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Impact of land cover change on aboveground carbon stocks in Afromontane landscape in Kenya

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ABSTRACT

Land cover change takes place in sub-Saharan Africa as forests and shrublands are converted to agricultural lands in order to meet the needs of growing population. Changes in land cover also impact carbon sequestration in vegetation cover with an influence on climate on continental scale. The impact of land cover change on tree aboveground carbon stocks was studied in Taita Hills, Kenya. The land cover change between 1987 and 2011 for four points of time was assessed using SPOT satellite imagery, while the carbon density in various land cover types was assessed with field measurements, allometric biomass functions and airborne laser scanning data. Finally, the mean carbon densities of land cover types were combined with land cover maps resulting in carbon stock values for given land cover types for each point of time studied. Expansion of croplands has been taking place since 1987 and before on the cost of thickets and shrublands, especially on the foothills and lowlands. Due to the land cover changes, the carbon stock of trees was decreasing until 2003, after which there has been an increase. The findings of the research is supported by forest transition model, which emphasizes increase of awareness of forests' role in providing ecosystem services, such as habitats for pollinators, water harvesting and storage at the same time when economic reasons in making land-use choices between cropland and woodland, and governmental legislation supports trees on farms.

1. Introduction

Human modification of land has been recognized as a major driver of change influencing the Earth's ecosystems and climate (Rockstrom et al., 2009; Steffen et al., 2015). Land conversions in forested areas are of special concern in the context of climate change. In Africa, significant amount of carbon is also sequestered in woody vegetation outside forests (Baccini et al., 2012). Land use change, deforestation in particular, is the second biggest driver for increased carbon dioxide (CO_2) emissions after the burning of fossil fuels according to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) (Ciais et al., 2013). It has been estimated that land use and land cover change caused 12.5% of all anthropogenic CO_2 emissions from 1990 to 2010, but the estimate is uncertain (Houghton et al., 2012).

Tropical forest regions are currently undergoing rapid changes with direct consequences to aboveground carbon (AGC) stocks (Feldpausch et al., 2012; Saatchi et al., 2011). For recent decades, a remarkable increase in cultivated areas has been detected in sub-Saharan Africa. An increase of 57% in cultivated area was reported between 1975 and 2000, being 2.3% per year (Brink & Eva, 2009), and between 1990 and 2010 in the Horn of Africa 28%, with yearly increase of 1.4%. (Brink et al., 2014). In East Africa, between 2002 and 2008, wooded vegetation cover decreased by 5.1%, 15.8% and 19.4% from forests, woodland and shrubland, consecutively (Pfeifer et al., 2012). Using historical land cover maps, Willcock et al. (2016) estimated 74% forest loss between 1908 and 2000 in Eastern Arc Mountain watershed in Tanzania causing a carbon release of 0.9 Pg C.

Total net emissions of carbon from deforestation and land cover change in tropical regions has been estimated to be 1.0 Pg C per year (Baccini et al., 2012). However, in Asia and Africa the rate of deforestation is expected to decrease in the 21th century compared with deforestation rates in 1990 due to the depletion of forests (Denman et al., 2007). Total AGC stocks in tropical Africa are estimated as 59.8 Pg C, with 45.9% in shrublands and savannahs and 54.1% in forest land (Baccini et al., 2012). Lack of data on carbon densities and land use/land cover changes cause large uncertainties in these estimates (Baccini et al., 2012).

Number of initiatives aim to reduce anthropogenic carbon emissions from changes in land cover. In REDD + program, for example, the changes in forest AGC stocks need to be quantified with scientifically

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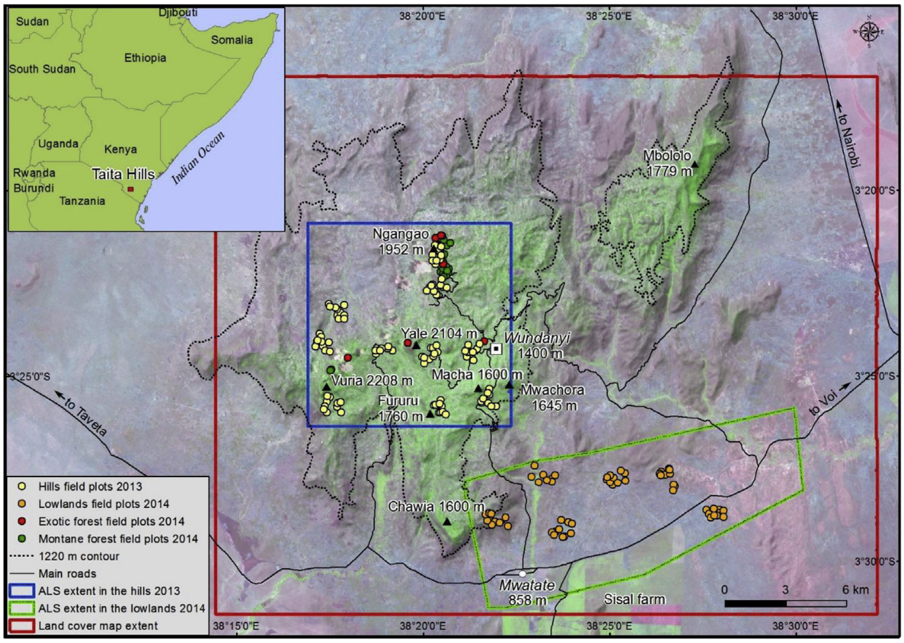

Fig. 1. Map of Taita Hills in southeastern Kenya representing the extent of study area (land cover map) and airborne laser scanning data, and positions of field plots. Background image is a false colour composite of Sentinel-2A MSI satellite image from 8 October 2016. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

rigorous monitoring systems (UN-REDD, 2011; GOFC-GOLD, 2014). In these initiatives, agroforestry is an important approach as a carbon sequestration strategy (Montagnini & Nair, 2004). AGC of trees in agricultural land play an important role in mitigating climate change, but agroforestry systems are often not accounted for in national and global assessments (Zomer et al., 2016).

Earth observation contributes to the monitoring of anthropogenic greenhouse gas emission. Remote sensing provides effective methods for observing changes in land cover over large areas with limited data availability or accessibility. Combined with tree measurements in the field, remote sensing data enable the mapping of AGC (Baccini et al., 2012; Willcock et al., 2012). The use of global default values for estimating carbon storage (Aalde et al., 2006) in data deficit areas may result in simplified estimations of local carbon stocks (Baccini et al., 2012). Efforts for more precise carbon estimations have been made on pan-tropical (Baccini et al., 2012; Saatchi et al., 2011), national (Tyukavina et al., 2013) and regional (Gonzalez, Kroll, & Vargas, 2014) scales.

