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

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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. Local knowledge and environmental perception are used as the basis for defining LULC classes and for training and validation of change detection. This study detects significant LULC changes in 41% of the investigated area, and 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 account for 44% of the detected changes, and can be traced back to increased habitation and farming, although 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. Our results emphasize the need to include local actors in the development of adaptation strategies and management guidelines for drylands.

KEYWORDS
Kenya, LANDSAT, land-use and land-cover change, local knowledge, Pokot Central, remote sensing

1 | INTRODUCTION

Rural communities in the drylands of sub-Saharan Africa (SSA) derive their livelihoods primarily from their natural resource base. Extensive 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. Palaeoenvironmental records over the past 2,000 years indicate that climate variations have always played an important role in shaping different livelihood pathways and migration patterns in Eastern Africa (Marchant et al., 2018; Verschuren, 2004). Current changes have been driven by local and external anthropogenic as well as ecological causes (Chalmers & Fabricius, 2007; Liao, Agrawal, Clark, Levin, & Rubenstein, 2020; Thondhlana, Vedeld, & Shackleton, 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, van Oldenborgh, van den Hurk, & van Aalst, 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 heterogeneous pattern of LULC change, with agricultural land replacing natural vegetation as the most prominent transformation (Ordway, Asner, & Lambin, 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, Aplin, Wilkinson, Field, & O'Regan, 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 (M. 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, Roden, & Nüsser, 2019). Changes in LULC patterns do have knock-on effects on the well-being 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, Diekkrüger, Borgemeister, & Kistemann, 2019; Levy, Woster, Goldstein, & Carlton, 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, Sandewall, Söderberg, & Campbell, 2009; Yiran, Kusimi, & Kufogbe, 2012). In order to better contextualise LULC change and its social and environmental impacts, an intimate understanding of local perceptions of landscapes is required. 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, Dougill, & Taylor, 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 formalized 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 can provide new insights (Herrmann, Sall, & Sy, 2014; Zaehringer, Llopis, Latthachack, Thein, & Heinimann, 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, van Vliet, & Verburg (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 equivalent sources of information, though each one might have specific features and contain certain pitfalls (e.g. Delgado-Aguilar, Hinojosa, & Schmitt, 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, Groot, DeClerck, & Estrada-Carmona, 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.

In the face of future environmental change, the demand for knowledge on site-specific adaptations strategies and management guidelines are considered to be increasingly important. A perspective on past human-environmental pathways adds further value as it helps to illuminate the reasons behind processes of change and adaptation. This study aims at identifying LULC changes and their drivers in the sub-Saharan dryland of Pokot Central, Kenya, over a time frame of 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 and thus become key to contextualize LULC change?

As 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.

