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ORIGINAL ARTICLE

Using multitemporal Landsat TM imagery to establish land use pressure induced trends in forest and woodland cover in sections of the Soutpansberg Mountains of Venda region, Limpopo Province, South Africa

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Abstract Globally, tropical forests are being perturbed by human activity. Tropical vegetation constitutes some of the largest terrestrial carbon stocks against the build up of greenhouse gases. In this paper, a local-scale case study utilising remote sensing methodology in estimating forest loss is presented, for a section of tropical South Africa's Soutpansberg Mountains where land use pressure threatens some of the last remaining indigenous forests. Landsat TM images from October 1990, August 2000 and September 2006 were used, together with municipality level demographic data. Hybrid image classification techniques distinguished forest cover on the images, which were classified into vegetation density categories. About 20% of forest and woodland cover was lost in the 16-year analysis period, mainly due to pine and eucalyptus plantation and residential housing expansions. The local-scale key drivers behind the deforestation are examined.

Keywords Deforestation · Vegetation · Remote sensing · South Africa

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Introduction

Removal of forest and woodland is of ecological concern in the contexts of, among others, biodiversity conservation and groundwater recharge (Shimabukuro et al. 1998), and carbon stock provision in buffering the build up of CO_2 as a greenhouse gas (Foody et al. 1996; Patenaude et al. 2005). Globally, tropical forests are being destroyed, mainly by human activity. In Africa, tree cover is perturbed by several natural and human factors, including fire, livestock grazing, human population and cultivation (Bucini and Hanan 2007), thereby contributing to deforestation. Deforestation is defined as conversion from forest land to non-forest land (subject to the definition of 'forest') (DeFries et al. 2007).

In South Africa's Limpopo Province, provision of energy from wood, urban expansion and agriculture are some of the key issues behind deforestation (Department of Environmental Affairs and Tourism 2003). Historical government settlement policies saw the relocation and concentration of native South Africans in 'homelands'. In the former Venda homeland, these high human concentrations affect the eastern edge of the Soutpansberg mountain range and have resulted in localised pressure on woodlands and forests for purposes of settlement and subsistence agriculture in places. The conservation status of the Soutpansberg mountain bushveld vegetation unit of the savannah biome is officially categorised as 'vulnerable' (Mucina and Rutherford 2006). The unit consists of a rainfall gradient distribution of dense deciduous woodlands and evergreen montane forests with a poorly developed grassy layer, as well as relatively open savannah in places (Mucina and Rutherford 2006). Outside the area under the former Venda homeland, exotic eucalyptus and pine plantations on the Soutpansberg range put added pressure on the maintenance of the status of the Soutpansberg mountain bushveld vegetation unit.

Multitemporal remote sensing is useful in monitoring the trends in status of tropical forests and woodlands (Myers 1988; Foody et al. 1996; Phua et al. 2008), and can provide data in support of decision making for the management of harvesting and protection of threatened tropical forests and woodlands, including in the context of international protocols (Stoms and Estes 1993; Archard et al. 2002; Patenaude et al. 2005; DeFries et al. 2007; Buchanan et al. 2008). The methods utilised in monitoring forest degradation and deforestation by remote sensing broadly measure indicators of the biophysical attributes of the surface (spectral information), the seasonality of these attributes (temporal information), and their fine-scale spatial pattern (spatial information) (Lambin 1999). One of the most commonly used approaches is pixel-based classification comparisons, in which the multitemporal images of forest locations are classified into categories that enable forest cover change mapping in a GIS framework (e.g. Prins and Kikula 1996; Sánchez-Azofeifa et al. 2001; Alves 2002; Dezso et al. 2005; Vågen 2006; Buchanan et al. 2008). Sub-pixel classification comparison approaches have also been used, for example spectral mixture analysis in which the relative abundance of specific components (end members) of the forest landscape is quantified on the multitemporal images to enable forest area change assessment. Brandt and Townsend (2006) used green vegetation, non-photosynthetic vegetation, dark soil, light soil and shade as end members on multitemporal imagery in a forest degradation study. Phua et al. (2008) have used a related technique involving change vector analysis and image differencing of multitemporal image pattern decomposition coefficients. Image segmentation, in which homogenous forest pixels are connected according to their properties, has also been utilised in deforestation assessment (e.g. Shimabukuro et al. 1998).

Coppin et al. (2004) provide an overview of the common change detection methods in remote sensing applied to ecosystem monitoring, and note that pixel-based classification comparisons have the advantage that separately classifying the multitemporal imagery minimises the problem of radiometric calibration between dates. A further advantage of classification comparisons is the capability to produce a matrix of change information (Lu et al. 2004). Key pre-requisites of successful post classification change detection include accurate image registration (Mouat et al. 1993; Serra et al., 2003; Lu et al. 2004; Lillesand et al. 2004; Jensen 2005) and accurate image classification (Serra et al. 2003; Coppin et al. 2004; Lillesand et al. 2004). However, often there is inadequate information for interpretation of historic images, making the classification process difficult (Lu et al. 2004). Classification and registration errors are compounded in the resulting change detection (Serra et al. 2003; Lillesand et al. 2004).

In this study, multitemporal image classification was utilised to quantify and map forest cover change on parts of the Soutpansberg mountain range in South Africa's Limpopo Province, which included the Venda region. A pixel-based classification approach was employed in the study. Deforestation is of concern in South Africa in general, with negative ecological and socioeconomic consequences on the livelihoods of some already impoverished people (Smith 1991; Du Plessis 2000; Binns et al. 2001). Mapping and quantifying the deforestation is potentially beneficial in the context of planning remedial measures. The study presents remote sensing derived data from a localised area on rates of tropical forest conversion.

The study area

The study area is located in Vhembe District in the north-eastern part of South Africa, in Limpopo Province (previously Northern Province) (Fig. 1). Administratively, Vhembe district is divided into four local municipalities: Makhado, Musina, Mutale, and Thulamela. The most densely populated areas are in Thulamela and Makhado municipalities. The area has a tropical climate favouring the fruit plantation agriculture that is common, with a distinct (summer) rain season from October/November to March/April.

Large parts of the region in which the study area is located were under nominal autonomy as the Venda 'homeland' from 1979 until the political changes of 1994 when it was reincorporated into the Republic of South Africa. Most of the homeland encompassed either eastern parts of the scenic hilly terrain landscape of the Soutpansberg range, or parts of the hot and relatively arid Limpopo valley. During the autonomy, the capital town was Thohoyandou (Fig. 1b), and the homeland encompassed mainly what is now under Thulamela and Mutale municipalities, as well as the eastern part of Makhado Municipality. The confinement to the homeland meant that in the semi urbanised villages surrounding Thohoyandou, demand for land for housing and agriculture inevitably resulted in encroachment onto the forests and woodlands of the Soutpansberg Mountains.

The vegetation communities in the Soutpansberg Mountains occur as east–west bands, following the orientation of the ridges of the mountain range. The topography changes drastically over short distances, resulting in orographic rain on the southern ridges and a rainshadow effect on the northern ridges (Mucina and Rutherford 2006). Higher rainfall on the southern slopes supports dense deciduous woodlands at lower altitudes consisting of small-tree species