Optical satellite imagery is often the primary data source for monitoring land changes in tropical forest areas (GOFC-GOLD, 2014). However, lidar (light detection and ranging), particularly airborne laser scanning (ALS), has been proven to provide more precise three-dimensional data on vegetation properties, including tree biomass and carbon stocks (Zolkos, Goetz, & Dubayah, 2013). Combining local scale carbon stock estimates from ALS with land cover maps produced from satellite imagery can yield regionally applicable carbon density values in a cost-efficient way (Willcock et al., 2012) allowing also change detection and projection of future scenarios of carbon storage (Gonzalez et al., 2014; Swetnam et al., 2011). It is also possible to extend the carbon storage monitoring backwards using historical land cover maps as in Willcock et al. (2016). A recent study by Baccini et al. (2017) based on MODIS satellite imagery from 2003 to 2014 presented that tropical forests are net carbon source rather than a sink as deforestation and forest degradation (reduction in carbon density) are faster than forest growth. The loss of carbon is the highest in Amazonia, while in Africa there are areas of gain and losses. This study presents a landscape-scale study of carbon stock changes between 1987 and 2011 in the Taita Hills in south-east Kenya.

The Taita Hills were once forested, but during last centuries most of the forests were cleared for agricultural purposes, while on surrounding lowlands, land is used for dryland agriculture, grazing, wildlife conservation and sisal farming to large extent (Pellikka et al., 2013). Despite of the clearance for agriculture, indigenous trees are left and exotic trees are planted for food production and timber on croplands. Trees on farms play an important role providing ecosystem services (Aerts et al., 2011). In the previous studies, land cover changes have been monitored with aerial photographs and satellite imagery (Clark & Pellikka, 2009; Pellikka, Lötjönen, Siljander, & Lens, 2009). According to the projected land cover changes, cropland could cover 60% of the area in 2030 (Maeda, Clark, Pellikka, & Siljander, 2010).

The aim of this study was to assess changes in tree AGC stocks in the Taita Hills and its foothills as a case study of land cover change impact on tree AGC stocks in East Africa. The Taita Hills are like a miniature of Kenya and East Africa having a range on land uses and cover types from grasslands in lowlands areas to indigenous moist evergreen montane forests on the hilltops. The more detailed objectives of this study were 1) to assess land cover change trends in the area from 1987 to 2011 using land cover maps derived from SPOT satellite images from four years, 2) to assess the amount of carbon sequestered across different land cover classes using field measurements and ALS, and 3) to assess the effect of land cover change on tree AGC stocks.

2. Study area and material

2.1. Study area

The study area covers 876 km^2 in Taita Taveta County in SE Kenya (3°25′ S, 38°20′ E). The lowest areas of the study area are at an average elevation of 700 m above sea level (m a.s.l.), while the Taita Hills rise on average up to 1500 m a.s.l. having the highest peaks between 1600 and 2200 m (Fig. 1). The area has two rainy seasons annually, the long rains occurring from March to May and short rains from November to December. The hottest and driest months are January and February, while the dry season from June to October is cooler. According to Maeda, Wiberg, and Pellikka (2011), the average temperature in Voi at 566 m a.s.l. is 27 °C in February and 23 °C in August. Annual rainfall in the Taita Hills is according to Erdogan, Pellikka, and Clark (2011) between 1100 and 1400 mm, while in the lowlands it is between 400 and 600 mm. Rainfall increases with altitude, but the higher elevations in the western parts of the hills receive less rainfall due to rain shadow effect. The reference evapotranspiration is the highest in the lowlands and the lowest in the hills. The maxima (> 7 mm/day) in the lowlands occurs in October at the end of the dry season, while the minima (4 mm/day) occurs in the hills in May during the rainy season (Maeda et al., 2011).

The Taita Hills are the northernmost part of the Precambrian Eastern-Arc mountain range known for its rich biodiversity (Platts et al., 2011). The hilltops are typically covered with indigenous moist evergreen montane forest with varying disturbance levels (Aerts et al., 2011) hosting endemic flora and fauna (Chege & Bytebier, 2005) of a specific scientific and conservation interest. The montane forest cover has decreased in the hills by 50% between 1955 and 2004, the largest patches being between 100 and 180 ha. Due to the establishment of exotic plantation forests, mostly of pines and eucalyptuses, the total forest area has remained about the same since 1950's (Pellikka et al., 2009). In the hills, outside of forests, the main land cover is cropland (Pellikka et al., 2013). The highest aboveground biomass have remained in the hills receiving more rainfall and on steep slopes, which have been too cumbersome for agricultural expansion (Adhikari et al., 2017).

The foothills and the lowlands are characterized by *Acacia-Commiphora* type dry thickets and shrublands, and croplands by dryland agriculture, cattle grazing, wildlife conservation and sisal farming. The area is divided into agro-ecological zones (AEZ) based on estimated yield and the length of growing period in different climate conditions occurring at different elevation ranges by Jaetzold and Schmidt (1983). In this study, we analyzed separately the land cover change and carbon stocks in the highland zone and upper midland AEZ above 1220 m a.s.l., and lower midland and lowland zones below it (Fig. 1). The croplands below and above 1220 m boundary are characterized by different crops, phenology and soil types, and also land cover change trend. Fig. 2 presents examples of cropland below and over 1220 m a.s.l. and montane forest of the Taita Hills.

2.2. Satellite imagery

Clark and Pellikka (2009) produced land cover classifications for 1987, 1992 and 2003 using 20 m spatial resolution SPOT HRV and SPOT HRVIR imagery applying an object-oriented approach, also referred to as a multi-scale segmentation and object relationship modelling (MSS/ORM) methodology. The same approach was used for processing and classification of the SPOT 4 HRVIR image from October 2011 to ensure comparability between the land cover maps from different dates. The HRVIR sensor contains spectral information on four spectral bands: green (0.50–0.59 μm (μm)), red (0.61–0.68 μm), near Infrared (NIR) (0.78–0.89 μm) and a middle infrared (MIR, 1.58–1.75 μm). The 2011 image was the most recent, relatively cloud-free SPOT 4 image available from the study area. Another SPOT 4 image from September 2008 was used for filling the clouds in the 2011 image. Additional reference data for the accuracy assessment were collected from aerial and satellite images available from Google Earth. Preprocessing of the SPOT imagery included geometric correction, DOS3 atmospheric correction (Clark, Suomalainen, & Pellikka, 2010) and topographic C-correction (Teillet, Guindon, & Goodenough, 1982). The SPOT data are characterized in Table 1.

2.3. Airborne laser scanning data

ALS data sets from two parts of the study area (Fig. 1) were utilized to make high-resolution AGB maps for computing mean AGB densities per land cover classes. The first scanning took place 4–5 February 2013 and covered 100 km^2 in the hills. The second scanning took place 17 January 2014 and covered 150 km^2 in the lowlands. The sensor was Optech ALTM 3100 in both campaigns. A maximum of four returns per pulse were recorded. Further survey and sensor specifications are given in Table 2.

The data vendor (Topscan GmbH) pre-processed both ALS data sets, including filtering of the ground returns using Terrascan software (Terrasolid Oy). The data were delivered as georeferenced point clouds in UTM/WGS84 coordinate system with ellipsoidal heights. Furthermore, buildings, powerlines and outliers (high points) were filtered using Terrascan, LAStools (Rapidlasso GmbH) and manual editing. Finally, the ground classified returns were used for generating digital elevation models (DEM) at 1 m cell size.

