Agriculture, Ecosystems and Environment 265 (2018) 307–319

Contents lists available at ScienceDirect

Agriculture, Ecosystems and Environment

journal homepage: www.elsevier.com/locate/agee

Sustainable intensification of dairy production can reduce forest disturbance in Kenyan montane forests

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ARTICLE INFO

Keywords:
Climate change mitigation
Feed intensification
Forest disturbance detection
Fuelwood
Livestock
Space-time extremes and features
Smallholder agriculture

ABSTRACT

Increasing demand for food and the shortage of arable land call for sustainable intensification of farming, especially in Sub-Saharan Africa where food insecurity is still a major concern. Kenya needs to intensify its dairy production to meet the increasing demand for milk. At the same time, the country has set national climate mitigation targets and has to implement land use practices that reduce greenhouse gas (GHG) emissions from both agriculture and forests. This study analysed for the first time the drivers of forest disturbance and their relationship with dairy intensification across the largest montane forest of Kenya. To achieve this, a forest disturbance detection approach was applied by using Landsat time series and empirical data from forest disturbance surveys. Farm indicators and farm types derived from a household survey were used to test the effects of dairy intensification on forest disturbance for different farm neighbourhood sizes (r = 2–5 km). About 18% of the forest area was disturbed over the period 2010–2016. Livestock grazing and firewood extraction were the dominant drivers of forest disturbance at 75% of the forest disturbance spots sampled. Higher on-farm cattle stocking rates and firewood collection were associated with 1–10% increased risk of forest disturbance across farm neighbourhood sizes. In contrast, higher milk yields, increased supplementation with concentrated feeds and more farm area allocated to fodder production were associated with 1–7 % reduced risk of forest disturbance across farm neighbourhood sizes. More intensified farms had a significantly lower impact on forest disturbance than small and resource-poor farms, and large and inefficient farms. Our results show that intensification of smallholder dairy farming leads to both farm efficiency gains and reduced forest disturbance. These results can inform agriculture and forest mitigation policies which target options to reduce GHG emission intensities and the risk of carbon leakage.

1. Introduction

Poor management of agricultural land and forests leads to deforestation and land degradation worldwide. The expansion of smallholder agriculture is one of the main drivers of deforestation in Sub-Saharan Africa (SSA) (Hosonuma et al., 2012). Such unsustainable land uses cause greenhouse gas (GHG) emissions and affect adversely ecosystem services such as soil carbon (C) sequestration and biodiversity (Barlow et al., 2016; Grassi et al., 2017; Herrero et al., 2016). Rising human population in many SSA countries has increased the demand for food and reduced the availability of arable land (Carter et al., 2017). Thus, climate–smart practices are required to intensify production on smallholder farms sustainably, which improve food security and contribute to climate change mitigation.

Recently, an intensification trend of smallholder farming has been documented for the East African highland regions, particularly in Kenya (Herrero et al., 2014). However, in the past large parts of the Kenyan montane forests have been converted to agricultural land. Remaining forests are threatened by ongoing anthropogenic disturbance causing GHG emissions from forests. The land use, land use change and forestry (LULUCF) sector contributes about 38% to total GHG emissions in Kenya (Government of Kenya, 2015b). Three quarters of forest-related GHG emissions result from small-scale forest disturbances such as fuelwood extraction, selective logging and wildfires (Pearson et al., 2017). Thus, mitigation efforts to effectively reduce these emissions are required. Kenya has committed to the United Nations framework

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https://doi.org/10.1016/j.agee.2018.06.011
Received 22 January 2018; Received in revised form 30 April 2018; Accepted 17 June 2018
0167-8809/

convention on climate change (UNFCCC) defining mitigation targets in its nationally determined contribution (NDC) (Government of Kenya, 2015a). However, mitigation planning at national level is separated in land use sectors, i.e. agriculture and forests, which is likely to render the reduction of GHG emissions ineffective. Quantifying the relationship between agricultural land use practices and forest disturbance could be used to develop integrated mitigation approaches that minimize the risk of spillover effects such as C leakage (Minang and van Noordwijk, 2013).

The Mau Forest located in the Kenyan highlands is the largest remaining montane forest complex in East Africa. The forest plays an important role as water tower for the whole region as it is the headwater area for 12 major rivers supplying freshwater to about 5 million people (Jacobs et al., 2017). The unsustainable use of the forest leads to disturbances that impair ecosystem services such as C storage, freshwater supply and biodiversity (Kinyanjui, 2011). To date, forest disturbance and its main drivers have not yet been quantified or characterized, neither for Kenya's forests nor for the Mau Forest, in particular.

The Mau region is dominated by smallholder crop-livestock production (Robinson et al., 2011). Smallholders throughout the highlands commonly engage in dairy farming contributing about 80% to Kenya's total milk production (Udo et al., 2016). Increasing the productivity of smallholder dairy farming throughout East Africa is promoted by several agricultural development programs to meet the demand for dairy products (Government of Kenya, 2010). Sustainable intensification of agricultural production is urgently required to improve the livelihood of smallholder farmers and is often reported as a promising measure to achieve climate mitigation targets (Campbell et al., 2014; Ortiz-Gonzalo et al., 2017; Vanlauwe et al., 2014). Human presence in landscapes that were formerly dominated by forests has been linked to changes in forest cover in SSA (Ryan et al., 2017; Sassen et al., 2013). However, an assessment of local human activities and their effects on adjacent forests is missing. A quantitative analysis of the relationship between specific practises of smallholder dairy farming and forest disturbance is needed to assess whether intensification is sustainable beyond individual farms. This analysis is also needed and highly relevant for other montane regions in East Africa that share comparable farming and forests systems and are exposed to similar pressures due to the increasing demand for food.

Intensification of smallholder dairy farming includes changes in cattle management e.g. feeds and breeds which have the potential to increase milk production (Rufino et al., 2009) and to reduce GHG emissions per unit of product (Herrero et al., 2016, Udo et al., 2016). To date, there are no comprehensive studies on the effects of intensification in smallholder dairy farming on adjacent forests, which can undermine the climate change mitigation effect of the farming practices promoted (Brandt et al., 2018). This study aims to answer two questions. First, what are the dominant anthropogenic drivers of forest disturbance across the Mau Forest? Second, what is the intensification effect of smallholder dairy farming on forest disturbance? The approach applied to answer these questions involved i) the quantification of forest disturbance and the characterization of the dominant drivers using a spatially-explicit framework to detect forest disturbance based on a Landsat time series and forest disturbance surveys and ii) the estimation of intensification effects of smallholder farms on forest disturbance based on empirically-derived farm indicators and farm types.

2. Methods

2.1. Study area

The Mau Forest is located in the Western highlands of Kenya (Fig. 1) and represents the largest remaining Afromontane forest in the country covering about 400,000 ha (Kinyanjui, 2011). It primarily consists of broadleaf tree species and bamboo forests, the latter in regions above 2400 m (Ng'eno, 1996). Large parts of forest have been converted to agricultural land due to favourable biophysical conditions such as high annual precipitation and well drained soils. The region is characterized by high densities of human and livestock populations (Herrero et al., 2014; Robinson et al., 2014). Apart from smallholder crop-livestock production systems there are large-scale tea plantations (Baldyga et al., 2008; Jacobs et al., 2017). The Mau Forest is used for fuelwood, for livestock grazing and for timber production, which is mainly harvested from tree plantations (Government of Kenya, 2009; Olang et al., 2011).

2.2. Analysis approach

The approach followed in this study is shown in Fig. 2. First, remote sensing data were acquired and pre-processed. Data on farm practices and forest disturbance were obtained through field surveys (Section 2.3). Second, forest disturbance was detected from remote sensing data using the space time extremes and features (STEF, Hamunyela et al., 2017) algorithm (Section 2.4). Third, farm indicators and farm types were derived from farm survey data (Section 2.5). Fourth, the effects of farm indicators and farm types on forest disturbance intensity were modelled by using generalized linear mixed effect models (GLMMs) (Section 2.6).

2.3. Acquisition and pre-processing of data

2.3.1. Remote sensing data

All available terrain-corrected (L1T) multi-spectral satellite images (n = 639) acquired by Landsat 5-TM, Landsat 7-ETM+, and Landsat 8-OLI sensors (Fig. 2, step 1) from January 2005 to December 2016 were downloaded from the United State of America's Geological Survey (USGS) Earth Explorer platform. The normalized difference moisture index (NDMI, Jin and Sader, 2005) was computed from each image. NDMI is sensitive to changes in canopy moisture. It was chosen as it is known to discriminate well changes in tropical wet forests (DeVries et al., 2015a). NDMI was used to study small-scale disturbance in another Afromontane forest (DeVries et al., 2016). Clouds and cloud shadows were masked using the cmask algorithm (Zhu et al., 2015).