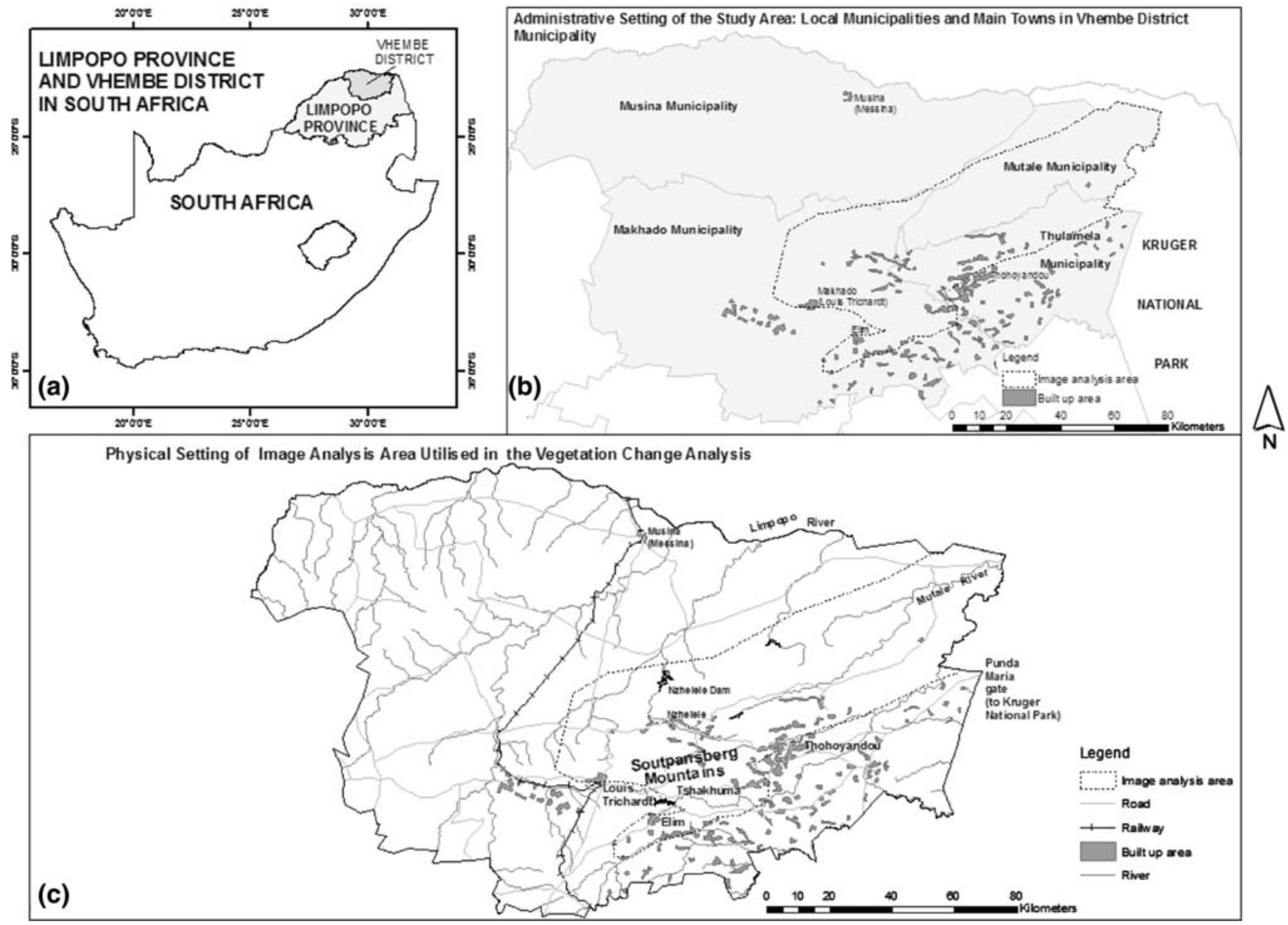

Fig. 1 Location setting of the study area

(dominated by *Englerophytum magalismontanum*, *Diospyros whyteana*, *Schefflera umbellifera*, *Tarchonanthus trilobus* subsp. *galpinii*, *Aloe vogtsii*) and dense evergreen montane forests consisting of small-tree species (e.g. *Rapanea melanophloeos*, *Podocarpus falcatus*, *P. latiflius*, *Celtis africana*, *Brachylaena discolour* subsp. *Transvaalensis*, *Nuxia floribunda*, *Cussonia spicata*), with the more arid northern ridges consisting of tall-tree (e.g. *Acacia nigrescens*, *Adansonia digitata*, *Brachystegia spiciformis* in places) and small-tree (e.g. *Combretum apiculatum*, *Commiphora glandulosa*, *C. mollis*) species (Butt et al. 1994; Mucina and Rutherford 2006). There are a number of tree species in the Soutpansberg Mountains that are endemic to the area (e.g. *Pavetta trichardtensis*, *Aloe vogtsii*, *Combretum vendae*, and about 13 others) and others that are protected plants in South Africa (Butt et al. 1994; Mucina and Rutherford 2006).

Parts of the Soutpansbergs to the north-west of the town Louis Trichardt (Makhado; Fig. 1b, c) are conserved. The image analysis in this study utilised the none-conserved areas to the east (about 535,124 ha in size), which includes high density human settlements and a number of softwood (pine, eucalyptus) forest plantations on the high rainfall southern slopes. The softwood from the plantations is utilised in industry elsewhere in South Africa (sawlogs, pulpwood, mining timber, poles and other log uses; DWAF 2005). The plantations are commercial, some owned by the South African Forestry Company Ltd (SAFCOL, some 14,000 ha) and others by the pulp and paper company Mondi.

Materials and methods

ERDAS Imagine 9.1 was used for image analysis, with additional analysis and supporting mapping undertaken using ArcGIS 9.0. A GPS with 5 m accuracy was used during field work.

Remotely sensed image data

Landsat TM imagery (30 m spatial resolution) were selected for use in the forest cover change study primarily because the swath width of Landsat images could cover the

Soutpansberg Mountains synoptically, thereby avoiding the difficulties involved if a mosaic of images from different dates were to be used as would be the case with smaller swath width (larger spatial resolution) images. Early spring time images were selected because, for this area, it is mainly trees (and little to no grass) that are in leaf in early spring, which reduced the spectral confusion between forest and grass during forest cover extraction from the images. The image dates used were 6 October 1990, 30 August 2000, and 16 September 2006 (WRS 169-76). All of the images were cloud free. From each image, the north-western quadrant, which covers the Soutpansberg Mountains, was utilised.

The South African National Land Cover (NLC) maps compiled for 1996 (NLC96) and 2000 (NLC2000) were used as base land cover maps for interpreting the location of forest cover types on the three image dates. Based on consideration of the time difference between the NLC maps and the image dates, the 1990 image was interpreted with respect to the NLC96 cover types (Fig. 2a), whereas the 2000 and 2006 images were interpreted with respect to the NLC2000 map (Fig. 2b).

Image preprocessing

The images were geometrically registered (UTM projection, Zone 36S, WGS 84) with sub-pixel root mean square error (RMSE). Being historic images, the required meteorological data at image acquisition time for use in atmospheric correction models, such as aerosol composition (Lu et al. 2002), was not available. Consequently, only correction for the additive effects of atmospheric back scattering was undertaken, using the dark object subtraction technique (Chavez 1988) for the visible TM bands.

From each image date, a subset was extracted that encompassed the Soutpansberg Mountains as closely as possible while at the same time including land close to the edge (slopes) of the mountains that is under forest perturbing human activity such as built-up (settlement) areas, forest plantations and orchards. This subset (Figs. 2, 3) thus included mountain slope areas near the towns Louis Trichardt (Makhado) in the west, the hills in the vicinity of Elim to the south, Nzhelele in the north, and just north of Thohoyandou (Fig. 1).

Delineation of forest cover from remotely sensed image data

Forest cover was delineated on each of the image subsets using an image classification approach that combined elements of unsupervised and supervised classification. In the process, unsupervised classification was employed in clustering the images into vegetation density classes. The resulting clusters served as spectral signatures that were then named (based on field-observed tree density) and edited, and on-screen digitizing of training areas for non-vegetated features (water, burnt land) present in the image scenes employed in generating spectral signatures for these features. The spectral signatures generated were then collectively used in a supervised maximum likelihood classification of the respective images that yielded the vegetation cover thematic layers with which forest cover change analysis was undertaken. The image classification approach utilised was, therefore, *hybrid classification*, which is particularly useful in analyses where there is complex variability in the spectral response patterns for individual cover types such as in vegetation mapping, as was the case in this study, and improves the accuracy of purely supervised or unsupervised classification alone (Clark et al. 2001; Lillesand et al. 2004).