2.4. Field data

The field data was collected from two parts corresponding to the ALS data collection (Fig. 1). The field work in the hills was carried out in January 2013 measuring 100 circular field plots, while 61 plots were measured in the lowlands in January 2014. The sampling followed spatially stratified and clustered design of the Land Degradation

Fig. 2. A) Cropland over 1220 m characterized by tree cover, B) Cropland below 1220 m on alluvial plane, C) Indigenous moist evergreen montane forest, D) Cropland over 1220 m with *Grevillea robusta* trees.

Table 1
Characteristics of the SPOT data used.

Date	Path and row	Sensor	Sensor view angle	Solar azimuth angle	Solar elevation angle
1 July 1987	143–357	SPOT 1 HRV 1	right 10.35°	41.4°	53.7°
25 Mar 1992	142–357[a]	SPOT 2 HRV 1	right 13.8°	79.0°	63.5°
25 Mar 1992	143–357[a]	SPOT 2 HRV 2	right 9.3°	78.7°	64.0°
15 Oct 2003	143–357	SPOT 4 HRVIR 1	right 10.4°	104.3°	69.0°
6 Sep 2008	143–357	SPOT 4 HRVIR 1	left 22.3°	23.5°	65.0°
23 Oct 2011	143–357	SPOT 4 HRVIR 1	right 26.2°	105.7°	58.1°

[a] Adjacent scenes captured simultaneously.

Table 2
Characteristics of the airborne laser scanning data sets.

Parameter	ALS1 over the hills	ALS2 over the lowlands
Coverage	100 km^2	150 km^2
Date	4–5 February 2013	17 January 2014
Sensor	Optech ALTM 3100	Optech ALTM 3100
Mean range (m)	760	1240
Pulse rate (kHz)	100	70
Scan rate (Hz)	36	37
Scan angle (°)	± 16	± 18
Pulse density (pulses m^{-2})	9.6	2.9
Return density (returns m^{-2})	11.4	3.3
Beam divergence at 1/e^2 (mrad)	0.3	0.3
Footprint diameter (cm)	23	37

Surveillance Framework (LDSF) by Vågen, Winowiecki, Tamene Desta and, Tondoh (2013). In addition, 24 plots were subjectively placed in montane forests and 9 plots in exotic plantation forests in the hills as random sampling did not cover different forest types properly. From 0.1 ha circular sample plots all trees with diameter at 1.3 m height (D) > 10 cm were identified and measured. Tree height (H) was recorded for at least three trees in each plot (minimum, median and maximum D) with a laser rangefinder (Laser Technology TruPulse 360) or a hypsometer (Suunto). In order to use the ALS data with the field measurements, the plot centre positions were measured with a GNSS receiver (Trimble GeoXH) equipped with an external antenna (Trimble Zephyr Model 2). We applied differential correction in relation to a GNSS base station recording determined using Trimble RTX post-processing service (Trimble, 2014).

3. Methods

3.1. Biomass calculation

Site-specific or regional tree aboveground biomass (AGB) allometric equations are scarce for the study area including a large number of tree species. Therefore, we calculated AGB for majority of the trees (Table 3) using the most recent pan-tropical tree AGB equation (Chave et al., 2014) based on D, H and wood density (ρ, g cm^{-3}). For trees with only D measurement, H was predicted using two-parameter Curtis's height function (Curtis, 1967) and non-linear mixed effect modelling (Valbuena, Heiskanen, Aynekulu, Pitkänen, & Packalen, 2016). Wood densities (ρ) were retrieved from the online databases (ICRAF, 2015; Zanne et al., 2009). If species-wise value was not found, genus-wise mean was used, and if genus-wise mean could not be calculated, the mean values for species in the lowlands and hills were used. Chave et al. (2014) found that single equation holds across tropical vegetation types when H is included. This is important as study area includes an elevation gradient and range of vegetation types. However, Chave et al. (2014) tree harvest dataset included only old-growth or secondary woody vegetation, not plantations or agroforestry systems. Therefore, we used separate equations for *Acacia* spp., *Eucalyptus* spp. and *Pinus* spp., which are common in plantations and agroforestry systems (Table 3). In the case of *Pinus* spp., stem volume (V) estimates were converted to AGB using wood density and biomass expansion factor for tropical pines (Penman et al., 2003). Furthermore, palm equation from Brown (1997) was used for *Phoenix reclinata*, which is a native palm tree in the Taita Hills.

The mean AGB was 118.1 Mg ha^{-1} for the 123 plots with trees in the hills (range 0.3–681.7 Mg ha^{-1}) and 9.3 Mg ha^{-1} for the 53 plots having trees in the lowlands (range 0.0–51.4 Mg ha^{-1}) indicating that the trees were much bigger and numerous in the hills.

3.2. Land cover classification

The 1987, 1992 and 2003 SPOT scenes were classified into 12 classes (Clark & Pellikka, 2009): cropland, shrubland, thicket, grassland, woodland, exotic plantation forest, water, indigenous evergreen moist montane forest, bare rock, bare soil, built up areas, and burned areas. As burnt areas did not exist in 2011 scene, and built-up areas and bare soil classes were combined into one class, the classification of 2011 scene resulted in 10 classes.

In the first step, multi-resolution segmentation was implemented in eCognition software (Trimble) with different scale parameters similar to Clark and Pellikka (2009). Based on a visual inspection of the segmentation results, the scale producing the most meaningful landscape patterns was chosen. Then, the objects were classified using a supervised nearest-neighbor classification. The objects for training the classifier were selected based on the field observations and image interpretation. Further knowledge-based rule sets were generated for adjusting the classification based on different object features and hierarchical relationships. Also manual class-assignment was used for editing the map. For example, croplands above and below 1220 m a.s.l. were classified separately due to the different spectral properties of the dry lowland agricultural areas and the moist and mixed upland

Table 3
Summary of the allometric equations.

Tree species	Equation	Reference	Trees
Acacia spp.	$AGB = exp(-1.59 + 2.19 \times \ln(D) \times 1.05$	Paul et al., 2013	214
Eucalyptus spp.	$AGB = exp(-1.71 + 2.21 \times \ln(D) \times 1.29$	Paul et al., 2013	244
Pinus spp.	$V = 8.42 \times 10^{-4} \times D^2 - 7.354 \times 10^{-3} \times D + 2.506 \times 10^{-2}$	Henry et al., 2011	125
Phoenix reclinata	$AGB = 10 + 6.4 \times H$	Brown, 1997	148
Other species	$AGB = 0.0673 \times (\rho D^2 H)^{0.976}$	Chave et al., 2014	2988

AGB = aboveground biomass (kg); V = stem volume (m^2); D = diameter at 1.3 m height (cm); ρ = wood density (g cm^{-3}); H = tree height (m).

agricultural lands caused by vegetation phenology and different soil types. Finally, cloudy areas in 2011 image (4% of the whole area) were filled by a classification of the 2008 image.

