

# Three decades of forest cover change in Uganda's Northern Albertine Rift Landscape

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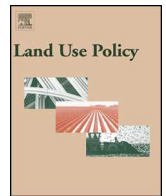
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# Three decades of forest cover change in Uganda's Northern Albertine Rift Landscape



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## ABSTRACT

Deforestation within and outside protected areas is widespread in Western Uganda, but quantification of such forest changes is rare. In this study, spatio-temporal forest cover patterns in the Northern Albertine Rift Landscape were reconstructed for the period 1985–2014, over a range extending from Bugoma forest in the South of the region to as far as Murchison Falls National Park in the North, an area approximately 225 km North–South by 63 km East–West. We examine both the spatial and temporal heterogeneity of the land cover changes. Seven 30 × 30 m resolution, ortho-rectified, cloud-free Landsat images obtained from the USGS archive were analysed at the landscape- and three smaller scales. Forest classification using Landsat imagery appears robust; similar amounts are obtained from a UK-DMCii image (22 m resolution) taken a day before the Landsat scene in Dec, 2010. Our results show that larger-scale aggregate measures of total change can obscure more local patterns, in which protected areas and the national park maintain or grow forest cover, whilst the forest corridor areas that are not protected suffer drastic losses. Time-series show that the loss continues nearly linearly into the present around Bugoma, but seems to level off around Budongo Forest after 2010, apparently because almost all forested corridor areas have been cleared. At the landscape scale, between 1985 and 2014, the data suggest approximately 0.4% of initial cover was lost per year. However, this was mostly a result of the large protected forest blocks remaining relatively stable; deforestation was mostly situated in the corridor and riverine areas. Local-scale losses were most prominent in unprotected forests around Budongo and Bugoma, with annual losses at a much higher average rate about of 3.3% per year in each case. The annual rates of loss are higher than Uganda's average (1–3%). Forest cover in the protected zones expanded only marginally, with annual average increases of order 0.03% and 0.5% in Budongo and Bugoma reserves, respectively. Our results suggest that forest protection in the gazetted areas is successful, and the protection policy is working, but these forests are being isolated by large losses immediately outside the protected zones, in the forest corridors. This may have severe social and ecological consequences—both within and outside protected forests.

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## 1. Introduction

Deforestation threatens biodiversity, climate and livelihoods (Bala et al., 2007). Deforestation rates in the African Tropics are some of the highest in the world (Achard et al., 2002), and accounted for over 23% of global forest loss between 1990 and 2009 (Houghton, 2012). Deforestation is reported to have increased in several parts of Uganda in the last half-century. Examples include conversion for coffee production around Mt. Elgon in Eastern Uganda (Sassen et al., 2013). Forest loss on protected and pri-

vate land around Kibale National Park in South-western Uganda is attributed to charcoal production (with preference for old-growth hardwood tropical species), high fuelwood demand by the tea industry, settlement and agricultural expansion (Naughton-Treves et al., 2007). Forest cover has been lost around Bwindi impenetrable forest in South-western Uganda, as a result of agricultural expansion and ambiguous forest boundaries (Twongyirwe et al., 2011). Recently, Ryan et al. (2014) found that population changes are correlated with forest loss along the whole Albertine Rift, but they sampled the region sparsely, excluding protected areas, and only looked at two time points.

There is however evidence of successful forest protection in some National Parks and Forest Reserves by Uganda's designated forest authorities (e.g., Bwindi impenetrable forest, see Hamilton et al., 2000; Budongo, Wambabya and Bugoma forests—this paper).

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There are some regions of forest stability and recovery/gain in various parts of the country between 2000 and 2010, according to recent global forest cover change mapping (Hansen et al., 2013).

The Northern Albertine Rift Landscape in Western Uganda is an iconic landscape endowed with the largest natural forests in Uganda (Budongo and Bugoma), with rich biodiversity (Plumptre et al., 2007), and yet it has suffered extensive deforestation. While discourses in local media highlight the prevalence of this deforestation (e.g., Mugerwa, 2011; Namutebi, 2013; Tenywa, 2014), the only published work found is fragmented and limited to Budongo forest (Nangendo, 2005; Nangendo et al., 2007; Mwavu and Witkowski, 2008). Forest loss around Budongo has been reported on private landholdings, and attributed to agricultural expansion, population growth, illegal timber harvesting, unclear land tenure systems and weak forest protection enforcement (Mwavu and Witkowski, 2008). There is however a dearth of information on Bugoma (another large forest in the landscape), and forest corridors in the region. Some studies exist by the Wildlife Conservation Society (WCS) and other NGOs working on forest loss in the Albertine Rift region, but only in unpublished reports and the methods used in the estimation are not rigorous.

The extent of forest cover change particularly at the landscape- and local-scales around Bugoma and Budongo forests in the last 30 years is not thoroughly understood. Providing unambiguous extents of historical vegetation cover changes could provide the impetus to address local, regional and national needs, and may prove critical for future planning. Efforts on Reducing Emissions from Deforestation and Forest Degradation (REDD) in the region will be enhanced by establishing the baseline deforestation rates. The focus here is mainly on identifying deforestation rates, and less on its drivers. Contrary to many studies we attempt to recover the time-series of change, rather than just looking at start and end points of the period: this helps to distinguish the deforestation signal from other temporal fluctuations. However, in order to get an unambiguous result it is also necessary to look at spatial patterns.

The issue of the spatial scale of analysis has received limited attention in forest cover change literature. A large-scale analysis (which in the current case is 4–5 times the size of the largest protected forest area – we refer to this as the “landscape” scale below – see Fig. 1) could provide insights into the connectivity of the forest cover mosaics, essential for biodiversity conservation, where, for instance, allowing free wildlife movement in a well-connected landscape is important for breeding; while a more localised investigation unearths intricacies in anthropogenic-related selection and exploitation biases, which could impact on the larger-scale processes. To understand the spatio-temporal complexity of forest cover change, our investigation explored the landscape scale, and three more local areas. The landscape scale covers the entire study area while each of the local-scale studies first exclude the national park region in the North, but include the forest corridors and riverine regions, and then focus in on the Budongo region, where the southern part has been less thoroughly studied, and the Bugoma forest which has been least studied of all. The objective of this paper was to understand the spatial distribution and patterns of the connecting forest patches influenced by anthropogenic activities within and between the main protected forests; namely Budongo, and Bugoma (and the smaller Wambabya forest) between 1985 and 2014.

## 2. Study area, data, materials and methods

### 2.1. Description of study area

The Northern Albertine Rift Landscape in Western Uganda lies approximately between 1°18'–2°11'N and 30°40'–31°52'E with an

estimated area of 14,098.9 km<sup>2</sup>. This is the delineated area for this study in Fig. 1; the full extent of the Albertine Rift covers many countries (see e.g., Ryan et al., 2014). The Albertine Rift is one of the most important conservation regions in Africa with extensive areas of both protected and unprotected forest (Owiunji & Plumptre 1998; McLennan & Hill, 2012), abundant bird species, high plant and tree species diversity (Eilu et al., 2004), and an unmatched animal species diversity, most of which are endemic to this ecosystem (Plumptre et al., 2007).

The landscape has a characteristically gently sloping terrain, and a tropical climate with two rainfall peaks, March to May and September to November (Eilu et al., 2004). The region's ecosystem is threatened by widespread deforestation (Mwavu & Witkowski, 2008) partially due to a dense population of approximately 123 people km<sup>-2</sup> (the majority living below the poverty line, on less than a dollar per day), and a population growth rate of about 3.2% per annum (UBOS, 2002), exacerbated by a large influx of refugees (Mwavu & Witkowski, 2008). Small-scale agriculture is the main way of life, although with limited commercial farming to provide raw materials for sugar, tea and tobacco industries in the region (Nangendo et al., 2007).

The landscape has attracted many government and non-government conservation and development organisations. Oil was discovered in the Albertine Rift in the mid 2000s and construction of an oil industry is underway. It is not clear how development goals and conservation will work simultaneously in this landscape.

### 2.2. Remote sensing data used in the analysis

Two remote sensing data sources are used in this study: (1) Landsat (30m resolution) and (2) UK-Disaster Monitoring Constellation International Imaging (UK-DMCii, 22 m resolution). Landsat images were the main data source, obtained from the USGS archive via the Earth Explorer web-link (<http://earthexplorer.usgs.gov/>). The archive has a large database from the 1970s which is now freely accessible to the public from the USGS web portal (Wulder et al., 2012). Good quality scenes for the study were available from January, 1985 to March, 2014 (to include the period of fieldwork). In total, a time-series of 80 scenes was downloaded.

Clouds obscure vegetation cover; the surface of the Earth can still be seen through haze, but the spectral characteristics are often changed and this can render imagery unusable (Mitchard, 2012). We screened images for those with more than 50% haze and cloud cover, especially in core case study areas. We excluded images that were not totally cloud-free, and those affected by Scan line Corrector (SLC)-error over the region of study. At both scales only 7 scenes were considered suitable (Table 1); essentially, only 8.8% of those downloaded. One cloud-free scene obtained and donated by UK-DMCii was also included to compare with estimates of forest quantities obtained using Landsat imagery.

The study area lies in a single Landsat Path and Row (172/059), and therefore a mosaic of multiple scenes was not required. Unsurprisingly, the useable imagery at the landscape and local scales proved to lie in the dry season, which is more likely to be cloud and haze free. This helps to control for seasonal variability that could confuse the overall change signal due to phenological effects on the classification.

#### 2.2.1. Image processing

Image processing was undertaken using Erdas Imagine 2013 and ArcGIS 10.0 in three phases: (1) Pre-classification processing, (2) classification and (3) post-classification change detection as summarised in Fig. 2. These are described in turn.

