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Assessment of Land Degradation in Semi-Arid Tanzania
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Using Remote Sensing to Inform the Sustainable Development Goal 15.3

Master Thesis

Submitted: June 22, 2020

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Study degree: M.Sc. Geography

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Abstract

Monitoring land degradation (LD) to inform the sustainable development goal (SDG) 15.3.1 ("proportion of land that is degraded over total land area") is key to ensure a more sustainable future. At the moment, there are only default medium-resolution datasets available to assess LD in Tanzania. They do not reflect local characteristics and cannot help to target exposed areas spatially.

Therefore, this thesis adapts local datasets in interplay with high-resolution imagery to find out how much land is degraded in the semi-arid districts of Kiteto and Kongwa (KK). This approach follows the recommended practice by the United Nations Convention to Combat Desertification (UNCCD). It incorporates freely available datasets like Landsat and uses open-source software in interplay with cloud-computing. Human-induced LD was assessed using the Normalized Difference Vegetation Index (NDVI) correcting it for precipitation variability with the Rain Use Efficiency (RUE). Based on Mann-Kendall's tau and using the mean NDVI per growing season, evidence suggests that 18.9 % of the study area degraded, while further 14.9 % showed early signs of decline. The land cover map by the Regional Centre for Mapping of Resource for Development (RCMRD) spans the years 2000-2018. It showed that in 9.3 % of the area there was land cover change and in 7.8 % degradation could be found. Forests lost a quarter of their initial size and grasslands decreased by 9.5 %, while croplands increased by over 30 %. Lastly, soil organic carbon (SOC) declined in 8.6 % of the study area. A total of 2.6 million tons SOC was lost, most of it in grass- and forestlands.

In total, 16.4 % of the area in KK districts is degraded for the LDN baseline period. The LD rose to 27.7 % for the first monitoring period in 2019. Thus, the regional baseline for the SDG 15.3.1 indicator is set and the first target period assessed. In order to verify these results and make the assessment more precise, an additional collection of SOC data and larger scale ground truth is necessary. To nonetheless achieve LD neutrality until 2030, spatial planning should focus on hotspot areas and implement sustainable land management practices.

Acknowledgment

I would like to thank both my supervisors PD Dr. Olena Dubovyk and Dr. Francis Muthoni who supported me throughout the whole time of this project with helpful advice and good ideas for the thesis. Furthermore, I'd like to thank Dr. Gohar Ghazaryan who also gave me helpful advice and helped when I was struggling with Google Earth Engine.

In addition, I am grateful that the Africa RISING project supported me logistically and financially on my trip to Tanzania and the IITA, which hosted me during that time. The fieldwork could not have taken place without the help of Frank, our driver, and especially Kigosi, who was of great help to assess the land degradation on the ground. Moreover, I would like to thank all the farmers and local people in Kongwa district, who helped us find the plots, allow us to go on their land, or helped us to get the car out a sandbank. Besides, PROMOS funded my flight to Tanzania and also supported my stay financially, thanks for that.

All the friends that spend time with me in the library, Cafete, Mensa, or elsewhere deserve a great thanks as well. Without you, this time would have been not as much fun as it was.

In particular, I would like to thank all the people, which helped me during my writing process, gave me feedback to the work, and made the thesis that way better. Special thanks, to my sister, Magdalena, who had to deal with my inability, to correctly use the comma, in English.

And then there is the special person that supported me during all these days, read the chapters and is probably as much an expert in land degradation as I am now. Vera, thanks for all the support and listening to all my talking about this thesis.

Lastly, I would like to thank my family, as I would not be here without them.

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List of Abbreviations

AA	Adapted Approach
CBD	Convention on Biological Diversity
CCI	Climate Change Initiative
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station Data
DA	Default Approach
ELD	Economic of LD Initiative
ESA	European Space Agency
FAMD	Factor Analysis of Mixed Data
FAO	Food and Agriculture Organization
GDP	Gross Domestic Product
GEE	Google Earth Engine
GEF	Global Environment Facility
GIS	Geographic Information System
GLADA	Global Assessment of Lands Degradation and Improvement
GLASOD	Global Assessment of Soil Degradation
GLADIS	Global Land Degradation Information System
GPG	Good Practice Guidance
ha	Hectare
IPCC	Intergovermental Panel on Climate change
IPBES	Intergovernmental Platform on Biodiversity and Ecosystem Services
KK	Kiteto and Kongwa
LADA	Land Degradation Assessment in Drylands
LC	Land Cover
LD	Land Degradation
LDN	Land Degradation Neutrality
LP	Land Productivity
LULC	Land Use and Land Cover
m	Meter
MCA	Multiple Correspondence Analysis
MEA	Millennium Ecosystem Assessment
MODIS	Moderate Resolution Imaging Spectroradiometer
NAFORMA	National Forest Resources Monitoring and Assessment of Tanzania Mainland
NDVI	Normalized Difference Vegetation Index

NPP	Net Primary Productivity
PCA	Principal Component Analysis
pp	Percentage Point
RCMRD	Regional Centre for Mapping of Resource for Development
SDG	Sustainable Development Goal
SLM	Sustainable Land Management
SOC	Soil Organic Carbon
SSA	Sub-Sahara Africa
t	ton
UNCCD	United Nations Convention to Combat Desertification
WOCAT	World Overview of Conservation Approaches and Technologies

1. Introduction

Land degradation (LD) is a global problem and affects mankind, their livelihoods as well as nature. Studies suggest that up to 3.2 billion people live and depend on degraded lands (Le, Nkonya, & Mirzabaev, 2016) and that approximately a quarter of the worlds lands are affected by LD (Bai, Dent, Olsson, & Schaepman, 2008). Poor people, who often rely on agriculture, are most vulnerable to LD (Barbier & Hochard, 2018; IPBES, 2018). Lost ecosystem services due to land use and land cover (LULC) change and LD account for up to 10.5 trillion US$ loss per year, which is about a sixth of the world's gross domestic product (GDP) (Stewart, 2015, p. 51). Hansen et al. (2013) state, that in the first 12 years of the new century 2.7 million square kilometers (km^2) were deforested worldwide. Furthermore, biodiversity is expected to decline globally with the greatest losses in sub-Saharan Africa (SSA) because of LD (IPBES, 2018, p. 547 ff.). Projections suggest that lower productivity in the face of climate change will drive LULC change globally and that population growth in combination with a changing dietary will have enormous influence on agriculture and thus LD (IPCC, 2019, chp. 4: p. 45). It is for these reasons that, the world community introduced the sustainable development goal (SDG) 15.3, which aims to "restore degraded land [...] and strive to achieve a LD-neutral world", highlighting the global importance of this issue (UN, 2015; UNCCD, 2013).

Tanzania is a hot spot of LD with more than half of its area showing signs of degradation (Le et al., 2016). It has the highest annual forest area net loss in East Africa and the fifth highest worldwide (FAO, 2015, p. 14 ff.). The cost of LD has been summed up to 2.3 billion US$ annually in the first ten years of the new millennium (Kirui, 2016). Tanzania is one of only ten countries in Africa where total wealth per capita has declined. This means, losses in renewable natural capital such as forests and agricultural lands were higher than the economic growth at the same time (Lange, Wodon, & Carey, 2018, p. 44). Furthermore, despite high economic growth rates in the last years and a decrease in the poverty rate, the absolute number of poor people actually grew due to a growing population (World Bank, 2019a). The projected population will double from around 45 million people in 2012 to nearly 90 million in 2035, it is thus likely that this trend will carry on (NBS, 2018b, p. 55 ff.).

Three forth of the total labor force, mostly rural people, are working in and depend on the agricultural sector, which is accountable for about 30 % of the GDP (FAO & NBS, 2020). While the agricultural area increased in the last years, the output per hectare (ha) decreased, both in annual and perennial crops, even though fertilizer consumption quadrupled in the same time (NBS, 2018a, p. 101/112). This trend is also reflected in the steady growth of the amount of undernourished people, who account for more than 30 % of the population (FAO, 2019). All these factors lead to a critical situation: The population is growing while the agricultural productivity is stagnating and the economic dependency on natural goods is still high. Consequences of this dilemma are on the one hand a persisting pressure on land and thus a probable conversion of natural into cultivated land in the coming years. On the other hand, food security of poor people is at risk and in the coming years, in the face of climate change, new insecurities are likely to arise (Wheeler & von Braun, 2013). This holds especially true for the rural semi-arid central districts of Kiteto and Kongwa (KK).

Agricultural intensification and sustainable land management (SLM) are key to halt and reverse LD (Kimaro et al., 2015; Liniger et al., 2019; Orr et al., 2017). One major constraint that prevents action is the lack of spatial information of LD (Kimaro et al., 2015). In contrast to the laborious fieldwork, remote sensing offers the unique opportunity to assess vast areas over long time spans consistently (Bai et al., 2008; Dubovyk, 2017; Le et al., 2016). Unfortunately, the estimates of LD-maps are often inconsistent concerning the affected area and of coarse spatial resolution (Gibbs & Salmon, 2015; IPCC, 2019). For example, LD estimates for Tanzania differ from a few percent to half of the country (Bai et al., 2008; Landmann & Dubovyk, 2014; Le et al., 2016). Differing definitions and methods, but also lack of appropriate data are the main reasons for this (Caspari, van Lynden, & Bai, 2015; IPBES, 2018).

In the course of the SDG implementation, standard methods to assess LD were introduced, making reports more comparable (Sims et al., 2019). Even though the Tanzanian national LD-neutrality report to inform the SDG 15.3 follows these guidelines, it only assesses LD for the first ten years of the century and mainly uses global default data with a medium spatial resolution (URT, 2018b). Therefore, it is important to overcome research gaps and use spatial high-resolution data to better inform the SDG 15.3 (Anderson, Ryan, Sonntag, Kavvada, & Friedl, 2017). Thus, this thesis follows the United Nations Convention to Combat Desertification (UNCCD) methodological guidelines and implements them up to the current year.

Hence, this thesis aims to adapt the Good Practice Guidance by UNCCD with high-resolution images and local data sources to assess LD in Kiteto and Kongwa districts of Central Tanzania. The research questions of this thesis are therefore:

- How much land is degraded in Kiteto and Kongwa?
- Where are hotspots of land degradation in the study area?
- How do the individual sub-indicators affect LD?
- Does the use of high resolution data improve delineation of LD compared to global default data?

2. State of the Art

Land degradation as a conceptual framework had diverging definitions in the past. Recently the emphasis shifted from the status to processes of LD. Thus, the LD estimates also differ substantially, depending on the framework used. Therefore, this chapter will clarify key concepts and discuss global and local estimates as well as drivers of LD. Furthermore, SLM as a way to avoid and reduce LD will be introduced and the impact of SLM will be analyzed.

2.1. Definitions and Concepts of Land Degradation

In order to fight LD internationally, 25 years ago the world community proclaimed the United Nations Convention to Combat Desertification (UNCCD). It aims at the reduction of LD and desertification — at that time the focus was on drylands — in all affected countries (UNCCD, 1994). Since then, the UNCCD had the leading role in establishing the definition of land degradation on an international level. In 1994 LD was defined as the

> reduction or loss of the biological or economic productivity and complexity of rainfed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from land uses or from a process or combination of processes, including processes arising from human activities and habitation patterns (UNCCD, 1994, Article 1).

After the Earth Summit in Rio de Janeiro 1992 and the following proclamation of the UNCCD, the Millennium Ecosystem Assessment (MEA) once more shed light on the ongoing degradation of ecosystems and ecosystem services as well as on the change humankind brought to the nature in the last decades (MEA, 2005). Further international organizations like the Intergovernmental Panel on Climate Change (IPCC) or the Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES) have their own context specific definitions. For example, the latter rather characterizes LD as a loss of ecosystem services than a loss of biological productivity by defining it as the "the state of land which results from the persistent decline or loss in biodiversity and ecosystem functions and services that cannot fully recover unaided within decadal time scales" (IPBES, 2018, p. 4). Thus, IPBES can be seen in a line with the Millennium Ecosystem Assessment (MEA), which also focused on the long-term loss of ecosystem services (MEA, 2005).

Several global commitments have been agreed upon to "halt and reverse land degradation": For example, the Aichi Biodiversity Targets aim, among other goals, to restore at least 15 % of degraded ecosystems (CBD, 2010). The Bonn Challenge on Forest Landscape Restoration wants to bring back 350 million ha of the world's deforested and degraded lands into restoration by 2030

(IUCN, 2020). Most recently and significantly, the Sustainable Development Goals (SDGs) were agreed upon. In particular SDG target 15.3 aims to "combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land-degradation-neutral world by 2030" (UN, 2015, p. 27). The world community thereby introduced a global goal for a more sustainable use of its ecosystems and made LD a focus again. The concept of land degradation neutrality (LDN) was introduced to enhance a more efficient policy response to land degradation. It represents a paradigm shift in land management as well as in planning policies. LDN was adopted as a target for SDG 15 and is defined as "a state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystems" (UNCCD, 2015a, p. 8). In order to achieve SDG target 15.3 and thereby create a LD neutral world, the indicator 15.3.1 "Proportion of land that is degraded over total land area" was agreed upon by the UNSTATS (2017, p.16). The concept tries to preserve the functioning of the ecosystem, while also allowing development to be realized. In doing so, no net loss will be achieved and possible degradation can be counteracted by rehabilitation measures (Cowie et al., 2018).

2.1.1. SDG 15.3 indicator reporting

LDN should be monitored in order to track the possible progress of staying neutral or even exceed the target. If it is not possible to avoid new degradation, then it is necessary to reverse past degradation in order to stay balanced or even to enhance the land-based capital (Cowie et al., 2018). To assess the performance of LDN, a baseline is required in order to have a reference which the progress can be compared to. The baseline year (or t_0) was set to be 2015, the year when the UNCCD adopted LDN (UNCCD, 2015a). This LDN-baseline, which defines the initial value, is relevant because it focuses on the goal of achieving LDN in a short time span of 15 years. Thus, neutrality is measured through change rather than the land degradation status. Land conditions — especially in drylands — are temporally highly variable due to climate fluctuations. Therefore, the baseline is computed as the average of the period leading up to t_0 (2000–2015). The indicators are then re-measured in regular time intervals (e.g. every five years, t_1) leading to t_n (2030) and change is used to monitor the progress to accomplish LDN (Orr et al., 2017, p. 43 ff.).

This arbitrarily set baseline date is not without controversy though: For example, the MEA used the concept of the potential natural area to assess the fraction of the earth surface already converted. It shows that most conversion or degradation happened before 1950 in the western world, whereas much of the transformation in the tropics will happen till 2050. Still, the fraction converted worldwide will be between 60 and 70 % on average at that point of time (MEA, 2005, p. 32). Thus, countries, which converted their ecosystems centuries ago, could be assumed to be much less ambitious than developing countries, which just began their transformation in the last decades (IPBES, 2018, p. 8/61 ff.). Therefore, the challenge to achieve LDN will probably lie in countries such as Tanzania which still hold great areas of natural landscapes (World Bank, 2019b, p. 25 f.) and are facing an enormous rise in population (NBS, 2018b, p. 55 ff.).

The neutrality mechanism should be realized in administrative boundaries or biophysical domains and should also be scalable, so that results can be reported nationally. Land use decision-makers need to plan gains within unique land types in order to counterbalance anticipated losses. Still, it is important that losses in conservation areas should not be counterbalanced by gains in land types for production and, in general, it is advised to avoid LD rather than trying to restore degraded lands (Orr et al., 2017, p. 49 ff.).

Monitoring of Land Degradation

Land degradation is usually context-specific, making it difficult for a single indicator to grasp the full complexity of the state of land and soil (Gilbey, Davies, Metternicht, & Magero, 2019). Indicators for LD are proxies to monitor the relevant processes and drivers that reflect natural capital and ecosystem services. The metrics behind the indicators should be universally applicable and interpretable as well as quantifiable with existing datasets. Hence, UNCCD chose three indicators that they were already using for reporting and that are proxies for change in land-based capital (UNCCD, 2013): Land cover (LC) change, land productivity (LP) and carbon stocks with their respective metrics of physical land cover, net primary productivity (NPP) and soil organic carbon (SOC). These three different metrics measure changes in distinct yet highly relevant ways and are thus complementary. NPP captures fast changes in ecosystem functions using earth observation-derived vegetation indices, while SOC indicates slower changes resulting from biomass alterations and is an indicator for resilience. LC reports changes in vegetation cover and, to an extent, reflects the land use as well. Transitions between LC classes (e.g. from forest to cropland) can be evaluated as positive or negative, depending also on the national context (Orr et al., 2017, p. 95 ff.). Besides these three indicators, countries are encouraged to supplement further indicators that are relevant in the national context. These can include metrics which are already used for other SDGs as well as national indicators reflecting e.g. biodiversity or metal contamination.

In order to form the land degradation indicator, the three sub-indicators have to be aggregated. Improvements in one indicator cannot compensate losses in others, as they are complementary and not additive. Thus, the “one-out, all-out” approach is used: Even if one indicator shows signs of decline and the others are positive, land is deemed to be degraded (Cowie et al., 2018, p. 32 f.). However, the "one-out, all-out" approach is becoming increasingly conservative as new indicators are added. Therefore, it is also possible to use additional indicators as supplement to farther inform LDN, whereby they are not influencing LDN reporting. However, this approach of aggregation is not set upon scientific basis (Orr et al., 2017).

It is necessary to verify the output of the LD monitoring with local or national data and experts. Through the nature of the application of global indicators, and sometimes datasets as well, it is clear that the results will at times not be applicable. The verification process should include the reflection of the output with ground truth, should check if land degradation classification is compatible with local definitions and see whether other parts of the ecosystems, which were not monitored, were affected. Furthermore, false positives or false negatives need to be identified. The former can happen if the metrics show positive trends, while actually undesirable processes are happening. For example, when bushes are encroaching in grass lands, the NPP is rising, while a loss of ecosystem services is happening for grazing animals and wildlife. On the other hand, the change from high intensity agriculture to extensive farming can lead to a lower risk of erosion and degradation, while concurrently the NPP is significantly lower (Orr et al., 2017, p. 102 f.).

SDG indicator 15.3.1 is based on the degradation or improvement per land area, thus assessing LDN in a binary way and per area. Yengoh et al. (2015) on the other hand recommends to also include the cause of degradation as well as the type and degree. Counterbalancing severe degradation, e.g. deforestation of a primary forest, with small improvements of the same area could sum up to an underestimation of land degradation. In addition, it could lead to further degradation practices, if offsetting with low conservation areas is cheaper than avoiding LD (Orr et al., 2017, p. 103).

Further information on the specific computation of the three indicators can be found in the methods chapter 3.2.

2.2. Estimates of Land Degradation

There were numerous studies in the last decades that tried to map the extent of LD on a global (Bai et al., 2008; Ivits & Cherlet, 2016; Le et al., 2016; Nachtergaele, Biancalani, & Petri, 2011; Oldeman, Hakkeling, & Sombroek, 1991) as well as on a local scale (Dubovyk, 2017; García et al., 2019). Even though several different approaches and indicators were used (e.g. X. Cai, Zhang, & Wang, 2011; Oldeman et al., 1991), the most relevant studies applied remote sensing techniques and investigated the degrading processes via land productivity. As already mentioned in chapter 2.1.1, these approaches differ in their underlying definitions, methods and thus also in their results.

2.2.1. Global Assessments

The first attempt to map human-induced LD globally was done by the Global Assessment of Soil Degradation (GLASOD). The land degradation assessment was based on expert opinions on type, extent, degree and cause of LD and focused rather on soil than on vegetation conditions. GLASOD shed a first light on LD and concluded, that about 2 billion ha of land, roughly 15 % of the total, had been degraded since the mid-twentieth century (Oldeman et al., 1991). Since the appraisal was mainly based on expert opinion, it was largely subjective. Furthermore, the estimates were very coarse, spanning over entire regions, hence making local assessments unreliable. Despite the low spatial resolution, it covered over more than 40 years of LD in the 20th century. Although the GLASOD approach was used later by others (e.g. MEA, 2005), there was no update whatsoever (Caspari et al., 2015, p. 21).

It took over 15 years for the next relevant global assessment of LD, this time using remote sensing and measuring vegetation productivity. The Food and Agriculture Organization's (FAO) Global Assessment of Land Degradation and Improvement project (GLADA) used the Normalized Difference Vegetation Index (NDVI) to quantify human-induced LD on a global scale for the years 1981–2003. In this assessment, a correction was applied to cater for climatic influences (Bai et al., 2008). The GLADA project defines land degradation as the long-term decline in ecosystem function and productivity and hence follows the MEA (2005) framework. According to GLADA, 24 % of the world's terrestrial surface was degraded, 16 % improved in the same time and 1.5 billion people depended on degraded land. In contrast to the common believe that LD is mainly happening in dry lands, Bai et al. (2008) found that 78 % of the degraded lands lie in humid regions and the correlation between LD and the aridity index is low.

Similar to GLADA, Le et al. (2016) investigated biomass-productivity on a global scale. NDVI was not only corrected for variations in precipitation, but also atmospheric fertilization. Even though Bai et al. (2008) & Le et al. (2016) used the same data in nearly the same time period, their results differed significantly. Due to the amended methodology 29 % of the global land surface was found degraded while only 3 % improved (Le et al., 2016). Also, the number of people living on degraded lands doubled from 1.5 to 3.2 billion although both used 2007 as the reference year.

The Land Degradation Assessment in Drylands (LADA) project was launched and executed by the FAO during the period 2006–2010. Locally, it draws on tools for the assessment of SLM (chapter 2.4), while globally it established the Global Land Degradation Information System (GLADIS) which assesses the *status* and *trends* of ecosystem goods and services (Nachtergaele et al., 2011). The *status* thereby represented the capability to provide ecosystem services at a certain moment, while the *trend* was defined as the ongoing change in the land. In contrast to the preceding studies, GLADIS had a more holistic view and encompassed indicators such as biomass, soil health, water and biodiversity, but also included the economic productivity and social and cultural services. Combining the LD *status* and *trend*, Nachtergaele et al. (2011) found that 33 % of the global land surface was subject to LD, with up to 45 % in the poorest countries. Similar to Bai et al. (2008) semi-arid areas were not among the worst affected and were even improving. However, these results were contrary to the LADA paradigm.

The third edition of the World Atlas of Desertification (Cherlet et al., 2018, p. 114 ff.) introduced an adapted the methodology of the land productivity mapping. Based on the work by Ivits, Cherlet, Mehl, and Sommer (2013) and Ivits and Cherlet (2016), not only the long term NDVI trend between the years 1999 and 2013 was mapped, but also non-parametric and qualitative analyses were introduced. Results suggest that 20.4 % of earth's vegetated lands were subject to persistent decline and that especially range- and croplands were affected with 27 % and 20 % respectively. Africa was among the most influenced continents and nearly a fourth of the croplands showed signs of decrease.

To help countries monitor LD in a standardized way, UNCCD endorsed the Trends.Earth tool (Conservation International, 2019; Gonzalez-Roglich et al., 2019). It is a QGIS plugin that operates in conjunction with Google Earth Engine (GEE) to support data preparation, processing and visualization. It has a low entry barrier and can generate both the sub-indicators and SDG indicator 15.3.1. Thus, it helps countries to analyze the relevant data and prepare LDN reports (chapter 2.1.1).

For deeper insights, the report by Yengoh et al. (2015) is giving a good overview over the computation of LD using NDVI and its state of the art.

2.2.2. National and Sub-National Assessment in East Africa and Tanzania

Analyses of LD or LP on a global scale are not suitable for discerning local trends of LD. Furthermore, it should be clear that LP trends detected in e.g. India have different drivers and symptoms than in East Africa (Bai et al., 2008). Little is known about the vegetation dynamic trends and underlying causes in East Africa and especially Tanzania (Gichenje & Godinho, 2018; Landmann & Dubovyk, 2014; Wei et al., 2018). For example, the combination of "Tanzania*" AND "land degradation"AND "NDVI" OR "land productivity*" OR "remote sensing" just yielded two hits in the years from 2010 to 2019 on Web of Knowledge, both focusing on soil organic carbon (Bhargava, Vågen, & Gassner, 2018; Winowiecki, Vågen, & Huising, 2016).

According to Wei et al. (2018), which used the NDVI data from the early 1980s to 2013, there was no steady trend of vegetation productivity in East Africa. After an initial greening in the first 20 years, productivity declined in the new century. Over half of the study area was subject to browning, with around 14 % experiencing a significant decrease. A further report by GEF investigated NDVI change from the 1982 till 2015, correcting it for variations in precipitation and soil moisture availability. NDVI trends, which where corrected for soil moisture, showed significant declines in Central Tanzania. Contrarily, NDVI trends, which were corrected for precipitation variations, did not signal decline, but even positive trends. Tucker and Pinzon (2017) conclude that soil moisture provides a more consistent identification of areas which declined in LP. Landmann and Dubovyk (2014) investigated the vegetation productivity using NDVI in the years 2001–2011. Human-induced LD, detected by the cumulative rain use efficiency differences (CRD), made up only 2.1 % of the land area in East Africa. A sharp contrast to the global assessments, which estimated about 41 % (Bai et al., 2008) and 51 % (Le et al., 2016) of LD in Tanzania.

The most recent assessment for LD in Tanzania was done within the framework of UNCCD for the national LDN reporting (URT, 2018b). UNCCD default data were used and adopted with local land cover datasets. The report revealed that in the first ten years of the new century 22 % of the land area showed signs of decline in land productivity, while another 10 % was stressed. Forest were the LC class, which improved over average and had, with just 23 %, the lowest proportion of degradation. On the other hand, croplands as well as artificial and bare lands were unproportionately affected by LD, thus showing a clear gradient from natural to artificial landscapes (URT, 2018b, p. 31). With 17 % of the land improving, this estimate also displays different trends than the other studies. Furthermore, Tanzanian officials also conducted a LD assessment based on expert opinions of local government authorities (URT, 2018c, p.). Two-thirds of them reported an increased rate of deforestation. More than half of the interviewed reported medium LD while nearly a tenth reported extreme degradation.