The reference dataset for accuracy assessment included 305 points collected in the field (161 points visited in 2013 and 2014 according to the random cluster sample, and 6 additional points from montane forest areas), and points interpreted from aerial photographs and satellite imagery available from Google Earth (138 random points covering the whole area). The points had not been used for training the classification.

3.3. Biomass mapping and modelling

The approach used for AGB modelling and mapping was similar for the hills and lowlands. First, an exhaustive set of ALS features was calculated for the field plots. The features included all height- and cover-related features provided by the FUSION software (McGaughey, 2014). A threshold of three meters was used to separate canopy and ground returns. A relatively high value was used because of large minimum diameter used in the field inventory (Hansen, Gobakken, Bollandsås, Zahabu, & Næsset, 2015). Then, the models for AGB prediction were fitted using multiple linear regression. The best models of 1–3 predictors were searched by an exhaustive search 'regsubsets' function in package 'leaps' (Lumley, 2017) in R (R Core Team, 2015). The models were assessed by leave-one-out cross-validation and ranked by the root mean square error (RMSE). The best models that had only significant predictors ($p < 0.05$) and no multicollinearity (variance inflation factors < 4) were selected. The models with three and two variables, and models with two and one variables were compared by the analysis of variance to see if additional predictors improved model fit significantly. Square root transformation was applied to AGB as it was found to improve model fits. The back-transformation bias was corrected by multiplying the predictions by the square of the standard error (Gregoire, Lin, Boudreau, & Nelson, 2008). Finally, the ALS features were calculated for 32 m × 32 m grid cells, and the selected models were used for predicting AGB maps for the hills and lowlands.

The AGB models for the hills and lowlands are presented in Table 4, and corresponding maps in Fig. 3. In the hills, the best model was based on 25% percentile of the height values (*H.p25*) and canopy cover based on all returns (*CC.all = all returns > 3 m/all returns × 100*). In the lowland area, the best model included the standard deviation of return heights (*H.stdev*) and the 60% percentile of the height values (*H.p60*) as explanatory variables. The model fits were acceptable in both areas in terms of adjusted coefficient of determination (R^2). However, RMSE was greater in the hills because of the higher mean AGB but relative RMSE (%) indicates similar performance in the both areas. According to the AGB maps, the highest values in the hills were found within the montane forests as well as in exotic forests, especially in the Yale hill. In the lowland area, the largest AGB was found in the hillsides and along moist river banks and the smallest AGB in dry croplands.

3.4. Calculation of carbon densities for each land cover type

The AGC for different land cover types were calculated as zonal averages from the AGB maps (Fig. 3) for each land cover class in the 2011 land cover map. A carbon fraction of 0.47 was used for converting AGB to AGC (IPCC, 2006). AGC for the montane forests, exotic forests and cropland above 1220 m a.s.l. were calculated based on the AGB map in the hills, and for shrubland and cropland below 1220 m a.s.l, mean AGC was calculated based on the AGB map in the lowlands (Fig. 3). For woodlands and thicket, mean AGC was calculated as an average from both AGB map extents. The AGC densities of grassland, bare soil and built up areas, bare rock, and water were assumed zero.

4. Results

The highest mean AGC density of trees was estimated for indigenous montane forest class, and lowest carbon densities were estimated for shrubland and cropland classes located below 1220 m a.s.l. (Table 5). Mean values were 89.5 Mg C ha^{-1} for montane forest, 29.4 Mg C ha^{-1} for exotic forest, 16.8 Mg C ha^{-1} for woodland, 6.0 Mg C ha^{-1} for thicket, 2.6 Mg C ha^{-1} for shrubland, 9.1 Mg C ha^{-1} for cropland above 1220 m a.s.l. and 2.3 Mg C ha^{-1} for cropland below 1220 m a.s.l.

4.1. Land cover change

Changes in the proportions of the most extensive land cover classes can be observed from the land cover maps from 1987 to 2011 (Fig. 4). Land areas and proportions of total mapped area are reported in Table 6. The proportion of cropland has increased from 30.1% to 42.8% between 1987 and 2011. At the same time, the area of thickets decreased from 29.3% to 23.2%, and shrublands from 29.4% to 18.9%. Area of woodland, exotic forest and montane forest have increased slightly since 1987 until 2011. The overall classification accuracies for 2003 and 2011 were 89% and 71.1%, respectively, while it was not possible to assess the accuracy of 1987 and 1992 classifications.

It can be seen in Fig. 4 that area of croplands increased in the foothills and lowlands from 1987 to 2011, while changes in area in the hills are small. The area of croplands decreased from 10028 ha to 9743 ha in the hills, while the area in the foothills and lowlands below 1220 m a.s.l. increased from 16361 ha to 27730 ha (Table 6).

In terms of conversion between specific land cover classes, the greatest change was observed between shrubland and cropland as 6414 ha of shrubland was converted into cropland between 2003 and 2011. At the same period, 3423 ha of cropland was converted to shrubland and 2567 ha to woodland, while 1103 ha woodland was converted to cropland. Based on the comparison of 2003 and 2011 land cover, the area of croplands expanded mostly in the lowland area in the previous shrubland and thicket areas, while conversion of cropland to shrubland and woodlands took place in the hills (Fig. 4). Above 1220 m a.s.l. croplands covered 40.4% in 2011 of the all the land cover classes with decreasing area from 2003.

4.2. Impact on carbon stock

Total AGC stock decreased between 1987, 1992 and 2003, but was increased in 2011 (Fig. 5, Table 7). Thickets stored the largest amount of carbon throughout the period but the storage decreased steadily due to the expansion of croplands to thickets. The second largest stock is either in cropland above 1220 m a.s.l. or in woodland depending on the year.

The carbon storage in the shrubland has decreased due to expansion of croplands to the shrublands in the lowlands. The carbon sequestered in croplands below 1220 m a.s.l. increased from 7% to 11%, along with the expansion of croplands. In the hills above 1220 m, carbon storage in croplands is stable due to no expansion of croplands there. Combining

Table 4
Selected models for mapping tree aboveground biomass (AGB).