**2.2.1.1. Pre-classification processing. Band selection:** After some preliminary trials with other band combinations, we settled on the

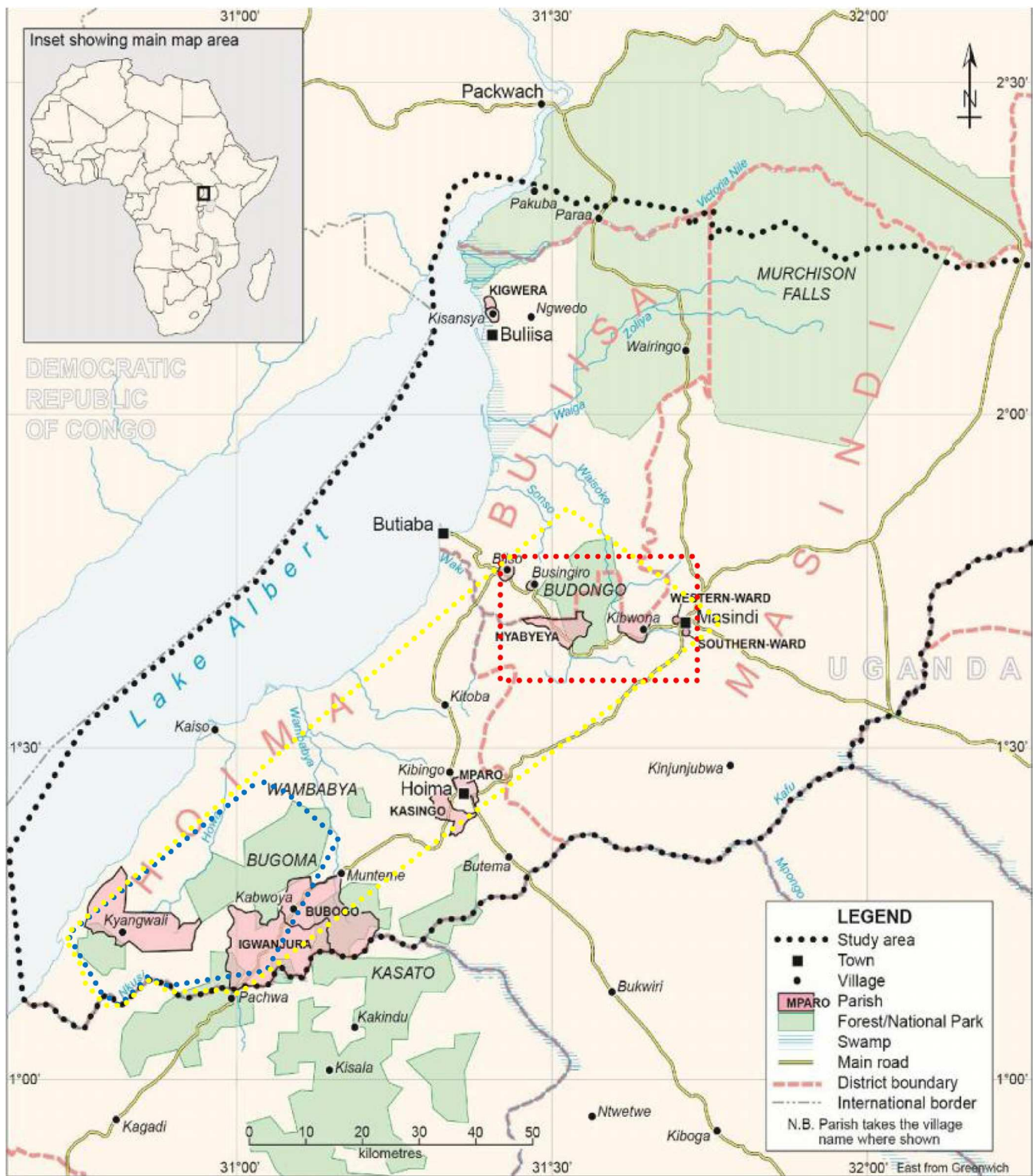


**Fig. 1.** Map of study area showing the landscape, and 3 case study areas: Budongo case (red), Bugoma case (blue) and forests including corridors (yellow). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

widely accepted 3-band false colour composite that includes at least red and infrared bands, known to provide distinct vegetation features (He et al., 2011). We therefore included red and infrared bands (for Landsat 8 classification), and infrared and short-wave infrared bands (for Landsat 4 and 5 classification), that provide additional benefits of further discrimination of vegetation and moisture content of the soil, useful in clear distinction of the for-

est from non-forest classes. The number of bands available per downloaded scene varied between 5 (e.g. Jan 14, 1985) and 11 (e.g. Jan 14, 2014), Table 1; this is due to the number of bands a sensor could provide at the time, but also possibly due to the pre-processing by USGS. Previous studies based on principal components analysis have shown that additional bands do not improve the classification but have redundant information (Harsanyi and

**Table 1**  
Attributes of imagery used in the analysis.

| Date acquired resolution (30 m) | Source (landsat)   | Number of bands available | Climatic season |
|---------------------------------|--------------------|---------------------------|-----------------|
| 1985-Jan-14                     | TM5                | 5                         | Dry             |
| 1986-Jan-17                     | TM5                | 7                         | Dry             |
| 1990-Dec-22                     | TM4                | 5                         | Dry             |
| 1995-Feb-27                     | TM5                | 5                         | Dry             |
| 2002-Feb-06                     | ETM                | 6                         | Dry             |
| 2010-Dec-05                     | TM5                | 5                         | Dry             |
| 2014-Jan-14                     | OLI & TIRS         | 11                        | Dry             |
| 2010-Dec-04                     | UK-DMC (SLIM-6-22) | 3                         | Dry             |

**Table 2**  
Selected bands and their wavelengths.

| TM5, ETM+ Bands selected | Band width ( $\mu\text{m}$ ) | OLI Bands selected | Band width ( $\mu\text{m}$ ) |
|--------------------------|------------------------------|--------------------|------------------------------|
| 2                        | 0.52–0.60                    | 3                  | 0.53–0.59                    |
| 4                        | 0.77–0.90                    | 4                  | 0.64–0.67                    |
| 5                        | 1.55–1.75                    | 5                  | 0.85–0.88                    |

The UK-DMC image has the same optical dimensions as Landsat; and has only 3 bands: 2, 3 and 4.

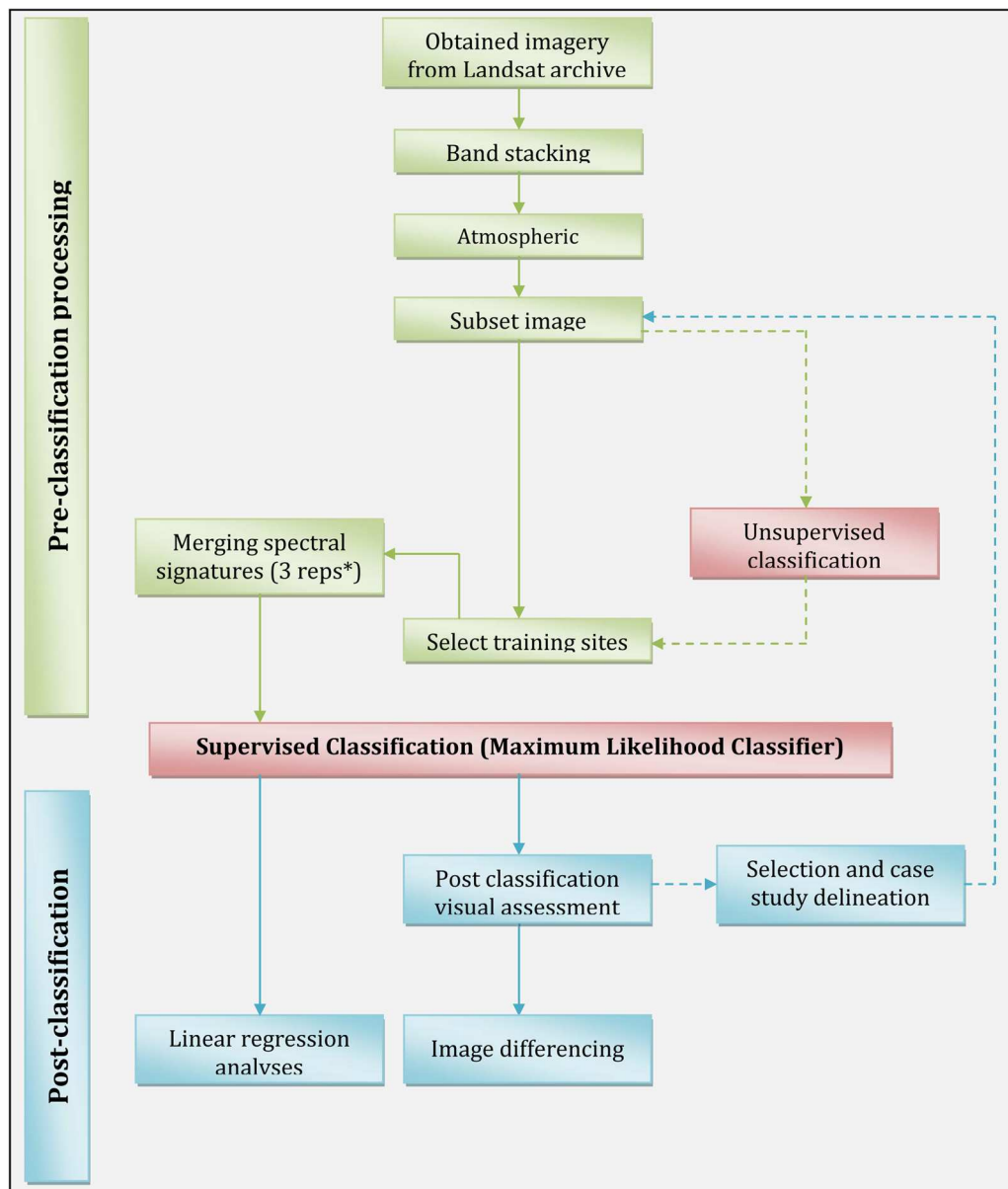


**Fig. 2.** Schematic illustration of Landsat image pre-processing, classification, and post-processing procedures undertaken. Unsupervised classification was not always strictly carried out: it was essential for exploratory assessment of how classes might be distributed in the landscape. 3 replications were undertaken per scene to assess classification variability. Dotted lines show optional procedures included—for instance the case studies were selected and delineated once.