A number of cover categories on the South African National Land Cover (NLC) maps are related to natural tree cover (excluding forest plantations) as shown in Table 1, in addition to the cover category termed 'forest'. On the older NLC map (NLC96) forest and woodland are combined in one cover category in addition to a separate 'forest' category as well as degraded forest and woodland, whereas on the NLC2000 forest and woodland are separate cover categories but combined in the class 'degraded: forest and woodland' (Fig. 2). Because of these overlaps and the fact that forest degradation opens up the forest, this study considered all areas under the natural tree-related NLC cover categories in Table 1 as important. Image areas covering all the NLC natural tree-related cover types in Table 1 were, therefore, of relevance to the analysis in this study. Thompson (2004) has similarly combined the NLC cover classes woodland, thicket, bushland, bush-clump and tall fynbos in a comparison with the 'savannah' category on another national database. As indicated in Table 1 forest is, by definition, linked to tree density. Based on this tree density criterion, unsupervised classification using the iterative self-organising data analysis (ISODATA) algorithm was employed in clustering each of the three image subsets into six classes showing a gradient of vegetation density and vigour from the most dense and vigorous to dry, bare land. The resulting spectral signatures were then edited and named, and signatures for water and burnt land added by digitising polygons representing these respective features and adding their spectral statistics to the signature file generated by the ISODATA clustering, resulting in eight classes (Fig. 4) whose spectral signatures were used for a final supervised maximum likelihood classification (bands RGB:345).

The eight classes used in the classification were defined on the basis of a combination of field observation and the spectral profiles in the TM bands compared to the known

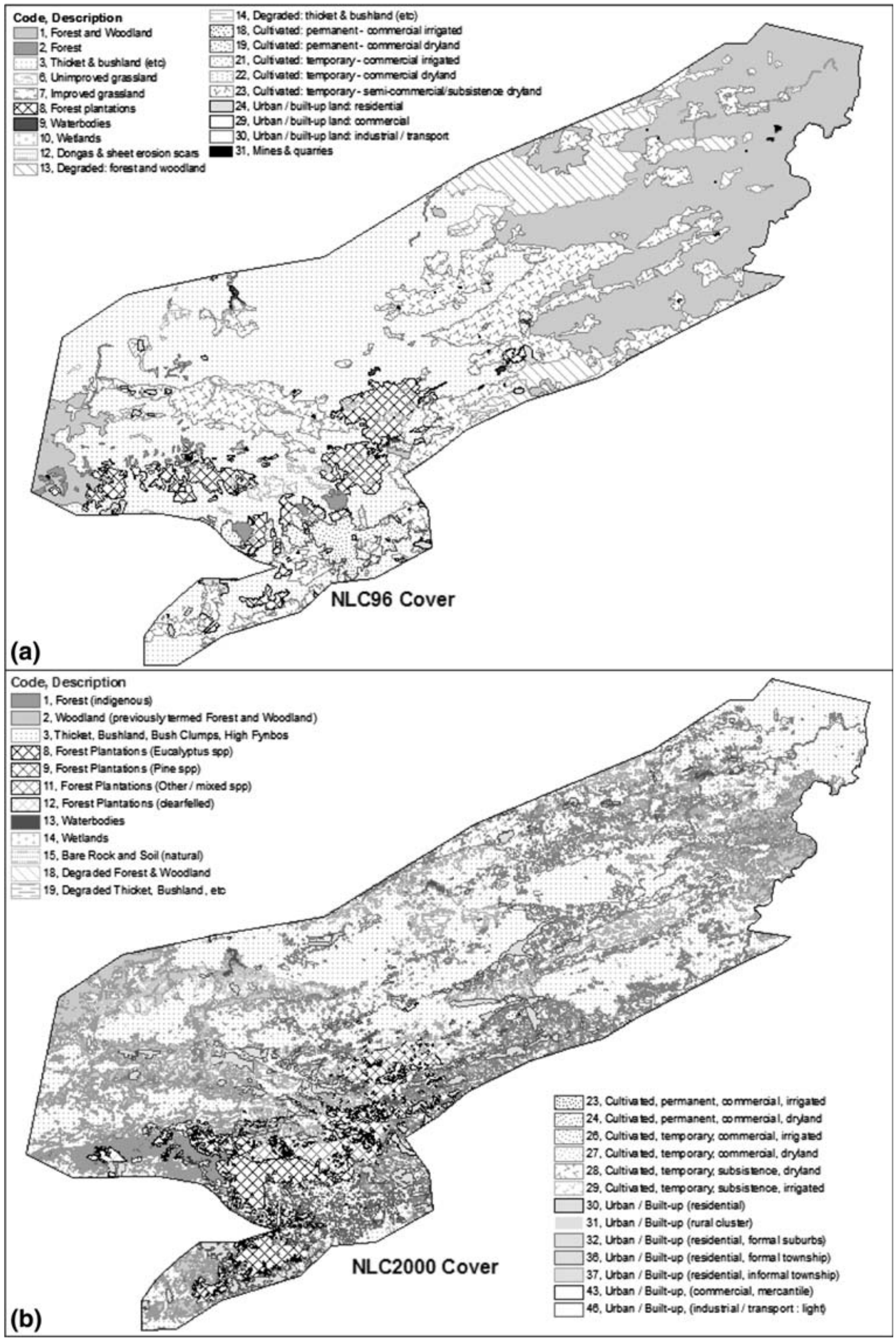

Fig. 2 Land cover maps of the image analysis area encompassing the Soutpansberg Mountains, from (**a**) the NLC96 (NLC96 Cover) and (**b**) the NLC2000 (NLC2000 Cover) maps of South Africa

typical spectral behaviour of vegetation in that healthy vegetation (dense) has high near infrared (TM4), low red (TM3) and decreasing mid-infrared reflectance (TM5, TM7) with increasing mid-infrared wavelength, whereas dry soil has higher red, lower near infrared and increasing (higher) mid infrared reflectance with increasing wavelength (Lillesand et al. 2004; Jensen 2005). Water and burnt land have low reflectance beyond the visible spectral region (TM1, TM2, TM3). Sparse vegetation has influence of dry soil and litter reflectance where present, lowering near infrared and increasing red reflectance. These patterns are depicted in Fig. 4, showing that the interpretation of the class spectral signatures was in accordance with established theory. Accordingly, Kogan et al. (2003) have

