Contextualizing land use and land cover change with local knowledge: a case study from Pokot Central, Kenya

Maike Petersen, Christoph Bergmann, Paul Roden, Marcus Nüsser*

SAI, Department of Geography | Heidelberg University

Voßstr. 2, Building 4130, 69115 Heidelberg, Germany

* Corresponding author: Marcus Nüsser

Corresponding address: SAI, Department of Geography | Heidelberg University

Voßstr. 2, Building 4130, 69115 Heidelberg, Germany

Tel.: +49 (0)6221 5415241

Email: marcus.nuesser@uni-heidelberg.de

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Abstract

Rural communities in the drylands of Sub-Saharan Africa (SSA) derive their livelihoods primarily from their natural resource base. Unprecedented changes in these environments over the past few decades are likely to intensify in the future and land users need to develop sustainable adaptation strategies. This study aims to identify land use and land cover (LULC) changes and their drivers in a Sub-Saharan dryland, between 1986 and 2017, by integrating local knowledge and remote sensing analysis. Local knowledge and environmental perception are used as the basis for defining LULC classes and for training and validation of change detection. This study identifies bush encroachment into former pastures as the dominant LULC change with an increase of woodland by 39 % and a decrease of grassland by 74%. This process is perceived as severe degradation by local respondents and is linked to changing management regimes and unreliable rainfall patterns. Deforestation and woodland thinning can be traced back to increased habitation and farming, though the local community also identifies charcoal production as a driving factor. The integration of remote sensing and local knowledge provides a holistic view on LULC change in Pokot Central, Kenya, and offers a solid base for site specific and actor-centred management approaches necessary for sustainable pathways of drylands.

Keywords: Remote sensing - Landsat - local knowledge - Land use and land cover change - Pokot Central - Kenya

Introduction

Rural communities in the drylands of Sub-Saharan Africa (SSA) derive their livelihoods primarily from their natural resource base.

Unprecedented changes in these environments over the past few decades are likely to intensify in the future and land users need to develop sustainable adaptation strategies. These changes have been driven by local and external anthropogenic as well as ecological causes (Chalmers & Fabricius, 2007; Liao et al., 2020; Thondhlana et al., 2012). Future climate predictions for SSA indicate that the region will experience (if it has not already) less reliable precipitation patterns, more frequent and severe droughts, and more intense rainfall events (Funk et al., 2008; IPPC, 2014; Niang et al., 2014; Serdeczny et al., 2017; Shongwe et al., 2010). As a result of these drivers, current and predicted changes in plant biodiversity and ecosystem functioning present new challenges to rural communities. An improved understanding of how local land users perceive of, and manage their environment, is therefore required so that more appropriate land use decisions can be made. One way to better understand human-environmental interactions and its effects on the environment is through the study of the patterns of land-use and land-cover (LULC) change.

The Sub-Saharan region of Africa shows a heterogenous pattern of LULC change, with agricultural land replacing natural vegetation as the most prominent transformation (Ordway et al., 2017; Rukundo et al., 2018; Xu et al., 2018) and with another major trend showing an increase of woody vegetation at the expense of grasslands (Archer et al., 2017; Brandt et al., 2017; Marston et al., 2017; Nüsser, 2002; Osborne et al., 2018). The rapid encroachment of woody species in the drylands has reduced the availability of grazing resources for pastoralists prompting them to adjust their land based livelihood strategies (Becker et al., 2016), for example by diversifying their livestock mix to include more browsers (goats and camels) so as to exploit these woody species (Kagunyu & Wanjohi, 2014; Ouko et al., 2020; Vehrs, 2016). Whilst some pastoralists increasingly include other non-land based livelihood strategies such as wage labour or small business (Bergmann et al., 2019). Changes in LULC patterns do have knock on effects on the wellbeing of land users that are not immediately obvious. For example, a reduction or complete loss of vegetation cover does not only cause more frequent flooding events and landslides, but can also increase the risk of vector- and waterborne diseases (Anthonj et al., 2019; Levy et al., 2016; Okaka &

Odhiambo, 2018), and, a decrease in tree cover reduces the availability of fuel wood and increases the workload, particularly for women, during wood collection (Garedew et al., 2009; Yiran et al., 2012).Therefore, in order to better contextualise LULC change and its social and environmental impacts requires an intimate understanding of local perceptions of their landscapes. Local knowledge is now accepted as a critical research component that can help fill the gap in our understanding on how to mitigate against and adapt to structural changes (Bollig & Schulte, 1999; Makondo & Thomas, 2018; Mistry & Berardi, 2016; Reed et al., 2007).

The present study defines local knowledge following Raymond et al. (2010) who demarcate it from scientific knowledge through its recognition of local nuances, often left unnoticed by external experts who generate their knowledge through formalised processes rather than traditional norms and recently experienced human-environment interactions (C. D. Becker & Ghimire, 2003; Olsson & Folke, 2001).

It is widely accepted that the integration of local knowledge and remote sensing analyses can provide new insights (Herrmann et al., 2014; Zaehringer et al., 2018) and further holds the potential to upturn popular narratives on forest and land degradation that place the blame squarely on the land users (Fairhead & Leach, 1995). In general, a high correspondence can be found between conventionally classified LULC change and local perceptions, as shown, for instance, by Ariti et al. (2015).