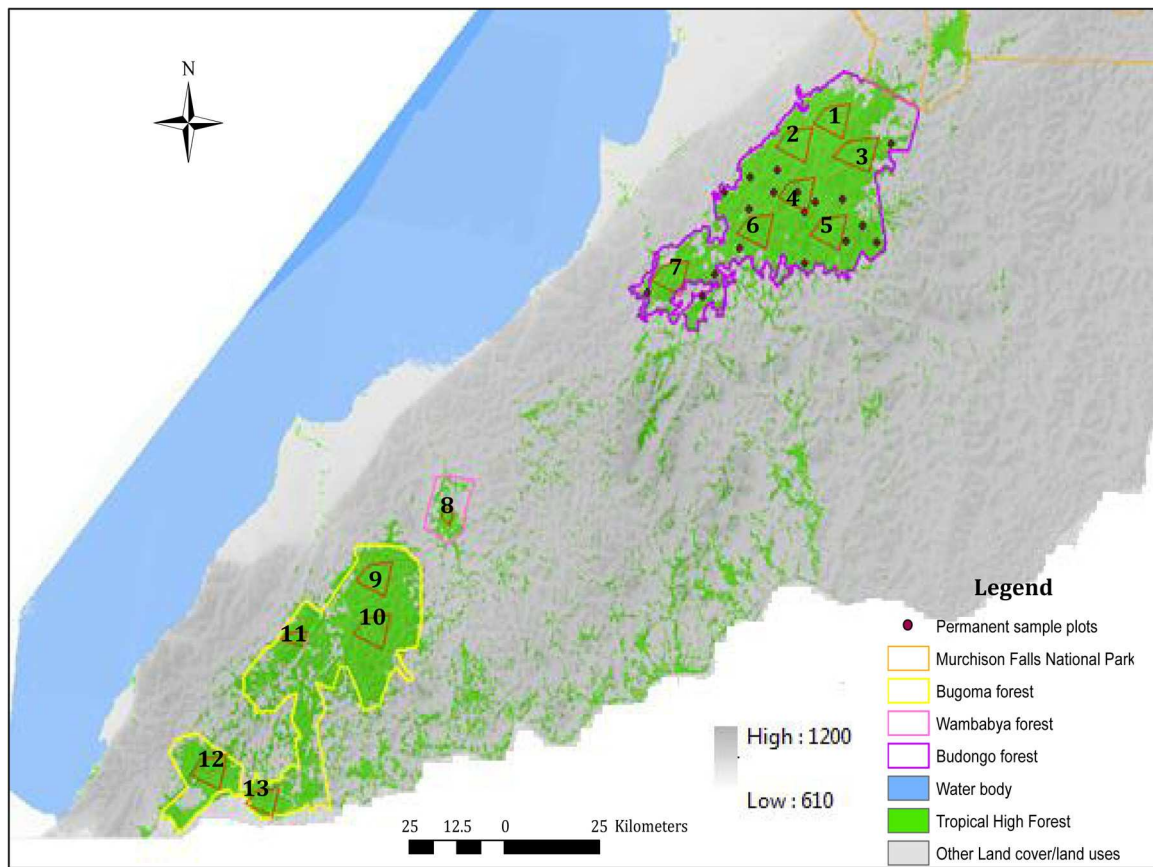


**Fig. 3.** Map of study area showing forest class training sites against the 1985 classification map (In the background is hill shading from a Digital Elevation Model [in m] supplied by Uganda Department of Lands and Survey. Training sites (numbered polygons) are situated in the protected forest areas. All permanent sampling plots were correctly located in the forested area, as expected).

Chang, 1994; Chang et al., 1999; Jia and Richards, 1999) that unnecessarily slows down the processing. We therefore used a band set that clearly distinguishes the forest class from the others. We selected a band combination of 2, 4 and 5 (green, infrared, and short-wave infrared bands respectively) for the classification of Landsat 4 and 5 imagery, while a combination of bands 3, 4 and 5 (green, red and near infra-red) was used to classify the only Landsat 8 image, since Landsat 8 has different wavelengths for each band compared to the other Landsat systems (Table 2). In spite of selection of a different band combination, distinguishing the forest class was consistent with the results from the UK-DMC image. The selected band responses from the different instruments produce remarkably consistent results: this case is shown by the fact that the protected areas remain stubbornly constant in size while the regions outside change steadily. This suggests that the trend in forest cover described below is a real effect and not an artefact of the bands selected or changing instrumentation between satellites. Processing of the one scene from UK-DMC followed that of Landsat images, using bands (2–4). *Atmospheric correction:* Data from remote sensing scanners are often distorted by variations in atmospheric conditions, solar angle, and sensor view angle (Townshend et al., 1991). Radiometric correction helps to reduce atmospheric variations between multiple images by adjusting the radiometric properties of target images to appear as if they were acquired from the same sensor (Hall et al., 1991). We used the Dark Object Subtraction method since it is simpler than absolute methods, and widely used to correct for radiometric errors (e.g. Song et al., 2001). In an ideal situation, a radiometrically ‘dark’ object (e.g. a clear water body) produces zero radiance in all wavelengths and hence any radiance received at the sensor for a dark object pixel is due to

atmospheric path radiance (Chavez, 1988). Thus, pixels over Lake Albert containing the lowest Digital Number (DN) values were selected (as the dark objects), and their representative value was subtracted from the DNs across the whole scene to reduce scattering influences (Song et al., 2001). Since Landsat satellites follow a sun-synchronous orbit, they image a particular latitude at the same time every day: as our imagery also comes from the same season each year, our results should not be very sensitive to sun-angle (Mitchard, 2012); there is only a  $5.5^\circ$  range in solar angle over the entire study period, whereas the seasonal differences can be up to  $15^\circ$ . *Image subset:* The delineation of the study area (at the landscape scale) largely followed Hoima, Masindi and Buliisa district boundaries, the international border to the west, with the extent limited to the single path/row of the image. The boundaries were used to extract the study area from each Landsat scene. The smaller-scale case studies excluded Murchison Falls National Park, as the focus was on anthropogenic influence around protected forest. We therefore delineated the forest corridors to observe the patterns and connectivity of the large protected forests (Budongo, “Wambabya” and Bugoma), and finally concentrated on the other two cases specifically looking at regions around Budongo (mostly to the South; as the Northern section has been previously studied) and Bugoma (which is less studied). Case studies were delineated around Budongo forest, Bugoma forest, and the forest corridors between (to understand the connectivity changes between the large forests).

**2.2.1.2. Classification.** Ideally we would have adopted the Uganda National Forest Authority definition of forest as “mature and/or regenerating natural forest with a minimum area of land of

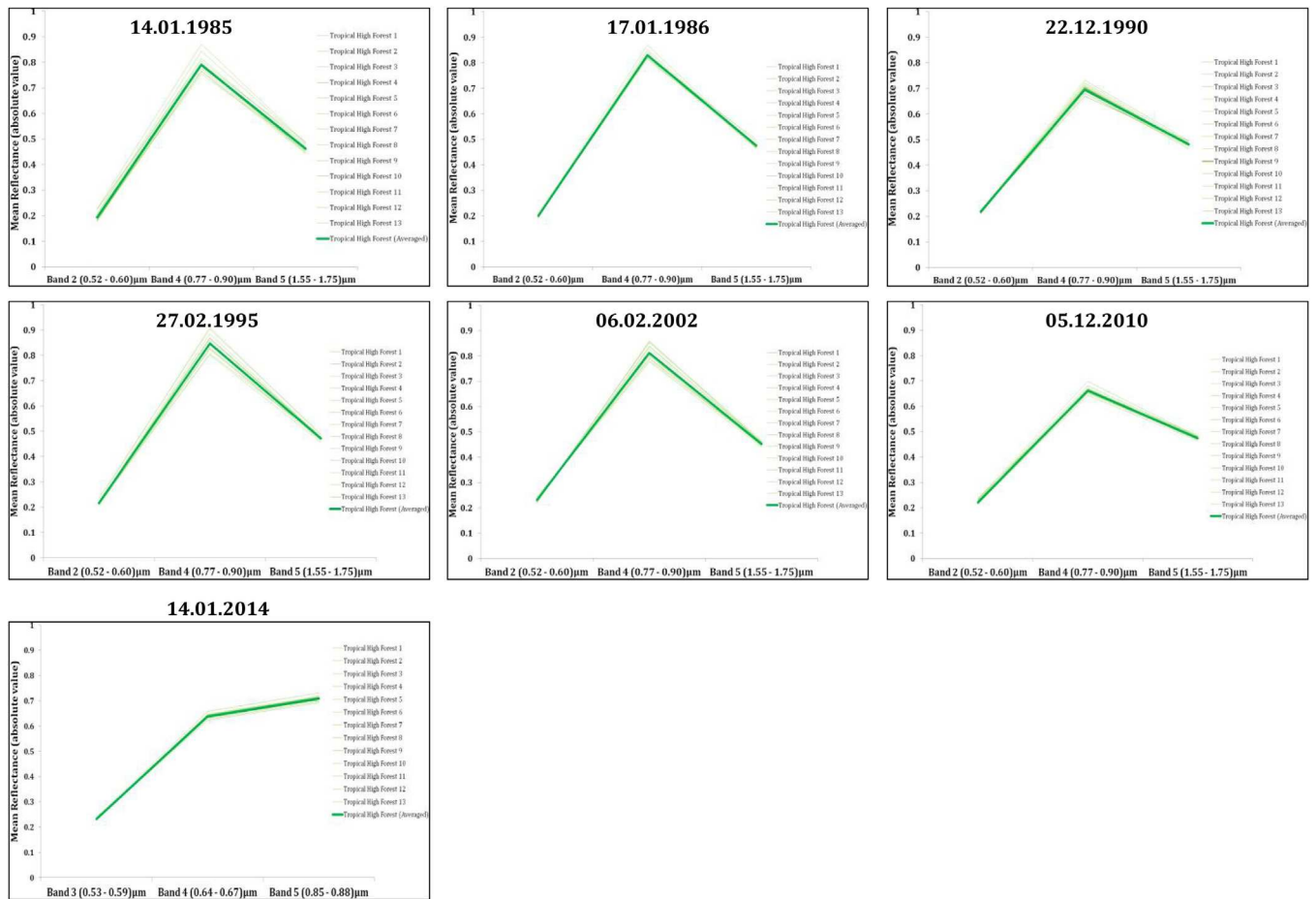


**Fig. 4.** Reflectance signatures from training sites of each image.

(Sampled signatures were merged to form an averaged signature for classification. To replicate the classification, sub-sampling of the signatures was undertaken. The spectral signatures across all the classified scenes consistently give a signal that is sufficiently similar and distinguishable from non-forest. Only in the 2014 case does the spectral signature derived for forests differ markedly from the other years, however the results below (a) still give a consistent spatial pattern for the large forest blocks and (b) are not critically dependent on this single image. The polygons used to extract these spectral signatures are located within the protected forests, shown in Fig. 3)