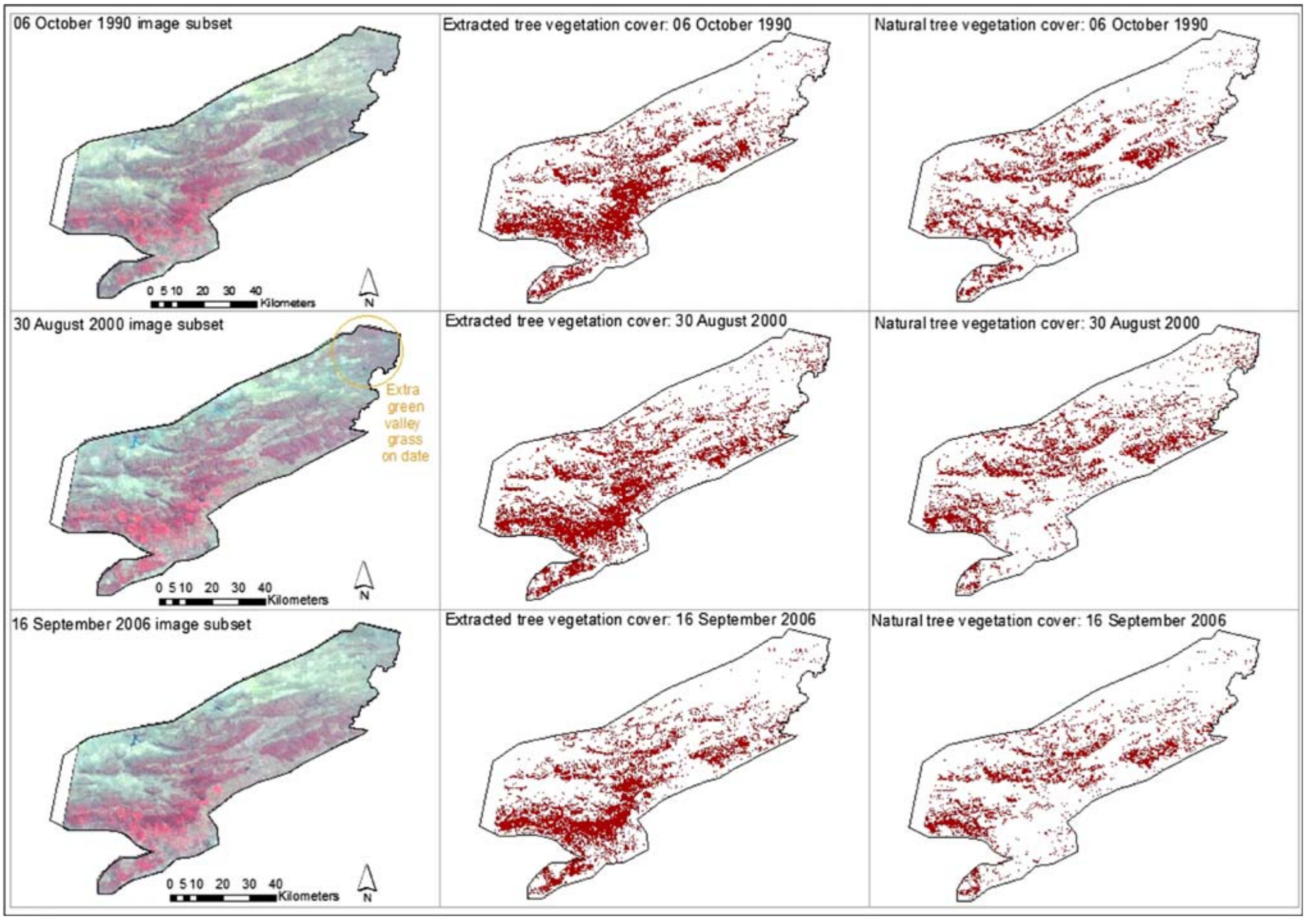

Fig. 3 Image analysis area subsets from the full WRS 169-76 Landsat TM scenes for the three analysis dates (RGB:432). For each subset, the tree vegetation cover delineated by the image processing procedures is mapped. The natural tree vegetation cover layer excludes forest plantations. Slight differences in image extent on the western edge of the image analysis area are due to slight drifts in ground coverage of WRS 169-76. The 30 August 2000 image depicts extra green grass in the Forest and Woodland class (Fig. 2b), resulting in forest cover area estimation error

Table 1 Definition of vegetation terms relevant to forest (tree) cover used on vegetation land cover classes on the South African National Land Cover (NLC) maps for 1996 (NLC96) and 2000 (NLC2000)

Term	Description/definition (Mucina and Rutherford 2006)	Relevant NLC96 land cover codes in Fig. 2a	Relevant NLC2000 land cover codes in Fig. 2b
Forest	A plant community having a continuous tree layer, with or without a shrub/herbaceous layer, or ‘vegetation type possessing canopy cover ≥75% of trees taller than 2 m’ (Edwards 1983).	1, 2, 13	1, 18
Woodlands (savannah)	Typically vegetation with a grass-dominated herbaceous layer and scattered low to tall trees. It includes the closed woodland and open woodland of Edwards (1983) with a tree cover less than 75% and generally greater than 1%.	1, 13	2, 18
Thicket	Very dense vegetation usually formed by low or tall shrubs and some trees.	3, 14	3, 19
Bush	A local regional term generally applied to various forms of savannah vegetation south of the miombo belts in southern Africa.	3, 14	3, 19
Fynbos	The dominant vegetation of the Fynbos Biome. The biome consists of shrublands, herblands, and grasslands.		3, 19

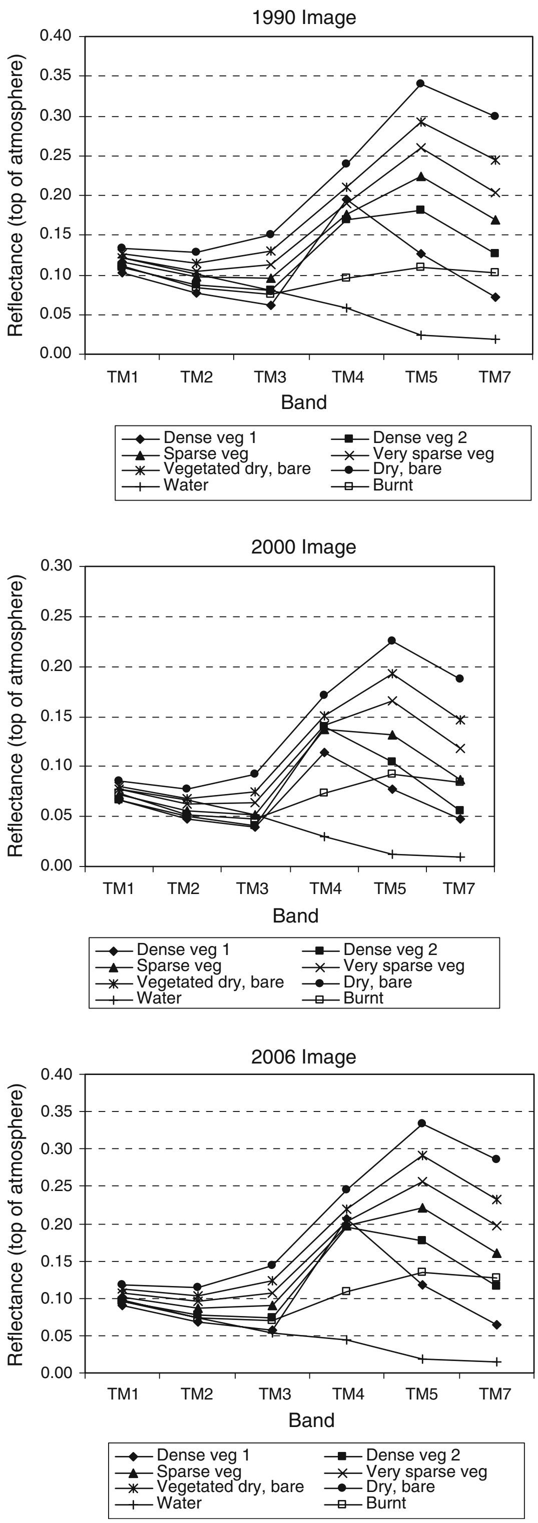

Fig. 4 Plots of mean top of atmosphere reflectance values per band for the eight classes into which the three images were classified. The eight classes used were: dense, vigorous vegetation 1; dense, vigorous vegetation 2; sparse vegetation; very sparse vegetation; vegetated dry, nearly bare; bare, dry; water; burnt land

shown that there is a strong positive correlation between vegetation (crop) density and a vegetation condition index based on the NDVI (which utilises the near infrared versus red reflectance contrast). Field site verification indicated that the unsupervised clustering could distinguish two categories of dense vegetation (dense veg 1, dense veg 2 in Fig. 4) on the basis of a gradient in near infrared (TM4) versus red (TM3) reflectance.

The spectral signatures of all eight classes were least separable in the visible bands TM1 and TM2 (Fig. 4), which were subsequently omitted from the image classification process in order to utilise the strong spectral contrast between vegetated and non-vegetated land on the red-near infrared (TM3, TM4) edge, along with band 5 (TM5). Foody et al. (1996) used a similar combination of TM bands in Landsat image classification, pointing out that Landsat TM data are generally three-dimensional with visible, near- and mid-infrared wavelength dimensions, which were represented by bands TM3, TM4 and TM5, respectively. This three band, three-dimensional representation of Landsat TM data in image classification for vegetation analysis has also been employed by other authors (e.g. Hill 1999; Clark et al. 2001; Buchanan et al. 2008), while Tottrup (2004) similarly omitted the visible bands due to their poor contribution to signature separability.