Following these different studies, it should be out of question that there is an urgent need for a steadier approach to assess LD in Tanzania. First, there are no peer-reviewed national LD estimates for Tanzania published. Second, all LD estimates use spatial coarse-resolution imagery that cannot detect heterogeneous landscapes and small scale farms as they can be found in KK districts. Third, the most recent assessments date up to the year 2015, but there are no current appraisals available for the LDN monitoring period. Lastly, the studies use a wide variety of methods, timespans and sensors resulting in estimates between a few percents and half of the country. Therefore, it is important to examine LD in KK districts with high-resolution imagery in accordance with the guidelines by UNCCD and up to the most recent point in time possible.

2.3. Drivers of Land Degradation

Land degradation is shaped by both natural and human drivers. Generally there is a distinction in direct (proximate) drivers, which immediately affect LD, such as overgrazing or fires, and indirect or rather underlying drivers, like poverty or public policies (IPBES, 2018). As LD is normally multi-causal, many driving factors have inter-linkages and thus their effects cannot be clearly separated from each other (IPCC, 2019, chp. 4, p. 15).

Agricultural activities are the main driver of LD globally (IPBES, 2018; Mirzabaev, Nkonya, Goedecke, Johnson, & Anderson, 2016) and in Tanzania (URT, 2018b). Natural lands are being transformed into agricultural lands and thus degraded. Moreover, unsustainable land management leads to erosion of the land (TFS, 2015). For example, cropland increased by 75 % in just 10 years in Tanzania, while grasslands and forests were lost (FAO, 2019). Furthermore, 28 % of croplands are declining or are showing signs of decline, while only 14 % of forest are in the same degrading state (URT, 2018b). Key drivers of LD in Tanzania are inadequate land-use management and unsustainable farming practices as well as deforestation and inadequate livestock infrastructure. More than 80 % of the government officials found the two former to be a high or extreme problem. Thus, it seems as if the absence of land tenure and land use plans hinders people to apply conservation practices and that herdsman are owning large herds of livestock as a sort of protection against problems without considering the carrying capacity of the land (URT, 2018c, p. 37 ff.). The situation is further aggravated by an inadequate land use plan, unsustainable farming, inadequate livestock infrastructure as well as overgrazing. The most efficacious impacts of LD in Tanzania are, inter alia loss of biodiversity, decline of agricultural productivity and food insecurity (URT, 2018c, p. 47 ff.). Kirui (2016) for example found that unsustainable agriculture, overstocking of herds as well as charcoal and wood extraction are main drivers of LD in Tanzania and that mainly poverty. Mainly poverty, land tenure as well as weak policy in the environmental sectors are underlying drivers. This means, that probably more virgin land will be transformed into croplands in the future, because agricultural productivity is declining due to LD (Kiage, 2013).

The most important drivers for deforestation are high energy demand, poverty, population growth and unsustainable farming practices, while the most relevant impacts of deforestation are biodiversity loss, economic loss and soil erosion (URT, 2018c, p. 15 ff.). Similar to LD, this leads to a vicious circle: Poor people cannot afford expensive gas, so they use the cheapest alternatives such as firewood or charcoal, cut trees, which in turn leads to more poverty and less ecosystem services (URT, 2018c, p. 15 ff.). There is not much information on drivers of LD in KK in particular, but main drivers in central semi-arid Tanzania are as well agricultural activities, deforestation, overgrazing and soil fertility decline (URT, 2018b). The expansion of farms and the subsequent cutting of forests as well as overgrazing due to livestock influx from outside the region are further direct drivers of LD in the study area. Relevant indirect drivers are inter alia the illegal permission to cut forests and the increased population size (URT, 2018b, p. 33 ff.).

2.4. Sustainable Land Management

In the face of ongoing land degradation and the aim to reduce and avoid it in the near future, the question arises how this goal can be attained. A key to achieve LDN is with the sustainable management of land (Orr et al., 2017), which is also explicitly mentioned in SDG 15 as it is supposed to "[...] promote sustainable use of terrestrial ecosystems [and] sustainably manage forests [...]" (UN, 2015, p. 27). At the UN Earth Summit of 1992, SLM is defined as:

> The use of land resources, including soils, water, animals and plants, for the production of goods to meet changing human needs, while simultaneously ensuring the long-term productive potential of these resources and the maintenance of their environmental functions (UN, 1992, p. 4).

The definition of SLM broadened into a more holistic perspective on land management. It encompasses socio-cultural, economic and environmental aspects and tries to achieve long-term productive ecosystems (Schwilch, Liniger, & Hurni, 2014). SLM, through its holistic approach, can be an instrument to firstly achieve the objectives of the three Rio Conventions (UNCCD, UNFCCC & CBD), and secondly — as already mentioned — the SDG 15(.3). Furthermore, it can help achieve other SDGs such as "No Poverty", "Zero Hunger", "Good Health and Well-Being", "Clean Water and Sanitations" as well as "Climate Action" (Sanz et al., 2017, p. 34).

2.4.1. SLM Technologies

In the year 2005 the UN compiled SLM practices applied in drylands for the MEA-report, but the World Overview of Conservation Approaches and Technologies (WOCAT) was the first institution to systematically document and review SLM practices (Liniger et al., 2019; Schwilch et al., 2014; van Lynden, Verzandvoort, Schwilch, & Liniger, 2012). In doing so, it helped spread SLM-practices and also assessed its impact (Schwilch et al., 2014). In 2015 the SLM database was officially recognized by UNCCD as the primary source for the reporting of "Best Practices in SLM" (UNCCD, 2015b). The database encompasses over 2000 SLM practices from countries around the world and is intended to offer the possibility to build on and share local knowledge between practitioners globally (Liniger et al., 2019).

As already mentioned in chapter 2.2.1, the LADA project assesses and maps LD at different spatial scales and commenced in drylands. Recently, the focus on LD and drylands was lifted in favor of a broader understanding and a reorientation towards the assessment of SLM using WOCAT tools (FAO, 2011d). Especially the "Questionnaire for Mapping Land Degradation and Sustainable Land Management (QM)" by the FAO (2011e) gives a good overview over the range of possible on-ground-measurements of LD and SLM (Petri, Biancalani, Lindeque, & Nachtergaele, 2019). The questionnaire recommends identifying the SLM practice, assigning the most widespread technology name to it and link it to its appropriate conservation group and measure. Agronomic measures are usually associated with annual crops which are repeated routinely each season, are of short duration and not permanent. Vegetative measures on the other hand include the use of perennial grasses, shrubs, or trees and thus are of long duration and often lead to a change in slope profile. Structural measures are of long duration as well, but frequently require substantial inputs of labor when first installed. They are regularly carried out to control runoff and erosion and often lead to a change in slope profile as well. Management measures involve a fundamental change in land-use and frequently lead to improved vegetation cover (FAO, 2011e, p. 19 ff.). Finally, also the purpose of the SLM practice is under investigation. Whether it is to prevent LD from happening, to mitigate ongoing LD or to try to rehabilitate the land, when the LD is already beyond original and practical use.

2.4.2. Effects of SLM

Several studies demonstrate that SLM practices facilitate the prevention, reduction or reversion of land degradation and help to achieve LDN as well as promote other benefits (García et al., 2019; GEF, 2016; Gonzalez-Roglich et al., 2019; Liniger et al., 2019; Schwilch et al., 2014; van Lynden et al., 2012). For example, Gonzalez-Roglich et al. (2019) compared over 1000 WOCAT SLM-intervention sites and similar comparison locations globally with NDVI LP trends. The sites were grouped into their main purpose, the related SLM measure and group. Furthermore, they were classified into the main LD type address and whether its purpose was to prevent, reduce or restore LD. All sites, no matter if SLM practices were applied or not, experienced more LP improvement than decline. The SLM-sites significantly improved more and had less sites with signs of decline. Furthermore, sites with agronomic, vegetative and structural measures also outperformed the comparison sites, while management measures, often related to fallow land, did not show differences. Interestingly, sites which started applying SLM practices in the last ten years also did not differ to the comparison areas. This leads to the conclusion, that SLM practices need a longer time span for their effect to be realized. In addition, the performance of SLM-practices also depended on the initial state of the site. Restoration activities, indicating a severely degraded site and thus a lower initial baseline, had the greatest improvement and contrasting, prevention sites showed lower changes, still being significant (Gonzalez-Roglich et al., 2019).

Similar to this study, the Global Environment Facility (GEF) also investigated the effects of SLM based on remotely sensed data. They compared 1700 project sites with comparable areas nearby and assessed their performance with metrics derived by the SDG 15.3 indicators: Vegetation productivity, forest cover change and forest fragmentation (chapter 2.1.1). The results also show, that SLM interventions positively affect the mean NDVI, lessened the deforestation rate and increased the size of forest patches (GEF, 2016). Similar to Gonzalez-Roglich et al. (2019), the study also ascertained a time lag between the beginning of a SLM project and its effects, even though it was, with 5.5 years, half as long. Furthermore, the initial values also had great effects on the performance, indicating that degraded sites were more likely to improve significantly. Even though SLM practices seemed to lessen its effects closer to urban areas, overall they were able to mitigate and reverse LD processes and improve the land (GEF, 2016).

Additionally, the IPCC report showed, that most SLM practices can become financially profitable within three to ten years and that the application of SLM and the subsequent prevention of LD is more cost-effective than allowing land to degrade and then attempt to restore it (IPCC, 2019, chp. 3, p. 5 ff.). A study conducted in Tanzania found that the cost of inaction was 3.8 times higher than action (Kirui, 2016). Thus, every dollar invested would return nearly four dollars, especially, because the prospective yields would sink by a third, if no SLM practices were applied (Kirui, 2016, p. 634 f.). The Economic of Land Degradation Initiative (ELD) found out that the profit could amount up to seven dollars in Africa (ELD, 2015, p. 66 ff.).

2.4.3. Upscaling and Adoption of SLM

Still, the adoption of SLM is restricted to just few land users and practitioners (Sanz et al., 2017). In the study conducted by Kirui (2016), two thirds of the surveyed households adopted at least one SLM practice, but on the other hand, only under a fourth used more than one, which was significantly lower than in Malawi. In a study by Jambo, Groot, Descheemaeker, Bekunda, and Tittonell (2019), which also compared several districts in Tanzania and Malawi, KK had the lowest implementation of SLM. Furthermore, the two districts also scored lowest in perceived benefits and had the highest perceived constraints to SLM. The authors conclude, that SLM practices are adopted more frequently, with increased intrinsic and extrinsic motivation. Another study conducted in semi-arid Tanzania saw economics as a driving factor for farm decision and stated farmers to be very cost-sensitive adopting SLM practices. The adoption of these practices is generally limited (Mwaijande, 2017). Therefore, it is necessary for more people to adopt to SLM practices and to enable conditions for the upscaling of SLM (FAO, 2017; Sanz et al., 2017). There are several initiatives in Tanzania to promote SLM, e.g. the Kagera Transboundary Agro-ecosystem Management Project (FAO, 2017) or the Africa RISING program, which has a focus in the study area of Kiteto and Kongwa (Jambo et al., 2019; Mwaijande, 2017).

Ways to promote the upscaling of SLM include the consideration of social systems as well as the mainstreaming of SLM as an answer to tackle LD and climate change adaptation (URT, 2018b, p. 20). In addition, it is essential to assess the status of the land and use spatial targeting to effectively use the limited resources available for SLM. Often, insufficient monitoring and evaluation of LD hinders the favorable adoption of SLM practices (Kirui, 2016; Sanz et al., 2017).

3. Materials and Methods

The following chapter gives an overview over the study area in the districts Kiteto and Kongwa and also features the methods used in this thesis. The calculation of the LD indicator and its sub-indicators with remote sensing methods is described. The fieldwork and the subsequent statistical analysis of the collected data is provided.

3.1. Study Area

The study area is located in Kongwa and Kiteto districts which are located in Dodoma and Manyara regions of Central Tanzania respectively (figure 3.1).

3.1.1. Location and People

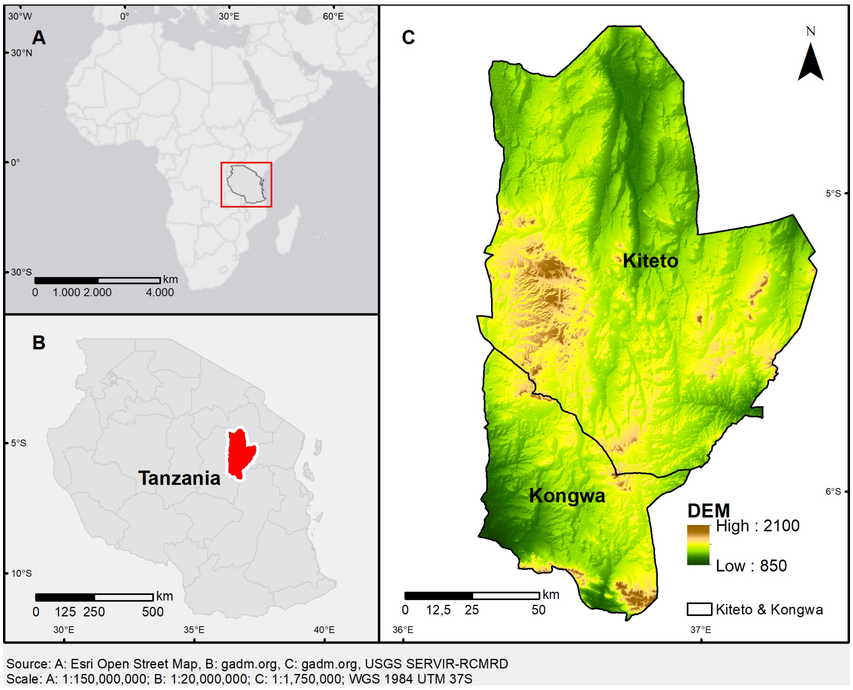


Figure 3.1.: Location of the study area in Central Tanzania superimposed over the digital elevation model.

The area of interest lies between latitude 4.4° and 6.4° South and longitude 36.2° and 37.4° East (figure 3.1). The elevation ranges between 850 meters and 2100 meters above sea level. It is inhabited by 554,642 people on a total of 17,102 km^2 (NBS, 2012, p. 20/196). Thus, the population density is 32 inhabitants/km^2 on average. While Kongwa has 78 inhabitants/km^2, Kiteto is much less populated with just 18 inhabitants/km^2, but having three times the size. The population growth of the past, which is a bit higher than the national average, and the expected growth till the year 2035, leads to the assumption that both districts could inhabit over a million people in the near future (NBS, 2018b).

The districts are very rural with nearly 90 % of the population living outside of urban areas (NBS, 2012). The literacy rate is low with approximately 40 % of the household heads being unable to read and write (Hillbur, 2013, p. 11). The mainstay of the majority of the people is agriculture, especially crop farming, but also to some extent lifestock keeping. Kiteto is a traditional home for pastoral communities. As agricultural areas are expanding, the conflict between farmers and pastoralists like the Masai is getting more tense (Hillbur, 2013, p. 9). For example, Kimaro et al. (2012, p. 24) found out that three-fourth of farmers in Kiteto stated that conflicts between the groups — like grazing on croplands and shortage of land for cropping — had been swelling for some time. The main road between the two biggest cities in Tanzania, Dar es Salaam and Dodoma, passes through the center of Kongwa and is lined with markets which belong to the major crop and cereal markets in Tanzania (Hillbur, 2013, p. 11 ff.).

3.1.2. Climate

In Tanzania, the tropical-savannah climate is prevailing, while the central highlands, due to its different topography, are rather influenced by arid to temperate climates. KK districts are on the eastern edge of the Hot-Arid-Steppe climate and have minor influences by a rather temperate climate with dry winters and hot summers (Beck et al., 2018). The rainy season in Tanzania in primarily driven by the movement of the Intertropical Convergence Zone. It moves southwards through Tanzania from October to December, hits the South of the country in January and February and then returns to the North in March, April and May. As a result, the North and

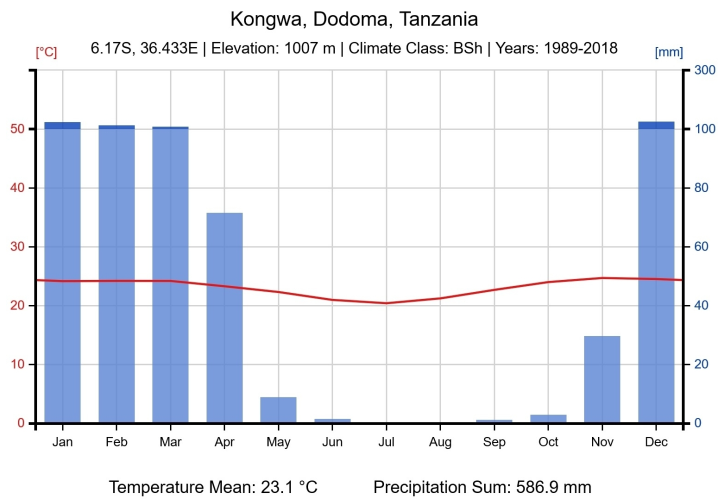


Figure 3.2.: Climate diagram of the city Kongwa. The rainy season is mainly from December till March and temperatures stay around 23° C throughout the year (climate-charts.net).

east of Tanzania experience two distinct rainy seasons; the short rains ("Vuli") from October to December and the long rains ("Masika") from March to May. In contrast, the South and West as well as the central part of Tanzania, including KK, undergo one wet season from October till April (McSweeny, New, & Lizcano, 2006). The southern area of KK experiences the peak of the rainy season from December to March (figure 3.2), while the northern part has a first peak in December and a second peak in March and April, though the precipitation pattern never really gets bimodal (Hillbur, 2013, p. 7). The average monthly temperature stays all year between 19° C and 25° C and the precipitation is roughly 600 mm a year, with interannual differences of 500 to 800 mm (Funk et al., 2015).

3.1.3. Land Use and Land Cover

The study area is part of the tropical grasslands, savannas and shrublands biom. It is dominated by the southern *Acacia-Commiphora* bushland and thicket ecoregions, while smaller parts in the (south)-east are covered by the dry *miombo* woodlands (Dinerstein et al., 2017). Thus, it was historically mostly covered by a mixture of tree- and grasslands. Tanzania, as well as KK, has seen an enormous land use and land cover change over the last decades. Forest was lost, while the agricultural area increased and the pressure of lifestock also intensified (FAO & NBS, 2020; Hansen et al., 2013; NBS, 2018a; URT, 2017). The most recent land cover maps suggest that just about 10 % of the study area is still covered by forests, while grass- and croplands occupy 44 % and 30 % respectively (figure 3.3). Another study, which compared satellite images from 1987 and 2010 found a decrease of the forest area by 30 percentage points (pp), while the area under cultivation increased by 31 pp. Kongwa was already quite transformed in 1987, with a quarter of the land under cultivation, but Kiteto made up for it, decreasing the forest area from 65 % to just 18 % in 23 years (Kimaro et al., 2012, p. 45 ff.).

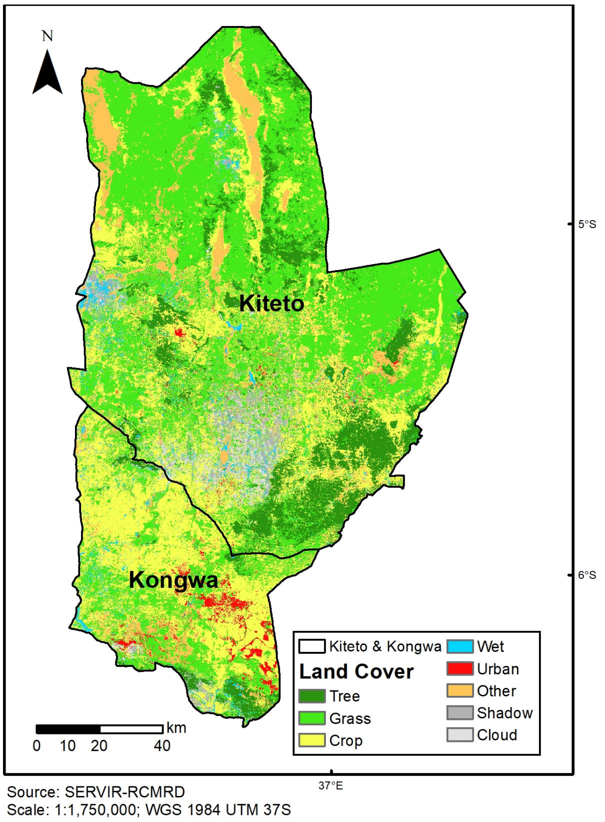


Figure 3.3.: The land cover classification for the year 2018.

The land is mainly covered by sandy soils with high infiltration rates and poor soil quality, which also results in low yields. Due to the arid conditions in the area, mainly drought-tolerant plants such as sorghum, bulrush millet and maize are grown (Timler et al., 2014, p. 24 ff.). As stated in the last national census of agriculture in 2008, average yields in both districts vary between half a ton and a ton for the main crops (URT, 2012a, 2012b). According to Kimaro et al. (2012, p. 63), these values did not increase significantly over the last 50 years and are way below the potential of 4.5 t per hectare. Deforested areas experienced a yield-decline by nearly 40 % over the first 23 years after LC change and then maintained their poor quality. Furthermore, the local farmers have an inadequate manure storage and deficient crop residue management. Manure is often stored open and plant residues are frequently removed from the fields and fed to livestock, decreasing the amount of organic matter available to the soil (Timler et al., 2014, p. 24 ff.).

Tanzania has the third largest livestock population in Africa and the study area is heavily influenced by grazers and browsers as well (NBS, 2018a, p. 117). Over 13 % of the national cattle herds are located in the two relevant regions and in the last 20 years the number of animals doubled in Tanzania. The trend of goat herds was even more drastic. It more than tripled in the same time to now 19 million. Manyara and Dodoma region together accumulate nearly 16 % of the nation's goats (FAO & NBS, 2020; URT, 2018a). Kiteto had appropriately 200,000 cattle in 2008, which is about twice the amount as in Kongwa (URT, 2012a, 2012b). Unfortunately, these animals are fed poorly in terms of fodder quality and quantity. This leads to lower animal productivity, affecting growth and production rates (Timler et al., 2014, p. 24 ff.). The study area is to some extent also part of protected areas. Several hills in Kongwa are forest reserves, while large parts of the northern Kiteto are Masai, Irkishbor and Talamai open areas as well as wildlife management areas (UNEP & IUCN, 2020).

3.2. Monitoring Indicators of Land Degradation with Remote Sensing Data

As already described in chapter 2.1.1, countries are encouraged to report their progress in achieving LDN. There are several ways to compute the SDG 15.3.1 (sub-)indicator: The UNCCD endorsed approach uses Trends.Earth and will be called the default approach (DA) in the following (Conservation International, 2019). My own approach is an adoption of the Good Practice Guidance (GPG) for SDG Indicator 15.3.1 by Sims et al. (2017) using the cloud-based Google Earth Engine to calculate the indices and will be called the adapted approach (AA) in the following. It should be noted that the differences between both approaches are concerning, inter alia, the datasets and the processing of these.

3.2.1. Land Productivity

Land productivity is described as “the biological productive capacity of the land” and is closely associated with NPP (chapter 2.1.1 and Clark et al.,2001) which can be measured with earth observation methods (Sims et al., 2017, p. 38). The NDVI is a widely used index to detect green leaf productivity and thus biomass or rather land productivity (Tucker, 1979). It uses the normalized difference in red and near-infrared wavelengths to detect changes in plant cover. As already mentioned in chapter 2.2.1, NDVI time series were extensively used to compute LD maps in several studies. The LP indicator consists of three distinct sub-indicators, namely Trend, State and Performance. In contrast to many studies published on LD, the recommended approach, which is based on Ivits et al. (2013) & Ivits and Cherlet (2016), also includes non-parametric and qualitative analyses (Sims et al., 2017, p. 39 ff.). While the Trend is based on statistical significant change of LP over time, State contrasts the present productivity level with historic observations of the same area. Finally, Performance compares local productivity to areas with similar soil and land cover conditions. These sub-indicators as well as the final indicator LP have to be calculated once for the baseline from 2000 till 2015 (t_o) and then again for the first intermediate time step in 2019 (t_1).

Cloud-computation has been become more widely applicable in the last years and especially in the case of remote sensing, it has found a wide use. Google Earth Engine is such a cloud-based platform to analyze geospatial data (Gorelick et al., 2017). With its huge data collection and the easy-to-use algorithms, it has seen a wide range of applications (Giuliani, Mazzetti, et al., 2020; Teich, Gonzalez Roglich, Corso, & García, 2019; **?**) including the above mentioned Trends.Earth (Conservation International, 2019). Due to the cloud-processing, users who do not have access to high-end computation devices, can analyze geospatial data as well. This is especially a benefit for people in poorer countries such as Tanzania (Mutanga & Kumar, 2019)

Trends.Earth uses the Moderate Resolution Imaging Spectroradiometer (MODIS) product *MOD-13Q1-coll6* for the NDVI calculation (Conservation International, 2019). It is a bi-weekly product with a spatial resolution of 250 m. Sims et al. (2017) recommend using the annual integrals of NDVI, but Trends.Earth rather works with the mean annual NDVI for simplicity reasons. To enhance the spatial resolution from 250 to 30 m, this study uses images by the Landsat-satellites, instead of MODIS. Landsat 5, 7 and 8 with their respective sensors Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and Operational Land Imager (OLI) scan the earth surface roughly every 16 days at the equator and record wavelengths in similar red and infrared spectrums (NASA & USGS, 2020). The trade-off is thus spatial versus temporal resolution. Due to the relatively small study area compared to the whole of Tanzania and the heterogenous landscape in KK with many small fields which are adjacent to grasslands, it is reasonable to make use of the Landsat time series.