Area	Model	Adj. R^2	RMSE (Mg ha^{-1})	RMSE (%)
Hills	$\sqrt{AGB} = -1.69 + 0.528 \times H.\,p25 + 0.116 \times CC.\,all$	0.93	56.9	48.5
Lowland	$\sqrt{AGB} = -0.192 + 1.13 \times H.\,stdev + 0.166 \times H.\,p60$	0.89	4.26	44.7

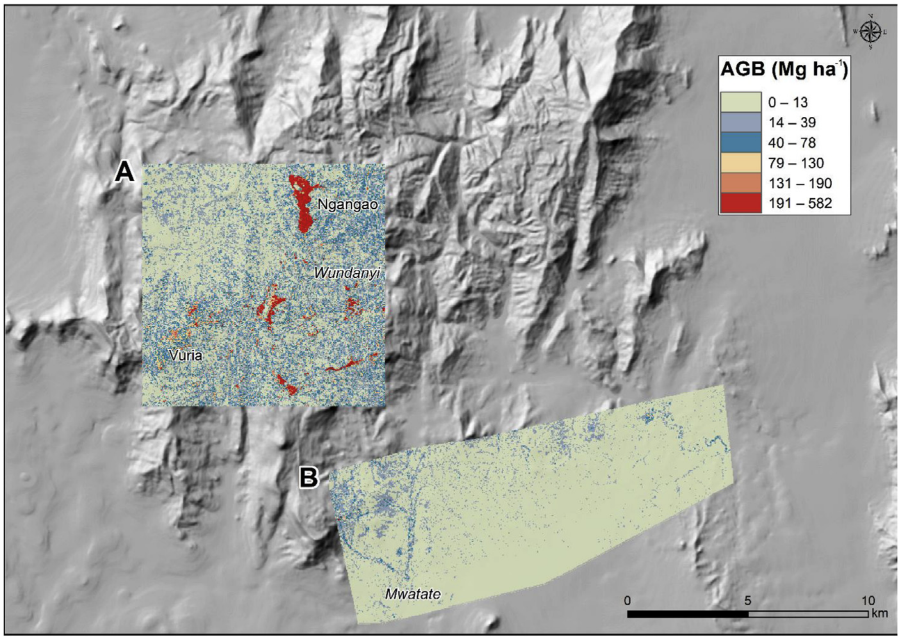

Fig. 3. Tree aboveground biomass (AGB) in the in the hills (A) and in the lowlands (B) mapped at 32 m × 32 m resolution.

Table 5
Mean, maximum and standard deviation of tree aboveground carbon (AGC) densities for different land cover types in 2011.

Land cover class	Area (ha)	AGC mean (Mg C ha^{-1})	AGC max (Mg C ha^{-1})	AGC sd (Mg C ha^{-1})
Cropland < 1220 m	27730	2.3	96	3.1
Cropland > 1220 m	9743	9.1	189	11.5
Shrubland	16577	2.6	71	3.5
Thicket	20364	6.0	169	7.4
Woodland	6392	16.8	216	17.5
Exotic forest	2656	29.4	273	30.7
Montane forest	813	89.5	254	56.1
Grassland	2234	0.0	0.0	0.0
Bare soil & built up areas	991	0.0	0.0	0.0
Rock	114	0.0	0.0	0.0
Water	17	0.0	0.0	0.0

the carbon stocks of the croplands below and above 1220 m a.s.l. shows that the cropland has the highest carbon stock of all the classes (153231 Mg). Croplands are the most significant carbon stock with its largest land cover share (43%) after thickets. Per hectare, the carbon stock is 4 Mg for croplands, while for thicket it is 6 Mg.

5. Discussion

5.1. Carbon stocks

The highest tree AGC densities were estimated for montane forests (Fig. 2C). However, as the area of this land cover class is relatively small, other land cover classes constituted most of the total AGC stock. Thicket, woodland and cropland above 1220 m a.s.l. were found to store most of the carbon, which can be generalized so that areas with open tree cover constituted most of the total AGC. Thus, the results show that carbon sequestration in trees with $D > 10$ cm is significant also outside forests. These findings are in line with the continent-level results from Baccini et al. (2012), which show that AGC stocks in woody vegetation outside the forests constitute almost half of the carbon stocks in Africa. Zomer et al. (2016) found out that 43% of agricultural land had globally at least 10% tree cover. The results differ from Baccini et al. (2017) presenting a loss of forest in tropical Africa and a net carbon source. However, in detailed inspection of the results of Baccini et al., one can note that the Taita Hills is shown as carbon increase area between 2003 and 2014, while nearby Mt. Kilimanjaro is shown as carbon decrease area. Although the scale of the study using MODIS data by Baccini et al. differs from our scale, it present the same trend which we observed for time period 2003 and 2011.

In this study, croplands were divided into two elevation zones for AGC density estimation. Higher carbon densities were estimated for the croplands above 1220 m (Fig. 2A and D), which indicates greater tree volume in the croplands in the hills, where agroforestry is practiced, which emphasizes the role of trees on farms in ecosystem functioning (Thijs et al., 2015). In addition to carbon sequestration, the forest can trap water from the air as fog deposit (Muchura, Min, Mworia, & Gichuki, 2014), store water in the tree biomass, epiphytes, litter and soil (Bruijnzeel, Scatena, & Hamilton, 2010), provide shade for the crops, and litter for fertilizing soils (Rhoades, 1996).

The highest mean carbon density for montane forest was estimated as 89.0 Mg C ha^{-1} and maximum density value for a 32 m × 32 m grid cell was 248 Mg C ha^{-1}. The mean density is less than global default values represented by Aalde et al. (2006), who used 141 Mg C ha^{-1} for tropical rain forests. According to Baccini et al. (2012), smaller carbon densities were reported for tropical Africa (82 Mg C ha^{-1}) compared with other tropical areas (116 Mg C ha^{-1} for America and 119 Mg C ha^{-1} for Asia), which supports the lower carbon densities for montane forests in the Taita Hills compared to the global default value. Furthermore, the indigenous montane forest fragments of the Taita Hills are badly degraded (Aerts et al., 2011) by removal of the largest trees, which decreases the carbon stock. Kenya Forest Research Institute evidenced this as the degraded forest stands were found to sequester less carbon (by 9–70%) compared to undisturbed ones (Wekesa et al., 2016).

The previous studies on carbon stocks in the Taita Hills had some methodological differences compared to this study making comparisons of the carbon stocks not straightforward. Omoro, Starr, and Pellikka (2013) reported plot-level mean AGC density for montane forests as 360 Mg C ha^{-1} and for exotic forests (cypress, eucalyptus and pine) 158, 221 and 195, respectively. Itkonen (2012) estimated that carbon density for montane forests was 231 ± 95 Mg C ha^{-1} and for exotic forests 133 ± 95 Mg C ha^{-1}. Both of the previous studies included measurements from Mbololo, the least disturbed forest fragment (Aerts