A benchmark forest mask was created (Fig. 2, step 1) to constrain the forest disturbance detection algorithm to forested areas. Clouds and cloud shadows were masked in the available Landsat spectral band images from 2009. Gaps were filled by mosaicking the images. A random forest model (Breiman, 2001) was trained to classify the study area into forest and non-forest regions using all Landsat spectral bands as predictors. The model was trained on randomly sampled polygons maintaining equal sample sizes (n = 40) for both classes each containing at least 10,000 Landsat pixels. This training dataset was obtained by visual interpretation of very high resolution Google Earth imagery. Forest patches smaller than 0.5 ha were excluded from the forest mask to satisfy the minimum forest area criterion of the Food and Agriculture Organisation (FAO) of the United Nations forest definition (FRA, 2000).

A time series dataset of all pre-processed NDMI images was created. In addition, tree plantation data (Government of Kenya, 2015c; Jacobs et al., 2017) were used to exclude forest plantation areas from the forest disturbance analysis. Monthly fire alert data (Giglio, 2015) from the Moderate Resolution Imaging Spectroradiometer (MODIS, MCD14ML) were used to determine the extent and proportion of burnt forests over the monitoring period.

Seasonal variability influences vegetation dynamics across the study area leading to fluctuating spectral signals which impair the accuracy of forest disturbance detection algorithms (Hamunyela et al., 2016b). A local spatial normalisation approach (Hamunyela et al., 2016a, 2017) was used to reduce the effect of seasonality in the NDMI time series (Fig. 2, step 2). The normalisation procedure was applied on each NDMI image in the time series prior forest disturbance detection. The local neighbourhood was defined using a spatially-moving window with a

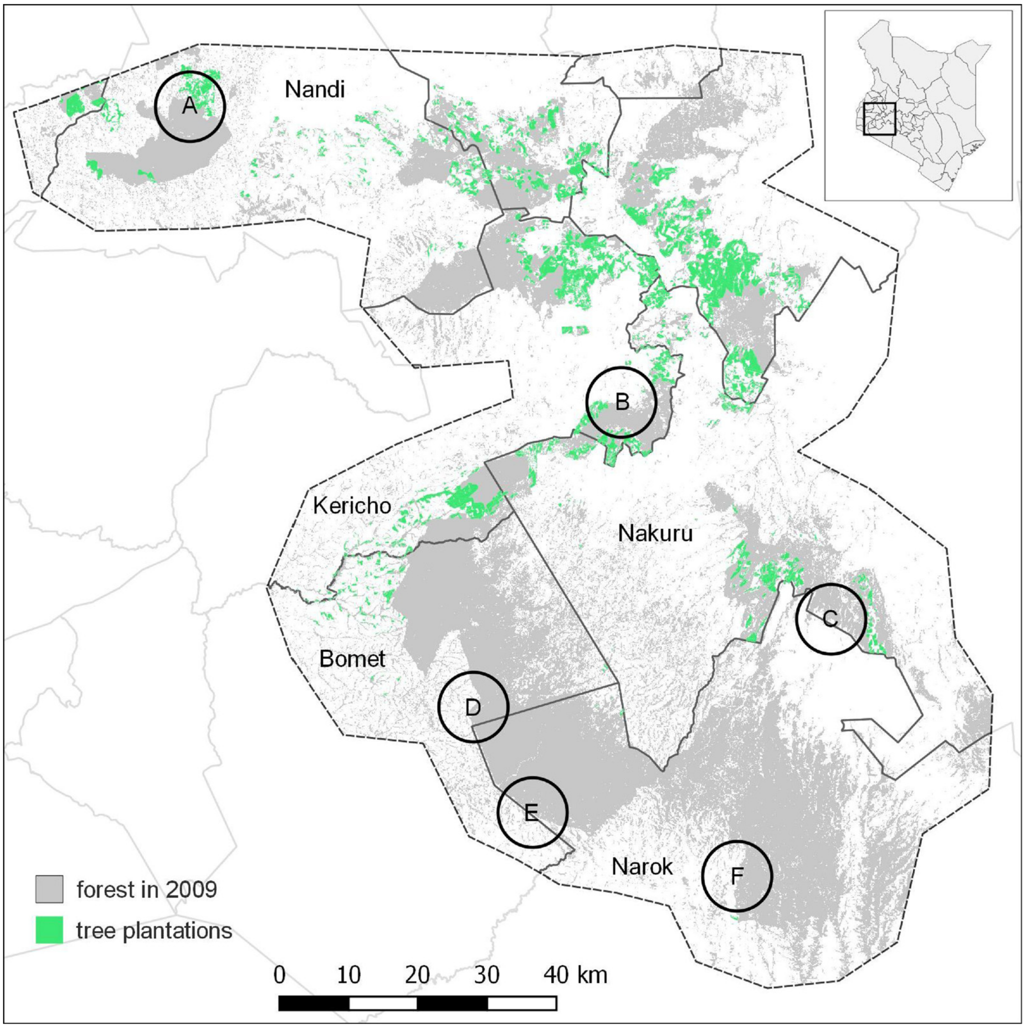

Fig. 1. The study area of the Mau Forest complex in Kenya. Circles and letters indicate sampling sites selected to conduct farm and forest disturbance surveys: A) South Nandi Forest, B) Western Mau Forest, C) Eastern Mau Forest, D) South West Mau Forest, E) Transmara Mau Forest, and F) Maasai Mau Forest.

size of 15 × 15 Landsat pixels. Each centre pixel within the window was divided by the 95th percentile computed from pixel values within the window (Hamunyela et al., 2016b). A 15 × 15 pixel window was deemed sufficient because forest disturbances in the study area occur at small-scale.

2.3.2. Field data

Two field surveys were conducted between November and December 2016 to collect information about smallholder farms (farm survey) and forest disturbance (forest disturbance survey) in adjacent forests by using open data kit (ODK) questionnaires (Fig. 2, step 3–4). Sampling sites for each survey were selected based on a stratified sampling design using spatially-explicit datasets on cattle density (Robinson et al., 2014) and forest loss (Hansen et al., 2013). Forest loss data were converted to forest disturbance density by using the kernel density tool in ArcGIS 10.3. Cattle and forest disturbance densities were reclassified based on quantile splits to derive six combinations of sampling strata ranging from low cattle and forest disturbance density to high cattle and disturbance density (Fig. S1). Circular sampling sites (radius = 5 km) were placed into the sampling strata derived. Furthermore, by ensuring a forest cover of 50% in each site and by excluding tree plantations (Fig. 1), the number of sampling sites was constrained, which led to the selection of the following areas: A) South Nandi Forest (n = 37 farms and m = 36 disturbance spots sampled), B) Western Mau Forest (n = 39, m = 30), C) Eastern Mau Forest (n = 34, m = 32), D) South West Mau Forest (n = 35, m = 44), E) Transmara Mau Forest (n = 39, m = 45), and F) Maasai Mau Forest (n = 32, m = 34). A minimum sample size of 30 farms and 30 forest disturbance sports per site was targeted. Often, additional farm and forest disturbance data could be obtained.

The farm survey was conducted to gather information on cattle numbers, milk yields, feed types, farm area allocated to fodder production, farm size, and amount of firewood collected from the forest. Farms were sampled based on locations randomly selected within each sampling site (n = 216). The forest disturbance survey characterized disturbance spots sampling randomly forest loss pixels derived from Hansen et al. (2013) that were still forest according to the forest mask created (n = 221) to avoid the sampling of deforested land. During this survey, information on disturbance types such as cattle grazing, firewood extraction, wildfires, and charcoal burning was collected. In this analysis, forest disturbance is defined as negative change in canopy cover over time directly or indirectly induced by anthropogenic activities. A detailed list of variables collected during the surveys is available in the supplementary information (Table S1 - 2). The field data gathered from this forest disturbance survey were used, in combination with additional forest disturbance data collected during a previous forest disturbance survey (n = 127). The later survey was conducted in the Mau Forest between March and April 2016 (Bewernick, 2016), to validate an earlier forest disturbance detection in a sub-region of the study area.

