not contain coarse fragments >2 mm.

To assess the soil fertility of the plots, we used the QUEFTS model (Janssen et al., 1990; Sattari et al., 2014). Using QUEFTS we predicted maize yields from our data on soil pH and concentrations of SOC, exchangeable K, total N, and plant-available P to 20 cm depth. We chose to predict maize yields since, of the crops grown in the region, it is the only crop included in the model. QUEFTS estimates crop yields under the assumption that N, P, and K are the only growth-limiting factors. Maize yields are calculated in four steps: (1) Calculation of the potential supply of N, P, and K based on empirically derived equations between soil chemical data and maximum nutrient uptake when no other nutrients or growth factors are yield limiting. We assumed no additional fertilizer input. (2) Quantification of the actual nutrient uptake from theoretical trends between potential nutrient supply and actual uptake. (3) Calculation of three yield ranges from the actual uptake of N, P, and K, respectively, with empirically derived equations for nutrient limiting and nonlimiting conditions. (4) Estimation of a final yield by combining the yield ranges calculated in step 3.

Statistical analyses were done in the statistical software R version 3.3.3 (R Core Team, 2017). To test whether agriculture and woodland in each cluster differed in SOC and nutrient contents

Table 2: Confusion matrix and accuracy assessment showing the agreement between the results of the land-use classification from Landsat data and class assignments derived from high-resolution imagery for 591 validation points (based on stratified random sampling), overall accuracy 0.795 (confidence interval 0.051).

Classification	Reference Points								User's Accuracy (UA)	UA Confidence Interval
	Woodland	Sparse Vegetation	Bare ground	Agriculture	Settlement	Seasonally Flooded	Water	SUM		
Woodland	26	29	0	0	1	3	0	59	0.441	0.128
Sparse Vegetation	8	249	10	0	0	2	0	269	0.926	0.031
Bare ground	0	21	34	0	0	0	0	55	0.618	0.13
Agriculture	1	12	7	32	0	0	0	52	0.615	0.134
Settlement	0	8	6	7	31	0	0	52	0.596	0.135
Seasonally Flooded	0	1	0	0	0	50	1	52	0.962	0.053
Water	0	0	0	0	0	4	48	52	0.923	0.073
SUM	35	320	57	39	32	59	49	591		
Producer's Accuracy (PA)	0.939	0.328	0.826	0.949	0.846	0.894	0.888			
PA Confidence Interval	0.056	0.042	0.079	0.035	0.257	0.088	0.195			

and stocks, soil pH, and predicted maize yields, we used linear mixed effects models (LME) using the nlme package (Pinheiro et al., 2012). Response variables were the selected soil properties or predicted maize yields, and cluster was included as a random factor. We included land-use type, study area, and the interaction between land-use type and study area as fixed effects. If the interaction term was not significant, we continued with a model without interaction. Post-hoc tests (Tukey's test from the lsmeans package [Lenth, 2016]) were performed for multiple comparisons between land-use types and study areas.

Results

Land-use change detection

Following the methodology suggested by Olofsson et al. (2014), classification accuracies for the recent date (2013) were validated using a stratified random sample approach with a total of 591 validation points and corresponding high-resolution imagery (Google Earth™), with a kappa index of 0.71 and an overall accuracy of 79.5 %. Difficulties were encountered mainly in highly heterogeneous areas with intricate mixtures of small agricultural plots, rural settlements constructed mainly of natural materials, and bare areas, which are spectrally highly similar

and where the absence of peak wet-season imagery means many fields are not recorded under fully cropped conditions.

Similarly, threshold-based differentiation of denser vegetation (class “forest”) from less dense vegetation (class “open vegetation”) caused some confusion (compare Tab. 2), which may be avoided by inserting density classes (tasselled cap greenness). However, distinguishing naturally vegetated areas from human-appropriated land as the basis for subsequent analyses was successful. For visualization purposes, we aggregated classes to five overarching categories: vegetation, bare, anthropogenic, water, and fire affected, where the latter includes pixels that were mapped as recently burned on one of the dates. Figure 2 illustrates the change processes during the investigation period.

By comparing the discrete classifications of 2002 and 2013, we were able to identify a net increase of agriculturally used areas by approximately 430 km² (+24%) between 2002 and 2013, added to by an increase in settlement area of 197 km² (+55%, Fig. 2). Mostly as a result