On the NLC96 map, the natural tree-related cover types that are of relevance to forest (as described in Table 1) are 1 (forest and woodland), 2 (forest), 3 (thicket and bushland, etc.), 13 (degraded: forest and woodland) and 14 (degraded: thicket and bushland, etc.). The parts of the 1990 image subset under other cover types except these were masked out in order for forest cover change detection to focus on these tree-related cover types that are of relevance to forest. On the NLC2000 map, the natural tree-related cover types are 1 (forest—indigenous), 2 (woodland—previously termed forest and woodland), 3 (thicket, bushland, bush clumps, high fynbos), 18 (degraded forest and woodland), and 19 (degraded thicket, bushland, etc.). Areas under all other cover types except these were masked out from the 2000 and 2006 image analysis area subsets. Thus, the delineation of natural forest cover (natural tree vegetation cover in Fig. 3) utilised all the unmasked tree-related cover classes on the respective image subsets, because they all have elements of tree cover in their definition (Table 1). Forest plantations were excluded from the forest cover mapping but their area of cover per image date was calculated using the NLC96 map for the 1990 image and the NLC2000 map for the 2000 and 2006 images as guides to forest plantation extents.

Mapping and quantification of forest cover change

On each of the classified images, the dense and sparse vegetation classes were interpreted as collectively mapping forest cover (based on Table 1) and were, therefore, merged to extract forest cover, resulting in the natural tree vegetation cover thematic layers in Fig. 3, which represent forest cover per respective date. The sparse vegetation spectral signature encompassed woodland areas as well and pixels classified as sparse vegetation were, therefore, included in extracting forest cover so as not to exclude woodland which was grouped with forest as ‘Forest and Woodland’ on the NLC96 map (Fig. 2a). Then the forest cover thematic layers for 1990, 2000 and 2006 were recoded as 2, 3 and 4, respectively, which gave unique resulting codes from the Boolean addition operation utilised, compared to the coding of 1, 2, 3. A Boolean addition model involving the intersection area of the three recoded thematic layers was then assembled in the image processing software, resulting in a forest cover change map (Fig. 5) in which, in addition to these three respective codes, 5 denoted forest cover in 1990 and 2000, 6 denoted forest cover in both 1990 and 2006, 7 denoted forest cover in both 2000 and 2006, and 9 denoted forest cover in 1990, 2000 and 2006 (i.e. locations with no forest cover change). From this forest cover change map, area of cover for the respective dates could be computed and the results assessed at municipality level in conjunction with demographic (socio economic) data from the South African government central statistics agency (Statistics South Africa, StatsSA).

Classification accuracy assessment and field verification

Field visits for purposes of determining vegetation characteristics for use in image interpretation were undertaken in September 2007, with follow-on visits for verification of change in October 2007 and as part of classification accuracy assessment in August 2008. Vegetation density characteristics were observed at eight forest sample sites during the first fieldwork phase, and site GPS positions and descriptive information on approximate canopy cover per 30 m plot taken. The sites were chosen largely on the basis of ease of access, and subsequently located on the classified images for purposes of interpreting and naming classes.

Classification accuracy assessment in a long time span multitemporal image data set has commonly been performed for the newest image only (e.g. Brandt and Townsend 2006; Buchanan et al. 2008). The accuracy assessment in this study was similarly more reliable for the newest (2006) image classification, from which a stratified random sample of 211 field points was generated for comparison against reference data from field visits in August 2008. These points were subsequently visited in the

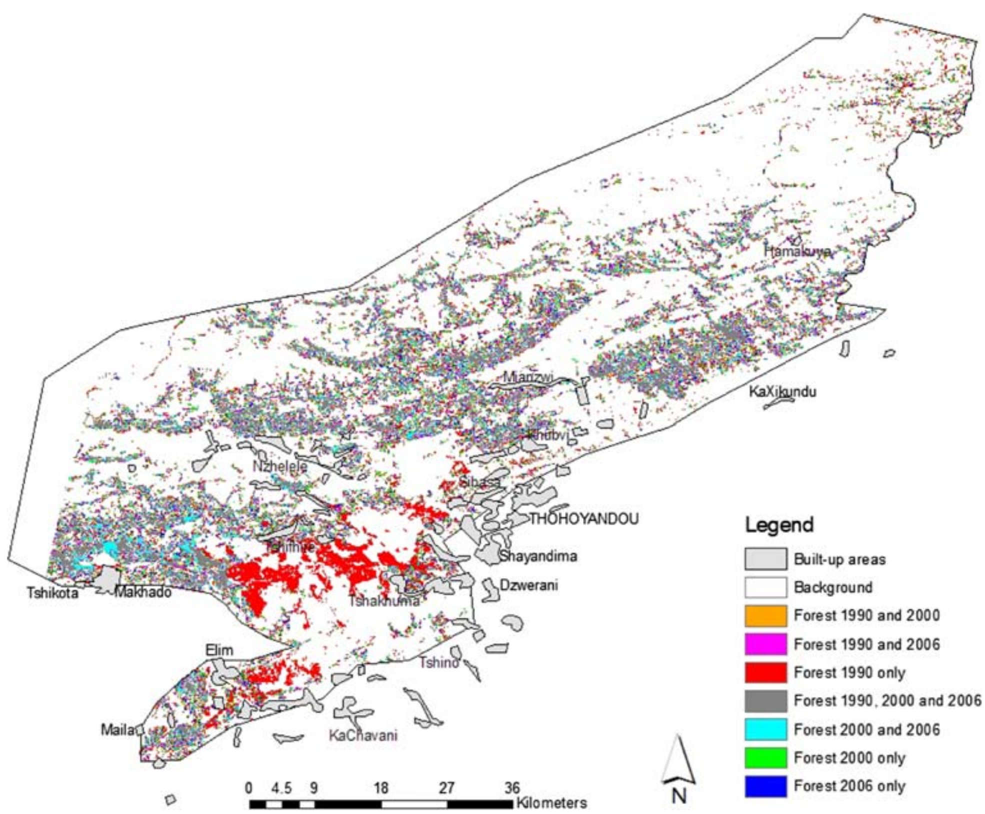

Fig. 5 Forest cover change map for the whole image analysis area. The image is a result of Boolean pixel overlay processing of the intersection area of the forest cover thematic layers in Fig. 3 (explanation in “Mapping and quantification of forest cover change”)

field wherever accessibility permitted, or as close to the point as possible where there were accessibility problems, which is usually the practical solution to field verification site accessibility problems (Brandt and Townsend 2006).

Based on field verification as reference data, the classification accuracy of the newest image was established to be 89.6% (Table 2). The classification procedures generally delineated the dense vegetation classes accurately (88.9 and 85.7%, respectively; Table 2), with the poorest predictions by the classification scheme being those for water and burnt land (75.0 and 71.4%, respectively). Verification for the burnt land class was particularly difficult due to the historical nature of the images. Consequently, burnt land verification sites were only indirectly judged correctly classified where grass was found to be the dominant cover type. Although widely varied, the dense vegetation category encompassed forest areas ranging from nearly complete canopy closure to more open locations with about 65% canopy closure per 30 m square. The classification accuracies of the 1990 and 2000 images, approximately 87 and 85%, respectively, were assessed using 1:50,000 topographic maps as surrogate reference data because they were less reliably assessed from field visits due to the large time difference since imaging dates, given the possibility of vegetation change.

The coordinates of sites identified as having undergone complete forest vegetation loss were entered into a GPS and visited. During the field visits the suspected cause of the forest loss was verified by establishing the current land use/land cover at the sites. A total of 16 sites in accessible locations were visited, 11 currently under residential housing and 5 under forest plantations.