However, the overall objective of most studies dealing with both local and scientific knowledge is to assess the reliability of stakeholders' perceptions by comparing it with conventional approaches rather than by integrating both sets as an equal source of information, though each one might have specific features and contain certain pitfalls (e.g. Delgado-Aguilar et al., 2019; Eddy et al., 2017). In order to foster the latter integrative approach, this study is based on the recognition of local knowledge as a sound and reliable source of information on LULC change (Del Rio et al., 2018). It thus includes local knowledge and environmental perception as the basis for the definition, training, and validation of LULC classes. As people whose livelihoods depend directly on their natural environmental resources are understood as local experts, a participatory approach frames the entire research design.

This study aims at identifying LULC changes and their drivers in a Sub-Saharan dryland over three decades. To better understand the underlying processes, it asks the following questions:

- What LULC changes can be observed in the study area between 1986 and 2017?
- What processes are driving these changes and how are they influenced by local perceptions and values?
- How can local knowledge be integrated into remote sensing techniques and thus become key to contextualize LULC change?

As a case study a remote dryland region of Kenya was chosen. While LULC change has been studied in neighbouring regions (Egeru et al., 2015; Nyberg et al., 2015), the lowlands of Pokot Central have largely been neglected, though the area typifies many of the livelihood possibilities and constraints faced by communities in Sub-Saharan drylands. It is therefore a representative case study to derive appropriate adaptation strategies that offer rural communities more sustainable and desirable development pathways.

Study area

The drylands of Pokot Central (West Pokot County) in northwestern Kenya are a border region with several ethno-linguistic groups, located at a distance of 350 km to Nairobi (Figure 1). The study area between 35°25’ and 35°41’ E and 1°24’ and 1°48’ N comprises approximately 705 km² and is bordered in the east, south and west by the Masol, Cherangani and Sekerr Hills, reaching altitudes of about 3,000 m a.s.l. Precipitation depicts a high interannual and spatial variability, ranging from 400 mm in the plains to 1,200 mm in the highlands, distributed over two rainy seasons (GeoInformatiks Ltd, 2017). The area is dominated by bush savanna mostly comprised of *Vachellia tortilis* (Forssk.) Galasso & Banfi and *Vachellia reficiens* (Wawra) Kyal. & Boatwr. Rivers and seasonal streams are lined by gallery forests, while in some areas dense evergreen thickets of *Euphorbia* spp. occur. The A1 Highway between Kapenguria and Lodwar (the capitals of West Pokot County and Turkana County) is the area’s only tarmacked connection with larger agglomerations of Kenya. While there are no urban areas, some basic facilities, including several small shops, weekly markets, health centres, and a police station can be found in small centres such as, Marich, Tikit and Orwa (Figure 1). The administrative centre of Pokot Central is Sigor, the only settlement in the study areas that can be considered a town. Pokot Central is one of five sub-counties in West Pokot County, where the majority of the Pokot ethno-linguistic group lives. The land assigned to the Pokot also includes East Pokot Sub-County in the neighbouring Baringo County. According to census reports, population numbers in the district of Pokot Central increased from 43,159 inhabitants in 1989 to 119,016 in 2019 with a corresponding rise in population density from 21 to 58 persons/km² (Central Bureau of Statistics, 1994; KNBS, 2019). Livelihoods in the study area are based primarily on agro-pastoral land use practices with an increasing importance of small businesses or wage labour. During the 1990s production of wood charcoal became a wide-spread source of income and has developed into a common part of many peoples’ livelihood portfolio (Bergmann et al., 2019).

Methods

The methodological approach integrates empirically based social scientific assessments of local stakeholder knowledge through focus group discussions (FGD) with ground validated remote sensing techniques. Based on Landsat imagery from 1986, 1995, 2000, 2010 and 2017 (USGS, 2017; Table 1) long-term vegetation change was monitored. Owing to high inter-annual variation in plant phenology in the region, the peak of the dry season around January was identified as the most appropriate time for analysis (Roden et al., 2016). In regions with a relatively low or irregular temporal availability of suitable Landsat imagery, such as in East Africa, changes are best detected through a post-classification comparison (Banskota et al., 2014). The accuracy of such a pixel-by-pixel comparison depends on the quality of initial classifications since errors are compounded in the final output. However, given a qualified sample of training and validation data this approach offers the advantage to support the generation of 'from-to' matrices that register detailed quantitative information of detected land-cover change, which can be visualized on easy-to-interpret maps (e.g. Biro *et al.*, 2011; Kamusoko & Aniya, 2009; Petit & Lambin, 2002).