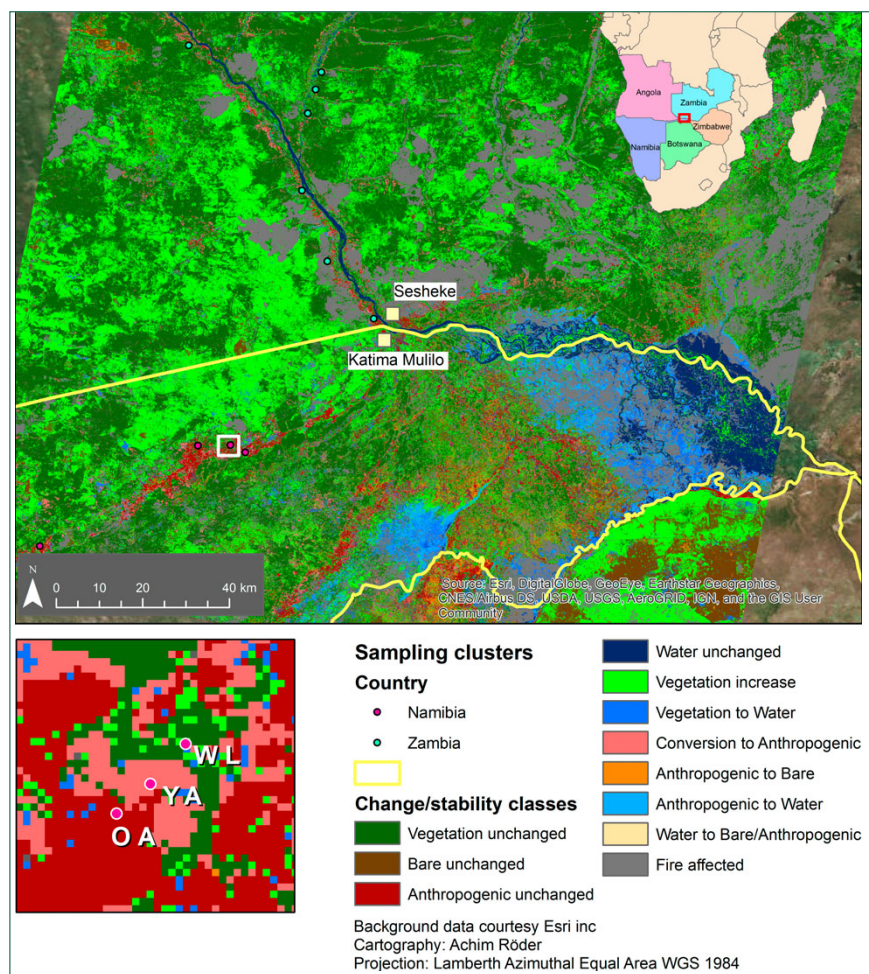


Figure 2: Change map summarizing major change processes between 2002 and 2013. The zoom subset corresponds to the white frame in the main map and illustrates placement of ground sampling points (WL = woodland, YA = young agricultural field, and OA = old agricultural field) for one sampling cluster.

of several preceding years of high precipitation, a significant increase in both surface water (226 km², 224%) and seasonal flooding (1,143 km², 107%) was observed. The increase of the anthropogenic class (cropland, settlement) was mainly at the expense of natural vegetation, while a number of previously existing fields were lost because of the expansion of water and flooded areas. Additional analyses of the location of the agricultural fields with auxiliary data showed their concentration next to newly created roads and settlements. The results of the classification appeared useful for selection of the sampling clusters for the following soil survey.

Differences in soil organic carbon and soil nutrient concentrations between woodland and agriculture

Compared to woodland, old agricultural fields had lower concentrations of total N ($p < 0.001$) and SOC ($p < 0.001$) in the topsoil (0–10 cm depth, Fig. 3a and Fig. 3d) in both study areas. Woodland had the largest element concentrations, followed by young agricultural fields and old agricultural fields (Tab. 1). However, the differences in total N and SOC between young agricultural fields and woodland were nonsignificant. Despite the difference in SOC concentrations between young and old agricultural fields ($p = 0.03$), we observed no significant difference in N concentrations between these land-use types. Comparing total SOC stocks down to 100 cm depth showed that woodlands had higher SOC stocks compared to young ($p = 0.02$) and old agricultural fields ($p = 0.01$) in the Namibian study area (Tab. 1 and Fig. 3e). The mean difference (agriculture minus woodland) in SOC stocks revealed a loss of $9.6 (\pm 8.9 \text{ SD}) \text{ Mg C ha}^{-1}$ (relative loss of $19.6 \pm 18.4 \text{ SD } \%$), with differences ranging from losses of $18.5 \text{ Mg C ha}^{-1}$ (relative loss of 38.6%) to 0.9 Mg C ha^{-1} (relative loss of 1.9%). The difference in SOC stocks between young and old agricultural fields in this study area was not significant. For the study area in Zambia, we did not observe significant differences in total SOC stocks between woodland and agriculture. However, SOC stocks in old agricultural fields were lower compared to those in young