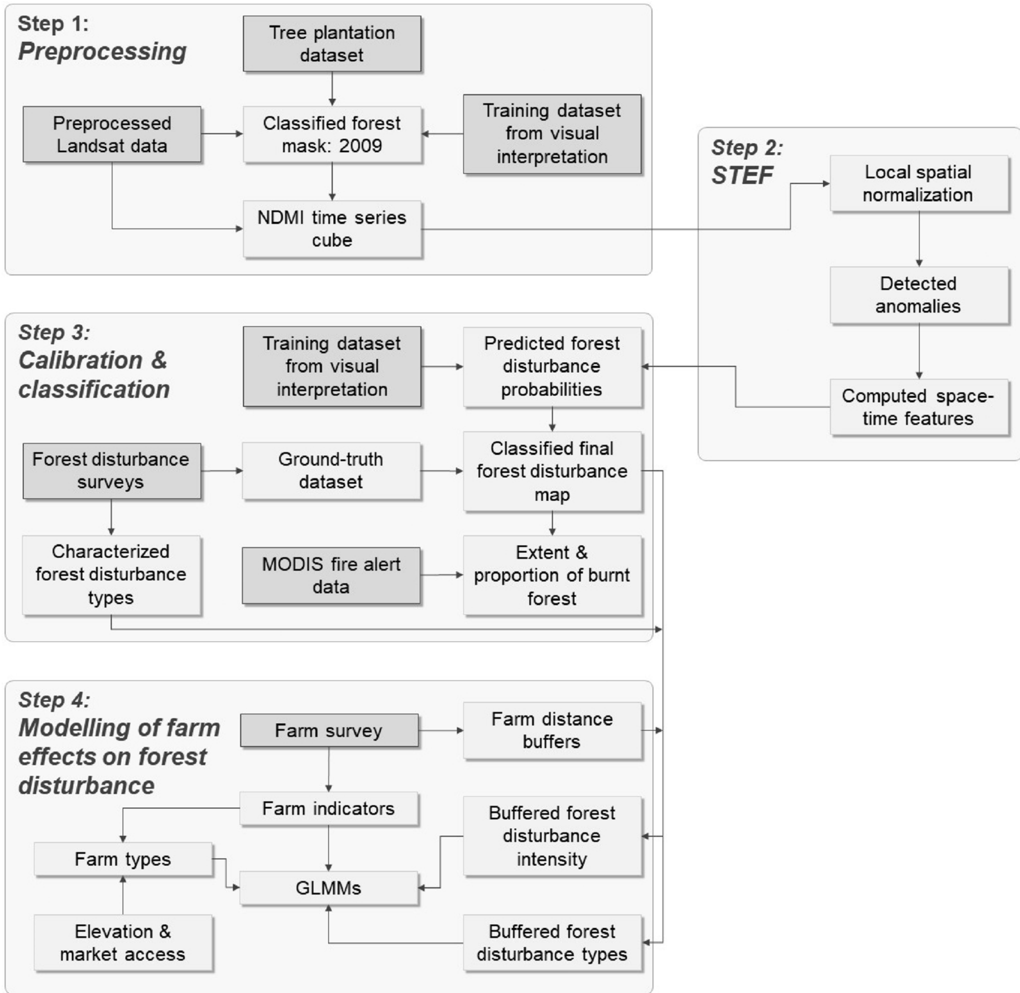

Fig. 2. Flowchart of analysis steps followed in this study. Dark boxes represent data inputs from remote sensing and field observations. NDMI = normalized difference moisture index, STEF = Space Time Extremes and Features approach, GLMMs = generalized linear mixed effect models.

2.4. Forest disturbance detection, calibration and classification

Forest disturbances were detected by using the STEF algorithm (Hamunyela et al., 2017). STEF detects forest disturbances as extreme events in local data cubes of satellite-derived time series (Fig. 2, step 2). A local data cube was defined around each pixel containing both spatial and temporal extents which are user-defined (Hamunyela et al., 2017).The temporal extent corresponded to the full length of the NDMI time series. A moving spatial window of 9 × 9 Landsat pixels was used as the spatial extent of the local data cube. STEF takes the spatio-temporal context of an observation into account to reduce the sensitivity to data noise, e.g. introduced by cloud remnants increasing the algorithm's accuracy (Hamunyela et al., 2016b, 2017). Extreme events are identified as abnormally low observations in the monitoring period, by using an extreme value approach (Zscheischler et al., 2013). A pixel was considered abnormally low if its value was below the threshold computed from spatio-temporal observations in the history period of the local data cube. The history period of the time-series analysis was defined from 2005 to 2009 and the monitoring period was set to 2010–2016. Following an application of STEF on Afromontane forests in Ethiopia (Hamunyela et al., 2017), the 5th percentile was chosen as the anomaly threshold. A pixel was flagged as potentially disturbed if the algorithm detected two consecutive anomalies in the monitoring period. Once consecutive anomalies are detected, STEF extracts 17 space-time features from the local data cube (Hamunyela et al., 2017). The features include information on the proximity of the extreme event to forest edges, existence and number of anomalies in the neighbourhood of the pixel where the extreme event is detected, and the spatial variability across the local data cube at the time step where a potential forest disturbance is detected (Hamunyela et al., 2017). These space-time features were subsequently used to confirm forest disturbances.

Forest disturbance was confirmed by first calculating the probability for forest disturbance by using the extracted space-time features as predictors of forest disturbances (Hamunyela et al., 2017). The probability of disturbance was calculated by using a trained random forest model. Random forest classifiers have the advantage to be of non-parametric nature and can handle many predictors without overfitting (Breiman, 2001). The random forest model was trained by using a calibration dataset (n = 204) acquired through visual interpretation of multispectral Landsat images (Fig. 2, step 3), complemented by very high resolution imagery available in the Google Earth, based on methodology proposed by Cohen et al. (2010). A stratified random sampling design was used to derive the calibration data. The magnitude of change, which is one of the features extracted by STEF indicating the deviation between detected anomaly and the 95th percentile of the history distribution, was used to stratify the map of potential disturbances, produced from STEF. The magnitude of change was sampled randomly along the quantiles to derive four strata ranging from high to low magnitude.

Moreover, ground-truth data (n = 348) from forest disturbance surveys (Section 2.3.2) were used to determine the optimal probability threshold (Fig. 2, step 3). A series of probability thresholds, ranging from 0 to 1 at an interval of 0.01 was created. Each probability threshold was used to classify the probability values derived for the ground-truth data into disturbed and undisturbed forest while calculating user's accuracy (UA = inverse of commission error) and producer's accuracy (PA = inverse of omission error). The probability threshold that indicated the lowest area bias, which is the minimum trade-off between commission and omission error was used to generate the final forest disturbance map (DeVries et al., 2015b; Hamunyela et al., 2017).

2.5. Defining farm types

Field data derived from the farm survey were used to cluster farms (Fig. 2, step 4) into distinct types based on indicators that reflected differences in the degree of intensification and which were expected to influence the effect of dairy farming on the forest. Indicators chosen to cluster the farms were: number of cattle, milk yields, proportion of grass from on-farm pastures in the diet, farm area allocated to fodder production, quantity of feed concentrates supplemented, farm size, and amount of firewood collected. A correlation analysis was conducted prior to the clustering to exclude highly correlated variables (Spearman's rho > = 0.7). The k-means partitioning algorithm was applied in R to cluster the farms, after farm indicators were standardized, by using the Euclidean distance measure (R Core Team, 2016). The number of farm types was determined visually based on the drop in intra-cluster variation as a function of increasing numbers of clusters (Kassambara, 2017). In addition, farm types were tested regarding differences in elevation and market access by using an elevation dataset (Shuttle Radar Topography Mission, SRTM) and a proxy dataset indicating travel time to cities with more than 50.000 inhabitants (Jarvis et al., 2008; Uchida and Nelson, 2009). This analysis enabled an interpretation of how the remoteness of farms affects intensification of smallholder dairy production.

2.6. Modelling the effects of farms on forest disturbances

Using the raster package in R (Hijmans, 2016), circular distance buffers with radiuses of 2, 3, 4, and 5 km were created around recorded farm centroids, henceforth called farm neighbourhoods (Fig. 2, step 4). The neighbourhood sizes were deemed to be appropriate to study the effects of local farm practices and characteristics on forest disturbance in forests adjacent to smallholder farms based on field observations and interviews with local forest rangers from the Kenyan Forest Service. The different neighbourhood sizes were chosen to assess the sensitivity of farm-related effects on forest disturbance over discrete changes of neighbourhood sizes through a sensitivity analysis. Two different response variables were generated. First, the proportion of forest disturbance pixels within each farm neighbourhood was calculated by dividing the number of these forest pixels by the total number of forest pixels. The proportion of forest disturbance pixels were used as a measure of 'disturbance intensity'. Second, forest disturbance sampled and characterized during the forest disturbance survey were counted within farm neighbourhoods to model farm effects on specific forest disturbance types.

GLMMs were used by applying the lme4 package in R (Bates et al., 2015) to model the association between farm characteristics and forest disturbance intensities. The associations were interpreted as driver-response relations, that is, farm characteristics were assumed to influence disturbance intensities. Farm indicators, farm types, and farm distances to the closest forest edge were included as fixed effects (explanatory variables). A categorical variable, which represented the sampling sites was included as a random effect. Binomial and Poisson GLMMs were run for the proportional disturbance intensity and the counted forest disturbance types derived from forest disturbance detection and survey data, respectively. Different GLMMs were run for each farm neighbourhood size separately (Fig. 2, step 4). Model evaluation and selection was based on the Akaike information criterion (AIC) by applying likelihood ratio tests (Zuur et al., 2009). The model candidates that showed the lowest AICs were chosen.