Focus group discussions

To integrate local knowledge from the beginning, eight one to three-day FGDs were conducted between March 2017 and January 2019. They were facilitated by four experienced Pokot field assistants and involved three to seven people from the study area, representing an age and gender sensitive cross-section of the community (Table 2). The purpose of the FGDs was to identify and map locally recognized land-cover classes, assess their criteria of differentiation, gather narratives of socio-environmental change, and discuss daily practices as well as the perceived value of individual land cover classes. During FGDs, notes were taken and later transcribed and coded in MaxQDA. In order to identify different LULC classes, participatory mapping was conducted in three FGDs. After presenting characteristic photographs of a broad range of vegetation types that were taken, with the guidance of local rangeland scouts, earlier during field surveys, the participants of the FGD discussed these characteristics and categorised their own LULC classes. In the next step, a large size printout of the most recent Landsat scene from 2017 was presented to the group. As participants were unfamiliar with maps, they had to be introduced to satellite imagery by trained research assistants. Together they identified, distinguished, and delineated specific areas, such as the approximate location of their homesteads, grazing grounds, water ponds, seasonal streams, and settlements. Subsequently, the group was split into subgroups to colour- or number-code the previously developed LULC classes on older Landsat scenes. Additions and changes could be made during a final plenary session. The repetition of this procedure during three workshops made it possible to identify LULC classes and their locations, agreed upon by all participants.

Training and validation of remote sensing data

Training and validation of remote sensing data was derived from field surveys, local stakeholder knowledge, and additional very high resolution (VHR) image data (Table 3). During two field campaigns in January 2016 and February-March 2017 a total of 93 sample plots (50x50 m^2) were selected based on a stratified random sampling strategy, with support of a knowledgeable local informant. Each plot's centre was GPS tagged, whilst the vegetation structure, dominant species, and other features of interest such as tree stumps, active charcoal kilns or kiln burn marks were documented. Approximately 30 % of these plots were revisited after heavy rains in November-December 2017 to document seasonal precipitation effects on land cover dynamics. This was particularly important to distinguish permanent bare ground from seasonal grasslands and to detect differences in the density of the herbaceous understory layer in bushy areas during the rainy season.

After some of the delineated classes from the FGD exercise were combined following Mialhe et al. (2015), thresholds were defined to allow operationalization and comparison with remote sensing procedures. The resulting LULC classes and their spatial distribution were used for training and validation of classifications, especially of older Landsat images. Wherever possible, visual interpretation of very high resolution (VHR) datasets including WorldView, Quickbird and Google Earth data as well as historical aerial photographs were used for cross-checking and contextualization (Table 3).

Image Classification

Image pre-processing and classification were conducted in R (R Development Core Team, 2008). The analysis comprised visual, near- and shortwave infrared bands, spectral vegetation indices (VI) and texture measures. Different predictors were tested as input (Table 1) in order to select only those with the highest variable importance. The preliminary results revealed the Green Normalized Difference Vegetation Index (Gitelson et al., 1996), the Soil Adjusted Vegetation Index (Huete, 1988), texture dissimilarity (Lu & Batistella, 2005) and the first three bands of a Tasseled Cap Transformation (Crist, 1985) as most relevant (Table 1).

The resulting 17 band composite stack was then used for the final image classification using non-parametric Random Forest (RF) classifier (Breiman, 2001) through the R function superClass (Leutner & Horning, 2017). This machine learning algorithm has already been successfully employed for land cover classifications (Adam et al., 2017; Gislason et al., 2006; Rodriguez-Galiano et al., 2012; Zoungrana et al., 2015). The default number of 500 decision trees (ntree) was adopted, as suggested by Belgiu & Drăguţ (2016). The superClass function provides an independent accuracy assessment by splitting the input into training and validation data before building the trees (train partition=0.7). It then builds the random forests with different values for mtry, defining the number of image layers considered at each node. In this case, mtry=9 was selected based on an internally calculated accuracy. The resulting model was then used for image classification.

Change detection

Subsequently, the oldest and newest scene (1986/2017) were compared on a pixel-by-pixel basis. The 'from-to' changes were quantified in change matrices (SI 1) and classified into five change classes. An accuracy assessment (Congalton, 1991; Story & Congalton, 1986) using a previously separated set of validation data was conducted for all scenes. A drawback of post classification change detection is the accumulation of classification errors in the final product (Congalton & Green, 2019, pp. 233–246). To estimate this error an additional accuracy assessment was conducted for detected changes between 1986 and 2017. For this purpose, 199 random points were generated. The LULC classes for the 1986 and the 2017 scenes were visually interpreted and classified according to the five change classes. This dataset was then used for accuracy assessment.

Results

Land use and land cover classes

During the FGDs nine LULC classes were identified, described, and mapped (Figure 2). Participants were able to distinguish LULC classes by small differences in species composition, herbal layer and phenological characteristics. Due to the spatial resolution of Landsat images, open (*wuw nyo tartar*) and closed (*wuw nyo anger*) woodland were combined into one class. W*uw nyo kieghe*, a special type of woodland where all trees are the same height, belong to one species and allow almost no herbal layer, is also included in this class. Farmland (p*aren*) is not separated into irrigated or rain-fed but could be further specified by its location next to a river (*paren pa lalwa*) or close to a homestead (*paren po kiror*). The Pokot names were used throughout the study and during all further conversations as an expression of appreciation for the local knowledge.