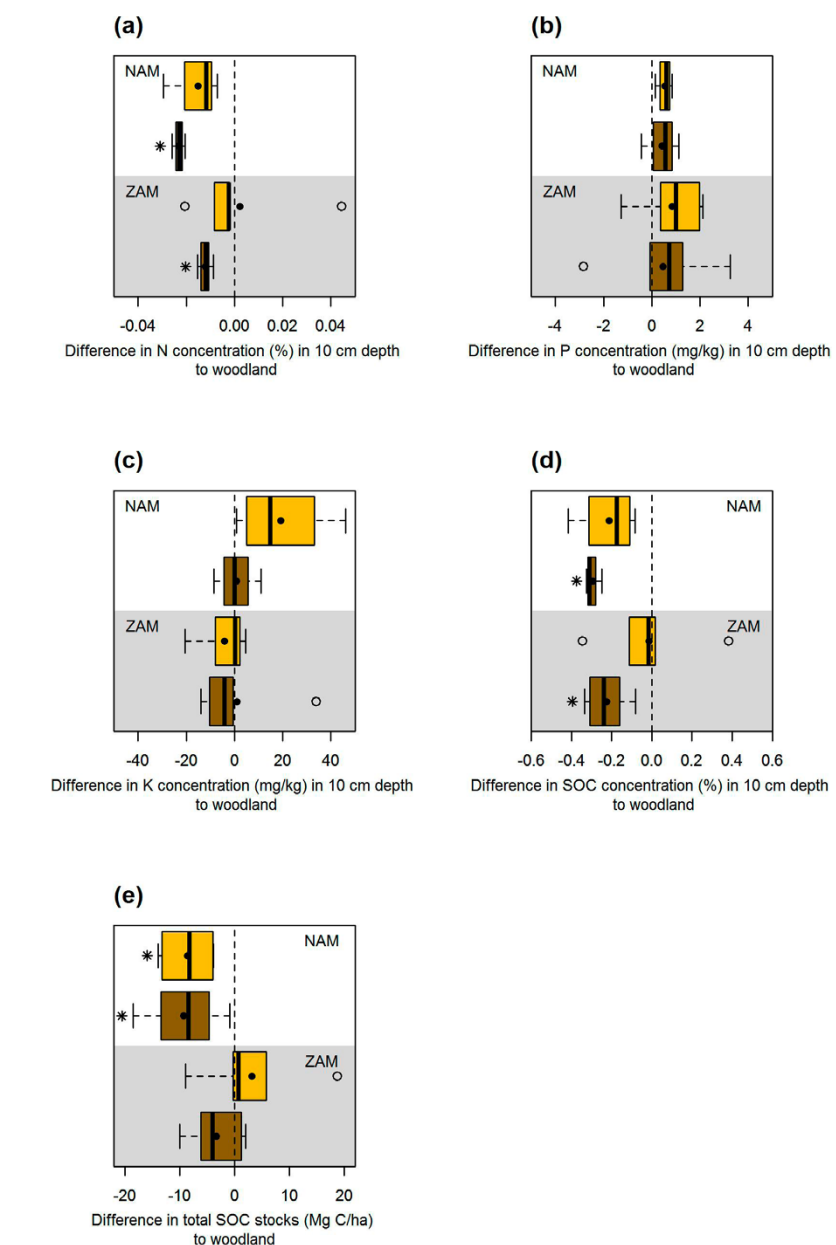


Figure 3: Difference of young agricultural fields (yellow box) and old agricultural fields (brown box) to woodland (agriculture minus woodland) in concentrations (%) of N (a), P (b), K (c), and SOC (d) in the topsoil (0–10 cm) and in total SOC stocks (Mg C ha⁻¹) to 100 cm depth (e) in NE Namibia (NAM) and SW Zambia (ZAM). In the boxplots, the box shows the 25th and 75th percentiles, the median (black line), the mean (black dot), and outliers (circles), and the whiskers extend to the data extremes that do not exceed 1.5 times the interquartile range. Asterisks show significant differences between agriculture and woodland ($p < 0.05$, LME models and Tukey's test).

fields ($p = 0.02$). Plant-available P and exchangeable K concentrations did not significantly differ between agriculture and woodland in either study area (Tab. 1, Fig. 3b and Fig. 3c). However, the majority of the sampled agricultural fields in both study areas had higher plant-available P concentrations compared to woodland, and the majority of sampled soils of young agricultural fields in the Namibian study area had higher exchangeable K concentrations than did woodland soil.

Predicted maize yields

The maize yields estimated with QUEFTS ranged from 470 kg ha⁻¹ to 1,300 kg ha⁻¹ (Tab. 3) and did not statistically differ between soils of woodland and young or old agricultural fields in either study area, nor did the predicted yields differ between the study areas. However, the maize yields predicted for old agricultural fields tended to be 15.2% (SD 28.2%) lower than those for woodland in both study areas ($p = 0.07$). Moreover, in the

Table 3: Predicted maize yields (means \pm SD) calculated with the QUEFTS model (Janssen et al., 1990) for soils of woodland (WL), young agricultural fields (YA), and old agricultural fields (OA); differences in potential maize yields between the soils of each land-use type per study area (NAM in NE Namibia and ZAM in SW Zambia); and the soil nutrients indicated to be yield limiting.

Study Area	Predicted Maize Yield (kg ha ⁻¹)			Differences in Maize Yields (kg ha ⁻¹) between Land-Use Types			Yield-Limiting Nutrients		
	WL (n = 4 for NAM, n = 7 for ZAM)	YA (n = 6 for NAM, n = 6 for ZAM)	OA (n = 4 for NAM, n = 7 for ZAM)	OA-WL (n = 3 for NAM, n = 5 for ZAM)	YA-WL (n = 4 for NAM, n = 5 for ZAM)	OA-YA (n = 4 for NAM, n = 3 for ZAM)	WL (n = 4 for NAM, n = 7 for ZAM)	YA (n = 6 for NAM, n = 6 for ZAM)	OA (n = 4 for NAM, n = 7 for ZAM)
NAM	1,017 (104)	908 (255)	744 (256)	-333 (189)	-119 (82)	-208 (104)	P (n = 4) ^a	N (n = 3), P (n = 3)	N (n = 3), P (n = 1)
ZAM	945 (239)	924 (231)	784 (158)	-77 (189)	-27 (254)	63 (228)	N (n = 6), K (n = 1)	N (n = 5), K (n = 1)	N (n = 6), P (n = 1)

^an indicates the number of sampling plots for which the given nutrient is yield limiting.

Namibian study area, we predicted lower yields for five of the six young agricultural plots than for woodland. QUEFTS indicated that in the Namibian study area, P was the element that was most limiting plant growth in eight sampling plots; in the other six plots, N was the yield-limiting element (Tab. 3). In the Zambian area, for all except three sampling plots N was the element that limited maize yield.

Discussion

Land-use change detection

We applied a hybrid classification methodology comprising a maximum likelihood-based classification and the calculation of a tasselled cap transformation to evaluate change processes in one Landsat full frame. Difficulties in class assignment resulted primarily from known effects in rural, savannah-type systems with distinct wet and dry season cycles. A lack of wet-season imagery and the utilization of natural building materials often result in spectral ambiguities and make it hard to distinguish settlements, bare ground, and agricultural plots; similarly, differentiation of vegetation in discrete cover classes is complicated as a result of strong inter-annual variations.

However, the ability to distinguish between natural and human-dominated classes overall was found to be reliable and allowed for a stratification of the subsequent ground-based soil analyses. Our results confirm the conversion of woodland to agricultural or settlement areas as the dominant conversion process, and

spatial analyses indicating the proximity to roads or other settlements as a major determinant agree with similar studies (e.g., Röder et al., 2015). Of particular interest is the impact of precipitation patterns preceding the 2013 period, which caused the significant extension of seasonal flooding areas and of Lake Liambezi, with an associated disappearance of all agricultural fields that had still been there in the earlier period. Again, this is a temporal phenomenon with process length corresponding to mid-term precipitation variation, and which might be better resolved using continuous time series (see for instance Schneibel et al., 2018).