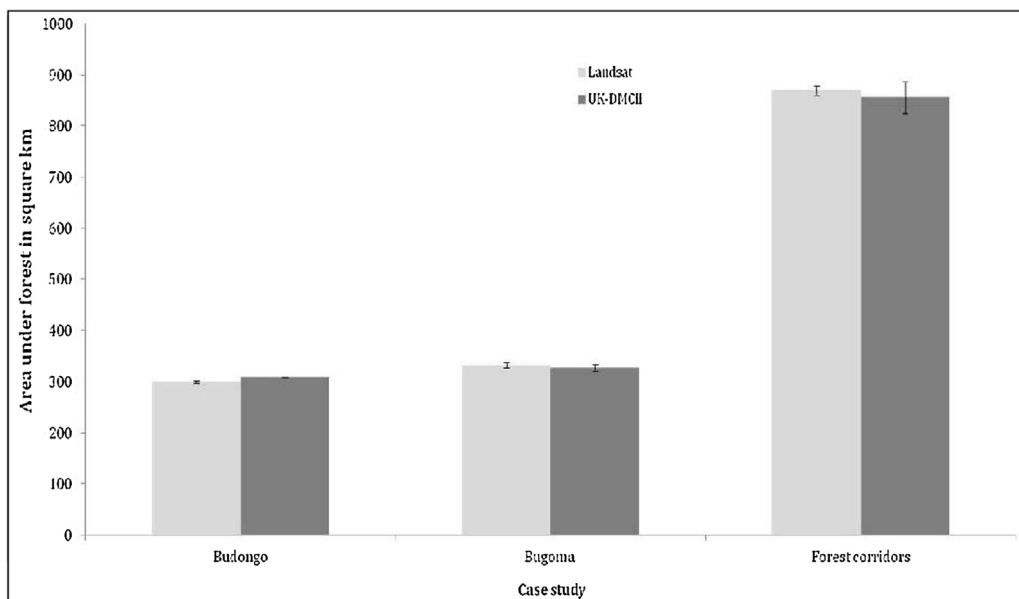


**Fig. 5.** Comparison of area of forest as estimated using Landsat and UK-DMCii imagery. Bars represent standard deviation.

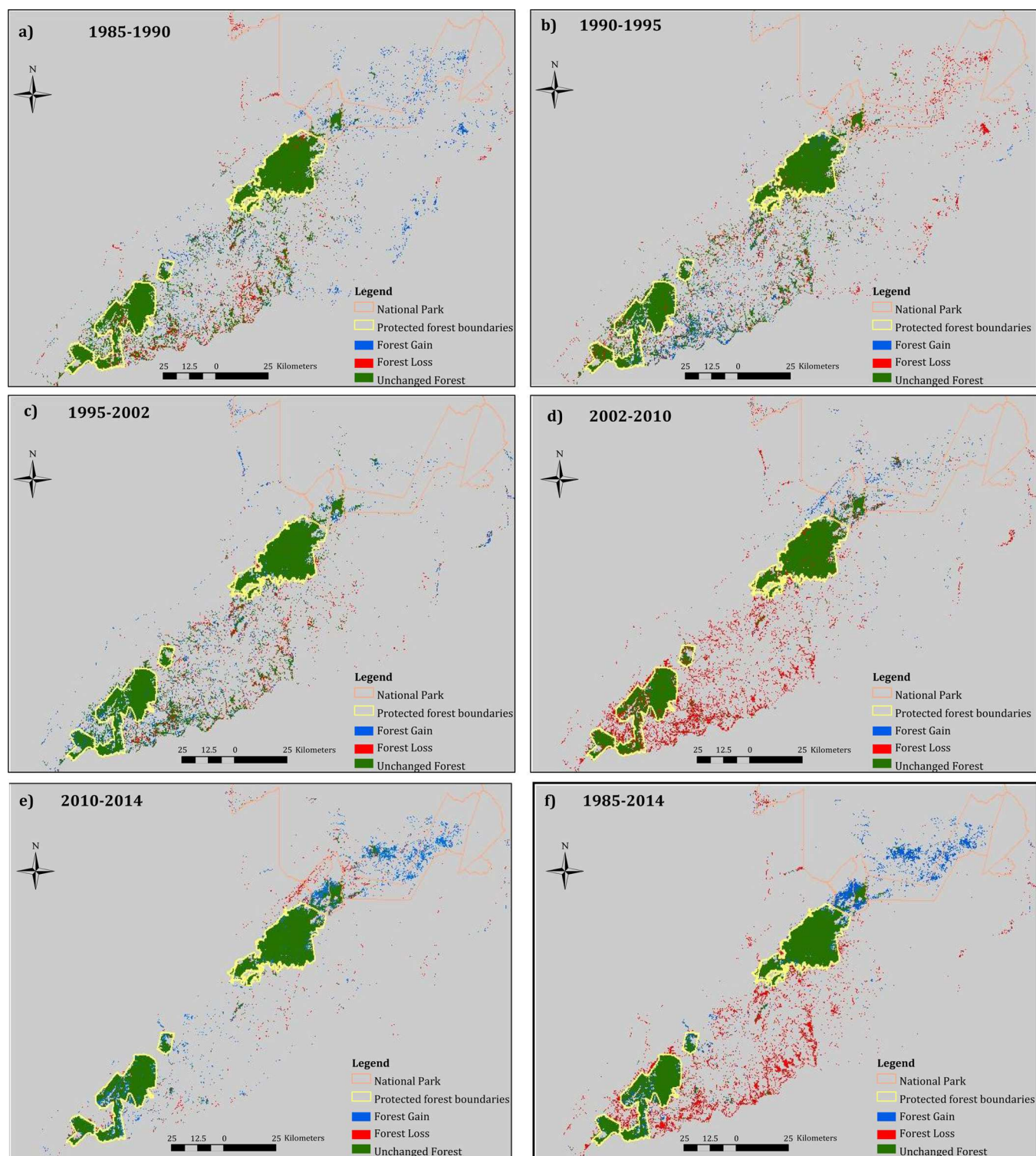


**Fig. 6.** Forest cover change at the landscape level between: (a) 1985–1990, (b) 1990–1995, (c) 1995–2002, (d) 2002–2010, (e) 2010–2014, (f) The whole period: 1985–2014.

1 hectare, with tree crown cover of more than 10–30% with trees having the potential to reach a minimum height of 2–5 metres at maturity in situ” (MWE, 2012). However, the resolution of the Landsat imagery is insufficient to detect individual trees, so we rely on the forest spectral signatures generated over known forested areas (e.g. Budongo, Bugoma and Wambabya) for each image, essentially creating a generalised empirical forest classification (e.g. in Hansen et al., 2013), without distinguishing forest classes (e.g. by

species and stocking densities). The training areas were therefore consistently obtained over known forested areas within the gazetted areas for classification of each image (Fig. 3). The underlying assumption is that all forests existing outside the protected areas will have similar reflectances. Essentially, we monitor forest cover patterns whose reflectance closely matches that of the protected forest: and, therefore, do not distinguish gazetted from non-gazetted forests in the classification. The classification run

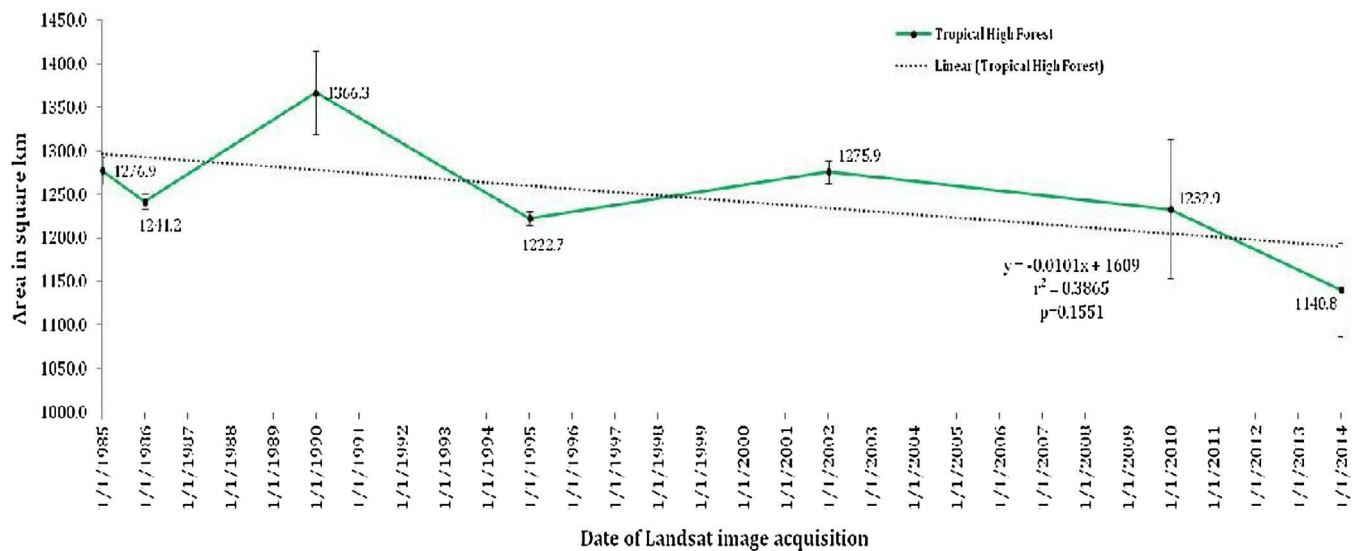


**Fig. 7.** Trend of total forest cover change at the landscape level (error bars represent standard deviations from the replication of the classification. There is a weak linear relationship between acreage of forest cover and time; which generally shows that forest cover has declined slightly over the 30-year period, although this relationship is not significant at the 95% level. The line in green labelled “Tropical High Forest” shows the trend of forest cover as drawn through each plotted point, while “linear [Tropical High Forest]” shows the regression line fitted to the entire time-series).

produces *total forest cover* (based on the protected forest spectral signature), and this is subtracted from the area of forest under gazetted areas to obtain what is in the unprotected zones. The landscape is flat, with minimal variation in altitude, and therefore variation in slope and aspect do not have a major effect on the spectral signature. Notably, the forest signal is robust (we drove through some of the forests during fieldwork and looked at other maps to ascertain this): crops (e.g. palm oil, bananas) that are known to have a similar signal are generally not grown in this region. Deforestation is defined as the direct human-induced total conversion of forested to non-forested land (Schoene et al., 2007). However, all we can actually detect is the change of land cover from “forested” to “not forested”; we cannot be definitive from the imagery alone what the mechanism is, although we mention some possibilities below.