In order to utilize the enhanced spatial resolution and continuity of more than one satellite mission, a spectral harmonization was applied. The newer OLI-sensor has improved calibration, signal-to-noise characteristics and spectral narrower wavebands. Thus, the two older sensors were harmonized with transformation functions using ordinary least squares regression to fit to the newest standard (Roy et al., 2016). As a further step to improve the image quality, the *fmask* was adopted to mask out clouds and cloud shadows (Foga et al., 2017; Zhu, Wang, & Woodcock, 2015). Generally, if images have cloud cover scores higher than 80 %, these were removed. Finally, the NDVI was calculated for each image and then the images of the same admission time were merged and clipped to the extent of the study area (figure 3.4).

It is recommended to constrain the observation period to the growing season in order to reduce the number of irrelevant assets for the computation and to enhance the quality of the time series (Sims et al., 2017, p. 46 ff.). For example, Fensholt et al. (2013) calculated the growing period as the point when the NDVI reaches 30 % of the yearly maximum for the first and last time each year. Thus, based on first, the precipitation pattern in KK (chapter 3.1.2), second, the local growing calendar for the main crops grown (URT, 2018a) and third, the usual month of the 30 % NDVI_{max}, the time of observations each year was set from November to June. Therefore, the time series for the year 2000 already starts in November 1999. Using Trends.Earh, there is no possibility to only apply the computation to the growing season, which is why, the DA uses the whole calendar year. In total, nearly 1050 Landsat images were used for the computation. Due to the large study area, the actual number of scenes per pixel is between 200 and 250. Thus, the temporal resolution is about 20 days on average.

Land Productivity Trend

The LP Trend measures the trajectory of change in productivity over time. It is calculated at the pixel level using a robust, non-parametric linear regressions model such as the Mann-Kendall significance test (Kendall, 1948; Mann, 1945), only considering changes which are greater than a p-value of 0.05 (Conservation International, 2019; Sims et al., 2019, 2017). Positive significant changes in NDVI would indicate an increasing productivity and negative scores signify decreasing productivity and thus also potential degradation. The baseline period till t_0 includes the years 2000–2015, while the comparing period involves the years 2011–2019. The eight most recent years of data are used in order to create a new distinct and significant time series as well as to be more responsive to present land conditions. Trend is the only LP indicator which is based

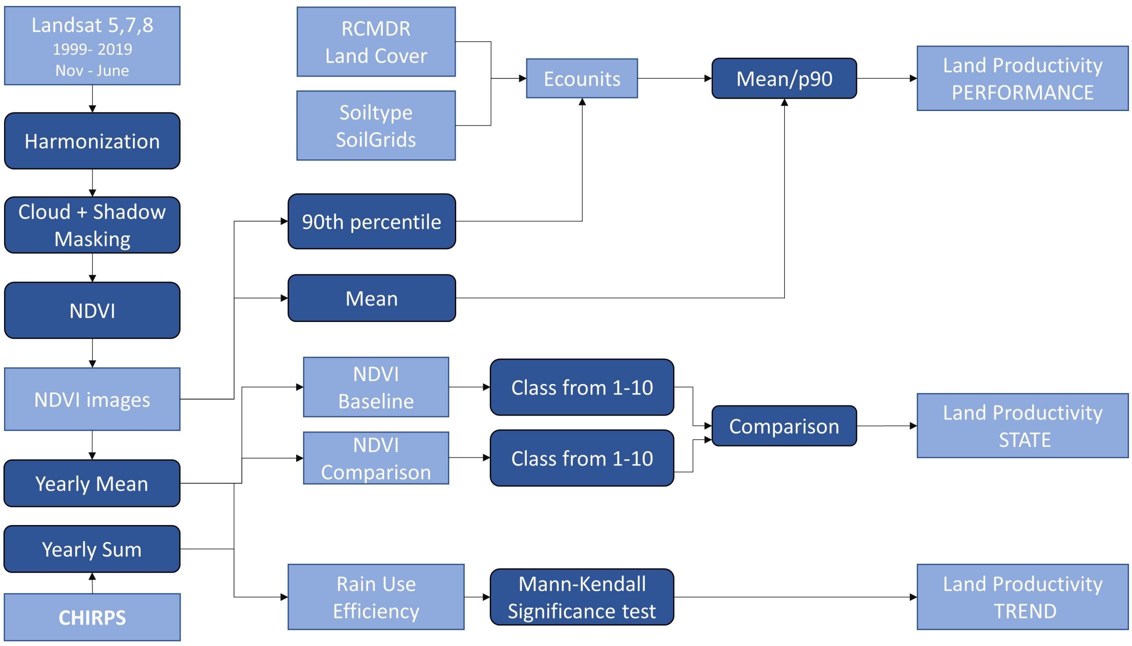


Figure 3.4.: Flowchart of the distinct steps to calculate the three land productivity sub-indicators Performance, State and Trend. Boxes in light blue depict products, while darker blue shows computation steps. Arrows symbolize the direction of the workflow (own graphic).

a statistical significant test and thereby is the most relevant indicator of the three (Sims et al., 2017, p. 48 ff.).

Variability of LP in ecosystems over time is influenced by various factors, such as temperature, nutrients and water availability. In order to detect the importance of human activities as drivers of LD, it is necessary to minimize the influence of climatic factors such as water availability. There are numerous approaches to tackle this problem, but choosing the right method can be challenging (Higginbottom & Symeonakis, 2014). As already mentioned in chapter 2.2.1, Bai et al. (2008) and Le et al. (2016) used the Rain Use Efficency (RUE) to separate the effect of human induced LD from climate variability. RUE is the ratio of the annual NPP to the annual precipitation (Le Houerou, 1984) and can improve the comparability between the years, if NPP is limited by water availability (Conservation International, 2019; Sims et al., 2017; Wessels, 2009). Thus, RUE helps to better assess the non-precipitation causes of LP change. The RUE calculated in the default as well as in the adapted approach is based on the mean annual NDVI divided by the yearly sum of the precipitation per pixel (figure 3.4). The rainfall dataset is derived by the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk et al., 2015).

Land Productivity State

The Land Productivity State indicator represents recent changes in LP compared to the baseline period. It was introduced because the Trend indicator often fails to recognize trajectories at the end of the time series and better detects significant change in the middle of the period. Hence, most recent degradation may not be detected and early signs of decline missed. The yearly NDVI mean of the shortened baseline period (2000–2012) is normalized and assigned to classes from 1 to 10 based on their percentiles. In order to avoid annual fluctuations, contemporary values of the three years anteceding t_0 and t_1 are then classified in this scheme. Areas with a reduction of two or more classes are reported as degraded, while the rise by two classes can be seen as an improvement. A change of just one class, maybe due to very small alterations, will be seen as being stable (Sims et al., 2017, p. 50 f.). Because the baseline period may not include the highest or lowest NDVI values, the normalization is based on the values from -5 to 105 %.

Land Productivity Performance

While the other two indicators compare LP over time, Performance examines local productivity in contrast to comparable ecoregions. Thus, it can detect areas where there is an increasing productivity, but which remain relatively low compared to similar ecozones. This can be based on climate, soil conditions or land cover (Sims et al., 2017, p. 51 ff.). For example, Conservation International (2019) uses the unique combinations of the soil great groups (Hengl et al., 2017) in combination with a land cover dataset. The 90^{th} percentile in each ecoregion is calculated as a proxy for the maximum productivity level. The LP Performance is then calculated based on the ratio of the observed mean NDVI value per pixel and the NDVI_{max}. Values below 0.5 indicate regions where the LP is low and LD may prevail. The baseline period is 2000–2015 and reporting takes place between 2016 and 2019.

Land Productivity Calculation

Based on the three sub-indicators LP has to be calculated (table 3.1). LP Trend is the only indicator which is calculated over the entire period and is also based on a statistical significant test. Therefore, if Trend is showing degradation, LP is also indicated as degradation and if Trend signals improvement, the same applies to LP. Only if both other sub-indicators display degradation, LP is also degraded (Sims et al., 2017, p. 55 f.). If two are stable and only State shows degradation, this could indicate "early signs of decline", because the most recent LD could not be detected by the Trend. On the other hand, if only Performance is degraded, it seems there is no temporal trend and the land is classified as "stable but stressed" (Conservation International, 2019, p. 50). In disagreement with the GPG, the Trends.Earth manual also refers to these two classes as degradation (the asterisks in table 3.1).

Table 3.1.: The default aggregation of the land productivity indicator based on the results from Trend, State and Performance following the Good Practice Guidance by Sims et al. (2017).

Trend	State	Performance	Land Productivity	
			5 classes	3 classes
Improvement	Improvement	Stable	Improving	Improvement
Improvement	Improvement	Degradation	Improving	Improvement
Improvement	Stable	Stable	Improving	Improvement
Improvement	Stable	Degradation	Improving	Improvement
Improvement	Degradation	Stable	Improving	Improvement
Stable	Improvement	Stable	Stable	Stable
Stable	Improvement	Degradation	Stable	Stable
Stable	Stable	Stable	Stable	Stable
Stable	Stable	Degradation	Stable but stressed	Stable*
Stable	Degradation	Stable	Early signs of decline	Stable*
Improvement	Degradation	Degradation	Declining**	Degradation
Stable	Degradation	Degradation	Declining	Degradation
Degradation	Improvement	Stable	Declining	Degradation
Degradation	Improvement	Degradation	Declining	Degradation
Degradation	Stable	Stable	Declining	Degradation
Degradation	Stable	Degradation	Declining	Degradation
Degradation	Degradation	Stable	Declining	Degradation
Degradation	Degradation	Degradation	Declining	Degradation

Contrasting to the Trends.Earth-manual published by Conservation International (2019), degrading conditions are set for * and stable conditions for **.

3.2.2. Land Cover

The second indicator is called land cover and describes the physical cover of the earth's surface. This refers to vegetation types, water bodies and human infrastructure and also includes land resources such as agriculture and forests. According to Sims et al. (2017), the indicator has two main functions. First, to reflect LD, if ecosystem services are lost and productivity thus declines, and second, to disaggregate the two other indicators LP and SOC. Land cover legends should be unambiguous, complete and exhaustive. For example, the IPCC uses a six class LC legend (Penman, 2003), whereas the European Space Agency's (ESA) Climate Change Initiative (CCI) LC includes 22 classes and is thus more complex (Plummer, Lecomte, & Doherty, 2017). LC change can be assessed by comparing two land cover maps and analyzing the change that occurred. There are several ways in which the land can degrade: For example, if the biodiversity or ecosystem complexity is reduced or if the land's resources for the population decline. In

Table 3.2.: Graphical summary of the default UNCCD land cover change matrix. Transitions from the original class on the left to the final class on top are shown based on Sims et al. (2019).

	Forestland	Grassland	Cropland	Wetland	Urban	Otherland
Forestland	0	–	–	–	–	–
Grassland	+	0	+*	–	–	–
Cropland	+	–*	0	–	–	–
Wetland	–	–	–	0	–	–
Urban	+	+	+	+	0	+
Otherland	+	+	+	+	–	0

* In contrast to the default LC change matrix, the adopted approach refers to these both alterations as stable.

addition, if the potential productive capacity of the land sank, for example by reducing the biomass, this would also be LD (Sims et al., 2017, p. 20 ff.). In order to define these changes, a coherent LC change matrix is useful (table 3.2). The transitions between the LC types are either classified as degrading, stable or improving.

The default LC map provided by the UNCCD is based on the ESA CCI LC global dataset, which provides annual LC datasets from 1992 to the present date at a 300 m resolution and is disaggregated into the six IPCC LC classes forestland, grassland, cropland, wetland, urban and otherland (Sims et al., 2019). In order to determine whether changes from one LC class to another are interpreted as degradation, a change matrix can help visualize the transitions. Countries are encouraged to define their own rules based on the national context and development objectives, but UNCCD gives guidance based on a default change matrix (table 3.2). Trends.Earth is following the GPG and uses the UNCCD default ESA CCI-LC dataset with the six IPCC classes and the generic change matrix, which can be adopted to local context. The baseline t_0 is based on the LC change from 2000–2015 and the first reporting t_1 is set to 2019. So depending on two land cover maps and the transition criteria, the potential LC degradation is assessed (Conservation International, 2019).

Besides the default UNCCD data, the LDN Target Setting Program Report uses the local LC dataset, which is based on the Regional Centre for Mapping of Resource for Development (RCMRD), to determine LD (URT, 2018b). This LC map was developed for the Greenhouses Gases Inventories (IPCC, 2008) to provide baseline data (2000–2010) for LULC change and the forestry sector (Al-Hamdan et al., 2017; Oduor et al., 2016; RCMRD, 2018). It is based on Landsat 5 imagery using the maximum likelihood classification method and has a resolution of 30 m. Additional procedures such as filtering, pixel editing, and density slicing were performed to refine the classification. Accuracy assessment was done using data collected in the field and point interpretation from Google Earth imagery. The coverage includes nine Eastern and

Southern Africa countries, including Tanzania. The map's reported overall accuracy is 87 % and 80 % for the 2000 and 2010 respectively (Oduor et al., 2016, p. 99).

To further improve the LD estimates, this study also uses the LC by RCMRD as it is better suited for the local context and has an improved spatial resolution of just 30 m compared to ESA's CCI LC 250 m. Unfortunately, this LC map only reflects the change between the years 2000 and 2010. Consequently, the Tanzanian LDN report also just reflects these ten years as their baseline which is in contradiction to the recommendations by UNCCD (Sims et al., 2017; URT, 2018b). Based on this product, RCMRD produced further annual maps for the partner countries. The process relies on a Continuous Change Detection and Classification algorithm which uses Landsat time series data and has a high accuracy (Zhu & Woodcock, 2014). In order to smooth and to create a more homogeneous and coherent the LC dataset, a weighted smoothing with Euclidean distance was applied to the map. Because there is not yet a LC map for the year 2019, 2018 was used instead for t_1-reporting.

A further change in comparison to the generic methodology pertains the change matrix (table 3.2). By default, the transition between grassland and cropland is seen as agricultural expansion or the withdrawal of agriculture (Sims et al., 2017), thus rather emphasizing the decline in productive capacity and reduction to provide resources than the loss of ecosystems and biodiversity. In order to not play off ecosystems versus food security and nomadic against sedentary living, these transitions will not be seen as improvement or degradation, but rather as stable. One could even argue that the change from grasslands to croplands can be seen as degradation, because of the low percentage of farmer adopting SLM practices (chapter 2.4) and the exalted LD values in croplands (URT, 2018b, p. 31).

3.2.3. Soil Organic Carbon

The last indicator for LD is the total terrestrial system carbon stock which relates to the amount of carbon in a pool that has the ability to accumulate or release carbon. The total carbon stocks are composed of biomass (above and below ground), dead organic matter and soil organic matter. However, at the moment this indicator is not yet operational, so that instead soil organic carbon is used (Sims et al., 2019, 2017; UNCCD, 2016).

SOC is defined as the amount of carbon in the soil and is the main constituent of soil organic matter. SOC stock is normally measured at a depth of 30 cm and is stated as mass per area (e.g. tons per hectare or kg per m^2). The importance of SOC lies, among other things in its huge storage capability for carbon worldwide. Estimates indicate that there is several times more carbon in SOC than in the atmos- and biosphere (FAO & ITPS, 2015; Lal, 2018). For example, Chotte et al. (2019) suggest that in the first three meters of the soil there is twice as

Table 3.3.: As land cover classes change, the depicted default land use change factors are applied. A factor of 1 indicates no changes (adapted by Mattina et al., 2018, p. 22 f.).

	Forestland	Grassland	Cropland	Wetland	Urban	Otherland
Forestland	1	1^{e}	0.58^{d}	2^{f}	0.32^{c}	0.1^{b}
Grassland	1^{e}	1	0.58^{d}	2^{f}	0.32^{c}	0.1^{b}
Cropland	1.72^{f}	1.72^{f}	1	2^{f}	0.32^{c}	0.1^{b}
Wetland	0.04^{a}	0.04^{a}	0.04^{a}	1	0.04^{a}	0.04^{a}
Urban	2^{f}	2^{f}	2^{f}	2^{f}	1	0.1^{b}
Otherland	2^{f}	2^{f}	2^{f}	2^{f}	0.32^{c}	1

a: All but refractory carbon is considered oxidized
b: Catastrophic loss of SOC due to loss of all vegetation inputs and subsequent erosion vulnerability
c: Average loss of 68 % for soil sealing
d: Adapted from Table 5.5 (IPCC, 2008), values are applied for tropical dry climate
e: Assumes no change in SOC levels
f: Restoration cases are assumed as the inverse of the opposite land use conversion and the land-use factor is capped at 2 for previous losses of SOC greater than 60 % or land-use fact or lower than 0.4.

much carbon as in the other two mentioned spheres combined. Thus, SOC has an enormous effect on CO_2 and the climate as well.

In contrast to the other two indicators, SOC is not easy to measure at large scales. Its density can vary greatly even within meters and there is also a fluctuation over time (Chotte et al., 2019; Sims et al., 2017). The GPG for the SDG indicator 15.3.1 follows—in its most basic methodology—the 2003 GPG for LULC Change and Forestry (Penman, 2003) and the IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 2008). It is based on the maximum equilibrium SOC content at a location which is controlled by environmental factors such as rainfall, evaporation, solar radiation and temperature (Sims et al., 2017, p. 69 ff.). The content can change based on three distinct change factors: First, the land-use factor, which represents SOC stock changes based on the type of land use. Secondly, the management factor which reflects the management practice of the land use (e.g. grazing intensity on grasslands) and finally, the input factor which represents the different amounts of carbon input into the soil (IPCC, 2008; Mattina et al., 2018; Sims et al., 2017). While the land-use change factor can be used with LC as a proxy, for the other two indicators, there are presently no sufficient datasets available to inform on the management or the input. Thus, the only indicator to inform changes in SOC is the second LD indicator LC change.

The GPG recommends using the SoilGrids250m map (Hengl et al., 2017) as the basis for SOC in case there are no better local estimates (Sims et al., 2017). There are several studies which modeled SOC or belowground carbon on a national level in Tanzania, but these estimates inherent great uncertainties and are not yet ready to use (Mauya, Mugasha, Njana, Zahabu,

& Malimbwi, 2019; Winowiecki et al., 2016). The SoilGrids250m dataset is based on 150,000 soil samples across the world combined with over 150 covariates in order to predict several soil variables at a 250 m resolution spatially. However, it is important to note that these soil samples were collected by many researchers over several decades, using various methods.

The DA therefore uses SoilGrids as the standard value for SOC and assesses the change over the baseline by examining the alteration in LC (Conservation International, 2019). Hence, the actual values of carbon in the soil are not of such a great importance, because LD is rather based on the change than the absolute values. After the detrimental conversion of land, SOC loss follows a negative log function, approximating to a new equilibrium (Bernoux, Feller, Cerri, Eschenbrenner, & Cerri, 2006). In just a few years, SOC values can decline by one- to two-thirds, depending on the type of LC change, while the restoration seldom reaches pre-disturbance levels and generally takes way longer (Chotte et al., 2019, p. 33 ff.). In the guidance document for UNCCD reporting, these changes are averaged over 20 years and then applied on an annual basis for the time of the examination till t_0 or t_1. If more than one change occurs during the baseline or reporting time, the LC change is applied to the SOC hitherto and then employed till the rest of the period (Mattina et al., 2018, p. 20 ff.). The land-use conversion coefficients can be found in table 3.3 and represent the change in SOC after 20 years and are based on a literature review by UNCCD (Mattina et al., 2018). As a last step, the relative alteration of SOC between the start and the end of the period is assessed and areas, which experienced more than 10 % of change, are classified either as degraded or improved. A statistically significant test is not applied for this indicator, as the inherent uncertainties in the dataset and the high variability of SOC will likely lead to false negatives and conceal the ongoing degradation. Having said this, the 10 % change is also an arbitrary threshold and further justification is needed (Sims et al., 2017, p. 85 f.). AS there are currently no reliable local SOC datasets available, the AA is the same as the default, except for the LC dataset. Contrary to the other two indicators, SOC was computed with Trends.Earth for both approaches.

3.2.4. Combining Indicators

The calculation of the SDG 15.3.1 indicator on LD is based on the "one out, all out" approach (chapter 2.1.1). This means, if one indicator signals degradation, the LD indicator will reflect this as well. On the other hand, if no degradation is apparent but one or more indicators show improvement, then the SDG 15.3.1 indicator will also show improvement. Hence, the only possibility for a stable indicator exists, if all three sub-indicators indicate stable conditions. In order to calculate the reporting at t_1, it is necessary to first compute the indicator for the baseline (t_0), then to calculate the change from the baseline to the reporting year 2019 and as a final step, combine both results. Following table 3.4, degradation is apparent if a degraded area did not improve in recent years, or if a stable or improving area did decline in the last years (Sims et al., 2019). On the other hand, if the land improved in the recent years or the improved area stayed stable, it can be seen as a positive change. Hence, the "proportion of land that is degraded over total land area" can be reported in that fashion.

3.3. Field Monitoring of Land Degradation in Kiteto and Kongwa Districts

Next to the LD assessment with remote methods, it is also necessary to conduct fieldwork on the ground. A two-month-engagement in KK was planned, but could not be accomplished, because of a delay of several months of Tanzanian officials issuing the research permit. Nevertheless, at the end of 2019, during a three-weeks stay in Tanzania, at least part of the originally planned program could be performed. Due to the lack of an official research permit and consequently also lacking research visa, the possibilities to do a LD assessment were very impaired. Overnight stays in the study area and more profound interactions with the local people were not possible. Consequently, only a part of the scheduled program was feasible. Nevertheless, the following chapter outlines the methodology behind the fieldwork and the subsequent statistical analysis of the collected data.

Table 3.4.: Table showing the LD status for the baseline, the monitoring period and the subsequent computation of the SDG 15.3.1 indicator.

Baseline Status t_0	Monitoring Period t_1	SDG indicator 15.3.1
Degraded	Degraded	Degraded
Degraded	Stable	Degraded
Degraded	Improvement	Stable
Stable	Degraded	Degraded
Stable	Stable	Stable
Stable	Improvement	Improvement
Improvement	Degraded	Degraded
Improvement	Stable	Improvement
Improvement	Improvement	Improvement

3.3.1. Sampling Design for the Field Monitoring

There are numerous studies that conducted LD assessments on the ground and also several guidance reports on how to best perform these. For example, the Land Degradation Surveillance Framework (Vågen & Winowiecki, 2018) is based on a biophysical baseline and is collecting data such as type of erosion, presence of trees or shrubs and the infiltration time. Sampling sites

($100\,\mathrm{km}^2$) are divided into 16 tiles ($2.5 \cdot 2.5\,\mathrm{km}$) which are again divided into ten plots ($1000\,\mathrm{m}^2$) which consist of four subplots ($100\,\mathrm{m}^2$). This means each sampling site consists of 160 plots with a total of 640 subplots. This approach was already applied in semi-arid Tanzania (Bhargava et al., 2018; Winowiecki et al., 2016) and as well in the study area by Kimaro et al. (2015). Furthermore, the framework is recommended to use as a verification tool for the LDN reporting (Chotte et al., 2019; Cowie et al., 2018).

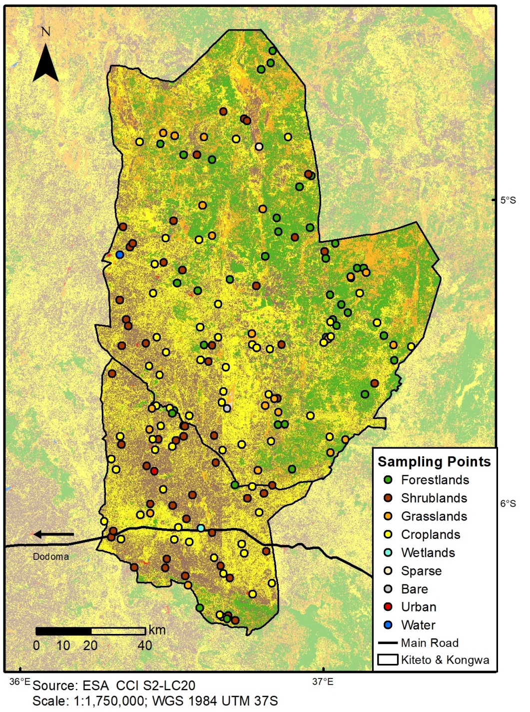
Another common approach to map land degradation is the framework by the LADA project (FAO, 2011a, 2011b, 2011c, 2011e; Liniger et al., 2019). This mapping tool is based on the land-use-system maps and measures the change in LULC. In addition, it evaluates typical LD types per land-use-system and land conservation measures as well as expert recommendations. Each system in an administrative zone is based on information that is given by local authorities or by maps and then evaluated by experts. The WOCAT-LADA approach was already used in the case study "Kagera Transboundary Agro-Ecosystem Management Project" (FAO, 2017) in western Tanzania and adjacent countries. To map an area of $60{,}000\,\mathrm{km}^2$ it took them six months and the cost totaled up to 100,000 $.

