Global Assessment of Land Degradation and Improvement: pilot study in Kenya

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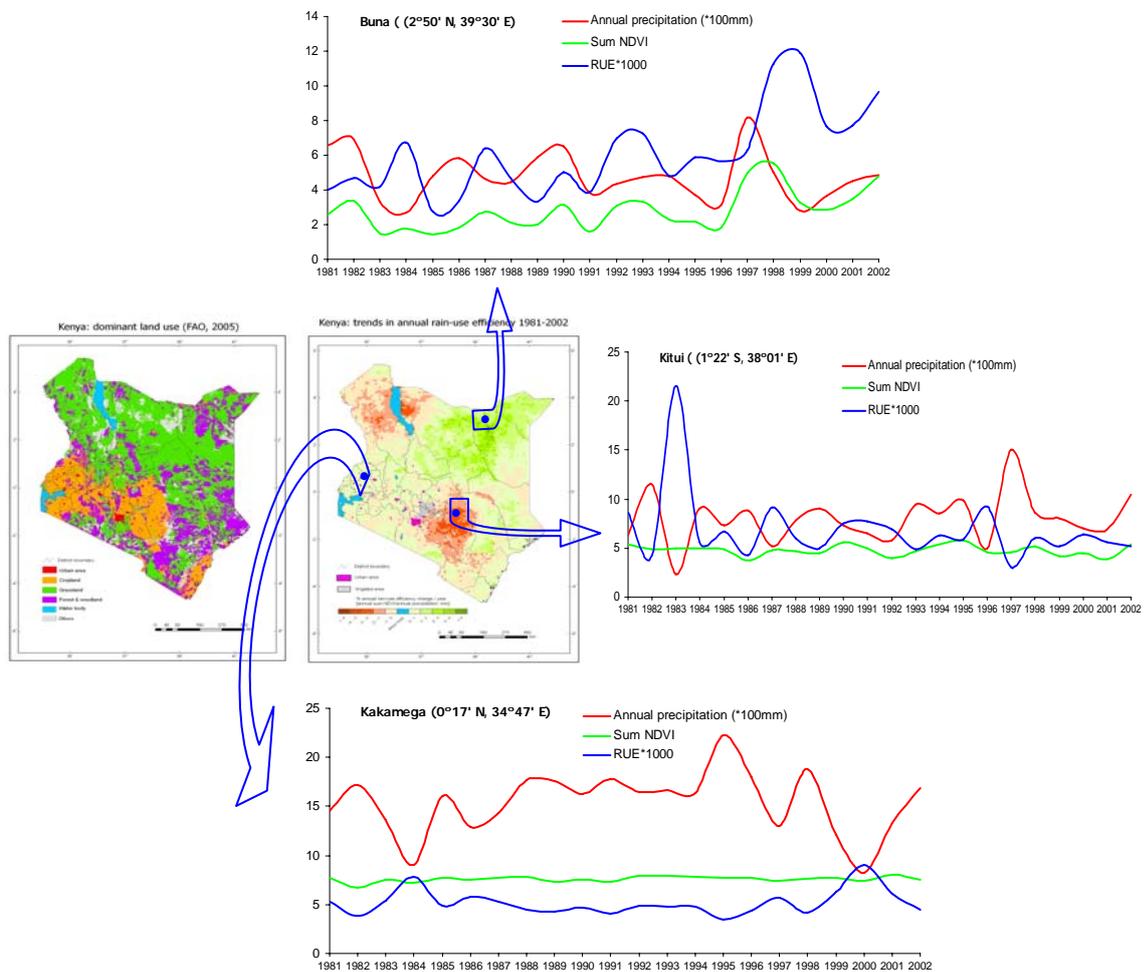
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Front cover: Trends of rain-use efficiency with biomass and rainfall for sites identified as stable, degraded and improved areas of land in Kenya

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EXECUTIVE SUMMARY

Land degradation is a global development and environment issue. It is pivotal to the United Nations Convention to Combat Desertification, the Convention on Biodiversity, the Kyoto Protocol on Global Climatic Change, and the Millennium Goals. However, there is no authoritative measure of land degradation or its counterpoint - land improvement. There is pressing need for an up-to-date, quantitative and reproducible assessment to support policy development for food and water security, environmental integrity, international aid programs, and national strategies for economic development and resource conservation. Within the GEF-UNEP-FAO program *Land Degradation in Drylands*, the *Global Assessment of Land Degradation and Improvement (GLADA)* will identify:

- The state and trends of land degradation;
- Areas suffering severe degradation or at severe risk;
- Places where degradation has been arrested or reversed.

Biomass is an integrated measure of productivity; its deviance from the norm may indicate land degradation or improvement. Biomass can be assessed by remote sensing of the normalized difference vegetation index (NDVI); norms may be established according to climate, soils and terrain and land use; deviance may be calculated regionally and combined globally to allow universal comparisons.