To understand the effects of farm indicators on forest disturbance intensity derived from the binomial GLMMs, a relative risk measure was used. The relative risk quantifies the likelihood of an outcome (forest disturbance intensity), as a result of exposure to specific treatments such as farm practices and farm characteristic represented by chosen indicators (Akobeng, 2005). The effects of interactions between farm types and farm distances to the closest forest edges were explored to show potential differences of farm type effects along a farm distance to forest gradient on forest disturbance intensity. To characterize the influence of farm types on certain types of forest disturbance, modelled farm type effects on forest disturbance types observed during the survey are shown.

3. Results

3.1. Forest disturbance across the Mau Forest

A lowest area bias of 0.7% was achieved at P = 0.39 where the UA was 77.9% and the PA was 78.6% (Fig. S2). Hence, the threshold of 0.39 was chosen as the probability threshold to classify each forest pixel into disturbed and non-disturbed forest.

In total, 17.7% of the forested land was found to be disturbed between 2010 and 2016. The intensity of forest disturbance varied across the Mau Forest complex with the largest impacts in central and southern forest regions (Fig. 3). Forest disturbance also strongly differed between sampling sites. The proportions of disturbed forest detected at the Western Mau Forest (42.4%) and the Maasai Mau Forest (17.0%) were the largest (inset Fig. 3). With 3.9%, the South Nandi Forest had the smallest proportion of disturbed forest.

3.2. Dominant drivers of forest disturbance across sampling sites

Firewood extraction and cattle grazing inside the forest were the most dominant drivers of forest disturbance at all six sampling sites. Firewood extraction was observed at 76% and cattle grazing at 75% of all disturbance spots visited. Burnt tree stems were observed on 31% of all spots sampled at four sampling sites, suggesting wildfires are an important driver of disturbance. Wildfire events observed on the ground were confirmed by MODIS fire alert data for three of the six sampling sites, detecting wildfires at the Western Mau Forest, Eastern Mau Forest, and Maasai Mau Forest at 25.6%, 1.5%, and 0.4% of the forested land respectively (inset Fig. 3). The most common combination of drivers observed on 48% of all visited spots was firewood extraction and cattle grazing inside the forest (Fig. 4). This co-occurrence of drivers was predominant across the sampling sites except for the Maasai Mau Forest site where forest grazing and wildfire were found to co-occur more often (Fig. 4).

3.3. Effects of farm indicators on forest disturbance intensity

Firewood collection rates, farm sizes, and cattle numbers were associated with a significantly increased risk of forest disturbance across farm neighbourhood sizes by 3–10 %, 1–5 %, and 1–5 % respectively ($p < 0.001$, Fig. 5). In contrast, higher milk yields were related to a significantly lower risk of forest disturbance by 3–7 % across farm neighbourhood sizes ($p < 0.001$, Fig. 5). Larger farm area allocated to fodder production, increased supplementation of dairy concentrates and higher proportion of grass from on-farm pastures in the diet were associated with a significantly lower risk of forest disturbance by 2–5 %, 1–2 %, and 1–2 % in 3 (Fig. 5B, C, D), 2 (Fig. 5A, D), and 2 (Fig. 5C, D) of the farm neighbourhoods respectively ($p < 0.001$). The risk of forest disturbance intensities decreased significantly by 8–15 % across all farm neighbourhood sizes ($p < 0.001$), when farms were located

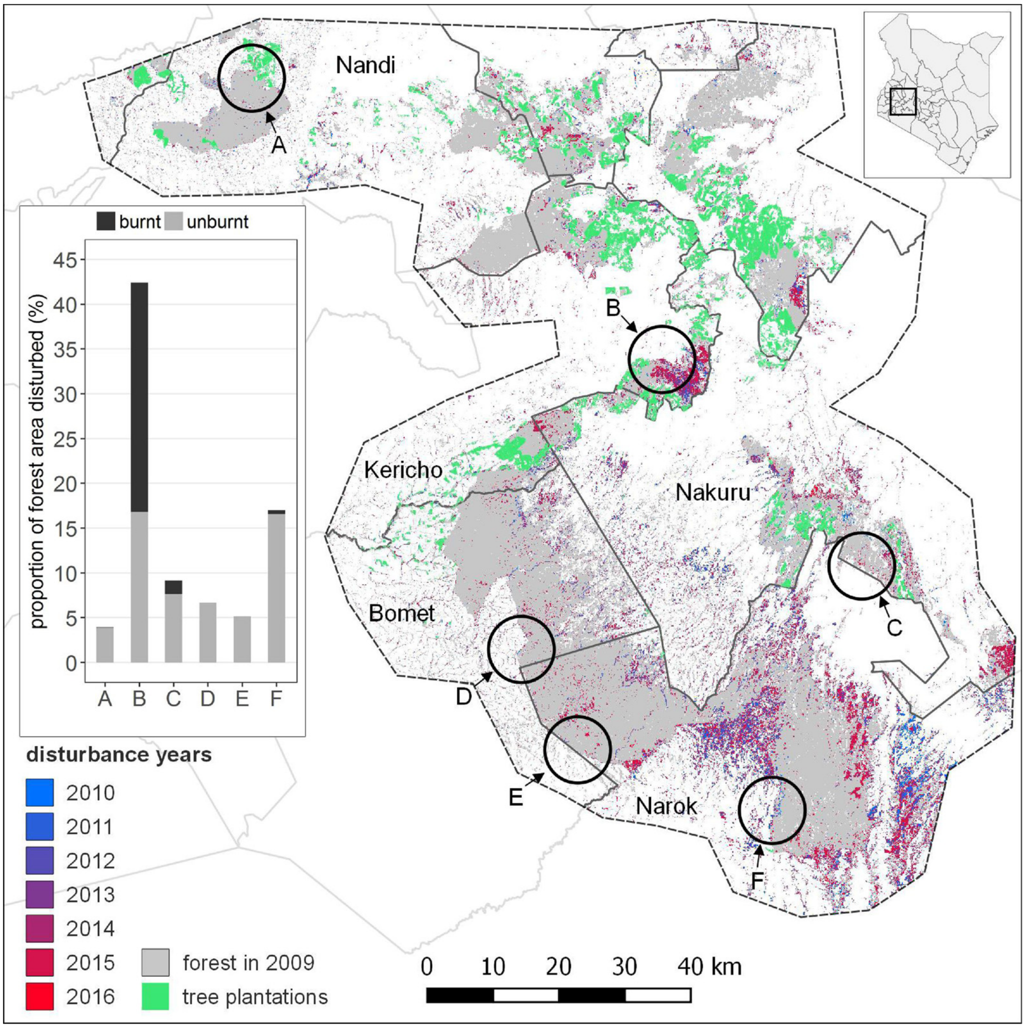

Fig. 3. Forest disturbance mapped for 2010–2016 across the Mau forest. Circles indicate sampling sites for the field surveys: A) South Nandi Forest, B) Western Mau Forest, C) Eastern Mau Forest, D) South West Mau Forest, E) Transmara Mau Forest, and F) Maasai Mau Forest. Inset bar plot shows proportions of disturbed forest area that was burnt and unburnt for each sampling site.

further away from the forest. In general, the effects of farm indicators to increase or reduce disturbance risks remained relatively constant over the different neighbourhood sizes. However, effects sizes of farm indicators became smaller with increasing size of farm neighbourhoods except for cattle numbers, which slightly increased the risk of forest disturbance in larger neighbourhoods (Fig. 5). The variability around the effects shown by their 95% confidence intervals was low across farm neighbourhoods. For details on model selection see Table S3.

3.4. Farm types

Three farm types were inferred from the cluster analysis:' small and resource-poor farms', 'large and inefficient farms' and 'intensified farms'. Small and resource-poor farms had the smallest mean sizes (0.7 ± 0.6 ha, Fig. 6A), the lowest total number of cattle herds (2.3 ± 1.8 heads, Fig. 6B) and the lowest number of dairy cattle (0.5 ± 1.0 heads). The quality of cattle feed was low indicated by a relatively low proportion of native grass from pastures in the diet (72.7 ± 30.4%, Fig. 6C), little farmland allocated to grow higher quality fodder (0.03 ± 0.04 ha, Fig. 6D) and the smallest supplementation rate of concentrated feed (0.08 ± 0.11 kg cow^{-1} day^{-1}, Fig. 6E). Milk yields were the lowest (1.2 ± 1.4 kg cow^{-1} day^{-1}, Fig. 6F). Firewood collection rates were intermediate (36.5 ± 79.3 kg week^{-1}, Fig. 6G). In addition, the farm survey data show for this farm type comparatively low proportions of farms with planted trees onfarm pastures (13%), cropland (5%), farm boundaries (84%), and in

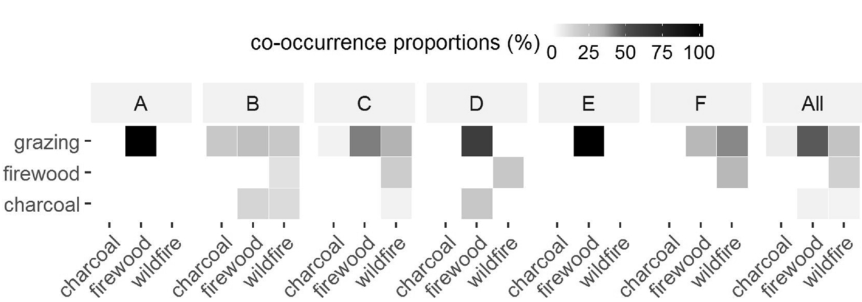

Fig. 4. Co-occurrence proportions of forest disturbance drivers (%). Forest disturbance spots were characterized during a forest survey at each sampling site: A) South Nandi Forest, B) Western Mau Forest, C) Eastern Mau Forest, D) South West Mau Forest, E) Transmara Mau Forest, F) Maasai Mau Forest, and All) all sampling sites.