It is obvious that such approaches are not feasible as part of a master's thesis. Thus, a hybrid approach was carried out in order to overcome time and workforce constraints, but still be able to generate sufficient results. A total of 150 sampling sites were selected, using a stratified sampling method based on the most up-to-date high resolution (20 m) LC map by ESA CCI LC (Sentinel 2 prototype LC 20 m map of Africa 2016) in QGIS Geographic Information System (GIS) (figure 3.5a & QGIS Development Team, 2019). According to the land cover proportion, the number of sampling points was evaluated, while large classes were reduced and small were enhanced (Wegmann, Leutner, & Dech, 2016). The plots are, similar to the Land Degradation Surveillance Framework, 100 times 100 m in size with three subplots of 30 times 30 meters, allocated at a distance of 12 m and oriented with 0°, 120° and 240° from the central point (figure 3.5b). The sub-plots thus represent 27 % of the total area of the plot and mimic the spatial resolution of the Landsat pixels.

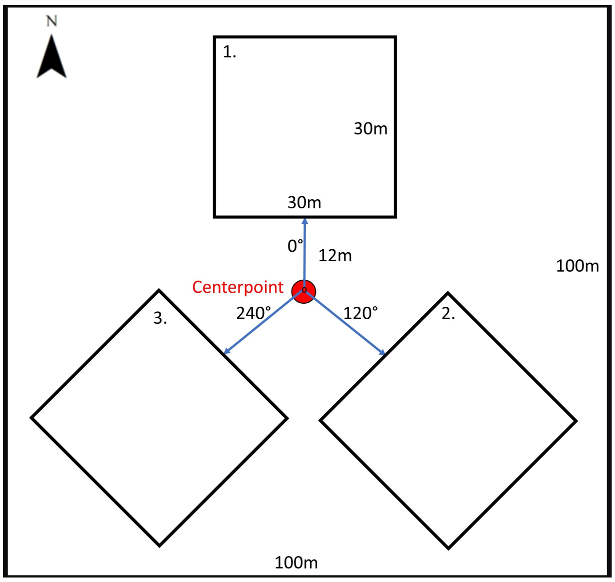
Due to the research permit constraints, no interviews with farmers or local officials were possible and the sampling had to be non-invasive. Thus, the Questionnaire for Mapping Land Degradation and Sustainable Land Management (FAO, 2011e) was used as a basis for the fieldwork but was adapted to solely include questions, which can be assessed visually. The used questions can be found in the appendix (tables A.11–A.15) This tool is based on the Open Data Kit system, a free and open source set of data collection tools that is made for collecting field data with mobile devices (Pham, Vinck, Kreutzer, & Milner, 2019).

Questions investigated refer to different categories. The first set of questions, 15 in total, concern the location and physical nature of the main plots and include questions like nearest village, GPS location, land use and soil color. The subsequent questions only apply to the individual sub-plots and thus are repeated three times per plot, if applicable. The first cluster refers to the visual assessment of LD: If there is none, this cluster will be skipped, otherwise the questions relate to the kind of LD. The main types are water and wind erosion as well as biological deterioration with their respective specifications, the extent in percent and the degree from light to extreme (FAO, 2011e, p. 5 ff.). The next set of questions concerning the direct causes of LD also just apply if LD is apparent (chapter 2.3). It includes seven distinct drivers, inter alia soil management, overgrazing as well as natural causes and their respective sub-types. The last cluster refers to land conservation or SLM practices applied on the plot (chapter 2.4). The conservative measures were grouped into agronomic, vegetative and structural as well as management measures and their respective sub-groups. Furthermore, the different measures were evaluated based on their extent and effectiveness and finally also the purpose of the SLM was assessed (FAO, 2011e, p. 16 ff.). In total 54 distinct questions were possible per plot.

After ten days of fieldwork, 34 plots were examined, hence only about one-fifth of the originally



(a) Map of the study area with the stratified sampling points based on the ESA CCI S2-LC20. A total of 150 points plus 27 just in Kongwa were created. In addition, the main road from Dodoma to Kongwa is depicted.



(b) Sampling design of the 1 ha plot. The centerpoint with its three 900 m^2 sub-plots. Each is 12 m apart from the center with a 0°, 120°, and 240° orientation.

Figure 3.5.: Figure a) shows the sampling design on the landscape level, while figure b) depicts the sampling design on the plot level.

planned plots. This was largely owed to the long distances between the overnight stays in Dodoma and the plots in the study area. It took about an hour to the border of Kongwa and approximately another hour to reach more distant plots in the district (map 3.5a). Thus, often the sole commuting time took three to four hours a day. In addition, it was necessary to find the nearest village and ask for permission to conduct research as well as to be accompanied by locals. This situation led to long hours of driving and waiting for permission, whilst it was not possible to examine plots. In the end, no plots were assessed in the northern district Kiteto. For one thing, the driving time was even longer, and second, there was also a permission needed to conduct research in Kiteto, thus a trip to the capital Kibaya would have been necessary. In order to increase our possibilities and get a broader picture of Kongwa, another 27 plots were added in GIS in the same fashion as before, except a buffer of 5 km was set around plots that were already sampled. The navigation and planning of the field trips was carried out with the QGIS plugin Qfields (OPENGIS.ch, 2019).

3.3.2. Analysis of Causes and Extent of Land Degradation from in-situ Data

After the completion of the fieldwork in Tanzania and the download of the online survey as a spreadsheet, the dataset was cleaned. For example, ordinal scaled answers such as moderate or strong were transferred into values and number-ranges like 51–75 % were averaged as 63 %. Furthermore, the questions were abbreviated and columns, that did not make sense anymore, deleted. In order to just have one value per plot, the sub-plots were averaged where necessary (e.g. mean shrub cover) and the maximum taken were appropriate (e.g. SLM practices in the plot visible). Statistical analysis was performed using R (R Core Team, 2020) and figures were produced using ggplot2 (Wickham, 2016). In addition to the existent, further variables were created: A new LD indicator called Magnitude was computed, based on the extent and the degree as well as the proportion of the presence of the sub-indicators (richness). Similar to this approach, also the quality of SLM was computed using the extent, effect and the richness of SLM.

In order to explain relationships and patterns between objects and their features, ecological data can be analyzed multivariate. One possible method is the direct gradient analysis. It includes only features and plots. The Principal Component Analysis (PCA) searches for a theoretical gradient that represents the variation in the plots best. The results of PCAs are reduced space-dimensions which represent the relationship of the examined variables. Since many environmental factors are similar, they can be reduced without large data losses and form a principal component. This new axis should reflect as much correlation between the variables as possible. Higher correlation corresponds with a higher inertia of the component. The eigenvalue is here referred to as the sum of all inertia on the main component and is a measure of the relationship between the original variables. The significance decreases with further axes and the eigenvalue is a measure of the relevance of the axis. Therefore, high values of the first axes are a good explanation of environmental variability. To get decent results with this analysis method, the PCA should — if possible — have more objects (in this case sample areas) than variables (Leyer and Wesche, 2008, p. 109 ff.; Borcard, Gillet, and Legendre, 2018, p. 153 ff.; Pages, 2015, p. 1 ff.).

Multiple Correspondence Analysis (MCA) is a factorial method, which is suited to describe several qualitative variables in contrast to the Correspondence Analysis which can only analyze two at a time. The main aim of a MCA is to examine the variability of the individuals from a multidimensional perspective. It can be seen as a counterpart to the PCA that is suited for categorical variables. Variables with more categories have a higher importance in the MCA, but are also distributed over more dimensions (axes). For example, the variable district can only relate to one axis between Kiteto and Kongwa, while the variable Wards can have much more distinctions on more dimensions (Borcard et al., 2018, p. 183 ff.; Pages, 2015, p. 39 ff.). Analyzing relationships of qualitative variables requires more objects than studying the connection between quantitative variables, thus more objects are needed compared to PCAs (in general more than 100) (Pages, 2015, p. 54 ff.).

If quantitative and qualitative variables are part of a factorial analysis — so called mixed data — it is possible to transform the numerical data into classes and analyze it with a MCA. In case of fewer individuals or a relatively small number of categorical data in contrast to numerical data, as it is in this dataset, a Factor Analysis of Mixed Data (FAMD) is recommended. FAMD is basically the integration of the PCA with a MCA, as it acts as a PCA for quantitative variables and as a MCA for qualitative variables and balances the two types (Pages, 2015, p. 67 ff.). The software package in R used for the FAMD-analysis is FactorMineR by Lê, Josse, and Husson (2008).The FAMD just included a subset of the dataset: The reference farm of Africa RISING was removed (plot 01) as well as the forest plot (32). Both are outstanding and disturb the distribution of the whole analysis. Quantative input variables such as cover, erosion magnitude, direct causes and SLM-impact were used as well as qualitative data such as vegetation type or ownership.

4. Results

The following chapter refers to the LD (sub-)indicator results based on the DA using Trends.Earth and the AA with high-resolution and local datasets. Furthermore, the statistical analysis of the field data is also depicted.

4.1. Monitoring Indicators of Land Degradation with Remote Sensing Data

The default dataset, which is provided by UNCCD and can be calculated using Trends.Earth (default approach), is based on data between the years 2000–2015 and thus, the baseline at t_0. At the moment, more recent results cannot be created with the Trends.Earth tool. As for the AA, not only t_0, but also the first monitoring period till 2019 (t_1) is assessed. Finally, the combined products for the whole time span of 20 years of the three sub-indicators are computed and out of these, the ultimate SDG 15.3.1 indicator is calculated. Thus, the results are presented in the following way: First, the DA and second, the AA for the baseline period is computed. Third, the AA for the first target period and finally, the combined indicator is shown.

4.1.1. Land Productivity

Table 4.1.: Juxtaposition of the three LP sub-indicators Trend, State and Performance as well as the combined LP. The results are depicted by the default approach using MODIS imagery and the adapted approach using Landsat imagery. The proportion of the degraded, stable and improved area is shown as well as solely the degraded area in KK districts.

LP (%)	Trend		State		Performance		Combined	
Baseline	Default	Adapted	Default	Adapted	Default	Adapted	Default	Adapted
Degraded	26.8	8.2	70.4	14.1	0.1	0	26.8[1]/71.1[2]	8.2[1]/18.7[2]
Stable	73.2	91.3	26.4	64.2	99.1	100	73.2[1]/28.9[2]	92.6[1]/82.1[2]
Improved	0	0.5	3.3	21.6	-	-	0	0.5
Kongwa	16.4	2.7	86.2	16.4	0	0	86.2	8.2
Kiteto	29.9	8.8	65.6	13.5	0.1	0	66.6	8.2

[1] just shows the *declining* area as degraded and *early signs of decline* and *stable but stressed* as stable (Sims et al., 2017).
[2] represents the combination of *declining*, *early signs of decline* and *stable but stressed* as degradation (Conservation International, 2019).
Table 3.1 shows the different aggregation methods for land productivity

Land productivity is the biological productive capacity of the land and is computed by aggregating the three sub-indicators Trend, State and Performance (chapter 3.2.1). The default dataset used by Trends.Earth is based on MODIS imagery, while the AA uses Landsat data. The percentages per LC classes are based on proportion of degraded area and are referring to the respective LC classification, that is ESA CCI 2015, RCMRD 2015 and 2018. Thus, a direct comparison of these percentages is of limited use.

Trend

The LP Trend measures the trajectory of change in productivity over time and is the only sub-indicator of LP which is based on statistical significance. Using MODIS and the RUE with the CHIPRS dataset, Trend.Earth computed LP Trends which resulted in degradation in over one fourth of the study area, while the rest stayed stable (table 4.1). Degradation is more apparent in the central part of Kiteto than in Kongwa, with 30 versus 16 % respectively (figure 4.1). Half of the total degradation is apparent in croplands, thus affecting it disproportionately. On the other hand, just 11 % of the degraded area is covered by forest, making it the least-affected LC class (table A.2).

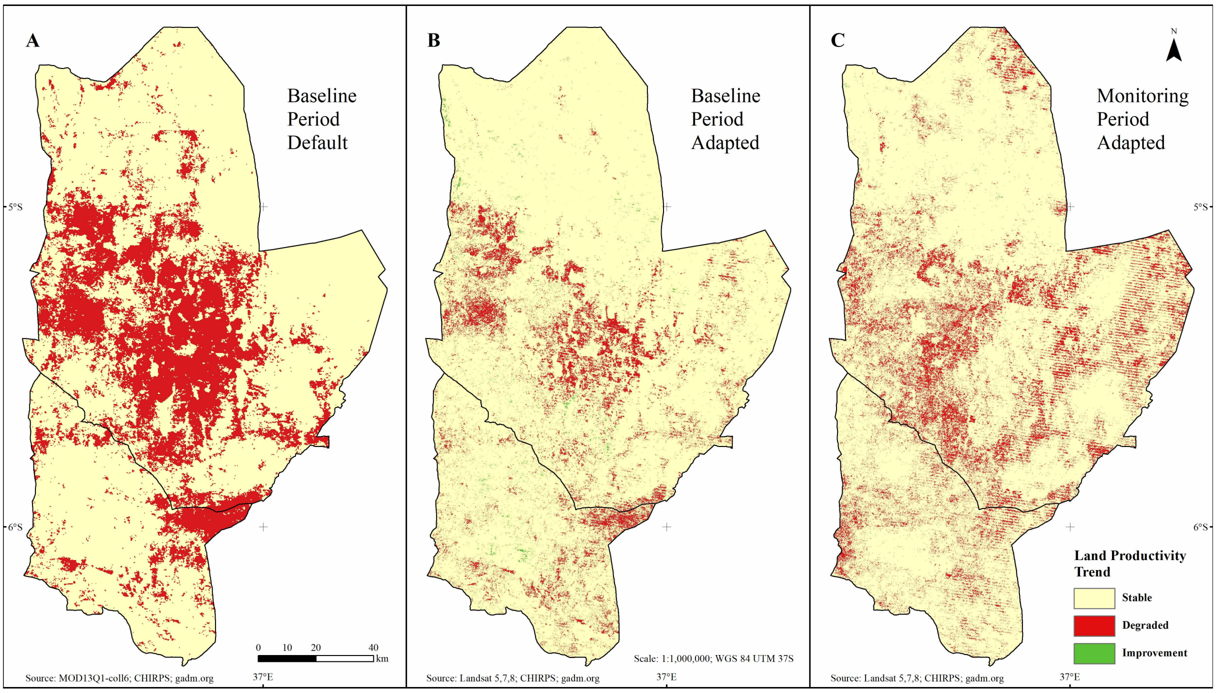


Figure 4.1.: Comparison of the land productivity Trend maps using rain use efficiency. (A) shows the default approach with MODIS imagery, while (B) depicts the adapted approach with Landsat for the baseline period and (C) covers the monitoring period with Landsat imagery. Comparison between (A) to (B) reveals that the default approach estimates the degradation much higher. The degradation pattern seems to change comparing (B) to (C).

Based on the AA, only 8.2 % of the study area degraded between 2000 and 2015, while half a percent improved (figure 4.1 B and table 4.1). Grass- and croplands account for 39 and 38 % respectively of the degraded area, while only 2.3 % is covered by forests A.3. Thus, croplands were disproportional affected with nearly 9 pp more than their cover should suggest. Similar to the Trend.Earth results, Kongwa is less affected with only 2.7 %.

In the monitoring period from 2011 to 2019 the tendency of the years before continued and even accelerated: 12 % of the area degraded, while nearly nothing improved (table A.1). Even though croplands were less severely affected, 34 % still showed signs of decline (table A.4). Most notably, the pattern of the degradation changed (figure 4.1 C). The degradation is less clustered and further spread across the study area, indicating new emerging hotspots, while other parts became stable.

State

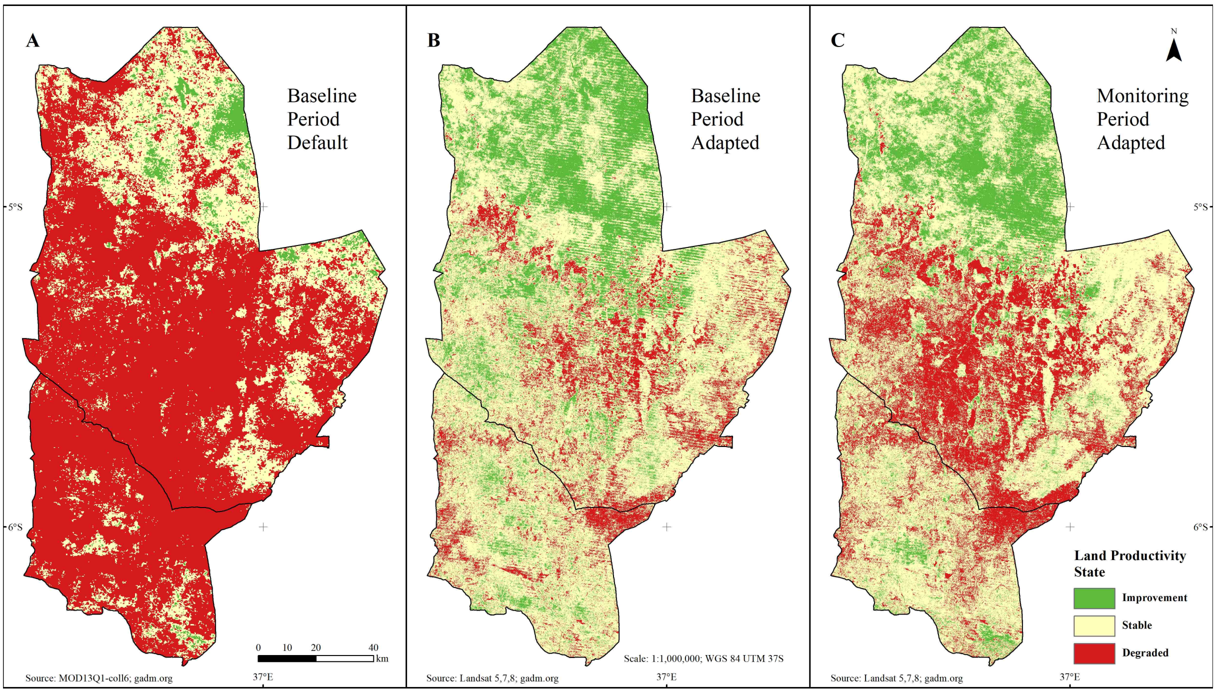


Figure 4.2.: The land productivity State is generated using the default approach with MODIS imagery and the adapted approach with Landsat for the baseline period. The monitoring period uses Landsat imagery as well (C). Comparison between (A) and (B) reveals that the default approach overestimated the extent of LD. Comparison between (B) and (C) revealed expansion of land degradation in Kiteto district.

The land productivity State indicator represents recent changes in LP compared to the shortened baseline period. Thus, it refers to changes which happened between 2013 and 2015 for the baseline period, and 2016 till 2019 for the monitoring period. Following the Trends.Earth methodology, over 70 % of the land is potentially degraded, while only 3.3 % showed signs of improvement (figure 4.2 A and table 4.1). Similar to the LP Trends results, State degradation is disproportionately apparent in croplands as well (table A.2). In contrast to Trend, Kongwa is more affected with most recent degradation (86,2 %), while Kiteto shows signs of decline in two thirds of the area.

Using the Landsat imagery, nearly two thirds remained stable, while even more land improved than degraded with 22 to 14 % respectively (figure 4.2 B). Contrary to the LP Trend, Kongwa experienced proportionality more degradation and less improvement than Kiteto. Croplands alone account for 42 % of the degraded area, while the other LC classes were less proportionately affected (table A.3). On the contrary, grasslands accounted for nearly 60 % of the improvement, mainly in the northern Kiteto.

Comparing the State of the study area of the years 2016 till 2019 with the shortened baseline, a quarter degraded, while 16 % improved (figure 4.2 C and table A.1). There are no relevant distinctions between KK. Similar to the baseline period, croplands were most affected negatively, while grasslands improved most (table A.4).

Performance

The last sub-indicator Performance compares local productivity to similar ecoregions. Based on the results of Trend.Earth, only 0.1 % of the land has this type of degradation. There was no improvement measurable, so nearly 100 % stayed stable (figure A.1 A and table 4.1). Using Landsat imagery, the degradation is in the per mil range and almost 100 % stayed stable (figure A.1 B). The same results are similar for the monitoring period (figure A.1 C and table A.1).

Computing Overall Land Productivity Indicator

The unique combination of the three sub-indicators results in the LP indicator. Following the Trends.Earth manual, there are two different aggregation methods (chapter 3.2.1 & Conservation International,2019, p. 50). The five-class method results in 26.8 % of the area declining, mainly as the result of the Trend component. Another 44.3 % show early signs of decline because of the State component. Finally, another 28.9 % stay stable (figure 4.3 A). As for the LP aggregation, the first two indicators were combined, leading to a total degradation of 71 % (table 4.1). Consequently, croplands are the most affected in absolute as well as total numbers. 49 % are degraded, thus over 10 pp more than one would expect. On the other hand, forestlands are disproportionately less affected, with only about 12 % and roughly a third less than on average (table A.2). In the southern Kongwa, which is also more covered with croplands, 86 % of the land is degraded, while this holds true for only two-thirds of the land in Kiteto. Of the protected areas, which are mainly situated in northern Kiteto, only about half is affected.

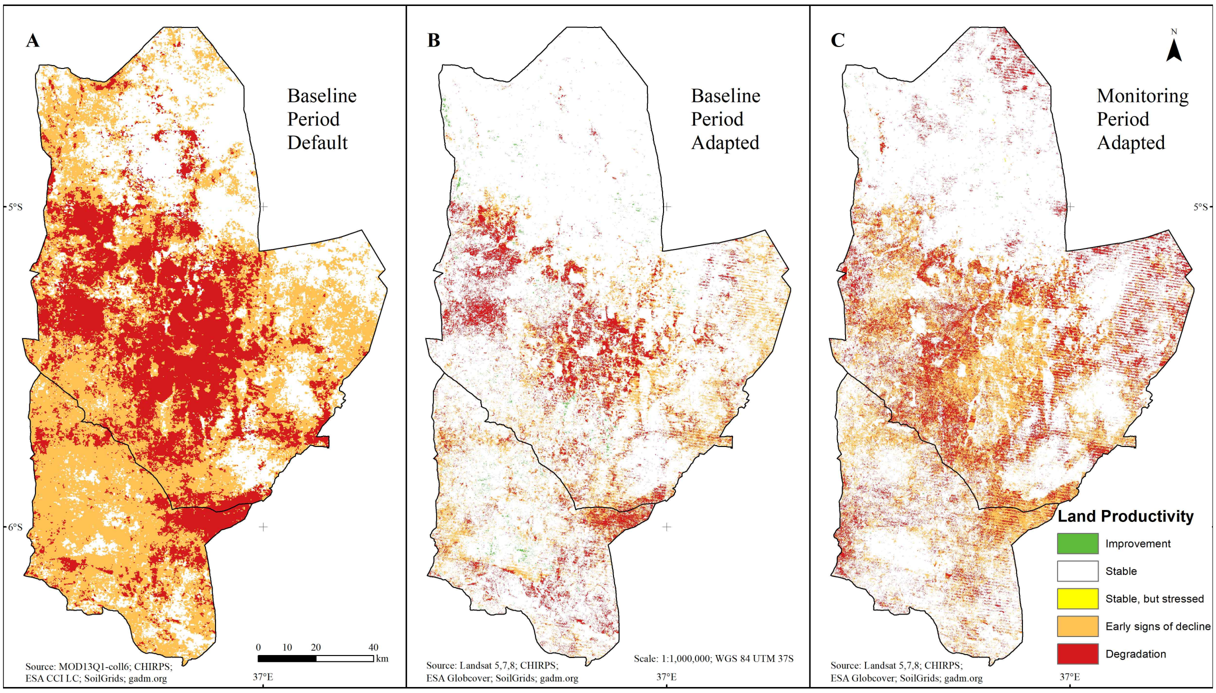


Figure 4.3.: The land productivity indicator is generated using the default approach with MODIS imagery and the adapted approach with Landsat for the baseline period. The monitoring period uses Landsat imagery as well (C).

Following the combination of the three Landsat sub-indicators, 8.2 % of the study area declined over the 16 years, while another 9.1 % showed early signs of decline. Only 1.4 % are stable but stressed (figure 4.3 B and table 4.1). Thus, referring to the Trends.Earth manual, 18.7 % of the total area is degraded. As mentioned in chapter 3.2.1, this is in disagreement with the GPG which is more conservative and only counts 8.2 %. More than 80 % stayed stable and only half a percent improved. There are no significant differences between KK. Following the GPG guidelines, the distribution of the declining area per LC is similar to the results of Trend (table A.3).

Referring to the first target period till 2019, 12.2 % of the area was declining (figure 4.3 C). With an increase of 17 %, the area which was affected by early signs of decline was higher than during the baseline as well. On the other hand, the area where LP was increasing, sank to just one thousand. Therefore, 70.7 % stayed stable during the monitoring period (table A.1). Kiteto was more affected than Kongwa with 13.1 to 9.1 %. As seen before, forests and grasslands were less affected by LP degradation (6.7 and 39 % respectively) and croplands were more dominant with 37.2 %. Furthermore, wetlands were also more afflicted with 4.2 % (table A.4).