2 | DATA AND METHODOLOGY

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 is located between 1°24′ and 1°48′ N (latitude) and 35°25′ and 35°41′ E (longitude) and comprises approximately 705 km^2. The area
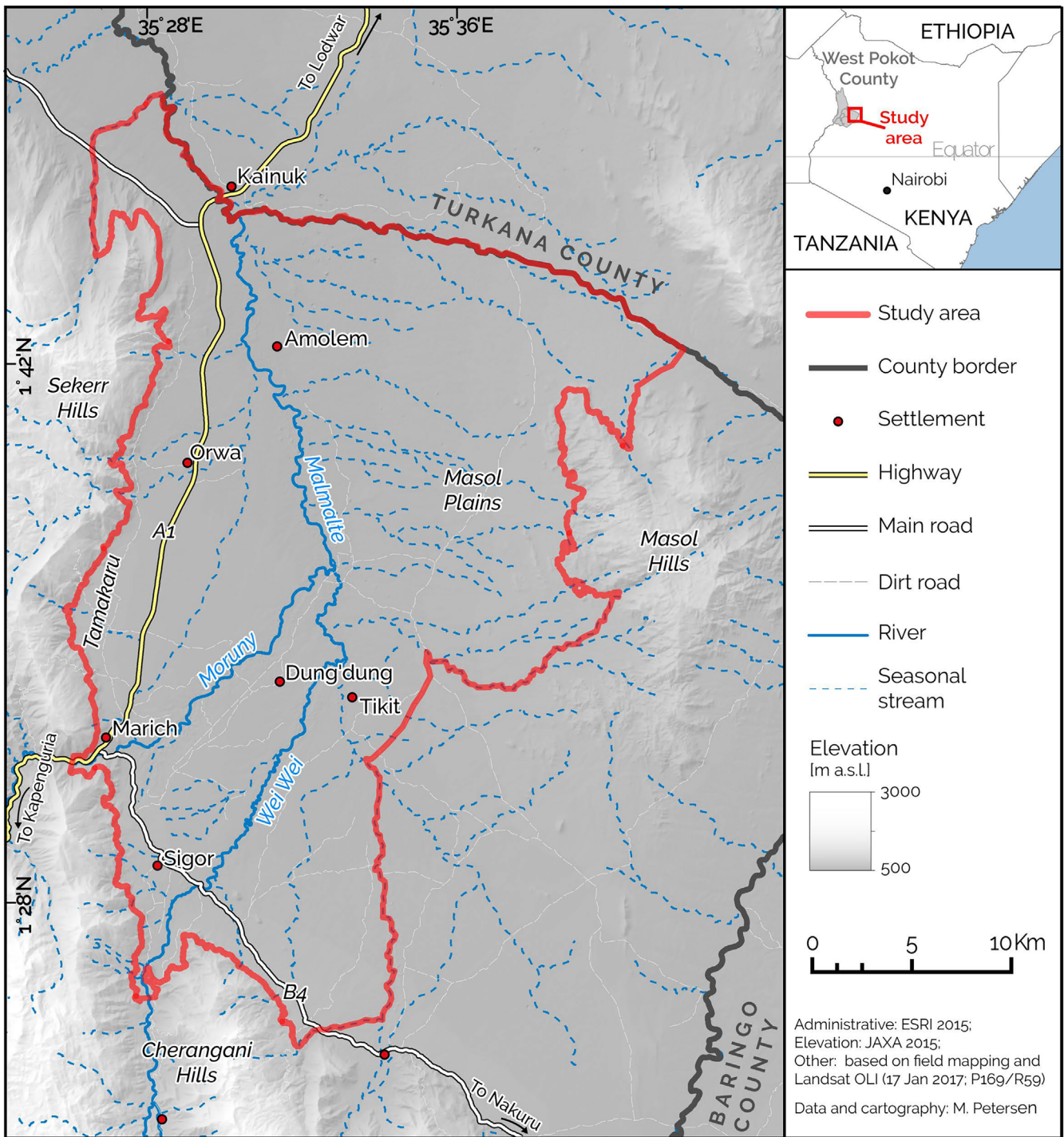
FIGURE 1 Topographic map of the study area in the Pokot Central region of West Pokot County (Kenya), with an indication of the hydrographic network, roads and settlements [Colour figure can be viewed at wileyonlinelibrary.com]

is bordered to the east, south and west by the Masol, Cherangani and Sekerr Hills, reaching altitudes of about 3,000 m a.s.l. Precipitation displays high interannual and spatial variability, ranging from 400 mm in the plains to 1,200 mm in the highlands, and is 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 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/km^2 (Central Bureau of Statistics, 1994; KNBS, 2019). Livelihoods in the study area are based primarily on agro-pastoral land-use practices with increasing importance of small businesses or wage labour. During the 1990s,

production of wood charcoal became a widespread source of income and has developed into a common part of many peoples' livelihood portfolio (Bergmann et al., 2019).