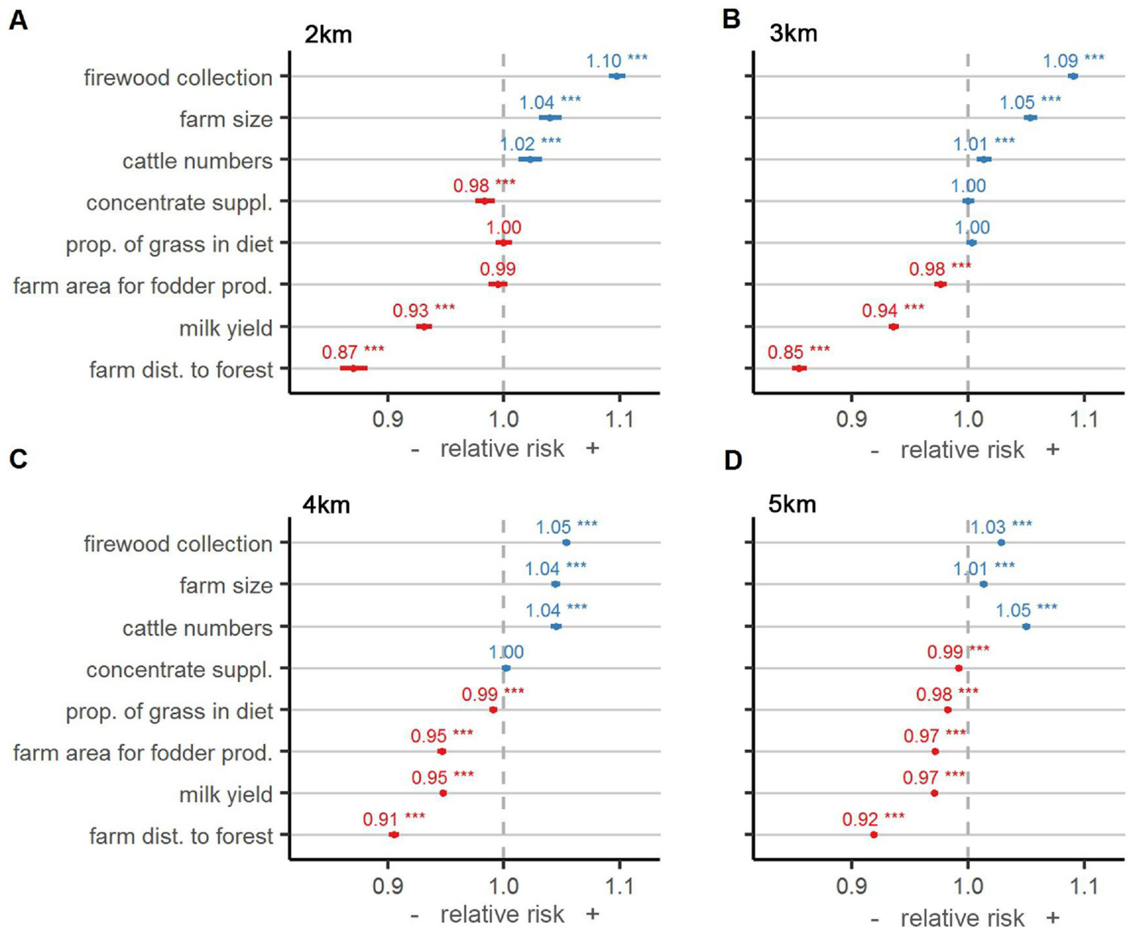

Fig. 5. Relative risks of forest disturbance as response to farm indicators. Relative risks were derived from GLMMs for different farm neighbourhood sizes (buffer radiuses): A) 2 km, B) 3 km, C) 4 km, and D) 5 km. Horizontal bars show mean effect and 95% confidence intervals for each indicator. Stars show significance levels. Vertical dashed lines indicate no effect.

woodlots (26%).

Large and inefficient farms had the largest mean sizes (4.9 ± 5.5 ha) and cattle herds (14.0 ± 16.7 heads) combined with a moderate number of dairy cattle (2.5 ± 11.4 heads). Feed quality was low shown by the highest proportion of native grass from pasture in the diet (86.5 ± 11.7%), little farmland allocated to grow high quality fodder (0.10 ± 0.45 ha), and low supplementation rates of feed concentrates (0.11 ± 0.14 kg cow^{-1} day^{-1}). Milk yields were only slightly higher than those of the small and resource-poor farms (1.8 ± 1.2 kg cow^{-1} day^{-1}). Firewood collection rates for this farm type were the highest (84.5 ± 160.6 kg $week^{-1}$). The farm survey data indicate that the proportions of farms with planted trees onfarm pastures (16%) and cropland (6%), farm boundaries (78%), and in woodlots (25%) were similar to those of the small and resource-poor farms.

Relatively more intensified farms had medium sizes (2.5 ± 2.1 ha), moderate cattle head sizes (5.0 ± 2.9 heads) but the highest numbers of dairy cattle (3.0 ± 3.5 heads). These farms had the best feed quality indicated by a moderate proportion of native grass from on-farm pastures in the diet (78.3 ± 16.4%), the largest farm area allocated to fodder production (0.23 ± 0.55 ha), and high rates of concentrated feed supplementation (0.9 ± 1.0 kg cow^{-1} day^{-1}). Milk yields were the highest (5.1 ± 2.2 kg cow^{-1} day^{-1}). Firewood collection rates were the lowest (31.2 ± 81.6 kg $week^{-1}$). This farm type had the highest proportions of farms with planted trees onfarm pastures (26%), cropland (14%), farm boundaries (90%), and in woodlots (40%).

Large and inefficient farms were located at higher elevation and show longer travel time to cities compared to small and resource-poor farms and intensified farms ($p < 0.001$, Fig. 7A–B). Therefore, large and inefficient farms were located more remotely and had less market access.

3.5. Farm types and forest disturbance intensity

Farm types had a significant effect on forest disturbance intensity ($p < 0.05$) for all farm neighbourhood sizes. Interactions between farm types and farm distance to forest edges show that more intensified farms had significantly smaller effects on the intensity of forest disturbance than the small and resource-poor farms and the large and inefficient farms for the different neighbourhood sizes ($p < 0.001$, Fig. 8). However, differences in effects between large and small farms were not significant for the 4 km farm neighbourhood size (Fig. 8C). In general, the effect of farm types on forest disturbance intensity became smaller with increasing farm distance to the forest edges. For the 5km neighbourhood size, effects of farm types were less distinguishable and their slopes decreased (Fig. 8D), indicating that the influence of farm types on forest disturbance intensity are more difficult to disentangle from external effects. The 95% confidence intervals around the effects indicate an increased variability of the interaction effects of farm types along farm distance to forests across farm neighbourhoods. The lowest variability of effects was shown for intensified farms in all farm neighbourhood sizes. For details on model selection see Table S4.