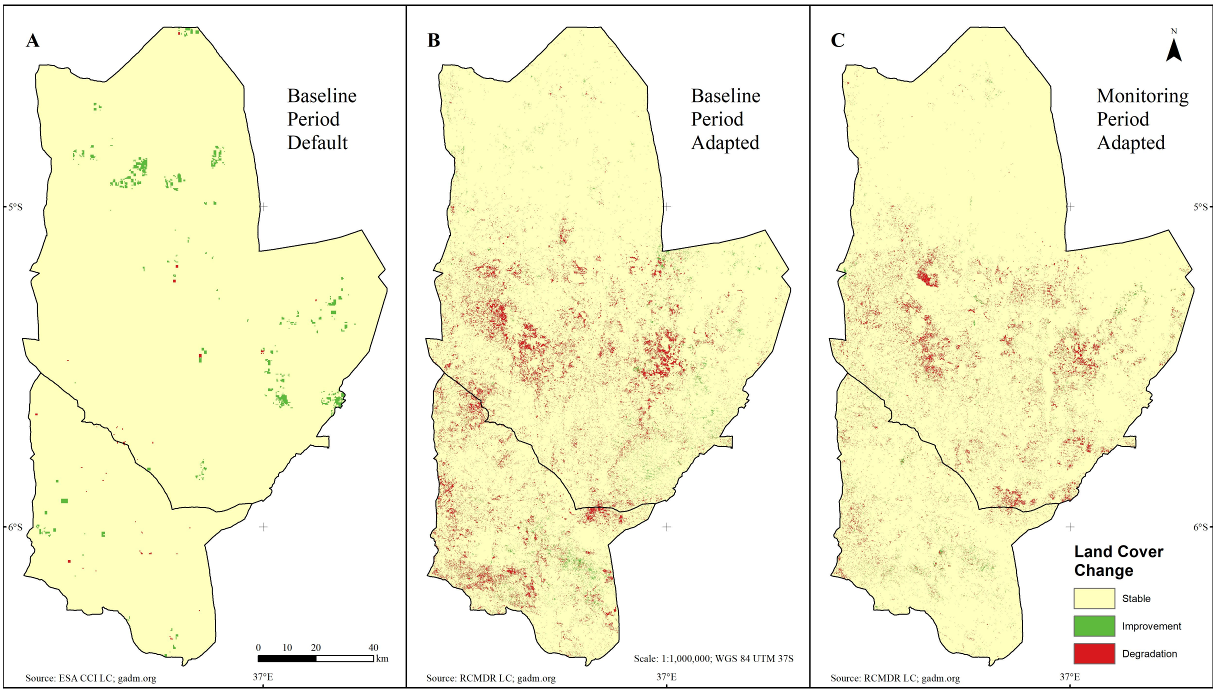


Figure 4.4.: The land cover change indicator computed with the default approach based on the ESA CCI land cover dataset and the adapted approach based on RCMRD land cover datasets for the baseline period. The monitoring period is based on the RCMRD land cover datasets as well (C). While (A) is mainly stable, (B) and (C) show degradation in the districts.

4.1.2. Land Cover

According to the default dataset, of the 17,090 km^2 in the study area nearly 16,930 km^2 stayed stable (figure 4.4 A). Thus, over 99 % of the two districts did not change over the course of 16 years. In the year 2015, the biggest LC classes belonged to grasslands, croplands, forestlands and wetlands with the respective proportions of 40.9, 38.7, 17.2 and 3.2 percent (table 4.2 and figure A.2a). Urban areas, covering less than 0.1 %, saw the greatest relative rise (+45.8 %). Interestingly, forestlands were the only other LC class which increased significantly (+4.4 %) in the baseline period. Following the default data, less than 0.1 % of the area degraded and about 0.9 % improved (table A.5).

In contrast to the default dataset, the RCMRD LC map has a higher spatial resolution and showed more changes in the same time span. Approximately 15 % of the land changed its cover and especially (semi-)natural landcovers like forest- or grasslands were transformed (−23 and −6.9 %), while croplands gained most (+20.2 %; see table 4.2 and figure A.2b). In absolute numbers, the biggest land covers in 2015 were grasslands, then crop- and forestlands as well as otherlands with the respective values of 45, 29.1, 12 and 7.1 %. Following the adopted LC change matrix, described in chapter 3.2.2, 5.2 % of the area degraded and — similar to the default

Table 4.2.: Comparison of the ESA CCI LC dataset with the RCMRD LC classification based on the change between the years 2000–2015. The main LC classes are depicted as well as the proportion of the total land in 2015, the relative change of the LC class from 2000–2015 as well as the absolute change in pp of the total landcover. Remaining proportion until 100 % are due to no data classes in the RCMRD dataset.

	ESA CCI			RCMRD		
Land Cover	LC 2015 (%)	Relative Change (%)	Absolute Change (pp)	LC 2015 (%)	Relative Change (%)	Absolute Change (pp)
Forestlands	17.2	4.4	0.7	12.0	−23.0	−2.8
Grasslands	40.9	−1.9	−0.8	45.0	−6.9	−3.3
Croplands	38.7	0.2	0.1	29.1	20.2	5.8
Wetlands	3.2	0.1	0	1	−50.2	−0.5
Urban	0.01	45.9	0	1.1	8.3	0.1
Otherlands	0	0	0	7.1	14.4	1

dataset — 1 % improved (table A.5). Thus, the difference between the degraded area in the two datasets relates to approximately 50 times. Kongwa is more degraded than Kiteto with 7.9 and 4.4 % respectively (table A.7).

The trend observed in the baseline period continued in the first years of the monitoring period as well (figure 4.6 and table A.6). Grass- and forestlands continued to decline by three to ten percent respectively, while anthropogenic-(influenced) covers such as cropland and urban areas grew further. While a tendency can be seen temporally, there is also spatial distinction between KK (table A.7). Kiteto is less transformed and over 60 % is covered by forest- and grasslands and only a fourth is covered by agricultural lands. On the other hand, 50 % of the way smaller Kongwa is dominated by agricultural lands and forest fragments can be found only on hills. 3.2 % of the total area degraded during this time, while 0.7 % of the area changed to a better LC. Kiteto was slightly more affected with 3.5 % to 2.4 % in Kongwa (table A.5).

4.1.3. Soil Organic Carbon

Soil organic carbon was not directly computed, but rather assessed through the change of LC classes and the related change factors depicted in table 3.3. Similar to the LC change computed by Trends.Earth, SOC did not change significantly either: 99.9 % of the land did not change the SOC-content by more than 10 %, thus only 0.1 % of the area experienced alterations (figure 4.5 A and table A.9). On average, the SOC content in tons per hectare was 51.23 and decreased over 16 years by 0.01. Changes in the individual LC classes are on average so low that they can only be found in the second decimal place or are even smaller. Anyhow, grasslands and forestlands have the highest amounts of SOC with 55.0 and 54.7 t/ha in 2015, followed by crop

Table 4.3.: SOC change from 2000 to 2015 based on the LC datasets by ESA CCI and RCMRD. The average SOC content in t per ha and the total SOC content are shown for the year 2015, as well as the change of the total content from 2000 to 2015 in percent. The information on LC is based on the area in the year 2015.

LC dataset	ESA CCI			RCMRD		
SOC 2015	SOC (t/ha)	SOC (t)	Change in SOC (%)	SOC (t/ha)	SOC (t)	Change in SOC (%)
Kiteto and Kongwa	51.2	87,542,132	0.0 %	50.2	80,507,479	-1.9 %
Forestlands	54.7	16,090,674	4.5 %	63.2	12,722,692	-18.9 %
Grasslands	55.0	38,390,588	-2.0 %	50.7	37,899,163	-8.4 %
Croplands	46.2	30,624,041	0.2 %	46.5	22,818.927	23.4 %
Wetlands	45.1	2,428,100	0.1 %	49.2	702,284	-38.8 %
Urban	36.2	8,728	56.0 %	39.5	810,333	16.0 %
Otherlands	0	0	0 %	46.2	5,554,077	17.4 %

and wetlands with 46.2 and 45.1 t/ha respectively. The lowest values can be found in urban areas with only 36.2 t/ha. In total, KK lost 17,889 t of SOC which equates to 0.02 % of the total

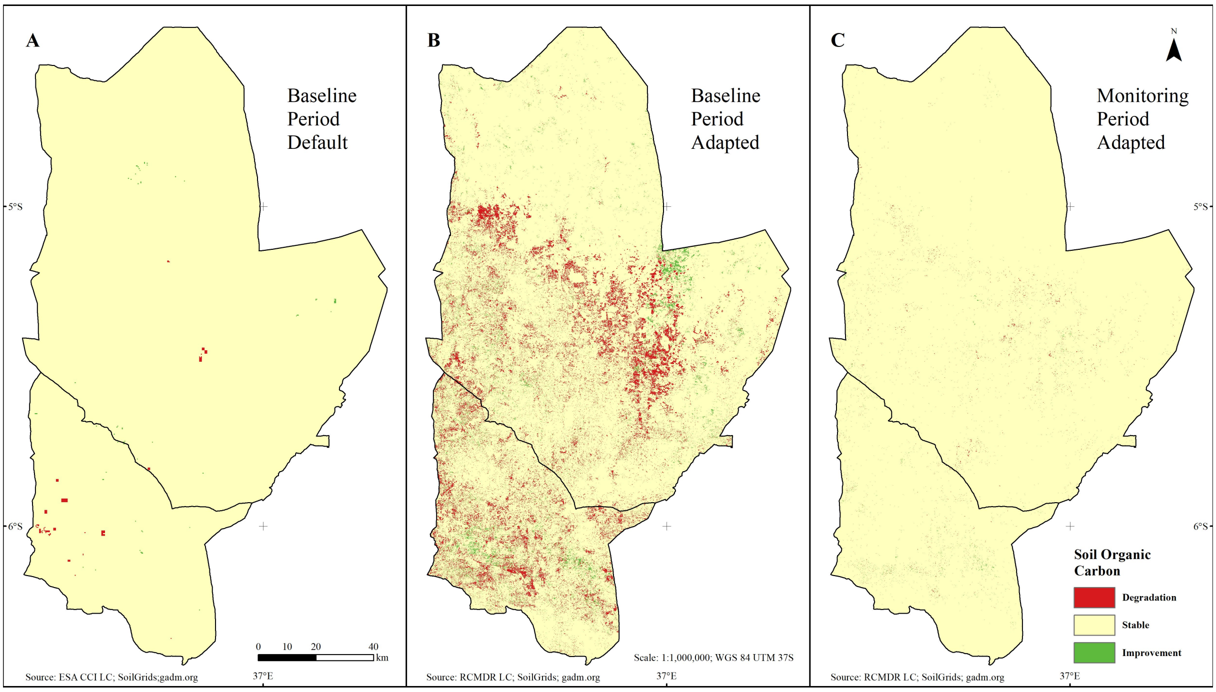


Figure 4.5.: The soil organic carbon indicator computed using the default approach based on SoilGrids and ESA CCI change, while the adapted approach is based on SoilGrids and the RCMRD land cover change for the baseline period (B). The monitoring period is based on SoilGrids and the RCMRD land cover change as well (C). Comparing (A) to (B), it is obvious that the degradation is quasi not existing in (A), while it is widespread throughout (B). (C) shows only little change, as carbon alteration happens in longer timescales than three years.

(table 4.3).

In contrast to the default data and in line with the change of the RCMRD LC dataset seen before, over 10 % of the land area changed the SOC value significantly (table A.9). The average SOC stock per hectare declined from 51.18 t to 50.19 t in 2015, thus losing a total of 1,592,423 t of carbon over 16 years which is 93 times more than the default dataset (table 4.3). The average SOC content per LC class is different to the default as well, because of the altered spatial distributions of the LC classes. Tree-covered areas differ from the other classes greatly and have 63.2 t/h SOC, while grass-, crop- and wetlands have 49.7, 46.9 and 47.0 t/ha on average respectively. Based on the transitions in LC, the amount of SOC in forests nearly dropped by 19 %, while SOC under agricultural use increased by nearly a fourth. During the baseline period, 8.4 % of the land were degraded due to SOC diminishment, while nearly 2.1 % of the land increased the SOC content (figure 4.5 B).

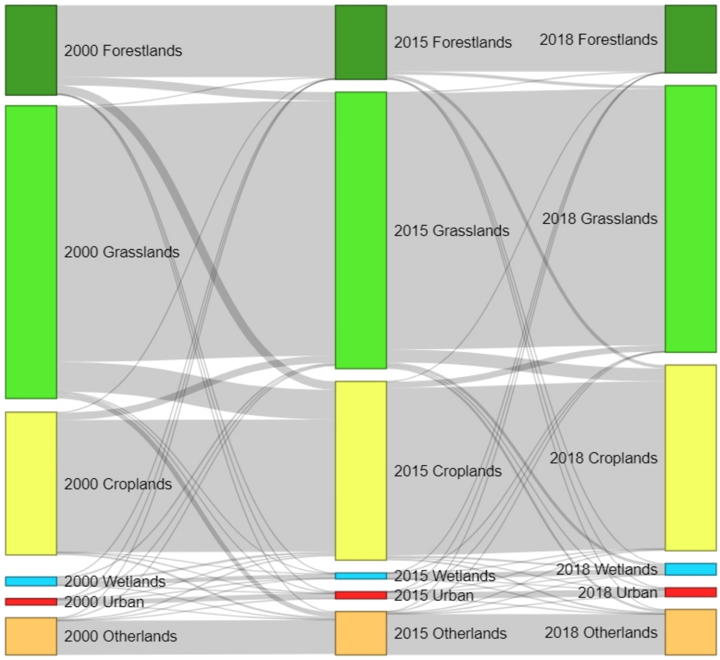


Figure 4.6.: Land cover transitions between the years 2000, 2015 and 2018 based on the RCMRD LC classification. Arrows represent the actual proportion of land that changed the class over time.

The change for the years 2016–2018 was calculated as well, even though alterations over such short periods may not reflect reality, as SOC changes rather happen in decades than in years (chapter 3.2.3). Over the course of three years, only 0.5 % of the land had changing SOC content of more than 10 % (figure 4.5 C): 0.3 % degraded and 0.2 % improved (table A.9). The trend thus continued with forest-, grass- and wetlands losing SOC as a whole, while croplands gained SOC, because they also expanded their area (table A.8).

4.1.4. Combined Land Degradation Indicator

As mentioned already in chapter 3.2.4, the indicator needs to be combined following the *one out, all out*-principle. Thus, first the three sub-indicators are calculated in their respective time spans and then, in a second step, the final indicator for the 20-year period will be aggregated based on the baseline and monitoring period.

Baseline period t_0

According to the default methodology and dataset, 71.1 % of the land in KK are degraded and only 0.5 % have improved (table 4.4 and figure 4.7 A). These numbers are mainly influenced by the sub-indicator LP, while the two other indicators LC and SOC showed nearly no degradation with only 0.06 % and 0.11 % respectively. Yet again, the LP degradation is mainly based on the State indicator, which contributes 70.3 % of the 71.1 %. Thus, the SDG 15.3.1 indicator "proportion of land that is degraded" is nearly solely effected by one (sub-)indicator. The statistics on LC proportions or administrative boundaries of the State indicator hold virtually true for the main LD indicator as well: 86 % of Kongwa and two thirds of Kiteto are degraded and nearly half of the degradation occurred in croplands.

On the contrary, the adapted methodology and datasets yielded quite different results. 81 % of the study area stayed stable during the 16 years, 2.7 % of the land improved and 16.4 % of KK degraded (table 4.4 and figure 4.7 B): The degradation is more widespread in Kongwa with 22.2 % of the area, while for Kiteto this only holds true for 14.6 %. Only 2 % of the degraded area is covered by forests, which is less than a sixth of the value one would expect. Grasslands cover roughly a third of the degraded area, still this is over 13 pp less than its overall coverage in 2015. On the other hand, agricultural lands with 46.9 % were the biggest LC class covering degraded lands and they are about two third over their value. The composition of the final indicator is more evenly distributed by the sub-indicators. Not only LP is influencing the final indicator, but SOC and LC add to the picture as well. Even though LP alone contributes 34 % to the indicator and another 17 % with the other two indicators combined, SOC has the same

Table 4.4.: Comparison of the default and adapted approach to calculate the SDG 15.3.1 indicator of LD and its sub-indicators for the baseline period.

LD (%)	LP		LC		SOC		SDG 15.3.1	
Baseline	Default	Adapted	Default	Adapted	Default	Adapted	Default	Adapted
Degraded	71.1	8.2	0	5.2	0.1	8.6	71.1	16.4
Stable	28.9	93.1	99.1	93.8	99.9	89.2	28.4	81
Improved	0	0.5	0.9	1	0	2.1	0.5	2.7

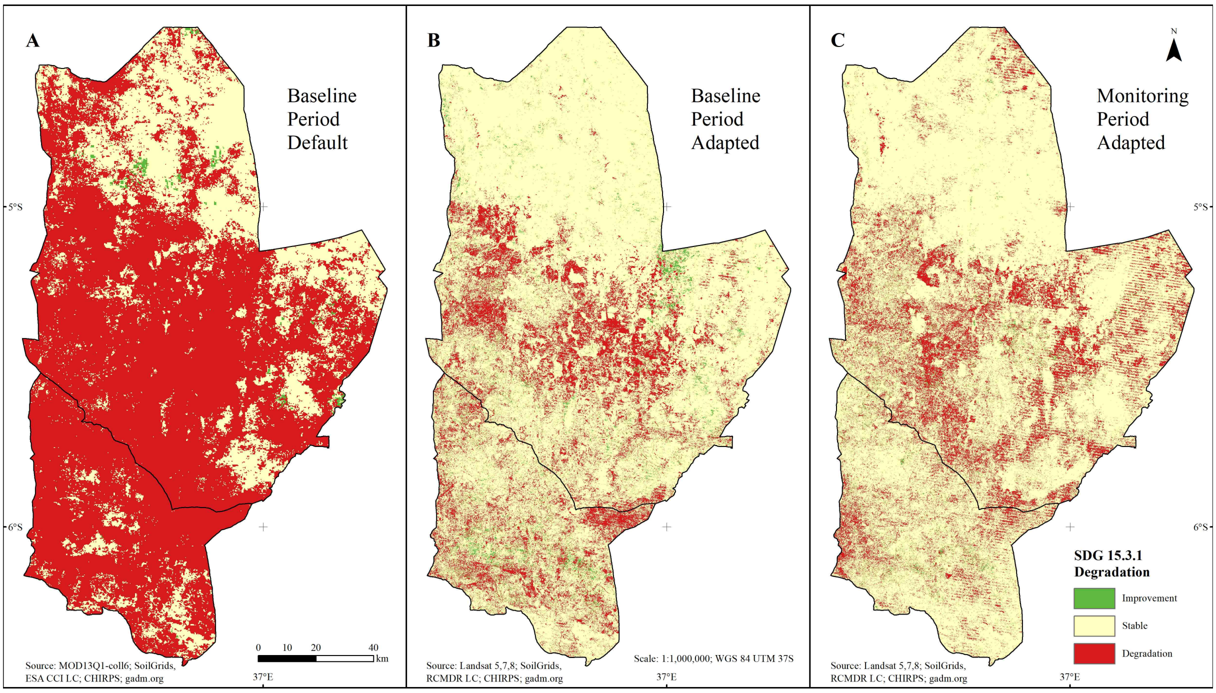


Figure 4.7.: Comparison the SDG 15.3.1 indicator. (A) shows the baseline period with the default approach, while (B) depicts the same period with the adapted approach. (C) shows the indicator for the years 2016–2019.

contribution in total. Thus, about 30 % of the total degraded area were affected by at least two indicators, 4 % even with all three, indicating areas of special interest.

Target period t_1

During the first target period from 2016 till 2019 and following the adapted methodology, 16 % of the area degraded, while 1.5 % improved (figure 4.7 C). Thus, more than 84 % stayed stable. Kiteto was slightly more affected than Kongwa with 17 to 14 %. Forests and grasslands were proportionally the least affected LC classes. The latter only had a 34.3 % share, which is more than 9 pp less than the average cover in 2018. On the other hand, crop- and wetlands degraded most: 38 % of the degraded area is covered by agriculture and 7 % by wetlands. The latter means that the chance that wetlands were degraded was more than three times higher than the original cover. Of the degradation, nearly 90 % were originating from LP degradation, more than a fifth from LC degradation and only about 2 % by SOC change. Less than a tenth was originating by two or more indicators.

Combination of Baseline and Target Period

In total, 19 % of the study area degraded over the first 20 years of the new century due to LP decline (figure 4.8 A). Further 14.9 % showed early signs of decline. There are quasi no stressed areas and about half a percent improved. Kiteto is more affected than Kongwa as well: A fifth of the district is degraded as compared to 16.3 %. Forest- and grasslands are less degraded than one would suspect (5 % and 38 % respectively), while croplands were disproportionately affected with 7 pp more than the average cover. Based on the indicator aggregation, Trend has the biggest impact on the final indicator, but it is clearly visible that also State displays the same areas as degraded. On the other hand, Performance shows nearly no degradation and has therefore quasi zero impact on the final results with less than one km^2 stressed.

Table 4.5.: Presentation of the SDG 15.3.1 indicator of LD and its sub-indicators for the years 2000 till 2019. Next to the land degradation metrics, the proportion degraded per district is shown as well as the share per land cover class.

2000 – 2019 (%)	LP	LC	SOC	SDG 15.3.1
Degraded	18.9	7.8	8.6	27.7
Stable	81.1	90.9	89.2	69.4
Improved	0.5	1.3	2.1	2.8
Kongwa	16.3	9.4	12.6	31.3
Kiteto	19.7	7.3	6.8	26.7
Forestland	4.9	0.2	1.1	3.9
Grassland	38.0	25.8	14.6	32.5
Cropland	37.4	28.4	62.7	41.9
Wetland	3.6	13.6	2.3	4.6
Urban	2.1	8.5	4.2	3.0
Otherland	6.8	23.2	13.9	9.0

Over the whole time span of 20 years, in total 7.8 % of the study area degraded due to LC change, while only 1.3 % improved over the same time (figure 4.8 B). Consequently, about 91 % of the land stayed stable, either on the account of no LC change, or because it was marked as stable, e.g. from grasslands to croplands. The southern district Kongwa experienced a slightly higher degradation with 9.5 %, while it also improved by 2 %. Kiteto, on the other hand, underwent less degradation and improvement and thus was more stable. Tree covered areas lost nearly 4 pp and grasslands almost 5 pp. On the other hand, cropland increased by 7 pp and now covers over 30 % of the study area (figure 4.6).

The combined degradation based on SOC diminishment for the baseline and monitoring period resulted in a degradation of 8.6 % of the study area and 2.1 % improvement. Thus, nearly 90 % did not change the SOC value by more than 10 % over the entire period. Due to the computation based on the LC change matrix (table 3.3), the transition to croplands, urban areas and other land often results in degradation. Thus, it is not surprising that 62 % of the degraded area is covered by croplands and another 14 % other land. These two LC classes are hence affected twice the area one would suspect based on their original size. On the other hand, just a tenth of the forests' normal area is degraded (1.1 to 11 %). In line with earlier observations, Kongwa with its many agricultural lands, is more affected than Kiteto (12.6 to 6.8 % respectively).

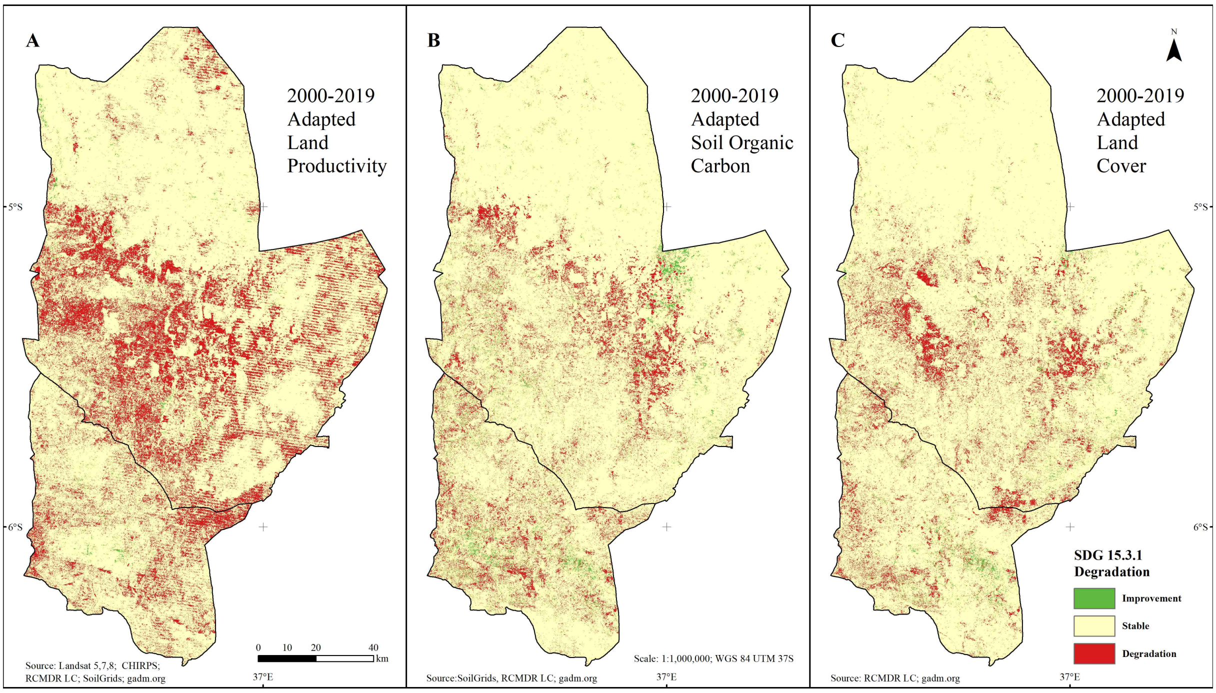


Figure 4.8.: Depiction of the SDG 15.3.1 sub-indicators land productivity (A), land cover (B) and soil organic carbon (C). The results of the baseline period are combined with the results of the first target period t_1 and span 20 years.

Over the whole period of 20 years and thus reporting for the SDG 15.3.1 indicator at timestep t_1, 27.7 % of KK degraded and 2.8 % improved (table 4.5 and figure 4.9 A). Thus, about 70 % stayed stable, which is more than 10 pp less than at t_0. The degraded area increased in both districts, while the raise being higher in Kiteto. Even though the land covered by forests decreased and the land covered by crops increased from 2015 to 2018, the degraded proportion changed conversely: The area degraded by forests rose to 3.9 %, while the area covered by crops sank to 41.9 %. Wetlands saw the biggest relative rise in LD: From 1.5 in the baseline to 4.6 % for the whole period.