Results

Overall forest cover change in image analysis area

Table 3 shows the resulting quantification of area of forest cover delineated by the image processing procedures that utilised the unmasked image sections under land cover classes on the South African National Land Cover maps with elements of natural trees taken as forest location indicator (see above, "Delineation of

Table 2 Classification error matrix for the newest image

Classification data	Reference data									
	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Total	User's accuracy (%)
Class 1	16								16	100.0
Class 2	2	24							26	92.3
Class 3		4	39						43	90.7
Class 4			1	40	2				43	93.0
Class 5				6	39	1			46	84.8
Class 6					3	23			26	88.5
Class 7							3	2	5	60.0
Class 8							1	5	6	83.3
Total	18	28	40	46	44	24	4	7	211	
Producer's accuracy (%)	88.9	85.7	97.5	87.0	88.6	95.8	75.0	71.4		
Overall accuracy (%) 89.6										
KHAT (overall, %) 85.4										

Class 1 Dense, vigorous vegetation 1; *Class 2* dense, vigorous vegetation 2; *Class 3* sparse vegetation; *Class 4* very sparse vegetation; *Class 5* vegetated dry, nearly bare; *Class 6* bare, dry; *Class 7* water; *Class 8* burnt land

Table 3 Area of natural tree (forest) cover resulting from image analysis per administrative unit (municipality) on the three image dates compared to area under vegetated forest plantation for the image analysis area

Image date	Natural tree cover area (ha)					Forest plantations area (ha)				
	Whole area	Thulamela	Makhado	Mutale	Musina	Whole area	Thulamela	Makhado	Mutale	Musina
6 October 1990	91,476.3	26,334.0	43,015.1	22,011.9	115.2	23,460.4	10,052.3	13,399.0	9.1	0
30 August 2000	93,170.9	25,702.9	38,212.6	29,187.9	67.5	36,422.2	11,653.2	24,640.6	128.4	0
16 September 2006	73,179.8	21,368.0	32,415.8	19,364.0	32.4	35,380.7	10,933.7	24,330.6	116.4	0

forest cover from remotely sensed image data"). For the whole image analysis area, the area under natural forest declined by about 20% (18,296.5 ha) from 91,476.3 ha in 1990 to 73,179.8 ha in 2006. In Fig. 5, the area that had natural forest in 1990 but none in both 2000 and 2006 (i.e. forest 1990 only) is indicated in red. Forest loss since 1990 is important since it indicates a non-reversed trend based on three observation dates as opposed to loss since 2000 or 2006. The location of this loss in natural forest cover is in the vicinity of human settlements in the vicinity of Elim and Tshakhuma, as well as the forest plantation zone east of Makhado to just west of Tshakhuma.

The slight increase in natural forest cover to 93,170.9 ha in 2000 can be attributed to presence of green grass (indicated by a yellow circle in Fig. 3) in the Limpopo-Mutale river valley section of the area, within the cover class Forest and Woodland on the NLC96 map, and mainly Thicket and Woodland on the NLC2000 map (compare circled area in Fig. 3 with respective locations in Fig. 2). This greenness was peculiar to the location on the date, resulting from a peculiar flood pattern prior to the date due to a small amount of dry season rains in June and July 2000 compared to little or none in the same period in 1990 and 2006 (Fig. 6a). The locations with peculiar greenness mainly fall within Mutale Municipality (Fig. 1a), and when the computation of area under forest cover per image date is narrowed to municipality level as shown in Table 3, it is clear that this increase in area under forest cover between 1990 and 2000 is isolated in this municipality alone because all the other municipalities show a decline in area under forest between the two dates. Makhado Municipality had the largest decrease in area under forest cover between 1990 and 2006 (10,599.3 ha, or 24.6%), followed by Thulamela (4,966.0 ha, or 18.9%), Mutale (2,648.0 ha, or 12%) and then Musina (82.8 ha, or 72%). The change in natural forest cover in Musina Municipality is disproportionate because only a small fraction of the municipality was included in the image analysis area (Fig. 1a).

In comparison, the area under vegetated forest plantations in the image analysis area, derived by delineation from the respective images using NLC forest plantation cover, increased from 23,460.4 ha in 1990 to 36,422.2 ha in 2000 (12,961.8 ha, or 55.2% increase) and 35,380.7 ha in 2006 (50.8% increase). The slight decrease in area under forest plantations between 2000 and 2006 is attributable to harvesting (clear felling) of the pine and eucalyptus trees between the two image dates in that by the 2006 image date some of the trees had been cut and, consequently, the fields with the harvested timber were not classified as vegetated (dense or sparse vegetation categories, Fig. 4). The increase in forest plantations was in all administrative units (municipalities) except Musina, with the largest increase being in Makhado, about 11,241.6 ha (83.9%) between 1990 and 2000. Therefore, of the 12,961.8 ha total increase in forest plantation in the whole image analysis area between 1990 and 2000, about 11,241.6 ha were within Makhado municipality (1,600.9 ha in Thulamela, and 119.3 ha in Mutale). From a direct computation of area under the forest plantation cover category for the entire image analysis area on the NLC maps in Fig. 2, there were 29,126 ha of forest plantation on the NLC96 map and 44,646 ha on the NLC2000 map, an increase of 15,520 ha (53.3%) between 1996 and 2000. The slight differences between these totals and those in Table 3 are, firstly, because of the time difference between the NLC maps and the image dates, during which the plantation area changed (1990 image versus NLC96 data from 1996 and NLC2000 data versus the 2006 image), and secondly because the data in Table 3 are for detected vegetated forest plantations excluding harvested (none vegetated) plantations at image time.

So whereas the total area under natural tree vegetation declined by 18,296.5 ha between 1990 and 2006, the area under forest plantation increased by up to 12,961 ha in 2000. Increase in forest plantations, therefore, appears to account for some 12,000 ha (about 66%) of the decline in natural forest cover, the remainder being attributable to other human perturbations such as settlement expansion which was verified in the field. The demographic data in Table 4 are indicative of these sources of perturbation.

Natural forest cover change related to causative factors

A number of socioeconomic and natural causative factors can be responsible for the forest cover change detected, including climatic factors, government policy, economics and tenure. In this study, the forest management policy by government (DWAF 2005) was judged little changed with respect to enforcement in the area, despite the political changes of 1994 and new regulations being passed since then. However, forest conservation policy seems to have improved given a number of relevant pieces of legislation passed since 1994 (DWAF 2005). There is an ongoing process of land tenure transformation since the political changes of 1994 that involves restitution of land to local communities, a politically sensitive issue, but as far as was known to the researchers at the time of the study no large tracts of land had been transferred to the communities in the Soutpansberg Mountain study area. Therefore, natural tree harvesting practices and clearing for alternative uses as part of economic development was assumed as the main driver of forest cover change in the area.