Impact of land-use change on soil organic carbon concentrations and stocks

Our findings of reduced SOC concentrations and stocks (Fig. 3d and Fig. 3e) in low-input agriculture following the conversion from woodland is typical (Ribeiro Filho et al., 2015; Walker & Desanker, 2004). The observed total SOC stock losses (100 cm depth) in the Namibian study area, which ranged from 38.6% to 1.9% with an average loss of 19.6% (\pm 18.4 SD), correspond well with the losses reported by the few other studies on the conversion to low-input agriculture in the semi-arid ecosystems of sub-Saharan Africa (Demessie et al., 2013; Luther-Mosebach, 2017; Touré et al., 2013; Walker & Desanker, 2004). A chronosequence study on an Andic Paleustalfs in southern Ethiopia showed that the conversion from forest to agriculture and agroforestry reduced

SOC stocks by 12% to 43% after 12 to 50 years of cultivation (Demessie et al., 2013). In central Senegal on Luvisols and Arenosols, total SOC stocks were 27% to 37% lower in groundnut fields with an age up to 25 years compared to savannahs (Touré et al., 2013). On Ferralsols in central Malawi (Walker & Desanker, 2004), SOC stocks were 40% lower in agricultural fields with a maximum age of 30 years than in miombo woodlands. In NE Namibia, Luther-Mosebach (2017) also reported lower SOC stocks in old agricultural fields compared to woodland, with differences in SOC stocks between agriculture and woodland being a maximum of 39%. Nevertheless, they observed little to no differences between woodland and slash-and-burn agriculture. All the above-listed losses in SOC stock have been reported for a soil depth of 100 cm. Possible reasons for the SOC losses are the reduced inputs of organic material in agricultural soils and enhanced mineralization rates as a result of soil disturbances from tillage. Burning of woodland may also have affected SOC levels by charcoal inputs, thermally induced SOC losses, and soil-heating effects on the chemical composition of soil organic matter. There is no consensus across studies, however, on the direction of fire effects on SOC levels (Eckmeier et al., 2007; Fynn et al., 2003).

Impact of land-use change on soil nutrient concentrations

The observed decline in total soil N concentrations in old agricultural fields following the conversion from woodland

(Fig. 3a) is consistent with the literature (Demessie et al., 2013; Giardina et al., 2000a; Ribeiro Filho et al., 2015). The decreases in total N are parallel to the SOC losses, which is typical, as the dynamics of both organic N and SOC are linked to the decomposition of soil organic matter. Crop harvesting without nutrient returns through fertilization may also have contributed to the N losses (Giller et al., 1997). Moreover, fire-related N losses due to volatilization and leaching, and limited N inputs from ash may have played a role. The N inputs from ash are generally low, as large proportions of N volatilize during biomass burning (Giardina et al., 2000a). Moreover, soil heating may volatilize part of the soil N and may transform non-plant-available N into mineral N readily available to plants (Giardina et al., 2000b), which is easily lost by plant uptake and leaching during rain events.

Though it was not statistically significant, in both study areas plant-available P increased in old and young agricultural fields (Fig. 3e), and exchangeable K concentrations increased in young agricultural fields in the Namibian study area; this tendency may be related to P and K fertilization from ash input caused by biomass burning (Giardina et al., 2000a,b). Increases in plant-available P after biomass burning could, besides ash fertilization, be related to mineralization from organic P. Plant uptake and the fact that K is highly soluble (Juo & Manu, 1996) may explain why we did not observe an increase in K concentrations in old agricultural fields. Similar to our results, Walenfang et al. (2015) observed an increase in soil K in young fields, but a decline with extended duration of agricultural use after slash-and-burn in SE Angola.

Impact of land-use change on predicted maize yield

The trend (not statistically significant) of lower predicted maize yields for old agricultural fields than for woodland (Tab. 3) indicates that soil fertility may decline with the long-term continuation of low-input arable farming. The decrease in predicted maize yields on the majority of the sampled old agricultural fields corresponds with the observed losses in SOC and total N concentrations for this

land-use type (Fig. 3a and Fig. 3d). Our maize yields that ranged from 470 kg ha⁻¹ to 1,300 kg ha⁻¹ were in line with predictions by Pröpper et al. (2015), who predicted potential maize yields between 800 and 1,200 kg ha⁻¹ for soils in the Kavango region that were selected by farmers as preferential for agricultural use. Yield data from field measurements on sandy soils in the region are hard to find; the only published study that we found reported average maize yields of 500 kg ha⁻¹ for nonfertilized field trials on aeolian sands in western Zambia (Cornelissen et al., 2013). The predictions by QUEFTS most likely overestimate actual yields, as QUEFTS does not consider the impacts of soil water availability and management practices (Tittonell et al., 2008). As is typical for sandy soils of the semi-arid tropics (Buresh et al., 1997; Giller et al., 1997), we found that soil N and soil P were the main yield-limiting nutrients (Tab. 3). Our result that soil P was yield limiting in half of the sampling plots in Namibia whereas in Zambia soil P was only yield limiting in one sampling plot, corresponds with the much lower concentrations of soil P in the Namibian study area compared to the Zambian study area (Tab. 1).

Conclusion

We found that between 2002 and 2013 the area under agricultural use increased by 24%, mainly at the expense of natural vegetation (i.e., woodland). This land-use conversion resulted in losses in SOC and total N and tended to increase of plant-available P. The SOC losses were most pronounced in the Namibian study area, where SOC stocks were reduced by 9.6 Mg C ha⁻¹ (~20%) over a depth of 100 cm. Furthermore, our findings show that long-term agricultural use tends to reduce soil fertility; predicted maize yields declined by ~15% (average for both study areas) when comparing soils of old agricultural fields and woodland, this reduction is attributable to the observed losses in SOC and total N.