Figure 4.9 B shows the final SDG 15.3.1 indicator dissolved by local administrative boundaries and overlayed with the protected areas in KK. Lenjulu is the worst affected ward with 56 % of the area degraded and is located in the north-east of Kongwa (figure 4.9 B). In total, there are four wards with over half of the area degraded which are equally divided between the districts. Of the ten worst affected wards, three are situated in Kongwa and the rest in Kiteto. On the contrary, the two least affected wards are both located in the northern part of Kiteto. As one can see in figure 4.9 B, both are nearly completely covered by protected areas. In total, only 14.6 % of the protected areas are degraded, which is about half of the average.

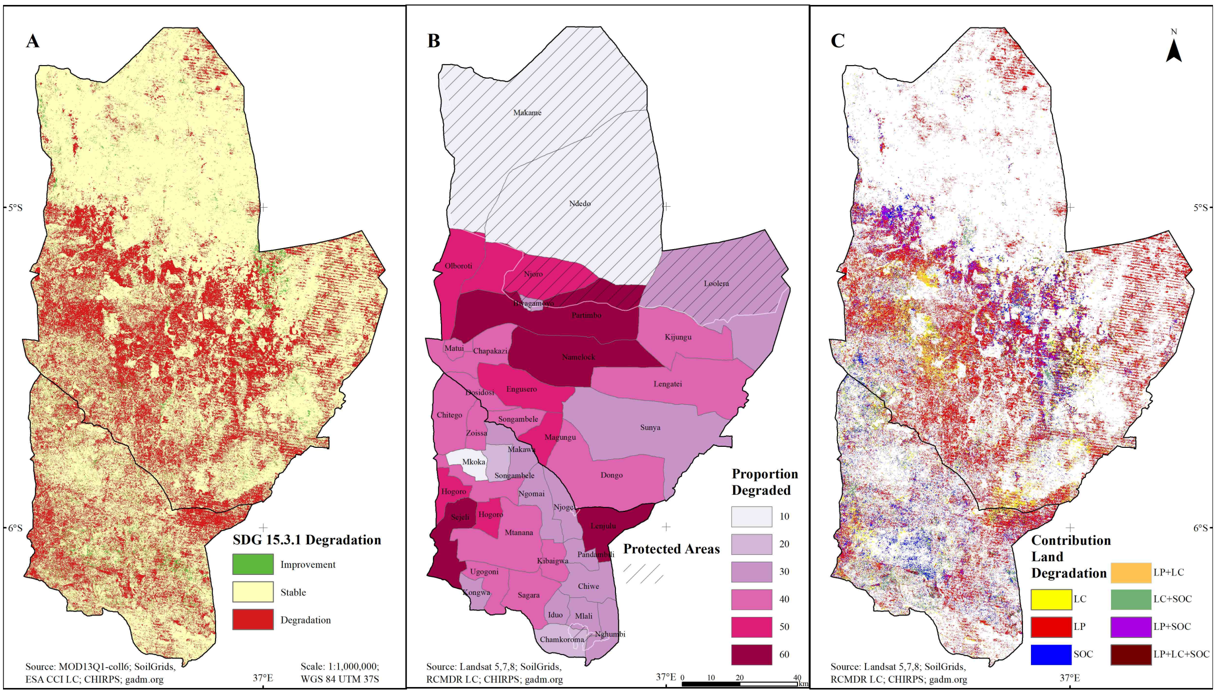


Figure 4.9.: The final SDG 15.3.1 indicator for land degradation for the period of 2000 till 2019 (A) and the same data aggregate by wards with arker colors representing higher proportions of degraded area per district (B). The contribution of the three land degradation sub-indicators on a pixel level is showns, namely land productivity, land cover and soil organic carbon. Combined contribution of the sub-indicators is shown in secondary colors (C).

Due to the increased degraded area, the contributions to the final LD indicator also shifted. While the degraded area by SOC only changed slightly, the relative contribution sank from 50 to 30 % (table A.10). On the other hand, the degraded area which is solely influenced by LP rose to over 50 % and in interplay with others to over 70 %. Figure 4.9 C shows the spatial distribution of the distinct contributions.

4.2. Land Degradation indicator monitoring in Kongwa District

(a) Picture showing a filled gully near plot 9 coming from the southern upland of Kongwa.

(b) Communal cattle grazing near plot 33 in a shrublands.

(c) Fallow land in plot 13 with low plant cover due to overgrazing.

(d) Applied SLM practices in plot 11 using hedgerows, cereal-legume intercropping and minimum tillage.

Figure 4.10.: Impression of the landscape near the plots in Kongwa. Photos are taken on or close by the sampled plots.

Over the time of ten days, 34 plots were examined in total, all being located in the district Kongwa (tables A.11–A.15). The lowest elevation recorded is about 900 m above sea level reaching up to the maximum of 1482 m. The mean is about 1200 m with only four plots below 1000 (table A.11). According to the LC dataset, crop- and shrublands were equally distributed with 16 plots, followed by grass- and forestlands both having only one plot. In the field, the plots were classified into forest-, crop- and shrublands as well as non-wooded and wooded grasslands. In comparison to the LC dataset, the in situ classification yielded more croplands and less shrublands with 21 and 5 plots respectively. Only three shrub-plots matched the field classification and the number only reaches six, if the wooded grassland class is also seen as a possible shrub class. Most misclassification happened within shrublands which in eight times were actually croplands. The land use often coincided with the land cover, especially in croplands. However, eight plots were used for grazing, while only four were natural and one was a woodlot, while another was fallow. 29 of 34 plots have a gentle slope and the same number of plots lie in mid-slope with only one plot in bottomlands and two at an upland topographical position. The soil color is primarily brown and red with some black and grey plots. The ownership of the plots is mainly private, except for one great state-run cattle farm, where seven plots were situated. Only two sites were communal. Of the 20 plots which cultivated annual crops, three forth planted maize, while sorghum and sunflower were popular among the farmers with eight and six counts respectively.

Bare soil covered on average more than two-thirds of the ground and, on contrary, the mean coverage of the herbaceous vegetation was only about a fifth of the ground. The cover of the sampled plots is heterogeneous and has a high standard deviation with values reaching from zero to nearly 100. Signs of LD could be found in 28 of 34 investigated plots, with water erosion being the most common, followed by biological deterioration with 20 counts (table A.12). Signs of wind erosion were only found eleven times. The most important forms of degradation are in descending order rill and sheet erosion followed by the reduction of vegetation cover and loss of top-soil due to wind erosion with 21, 19, 16 and 11 counts respectively.

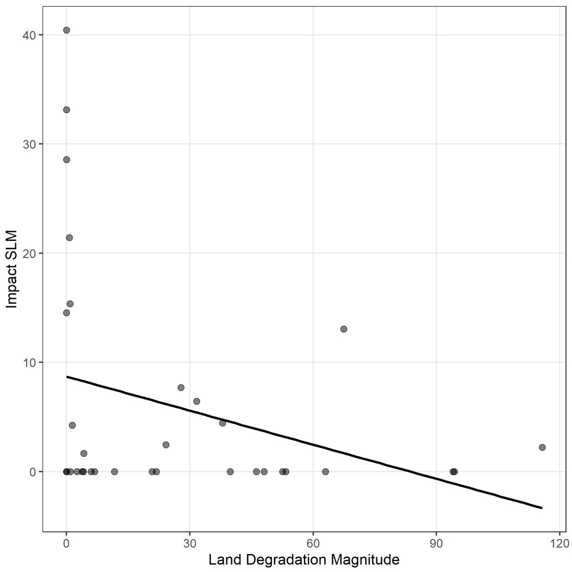
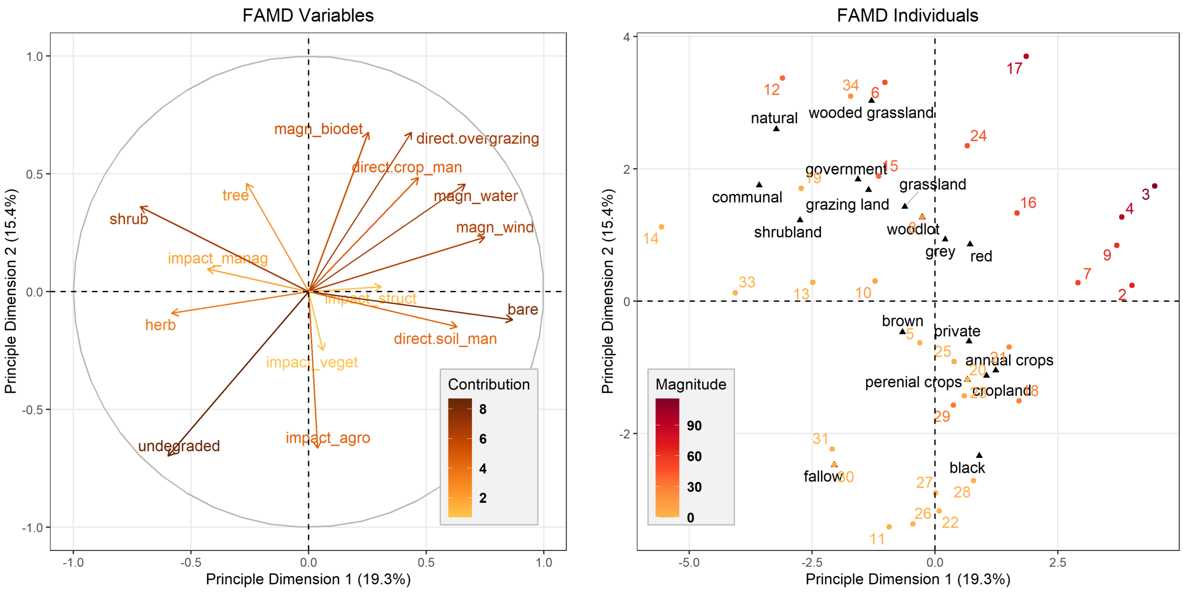


Figure 4.11.: Comparison of land degradation magnitude with the impact of sustainable land management. The black line shows the linear regression between the two axes. The r-value is 0.0978 and the p-value 0.0761.

The most common driver in Kongwa was overgrazing, affecting over 70 % of the plots (table A.13). This was followed by 13 counts for improper soil management and improper crop and rangeland management, which mainly affected croplands. If LD was apparent in the plots, land conservation practices were investigated (chapter 2.4). In total, some form of SLM was applied in 21 out of 34 plots (table A.14 & A.15). The most apparent measures were vegetative and agronomic measures with 13 and 12 plots, followed by management and structural measures with 7 and 2 counts respectively. Examples of these measures applied are intercropping (8), contour tillage (8) and mulching (4) for agronomic measures and cover crops (9), hedgerow (7) and agroforestry (4) for vegetative measures. The most popular management measure is fallow with four plots. The purpose of the SLM was



(a) Quantative variables are depicted and colored by their contribution to the axes.

(b) Qualitative variables and plots are depicted. The latter are colored by the magnitude of degradation.

Figure 4.12.: Figure a) and b) show the biplot of the factor analysis of mixed data. The first two axes are shown and represent 19 % and 15 % of the variance respectively.

equally distributed between the prevention and mitigation of LD.

In figure 4.11, one can see the LD magnitude plotted against the impact of SLM and the corresponding linear regression. Similar to the effects one would expect of SLM practices (chapter 2.4), there is a negative relationship between SLM and LD: All plots with values higher than 15 SLM-impact do not show signs of LD and, on the contrary, plots with high values tend to have low SLM values which is also visible in the negative linear regression line. Anyhow, the r-value is just 0.0978, thus the linear regression only explains a small part of the proportion of variation. Furthermore, the p-value is 0.0761 and therefore not statistically significant.

Figure 4.12a shows the variables and the first two dimensions of the factor analysis with mixed data, with their respective contribution of 19.3 % and 15.4 %. The individual values such as plot information and qualitative data are depicted in figure 4.12b as dots and triangles respectively and information of the total magnitude of degradation is visible as the color of the dots. The x-axis is mainly influenced by the variable *bare* and wind erosion (*magn_wind*) on the one hand and *shrub* cover on the other hand (figure 4.12a). The second axis is for the most part influenced by the vegetation type and the land use as well as the variable *undegraded*. The individual values form several clusters on the graph. Crop-plots, which are not severely degraded can be found on the negative part of the second axis (plots 11, 27, 31), while plots with higher shrub and tree cover and (semi-)natural features are situated in the upper left corner (plots12, 19, 34) (figure

4.12b). Finally, the most severely degraded plots can be found in the upper right corner, where many magnitude and direct drivers point at (plots 3, 4, 9).

One hypothesis would be that the SDG 15.3.1 indicator for LD reflects a high LD magnitude, i.e. a great extent and degree of erosion as well as the number of erosive features on the ground. Looking at figure 4.13, one hence would expect a more or less linear relationship between both variables. It is obviously not the case: The linear regression is slightly positive, but has a great standard error and is not significant with a p-value of 0.295. Many Plots with a low magnitude (less than 10) were classified as degraded (2), while plot 3, which has the highest magnitude (115) is said to be stable (1). Furthermore, the impact of SLM measured in the field was also color-coded in the figure. The hypothesis is hence that SLM prevents LD (chapter 2.4). Thus, the higher the SLM value, the lower the LD. This is also not true, as there is a negative relationship, but it is not significant with a p-value of 0.165.

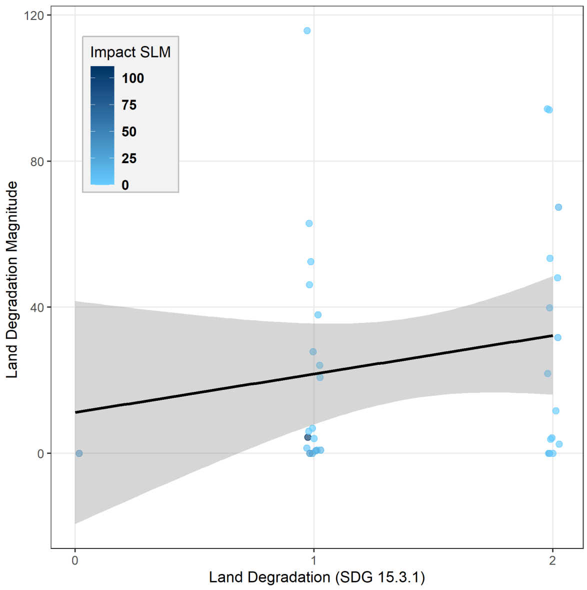


Figure 4.13.: Comparison of the SDG 15.3.1 indicator land degradation with the combined land degradation magnitude indicator from field samples. Higher values on both axes signal more degradation. 0 on the x-axis shows improved, 1 stable and 2 degraded conditions. A darker blue color symbolizes a stronger impact of sustainable land management practices. The black line shows the linear regression and the grey area the standard error.

5. Discussion

The key contribution of this research is the land degradation assessment in central semi-arid Tanzania. So far, only global assessments with medium resolution (Conservation International, 2019) and local hybrids still relying on default datasets were available in the study area (URT, 2018b). This research follows the Good Practice Guidance by the UNCCD and implements local adoptions with high-resolution imagery. Furthermore, it is the first study, which assesses the SDG 15.3.1 indicator in Tanzania not only for the baseline period but also includes the target period until 2019. The first four out of 15 years of the SDG timeframe are thus assessed as well and can help to prioritize hotspot areas to combat land degradation.

The results of these LD assessments in interplay with the questions raised in the introduction lead to a number of interesting findings. The degraded area is very similar for both the baseline and the first monitoring period with 16.4 % and 16.0 % respectively. Over the whole time span, 27.7 % degraded, thus great parts did not overlap and formed new areas of degradation. Furthermore, the degradation is not equally distributed over the study area: Central and Western Kiteto as well as Western Kongwa are especially affected hotspots with over half of the area being degraded. On the other hand, the two biggest wards in the north are the least affected and are almost completely protected. The LP indicator dominates the results: Half of the degradation is solely influenced by LP, the remaining half is affected by SOC, LC, or by the combination of more than one indicator. As already described in the previous chapter, the differences between the default and the adapted approach are staggering and can only partly be explained by differing datasets and methodologies. The following chapter will discuss the results, relate the findings to the literature and consider possible explanations for the results. Further, an outlook is given and possible errata will be discussed.

5.1. SDG 15.3.1 Indicator

The results of the LD assessment in Kiteto and Kongwa lead to a quite pessimistic view on the status of the landscape and its nature. The Tanzanian target is to achieve LDN until 2030 and to improve a fourth of the forested area (URT, 2018b, p. 19 ff.). Both Kiteto and Kongwa are part of hotspot regions, which should improve 25 % of the area based on the status at t_0. So far, only 1.5 % of the area improved, but 14 % degraded. Next to the (sub-)national targets, there are also specific targets to avoid, minimize and reverse LD: Inter alia, about half of the current national forest area should be restored, half of the national croplands should improve LP and the SOC content in croplands should rise to 54.5 t/ha. The results for these more specific and ambitious targets rather show a negative trend as well. Instead of restoring vast forests, even more trees were cut. Lastly, in croplands, LP degradation was above average, while the SOC content in t/ha improved marginally. A possible explanation could be that restoration attempts using SLM practices did not go into effect because of the described time-lag (chapter 2.4) and the time it takes for SOC to change (chapter 3.2.3). Still, the overall trend indicates negative effects and it is clear that further efforts to combat LD are needed.

Comparing the LD results with the field data which were retrieved in December 2019 did not show clear results (figure 4.13). There is no statistically significant relationship between LD magnitude and the LD derived by remote sensing. Further, the SLM impact sampled on the ground neither showed a statistically significant relationship to the adapted LD indicator nor the LD magnitude (figure 4.11). A problem comparing the two datasets is for one that both are (mainly) working with ordinal scales such as improving or degrading and not with actual numerical values. Therefore, gradients cannot be shown. Furthermore, the fieldwork was just able to assess a momentary estimation of the status of the sampled area. In contrast, the LD assessment for the SDG indicator shows change over 20 years and only considers relative changes. Due to the methodology and research constraints, it was not possible to e.g. assess how the plots changed over time and if they were less degraded before. Comparing these findings to the literature, García et al. (2019) conducted a LD assessment based on the WOCAT framework as well and compared it to NDVI trends. Land degradation trends found on the ground did not match trends detected by remote sensing in northern Argentina. Additional studies, which compared NDVI values with SLM practices, found a time-lag in the effect of SLM practices. This could be another explanation why there is no significant correlation detectable between the remotely sensed indicators and the findings detected on the ground (GEF, 2016; Gonzalez-Roglich et al., 2019). Hence, it is necessary to perform the fieldwork and the LD assessment regularly, as suggested by the UNCCD (Sims et al., 2017).

Comparing the two districts, there are several interesting findings to make. As shown in table 4.5, Kongwa is more degraded than Kiteto for the final indicators as well as LC and SOC change. Contrary, Kiteto was more affected by LP degradation. Kongwa has a longer history of LULC change than Kiteto, as already a quarter of its land was used for agricultural purposes in 1987 (Kimaro et al., 2012, p. 36). Even though Kongwa, was already quite transformed before, over 19 years, the amount of cropland grew by another 9 pp, thus increasing more than twice the amount of pps as Kiteto A.7. Despite the fact, that Kongwa has a longer history of transformation, the LP was better off. Thus, it seems a bit contra intuitive that Kiteto, regardless of low LC change and more untransformed landscapes, has more vegetation decline.

The Tanzanian LDN report (URT, 2018b) depicts four classes of degradation in its hotspot map but does not make clear how the individual classes were obtained. Anyhow, the two districts

KK are severely degraded and the map shows that northern Kiteto is not as harshly affected as well (URT, 2018b, p. 17). Furthermore, the study indicates that LP declined most in croplands and that forests improved above average, both observations hold true for the AA as well. Thus, the results by the AA are, at least partly, reflected by the national LDN report, even though a shorter timespan was used. Unfortunately, there is no disaggregation for districts available to further compare the LD results.

As described in chapter 3.2.1, Trends.Earth did apply some alterations to the methodology, hence the results differ quite significantly as well. Similar to the LDN report, the default results of Trends.Earth also show widespread LD in KK. This is quasi solely based on the LP indicator, while SOC and LC change do not show degradation. Contrarily, the AA has higher values in SOC and LC, but significantly lower values in LP, which ends up in a lower total degradation.

5.1.1. Land Productivity

The LP indicator shows a clear trend towards more degradation. Firstly, the area degraded rose from 8.2 % to 12.2 % between the baseline and the monitoring period. Secondly, also the *early signs of decline* sub-component increased from 9.1 % to 17 %, hence nearly doubling. Lastly, the improved area sank from 0.5 to 0.01 %. Thus, not only did the degradation increase, but the possibility, that this trend will carry on is also given. Furthermore, the areas degraded did also change spatially during the time and there was little overlap between t_0 and t_1: 18.9 % of the area degraded over the 20-years. Kiteto degraded more than Kongwa, as opposed to LC and SOC.

Interestingly, croplands were the worst affected land cover class, not only in LP but also in SOC. This goes in line with what other researchers found out in the study area. Due to the continuous cultivation of the agricultural lands in combination with overgrazing and little inputs of fertilizers, the crop yields stay low (Kimaro et al., 2012, p. 63). Limited availability of soil nutrients and organic matter are the main reasons for this (Kimaro et al., 2015, p. 1). This can be detected by the LP values in croplands, which declined more often than other LC classes. Another study, which assessed LD in Kenya, also found that croplands had the greatest decline in LP, which indicates that bad farming practices are widespread throughout Eastern Africa (Gichenje & Godinho, 2018).

As already described in chapter 2.2, LD, or rather LP, assessments for Tanzania vary widely in the area affected. There are no studies for KK directly, but the national estimates give some overview of the study area. With around 27 % of the area degraded, or rather 18.9 % for the LP indicator, it is roughly only half as affected as the LD assessments by Bai et al. (2008) or Le et al. (2016) would suggest, but several times more than the assessment by Landmann and

Dubovyk (2014) indicates. The former studies show hotspots in the study area and thus higher values than their national averages of 41 % and 51 % respectively would suggest. It is important to mention that the two studies used different periods (ending in the 2000s) and only a subset of the methodology (LP Trend) and coarse resolution imagery as well (64 km^2 to 0.0009 km^2). The latter is also apparent in the default and AA: Even though the difference in the spatial resolution is not that big it is still a difference in the pixel size of 6.25 ha (MODIS) versus 0.09 ha (Landsat), thus a factor of nearly two. There are several studies which highlight the importance of using high-resolution imagery to detect LD also on spatial heterogeneous landscapes such as KK districts with small farm patches (Akinyemi, Ghazaryan, & Dubovyk, 2020; Fiorillo, Maselli, Tarchiani, & Vignaroli, 2017; Gichenje & Godinho, 2018; Giuliani, Chatenoux, et al., 2020; Venter, Scott, Desmet, & Hoffman, 2020). The most significant drawback of the AA is the worse temporal resolution: Instead of a return period of one to two days, which results in a merged unclouded NDVI image every two weeks, Landsat only has a return rate of two weeks, which can be compromised by clouds. Fortunately, the temporal resolution is increased due to the usage of Landsat 5, 7, and 8 in conjunction, thus allowing for a higher return period.

As LP is a combined indicator, the aggregation method is crucial for the final output. As described in chapter 3.2.1, Trends.Earth uses another system to aggregate LP. Due to this, the State indicator has a higher importance in the overall LD indicator. Table 4.1 shows the differences of the two aggregation methods: Because LC and SOC are insignificant for LD using the default data, changes in the aggregation methods of LP have direct influences on the final indicator: Instead of more than 70 % being degraded, it would have been less than 30 %. Thus, it seems, as if the greatest influence is not originating from the computation and the underlying methods and datasets, but the aggregation scheme. Using Trends.Earth for the LD assessment and consequently also the LDN reports would, therefore, shed a worse light than it had to be.

Another relevant difference in the computation and a drawback of the DA by Trends.Earth is that they did not apply the NDVI time-series to the growing season, but used the mean value of the whole year (Wessels, 2009). Hence, in the dry season from June to November the sensors are mainly detecting soil rather than vegetation. Further, the growing year does not collide with the calendar year, so the effects of one growing season are affecting two calendar years (chapter 3.2.1).

Furthermore, in 2003 the Landsat 7 scan line correction failed with the effect that it consequently had data gaps on the edges of the images and only 78 % of the pixels are working properly (Wulder et al., 2016). There are various methods to try to address this issue, like spatial regression or multi-scene gap-fill (USGS, 2004). Yet, this still cannot retrieve the uncaptured pixels and may distort the results, e.g. by imputing the gaps with incorrect nearby values or by values, which are not fitting temporally. The ultimate solution could be to only use

Landsat 5 and 8. Unfortunately, there would be a gap for the year 2012 because only Landsat 7 was operational then. Furthermore, the temporal resolution would also be diminished.

The GPG recommends smoothing the time-series to remove noise from the dataset. There are different smoothing techniques available, such as the Savitzky-Golay filter (Z. Cai, Jönsson, Jin, & Eklundh, 2017), but these methods also distort the data. As the AA does not work with the time series itself but with the mean value of the growing season, possiblly positive or negative outliers should not influence the results significantly.

As already discussed in chapter 2.1.1 there is also the question whether NPP or NDVI can capture land degradation correctly without creating false alarms. For example, bush encroachment is often seen as a form of LD, but also leads to higher NDVI values. This was investigated in the field and, at least for the areas sampled, there seems to be no urgent problem with bush encroachment, with only 5 of 34 plots being affected (table A.13). Though in northern Kiteto the LP State indicator improved, which could reflect bush encroachment. Unfortunately, there was no validation possible. Another example is high productive farms which just sustain their productivity through intensive use of fertilizers (Caspari et al., 2015; Dubovyk, 2017; Engel-Di Mauro, 2014; Orr et al., 2017). As for that: There are nearly no high-biomass production systems in KK. Thus, these effects will probably also not be captured by the LP indicator.