Image classification and change detection

Image classification reveals a dynamically changing mosaic of wood- and grasslands across the study area (Figure 3). In 1986, half (51 %) of the area was covered by open to closed woodlands while 27 % were grasslands. This LULC class was typically found in areas with a loose, sandy soil, as prevalent in the Masol Plains but also on several alluvial fans west of the A1 highway (Tamakaru) and some smaller ones along the foot slopes of the Cherangani Hills. Another 16 % were comprised of *Euphorbia* spp. thickets and gallery forest (4 %) along the main rivers, covering a larger area between Marich, Sigor and Tikit.

In the 2017 scene, which has the highest overall accuracy and the most reliable training and validation data, many patches along the rivers were classified as bare areas or farmland. Bare areas are particularly noteworthy, as they increased by 490 % from 1.3 % in 1986 to 8 % in 2017. Grassland is only found in small patches in the Masol Plains (7 %) while open top closed woodlands dominate the scene by 71 %. Field observations have shown that bare areas along the rivers are usually sandy riverbeds, indicating an increased vulnerability to flood erosion, or fallow farms. Many fields were harvested shortly before the Landsat image acquisition in January, and not yet tilled, again. Furthermore, the Sigor irrigation scheme reached its third phase of expansion in December 2016, explaining the large patch of bare ground, north of the farmlands at Sigor. This irrigation scheme was implemented in 1987 by the Government of Kenya, in cooperation with Italian partners.

Whereas the overall accuracies for the 2000 and 2017 classification are very high (95 % and 97 % respectively), those for the remaining scenes are lower but still within an acceptable range (1986: 87 %; 1995: 89 %; 2010: 78 %; for detailed accuracies: SI 2.1 – 2.5).

Change detection between 1986 and 2017 reveals significant shifts in vegetation cover for 46 % of the study area. Only transitions between two clearly distinguishable LULC classes were considered significant (Figure 4). The change between open to closed woodland and sparsely vegetated areas for example was considered too subtle and might be due to slight changes in the phenology due to rainfall variability.

An increase in canopy cover accounts for 50 % of change detected in the study area, most of which (117 km^2) is associated with bush encroachment into former grasslands. Evidence can be found in the Masol Plains, which have recently been dominated by homogenous communities of *V. reficiens* with little to no herbaceous or grass layer, even during the rainy season.

Hotspots of forest and woodland thinning are located in the vicinity of Marich, Sigor and Tikit (Figure 4). Around these more densely populated areas, thickets have widely been transformed into open to closed woodlands (67.5 km^2 or 61 %; SI 1). Field observations and participatory analysis of the LULC classifications, confirm that deforestation is mostly associated with agricultural expansion. Along both the Wei Wei and the Moruny River, gallery forests and thickets have been cleared for irrigated farming, now covering 16 km^2 across the whole study area (Table 4).

As errors from the LULC classification accumulate in the post classification change detection, the accuracy assessment of the change detection shows a larger error than those for the single scenes. The overall accuracy is 60 %, while the user’s 50 % and producer’s accuracy 40 % for the change class of decrease in canopy cover is lowest.

Drivers of change

The LULC thickets class shows a pronounced decline between 1986 and 2017. This LULC class has “no importance for the people” and is perceived as dangerous because of the wild animals living in there (FGD3). Families would clear the area close to their homestead or fields to avoid encounters with these (FGD3). The expansion of human settlements explains the large decrease in thickets, especially in the triangle between Marich, Sigor and Tikit (Figure 4).

The most prevalent change observed in the image analysis is the encroachment of bushes into former grasslands. These former pastures are now vastly dominated by two species of *Vachellia*. While the majority of the Masol Plains have been encroached by *V. reficiens*, Tamakaru is covered almost exclusively with *V. nubica*. Typical for both is the almost complete absence of an herbal layer and existence of homogenous tree height. Locals have repeatedly mentioned the increase of these species as now "Pilil [*V. nubica*] is everywhere" (FGD1). They evaluated its expansion as a degradation of former pastures and identified overgrazing, reduction in rainfall (FGD2) and introduction of *Vachellia* seeds into the grasslands through smallstock (FGD6) as main drivers. Another important factor, brought up by the respondents is the discontinuation of traditional pasture burning due to its banning by government decree in the 1980s (FGD3).

The increase of sparsely vegetated areas is characteristic for woodlands that have been thinned out, typically around settlements. Population growth and the increased demand for wood for building and fuel was also identified as a driving factor for the thinning of bushland by FGD participants (FGD3, FGD5, FGD6). However, most people were said to leave some trees and bushes on their homesteads and tend to them "because the shade is needed for kids and small animals" (FGD7). Except for the surroundings of Sigor Centre, where there is almost no vegetation left, other relatively denser populated villages, such as Marich or Tikit, some fractional vegetation cover remains.