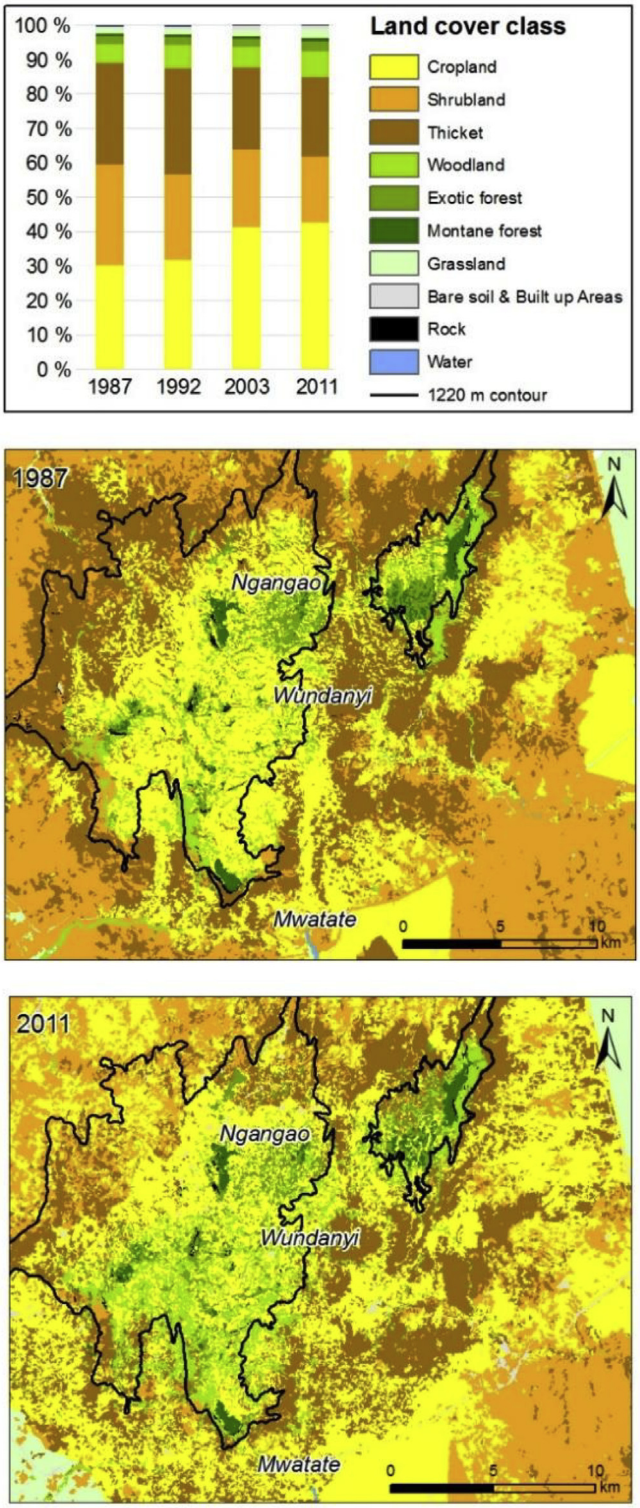

Fig. 4. Land cover classifications and proportions of different land cover classes for 1987 and 2011.

et al., 2011), and used allometric models, which did not consider tree height. If height is excluded from the AGC calculations, the estimates can be significantly smaller (Valbuena et al., 2016). For example, Marshall et al. (2012) showed that mean AGC was 174.6 Mg C ha^{-1} when height was included and 229.6 Mg C ha^{-1} when it was excluded along a forested elevation gradient in Tanzania. Furthermore, the previous studies assumed carbon fraction to be 50%, which makes a small difference.

The results compared with a REDD + project undertaken in the Kasigau near the Taita Hills are more similar (Wildlife Works, 2008). Carbon densities estimated using destructive methods were reported as 55.7 Mg C ha^{-1} for montane forest, 4.7 Mg C ha^{-1} for agricultural encroachments, 35.0 Mg C ha^{-1} for dryland forest and 2.8 Mg C ha^{-1} for savannah grassland. Glenday (2006; 2008a,b) has assessed carbon stocks in other parts of Kenya. The aboveground carbon density of lowland rain forest in Kakamega was 200 Mg C ha^{-1} (Glenday, 2006), in Arabuko Sokoke coastal forest between 36 and 48 Mg C ha^{-1} depending on the tree species (Glenday, 2008b), and 140 Mg C ha^{-1} for Tana levee riverine forests (Glenday, 2008a). However, the indigenous montane forests of Taita Hills being degraded and close to coastal forests, the carbon density values may be comparable with the Arabuko Sokoke forests, at least with the tall *Brachystegia* forest.

The land cover change between 1987, 1992, 2003 and 2011 had an impact on the total carbon stock in the study area. Between 1987, 1992 and 2003, a decreasing trend in total carbon stocks was detected, but there was an increase in the total amount of carbon sequestered in 2011. An increasing trend in croplands and a decreasing trend in thickets are the most notable changes. Results for croplands below 1220 m a.s.l. follow the observed (Clark & Pellikka, 2009) and predicted (Maeda et al., 2010) trends in the study area, a clear reduction in the area of thickets translated into reduced carbon storage in the area. Clearing thickets for agricultural use decreases the amount of woody vegetation in the landscape resulting in lower total carbon stocks. On a continental scale, Baccini et al. (2012) observed that clearing of trees in areas outside forests may have a significant impact on changes in carbon stocks.

5.2. Methodological considerations

The landscape of the Taita Hills is highly heterogeneous (Fig. 2A) and land cover classification is challenging using satellite imagery and even with very high resolution hyperspectral data classification of agricultural crops is a challenge (Piiroinen et al., 2015, 2017). There was confusion especially between the cropland and shrubland classes, shrubland and thicket classes, as well as between thicket and woodland, which are likely caused by spectral overlap between the classes consisting of vegetation and open soil. Confusion between croplands and shrublands is inevitable, as the croplands are characterized with trees and bushes. However, the accuracy is considered satisfactory as the most confusing misclassifications were between shrubland, woodland and thicket, while croplands were classified with high accuracy (81.5% user's accuracy). The object-based method was useful in detecting meaningful image objects in the landscape scale, but on the other hand, the object-based classification produces also a more generalized output (Blaschke et al., 2014), which may affect the final carbon density values.

In this study, only tree with D > 10 cm were considered, but smaller trees and shrubs might constitute a considerable fraction of the woody biomass, especially in the lowlands. Thus part of the AGC may have been evidently excluded in thicket and shrubland land cover classes. Last, carbon densities were averaged over land cover classes from the AGB maps instead of direct plot measurements to enable a representative sample for each land cover class. Thus, an average carbon density value is given to a land cover class (area with heterogeneous properties), and the comparison of these results with measurements from homogenous forest plots is not straightforward.

In a multitemporal study expanding over several decades, one has to use various data types collected using various sensors, which may cause uncertainties to the results. We used data from SPOT HRV 1, HRV 2, and HRVIR 1, but the wavebands and spatial resolution used for the classification were the same for each individual classification. We do not see any significant impact on using various sensor types to the confidence on the results as each image was analyzed separately.

Table 6
Land cover in the Taita Hills, SE-Kenya in 1987, 1992, 2003 and 2011.