Trend

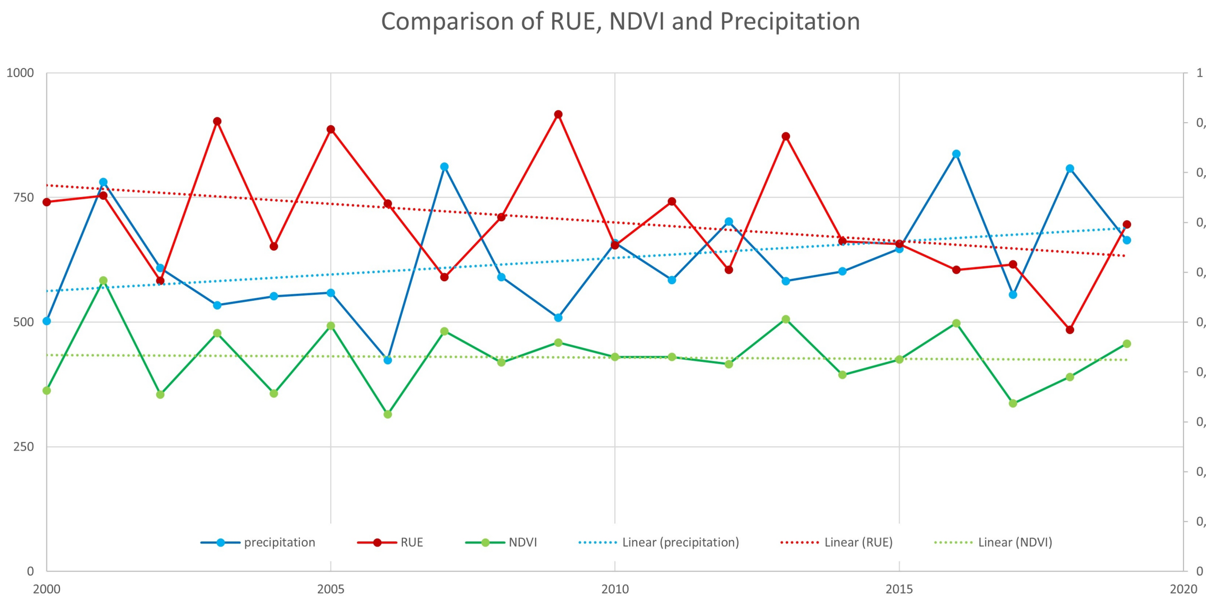


Figure 5.1.: Depiction of RUE, NDVI and Precipitation over the years. The average annual mean for RUE and NDVI and the sum of the precipitation is shown. RUE values were multiplied by 1000 to better fit them to the scale.

The LP Trend is based on the RUE, which is said to be negatively correlated with precipitation, thus showing lower values in RUE, even if the rainfall and NDVI both increased (Fensholt et al., 2013; Wessels et al., 2007). As for our dataset, there is indeed a negative correlation visible between RUE and rainfall. A positive correlation between NDVI and precipitation on the one hand and RUE on the other is also detectable (figure 5.1). Therefore, years with high rainfall resulted in unusually low RUE values. For example, there were three years (2007, 2016 and 2018) with precipitation higher than 800 mm and the respective RUE values belonged to the lowest four in the time series (tableA.16). Thus, the RUE may overcompensate the effects of the vegetation growth in rainy years. As one can see in figure 5.1, the NDVI trend is relatively steady over the years, while the precipitation trend is positive. Consequently, the RUE trend decreased as well, both in the baseline period and the first monitoring period.

To overcome these drawbacks of RUE, RESTREND was developed in order to predict the NDVI for a given amount of rainfall (Wessels et al., 2007). Tendencies in the difference between the predicted NDVI and the observed NDVI are interpreted as non-climatically related productivity change (Fensholt et al., 2013; Wessels, van den Bergh, & Scholes, 2012). Unfortunately, RESTREND has problems detecting LD as well. Wessels et al. (2012) found out that RESTREND becomes unreliable detecting significant negative trends if the reduction of the NDVI is less than 30 % and if the rainfall variability is high, as in our study area. Therefore, it seems that the "RESTREND method has a limited ability to solve the challenge of correcting for rainfall variability and trends to facilitate land degradation monitoring" (Wessels et al., 2012, p. 19).

Furthermore, Wei et al. (2018) detected a general trend of vegetation decline for the study area due to a lack of soil water availability as well as the dependency of precipitation. Contrasting,Tucker and Pinzon (2017) detected a decline in LP with RESTREND, even though the dataset was corrected for variations in soil moisture, but found increasing values, when correcting it for variations in precipitation. Thus, it is obvious that choosing the appropriate climate calibration method is indeed challenging and that (Higginbottom & Symeonakis, 2014).

State

LP State can help identify the most recent degradation and assist spatial targeting of emerging hotspots. Interestingly, the DA does not show hotspots, but rather declares KK a "hotarea", with more than two thirds of the study area degraded. On the other hand, the State indicator for the AA showed two sides: Both improvement and degradation are happening simultaneously. Over 35 % did not stay stable, while the proportion changed over time. During the baseline period, more improvement was apparent, while the trend changed for the monitoring period, where degradation reached a quarter of the area. Not included in the GPG, the category *early signs of improvement* could be added which would only reflect the positive State indicator if no other indicators are negative (figure 4.2 B & 4.2 C). This holds true for the vast northern part of Kiteto, where there are several protected areas.

Comparing the computation of the State indicator to the other two, it seems a bit peculiar that the degradation is based on the change of two classes and not on relative change or of pp as the other two indicators do. As for now, two pixels may be classified as improving or stable, even though the difference in between the years is the same. For example, irrelevant if the normalized value is 20 or 29, the pixel will be ranked in class 2 in the first year. For the final year, the former value may have increased by 19 to 39, still, it would have stayed in class 3, thus not "significantly" changing the class and staying stable. On the other hand, the latter value of 29 only needs to improve by 11 to rank two classes higher and therefore improve. Thus, the methodology behind the State indicator seems to be inconsistent to a certain extent and could be improved further.

Performance

The sub-indicator LP Performance does not yield significant degradation (table 4.1 and figure A.1). Both approaches and timesteps result in over 99 % of the area staying stable. As soil and LC classes are used to create distinct ecoregions, the low change rate could be partially resulting from the dataset. For example, Sims et al. (2017, p. 52 f.) recommend to also include climate or soil moisture data to create unique "land capability units" (Wessels et al., 2007). Furthermore, Ivits and Cherlet (2016, p. 40 ff.) use the concept of Ecosystem Functional Types. These types are based on climate data as well as land use system classes and are fit globally as well as for Europe. Thus, another reason for the low degradation values could be the scale of the study area. The original methodology is based on global and continental LD assessments, thus the 17,000 km^2-comprising study area may be too small, to reflect changes between similar ecoregions. Another possibility is, that there are simply too many ecoregions. In total, 408 distinct regions were computed, of which nearly 250 had less than 1 km^2 in size. Unfortunately, there are just limited papers about LD assessment published, which also follow the GPG and implemented the LP Performance in their methodology (Giuliani, Chatenoux, et al., 2020; Giuliani, Mazzetti, et al., 2020; Gonzalez-Roglich et al., 2019). Others only partly apply the methodology and exclude the Performance indicator (Akinyemi, Tlhalerwa, & Eze, 2019; Teich et al., 2019). Unfortunately, there are no distinct results on LP Performance available of the former papers, thus making a comparison to literature difficult. As the LP Performance indicator does not yield any information on degradation in the study area — neither for the AA nor for the DA —

it seems appropriate to exclude it from the LD calculations.

5.1.2. Land Cover Change

As already described in chapter 3.1 and 3.2.2, the land cover in the study area changed for many decades and the trend continues until the present day. Natural land covers were lost while croplands increased: Over 20 years, the percentage covered by forests sank from 14.9 to 11 and for grasslands from 48.3 to 43.5. On the other hand, croplands were expanding from 23.4 % to 30.3 % of the study area. The higher pace of the transformation is daunting: The change-rate per year in ha is higher in the monitoring period (2015–2018) than during the baseline period of 16 years. For example, instead of about 3000 ha forests lost per year the rate increased by 50 % to 4500 ha in the monitoring period. The only land cover class which reduced the speed of change was croplands, from 6100 ha to 5300 ha. If this land cover change rate continues at the same pace, there could only be 8.3 % of forests left at the end of the SDG period in 2030, thus failing the above mentioned LDN targets completely.

According to Kimaro et al. (2012, p. 34 ff.), who investigated the LC change for the study area from 1987 to 2010, the LC change was already in progress over 30 years ago with heavy declines in (semi)-natural landscapes. Forests, shrubs-, and woodlands lost 46.4 % of their area, while croplands increased at the same time by roughly 31 %. Therefore, LC change, especially the agricultural expansion and deforestation, can be seen as a key historic and present driver of LD in KK. With the ongoing population growth and the still stagnating agricultural production, it seems as if the observed trend in LC change is probable to continue in the next years.

Interestingly, the ESA CCI LC dataset did not seem to reflect major changes during the baseline period in KK districts. In contrast to many other deforestation estimates (table 5.1), it even saw a rise of 4.4 % for forests, while most other LC classes stayed stable. A comparison between several deforestation estimates for the whole of Tanzania shows a similar trend (table 5.1). The LC dataset by ESA only shows an annual deforestation rate of 23,860 ha and thus is the most conservative assessment. Other local estimates, like the National Forest Resources Monitoring and Assessment of Tanzania Mainland (NAFORMA) (cited in URT,2018b, p. 15 f.) or the Tanzanian Forest Reference Emission Level (FREL) (URT, 2017, p. 31) suggest a change rate that is three to twenty times higher respectively for similar periods. The LDN report concludes that the estimate by RCMRD, which assumes a change rate of 157,900 ha per year and lies between the estimates of NAFORMA (TFS, 2015, p. 55) is best suited to reflect the change that happened in the country (URT, 2018b, p. 15 f.).

Furthermore, the ESA CCI LC dataset does not reflect the change in the agricultural sector. Statistics by the FAO about the LULC change in Tanzania suggest that the agricultural land expanded from 150,000 km^2 to 461,326 km^2 in just 15 years and thus more than tripled, while the LC by ESA only changed by 2 % for the whole country (FAO & NBS, 2020). Furthermore, Laso Bayas et al. (2017) compared four different African LC maps by validating them with field data of agricultural activities in Tanzania. The study found that ESA CCI LC overestimated cropland, while the product by RCMRD was in line with the FAO estimates as well as the field data. The question arises, why the ESA CCI LC seems not to detect LULC change in Tanzania as well as in KK districts. Possibly, it is also due to the medium resolution of 250 m that the dataset cannot detect these changes, even though such large scale deforestations should be detectable with medium resolution.

Table 5.1.: Comparison of major deforestation estimates for Tanzania. Appraisals, which are based on LC change, are highlighted in grey.

Forest lost	annual (ha)	total (ha)	year
ESA CCI[1]	23.860	238.600	2000–2010
NAFORMA[1]	81.000	810.000	2000–2010
RCMRD[1]	157,900	1,579,000	2000–2010
TFS[2]	236,711	710,133	2015–2018
NAFORMA[3]	372,816	5,592,240	1995–2010
FREL[4]	469,000	5,159,000	2002–2013

[1] based on data cited in URT (2018b, p. 15 f.)
[2] URT (2018c, p. 14)
[3] TFS (2015, p. 55)
[4] URT (2017, p. 23)

In a further step, also the land cover change matrix needs to be reflected upon critically (table 3.2). For the DA, changes from grasslands to croplands are being evaluated as an improvement. For the AA, it is marked as stable due to the consideration of the enhanced agricultural production versus ecosystem services and biodiversity (chapter 3.2.2). As described by Kimaro et al. (2015, 2012), and apparent through the low LP in croplands, local farming practices are not sustainable and do not lead to higher productivity. Though, grass- and shrublands are often intensively used for grazing and as woodlots, hence making them not necessarily more sustainable or less prone to degradation. Thus, it seems appropriate to let the change from grasslands to croplands be considered stable, instead of improving and therefore, not encouraging further expansion of agricultural areas.

The used LC dataset for the AA is based on maps created for the Greenhouses Gases Inventories by RCMRD for the years 2000 and 2010. The land cover map of the year 2010 also includes cloud and shadow artifacts in Central Kiteto (Oduor et al., 2016; RCMRD, 2018). These artifacts are also present in the adapted dataset. Thus, these maps are partly compromised with land cover classes, which have no meaningful counterpart on the ground. Furthermore, the RCMRD LC map does not seem to fully capture periodic or episodic wetlands and riverbeds. For example, the large areas in northern Kiteto, which are classified as otherland, are being classified as wetlands in other LC datasets (figure 3.3). Lastly, the urban LC class seems to be too prevalent in Kongwa and includes areas that are in the proximity of villages and settlements.

Therefore, collecting ground truth data in the study area on a greater scale to validate the LC map would improve future assessments further, especially focusing on the above mentioned LC classes. Nonetheless, the LC transitions over the 20 years are reflecting changes, that are well documented by several other sources and are a great asset for the LD assessment (FAO & NBS, 2020; TFS, 2015; URT, 2017, 2018c).

5.1.3. Soil Organic Carbon

Over the 20-years, 8.6 % of the study area degraded as of SOC change. Due to the time lag of the metric, the overall indicator is only marginally influenced by the first monitoring period and mainly reflects the baseline period. Comparing the LC transitions map (figure A.2b) for the baseline period with the respective SOC degradation map (figure 4.5 B), shows that the main degradation was happening in lost grasslands with about half of the area. The deforested sites were the second biggest area, were SOC degradation was happening. This is especially significant as forests are also the LC class with the highest SOC content, thus every ha of lost forests leads to a higher absolute reduction in SOC. For example, a hectare of forest converted to cropland in 2000 (63.2 t/ha) would result on average in losses of more than 26 t SOC over the 20-year period (tables 4.3 and 3.3).

In total, the KK districts lost 1.6 million t of SOC. Models suggest that due to LULC change 27 Gt of SOC will be lost in the next 40 years, mainly in SSA (FAO & ITPS, 2015; van der Esch et al., 2017). This is especially dire, as SOC is important for the soil quality and thus a key ecosystem indicator (Chotte et al., 2019). Studies conducted in Tanzania found out that higher values in SOC on the farm level resulted in financial benefits and that farmers with poor soils benefited from it all the more (Bhargava et al., 2018). Thus, obviously increasing the SOC would not only improve the living conditions of farmers but also benefit the climate. Furthermore, Winowiecki et al. (2016) conducted a SOC assessment in Tanzania as well and detected a significant relationship between eroded sites and low SOC values. Thus, it is all the more relevant to prevent from erosion happening.

Looking at tables 4.3 and A.8 it seems as if the SOC content in croplands improved, both in t/ha and in total carbon. Even though this is true, it does not actually reflect reality. The SOC degradation is based on LC change, thus, the newly cultivated and incorporated land for one adds to the total SOC value. Second, the new land often has a higher SOC content than croplands, hence also increasing the relative amount per ha. Thus, croplands are improving their SOC content at the expense of other LC classes and the ostensible gains are losses at other sites

The third indicator should reflect the change in soil organic carbon but is directly related to the

LC indicator. Therefore, it is not remarkable, that SOC did not change, when the LC indicator also did not change, as it happened for the DA. Hence, as the SOC indicator is structured at the moment, it does not measure changes in a distinct and also not complementary way (Orr et al., 2017, p. 95 ff.). SOC should monitor slow changes that result from biomass changes, but as for now the only difference between LC and SOC are the change matrices (tables 3.2 and 3.3). For the SOC-matrix, transitions between grass- and forestlands are marked as stable, and in general, transitions to wetlands are seen as positive. Finally, changes from crop- to grasslands are evaluated as positive and vice versa. Except for these, the only other difference is that the SOC values adjust over 20 years, while the LC degradation is happening immediately after a LC conversion (chapter 3.2.3).

As for now, there are no national or even sub-national SOC datasets available for Tanzania, therefore the global SOC model by Hengl et al. (2017) was used. But the SoilGrids dataset is not without criticism, as it for one does not reflect a single year, but rather represents legacy soil data (Mattina et al., 2018). Furthermore, Chotte et al. (2019) remark that this soil model does not reflect the actual state of SOC in the ground and often contains uncertainties. Tifafi, Guenet, and Hatté (2018) for instance compared several global SOC estimates and found that Hengl et al. (2017) represent reality better than other assessments. Nevertheless, the examined appraisals differ greatly, are not in agreement with field data, and underestimated SOC by up to 40 %. Therefore, large uncertainties are inherent in the dataset as well, especially in Tanzania, where there are few SOC samples taken. Thus, the SOC estimates have to be taken with caution.

The pristine third indicator was set to be "total terrestrial system carbon stock", but was substituted with SOC, because of insufficient datasets. SOC should have been computed based on three distinct factors (land use, management, and input factor) of which only the land use factor is operational and which again is surrogated by land cover change. To sum it up, the originally planned indicator is not being used and the substitute is only based on one of three factors, which again is replaced by a proxy.

Consequently, Gonzalez-Roglich et al. (2019) did not apply SOC as a sub-indicator of LD, because they stated that the SOC database, the LC map, and the SOC conversion matrix can all contain errors, which subsequently also lead to high error margins in the final LD map. The GPG recognizes these high uncertainties also to a part, not using a statically significant test and applying the 10 % margin as an arbitrary threshold for LD change (Sims et al., 2017, p. 87 f.). Thus, the question arises, whether the current methodology even reflects LD, and if the SOC change is a valuable benefit for the SDG 15.3.1 indicator. In light of absent local SOC data and thus, also no validations for the SOC change, the SOC indicator cannot be evaluated. Concluding, it seems advisable not to involve the SOC sub-indicator into the final SDG 15.3.1 reporting, but rather keep it as ancillary information.

5.2. Statistical Analysis of the Fieldwork

The 34 plots, which were assessed during the 10-day fieldwork trip are not representative for the whole study area, and also only partly for Kongwa. Even though the coordinates were distributed randomly by land cover class, just a part of the proposed sites was sampled. Therefore, one could argue that there is an inherent bias inside the data. Furthermore, because of the time and permit constraints, the plots were sampled cluster wise, so that as many sites could be reached within one day. Hence, plots, which were located in remote areas with no nearby sites had a lower possibility of being assessed. Anyhow, the sampled sites still reflect crop-, grass- and shrublands in Kongwa quite well and can give insights into the interrelations between, biophysical aspects, LD, drivers of LD, and SLM practices.

Of the 34 plots, only six did not show signs of degradation, making more than 80 % degraded. A way higher value than the results which were gathered by remote sensing. Even though each subplot represented the size of a Landsat scene, the satellites cannot detect small erosive features such as sheet or rill erosion and neither invasive species nor bush encroachment. Interestingly and in opposition to the remote results, croplands were underrepresented in the degraded sites, with five out of six plots being undegraded (table A.11). This is also visible in the factor analysis (figure 4.12). The *undegraded* variable is associated with several agricultural plots. On the other hand, of the 13 remaining (semi)-natural land cover sites, 12 were degraded. Thus, it seems clear, that also the seemingly natural sites are under pressure, for example by excessive grazing mammals or wood extraction. More than two thirds of the degraded site had signs of overgrazing, making it the by far most frequent driver. These results fit in line with the findings in chapter 2.3, which also emphasizes the overstocking of herds as a relevant problem (Kirui, 2016). The second most frequent driver found in the sampling sites is insufficient soil conservation measures, which lead to soil erosion and consequently to soil fertility decline. These drivers are described by Tanzanian officials as unsustainable farming practices as well URT (2018c). Other mentioned drivers, which are hard to juxtapose in the field are inadequate land-use management and livestock infrastructure. Furthermore, processes, such as deforestation, are difficult to detect in the field, as they cannot be captured in such an instantaneous fieldwork.

The FAMD reflects the effects of the different drivers well. Overgrazing and insufficient crop management are closely related and are associated with the LD indicator biological deterioration as well (figure 4.12). These relations are reasonable, as excessive grazing often leads to diminished vegetation (Kiage, 2013). On the other hand, the bare soil variable is closely related to the improper management of the soil. Therefore, it seems as drivers, which are related to vulnerable soil and soil erosive features are the most relevant factor for sufficient vegetation cover.

In general, it was challenging to assess the full spectrum of processes and degradation on the ground. Degradation types such as chemical or physical soil deterioration were difficult to detect without proper equipment and questions about the decline of certain natural features cannot be answered without knowledge about prior conditions in the field (FAO, 2011e, p. 5 ff.). Drivers, such as overgrazing, were also complicated to assess, as the assessment needed to focus on proxies for these indicators, such as cattle trampling on the ground.

Sustainable practices were applied in nearly two thirds of the sampled sites. This is surprisingly high, as several researchers found relatively low dissemination of SLM practices in Tanzania (Jambo et al., 2019; Mwaijande, 2017). Sites, where there is little or no degradation apparent, often coincidence with effective SLM practices, while highly degraded sites did not have adequate SLM practices in place. It is also remarkable, that the highest SLM impact value detected was only 40 if one leaves out the Africa RISING reference site with a value of 111. The maximum possible value is 400, thus the highest value detected only reflects a tenth of the maximum possible. Already with values above 15, strong effects are measurable. This indicates for one, that the potential for SLM is not nearly exhausted, and second, that even small-scale adoption of SLM can have relevant effects to reduce or prevent LD. Third, these values seem to fit the results, which Kirui (2016) found, namely a relatively high prevalence of SLM practices, but only a few study sites, where SLM was applied effectively (e.g. higher SLM impact than 10).

To sum it up, the sampled sites have had more apparent degradation than expected as well as more SLM practices. Throughout the whole fieldwork, we did not see actual pristine nature, as even forest reserves on hills were affected by logging. A bigger sampling size on a greater scale in both districts would be desirable to make the results firmer.

6. Conclusion

This study successfully informed the SDG indicator 15.3.1 in KK districts adopting two approaches. For one, it used the global default dataset proposed by the UNCCD — implemented in Trends.Earth — for the baseline. Second, an AA using local datasets and high-resolution imagery was conducted not only for the baseline period but also for the first monitoring period until 2019. Using these freely available datasets and implementing them with the cloud-computation platform GEE, helped to monitor LD on a sub-national scale. For example, it is relatively easy to upscale this research to the whole of Tanzania or neighboring countries with similar environmental conditions.

Comparing the results of the LD assessment for the baseline period reveals large differences between the DA and AA: The former shows that degradation is happening in over 70 % of the study area, whereas the latter only reflects this tendency in 16 % of KK districts. Nearly all degradation of the DA is originating from the LP indicator using MODIS imagery, whereas the degradation is under 1 % for LC and SOC change indicators, based on ESA CCI LC. On the contrary, the degradation captured by the AA is evenly distributed between the three indicators using Landsat time series and RCMRD. Thus, the results derived from coarse resolution datasets are at the same time over- and underestimating LD for the sub-indicators and cannot help prioritize spatial planning. Further, the AA shows that local datasets and high-resolution imagery are important to capture the heterogeneous landscape in Central semi-arid Tanzania and help to better target SLM measures. The SDG 15.3.1 indicator for the year 2019 reveals that degradation is ongoing until the present date. The degradation did not halt after 2015, but spread further across the districts and formed several clusters of severe LD. Therefore, it is important to combat the most relevant drivers of LD, such as overgrazing and unsustainable farming. Furthermore, SLM and agricultural intensification is needed to enhance the low LP in croplands and prevent the ongoing LULC change in KK districts. Otherwise, it might soon be too late to reach the LDN goal in 2030 for KK districts.

Moreover, local evaluation is needed to check whether the assessed LD reflects reality. At the moment, the SOC indicator is no ideal asset for the SDG 15.3.1 indicator, as it uses a wide range of assumptions to reflect SOC change. Thus, further information on the SOC values is needed in Tanzania. Besides, management and land-use practices would be a benefit for LDN monitoring as well. Nevertheless, the study demonstrated the potential of remote sensing for LD monitoring with higher resolution data and informed the SDG 15.3.1 indicator for KK districts up until the most recent year.

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A. Appendix

Table A.1.: Juxtaposition of the three land productivity sub-indicators Trend, State and Performance as well as the combined LP. The results depict the adapted approach using Landsat imagery for the first monitoring period. The proportion of the degraded, stable and improved area is shown as well as the specific LP metrics of *declining*, *early signs of decline* and *stable but stressed*. Lastly solely the degraded area in KK districts is shown.

LP t_1 (%)	Trend	State	Performance	Combined
Degraded	12.1	25.3	0	12.2
Stable	87.8	58.4	100	87.7
Improved	0.1	16.4	0	0.1
Declining				12.2
Early signs of decline				17
Stable but stressed				0
Kongwa	9	23	0	9.1
Kiteto	13	26	0	13.1

Table A.2.: Distribution of the adapted land productivity degradation indicators into their respective land cover classes for the baseline period. The difference to the respective land cover percentage of the total area.

Default	Trend		State		Combined	
Baseline Period	%	Δpp	%	Δpp	%	Δpp
Forestland	10,88	-6,32	11,6	-5,6	11,7	-5,5
Grassland	39,80	-1,06	37,3	-3,6	37,2	-3,7
Cropland	47,27	8,50	48,4	9,7	48,4	9,6
Wetland	2,04	-1,11	2,6	-0,5	2,7	-0,5

Performance was left out, because the degradation was 0 %

Table A.3.: Distribution of the adapted land productivity degradation indicators into their respective land cover classes for the baseline period. The difference to the respective land cover percentage of the total area.