Gallery forests were identified as a valued LULC class by local stakeholders, especially due to its ability to limit flood erosion (FGD3) and owing to the higher prevalence of *V. tortilis*, that provides much needed leaves and pods that are valued as nutritious livestock fodder (FGD3, FGD5). Thus, informal regulations exist to protect these forests (FGD4, FGD7), even though wood from these forests are most preferred for charcoal production, building material and beehive construction (FGD5). Nevertheless, competing resource use for wood-based forest products and expansion of land for crop cultivation has led to deforestation along rivers. The from-to-change matrix between 1986 and 2017 (SI1) shows many patches of gallery forest that have been transformed into agricultural land or bare areas (with a dominance of bare fields according to field observations). However, locals do not usually mention the expansion of agriculture as a driver of deforestation. It was even stated, that “as long as the intention is to farm, the clearing of the bush is not a problem with the government” (FGD3). Only when they were asked directly for the effects of clearings for agriculture, participants agreed that cutting of trees along the rivers is worse than further away from it, because “it has more negative effects on soil and the river” (FGD3). It was also explained that farming too close to the river is responsible for the widening of the riverbed with farmland often swept away during floods in the rainy season (FGD3). Nevertheless, agricultural land is perceived very positively, with only the unreliability of the harvests and the prevalence of crop pests considered to be a negative feature of this land use class (FGD3). There was a considered downside to gallery forests in that they provide cover to wild animal pests (porcupines, antelope, monkeys, and elephants) which invade and destroy riverine based crop fields (FGD3). Despite local demands for arable land, the net amount of gallery forests remained comparatively stable between 1986 and 2017. While one explanation for this is that up until recently, shifting cultivation was a common practice, also the abandonment of Amolem (Figure 1) due to conflict (FGD3), allowed forest regeneration in this area.

In addition to increased settlements and farming, local stakeholders regularly mention wood extraction for charcoal production as an important driver of tree cover loss (FGD2, FGD6). Image analysis, however, does not reveal a correlation between charcoal production hotspots along the A1 highway (Bergmann et al., 2019) and a decrease in vegetation cover. But while the spatial resolution of Landsat data cannot offer details on species composition, local respondents observed that in certain areas, “trees used for charcoal production are almost gone“ (FGD6). As tree species most preferred for charcoal production respondents named *V. reficience*, *V. tortilis*, *Senegalia mellifera* (M. VAHL) SEIGLER & EBINGER, and *Vachellia nubica* BENTH. (FGD5, FGD6, FGD7) though informal rules aim at protecting the more valued trees species (FGD1, FGD4, FGD6). Other drivers of change include wood extraction for timber (FDG2, FGD5) and the felling of trees by elephants (FGD2).

Discussion

LULC change in the drylands of Pokot Central shows dynamic pathways over the past three decades and a better understanding of driving forces requires an analysis of local histories of development and human-environmental interactions.

The present change detection revealed that the most prevalent change between 1986 and 2017 in the study area is the increase in woody vegetation at the expense of grassland. The phenomenon of bush encroachment or “green desertification” has been observed in several regions across Sub-Saharan Africa (M. Becker et al., 2016; Liao et al., 2018; Venter et al., 2018). In many East African drylands, including Baringo and Turkana County neighbouring Pokot Central (Maundu et al., 2009; Mwangi & Swallow, 2005), the South American tree *Prosopis juliflora* plays a major role in this process (Shiferaw et al., 2019), but only single specimen of this particular tree species were found in the present study. For the adjoining plains of East Pokot, located in Baringo County, Vehrs (2016) also reported a transformation from grasslands to *Vachellia* dominated woodlands starting in the 1950s, based on oral evidence. Likewise, in the study area, this process was already detected in the Masol Plains for the time between 1973 and 1978 by Conant (1982), who identified reduced rains and changing management regimes as main drivers based on analysis of early Landsat imagery. A series of violent conflicts, droughts and government regulations had led to the near complete abandonment of the Masol Plains in 1976 (Roden & Bergmann, 2015; Zaal et al., 1985). The present study traces an intensification of the process of bush encroachment between 1986 and 2017 and temporally and spatially expands the underlying causes of reduction in annual rainfall, overgrazing and the lack of pasture burning. These findings are similar to studies in other regions of Africa that identify a correlation between woody plant proliferation with changing rainfall patterns and reduction in the use of fire for pasture management (J.N. de Klerk, 2004; Stevens et al., 2017). Reduced mobility of pastoralists communities has recently been discussed thoroughly by Liao et al. (2020) as a crucial cause of dryland degradation and unsustainable rangeland management.

Abandonment of former grazing areas is one of several factors that forced the Pokot to adjust their cattle-centred economic and cultural fabric to altered structural conditions from the mid-1980s onwards (Bollig, 2016). An increasing importance of sedentary and market-oriented small-stock keeping, especially of goats, and “the adoption of farming as a key element in the overall process of economic diversification" are identified as dominant regional trends (Österle, 2008). Several projects by the Kenyan government and international partners are furthering this transition through the promotion of modern irrigation farming (Adams, 1990; Government of the Republic of Kenya, 2012; Mugova & Mavunga, 2000) even though the expansion of cropland is known to contribute to deforestation (Shiferaw et al., 2019). In the present study, increased settlements and farming were found to be the main drivers for deforestation and decrease in forest cover. However, LULC change is also effected by cultural perceptions and values as has been demonstrated in the massive decline of thickets that are deemed dangerous, while food provision is regarded as the most relevant service a LULC class can deliver to local communities.