The methodological approach integrates qualitative social scientific assessments of local stakeholder knowledge through focus-group discussions (FGDs) and participatory mapping with quantitative ground-validated remote sensing. 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, the peak of the dry season around January was identified as the most appropriate time for analysis (Roden, Bergmann, Ulrich, & Nüsser, 2016). In regions with relatively low or irregular

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 January 1986: LANDSAT 5 TM L1TP 21 January 1995: LANDSAT 5 TM L1TP 27 January 2000: LANDSAT 7 ETM L1TP 30 January 2010: LANDSAT 5 TM L1TP 17 January 2017: LANDSAT 8 OLI L1TP Path: 169; row: 59; 30 m resolution	(USGS, 2017)
Vegetation indices				
GNDVI	Green normalized difference vegetation index	$\frac{NIR-G}{NIR+G}$		(Gitelson, Kaufman, & Merzlyak, 1996)
SAVI	Soil adjusted vegetation index	$\frac{(NIR-R)*(1+L)}{NIR+R+L}$	Coefficient: L = 0.5	(Huete, 1988)
Texture variables				
Dissimilarity		$\sum_{i,j=0}^{N-1} i\,P_{i,j}\lvert i-j\rvert$ where: $P_{i,j}=V_{i,j}/\sum_{i,j=0}^{N=0} V_{i,j}$ where $V_{i,j}$ = value in cell i (row) j (column) of moving window and N = number of rows and columns	Window size: 3 × 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, Zhang, Shuai, & Tong, 2014 (OLI); Crist, 1985 (TM); Huang, Wylie, Yang, Homer, & Zylstra, 2002 (ETM))
Tested vegetation indices				
Modified soil adjusted vegetation index (MSAVI: Qi, Chebebouni, Huete, Kerr, & Sorooshian, 1994); Normalized difference vegetation index (NDVI: Rouse Jr, Haas, Schell, & Deering, 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, Shanmugam, & Dinstein, 1973; Lu & Batistella, 2005)				

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, Pradhan, Buchroithner, & Makeschin, 2011; Kamusoko & Aniya, 2009; Petit & Lambin, 2002).

2.1 | Focus-group discussions

To integrate local knowledge in the study from the beginning, eight FGDs were conducted over one to 3 days each, between March 2017 and January 2019. They were facilitated by four experienced Pokot field assistants and involved between three and seven individuals 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 following the same semi-standardized procedure. For this purpose, characteristic photographs of a broad range of vegetation types were presented to all participants. These photographs had been taken during earlier field surveys, with the guidance of local rangeland scouts. Afterwards, the participants discussed the characteristics and categorized their own LULC classes. The Pokot names for LULC classes were used throughout the study and during all further

conversations as an expression of appreciation of their knowledge. In the next step, a large-size print 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.

2.2 | 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 (50 × 50 m²) were selected based on a stratified random sampling strategy, with support of a knowledgeable local informant. 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 VHR datasets including World View, QUICKBIRD and Google Earth data as well as historical aerial photographs were used for cross-checking and contextualization (Table 3).

2.3 | Image classification

Image pre-processing and classification were conducted in R (R Development Core Team, 2008). The analysis comprised a 17-band composite stack of visual, near- and shortwave infrared bands, spectral vegetation indices (VI) and texture measures for each timestep (Table 1). These were 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, Mureriwa, & Newete, 2017; Gislason, Benediktsson, & Sveinsson, 2006; Rodriguez-Galiano, Ghimire, Rogan, Chica-Olmo, & Rigol-Sanchez, 2012; Zoungrana et al., 2015). In order to better understand classification errors and misclassifications

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

Note: Abbreviations for participants' occupations: P, pastoralists; C, charcoal producer; F, farmer; B, business owner; G, gold panning; FW, firewood seller; Abbreviations for covered topics: E, FGD only with village elders; 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
SENTINEL 2	ESA 2017	12 January 2017	10 m	705 km^2	2017
Google Earth	Google Inc. 2017	May/June 2017		300 km^2	2017
World View 2	Digital Globe 2017	24 June 2013	0.5 m	100 km^2	
Google Earth - historical	Google Inc. 2017	2013			2010
VHR QUICKBIRD	Digital Globe 2017	10 December 2011	0.6 m	100 km^2	2010
Google Earth - historical	Google Inc. 2017	2001			2000
Historical aerial images[a]	Royal Air Force; Hunting Aerosurveys Ltd.	1950s–1970s	1:50,000 1:12,500		1986