We used a hybrid of the unsupervised and supervised classification techniques (Sassen et al., 2013). An unsupervised classification involves assigning a given number of classes and letting computer algorithms place similar objects in one category using a statistical method. Unsupervised exploratory classification was used to identify areas of interest. We used the unsupervised classification to identify regions expected to be forested. This then formed the basis for the selection of ‘training’ sites (whose band characteristics enable extraction of all other similar pixels), although some previous knowledge of the landscape, and comparison with some existing maps (by WCS, and National Forest Authority) was also valuable. We adopted a pixel-based classification criterion in preference to an object-based one, and although results from the two techniques have not been found to differ significantly, the results from the former have been found to be comparatively better (Duro et al., 2012).

13 training sites (in total) from large, continuous, unambiguous protected forest expanses (in Budongo, Wambabya and Bugoma), referred to as ‘Areas of Interest’ (AOIs), were selected across each image to extract the spectral signatures for the forest class (Fig. 3). The statistical properties of the selected AOIs were visually assessed. The group signatures (that is, reflectance as a function of satellite band, for a given land-cover) were then merged into one (averaged), and were used in the supervised classification of the forest in each scene (Fig. 4). To test for variability in the classifica-

tion, the signatures collected for the forest class were re-sampled in random combinations and merged to provide an average signature, and the classification rerun. Because of the consistency of the forest signatures, three replications were considered sufficient. Although only the forest class is presented in this paper, the classification was undertaken to define multiple classes following similar procedures. We later created a binary map with forest, and non-forested (including all other land uses/cover) classes for the purpose of forest change detection.

We used the Maximum Likelihood Classifier (MLC) in Erdas Imagine to classify the forest. The MLC is widely used and is able to recognise the spectral characteristics of each class in an unknown dataset by means of the statistical data (premised on Bayes’ theorem) obtained beforehand from digitised training sites, to assign pixels to the particular classes that have the maximum probability (Coppin et al., 2004; Tempfli et al., 2009 pg. 304; Srivastava et al., 2012). The landscape-level classification was rerun at the case study scale by following similar procedures, also with 3 replications to test for variability in forest quantities.

**2.2.1.3. Post-classification processing. Detection of forest cover change:** the forest class was created as a binary image in ArcGIS 10, with forest allocated values of “1” and the other classes assigned “0”. Image differencing was then undertaken, where more recent scenes were subtracted from older ones. The protected forest boundaries obtained from Uganda’s National Forest Authority were overlaid on each binary image, and the forest cover within each boundary was delineated and computed in ArcGIS. It was therefore possible to compute areas of forest on private land by subtracting the area under protected forest from the total forest cover within each case. Protected forests are government owned: all forests outside delineated areas are on private land, and are categorised as unprotected. **Statistical analyses:** regression analyses of the area under forest versus time were undertaken for the entire time-series at the landscape and local scales, with the level of statistical significance set at  $p < 0.05$ . The fact that for most cases we get very clear linear trends with highly significant  $p$ -values at such small sample sizes arguably favours an interpretation in which the trend line really represents a systematic decline, rather than the effects of a random process. However, the fact we have only 7 time data points

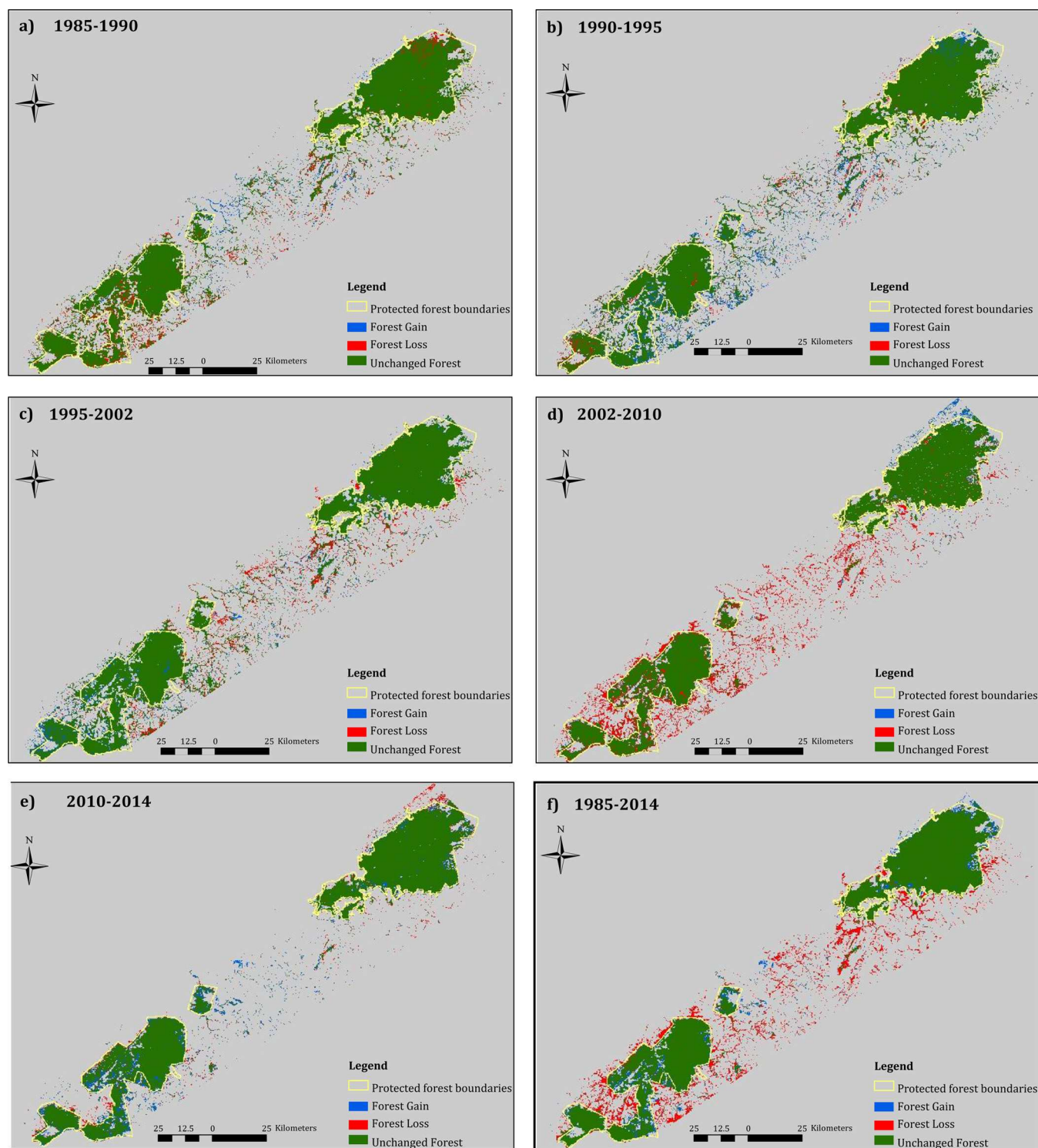


**Fig. 8.** Forest cover change in and around Budongo and Bugoma between (a) 1985–1990, (b) 1990–1995, (c) 1995–2002, (d) 2002–2010, (e) 2010–2014, (f) The whole period: 1985–2014.

suggests that the actual rate estimates should be treated with caution. As will become clear, the way in which boundaries are drawn around different spatial structures can have a very large effect on estimates of average deforestation rates. *Accuracy assessment:* we lacked historical maps to test the derived forest extents, and therefore relied mostly on the consistency of the forest signal to pick out patterns (as is the case in Hansen et al., 2013). We obtained 20 permanent sampling plots demarcated by Uganda's National Forest Authority within Budongo, all of which were correctly mapped

within our classification, and appeared to lie consistently in the forest in the entire time-series. The forestry body has plots in Bugoma too, although these are not geo-referenced. We assessed the accuracy of the Landsat image obtained on 5th Dec, 2010 with a UK-DMC image obtained on 4th Dec, 2010. UK-DMC image (22 by 22 m pixels) are of better quality than Landsat (30 by 30 m pixels) both in terms of spatial resolution and visual enhancement. A comparison of the Landsat image classification obtained with the UK-DMC image indicates that forest classification using Landsat imagery is

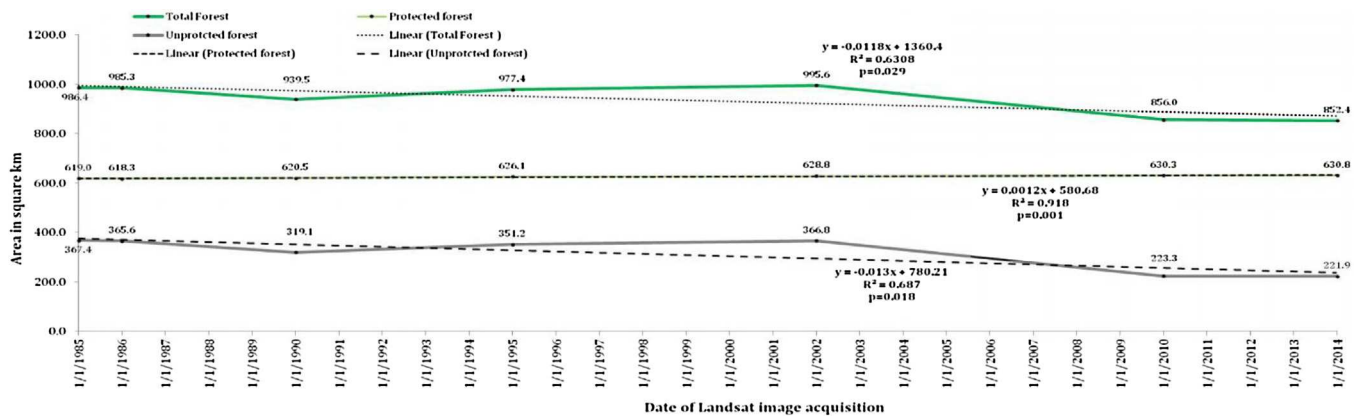


Fig. 9. Forest cover trend of protected and unprotected forests in the forest corridors (includes Budongo and Bugoma).

robust. The absolute differences in the Budongo, Bugoma and forest corridor cases are 2.9%, 1.3% and 1.5% respectively (Fig. 5). A comparison at the entire landscape level was not possible as the UK-DMC scene did not cover the entire landscape adequately.