Repeatedly mentioned by respondents as a driver of negative environmental change, was the production of wood charcoal which was widely adopted as a source of income by people in the study area since the 1990s. These people were forced to adopt thus activity as a consequence of conflict, displacement and socio-economic change (Roden & Bergmann, 2015). Many studies in other areas report the harmful effects of wood extraction for commercial charcoal production on woodland resources (Kutsch et al., 2011; Rembold et al., 2013; Sedano et al., 2016). The Landsat analysis, however, does not reveal such link in our study area. And, in contrast to findings by Kiruki et al. (2017) from Kitui County, in south-eastern Kenya, increased charcoal production in areas of decreased canopy cover cannot be observed. It can be assumed that the scale of charcoal production in Pokot Central is still at a level where environmental effects are not as pronounced as in primary production regions such as Kitui County and are thus currently not observable with the spatial resolution of Landsat imagery. The local perceptions give a more fine grained picture on decreasing tree species, though they could also be clouded by a widespread negative image of this activity (Mwampamba et al., 2013). Respondents stated that the encroaching *V. reficiens* is predominantly cut as wood for charcoal production while trees that are more valuable for livestock are tried to be preserved. This can be interpreted as an adaptation strategy by local communities that should be taken into consideration by higher-level decision-making actors in government. Similarly, Oduor & Githiomi (2013) prescribe community management of invasive *P. juliflora* in Baringo, Kenya as one means to control its spread whilst securing a livelihood for local inhabitants. Further developments of this activity, however, should be closely monitored, as an expected growing demand for wood charcoal could alter local practices and rapidly increase the pressure on woodland resources (Taylor et al., 2020). A marked empathy for local producers, as well as consideration of their knowledge and development solutions are crucial for successful management.

The present study further promotes the integration of local knowledge and remote sensing approaches. While a LULC change analysis based on Landsat imagery has proven to be a solid scientific approach, subpixel changes may go undetected. At the same time, the drivers of LULC change can only partially be reconstructed using remote sensing approaches as a stand-alone technique. While the correlation between deforestation and agricultural expansion can be made based on multitemporal image analysis alone, the complexities of canopy increase in former grasslands as well as the reasons behind agricultural expansion need ground-based information. Against this background the study on Pokot Central adds to the growing number of studies that demonstrate the usefulness of integrating remote sensing techniques with local stakeholder knowledge (Del Rio et al., 2018; Egeru et al., 2015; Sulieman & Ahmed, 2013). Chalmers and Fabricius (2007) stress that ecological knowledge can be unevenly distributed among local communities and advise to carefully select local experts. They define those experts as people whose livelihoods are directly based on surrounding natural resources. As all respondents from the present study were either livestock keepers, farmers or both and had grown up in the study area they do fulfil this criterion. The broad ecological knowledge of the Pokot has also been confirmed by Wasonga et al. (2003). The present study takes local knowledge one level further into the remote sensing approach.

While most studies incorporate local knowledge at the end by comparison with results from remote sensing approaches or to add depths, here, local knowledge contextualized every step of the remote sensing analysis; from the delineation of LULC classes, collecting of training and validation data and finally the discussion of driving factors. Applying local terms and definitions facilitated discussions about changes, validation of results and communication of findings. It furthermore helped to understand the way the environment is categorized by the Pokot and their motivation to protect certain ecosystems or not. The integration of remote sensing and local knowledge provides an holistic view on LULC change in Pokot Central and offers a solid base for site specific and actor-centred management approaches as will be needed for the sustainable development of drylands (Fu et al., 2021).

Conclusion

This study identifies LULC changes and their drivers in a Sub-Saharan dryland over three decades between 1986 and 2017. Bush encroachment into former grasslands was recognized as the most prevalent change, while deforestation and decrease in canopy cover occurred mainly in the context of agricultural expansion and increased settlements. By relying strongly on local land user perceptions of LULC change it was possible to not only identify changes and their drivers but also the intrinsic motivations of the local community to prefer certain LULC classes over others. This study will help understand environmental changes of the past and their linkages with the livelihoods of the dryland population. Future programs to develop adaptation strategies for climate change or management guidelines for drylands can draw from this study the value of local perceptions and the need to include them and their ecological understandings into decision making processes.

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Conflict of interest

The Authors declare no conflict of interest.

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Tables

Table 1. Summary of satellite imagery, derived classification parameters and tested parameters