Note: Collected training data: 4.5–9 km^2
[a]Available through Bodleian Libraries of the University of Oxford

between scenes, an additional accuracy assessment (Congalton, 1991; Story & Congalton, 1986) using a previously separated set of validation data was conducted for all scenes.

2.4 | 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 2.1; for changes between successive timesteps see SI 2.2–SI 2.5) and classified into four change classes: deforestation, decrease in canopy cover, increase in canopy cover and other/no changes. Only transitions between two clearly distinguishable LULC classes were considered significant (Figure 4). For example, the change between the LULC class 'open to closed woodland' and 'sparsely vegetated areas' for example was considered too subtle and might be due to slight changes in plant phenology associated with rainfall variability. These changes were thus classified as 'other changes' and grouped together with 'no change' (Figure 4).

A drawback of post-classification change detection is the accumulation of classification errors in the final product (Congalton & Green, 2019, pp. 233–246). In order to estimate this error, an additional accuracy assessment was conducted for detected changes between 1986 and 2017. For this purpose, a total of 199 random points were generated. LULC classes for the 1986 and 2017 scenes were visually interpreted and their transition (e.g. gallery forest in 1986 to bare area in 2017) classified into one of the five change classes (e.g. deforestation). The visually interpreted change detection was then used for the accuracy assessment. A more detailed workflow of data analysis in the context of image classification and change detection is provided in the Appendix S1 (SI 1.1–SI 1.3).

3 | RESULTS

3.1 | 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 relatively low 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 (*paren*) 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*).

3.2 | 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 4% of gallery forest 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 almost fivefold from 1.3% in 1986 to 8% in 2017. Grassland is only found in small patches in the Masol Plains (7%) while open to 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 but 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; Table 4), those for the

LULC class	Characteristics	Pokot name	Explanation	Photo
Gallery forest	Height > 10 m; Canopy cover > 70 %; dominantly single stemmed trees; with/without subcanopy layer; impenetrable in some parts (*Vachellia tortilis* (Forssk.) Galasso & Banfi.)	*Wuw po lalwa*	Larger communities of mostly higher trees along the rivers	
Thicket	Height <10 m; canopy cover >70 %; impenetrable; with dense subcanopy layer; evergreen (*Euphorbia* spp.)	*Skwür*	Impenetrable mix of short trees and shrubs, 'one cannot see through'	
Woodland (continuum from open to closed)	Height <10 m; canopy cover 15-70 %; with scattered larger trees; single- but mostly multi-stemmed trees; with subcanopy layer; deciduous (*Vachellia* spp.) (Where dominated by multi-stemmed, deciduous *Vachellia reficiens* (Wawra) Kyal. & Boatwr. usually no subcanopy layer)	*Wuw nyo anger*	Dense mix of short trees and shrubs, with few larger trees in between, where you can hardly walk through and where people would not settle	
		Wuw nyo tartar (*also*: *Sarsar*)	A bushy area where you can easily walk through and where people settle; often a mixture of tall and short trees with foot trails in between	
		Wuw nyo kieghe	The trees are all the same height, and nothing grows below	
Sparsely vegetated	<15 % cover, very scattered trees/bushes; no grass layer	*Nameywa*	Vegetation is very scattered and appears in small 'islands' of an individual tree and some shrubs; no grass appears after the rains	
Grassland	Cover of woody plants <15 %; annual grassland	*Korosus*	An area where you find plenty of grass	
Farmland	Cultivated fields	*Paren*	Farmed land, no differentiation between irrigated and rainfed	
Bare areas	Land with limited vegetation, such as sandy or rocky riverbeds, wasteland, land recently cleared for future farming or recently harvested farmland	*Korron*	Bare ground, nothing grows, no grass appears after the rains	