The two scale analysis – the landscape and local levels – enabled two, independent classifications, and provided another measure of consistency of allocation of pixels to the forest class. Variability in classification between the two scales of analysis, and within each scene, is minimal, often deviating in the range of 5–10%, suggesting that the forest signal is consistent and therefore the derived quantities are mostly meaningful. While the classification was re-run at the two scales, we see general agreement in the allocation of pixels and forest extents—but the local scale analysis at least highlights the regions where changes have been most prominent (in more detail with easier visualisation).

### 3. Results

#### 3.1. Forest cover change at the landscape-scale

Overall, between 1985 and 2014, there was a 10.7% loss in total forest cover at the landscape scale, an average rate of 0.4% initial forest cover lost per year, although a linear regression this loss rate was not significant ( $p = 0.16$ ) at the 5% level, reflecting the rather noisy temporal pattern. Forest increased in the earlier period of analysis, 1985–1990 by 7.0%, but this is rapidly followed by a 10.5% loss between 1990 and 1995, in the same regions where there had been regrowth, and some 4.4% gains in 1995–2002. This rather confused picture begins to become clearer when the spatial patterns are examined. The initial increases appears to be widely distributed across the landscape (Fig. 6a), whereas later gains (after 2002) seem to be concentrated in the north (Fig. 6b and c, respectively), located especially in Murchison Falls National Park. Many of the more southern regions that had experienced recovery were followed by losses especially in the forest corridors, and 3.3% was lost in total between 2002 and 2010 in spite of gains in the National Park (Fig. 6c). Further forest loss of 7.7% occurred in the most recent period 2010–2014 (Figs. 6 e and 7).

Spatially, the large protected forest blocks remained relatively stable; deforestation was mostly patchy, situated in the corridor and riverine forests. There were, however, some regions of forest expansion in the period of analysis (Fig. 6). Forest losses were predominantly in the regions south of Budongo, in the forest corridors ('linking' Budongo and Bugoma), and south (and west) of Bugoma. Forest gain can mostly be seen in the region immediately North of Budongo forest (located in Murchison Falls National Park), and in

relatively recent periods, 2002–2010 and 2010–2014 (Fig. 6d and e, respectively). Fig. 6f shows the total change over the whole period, indicating large overall losses in the riverine and forest corridor areas. Forest gains and offsets in various parts of the landscape obscure local level dynamics and provide a trend that shows a small overall decrease (Fig. 7). The noisy signal reflects the spatial pattern of loss and gain, but, the largely unchanged protected forest areas mask the more serious local losses in the rest of the region. For this reason the analysis focussed further on the two major protected forests and the area between them in order to gain a finer-detailed view of the changes.

#### 3.2. Forest cover change between the protected forests: forest corridors

To assess these local changes in more detail, we examined them in the area between the large protected forest blocks, of Budongo (to the NE), 'Wambabya' (central) and Bugoma (to the SW of Fig. 8). There is a marked overall forest cover loss of 134 km<sup>2</sup> between 1985 and 2014. Much of this loss has occurred on private land (Fig. 8). Losses are most extensive in a relatively recent period, 2002–2010 (Fig. 8d), although the periods compared are not of equal length and notwithstanding a slight increase from 1990 to 2002. Temporally, however, major losses can be traced from 1995 to 2014 ( $r^2 = 0.93$ ,  $p = 0.03$ ; Fig. 9). Thus, although there is an overall decline of 134 km<sup>2</sup> in the total forest cover, the temporal pattern shows that this is mixed with some increases, mostly dominated by the protected forest blocks (Fig. 9). The protected forest blocks appeared to be stable in the entire period with an overall marginal increase of 1.9% ( $r^2 = 0.9$ ,  $p = 0.001$ ); with some regions of recovery and fresh growth, especially in Bugoma forest.

#### 3.3. Forest cover change in the Budongo case study

At this more local spatial scale, the delineation between protected and unprotected forest is clarified in each scene with a clear boundary defining the protected area. The total forest in this case is dominated by the protected forest, which remains relatively stable in the 30-year period of analysis (central light green line, Fig. 11). Generally, approximately 18.8% of the total forest present in the Budongo case study in 1985 was lost by 2014. The piecewise plot suggests that there was some forest gain prior to 1990, but following that period, there is more of a decline. Remarkably, though, 99% of the unprotected forest in 1985 was lost by 2014; a high annual average loss rate of –3.3% (compare the lower grey line (unprotected forest) with the protected forest (central light green line) and

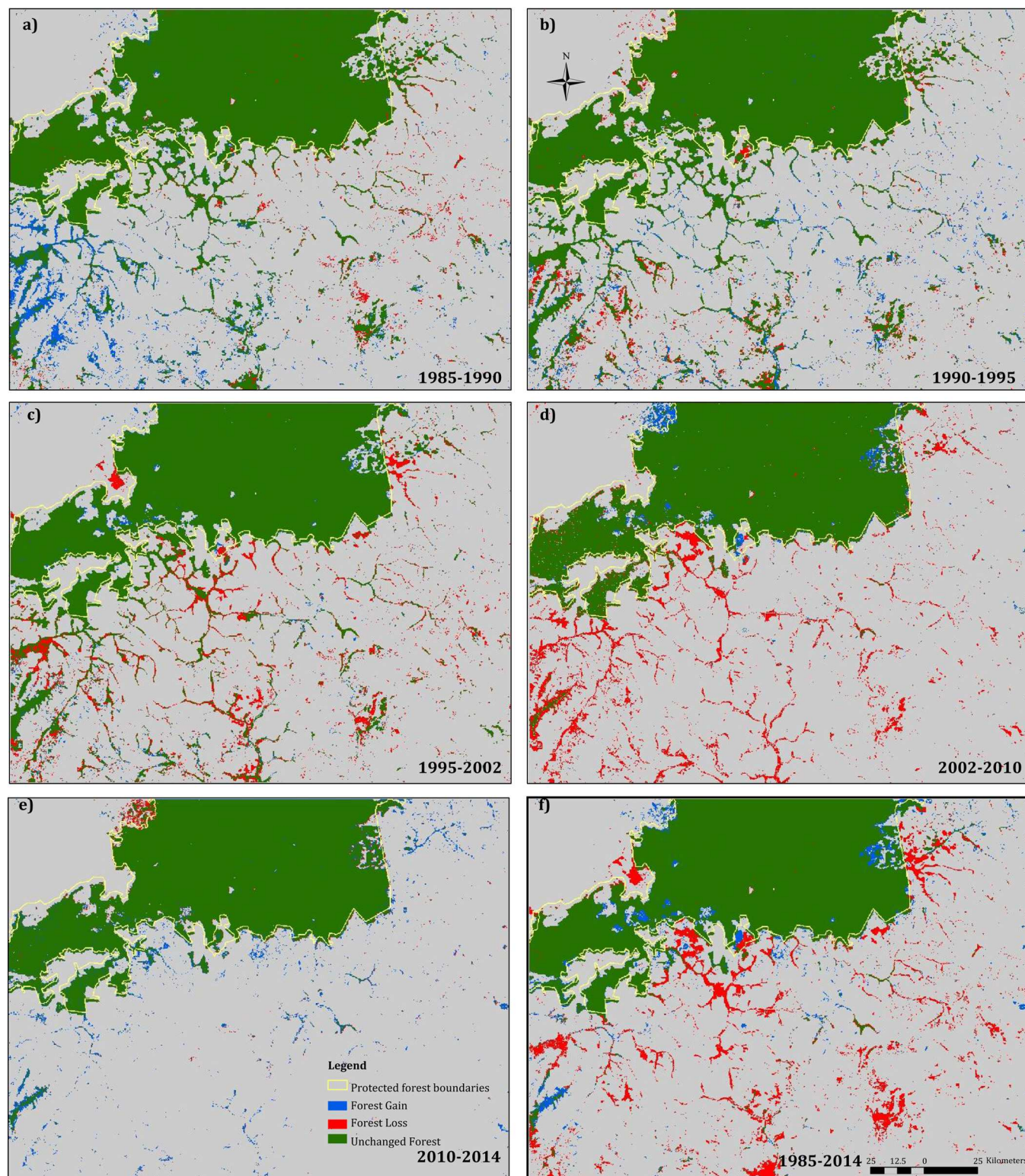


**Fig. 10.** Forest cover change in and around Budongo between (a) 1985–1990, (b) 1990–1995, (c) 1995–2002, (d) 2002–2010, (e) 2010–2014, (f) The whole period: 1985–2014.

total forest (upper green line) in Fig. 11 – almost all change is dominated by loss of unprotected cover). The losses in unprotected forest are mostly visible in the small fragments away from the protected forest block (Fig. 10). There is a 6.9% increase in unprotected forest between 1990 and 1995, but most of this was again lost in subsequent periods, until there was nearly no forest left to be cleared (Fig. 8e – changes between 2010 and 2014 are negligible as a result

of the almost total disappearance of the unprotected woodland). On the other hand, one could argue for a slight increase of 0.8% of the *protected* forest in 2014 compared to what was available in 1985, although the rate is barely detectable. While the protected forest has an overall increase in area, with a nearly flat temporal pattern, spatially, there is evidence of some encroachment. Losses are mostly visible at the edges, and less in the interior, although some