Effects of farm types on the two most important forest disturbance types (i.e. disturbance drivers) observed during the survey (Fig. 4) also differ (Fig. 9). Intensified farms were associated with significantly lower intensities of forest disturbance ($p < 0.05$) where firewood collection (Fig. 9A, C) and cattle grazing (Fig. 9D) were recorded,

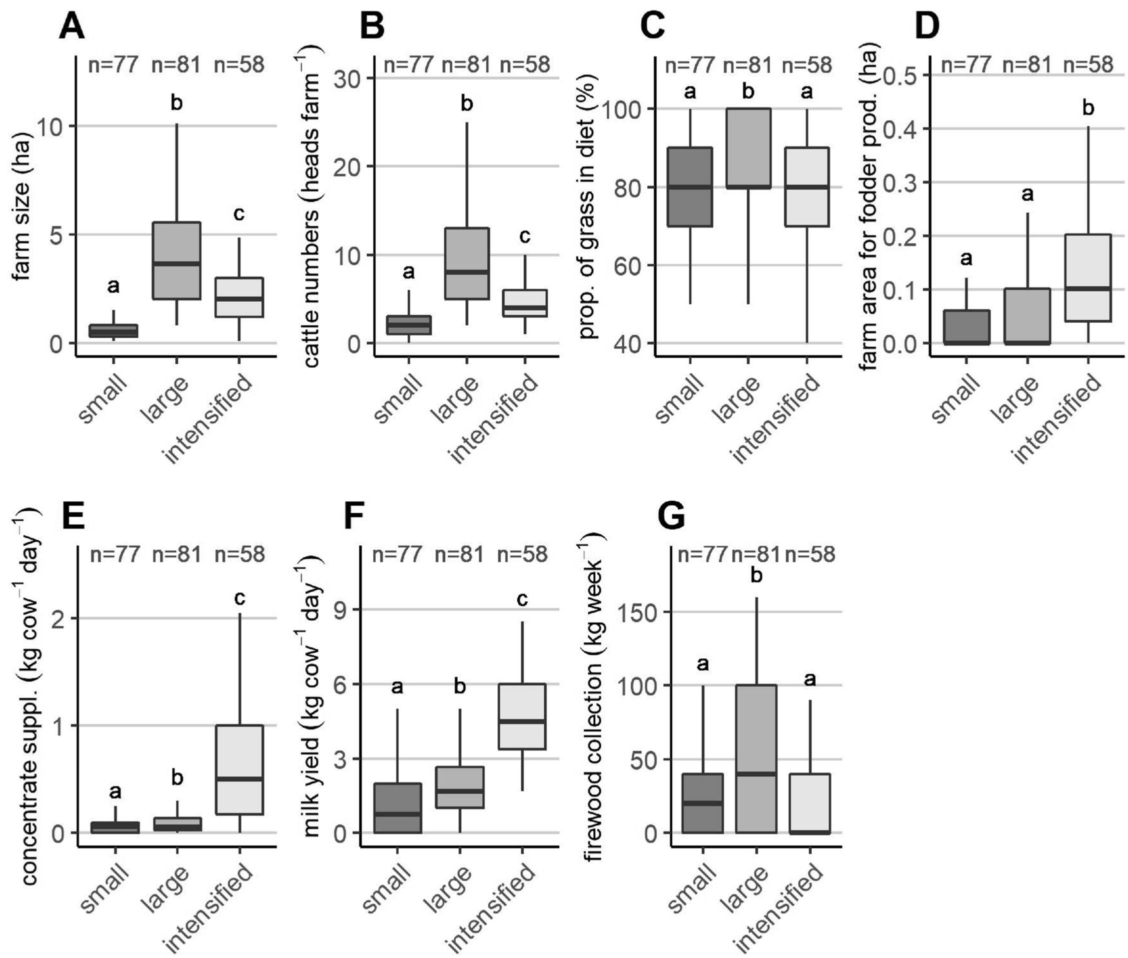

Fig. 6. Farm indicators used to cluster farm types. Farm types were (x-axes): small = small and resource-poor farms, large = large and inefficient farms, intensified = intensified farms. Included indicators were: A) cattle numbers, B) milk yields, C) proportion of grass from on-farm pastures in the diet, D) farm area allocated to fodder production, E) concentrate supplementation, F) farm size, and G) firewood collection. Different letters above whiskers indicate significant differences between farm types by using pairwise Wilcoxon rank sum tests (p-values were corrected for multiple testing).

compared to small and resource-poor farms as well as large and inefficient farms. An exception is shown for forest grazing within the 2 km farm neighbourhood where large farms were associated with a significantly higher disturbance intensity ($p < 0.05$) than small and resource-poor farms and intensified farms (Fig. 9B). Results are only shown for the 2 and 3 km farm neighbourhoods due to few disturbance samples from the forest survey within the 4–5 km farm neighbourhoods (Fig. 9D). The variability around the farm type effects was smallest for intensified farms shown by 95% confidence intervals. For details on model selection see Table S5.

4. Discussion

4.1. Drivers of forest disturbance in context

Forest disturbance across SSA is responsible for large parts of the land-based GHG emissions (Bailis et al., 2015; Pearson et al., 2017). In this study, the dominant drivers of forest disturbance were the extraction of firewood primarily used by local smallholder farmers living adjacent to the Mau Forest and cattle grazing inside the forest as opportunistic feed resource for cattle owned by local smallholders (Fig. 4). Grazing happens mostly on forest land opened through fuelwood extraction or wildfires. Although grazing is not a primary driver of forest disturbance in the montane forests studied, it prevents the regrowth of woody vegetation, affects negatively C sequestration and, thus, reduces the C sink capacity of forests (Samojlik et al., 2016). Wildfires occur across the Mau Forest, often caused by human activities such as charcoal production or attempts to clear forested land, which increase the risk to spread fire during dry seasons.

Firewood extraction from forests partly covers the demand for fuelwood, which is the main driver of small-scale forest disturbance in SSA (Hosonuma et al., 2012). The high demand for fuelwood in East African countries such as Kenya exceeds the supply capacity of forest ecosystems (Mutoko et al., 2015). Therefore, Kenya is among the countries that show the most unsustainable fuelwood production across the tropics (Bailis et al., 2015). GHG emissions from fuelwood extraction and utilization in tropical forests account with 0.62 Gt CO_2eq year^{-1} for about one third of the forest emissions, compared to timber production (1.09 Gt CO2eq year^{-1}) and wildfires (0.35 Gt CO_2eq year^{-1}) as estimated by Pearson et al. (2017). Livestock grazing in forests is with 8% ranked as the third most important driver of disturbance as estimated by Hosonuma et al. (2012) after fuelwood extraction (58%) and timber production (33%) for SSA countries that are in their late forest transition phase such as Kenya. In this study, forest livestock grazing showed a more prominent role on forest disturbance, as it occurred at all six sampling sites at 75% of all spots visited (Section 3.2). Forest disturbance spots located deep inside the forest were not visited. It is likely that the intensity of forest grazing decreases further inside the forest with limited access. In addition to negative effects of C storage in forests, livestock grazing was shown to modify nutrient cycles and to reduce species richness in forests (Close et al., 2008; Denmead et al., 2015).

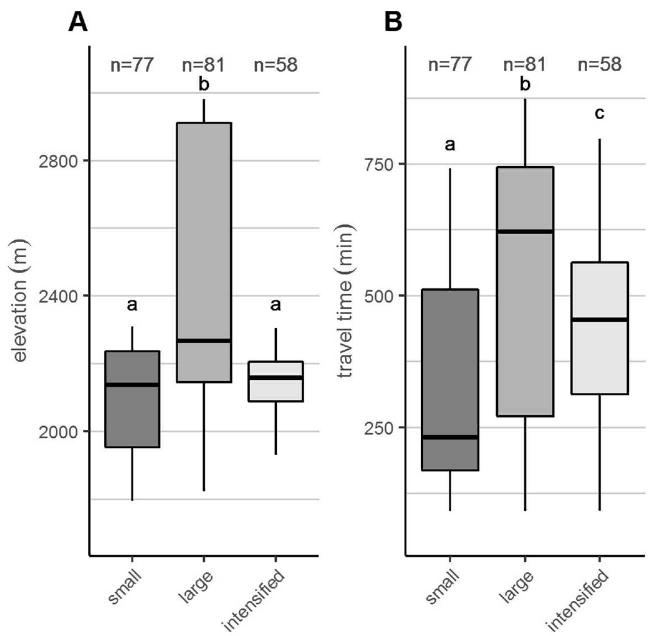

Fig. 7. Elevation and remoteness of farm types. Boxplots show A) elevation and B) travel time to cities by farm type: small = small and resource-poor farms, large = large and inefficient farms, intensified = intensified farms). Different letters above whiskers indicate significant differences between farm types by using pairwise Wilcoxon rank sum tests (p-values were corrected for multiple testing).