As a pilot for a *Global Assessment of Land Degradation and Improvement*, spatial patterns and temporal trends of green biomass across Kenya were analysed using 23 years of fortnightly NOAA-AVHRR time series NDVI data and CRU TS 2.1 station-observed monthly precipitation. ArcGIS Spatial Analyst and ERDAS IMAGINE were used to calculate various biomass indicators and climate variables; their trends were determined by linear regression at annual intervals and mapped to depict spatial changes. Green biomass and net primary productivity were estimated from NDVI data using MODIS 8-day values for the 4 years 2000-2003. The validity of this procedure was confirmed by comparison with measured values of net primary productivity for grassland in Kenya for the years 1984-1994. Percentage and absolute changes in net primary productivity were calculated for dominant land cover types – grassland, cropland and forest and woodland; urban and irrigated areas were masked. Comparison was made with high-resolution land cover data produced by the Global Land Cover Network.

In Kenya, over the period of 1981-2003, green biomass and net primary productivity increased over 80 per cent of the land area and decreased over 20 per cent. Overall, net primary productivity increased for all dominant land cover types - but hardly at all in cropland; overall, cropland productivity increased by 3.4 kg per hectare per year but over 40% of the cropland area there was a decrease of 13 kg per hectare per year and this decrease is most marked where cropping has extended into marginal lands.

Land cover	Pixels (%)		% NPP change/year			Δ NPP [Kg dry matter ha⁻¹year⁻¹]		
	+	-	+	-	average	+	-	average
Grassland	86	14	0.36	0.09	0.30	32.3	10.5	26.5
Cropland	58	42	0.09	0.07	0.02	15.4	12.9	3.4
Forest & woodland	80	20	0.42	0.09	0.32	31.0	12.3	22.2

To assess whether this trend reflects land degradation or variability in rainfall, rain-use efficiency (the ratio between green biomass (NDVI) and rainfall) was calculated; combined trends of biomass and rain-use efficiency may be a more robust indicator of land degradation than biomass alone in areas where productivity is limited by rainfall.

Potential areas of severe land degradation (referred to within LADA as *hot spots*)were identified as those areas with both declining net primary productivity and declining rain-use efficiency. These areas occupy 17% of the country and 30 % of the cropland. The combined index shows sharpest decline in two areas: the drylands around Lake Turkana and marginal cropland in Eastern Province.

1 INTRODUCTION

Ever-increasing demands on the land from economic development, burgeoning cities and growing rural populations are driving unprecedented land use change. In turn, unsustainable land use change is driving land degradation: soil erosion, nutrient depletion, salinity, water scarcity, pollution, disruption of biological cycles, and loss of biodiversity. This is a global development and environment issue, highlighted in the UN Convention to Combat Desertification, the Convention on Biodiversity, the Kyoto Protocol on Climatic Change and the Millennium Goals (UNCED 1992, UNEP 2007) yet there is no authoritative measure of land degradation or its counterpoint – land improvement. The only harmonized assessment, the *Global assessment of human-induced soil degradation* (Oldeman and others 1991) is a map of perceptions - the kinds and degree of degradation - not a measure of degradation. It is now out of date; land degradation and perceptions have moved on.

There is pressing need for a quantitative and reproducible assessment to support policy development for food and water security, environmental integrity, and national strategies for economic development and resource conservation. In response, within the GEF-UNEP-FAO program *Land degradation in drylands* (LADA), the *Global assessment of land degradation and improvement (GLADA)* will identify: 1) the state and trends of land degradation, 2) places suffering extreme constraints or at severe risk (referred to within LADA as *hot spots*) and, 3) places where degradation has been arrested or reversed.

Biomass is an integrated measure of biological productivity. Its deviance from the local norm may be taken as a measure of land degradation or improvement. Changes in biomass may be measured by remote sensing of the normalized difference vegetation index (NDVI - the difference between reflected near-infrared and visible wavebands divided by the sum of these two wavebands). NDVI has a strong, linear relationship with the fraction of photosynthetically-active radiation absorbed by the plant (Asrar and others 1984, Sellers 1987, 1994, Sellers and others 1997, Fensholt and others 2004, Alexandrov and others 1997, Goetz and others 1999, Rasmussen 1998 a,b, Seaquist and others 2003, Turner and others 2002); many studies have shown strong correlation between NDVI and vegetation cover (e.g. Purevdoj and others 1998) and above-ground net primary productivity (Running and Nemani 1988, Potter and others 1993, Field and others 1995, Prince and Goward 1995, Paruelo 1997, Nemani and others 2003, Wang and others 2004, Maselli and Chiesi 2006). It has been applied in studies of land degradation from the field scale (1:10 000) to the degree of generalization required for national action or international policy development (1:1 million to 1:5 million) (e.g. Tucker and others 1991, Bastin and others 1995, Stoms and Hargrove 2000, Wessels and others 2004, 2007, Singh and others 2006).