Results from our remote sensing analyses showed that even in areas with heterogeneous patterns of land use, in par-

ticular in areas dominated by small-scale agriculture, broad change patterns may reliably be identified and used to stratify subsequent analyses. We showed that classic change analysis is a suitable tool to achieve this, whereas more enhanced methods, such as the recently developed CAT transformation (Frantz et al., 2017; Hird et al., 2016) would be well suited to illustrate more subtle processes by making use of full time series rather than a limited number of dates. Furthermore, combining remote sensing techniques to detect land-use changes followed by the selection of sampling clusters with stratified random sampling and field sampling has the advantage that it enables the extrapolation of change effects over entire landscape units.

Acknowledgements

The research was carried out in the framework of SASSCAL and was sponsored by the German Federal Ministry of Education and Research (BMBF) under promotion numbers 01LG1201C and 01LG1201M. We thank Robert Mukuya for his assistance with the fieldwork.

References

- Blake, G.R. & Hartge, K.H. (1986) Bulk density. *Methods of soil analysis, part 1: Physical and mineralogical methods* (ed. by A. Klute), pp. 363–375. Soil Science Society of America, Madison, WI.
- Buresh, R.J., Smithson, P.C. & Hellums, D.T. (1997) Building soil phosphorus capital in Africa. *Replenishing soil fertility in Africa* (ed. by R.J. Buresh, P.A. Sanchez, & F. Calhoun), pp. 111–149. Soil Science Society of America and American Society of Agronomy, Madison, WI.
- Chomba, B.M., Tembo, O., Mutandi, K., Mtongo, C.S. & Makano, A. (2012) *Drivers of deforestation, identification of threatened forests and forest co-benefits other than carbon from REDD+ implementation in Zambia*. Ministry of Lands, Natural Resources and Environmental Protection, Lusaka, Zambia.
- Cornelissen, G., Martinsen, V., Shitumbanuma, V., Alling, V., Breedveld, G., Rutherford, D., Sparrevik, M., Hale, S., Obia, A. & Mulder, J. (2013) Biochar effect on maize yield and soil characteristics in five conservation farming sites in Zambia. *Agronomy*, **3**, 256–274.
- DeFries, R.S., Foley, J.A. & Asner, G.P. (2004) Land-use choices: Balancing human needs and ecosystem function. *Frontiers in Ecology and the Environment*, **2**, 249–257.