Land cover class	1987		1992		2003		2011	
	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
Cropland < 1220 m	16361	62	17955	67	24864	69	27730	74
Cropland > 1220 m	10028	38	8843	33	11171	31	9743	26
Total cropland	26389	30.1	26798	30.6	36035	41.1	37473	42.8
Shrubland	25726	29.4	21136	24.1	19567	22.3	16577	18.9
Thicket	25711	29.3	25893	29.5	20814	23.8	20364	23.2
Woodland	4827	5.5	5758	6.6	5043	5.8	6392	7.3
Exotic forest	2057	2.3	1830	2.1	2039	2.3	2656	3.0
Montane forest	779	0.9	738	0.8	697	0.8	813	0.9
Grassland	1314	1.5	1304	1.5	1607	1.8	2234	2.5
Bare soil and built-up areas	448	0.5	761	0.9	1016	1.2	991	1.1
Rock	235	0.3	225	0.3	189	0.2	114	0.1
Water	84	0.1	50	0.1	19	0.0	17	0.0
Burned area	59	0.1	262	0.3	603	0.7	0	0.0
Cloud	0	0.0	2874	3.3	0	0.0	0	0.0
Total	87629	100.0	87629	100.0	87629	100.0	87629	100.0

Another concern is impact of time of year to the interpretation of the land cover classes. Varying solar azimuth and zenith angles causes variations in the illumination (Pellikka, 1996) especially in rough topography as in the Taita Hills, but topographic effects were removed with C-correction (Adhikari, Heiskanen, Maeda, & Pellikka, 2016; Teillet et al., 1982). Another impact caused by time of the year is phenological status of the both natural and cultivated vegetation. The lowland forests consists typically deciduous trees shedding the leaves during dry season, while native and exotic forests in the hills are typically evergreen throughout the year. Agricultural fields are verdant during the rainy season, while during the dry seasons and especially at the end of them fields are mostly barren. The 1992 images were taken during rainy season, 1987 image was taken right after a rainy season, while 2003, 2008, and 2011 images were taken at the end of the dry season. As a consequence, one could make serious false interpretations on land cover change if not taking the phenological differences into account. We performed an independent classification for each imagery knowing the phenology of the study area. In order to retrieve the carbon stocks, many steps including field measurements, allometric models, ALS-based maps and classifications were made. Further studies are required to understand the total effect of uncertainties involved in each step.

5.3. Land change trend

The need for more efficient methods of quantifying aboveground carbon stocks is often stated (Baccini et al., 2012; Chave et al., 2014; Feldpausch et al., 2012). In this study we used our land cover change results together with field measurements and ALS data for estimating the impacts of land cover change on carbon stocks. ALS has proofed to be an accurate and efficient method in carbon inventories (Zolkos et al., 2013), and in forestry studies in general, but more case studies from the tropics are needed (Maltamo et al., 2014). Cost-effectiveness needs also to be taken into account. Organizing ALS campaigns is expensive, especially in Africa, so it may not be viable to use ALS for carbon monitoring only. Thus, a combination of satellite image classification is a relevant approach, and a necessity in assessing historical carbon stocks. Applying global default values (Aalde et al., 2006) especially in a fragmented landscapes of Africa might overestimate the size of carbon stocks.

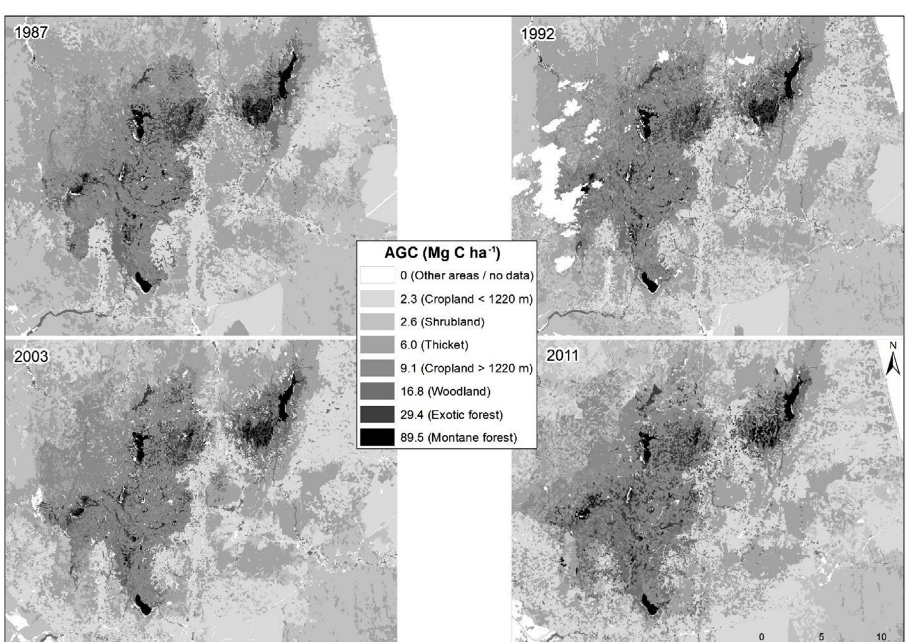

Fig. 5. Aboveground tree carbon (AGC) density (Mg C ha^{-1}) in 1987, 1992, 2003 and 2011.

Table 7
Aboveground tree carbon (AGC) stock in Megagrams (Mg). AGC for grassland, bare rock, bare soil and built-up areas were set to zero and are not presented in the table.

Land cover class	1987		1992		2003		2011	
	AGC	% of total	AGC	% of total	AGC	% of total	AGC	% of total
Cropland < 1220 m	37631	7%	41295	7%	57187	11%	63779	11%
Cropland > 1220 m	91253	16%	80474	15%	101655	19%	88660	15%
Shrubland	66888	12%	54953	10%	50874	9%	43100	7%
Thicket	154267	27%	155355	28%	124881	23%	122185	21%
Woodland	81087	14%	96738	18%	84726	16%	107382	19%
Exotic forest	60461	11%	53811	10%	59947	11%	78075	14%
Montane forest	69774	12%	66060	12%	62364	11%	72746	13%
Total	563348		550678		543637		577938	