Parameter	**Description**	**Equation**	**Specifications**	**Reference**
Landsat bands	Blue (B), Green (G), Red (R), NIR, SWIR1, SWIR2		28.01.1986: Landsat 5 TM L1TP 21.01.1995: Landsat 5 TM L1TP 27.01.2000: Landsat 7 ETM L1TP 30.01.2010: Landsat 5 TM L1TP 17.01.2017: Landsat 8 OLI L1TP Path: 169; Row: 59; 30m resolution	(USGS, 2017)
Vegetation Indices				
GNDVI	Green Normalized Difference Vegetation Index	$\frac{NIR-G}{NIR+G}$		(Gitelson et al., 1996)
SAVI	Soil Adjusted vegetation Index	$\frac{(NIR-R)*(1+L)}{NIR+R+L}$	Coefficient: L=0.7	(Huete, 1988)
Texture Variables				
Dissimilarity		$\sum_{i,j=0}^{N-1} i P_{i,j} \lvert i-j \rvert$ Where: $P_{i,j} = V_{i,j} / \sum_{i,j=0}^{N=0} V_{i,.}$ Where $V_{i,j}$ = Value in cell *i* (row) *j* (column) of moving window and *N* = number of rows and columns	Window size: 3 x 3 Offset distance: 1 Grey level quantization: 64 (Karlson et al. 2015)	(Lu & Batistella, 2005)
Transformations				
TCT 1-3	Tasselled Cap Transformation (Brightness ($_1$), Greenness ($_2$) and Wetness ($_3$))	$B*a_{1/2/3}+G*b_{1/2/3}+R*c_{1/2/3}+NIR*d_{1/2/3}+SWIR1*e_{1/2/3}+SWIR2*f_{1/2/3}$;	Coefficients a-f see references	(Baig et al., 2014 (OLI); Crist, 1985 (TM); Huang et al., 2002 (ETM))
Tested Vegetation Indices				
Modified Soil Adjusted Vegetation Index **(MSAVI: Qi et al., 1994)**; Normalized Difference Vegetation Index **(NDVI: Rouse Jr et al., 1974)**; Ratio Vegetation Index (RVI: Jordan, 1969); Transformed Vegetation Index (TVI: Deering & Haas, 1980); Thiam's Transformed Vegetation Index (TTVI: Thiam, 1997)				
Tested Texture Variables				
Mean, Variance, Homogeneity. Contrast, Entropy, Second Moment, Correlation **(Haralick et al., 1973; Lu & Batistella, 2005)**				

Table 2. List of focus group discussions (FGD) between 2017 and 2019 with details on the participants and discussed topics

FGD	Date (duration)	Number of participants (women)	Sources of income	Discussed topics, *methods*
FGD1	03/2017 (3d)	5 (4)	P, C, F	EC, CCP, R
FGD2	03/2017 (1d)	4 (0)	P	EC
FGD3	11/2017 (3d)	6 (2)	P, F, C	EC, CCP, *PM*, *FS*
FGD4	11/2017 (3d)	7 (2)	P, F, C, B	EC, CCP, *PM*, *FS*
FGD5	12/2017 (3d)	6 (4)	P, F, C, B, G, FW	EC, CCP, *PM*, *FS*
FGD6	12/2018 (1d)	3 (3)	C, B,	CCP
FGD7	01/2019 (1d)	5 (0)	P, F, C, E	EC, CCP, R

Occupations: P= Pastoralists; C= Charcoal Producer; F= Farmer; B=Business Owner; G= Gold Panning; FW= Firewood Seller; **E**= FGD only with Village Elders

Topics: CCP= Charcoal Production; EC= Environmental Change; R= Rules and Regulations; *PM*= Participatory Mapping; *FS*= Future Scenario

Table 3. Additional data sources used to train the image classification

Image type	Image source	Date	Resolution	Extent	Training for
Sentinel2	ESA 2017	12.01.2017	10 m	705 km^2	2017
GoogleEarth	Google Inc. 2017	May/June 2017		300 km^2	2017
WorldView2	DigitalGlobe 2017	24.06.2013	0.5 m	100 km^2	
GoogleEarth - historical	Google Inc. 2017	2013			2010
VHR Quickbird	DigitalGlobe 2017	10.12.2011	0.6 m	100 km^2	2010
GoogleEarth - historical	Google Inc. 2017	2001			2000
Historical aerial images*	Royal Airforce; Hunting Aerosurveys Ltd.	1950s – 1970s	1:50,000 1:12,500		1986

Collected training data: 4.5 – 9 km^2; *available through Bodleian Libraries of the University of Oxford

Table 4. Land use and land cover (LULC) change for the years 1986, 1995, 2000, 2010 and 2017

	Area [km²]					Net changes [km²]
	1986	1995	2000	2010	2017	1986-2017
Gallery Forest	27.15	31.66	24.86	28.74	34.92	+7.77 (29 %)
Thicket	110.45	105.62	85.52	76.17	34.16	-76.29 (69 %)
Woodland	350.70	368.42	410.33	484.33	486.09	+135.39 (39 %)
Sparsely vegetated	0.00	6.70	21.89	21.60	13.38	+13.38
Grassland	180.93	147.99	110.92	59.85	46.92	-134.01 (74 %)
Farmland	7.81	13.36	17.56	10.85	16.11	+8.30 (106 %)
Bare areas	9.25	12.76	15.13	4.65	54.59	+45.34 (490 %)
Overall Accuracy	0.87	0.89	0.95	0.78	0.97	

Figure legends

Figure 1. Study area in West Pokot County, Kenya.

Figure 2. Land use and land cover (LULC) classes as defined in participatory workshops and used for image classification.

Figure 3. Land use land cover (LULC) classifications for 1986, 1995, 2000, 2010 and 2017 based on Landsat scenes (path 169, row 59) and the resulting percentages for the respective LULC classes.

Figure 4. Land use land cover (LULC) changes between 1986 and 2017 based on Landsat image classification (path 169, row 59) and the change matrix, colour coded in accordance with the defined change classes.