- Demessie, A., Singh, B.R. & Lal, R. (2013) Soil carbon and nitrogen stocks under chronosequence of farm and traditional agroforestry land uses in Gambo District, Southern Ethiopia. *Nutrient Cycling in Agroecosystems*, **95**, 365–375.
- Dijkshoorn, J.A. (2003) *SOTER database for Southern Africa (SOTERSAF)*. ISRIC-World Soil Information, Wageningen, the Netherlands.
- Eckmeier, E., Gerlach, R., Skjemstad, J.O., Ehmann, O. & Schmidt, M.W.I. (2007) Minor changes in soil organic carbon and charcoal concentrations detected in a temperate deciduous forest a year after an experimental slash-and-burn. *Biogeosciences*, **4**, 377–383.
- Ellert, B.H. & Bettany, J.R. (1995) Calculation of organic matter and nutrients stored in soils under contrasting management regimes. *Canadian Journal of Soil Science*, **75**, 529–538.
- Frantz, D., Röder, A., Stellmes, M. & Hill, J. (2016) An operational radiometric Landsat preprocessing framework for large-area time series applications. *IEEE Transactions on Geoscience and Remote Sensing*, **54**, 3928–3943.
- Fynn, R.W.S., Haynes, R.J. & O'Connor, T.G. (2003) Burning causes long-term changes in soil organic matter content of a South African grassland. *Soil Biology and Biochemistry*, **35**, 677–687.
- Giardina, C., Sanford, R., Döckersmith, I. & Jaramillo, V. (2000a) The effects of slash burning on ecosystem nutrients during the land preparation phase of shifting cultivation. *Plant and Soil*, **220**, 247–260.
- Giardina, C.P., Sanford Jr., R.L. & Döckersmith, I.C. (2000b) Changes in soil phosphorus and nitrogen during slash-and-burn clearing of a dry tropical forest. *Soil Science Society of America Journal*, **64**, 399–405.
- Giller, K.E., Cadisch, G., Ehaliotis, C., Adams, E., Sakala, W.D. & Mafongoya, P.L. (1997) Building soil nitrogen capital in Africa. *Replenishing soil fertility in Africa* (ed. by R.J. Buresh, P.A. Sanchez, & F. Calhoun), pp. 151–192. Soil Science Society of America and American Society of Agronomy.
- Hansen, M.C., Potapov, P. V., Moore, R. et al. (2013) High-resolution global maps of 21st-century forest cover change. *Science*, **342**, 850–854.
- Helmke, P.A. & Sparks, D.L. (1996) Lithium, sodium, potassium, rubidium, and cesium. *Methods of soil analysis, part 3: Chemical methods* (ed. by D.L. Sparks), pp. 551–574. Soil Science Society of America, Inc., Madison, WI.
- Hird, J.N., Castilla, G. McDermid G.J.B., Bueno, I.T. (2016) A simple transformation for visualizing non-seasonal landscape change from dense time series of satellite data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, **9**, 3372–3383.
- IUSS Working Group WRB (2014) *World reference base for soil resources 2014, update 2015. International soil classification system for naming soils and creating legends for soil maps*. World Soil Resources Reports No. 106. FAO, Rome.
- Janssen, B.H., Guiking, F.C.T., Van der Eijk, D., Smaling, E.M.A., Wolf, J. & Van Reuler, H. (1990) A system for quantitative evaluation of the fertility of tropical soils (QUEFTS). *Geoderma*, **46**, 299–318.
- Jayne, T.S., Chamberlin, J. & Headey, D.D. (2014) Land pressures, the evolution of farming systems, and development strategies in Africa: A synthesis. *Food Policy*, **48**, 1–17.
- Jones, A., Breuning-Madsen, H., Brossard, M. et al. (2013) *Soil atlas of Africa*. European Commission, Publications Office of the European Union, Luxembourg.
- Juo, A.S.R. & Manu, A. (1996) Chemical dynamics in slash-and-burn agriculture. *Agriculture, Ecosystems and Environment*, **58**, 49–60.
- Kauth, R.J. & Thomas, G. (1976) The tasseled cap—A graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. *LARS Symposia*, p. 159.
- Kim, D.G., Thomas, A.D., Pelster, D., Rosenstock, T.S. & Sanz-Cobena, A. (2016) Greenhouse gas emissions from natural ecosystems and agricultural lands in sub-Saharan Africa: Synthesis of available data and suggestions for further research. *Biogeosciences*, **13**, 4789–4809.
- Kleinman, P.J.A., Pimentel, D. & Bryant, R.B. (1995) The ecological sustainability of slash-and-burn agriculture. *Agriculture, Ecosystems & Environment*, **52**, 235–249.
- Kuo, S. (1996) Phosphorous. *Methods of soil analysis, part 3* (ed. by D.L. Sparks), pp. 869–919. SSSA Book Series 5. Soil Science Society of America, Inc., Madison, WI.
- Lenth, R.V. (2016) Least-squares means: The R package lsmeans. *Journal of Statistical Software*, **69**, 1–33.
- Luther-Mosebach, J. (2017) *Soil carbon stocks and dynamics in soils of the Okavango Catchment*, vol. 89. Hamburger Bodenkundlichen Arbeiten, Hamburg, Germany.
- Mendelsohn, J., Jarvis, A., Roberts, C. & Robertson, T. (2002) *Atlas of Namibia: A portrait of the land and its people*. David Philip Publishers, Cape Town, South Africa.
- Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E. & Wulder, M.A. (2014) Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, **148**, 42–57.
- Petit, C., Scudder, T. & Lambin, E. (2001) Quantifying processes of land-cover change by remote sensing: Resettlement and rapid land-cover changes in south-eastern Zambia. *International Journal of Remote Sensing*, **22**, 3435–3456.
- Pinheiro, J., Bates, D., DebRoy, S., Sarker, D. & R Core Team (2012) *nlme: Linear and nonlinear mixed effects models*. R package version 3.1-131. <https://cran.r-project.org/package=nlme>
- Pröpper, M., Gröngroft, A., Finckh, M., Stirn, S., Cauwer, V. De, Lages, F., Masamba, W., Murray-Hudson, M., Schmidt, L., Strohbach, B. & Jürgens, N. (2015) *The future Okavango – Findings, scenarios and recommendations for action*. Hamburg, Germany.
- R Core Team (2017) *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. <https://www.r-project.org/>
- Ribeiro Filho, A.A., Adams, C., Manfredini, S., Aguilar, R. & Neves, W.A. (2015) Dynamics of soil chemical properties in shifting cultivation systems in the tropics: A meta-analysis. *Soil Use and Management*, **31**, 474–482.
- Richards, J.A. (2013) *Remote sensing digital image analysis*. Springer, Berlin.
- Röder, A., Pröpper, M., Stellmes, M., Schneibel, A. & Hill, J. (2015) Assessing urban growth and rural land use transformations in a cross-border situation in Northern Namibia and Southern Angola. *Land Use Policy*, **42**, 340–354.
- Röder, A., Stellmes, M., Frantz, D. & Hill, J. (2018) Remote sensing-based environmental assessment and monitoring – generation of operational baseline and enhanced experimental products in southern Africa. This volume.
- Sattari, S.Z., van Ittersum, M.K., Bouwman, A.F., Smit, A.L. & Janssen, B.H. (2014) Crop yield response to soil fertility and N, P, K inputs in different environments: Testing and improving the QUEFTS model. *Field Crops Research*, **157**, 35–46.
- Schneibel, A., Röder, A., Stellmes, M. & Frantz, D. (2018) Long-term land use change analysis in south-central Angola. Assessing the trade-off between major ecosystem services with remote sensing data. This volume.
- Stephene, N. & Lambin, E. (2001) A dynamic simulation model of land-use changes in Sudano-Sahelian countries of Africa (SALU). *Agriculture, Ecosystems & Environment*, **85**, 145–161.
- Tittonell, P., Vanlauwe, B., Corbeels, M. & Giller, K.E. (2008) Yield gaps, nutrient use efficiencies and response to fertilisers by maize across heterogeneous smallholder farms of western Kenya. *Plant and Soil*, **313**, 19–37.
- Touré, A., Temgoua, E., Guenat, C. & Elberling, B. (2013) Land use and soil texture effects on organic carbon change in dryland soils, Senegal. *Open Journal of Soil Science*, **3**, 253–262.
- Walker, S.M. & Desanker, P.V. (2004) The impact of land use on soil carbon in miombo woodlands of Malawi. *Forest Ecology and Management*, **203**, 345–360.
- Wallenfang, J., Finckh, M., Oldeland, J. & Revermann, R. (2015) Impact of shifting cultivation on dense tropical woodlands in southeast Angola. *Tropical Conservation Science*, **8**, 863–892.
- Wulder, M.A., Masekd, J.G., Cohen, W.B., Loveland, T.R. & Woodcock, C.E. (2012) Opening the archive: Hot free data has enabled the science and monitoring promise of Landsat. *Remote Sensing of Environment*, **121**, 2–10.
- Yang, J. & Prince, S.D. (2000) Remote sensing of savanna vegetation changes in Eastern Zambia 1972–1989. *International Journal of Remote Sensing*, **21**, 301–322.