4.2. Mitigation potential on forested and agricultural land

4.2.1. Intensification may reduce the impact of smallholder farms on forests

The increase in agricultural production in SSA has been mostly achieved through expansion of agriculture into natural ecosystems, including forests (Fisher, 2010). Increasing productivity without compromising environmental goals is required to meet future food demand and to contribute to climate change mitigation (Smith et al., 2013). This study shows that larger farms and higher cattle numbers increased the risk of forest disturbance by 1–5 % (Fig. 5). Higher firewood collection rates had an even stronger impact on the forest increasing the risk of disturbance by 3–10 % (Fig. 5). On the contrary, higher milk yields decreased these risks by 3–7 % (Fig. 5). The effects of indicators related to feed intensification such as larger farm area allocated to fodder production, supplementation of dairy concentrate and increased proportion of grass in the diet were less pronounced. These indicators reduced the risk of forest disturbance by 1–5 % (Fig. 5). The results indicate that farms which own more cattle and collect more firewood are likely to cause more disturbance in the nearby forest than more intensified farms with high milk productivity and improved feed quality. The analysis of farm type effects on forest disturbance confirmed this pattern. More intensified farms had a lower impact on forests in general but also on disturbance caused by firewood extraction and livestock grazing in particular (Figs. 8 and 9). Compared to small and resource poor farms and large but inefficient farms, intensified farms planted more trees on farmland (Section 3.4) e.g. in woodlots or on farm boundaries. These trees represent fuelwood sources available on-farm (Mbow et al., 2014), potentially translating into lower firewood extraction from the forest (Fig. 6G). Small farms that lack resources such as land and access to higher quality feeds, and large but inefficient farms with many low productivity cattle (Fig. 6A–F) increase the risk to remove biomass from local forests unsustainably by exceeding the regrowth rates. Yet, effect sizes of farm indicators and differences among the effects of farm type on forest disturbance were, despite significant, relatively small. The inefficiency of large farms is likely related to their location at higher elevation (Fig. 7). Remoteness and lack of infrastructure result in reduced market access for these farms, rendering it more difficult for smallholders to buy higher quality feeds and feed supplements, and to sell the milk produced (Makoni et al., 2014).

The effects of dairy production and intensification on local forests can be quantified by relating farm practices and characteristics to forest disturbance patterns. Including farm-related activities outside the farm boundaries that affect the broader landscape is relevant to assess the effectiveness and sustainability of policies that target climate change mitigation and food security (DeFries and Rosenzweig, 2010). Potential spill over effects can be revealed, causes be identified and the risk of C leakage be minimized.

4.2.2. Increase of farm efficiency and on-farm tree cover

Dairy production in SSA shows the highest GHG emission intensities compared to dairy production in other continents which points to low efficiency of smallholder dairy production (Gerssen-Gondelach et al., 2017). Mitigation and development policies seek for ‘win-win’ situations where increased farm production goes hand in hand with the avoidance of additional GHG emissions (Brandt et al., 2018). Low quality feed from natural pastures and from opportunistic cattle grazing inside the forest result in low milk yields and high GHG emission intensities (Lukuyu et al., 2012). Increasing milk yields on smallholder farms can be achieved through feed intensification by improving the protein and energy density in feeds (Agle et al., 2010; Trupa et al., 2015). The intensified farm type showed the highest milk yields (Fig. 6F). The quality of feed that is either grown on-farm such as fodder grasses or supplemented as concentrated feed such as dairy meals was also highest for intensified farms compared to the other two farm types (Fig. 6D–E). Perennial fodder grasses such as Napier grass show high potential for feed intensification as it has a higher quality than native grass from pastures and is widely accepted by smallholders across the Kenyan highlands (Katiku et al., 2011). Higher supplementation of concentrates during lactation periods was related to the increase in milk yields in this study (Fig. 6E) and was also reported to improve milk yields in Kenya (Rufino et al., 2009; Richards et al., 2016).

However, C leakage emerging from intensification processes have to be considered. Feed imports from other regions or countries may raise due to feed intensification if the increased demand of higher quality feeds cannot be covered locally (Meyfroidt et al., 2014). GHG emissions from indirect land use changes due to agricultural expansion could be the consequence. Styles et al. (2017) conducted a life cycle assessment (LCA) of dairy intensification in the United Kingdom showing possible cascade effects of pasture-crop displacement and expansion of pastures that lead to deforestation in Brazil. Therefore, appropriate mitigation policies and funding schemes need to integrate measures (e.g. protocols on land use legacies, certification) that enable feed production which does not undermine effective climate change mitigation.

Depleted soils due to nutrient mining is a common reason for stagnating or falling crop yields in Kenya (Tittonell et al., 2010). Increasing the efficiency of nutrient cycling through improved manure management can increase soil fertility and crop yields as shown by Castellanos-Navarrete et al. (2015) for smallholder crop-livestock production systems in Kenya. Closing the yield gap is especially important for small farms that lack land to grow fodder. Furthermore, intensified farms had less cattle than large and inefficient farms (Fig. 6B, F), and instead owned more improved breeds (Section 3.4). Reduced stocking rates with higher herd efficiency and the replacement of local cattle with improved breeds that produce more milk accompanied by better access to animal health services are additional factors to increase the efficiency of milk production and to reduce GHG emission intensities on smallholder dairy farms in Kenya (Bryan et al., 2013; Mottet et al., 2016). Adopting the dairy hub model, developed by the East African dairy development program (EADD), could facilitate the improvement of market access. This can be achieved by infrastructure funds and by linking the different actors throughout the dairy value chain such as dairy farmers, feed producers and dairy companies (EADD, 2014).

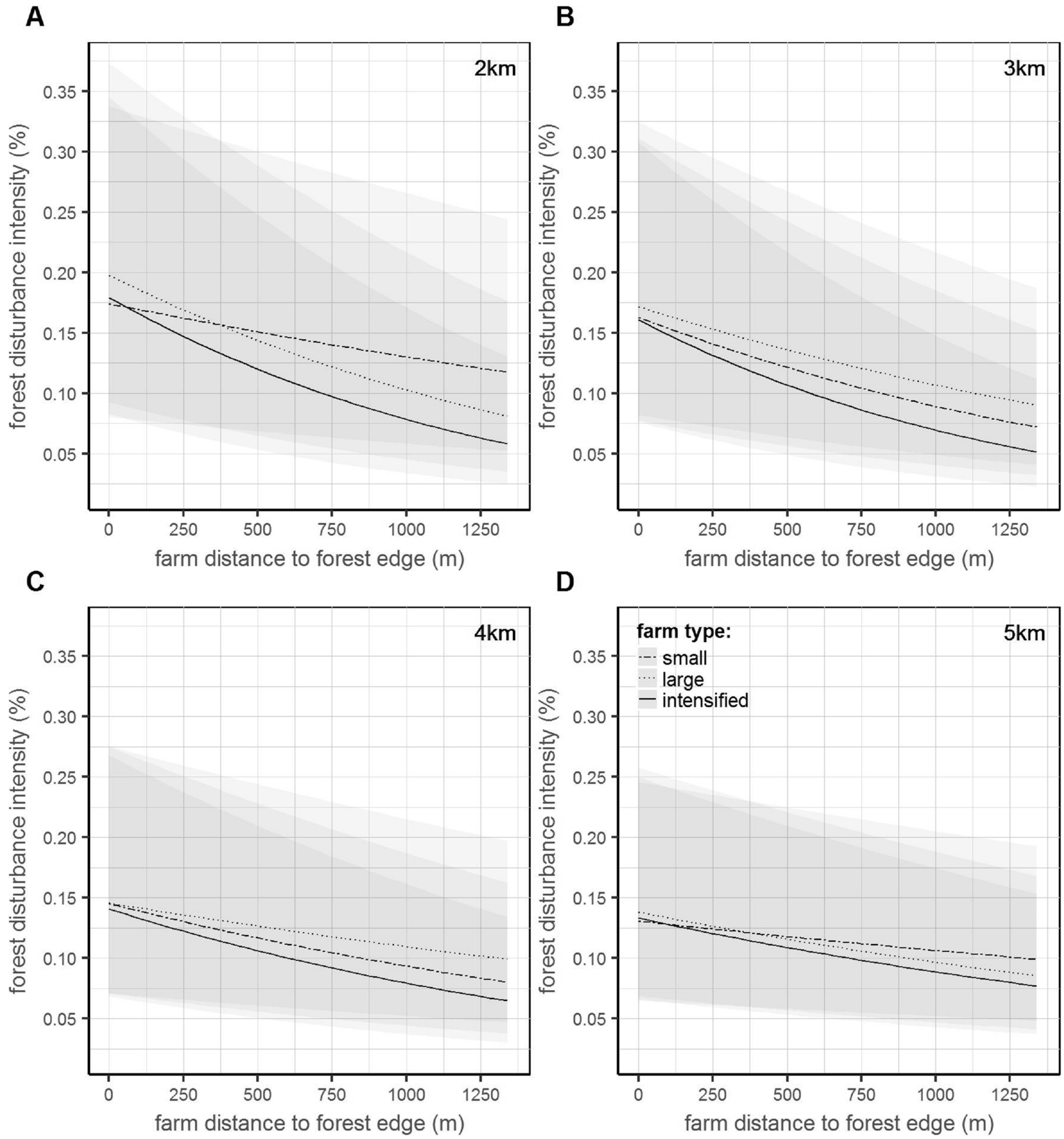

Fig. 8. Effects of farm types on forest disturbance intensity. Effects of farm types interacting with farm distance to forest edges were derived from GLMMs for different farm neighbourhood sizes (buffer radiuses): A) 2 km, B) 3 km, C) 4 km, and D) 5 km. Shaded areas indicate 95% confidence intervals for each farm type (small = small and resource-poor farms, large = large and inefficient farms, intensified = intensified farms).