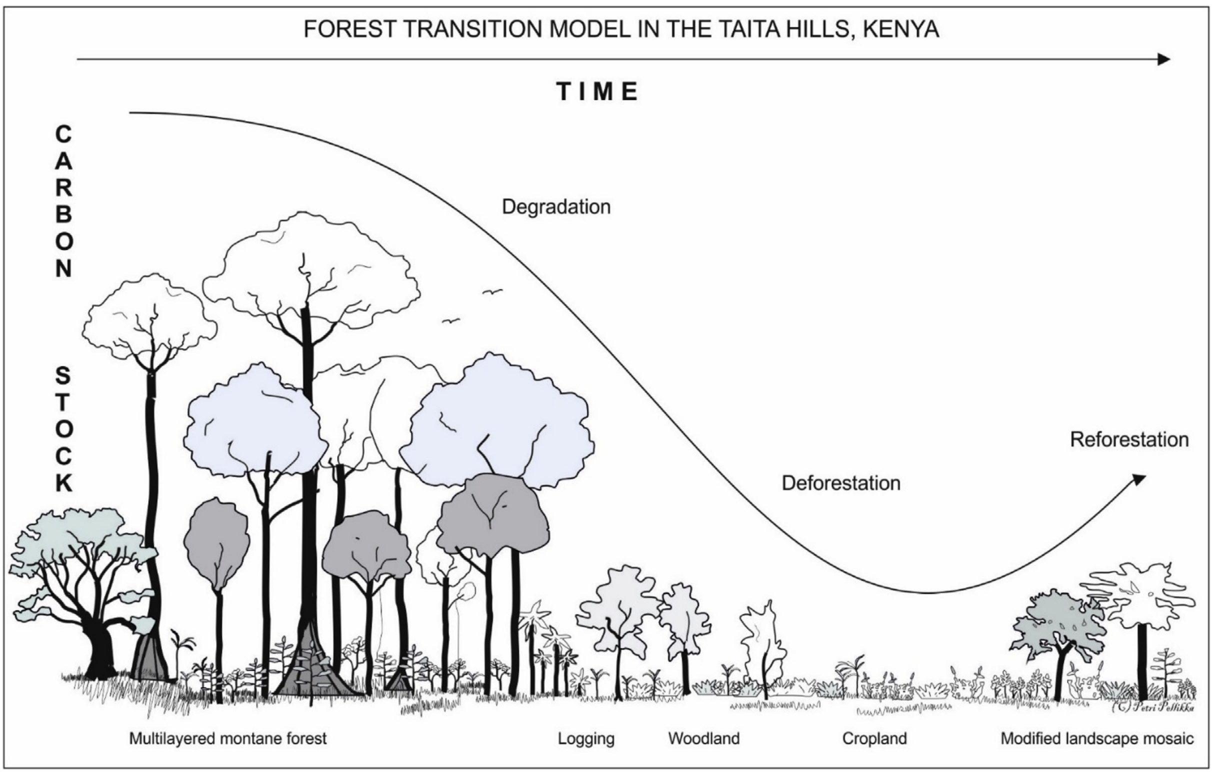

Fig. 6. Forest transition model modified from Reed et al. (2017) for the Taita Hills.

Detailed study by Pellikka et al. (2009) documented a rapid loss in the extent of indigenous montane forests since 1955. The process of deforestation has more recently slowed down and the total area of montane forests in the hills has not further decreased between 2003 and 2011 (Pellikka et al., 2013). The slowing trend of expansion of croplands seems to favor carbon sequestration. Similar slowing trends in expansion of agriculture was reported also by Olang and Fürst (2011) in Nyando river basin in Kenya, but on the other hand Were, Dick, and Singh (2013) reported an ongoing expansion of croplands in the Mau forest, Kenya up to 2011. This alarming decrease of forests in the Mau forest, can be seen also in Baccini et al. (2017). Increase of carbon stocks in 2011 over 1220 m a.s.l. is presumably due to growing number of trees on farms compared to late 1900s and early 2000s, which has been identified also visually by the research team after working in the Taita Hills in 1989 (Pellikka, 1990) and again since 2004 (e.g. Pellikka et al., 2004).

Analyzing drivers of land cover and land use change is often simplified in land change studies (Lambin et al., 2001). In this study, land cover change was seen as a driving force for changes in carbon stocks. In Maeda et al. (2010), the most significant drivers in the Taita Hills were modelled to be distance to markets, roads and drivers causing the expansion of agricultural areas. Muriuki et al. (2011) found in studies close by Chyulu hills in Kenya an increase in built-up areas and squatters causing land cover change and fragmentation of vegetation. Evidently, the main reason for expansion of croplands is a need for daily bread and food security, at least in the lowlands, but in the hills the drivers may be different.

The environmental and social drivers as well as governmental decision systems at different scales need to be recognized in order to understand ongoing changes in land cover and carbon stocks (Were et al., 2013). The increase of carbon stock in the Taita Hills after 2003 can be explained by environmental legislation, climate change, and effects of conservation education (Himberg, Omoro, Pellikka, & Luukkanen, 2009). A lot of environmental conservation work by government, non-governmental organizations, and academic research organizations has been carried out, and the findings have been disseminated in the Taita Hills. The increase of carbon stock especially in the croplands after 2003 and also the change from croplands to shrublands and woodlands, may be caused by the fact that farmers are changing from agriculture to forestry since there has been less rainfall for cultivation during recent years (Rikkinen, Laine, & Pellikka, 2015), or less labor available for agriculture (Angelsen & Rudel, 2013). The reasons may be purely economic; farmer expects more income from trees than from crops, or farmer is working elsewhere and converts the fields to self-maintained forest (Rudel et al., 2005). Based on detailed interviews, Hohenthal, Owidi, Minoia, and Pellikka (2015) found that governmental policy has played a role in the Taita Hills. A Forest Act from 2005 and Agriculture (Farm Forestry) Rules 2009 requires farm owners to maintain at least 10% of forest cover on their holdings. Also water and soil conservation measures are intensifying tree cover as riverbanks are protected. Shifting cultivation (Heinimann et al., 2016) is not common in the Taita Hills, although time to time some fields are left to fallow for few years, but reason behind is partly the cropland abandonment for cultivation of trees.

These findings are supported by Reed et al. (2017), who represented reforestation taking place after clearance of the forests for croplands in their forest transition model (Fig. 6). The forest transition framework was first suggested by Mather (1992) suggesting that over time a country or region moves from high forest cover and low deforestation through accelerated deforestation and shrinking forest cover to stabilization and reversal of deforestation process. Several authors have since modified the framework (e.g. Angelsen & Rudel, 2013). Globally, Zomer et al. (2016), presented a 2% increase of carbon stocks on agricultural lands. It may be concluded that research on land cover changes and carbon sequestration should be linked to forest dynamics on various timescales via historical comparisons and interdisciplinary theoretical methods (Perz, 2007). Another factor in carbon increase is conservation, which was found to increase carbon stocks in East African in protected areas since 1951 (Willcock et al., 2016). Wekesa et al. (2016) reported improvement in forest condition compared with previous studies, for example in Chawia forest, which has been a model of community based forest conservation.

As land use change has been detected as one of the major sources for anthropogenic carbon emissions, studies quantifying these changes should also have a link to reasons behind such change (Meyer & Turner, 1994). Assessing carbon stock change with spatially explicit data allows for further identification of possible drivers in time and space.

6. Conclusions

Application of airborne laser scanner data provide a powerful method for assessing carbon stocks together with field measurements, but adapting the land cover specific carbon values for land cover classes mapped with satellite imagery is challenging. The average carbon density was the highest for indigenous montane forests compared to exotic forests and woodlands suggesting saving montane forests for carbon sequestration. Croplands above 1220 m a.s.l. had much higher carbon density compared to croplands in the lowlands showing important role of agroforestry practiced in the hills for carbon sequestration. The highest carbon stocks were in croplands due to largest land cover area of croplands in the study area.

Croplands have been expanding rapidly in the Taita Hills and its surrounding lowlands, but since 2003 a slowing trend in the process is recognized. Moreover, changes identified between 2003 and 2011 show that while shrublands are still cleared for croplands in the lowlands, in the hills croplands are recently converted to shrublands and woodlands. Land cover change has direct impact on carbon stocks as clearance of forest and shrublands leads to decreased carbon sequestration. A slight increase in carbon stocks from 2003 to 2011 is recognized, which follow the model of forest transition of native forests through logging and clearance for croplands to reforestation. The underlying reasons for the increase of shrublands and woodlands in the hills and increased carbon stocks in croplands are related to forests' role in conservation and increasing biodiversity, providing ecosystem services such as water harvesting and storage, economic reasons in making land-use choices between cropland and woodland, and governmental legislation supporting trees on farms.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.apgeog.2018.03.017.

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