References [CrossRef]

- Blake, G.R. & Hartge, K.H. (1986) Bulk density. *Methods of soil analysis, part 1: Physical and mineralogical methods* (ed. by A. Klute), pp. 363–375. Soil Science Society of America, Madison, WI.
- Buresh, R.J., Smithson, P.C. & Hellums, D.T. (1997) Building soil phosphorus capital in Africa. *Replenishing soil fertility in Africa* (ed. by R.J. Buresh, P.A. Sanchez, & F. Calhoun), pp. 111–149. Soil Science Society of America and American Society of Agronomy, Madison, WI.
- Chomba, B.M., Tembo, O., Mutandi, K., Mtongo, C.S. & Makano, A. (2012) *Drivers of deforestation, identification of threatened forests and forest co-benefits other than carbon from REDD+ implementation in Zambia*. Ministry of Lands, Natural Resources and Environmental Protection, Lusaka, Zambia.
- Cornelissen, G., Martinsen, V., Shitumbanuma, V., Alling, V., Breedveld, G., Rutherford, D., Sparrevik, M., Hale, S., Obia, A. & Mulder, J. (2013) Biochar effect on maize yield and soil characteristics in five conservation farming sites in Zambia. *Agronomy*, **3**, 256–274. [CrossRef](#)
- DeFries, R.S., Foley, J.A. & Asner, G.P. (2004) Land-use choices: Balancing human needs and ecosystem function. *Frontiers in Ecology and the Environment*, **2**, 249–257. [CrossRef](#)
- Demessie, A., Singh, B.R. & Lal, R. (2013) Soil carbon and nitrogen stocks under chronosequence of farm and traditional agroforestry land uses in Gambo District, Southern Ethiopia. *Nutrient Cycling in Agroecosystems*, **95**, 365–375. [CrossRef](#)
- Dijkshoorn, J.A. (2003) *SOTER database for Southern Africa (SOTERSAF)*. ISRIC-World Soil Information, Wageningen, the Netherlands.
- Eckmeier, E., Gerlach, R., Skjemstad, J.O., Ehrmann, O. & Schmidt, M.W.I. (2007) Minor changes in soil organic carbon and charcoal concentrations detected in a temperate deciduous forest a year after an experimental slash-and-burn. *Biogeosciences*, **4**, 377–383. [CrossRef](#)
- Ellert, B.H. & Bettany, J.R. (1995) Calculation of organic matter and nutrients stored in soils under contrasting management regimes. *Canadian Journal of Soil Science*, **75**, 529–538. [CrossRef](#)
- Frantz, D., Röder, A., Stellmes, M. & Hill, J. (2016) An operational radiometric Landsat preprocessing framework for large-area time series applications. *IEEE Transactions on Geoscience and Remote Sensing*, **54**, 3928–3943. [CrossRef](#)
- Fynn, R.W.S., Haynes, R.J. & O'Connor, T.G. (2003) Burning causes long-term changes in soil organic matter content of a South African grassland. *Soil Biology and Biochemistry*, **35**, 677–687. [CrossRef](#)
- Giardina, C., Sanford, R., Døckersmith, I. & Jaramillo, V. (2000a) The effects of slash burning on ecosystem nutrients during the land preparation phase of shifting cultivation. *Plant and Soil*, **220**, 247–260. [CrossRef](#)
- Giardina, C.P., Sanford Jr., R.L. & Døckersmith, I.C. (2000b) Changes in soil phosphorus and nitrogen during slash-and-burn clearing of a dry tropical forest. *Soil Science Society of America Journal*, **64**, 399–405. [CrossRef](#)
- Giller, K.E., Cadisch, G., Ehaliotis, C., Adams, E., Sakala, W.D. & Mafongoya, P.L. (1997) Building soil nitrogen capital in Africa. *Replenishing soil fertility in Africa* (ed. by R.J. Buresh, P.A. Sanchez, & F. Calhoun), pp. 151–192. Soil Science Society of America and American Society of Agronomy.
- Hansen, M.C., Potapov, P. V., Moore, R. et al. (2013) High-resolution global maps of 21st-century forest cover change. *Science*, **342**, 850–854. [CrossRef](#)
- Helmke, P.A. & Sparks, D.L. (1996) Lithium, sodium, potassium, rubidium, and cesium. *Methods of soil analysis, part 3: Chemical methods* (ed. by D.L. Sparks), pp. 551–574. Soil Science Society of America, Inc., Madison, WI.
- Hird, J.N., Castilla, G. McDermid G.J.B., Bueno, I.T. (2016) A simple transformation for visualizing non-seasonal landscape change from dense time series of satellite data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, **9**, 3372–3383. [CrossRef](#)
- IUSS Working Group WRB (2014) *World reference base for soil resources 2014, update 2015. International soil classification system for naming soils and creating legends for soil maps*. World Soil Resources Reports No. 106. FAO, Rome.
- Janssen, B.H., Guiking, F.C.T., Van der Eijk, D., Smaling, E.M.A., Wolf, J. & Van Reuler, H. (1990) A system for quantitative evaluation of the fertility of tropical soils (QUEFTS). *Geoderma*, **46**, 299–318. [CrossRef](#)
- Jayne, T.S., Chamberlin, J. & Headey, D.D. (2014) Land pressures, the evolution of farming systems, and development strategies in Africa: A synthesis. *Food Policy*, **48**, 1–17. [CrossRef](#)
- Jones, A., Breuning-Madsen, H., Brossard, M. et al. (2013) *Soil atlas of Africa*. European Commission, Publications Office of the European Union, Luxembourg.
- Juo, A.S.R. & Manu, A. (1996) Chemical dynamics in slash-and-burn agriculture. *Agriculture, Ecosystems and Environment*, **58**, 49–60. [CrossRef](#)
- Kauth, R.J. & Thomas, G. (1976) The tasselled cap--A graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. *LARS Symposia*, p. 159.
- Kim, D.G., Thomas, A.D., Pelster, D., Rosenstock, T.S. & Sanz-Cobena, A. (2016) Greenhouse gas emissions from natural ecosystems and agricultural lands in sub-Saharan Africa: Synthesis of available data and suggestions for further research. *Biogeosciences*, **13**, 4789–4809. [CrossRef](#)
- Kleinman, P.J.A., Pimentel, D. & Bryant, R.B. (1995) The ecological sustainability of slash-and-burn agriculture. *Agriculture, Ecosystems & Environment*, **52**, 235–249. [CrossRef](#)
- Kuo, S. (1996) Phosphorus. *Methods of soil analysis, part 3* (ed. by D.L. Sparks), pp. 869–919. SSSA Book Series 5. Soil Science Society of America, Inc., Madison, WI.
- Lenth, R.V. (2016) Least-squares means: The R package lsmeans. *Journal of Statistical Software*, **69**, 1–33. [CrossRef](#)
- Luther-Mosebach, J. (2017) *Soil carbon stocks and dynamics in soils of the Okavango Catchment*, vol. 89. Hamburger Bodenkundlichen Arbeiten, Hamburg, Germany.
- Mendelsohn, J., Jarvis, A., Roberts, C. & Robertson, T. (2002) *Atlas of Namibia: A portrait of the land and its people*. David Philip Publishers, Cape Town, South Africa.
- Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E. & Wulder, M.A. (2014) Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, **148**, 42–57. [CrossRef](#)
- Petit, C., Scudder, T. & Lambin, E. (2001) Quantifying processes of land-cover change by remote sensing: Resettlement and rapid land-cover changes in south-eastern Zambia. *International Journal of Remote Sensing*, **22**, 3435–3456. [CrossRef](#)
- Pinheiro, J., Bates, D., DebRoy, S., Sarker, D. & R Core Team (2012) *nlme: Linear and nonlinear mixed effects models*. R package version 3.1-131. <https://cran.r-project.org/package=nlme>
- Pröpper, M., Gröngroft, A., Finckh, M., Stim, S., Cauwer, V. De, Lages, F., Masamba, W., Murray-Hudson, M., Schmidt, L., Strohbach, B. & Jürgens, N. (2015) *The future Okavango – Findings, scenarios and recommendations for action*. Hamburg, Germany.
- R Core Team (2017) *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. <https://www.r-project.org/>
- Ribeiro Filho, A.A., Adams, C., Manfredini, S., Aguilar, R. & Neves, W.A. (2015) Dynamics of soil chemical properties in shifting cultivation systems in the tropics: A meta-analysis. *Soil Use and Management*, **31**, 474–482. [CrossRef](#)
- Richards, J.A. (2013) *Remote sensing digital image analysis*. Springer, Berlin. [CrossRef](#)
- Röder, A., Pröpper, M., Stellmes, M., Schneibel, A. & Hill, J. (2015) Assessing urban growth and rural land use