Norms may be established by stratifying the land area according to climate, soils and terrain, and land use/vegetation; deviance may then be calculated regionally and combined globally to allow universal comparisons.

This pilot study was commissioned by FAO to:

1. Derive and map indicators of land degradation by analysis of the GIMMS NDVI data (8km-resolution, 23 years);

2. Support with other global data (climate, SOTER, land cover, socio-economic);

3. Illustrate with a case study in Kenya, incorporating high-resolution data on land cover change from Global Land Cover Network.

Bai and others (2005) reported on previous usage of NDVI data, the specific characteristics of the GIMMS dataset, and the development of NDVI indicators of land degradation in a case study in North China. Here, we present NDVI indicators and trend analysis over a 23-year period (1981-2003) with information on climate and land use and biomass productivity from Kenya.

2 METHODOLOGY

2.1 Study area

Kenya depends almost entirely on its land for rural livelihoods, food and water security, and economic development. But more than 80 percent of Kenya is dryland; agriculture is concentrated in the high-rainfall area which also supplies the water for urban centres, hydro-electric power and irrigation. Exploitation of the land without compensating investment in soil and water conservation threatens irreversible land degradation - which means loss of rural livelihoods, water supplies, and wildlife habitat, as well as damage to infrastructure from flooding, sedimentation and landslides. Kenya has made substantial efforts in soil and water conservation and has built up a high level of expertise, yet it is apparent that these efforts have failed to arrest degradation. Information from the present study may focus attention on key areas.

2.2 Methods

The GLADA approach involves a sequence of analyses to identify *hot spots* of land degradation using remote sensing and existing datasets: first using simple NDVI indicators such as mean annual sum NDVI (surrogate for mean annual biomass productivity) and the trend of biomass productivity; secondly, integration of biomass and climatic data (rain-use efficiency); thirdly, linking NDVI to net primary productivity and calculating the changes of biomass production for dominant land use types; fourthly, stratification of the landscape using land cover and soil and terrain data to enable a more localised analysis of the NDVI data. Urban and irrigated areas were masked using contemporary global datasets. Much work has gone into algorithms that enable these screening analyses to be undertaken automatically.

At the next stage, the *hot spots* will be characterised manually, using 30m-resolution Landsat data, to identify the probable kinds of land degradation. At the same time, the continuous field of the index of land degradation derived from NDVI and climatic data will enable a statistical examination of other data for which continuous spatial coverage is not available - for instance spot measurements of soil attributes, and social and economic data that may reflect the drivers of land degradation, providing these other data are geo-located.

Finally, field examination will be undertaken by national teams within the wider LADA program.

2.3 Data

NDVI: The Global Inventory Modelling and Mapping Studies (GIMMS) data set comprises very high resolution radiometer (AVHRR) data collected by National Oceanic and Atmospheric Administration (NOAA) satellites. The fortnightly images of 8km-spatial resolution are corrected for calibration, view geometry, volcanic aerosols, and other effects not related to actual vegetation change (Tucker and others 2004). The accuracy of GIMMS is proven to be suitable for a global assessment and it is compatible with NDVI data from other sensors such as MODIS, SPOT Vegetation, SeaWIFS and LandSAT ETM+ (Tucker and others 2005, Brown and others 2006). GIMMS data from July 1981 to December 2003 were used for this study.

Climate: The CRU TS 2.1 dataset, created by the Climate Research Unit of the University of East Anglia, UK, comprises 1224 monthly grids of meteorological station-observed data for the period 1901-2002 covering the global land surface at 0.5 degree resolution. The data were collated from as many stations as possible to develop both monthly mean climatology (1961-1990) and time series (1901-2002) of various climate variables (New and others 1999, 2000), using thin-spline interpolation (Hutchinson 1995) with consideration of elevation effects. Data are available for: daily mean, minimum and maximum temperature; diurnal temperature range; precipitation, wet-day frequency; frost-day frequency; vapour pressure; and cloud cover (Mitchell and Jones 2005). Monthly precipitation data from January 1980 to December 2002 were used for the Kenya analysis.

Also available for this application is the VASClimO Climatology 1.1 (Variability Analyses of Surface Climate Observations), a globally gridded data set of observed station precipitation at the Global Precipitation Climatology Centre (GPCC) assembled by the German Met Service (DWD). It consists of gridded monthly data for the global land area (excluding Greenland and Antarctica) from January 1951 to December 2000 at various resolutions on the basis of long and nearly gap-free, quality controlled station records. The gridded monthly precipitation at resolution of 0.5°x0.5° which includes 65 617 grid points with 9 343 stations (Beck and others 2005) will be tested for GLADA application once it has been converted to an automatically readable format.