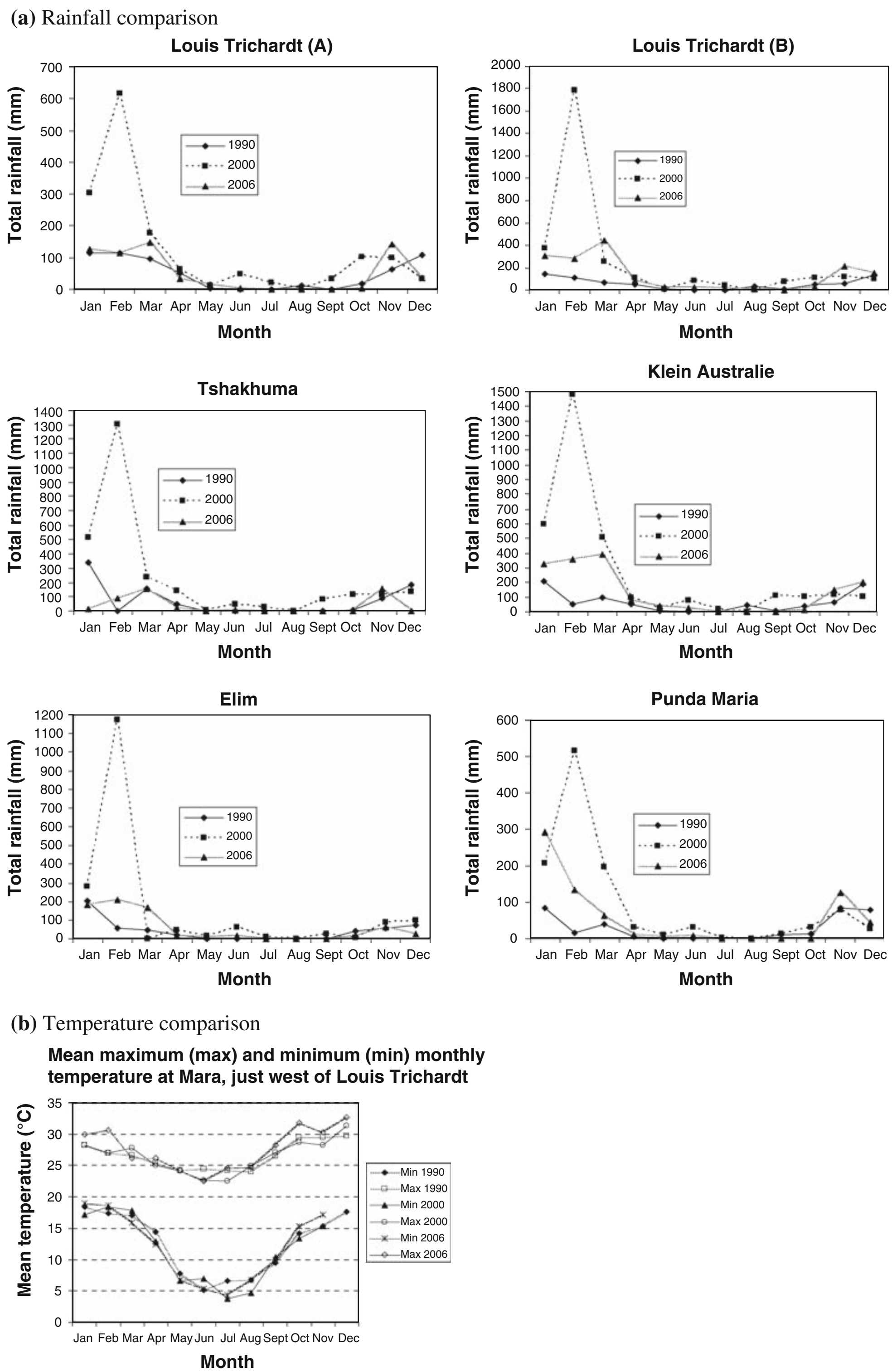

Fig. 6 Comparison of rainfall (**a**) and temperature (**b**) in the image acquisition years using data from weather stations in the vicinity of the Soutpansberg Mountain study area (see Fig. 1c for station locations. Station Klein Australie is on a forest plantation just west of Tshakhuma). The image acquisition dates were 6 October 1990, 30 August 2000 and 16 September 2006. Most stations recorded some rainfall in the months June/July 2000 compared to little or no rainfall in the same period in 1990 and 2006, helping explain the downstream valley extra green grass on the 2000 image indicated in Fig. 3. *Data* South African Weather Service

Table 4 Demographic data for Vhembe District: municipality population, income levels (15–65 year age group), number of households per selected source of energy/fuel for cooking, and number of household dwellings per category

Municipality	Selected summaries of income status from 2007 Community Survey (15–65 age group, black individuals)		Population (2001 Census)[a]	Cooking energy source: number of households				Household dwellings			
				2001		2007		2001		2007	
	No income	Income less than R800 (US$100)		Electricity	Wood	Electricity	Wood	House or brick structure on separate stand (plot)	Traditional dwelling/hut/structure	House or brick structure on separate stand (plot)	Traditional dwelling/hut/structure
Mutale	56.3%	83.7%	18,433	1,565	16,011	2,507	17,357	9,484	8,121	14,669	5,732
Makhado	55.4%	79.4%	113,141	23,599	79,787	34,846	73,508	72,599	27,551	98,046	12,064
Musina	34.9%	62.7%	13,955	5,207	6,872	9,459	3,336	6,537	3,040	8,000	1,418
Thulamela	58.3%	80.3%	128,365	24,773	94,992	38,895	91,856	68,176	51,528	109,962	24,774

Source of data: Statistics South Africa (StatsSA), http://www.statssa.gov.za/ (accessed 25 August 2008)

Electricity chosen in view of government electrification programme, wood chosen due to impact of wood consumption on forests

[a] Since 1994 the administrative units have changed, so there are no comparable municipality data for censuses before and including the 1996 census

Climate

Dry season rainfall in the three months prior to image acquisition date explains the detected slight increase in natural forest cover to 93,170.9 ha in 2000 attributed to presence of green grass (indicated by a yellow circle in Fig. 3). There was some rainfall in the months June/July 2000 compared to little or no rainfall in the same period in 1990 and 2006 (see Fig. 6a), helping explain the downstream valley extra green grass on the 2000 image. The drainage flow direction is generally north-eastwards (Fig. 1c) towards the flat Limpopo valley, hence the extra green grass vegetation in the Limpopo valley circled in Fig. 3. In the long term, the rainfall patterns of the southern Africa region has been in cyclic periods lasting about two decades, with the 1970s having been wet, and the period from the late 1970s into the mid 1990s dry (Mason 2001). The image analysis period in this study was, therefore, largely in the dry phase of the cycle and, therefore, long term change in total seasonal rainfall is unlikely to have caused the large shifts in forest cover observed. Differences in temperature in the months prior to image acquisition dates, through influence in onset of spring, could have affected the mapped vegetation but a comparison of the temperatures (Fig. 6b) shows that there were no large differences prior to the three image acquisition dates (June–July 2000 slightly cooler in association with the off-season rains).

Socioeconomic factors

Forest exploitation for wood fuel in the area can be examined in the context of income levels. Government social improvement measures have seen an increase in household access to electricity and better housing (Table 4). However, despite the increase in household access to electricity, wood is still preferred for cooking to electricity by some households, due to the costs involved in using electricity. Data from the 2007 Community Survey by the state statistics agency Statistics South Africa (StatsSA) shows that about 80% of individuals in the 15–65 years age group have income less than R800 (1US$ = R8.00) per month (i.e. less than US$100 per month) in the municipalities Makhado, Mutale, and Thulamela (Table 4) that also constituted most of the study area (Fig. 1b). Between 34.9 and 58.3% of individuals in the 15–65 age group in the study area have no income (Table 4). Given the traditional 'extended family' structures (i.e. societal obligation to support relatives) and financial demands of higher priority, electricity (and the required electric cooking appliances) is relegated to the status of a luxury in terms of domestic cooking by some households, hence the continued usage of wood.

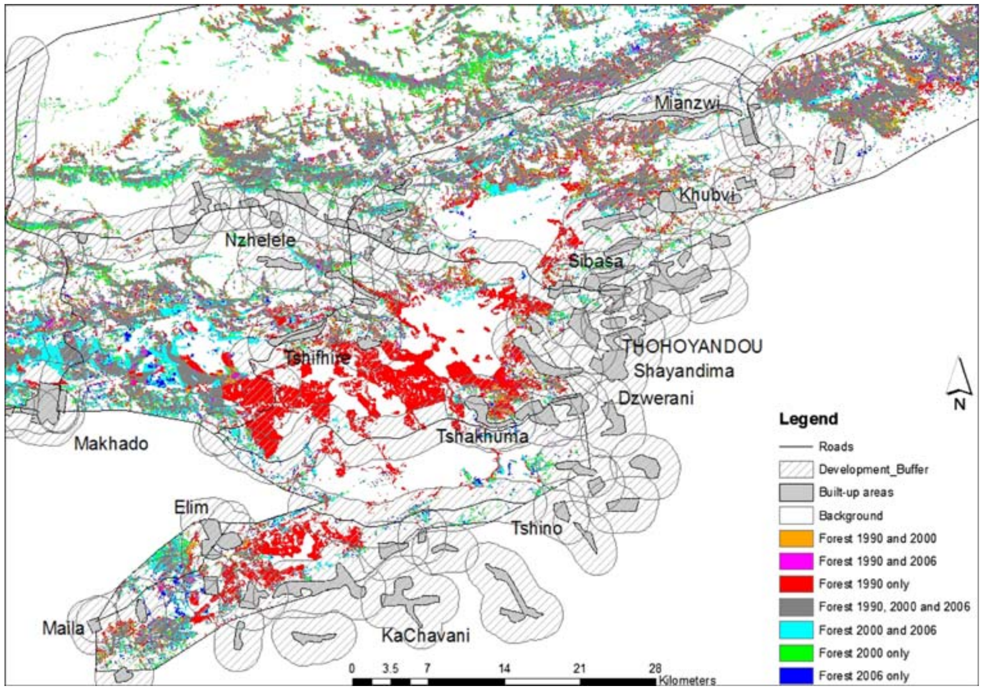

Fig. 7 The southwestern sector of Fig. 5 at larger scale, illustrating the spatial association of natural forest loss with exotic species forest plantation expansion and built up areas, using a 2 km buffer around roads and settlements (termed 'development buffer'). Most of the locations in Fig. 5 with consistent forest loss since 1990 (Forest 1990 only) are within this buffer