Agroforestry could increase the C sequestration potential of smallholder farms in the tropics and offset GHG emissions resulting from agricultural production (Abbas et al., 2017; Mutuo et al., 2005; Ortiz-Gonzalo et al., 2017). Kenya's target to increase the tree cover from about 6% in 2000 to 10% by 2030 is the policy frame to improve the tree cover on farm land (Government of Kenya, 2015a). However, between 2000 and 2010, the tree cover on farm land in Kenya on average increased by about 1% (Zomer et al., 2016). Thus, incentives such as climate financing schemes are required to encourage smallholder farmers to plant trees on their farms which could be used as fodder trees or as fuelwood source. Moreover, more efficient cooking stoves would reduce the demand of fuelwood and indoor air pollution translating into health improvements (Malla et al., 2011). Improved forest management that actively involves local communities could enable the sustainable use of forest resources e.g. by establishing regulated wood pastures located at the forest edges or tree plantations used for a certified fuelwood production (Börner and Wunder, 2012; Chidumayo and Gumbo, 2013; Mutoko et al., 2015).

4.3. Limitation and benefits of the approach

This is the first study that combines a remote sensing approach with an analysis of farm production to investigate the connection between dairy production and forest disturbance in Africa. It is also one of the first studies that applied a forest disturbance detection approach utilizing the spatio-temporal information from Landsat time-series (Hamunyela et al., 2017). The approach was shown to outperform change detection based on temporal information only in terms of accuracy especially in environments where forest disturbances occur mainly at small-scale (Hamunyela et al., 2016b, 2017). The spatial accuracy achieved here (UA = 77.9%, PA = 78.6%) is comparable to Hamunyela et al. (2017) who studied small-scale disturbances in the Ethiopian highlands (UA = 76.8%, PA = 78.3%). By reducing false detections of small-scale disturbances, STEF could improve national forest monitoring capabilities especially in regions where these disturbance patterns are dominant such as in many SSA countries (DeVries et al., 2015b). The spatial resolution of Landsat sensors limits the

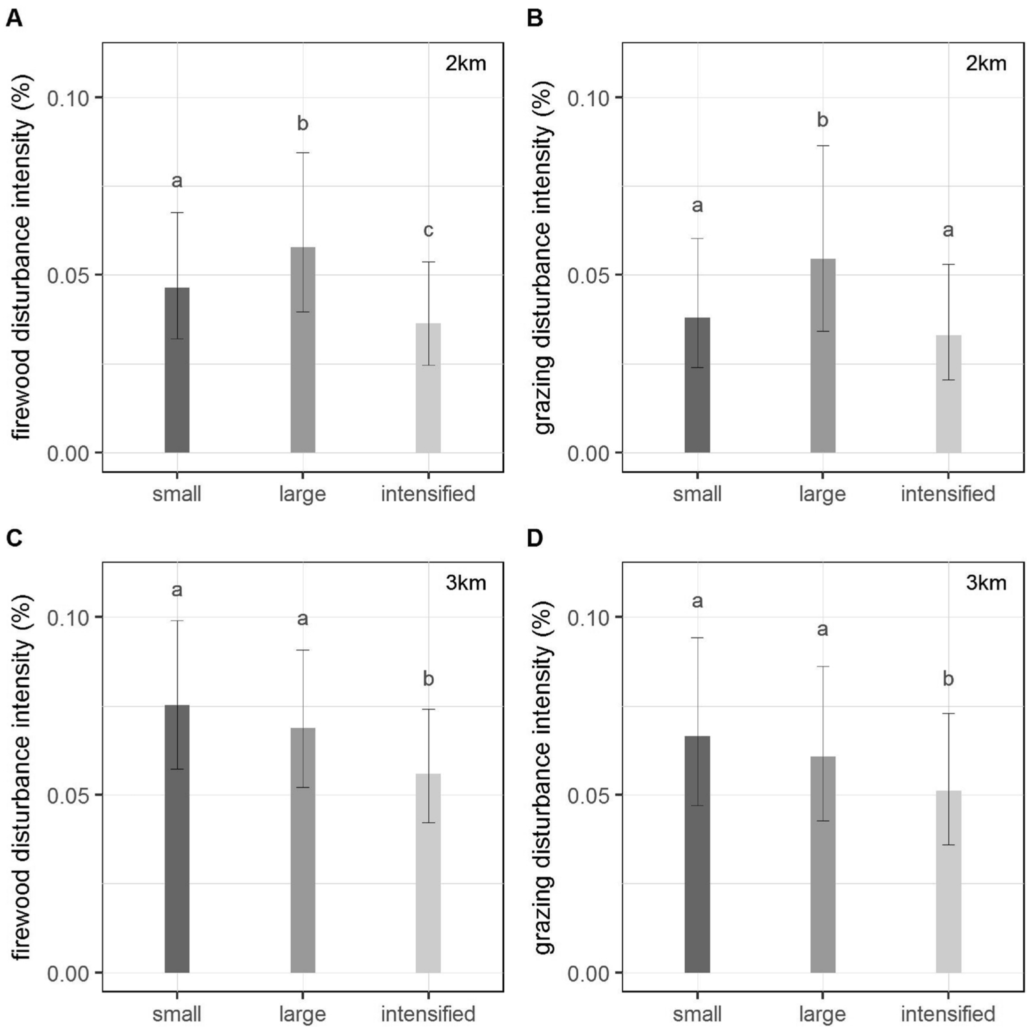

Fig. 9. Farm types effects on forest disturbance types. Effects of farm types are shown for firewood collection (A, C) and cattle grazing in the forest (B, D) modelled for the 2 and 3 km farm neighbourhood sizes. Different letters above bars indicate significant differences between farm types (small = small and resource-poor farms, large = large and inefficient farms, intensified = intensified farms). Vertical bars indicate 95% confidence intervals.

detection of small-scale disturbances. However, new satellite systems such as the Sentinal platform bears high potential for forest monitoring applications due to increased spatial and temporal resolution (Mitchell et al., 2017).

Training and validation data obtained from the ground are necessary to improve the detectability of forest disturbances even more so if they occur at small-scale and visual interpretation methods based on high resolution satellite imagery become unsuitable. Involving local experts into the monitoring can enhance the validity of detected changes and enable the characterization of their drivers e.g. through community-based forest monitoring integrating remote-sensing and smart phone technologies (DeVries et al., 2016).

Higher variability in the effects of farm type on forest disturbance reflected uncertainties that were introduced through the clustering of farm types by using farm survey data. Such uncertainties have to be reduced to improve the quantification of agricultural drivers and GHG emissions resulting from forest disturbance – e.g. through comprehensive measuring and reporting efforts.

5. Conclusion

This study revealed that the main anthropogenic drivers of forest disturbance across the Mau Forest are extraction of firewood and cattle grazing inside the forest. Both drivers are related to farm practices and characteristics of local smallholder farms. Intensification of smallholder dairy farming was associated to a lower risk of forest disturbance. Less forest disturbance translates eventually into reduced GHG emissions from forests. Thus, these results are informative for policy formulation and decision-making targeting mitigation options that increase farm efficiency and minimize negative effects on forests at the same time.

Incentive-based climate financing instruments are required for stakeholders such as farmers, cooperatives and the private sector involved in dairy production. These funds could be accessed once certain criteria are fulfilled such as the implementation of on-farm practices such as feed intensification that mitigate direct and indirect GHG emissions and increase farm productivity. A nationally appropriate mitigation action (NAMA) currently in development for the dairy sector in Kenya offers a promising policy framework to develop low emission dairy production, including capacity development and investment support targeting about 2 million smallholder households. However, assessments and criteria that minimize the risk for carbon leakage through indirect land use changes have to be integrated into policy development to achieve effective mitigation in the land use sector.

Based on the key results, policy recommendations are: i) reducing the emission source potential of agriculture through the increase of production efficiencies on dairy smallholder farms and through the improvement of their offsetting potential (i.e. the increase of tree cover on farmland) and ii) enhancing the C sink potential of forest systems by minimizing forest disturbances through sustainable intensification of farming and improved forest management.

Acknowledgements

This study was funded by the CGIAR program on Climate Change, Agriculture and Food Security (CCAFS) and the IFAD project "Greening livestock: Incentive-based interventions for reducing the climate impact of livestock production in East Africa". The authors thank the forestry department of the Food and Agriculture Organization of the United Nations (FAO) for technical support and curtesy to use the system for earth observations, data access, processing & analysis for land monitoring (SEPAL). Additionally, the research was supported by the Norwegian Agency for Development Cooperation (NORAD) and Germany's International Climate Initiative (IKI) through CIFOR's Global Comparative Study on REDD+, and the CGIAR Research Program on Forests, Trees and Agroforestry (CRP-FTA) with financial support from the CGIAR Fund.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.agee.2018.06.011.

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