FIGURE 2 Land-use and land-cover (LULC) classes for Pokot Central as defined in participatory workshops, and used for LUCC classification of LANDSAT remote sensing images in this study [Colour figure can be viewed at wileyonlinelibrary.com]
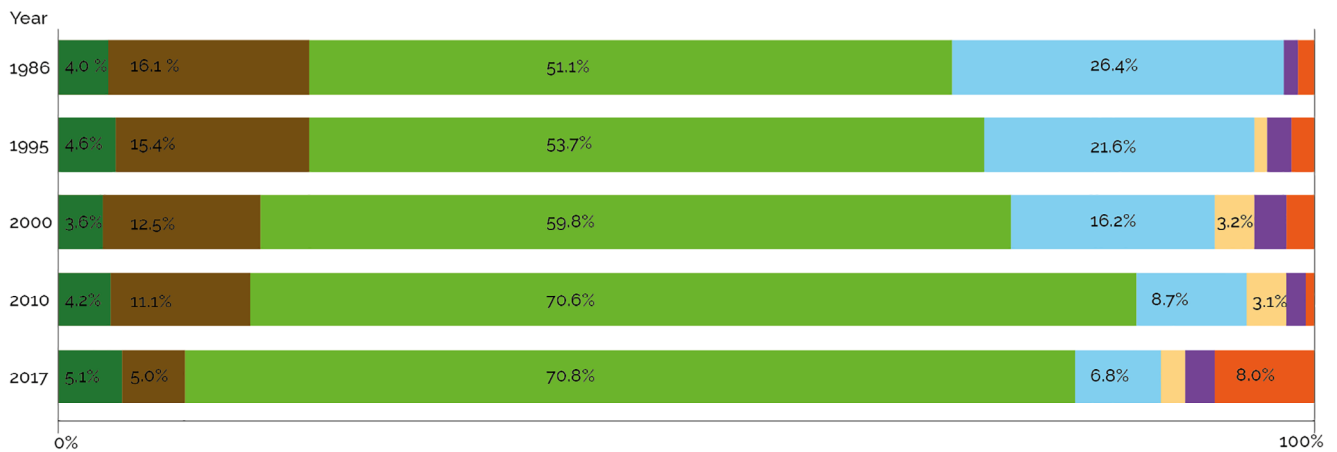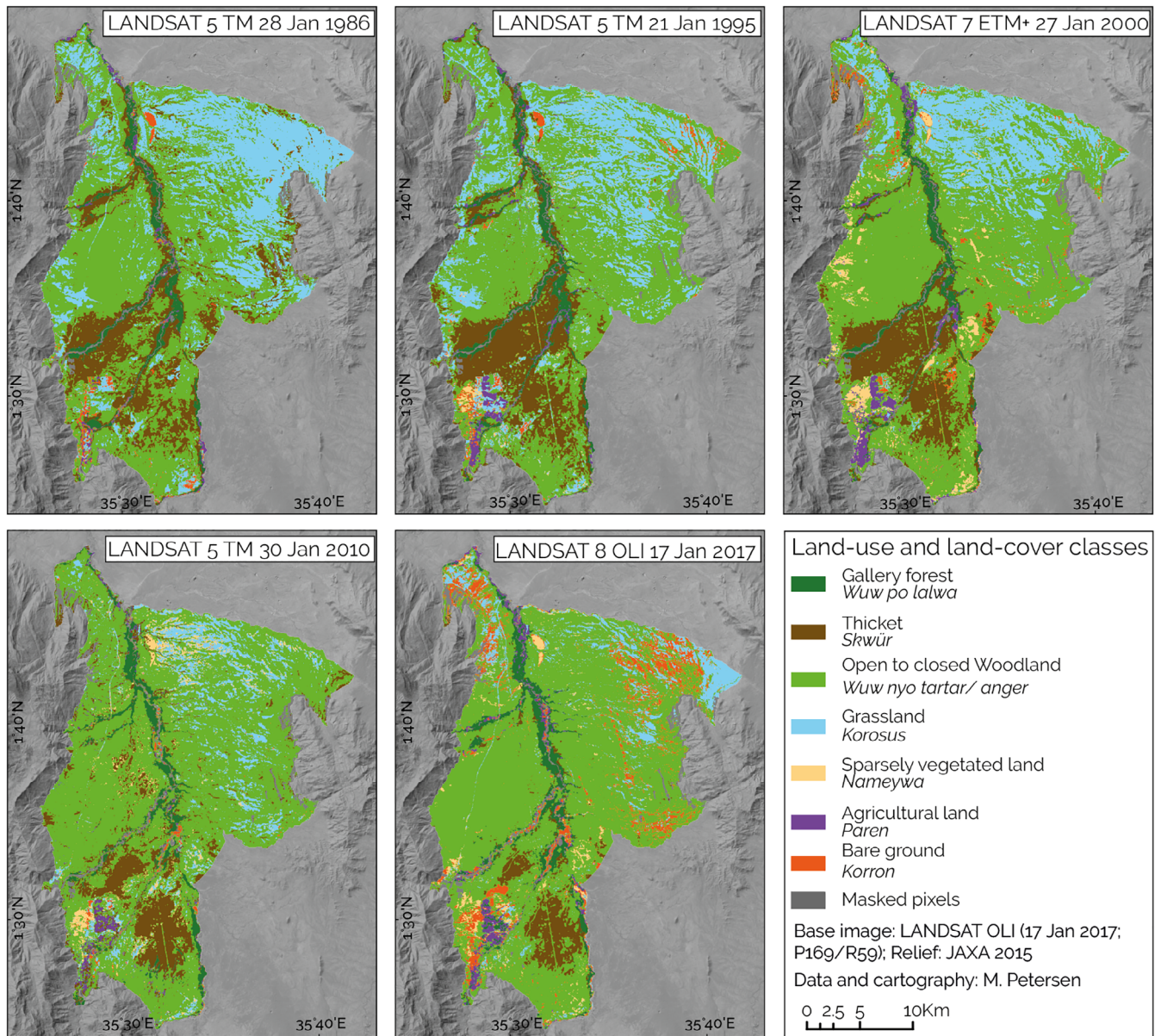