Adapted	Trend		State		Combined	
Baseline Period	%	Δpp	%	Δpp	%	Δpp)
Forestland	2.3	-9.7	7.0	-5.0	2.3	-9.7
Grassland	39.0	-5.9	34.1	-10.9	39.0	-5.9
Cropland	37.7	8.6	42.0	12.9	37.7	8.6
Wetland	1.1	0.1	1.1	0.1	1.1	0.1
Urban areas	2.1	0.9	1.2	0.1	2.1	0.9
Other Land	7.5	6.6	6.6	-0.5	7.5	0.5

Performance was left out, because the degradation was 0 %

Table A.4.: Distribution of the adapted land productivity degradation indicators into their respective land cover classes for the monitoring period. The difference to the respective land cover percentage of the total area.

Adapted	Trend		State		Combined land producitvity	
Monitoring Period	%	Δpp	%	Δpp	%	Δpp)
Forestland	6,7	-4,3	4,6	-6,3	6,7	-4,3
Grassland	39,1	-4,4	31,5	-12,0	39,0	-4,5
Cropland	37,2	6,9	42,9	12,6	37,2	6,8
Wetland	4,1	2,1	3,7	1,7	4,2	2,2
Urban	1,4	-0,1	2,0	0,5	1,4	0,0
Other Land	5,7	-1,8	6,8	-0,6	5,7	-1,7

Performance was left out, because the degradation was 0 %

Table A.5.: Land cover degradation of the default and adapted approach for the respective baseline and monitoring period.

	Baseline Period		Monitoring Period
LC (%)	Default	Adapted	Adapted
Degradation	0.1	5.2	3.2
Stable	99	93.8	96.1
Improvement	0.9	1	0.7

Table A.6.: Land cover change between the years 2000, 2015 and 2018. The RCMRD LC is depicted and the relative

RCMRD (%)	2000	2015	2018	2000–2018 (Δpp)
Forestlands	14.9	12.0	11.0	-3.9
Grasslands	48.3	45.0	43.5	-4.8
Croplands	23.4	29.1	30.3	7.0
Wetlands	1.5	1.0	2.0	0.5
Urban	1.1	1.1	1.5	0.4
Otherland	6.1	7.1	7.5	1.4

Table A.7.: Land cover class proportion of the years 2000, 2015 and 2018 in Kiteto and Kongwa are depicted as well as the change over the whole period in percent points.

	2000		2015		2018		2000–2018 (Δ pp)	
RCMRD LC (%)	Kongwa	Kiteto	Kongwa	Kiteto	Kongwa	Kiteto	Kongwa	Kiteto
Forestlands	7.0	17.1	4.8	14.2	4.7	12.9	−2	−4
Grasslands	36.3	51.6	31.1	49.1	28.9	47.9	−7	−4
Croplands	41.3	17.8	49.4	23.0	50.8	24.2	9	6
Wetlands	2.8	1.1	1.1	0.9	2.4	1.9	0	1
Urban	4.1	0.1	4.5	0.1	4.6	0.5	1	0
Otherlands	4.9	6.4	6.8	7.2	6.4	7.8	1	1

Table A.8.: SOC change from 2015 to 2018 based on the RCMRD LC dataset. The average SOC content in t per ha and the total SOC content are shown for the 2018, as well as the change of the total content from 2015 to 2018 in percent. The information on LC is based on the area in the year 2018.

RDMDR LC t_1	SOC (t/ha)	SOC (t)	Change in SOC (%)
Kiteto and Kongwa	49.9	80,446,681	-0.1%
Forestlands	62.2	11,653,997	-8.9%
Grasslands	49.7	36,710,048	-3.3%
Croplands	46.9	23,745,906	4.2%
Wetlands	46.9	1,454,400	101.7%
Urban	42.8	1,023,638	27.1%
Otherlands	47.6	5,858,690	5.7%

Table A.9.: SOC change degradation for the baseline and monitoring period. The default and adapted approach are shown.

	Baseline period		Monitoring period
SOC (%)	Default	Adapted	Adapted
Degraded	0,11	8,08	0,06
Stable	99,85	89,96	99,71
Improved	0,04	1,96	0,23

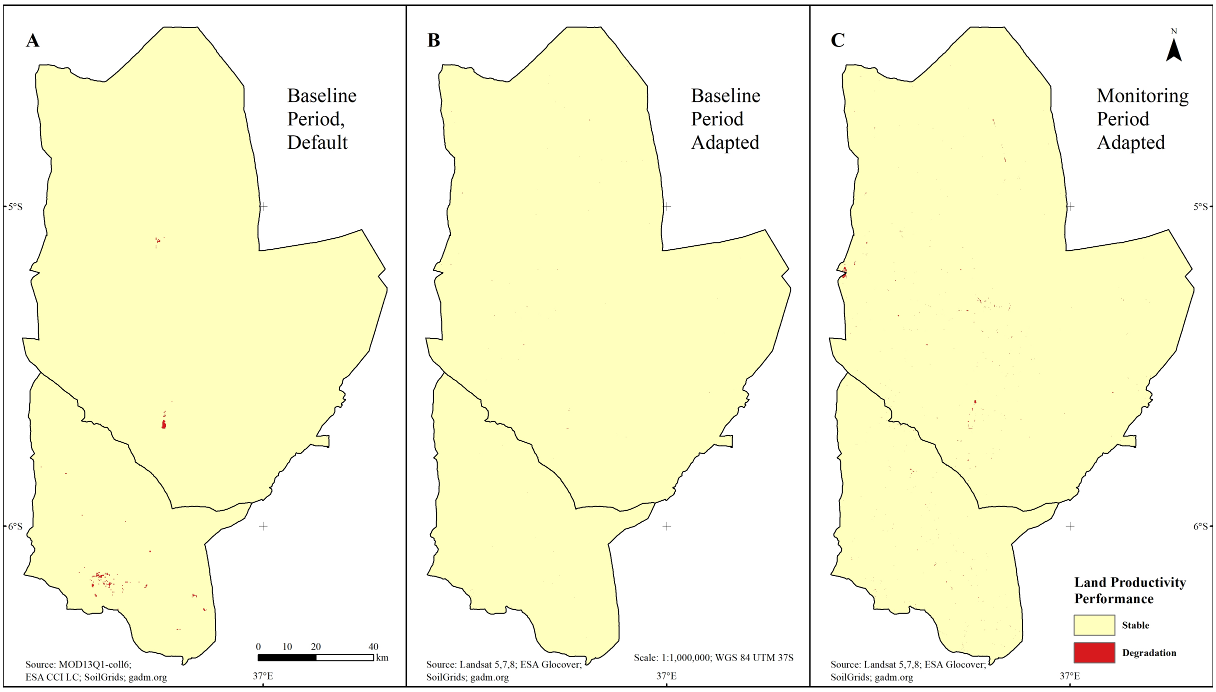
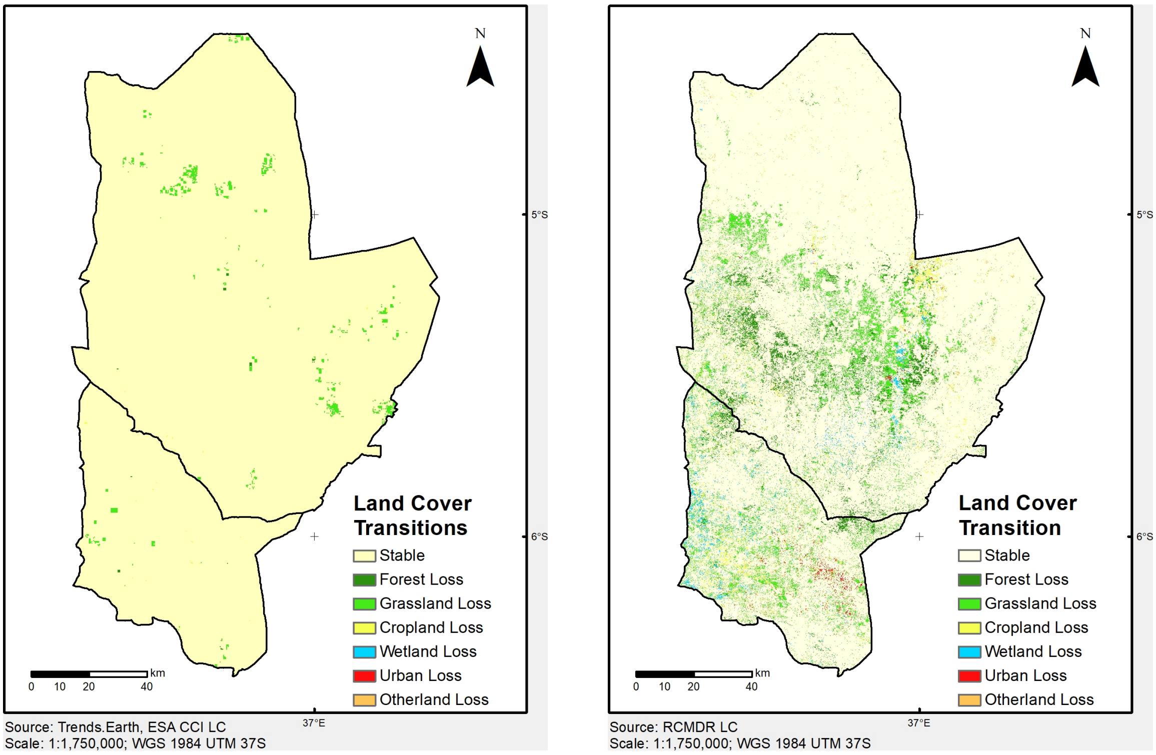


Figure A.1.: Comparison of the land productivity Performance. (A) shows the default approach with MODIS imagery, while (B) depicts the adapted approach with Landsat for the baseline period. (C) covers the monitoring period with Landsat imagery. All approaches and baseline have very limited degradation.

Table A.10.: Contribution of the three sub-indicators on LD for the baseline period. Headers show the number of indicators contributing to LD, while the first three rows show the cummulative percentage of contribution

LD	Single (%)	Double (%)	Triple (%)
LP	34	46	50
LC	13	28	32
SOC	26	45	50
LC LP		4	
SOC LC		11	
SOC LP		8	
SOC LP LC			4
Total	72	24	4



(a) Land cover transitions between the years 2000 and 2015 based on the ESA CCI LC dataset.

(b) Land cover transitions between the years 2000 and 2015 based on the RCMRD LC dataset.

Figure A.3.: Comparison of land cover transitions between a) ESA CCI and b) RCMRD LC. The latter changed more, while the former stayed basically stable.

Table A.11.: Investigated plot features during fieldworlk. The variables are concerning mainly qualative aspects and the vegetation cover.

ID	Plot	Ward	Land Cover	Alti-tude	Vegetation Type	Slope	Topography	Soil-color	Owner-ship	Landuse	Treecover	Shrub-cover	Herb-cover	Bare-cover
1	151	Mlali	Crop	1164	Cropland	Gentle	Midslope	Grey	Private	A. Crops	3	63	7	55
2	132	Mlali	Crop	1279	Cropland	Gentle	Midslope	Brown	Private	A. Crops	0	1	0	100
3	109	Chiwe	Crop	1243	Cropland	Gentle	Midslope	Grey	Private	A. Crops	0	0	0	98
4	144	Chiwe	Crop	1220	Cropland	Gentle	Midslope	Brown	Private	A. Crops	1	2	1	97
5	122	Sejeli	Crop	916	Cropland	Gentle	Midslope	Red	Private	A. Crops	3	3	38	58
6	44	Sejeli	Shrub	898	W. Grassland	Gentle	Ridge	Red	Private	Natural	11	23	16	67
7	139	Sejeli	Crop	928	Cropland	Steep	Ridge	Red	Private	A. Crops	2	1	1	95
8	49	Sejeli	Shrub	904	Shrubland	Gentle	Midslope	Red	Private	Woodlot	1	6	23	78
9	39	Kongwa	Shrub	1054	Cropland	Gentle	Midslope	Red	Private	A. Crops	0	1	3	95
10	54	Kongwa	Shrub	1122	Grassland	Gentle	Midslope	Brown	Private	G. Land	0	6	46	53
11	73	Sagara	Shrub	1180	Cropland	Gentle	Midslope	Brown	Private	A. Crops	0	31	3	72
12	94	Sagara	Shrub	1276	W. Grassland	Steep	Midslope	Brown	Commu-nal	Natural	16	46	23	38
13	127	Mtanana	Crop	1090	Grassland	Gentle	Midslope	Brown	State	G. Land	0	7	63	42
14	97	Mtanana	Crop	1122	Shrubland	Gentle	Midslope	Brown	State	Natural	1	80	11	28
15	58	Mtanana	Shrub	1192	Shrubland	Gentle	Midslope	Brown	State	G. Land	0	16	16	72
16	121	Hogoro	Crop	1127	Cropland	Gentle	Midslope	Red	Private	A. Crops	0	7	11	82
17	66	Mtanana	Shrub	1136	Grassland	Gentle	Midslope	Red	State	G. Land	0	1	1	95
18	74	Mtanana	Shrub	1192	Cropland	Gentle	Midslope	Black	Private	A. Crops	0	3	11	87
19	131	Mtanana	Crop	1146	Shrubland	Gentle	Midslope	Brown	State	G. Land	1	46	31	33
20	168	Mkoka	Crop	1204	Cropland	Gentle	Midslope	Brown	Private	P. Crops	7	11	3	80
21	155	Matongoro	Shrub	1216	Cropland	Gentle	Midslope	Brown	Private	A. Crops	0	11	3	83
22	167	Zoissa	Grass	1237	Cropland	Flat	Bottomland	Black	Private	A. Crops	1	2	2	95
23	63	Mkoka	Shrub	1106	Cropland	Gentle	Midslope	Red	Private	A. Crops	0	0	11	70
24	170	Mkoka	Crop	1157	W. Grassland	Gentle	Midslope	Red	State	G. Land	0	16	3	83
25	171	Matongoro	Crop	1219	Cropland	Gentle	Midslope	Red	Private	A. Crops	0	2	16	82
26	160	Makawa	Shrub	1286	Cropland	Gentle	Midslope	Brown	Private	A. Crops	0	2	11	83
27	115	Makawa	Crop	1272	Cropland	Gentle	Midslope	Red	Private	A. Crops	0	3	3	93
28	68	Makawa	Shrub	1270	Cropland	Gentle	Midslope	Brown	Private	A. Crops	0	0	1	98
29	159	Makawa	Shrub	1238	Cropland	Gentle	Midslope	Brown	Private	A. Crops	0	2	47	52
30	96	Lenjulu	Crop	1337	Cropland	Gentle	Midslope	Brown	Private	Fallow	0	16	88	40
31	177	Chamko-roma	Crop	1430	Cropland	Gentle	Upland	Brown	Private	A. Crops	0	2	80	28
32	153	Njoge	Tree	1482	Forest	Steep	Upland	Brown	State	Natural	31	88	23	8
33	35	Chamko-roma	Shrub	1361	Shrubland	Flat	Midslope	Grey	Commu-nal	G. Land	0	31	55	32
34	161	Lenjulu	Shrub	1323	W. Grassland	Gentle	Midslope	Red	Private	G. Land	11	47	46	42

W. = Wooded, A. = Annual, P. = Perennial, G. =Grazing

Table A.12.: Land degradation types found in the plots and their specific erosive types, as well as the degree and the extent is shown.

		Water Erosion						Biological Deteroation						Wind Erosion			
ID	LD	Sheet	Rill	Gully	Sedimen-tation	Ex-tent	De-gree	Vegetation Cover	Fires	Invasive Species	Bush Encroachment	Ex-tent	De-gree	Top-soil	Ex-tent	De-gree	Unde-graded
1	1	1	0	0	0	17	1	1	0	0	0	13	2	0	0	0	78
2	1	1	1	1	1	50	2	1	0	0	0	83	3	1	90	2	17
3	1	1	1	1	1	73	3	1	0	0	0	100	3	1	97	3	0
4	1	1	1	0	1	90	2	1	0	0	0	100	3	1	100	3	2
5	1	0	0	0	0	7	1	0	0	0	0	0	0	0	0	0	57
6	1	1	0	0	0	33	1	1	0	0	0	83	3	0	0	0	15
7	1	1	1	1	0	47	3	0	0	0	0	0	0	1	73	3	5
8	1	1	0	0	0	27	2	1	0	0	0	73	3	0	0	0	10
9	1	1	1	1	1	40	3	0	0	0	0	0	0	1	93	3	3
10	1	0	0	0	0	7	1	0	0	0	0	23	1	1	33	2	57
11	0																
12	1	1	1	0	0	37	3	1	0	0	0	63	3	0	0	0	30
13	1	0	0	0	0	0	0	0	0	1	0	30	1	0	0	0	37
14	1	0	0	0	0	0	0	0	0	1	0	17	1	0	0	0	82
15	1	1	1	0	0	50	2	1	0	1	0	53	3	0	0	0	23
16	1	1	1	0	0	37	2	1	0	1	0	87	2	0	0	0	13
17	1	1	1	0	0	80	3	1	0	1	0	93	3	1	70	2	3
18	1	1	1	0	0	57	2	0	0	1	0	20	1	1	30	1	48
19	1	0	0	0	0	0	0	0	0	1	1	23	1	0	0	0	65
20	0	1	0	0	0	13	1	0	0	0	0	0	0	0	0	0	30
21	1	1	1	0	0	43	2	0	0	0	0	0	0	1	57	2	28
22	0																
23	1	0	1	1	0	10	2	0	0	0	0	10	2	0	0	0	47
24	1	1	1	1	0	77	3	0	0	0	0	0	0	0	0	0	20
25	1	0	0	0	0	0	0	1	0	0	0	13	1	1	27	1	70
26	0																
27	0																
28	1	0	1	0	0	10	1	0	0	0	0	0	0	0	0	0	57
29	1	1	1	1	0	47	2	0	0	0	0	13	1	1	53	2	38
30	1	0	1	1	1	7	3	0	0	0	0	0	0	0	0	0	83
31	0					0											
32	1	0	1	0	0	10	2	1	0	0	0	33	2	0	0	0	33
33	0																
34	1	1	0	0	0	27	1	1	0	0	1	57	2	0	0	0	33

Table A.13.: Direct driver categories of land degradation found in the plots and their specific types.

	Soil Management				Crop Management			Deforestation		Natural Resources				
ID	Soil Conservation	Tillage	Soil Vulnerability	Heavy Machines	Plant Cover	Bush Encroachment	Weeds	Settle-ments	Other	Fuel	Fooder	Other	Overgraz-ing	Min-ing
1	0	0	0	0	0	0	1	0	0	0	0	0	0	0
2	1	1	1	1	1	0	0	0	0	0	1	0	1	0
3	1	1	1	1	1	0	0	0	0	0	1	0	1	0
4	1	1	1	1	1	0	0	0	0	0	1	0	1	0
5	0	0	0	0	0	0	0	0	0	0	0	1	1	0
6	0	0	0	0	0	0	0	1	0	1	0	0	1	0
7	1	1	1	1	0	0	0	0	0	0	0	0	1	0
8	0	0	0	0	0	0	0	0	0	1	0	0	1	1
9	1	0	1	0	1	0	0	0	0	0	0	0	1	0
10	0	0	0	0	0	0	0	0	0	0	0	0	1	0
11														
12	0	0	0	0	0	0	0	0	0	0	0	0	1	0
13														
14														
15	0	0	0	0	0	0	0	0	0	0	0	0	1	0
16	0	0	0	0	1	0	0	0	0	0	0	0	1	0
17	0	0	0	0	1	0	0	0	0	0	0	0	1	0
18	1	0	0	0	0	0	0	0	0	0	0	0	1	0
19	0	0	0	0	0	1	0	0	0	0	0	0	1	0
20	1	0	0	0	0	0	0	0	0	0	0	0	1	0
21	1	0	0	0	0	0	0	0	0	0	0	0	1	0
22														
23	1	0	0	0	0	0	0	0	0	0	0	0	0	0
24	1	0	0	0	0	0	0	0	0	0	0	0	1	0
25	0	0	0	0	0	0	0	0	0	0	0	0	1	0
26														
27														
28	1	0	0	0	0	0	0	0	0	0	0	0	0	0
29	1	1	0	0	0	0	0	0	0	0	0	0	0	0
30	1	0	0	0	0	0	0	0	0	0	0	0	0	0
31														
32	0	0	0	0	0	0	0	0	1	1	0	1	0	0
33														
34	0	0	0	0	0	1	0	0	0	0	0	0	1	0

Table A.14.: Sustainable land management measures in the plots and their specific types (first part).

		Agronomic						Vegetative						
ID	SLM	Intercrop-ping	Mulching	Minimum Tillage	Contour Tillage	Ex-tent	Ef-fect	Agro-forestry	Hedgerow	Cover-crops	Alley Cropping	Natural Reseeding	Ex-tent	Ef-fect
1	1	1	1	1	1	90	4	1	1	1	1	0	80	4
2	1	1	1	0	1	74	1	0	0	1	0	0	90	2
3	1	0	0	0	0	0	0	0	0	1	0	0	80	1
4	1	0	0	0	0	0	0	1	0	0	0	0	5	0
5	1	0	0	0	0	0	0	0	1	0	0	0	7	0
6														
7														
8														
9	1	0	0	0	1	7	0	0	0	0	0	0	0	0
10														
11	1	1	0	1	1	97	3	1	1	1	0	0	37	3
12	1	0	0	0	0	0	0	0	1	0	0	1	40	2
13	1	0	0	0	0	0	0	0	0	0	0	0	0	0
14	1	0	0	0	0	0	0	0	0	0	0	0	0	0
15														
16	1	0	0	0	0	0	0	0	0	0	0	0	0	0
17														
18	1	0	0	0	1	100	2	0	0	1	0	0	20	1
19														
20	1	0	0	1	0	50	3	1	1	1	0	0	40	3
21	1	1	0	0	0	24	3	0	0	1	0	0	17	0
22	1	1	1	0	0	50	3	0	1	1	0	0	24	3
23	1	0	0	0	0	0	0	0	0	0	0	0	0	0
24														
25														
26	1	1	1	1	1	57	4	0	1	0	0	0	10	2
27	1	1	0	0	1	100	4	0	0	0	0	0	0	0
28	1	1	0	1	0	100	3	0	0	0	0	0	0	0
29	1	0	0	0	1	60	3	0	0	0	0	0	0	0
30	1	0	0	0	0	0	0	0	0	1	0	0	30	2
31														
32														
33														
34														

Table A.15.: Sustainable land management measures in the plots and their specific types (second part).

	Structural						Management					Purpose
ID	Fanyajuu	Contour Bunds	Open Ridges	Plant Barrier	Extent	Effect	Bushclearing	Fallow	Extent	Effect	Extent not SLM	Purpose SLM
1	1	1	1	1	64	3	1	0	40	2	14	Mitigation
2	0	0	0	0	10	1	0	0	0	0	25	Mitigation
3	0	0	0	0	0	0	0	0	0	0	20	Mitigation
4	0	0	0	0	0	0	0	0	0	0	43	Prevention
5	0	0	0	0	0	0	0	1	100	3	0	Mitigation
6												
7												
8												
9	0	0	0	0	0	0	0	0	0	0	54	Prevention
10												
11	0	0	0	0	0	0	0	0	0	0	34	Prevention
12	0	0	0	0	0	0	0	0	0	0	60	Mitigation
13	0	0	0	0	0	0	1	0	30	0	37	Prevention
14	0	0	0	0	0	0	1	0	17	3	84	Prevention
15												
16	0	0	0	0	0	0	0	1	100	2	0	Mitigation
17												
18	0	0	0	0	0	0	0	0	0	0	0	Mitigation
19												
20	0	0	0	0	0	0	0	0	0	0	54	Prevention
21	0	0	0	0	0	0	0	0	0	0	77	Mitigation
22	0	0	0	0	0	0	0	0	0	0	25	Prevention
23	0	0	0	0	0	0	0	1	100	3	0	Prevention
24												
25												
26	0	0	0	0	0	0	0	0	0	0	57	Prevention
27	0	0	0	0	0	0	0	0	0	0	0	Prevention
28	0	0	0	0	0	0	0	0	0	0	0	Prevention
29	0	0	0	0	0	0	0	0	0	0	40	Prevention
30	0	0	0	0	0	0	0	1	100	3	0	Prevention
31												
32												
33												
34												

Table A.16.: Comparison of the annual values of the Rain Use Efficiency, the Normalized Vegetation Difference Index and the precipitation.

Year	RUE	NDVI	Precipitation (mm)
2000	0,741	0,363	502,251
2001	0,754	0,584	781,433
2002	0,583	0,355	608,557
2003	0,903	0,478	533,901
2004	0,652	0,357	551,975
2005	0,887	0,493	558,823
2006	0,738	0,315	423,903
2007	0,59	0,482	812,001
2008	0,711	0,419	590,607
2009	0,917	0,459	508,987
2010	0,654	0,43	658,957
2011	0,742	0,43	584,506
2012	0,605	0,416	701,784
2013	0,873	0,506	582,479
2014	0,662	0,394	601,999
2015	0,657	0,425	646,904
2016	0,605	0,498	837,799
2017	0,616	0,337	554,985
2018	0,485	0,39	808,424
2019	0,696	0,457	664,33
Correlations			
RUE-Precipitation	-0.57		
RUE-NDVI	0.40		
NDVI-Precipitation	0.49		

Statutory Declaration

I hereby declare that I have authored this Master thesis independently and that I have not used other than the declared sources/resources.
I confess to the examination regulations. So far, I never handed in a Master thesis in an geography Master's program. Neither the whole thesis nor parts of it have been published yet. All material has been explicitly marked which has been quoted either literally or by content from the used sources.

Jonathan Andreas Reith
Bonn, June 22, 2020