Figure 5 shows that the largest area of consistent spatial loss in forest since 1990 (indicated in red) is in the relatively affluent triangular region between Louis Trichardt, Thohoyandou and Elim, which also encompasses the area of growth in forest plantations (Fig. 2). As shown in Table 4, the number of permanent (brick) houses has also increased, resulting in expansion of settlements. The expansion in the settlements was judged in the field to be less than 2 km from the position of old housing as existed in 1990. Using this 2 km distance, a 2 km buffer around major roads and settlements (built up) areas is shown in Fig. 7 in order to illustrate the relationship between land development and loss of natural tree vegetation since 1990 (indicative of a continuous loss trend as opposed to since 2000 or 2006 only). This combined buffer around roads and settlements ('development buffer') encompasses 16,582 ha of natural forest land that has been lost since 1990, accounting for 90.6% of the 18,296.5 ha total decline in area under natural tree vegetation between 1990 and 2006. Therefore, expansion in exotic species forest plantations and urban expansion appear to be the main causes of the loss of natural forest in the area. Though the correlation analysis is limited by there being only three observations in Table 3, there is a negative correlation between the total area of natural tree cover and area of forest plantations ($r = -0.366$, $P > 0.05$, not significant).

Discussion

As established in "Natural forest cover change related to causative factors", expansion in forest plantations between 1990 and 2006 in the image analysis area is one of the main causes of decline in natural woodland and forest cover in the study area. The other perturbing factors are wood collection and settlement expansion. Some locations in Fig. 5 appear to have no forest in 1990 but with forest in 2000 and 2006, which is attributable to slight differences in grass greenness as influenced by microclimate, for example the dry season rainfall experienced prior to the 2000 image (see Fig. 6a). Whereas the number of households using wood as the energy source for cooking is generally on the decline (except in the more rural Mutale Municipality) and the use of electricity is generally on the increase (Table 4), the number of planned brick houses on separate plots is on the increase. The housing infrastructure requires land, resulting in encroachment on the natural forest and woodland areas. The increase in number of brick housing has apparently resulted in decline in number of traditional mud-and-thatch dwellings. Both the increase in use of electricity and in the number of brick housing is due to government development policies since the political changes in 1994. Despite increase in use of electricity, wood is still in use as a supplementary energy source, based on the fact that wood is largely free whereas electricity is not. Of the four municipalities in which the image analysis area extended, Makhado is the most affluent, followed by Thulamela and Musina. Makhado and Thulamela municipalities have the largest increase in brick housing infrastructure 25,447 and 41,786, respectively, between 2001 and 2007. The two municipalities are also the location of the largest amounts of decrease in natural woodland and forest cover between 1990 and 2006, totalling 10,599.3

and 4,966.02 ha, respectively, for Makhado and Thulamela. Whereas most of this decline is due to expansion in forest plantations in Makhado municipality, in Thulamela the increase is largely due to expansion of residential settlements (Fig. 7).

The classification scheme was generally accurate with respect to classes that were utilised in delineating forest cover, and generally consistent for the three images (see Figs. 3 and 4), making the change detection reasonably accurate. The relatively low prediction accuracies for water and burnt land (Table 2) did not limit the accuracy of change detection because these cover classes were not utilised in the final forest cover change detection. Given the classification accuracies of the 1990 and 2006 images (87 and 89.6%, respectively), the accuracy of the resulting change map between the two images at approximately 78% is reasonably indicative of the trend in woodland loss in the area. This trend would not be sufficiently indicated by a mere differencing of the 1990 and 2000 NLC land cover maps because the differencing would not detect changes in amount of woodland and forest that have resulted from tree harvesting within the areas delineated as forest and woodland on the NLC maps. As shown in Fig. 5, the multitemporal image classification and GIS overlay analysis employed in this study was able to detect such change, particularly in relation to settlement (built up) areas (Fig. 7). In addition, the NLC96 and NLC2000 cover categories (Fig. 2) are not directly comparable. For example, the results from the study could have been narrowed down to change in indigenous forest only, excluding woodland and thickets. This, however, could not be undertaken because the older land cover map of South Africa (NLC96) used in support of interpretation of the 1990 image grouped woodland categories together with forest, hence the wider analysis involving all tree-related land cover classes (including thickets). Woodlands are, however, included in the South African National Forests Act which seeks to promote the sustainable management and development of forests, which makes their inclusion in this study important. The inclusion of all tree cover land cover categories places the results of the study in the context of studies in other parts of Africa that stress the importance of tree cover (e.g. Grouzis and Akpo 1997; Hansen et al. 2002; 2003; Bucini and Hanan, 2007). For example, Bucini and Hanan (2007) and Hansen et al. (2003) have used MODIS-derived tree cover data sets as opposed to forest cover in their analysis. Compared to continent-wide studies of tree cover in Africa that are spatially less detailed, this study presents results from at a localised scale to yield finer scale estimates of the effect of land use pressure on tree cover, using comparatively high spatial resolution imagery. Friedl et al. (2002) highlight the effect of spatial detail in land cover monitoring, stating that at the 1 km spatial resolution scale, land cover is largely static at quarterly (96 day) intervals.

Tree cover mapping using MODIS imagery (Hansen et al. 2003) has shown that in southern Africa land use pressure (from land development and human population density) have a negative impact on tree cover, and that at the regional scale these pressures vary per country depending on land development and human population density. This study is in accordance with these lower spatial resolution mapping results and shows the nature of the land use pressures at a local scale for South Africa which is relatively more developed than the other countries in the sub region. Remote sensing methodology in conjunction with demographic data at administrative unit (municipality) level has, therefore, established that expansion in forest plantations and settlements are the main threats to the Soutpansberg mountain bushveld vegetation unit of the savannah biome (see "Natural forest cover change related to causative factors"), whose conservation status is officially categorised as 'vulnerable' (Mucina and Rutherford 2006). The plantations are mainly located on the higher rainfall southern slopes where dense woodland and evergreen forests are located, thereby replacing these indigenous forests. The forest plantation industry is, however, important to the economy in the area, and Vhembe district is noted as part of the planned 'forestry development cluster' in the 2004–2014 Limpopo Provincial Development Plan (in addition to Mopani district to the south-east), providing employment not only directly in the plantations themselves but also in the 'down-stream' activities of saw mills and other timber processing facilities (Limpopo Provincial Government 2004). The forestry industry generally plays an important role in poverty alleviation in South Africa (DWAF 2005) and is, therefore, socioeconomically desirable. In all of Limpopo Province the sector employed some 3200 people as of 2004 (DWAF 2005). Ecologically, however, the exotic species forest plantations can be a source of concern. Although they can play some role in the carbon cycle in the global warming context, they are somewhat less effective in this regard compared to the indigenous forest they replace due to their comparatively less vegetation biomass per unit area. The pine and eucalyptus forest plantations have alien species, thereby being a disturbance to the local ecology. The results from the study demonstrate the usefulness of remote sensing in providing estimates of rates of deforestation, particularly in tropical third world areas that are some of the largest carbon stocks buffering against climate change.

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