FIGURE 3 Land-use and land-cover (LULC) classification for Pokot Central in 1986, 1995, 2000, 2010 and 2017 based on LANDSAT images (path 169, row 59), and the resulting percent distribution values for each LULC class; see Table 4 for the corresponding absolute values [Colour figure can be viewed at wileyonlinelibrary.com]
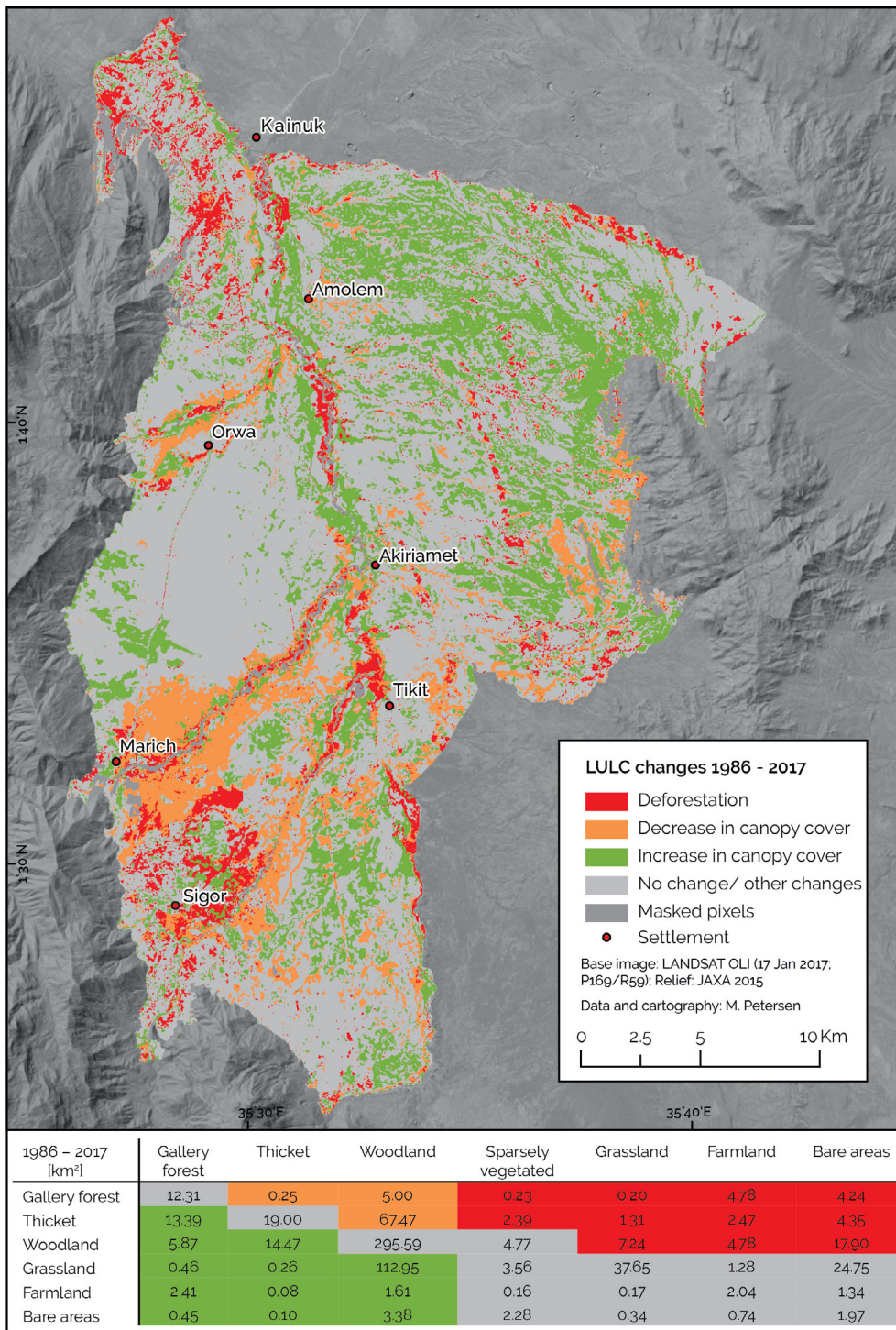
FIGURE 4 Total land-use and land-cover change in Pokot Central between 1986 and 2017, with change matrix colour-coded in accordance with the four defined classes of change [Colour figure can be viewed at wileyonlinelibrary.com]