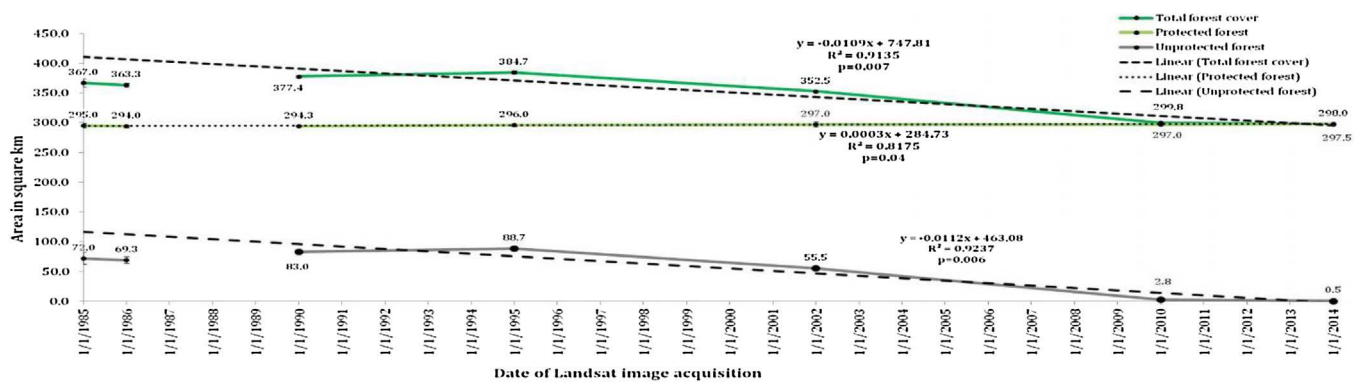


**Fig. 11.** Piece-wise plot of forest cover trend in the protected and unprotected areas in and around Budongo (Error bars represent standard deviations. Protected forest remained relatively stable, and the most dramatic losses took place in the unprotected forest zones).

losses in the interior can be seen in the earliest period, 1985–1990, especially in the strict nature reserve.

#### 3.4. Forest cover change in the Bugoma case study

In this case study, as in the previous one, the overall signal is dominated by the protected forest; the total forest cover declined by about 55.5 km<sup>2</sup> in the last 30 years. There is a marginal gain of 3% in the amount of *protected* forest cover in the 30-year period (Fig. 12); although major losses to the magnitude of 62.6 km<sup>2</sup> occurred in the unprotected zones (Fig. 13)

Generally, 15.0% of the *total* forest (when protected forest is included) present in 1985 was lost by 2014 an annual average loss of −0.5%. Again as in Budongo, 99% of *unprotected* forest present in 1985 was lost by 2014, which translates to an annual average loss rate of −3.3%. Forest loss in unprotected forest is most dramatic in the period after 1995 (Fig. 12). While there are some fluctuations in the earlier period (to 1995), real deforestation seems to take off in the Eastern part after 1995 (Fig. 12c). As the Eastern areas decline, forest patches in the West are cleared after 2002 (Fig. 12d). By 2010 most of the Eastern forest patches are gone, leaving a continual decline to the West, taking the removal of forest right up to the protected boundary and continuing into the 2010–2014 period (Fig. 12e). There was evidence of continued deforestation in unprotected areas in the period during fieldwork in unprotected forests adjacent to Bugoma. The fields were reportedly cleared for small scale farming of food crops (see Plate 1). The spatial pattern of the protected forest is mixed; there are regions of infilling, at the western boundary, and small patches attached lost at the boundaries. There are also some patches that were depleted in the protected zones between 2002 and 2010 (Fig. 12). Fig. 12f summarizes the situation over the whole period. While the protected forest really has been protected and even shows a slight net gain, the remaining area has been cleared right up to the boundary.

## 4. Discussion

This study set out to reconstruct detailed forest cover patterns and their changes for the Northern Albertine Rift Landscape between 1985 and 2014. While the investigation began at the landscape-scale, in the course of the analysis, it was clear that spatial scale had implications for the results obtained, and changing scale could offer interesting insights into more local-scale processes in different parts of the landscape.

#### 4.1. On forest cover patterns at the landscape-scale

Forest classification is robust and consistent across the landscape; errors from pixel mismatches are mostly between 5 and 10%, and a spatial assessment indicates that they are located at the forest edges, where there is transition from forest to other land uses (e.g. farming). The landscape-scale analysis shows that forest cover patterns are largely driven by more local-scale processes. Gains for instance, in the National Park, offset large losses south of the protected forests. The patterns highlighted in local media and unpublished reports stress losses and ignore local gains (see Section 1). Forest growth on some private landholdings is supported by funding support from various initiatives (e.g. FACE Foundation Forest Rehabilitation Project, PlanVivo Project, Nile Basin Reforestation Project, and Namwasa Forestation Project; for detailed reviews see Jindal et al., 2008; Peskett et al., 2011). Although afforestation and reforestation projects are on the rise, it remains unclear whether they are reducing pressure on natural forests (Ainembabazi and Angelsen, 2014). This analysis indeed shows that at the landscape scale, the overall temporal patterns are obscured by dissimilar spatial processes (e.g. 2002–2010, 1985–2014), where losses in the forest corridors and forests on private land are offset by gains in the Murchison Falls National Park, in the region immediately north of Budongo forest.

The expansion of forest in the National Park is not an artefact of the imagery. A recent global forest mapping project for the period 2000–2012 (Hansen et al., 2013) shows general spatial agreement with this study between 2002 and 2010 in spite of the different periods. It shows the existence of forest in the region, and largely agrees with other regions having losses and regeneration in other parts of the landscape. Although the Hansen et al. (2013) work has been criticised for possible misrepresentation of the forest class (Tropek et al., 2014), they rebut this criticism by arguing that ambiguities mostly arose from their definition of ‘tree cover’ which essentially included all plantations (rubber trees, plantation forests) above 5 m (Hansen et al., 2014). Their work shows that a spectral-driven classification offers useful insights at a large spatial scale. We do not use their work for a comparative accuracy assessment of our classification, however, because of the different periods covered. The Hansen et al. results only cover two relatively recent dates (2000 and 2012) compared to this study.

Tree regeneration in Murchison Falls National Park is attributable to improved Park management, which has kept at bay encroachment from illegal slash and burn, and agricultural activities (Nangendo, 2005), and change in grazing regimes especially by the reducing elephant populations (Eltringham & Malpas, 1980; Smart et al., 1985; Lock, 1993). The section of the National Park immediately north of Budongo forest has similar climatic condi-

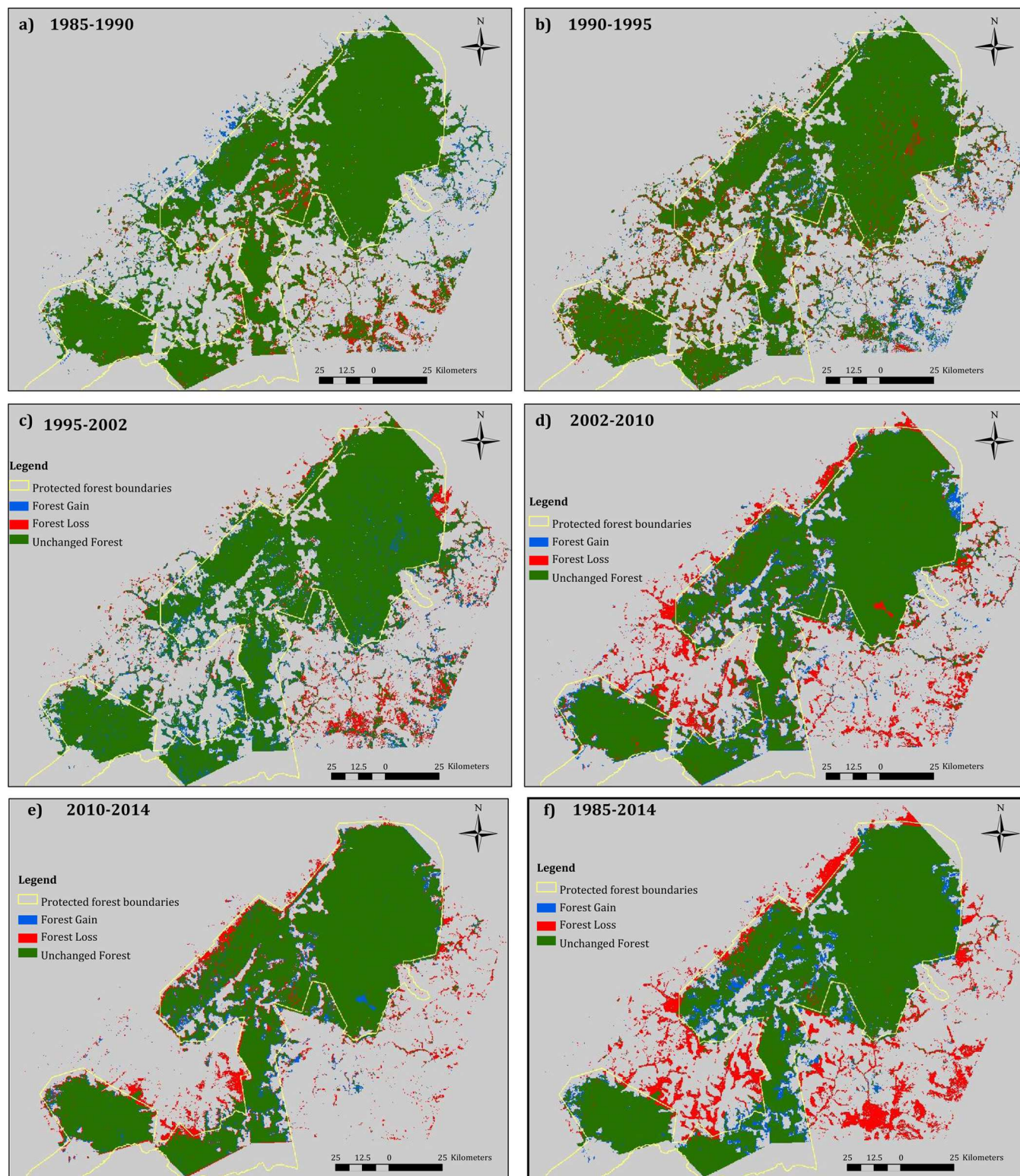


**Fig. 12.** Forest cover change in and around Bugoma between (a) 1985–1990, (b) 1990–1995, (c) 1995–2002, (d) 2002–2010, (e) 2010–2014, (f) The whole period: 1985–2014.

tions to Budongo, which favours tropical forest regeneration (Smart et al., 1985); and with better protection in the recent past, tree growth is inevitable. Elephants feed on a large volume of herbage per day, and disrupt vegetation regeneration (Ssali et al., 2012); therefore their reduction should allow forests stability. The notion of elephant decline as a basis for explaining forest regeneration in

this part of the landscape is, however, largely based on old studies and some recent anecdotal evidence, and therefore requires further research.