- transformations in a cross-border situation in Northern Namibia and Southern Angola. *Land Use Policy*, **42**, 340–354. [CrossRef](#)
- Röder, A., Stellmes, M., Frantz, D. & Hill, J. (2018) Operational generation of baseline products for environmental assessment and monitoring based on optical remote sensing data. *This volume*. [CrossRef](#)
- Sattari, S.Z., van Ittersum, M.K., Bouwman, A.F., Smit, A.L. & Janssen, B.H. (2014) Crop yield response to soil fertility and N, P, K inputs in different environments: Testing and improving the QUEFTS model. *Field Crops Research*, **157**, 35–46. [CrossRef](#)
- Schneibel, A., Röder, A., Stellmes, M. & Frantz, D. (2018) Long-term land use change analysis in south-central Angola. Assessing the trade-off between major ecosystem services with remote sensing data. *This volume*.
- Stephene, N. & Lambin, E. (2001) A dynamic simulation model of land-use changes in Sudano-Sahelian countries of Africa (SALU). *Agriculture, Ecosystems & Environment*, **85**, 145–161. [CrossRef](#)
- Tittonell, P., Vanlauwe, B., Corbeels, M. & Giller, K.E. (2008) Yield gaps, nutrient use efficiencies and response to fertilisers by maize across heterogeneous smallholder farms of western Kenya. *Plant and Soil*, **313**, 19–37. [CrossRef](#)
- Touré, A., Temgoua, E., Guenat, C. & Elberling, B. (2013) Land use and soil texture effects on organic carbon change in dryland soils, Senegal. *Open Journal of Soil Science*, **3**, 253–262. [CrossRef](#)
- Walker, S.M. & Desanker, P.V. (2004) The impact of land use on soil carbon in miombo woodlands of Malawi. *Forest Ecology and Management*, **203**, 345–360. [CrossRef](#)
- Wallenfang, J., Finckh, M., Oldeland, J. & Revermann, R. (2015) Impact of shifting cultivation on dense tropical woodlands in southeast Angola. *Tropical Conservation Science*, **8**, 863–892. [CrossRef](#)
- Wulder, M.A., Masekd, J.G., Cohen, W.B., Loveland, T.R. & Woodcock, C.E. (2012) Opening the archive: Hot free data has enabled the science and monitoring promise of Landsat. *Remote Sensing of Environment*, **121**, 2–10. [CrossRef](#)
- Yang, J. & Prince, S.D. (2000) Remote sensing of savanna vegetation changes in Eastern Zambia 1972–1989. *International Journal of Remote Sensing*, **21**, 301–322. [CrossRef](#)