1986 – 2017 [km²]	Gallery forest	Thicket	Woodland	Sparsely vegetated	Grassland	Farmland	Bare areas
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

remaining scenes are lower but still within an acceptable range (1986:87%; 1995:89%; 2010:78%; for detailed accuracies: SI 3.1–3.5).

Change detection between 1986 and 2017 reveals significant shifts in vegetation cover for 41% of the study area (Figure 4). While deforestation was observed in an area of 50 km² (18% of detected changes), a decrease in canopy cover was detected in a total area of 73 km² (26% of detected changes). The most prevalent transformation was the increase in canopy cover in an area of 155 km² (56% of detected changes), most of which (114 km²) is associated with bush

encroachment into former grasslands. A striking example can be found in the Masol Plains, where homogenous communities of *V. reficiens* with little to no herbaceous or grass layer are now dominating former pastures.

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 km² or 61%; SI 2.1). Field observations and participatory analysis of the LULC classifications, confirm that

TABLE 4 Areal distribution (in km²) of the seven main land-cover classes in the study area, during January in each of 5 years (1986, 1995, 2000, 2010 and 2017), and the total net change from 1986 to 2017 (see SI 2.2–SI 2.5 for change matrices between successive timesteps)

	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	

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 km² across the whole study area (Table 4).

As errors in 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 of the change detection is 60%, while the lowest user's accuracy was 50% and the lowest producer's accuracy was 40%, both calculated for the change class of decrease in canopy cover.

3.3 | Drivers of change

Unlike the data in the remote sensing analysis, the qualitative nature of the data obtained from FGDs and related participatory methods does not allow for a quantifiable comparison of driving factors. The LULC class 'thickets' shows a pronounced decline between 1986 and 2017 (by 69%; Table 4). This LULC class has 'no importance for the people' and is perceived as dangerous because of the wild animals living there (FGD3). Families would clear the area close to their homestead or fields to avoid encounters with these animals (FGD3). Therefore, the large reduction in thickets is explained mainly by the expansion of human settlements, 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 '[*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 [young children] and small animals' (FGD7). Except for the surroundings of Sigor Centre, where there is almost no vegetation left, at other rather densely 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*, which 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 being 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 considerable 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 a decrease in vegetation cover and charcoal production hotspots along the A1 highway (Bergmann et al., 2019). But while the low 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. reficiens*, *V. tortilis*, *Senegalia mellifera* (M. Vahl) Seigler & Ebinger and *Vachellia nubica* Benth. (FGD5, FGD6, FGD7) though informal rules aim at protecting the more valued tree species (FGD1, FGD4, FGD6). Other drivers of change include wood extraction for timber (FDG2, FGD5) and the felling of trees by elephants (FGD2).

4 | DISCUSSION

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

Our change detection analysis 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, Clark, & DeGloria, 2018; Venter, Cramer, & Hawkins, 2018). The introduced tree Prosopis juliflora plays a major role in this process in many East African drylands (Shiferaw et al., 2019), including Baringo and Turkana County, both located in close proximity of Pokot Central (Maundu, Kibet, Morimoto, Imbumi, & Adeka, 2009; Mwangi & Swallow, 2005). However, only isolated specimens 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, van Tienhoven, & Schomaker, 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 (de Klerk, 2004; Stevens et al., 2017). Reduced mobility of pastoralist 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 affected 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 this 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, Oduori, Gadain, & Toselli, 2013; Sedano et al., 2016). The LANDSAT analysis, however, does not reveal such a link in our study area. In contrast to findings by Kiruki, van der Zanden, Malek, & Verburg (2017) from Kitui County in southeastern 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, Ghilardi, Sander, & Chaix, 2013). Respondents stated that the encroaching *V. reficiens* is predominantly cut as wood for charcoal production while efforts are made to try to preserve trees that are more valuable for livestock. 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, Wanjiru, Johnson, & Johnson, 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 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 in 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 & 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, Ngugi, & Kitalyi (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 a 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).

5 | CONCLUSIONS AND POLICY IMPLICATIONS

This study identifies LULC changes and their drivers in a sub-Saharan dryland over three decades between 1986 and 2017. Our integrated approach contextualizes remotely sensed LULC changes with local perceptions of land-cover categories and degradation processes. 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 helps to understand the linkages between environmental change and livelihood dynamics of dryland populations across historical developments. The consequent participatory approach employed in this study combines the delineation of locally perceived and accepted land-cover categories with a qualitative interpretation of the driving factors behind LULC change and land degradation. This combined approach helps to unravel the complexities of land-use decision making, and may therefore serve as a basis for future programs that aim to foster locally accepted adaptation strategies and management guidelines for sub-Saharan drylands.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data available on request from the authors.

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SUPPORTING INFORMATION

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