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

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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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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