In contrast, there is evidence of dramatic loss of forest corridors, riverine forests, and forests on private landholdings in the regions south of Budongo forest, but with some cycles of regener-

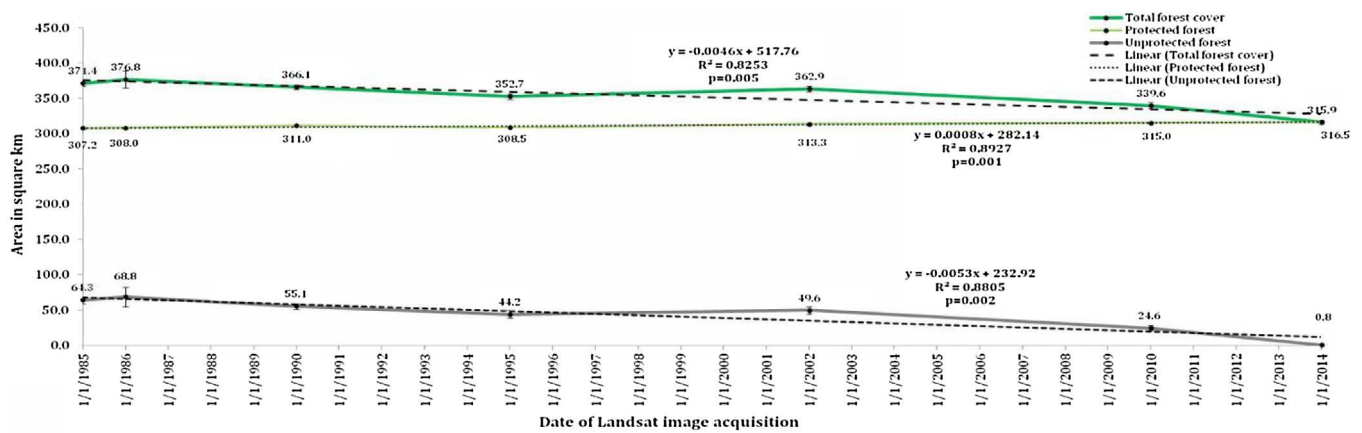


Fig. 13. Forest cover trend in the protected and unprotected areas in and around Bugoma (Error bars are standard deviations).



Plate 1. Forest clearance on private land around Bugoma (Taken during fieldwork: Feb, 2014).

ation and loss, as in other regions of the country (Majaliwa et al., 2010; Twongyirwe et al., 2011; Sassen et al., 2013). The local-level losses are examined more closely in the following sections.

#### 4.2. On forest cover patterns in the Budongo case study

Based on the remote sensing evidence, the protected forest appears to have remained relatively stable over 30 years, an indication of successful management although some encroachment is visible in the forest interior and at the boundaries. Spatially, deforestation is mostly patchy, and more prevalent in forests on private land, including corridor forests and those close to protected forests. The protected forest boundary delineation seems to have been mostly clear throughout the study period. Cleared forest patches immediately surrounding the forest follows the boundary extents. There is a small section of forest in the south and south-west of Budongo accounting for less than 1% of the total forest that has remained stable for the last 30 years. It is not clear whether this is protected, but if so there may be a boundary registration problem; or whether it has not yet been discovered to be unprotected, in which case, it may become threatened like the other small patches that were directly connected to the protected forest. The flattening off of forest change in unprotected areas in the recent period (2010–2014) could be an indicator that nearly all the exploitable forest has gone, suggesting that a potential threat now exists to the remaining protected forest. Annual average forest loss rates (3.3%) in this case study are slightly higher than the projected national

forest loss rate of 1–3% (Kayanja and Byarugaba, 2001), although this estimation was based on expert judgement.

Expansion of commercial farming of sugarcane and built-up areas are the major land uses changes that replace forest cover in this part of the landscape (Mwavu and Witkowski, 2008). Commercial farming expansion accelerated rapidly after 2002, mostly as a result of aggressive expansion of the out-grower scheme which eroded some of the existing forest on private land. This is qualified by a key informant who provided a detailed account of the policies and management regimes and targets of the company after re-opening, as follows: “Kinyara Sugar Works started in 1972, and due to regime changes it collapsed in the late 1970s. It was rehabilitated in 1996 and re-opened. After opening, it was managed by ‘Bukotite’, and a UK board, who were the leading company at the time. They concentrated on the sugar estate. 1500 tonnes of sugar was produced per day by 1996, and out-growers were few at the time, contributing between 3000 and 4000 ha, although sugar production went up to 50,000 tonnes/annum until 2006. In 2006, the government privatised the company, and remained with 51% shares while the 49% was taken by the ‘RAI’ group. Between 2006 and 2008, a new management team, SMC senior management consultants, was hired from Mauritius; they maintained the management plan, and remained at the same production levels, but the expansion plan fell through. In 2008, a new team (Agro-management Resources, UK) came in and exploited the potential in the area. They surveyed and looked for untapped potential: coffee was on the decline, having suffered from pest and disease infestation, they provided sugarcane as an alternative, and the out-grower scheme grew from 15,000 ha

to 20,000 ha: increasing at a rate of an additional 3500 ha of new land from 2010 to 2013, in a radius of 35–40 km. Land belonging to the company alone is 8600 ha. The annual production of sugar currently stands at 100,000 tonnes per annum [at the time of the interview]. In the out-grower scheme, the owner registers his/her land, and Kinyara covers all costs of opening it up, weeding, seedlings, and costs are recovered at harvest time when cane is supplied to the factory. The contracts go up to 5–6 years with 3 ratoon crop harvests.”

#### 4.3. On forest cover patterns in the Bugoma case study

The analysis shows that the protection of Bugoma forest reserve over the 30 years was largely successful although there is some evidence of encroachment in the nature reserve. Losses in other areas of the protected forest might be related to management harvesting. This takes place between 30 and 60 years for trees with a minimum dbh ~40 cm (MWE, 2013). Guidelines to avoid loss of standing crop not ready for harvesting are known, and often, there is a forest supervisor available to control thinning (MWE, 2013). Illegal logging as an additional cause for some losses cannot be dismissed. Later recovery (and an overall marginal increase) in some areas, and infilling at the boundaries are also evident, possibly due to the clear demarcation and regular surveillance.

Expansion of small-scale farming and a shifting cultivation frontier explains the majority of forest loss in fragmented unprotected landscapes in this region, and poses a potential threat to the remaining protected forest. There was evidence of this during fieldwork. The length of fallow periods is declining in many tropical regions (Houghton, 2012), and the lack of agricultural inputs with continuous tillage exhausts soil nutrients (Lambin and Meyfroidt, 2011). While this is one potential explanation for agricultural frontier expansion into forested zones, the contribution of expanding populations, and the underlying and proximate drivers, remain largely speculative. The role of livelihood conditions (rural incomes, levels of education, land tenure systems, cropping patterns, etc), and bio-physical conditions including but not limited to slope, aspect, and soil quality, may all provide an explanation of the observed trends.

In both the Budongo and Bugoma case studies, it is somewhat surprising that no large compartments in the protected blocks were cleared in the last 30 years (based on the image analysis). Management plans for both forests point to the strict surveillance of the boundaries and maintaining of clear borders with private areas. Weaknesses in staffing levels and remuneration (contributing to corruption), and funding constraints are among the main problems highlighted (MWE, 2012, 2013). However, we note that we do not address in this study the issue of forest quality, or the possibility that there may be degradation in the protected areas. More information on this might be obtained from texture-based examination of aerial photographs. Certainly, it is possible to see areas on aerial imagery that suggest removal of natural forest and subsequent replacement with regular plantations. However, availability of historical cloud-free aerial photography is patchy and incomplete, and getting consistent coverage that would give as complete a picture as the satellite archive is likely to be very challenging.

## 5. Conclusions

A “bird’s eye view” is necessary to understand forest cover patterns in a complex and diverse landscape. The established, rich Landsat archive was thoroughly explored, and the analysis suggests that dominant patterns have been rigorously identified in the Northern Albertine Rift Landscape even though with a limited number of images. This analysis is more detailed both in the spatial and

temporal patterns it reveals, than has previously been published in the literature, where, for instance, only a starting and an ending point have been considered. This conclusion is strengthened by zooming down to smaller scales, where statistically significant trends can be extracted. This work could have made use of some recent cloud free scenes obtained after 2004, but these were made unusable due to the scan-line corrector failure; future research is required to fill the gaps. Algorithms (e.g. Zeng et al., 2013) for infilling the Scan-line Corrector (SCL)- error gaps could be tested whether they provide forest areas that lie on this study’s temporal regression trends. However, it would take an irregular temporal process (of drastic deforestation and then recovery) to refute the deforestation trends constructed for the last 30 years in this paper.

This study examined forest cover changes within the Northern Albertine Rift Landscape at two scales: landscape- and local-scales. At the landscape-scale changes were obscured by dissimilar processes in the landscape, where gains mostly in Murchison Falls National Park offset widespread losses in the forest corridors and around the protected forest blocks. The apparent recent recovery in the national park is encouraging. However, signals that appear evident at a large scale may misrepresent local-level dynamics. Forest losses were more dramatic in regions south of Budongo and around Bugoma, and mostly on privately owned (“unprotected”) land. The protection of the gazetted areas was to a great extent successful, with some regions of infilling in Bugoma forest, although there may have been some (‘minimal’) encroachment in both Bugoma and Budongo in the period of analysis. It was not possible to establish from this analysis whether this was purely management-related or due to illegal logging or a combination of both. Forest losses are relatively recent, tending to be between 1995 and 2010, and not much activity is detectable between 2010 and 2014 as possibly all the available clearable forests have already been destroyed. This suggests a potential threat to the remaining protected areas, and indicates that continued efforts to preserve the woodland within the boundaries are likely to be essential. Meanwhile, the small amounts of corridor forest will require extra protection if the last few regions are to be maintained.

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