Supplementary Information

SI 1. Change Matrix 1986 - 2017

		2017[km²]						
		Gallery Forest	Thicket	Woodland	Sparsely vegetated	Grassland	Farmland	Bare areas
1986 [km²]	Gallery Forest	12.31	0.25	5.00	0.23	0.20	4.78	4.24
	Thicket	13.39	19.00	67.47	2.39	1.31	2.47	4.35
	Woodland	5.87	14.47	295.59	4.77	7.24	4.78	17.90
	Grassland	0.46	0.26	112.95	3.56	37.65	1.28	24.75
	Farmland	2.41	0.08	1.61	0.16	0.17	2.04	1.34
	Bare areas	0.45	0.10	3.38	2.28	0.34	0.74	1.97

SI 2.1. Error Matrix for 1986

		Reference								
		Gallery Forest	Thicket	Woodland	Grassland	Farmland	Bare areas	Sum	PA	UA
Prediction	Gallery Forest	618	0	0	0	0	0	618	1.00	1.00
	Thicket	0	591	3	2	1	3	600	0.79	0.99
	Woodland	0	158	723	190	0	0	1071	0.94	0.68
	Grassland	0	0	45	678	0	0	723	0.78	0.94
	Farmland	1	0	0	0	22	0	23	0.96	0.96
	Bare areas	0	0	0	2	0	53	55	0.95	0.96
	Sum	619	749	771	872	23	56	3090		

Overall Accuracy	0.87
Kappa (Cohen, 1960)	0.83

SI 2.2. Error Matrix for 1995

Prediction	Reference: Gallery Forest	Thicket	Woodland	Sparsely vegetated	Grassland	Farmland	Bare areas	Sum	PA	UA
Gallery Forest	195	1	0	0	0	0	0	196	0.98	0.99
Thicket	3	231	0	0	0	0	0	234	0.77	0.99
Woodland	0	68	426	1	0	1	0	496	0.96	0.86
Sparsely vegetated	0	0	1	19	14	0	0	34	0.76	0.56
Grassland	0	0	17	5	201	0	0	223	0.85	0.90
Farmland	2	0	0	0	0	39	0	41	0.98	0.95
Bare areas	0	0	0	0	22	0	36	58	1.00	0.62
Sum	200	300	444	25	237	40	36	1282		
Overall Accuracy		0.89								
Kappa (Cohen, 1960)		0.86								

SI 2.3. Error Matrix for 2000

Prediction	Reference: Gallery Forest	Thicket	Woodland	Sparsely vegetated	Grassland	Farmland	Bare areas	Sum	PA	UA
Gallery Forest	194	0	0	0	0	0	0	194	0.95	1.00
Thicket	2	307	0	0	0	0	0	309	1.00	0.99
Woodland	0	0	667	2	6	0	14	689	0.98	0.97
Sparsely vegetated	0	0	7	114	5	0	8	134	0.79	0.85
Grassland	0	0	6	16	425	0	7	454	0.96	0.94
Farmland	8	0	0	0	0	89	0	97	1.00	0.92
Bare areas	0	0	0	13	6	0	21	40	0.42	0.53
Sum	204	307	680	145	442	89	50	1917		
Overall Accuracy		0.95								
Kappa (Cohen, 1960)		0.93								

SI 2.4. Error Matrix for 2010

		Reference									
		Gallery Forest	Thicket	Woodland	Sparsely vegetated	Grassland	Farmland	Bare areas	Sum	PA	UA
Prediction	Gallery Forest	259	50	0	0	0	0	0	309	0.97	0.84
	Thicket	8	167	19	0	0	12	2	208	0.73	0.80
	Woodland	1	7	474	39	71	0	10	602	0.86	0.79
	Sparsely vegetated	0	0	18	9	0	0	28	55	0.15	0.16
	Grassland	0	0	38	12	105	0	0	155	0.60	0.68
	Farmland	0	4	0	0	0	64	0	68	0.84	0.94
	Bare areas	0	0	0	1	0	0	36	37	0.47	0.97
	Sum	268	228	549	61	176	76	76	1434		
Overall Accuracy			0.78								
Kappa (Cohen, 1960)			0.71								

SI 2.5. Error Matrix for 2017

		Reference									
		Gallery Forest	Thicket	Woodland	Sparsely vegetated	Grassland	Farmland	Bare areas	Sum	PA	UA
Prediction	Gallery Forest	372	0	0	0	0	2	0	374	0.99	0.99
	Thicket	3	118	0	0	0	0	0	121	1.00	0.98
	Woodland	0	0	817	6	1	0	9	833	0.99	0.98
	Sparsely vegetated	0	0	1	60	3	0	1	65	0.85	0.92
	Grassland	0	0	1	3	281	0	4	289	0.99	0.97
	Farmland	2	0	0	0	0	66	0	68	0.97	0.97
	Bare areas	0	0	8	2	0	0	35	45	0.71	0.78
	Sum	377	118	827	71	285	68	49	1795		
Overall Accuracy			0.97								
Kappa (Cohen, 1960)			0.96								