Land use: For this preliminary comparison, land cover data interpreted manually from satellite imagery (FAO 2005) have been generalised to three broad land use types: cropland, grassland, and forest and woodland (Figure 1).

Kenya: dominant land use (FAO, 2005)
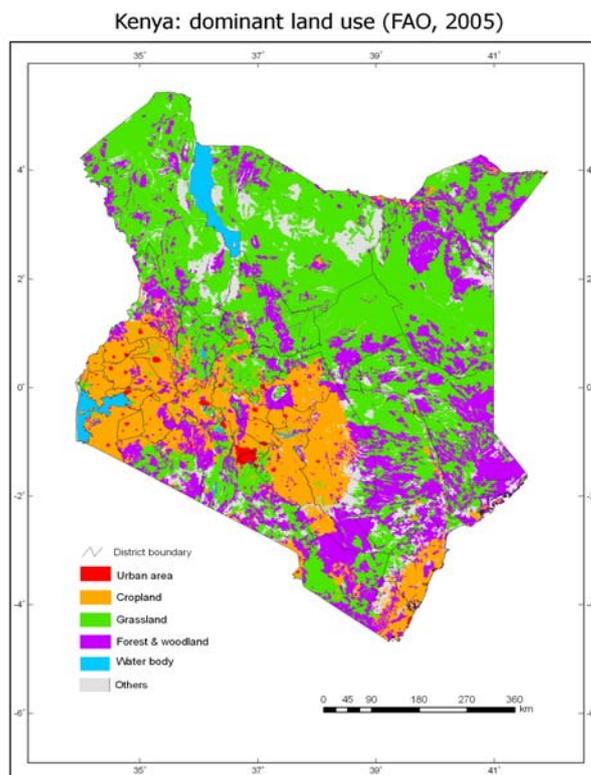
Figure 1.   Kenya: dominant land use types (FAO 2005)

Soil and terrain: The global Soil and Terrain database (SOTER) comprises harmonized spatial and soil attribute data incorporating the 90m-resolution SRTM digital elevation model (van Engelen and others 2005). The KENSOTER database at 1:1 M for Kenya has been prepared to stratify the study area according to the kinds of soil and terrain (Batjes and Gicheru 2004).

Net primary productivity (NPP): MODIS NPP data (MOD17A3) is a global dataset of terrestrial gross and net primary productivity derived from moderate-resolution imaging spectroradiometer data at 1-km resolution at an 8-day interval (Heinsch and others 2003). The 8-day NPP was computed from the product of PAR, f_{APAR} (fraction of absorbed photosynthetically active radiation) and conversion efficiency coefficients obtained from other MODIS (MOD15A2) and ancillary data (biome properties look-up table). The MOD17 NPP is comparable to the Ecosystem Model–Data Intercomparison (EMDI) NPP data set; global total MODIS GPP and NPP are inversely related to the observed atmospheric CO_2 growth rates, and multivariate ENSO index, indicating that MOD17 is reliable (Zhao and others 2005, 2006). The dataset has been validated in various landscapes (Fensholt and others 2004, 2006, Gebremichael and Barros 2006, Turner and others 2003, 2006).

For Kenya, the annual MODIS NPP dataset between 2000 and 2003 was used to calibrate NDVI in terms of NPP. In addition, the relation was tested by comparison with field measurements of net primary productivity of savanna grassland in Nairobi National Park (Kinyamario 1996).

Urban/Rural extent: Global Rural-Urban Mapping Project (GRUMP) produced by the Center for International Earth Science Information Network (CIESIN) of the Earth Institute at Columbia University renders human populations in a common geo-referenced framework. Data include: gridded population of the world with urban reallocation, in which spatial and population data of both administrative units and urban extents are gridded at a resolution of 30 arc-seconds; a 30 arc-second land area grid showing urban areal extents worldwide; and a database of human settlements, their spatial coordinates, and populations (CIESIN 2004). In this study, the Urban/Rural Extents dataset is used to mask the urban area.

Global map of irrigated areas: The digital global map of irrigated areas was developed by combining irrigation statistics for 10 825 sub-national statistical units and geo-spatial information on the location and extent of irrigation schemes (Siebert and others 2006). The map shows the percentage of each 5 arc-minute by 5 arc-minute cells that was equipped for irrigation around the year 2000. The latest version (4.0) was used to mask irrigated land areas. We have considered only those pixels in which more than 5 per cent of the area is irrigated.

2.4 Analysis

ArcGIS Spatial Analyst and ERDAS IMAGINE were used to calculate various biomass indicators: NDVI minimum, maximum, maximum-minimum, mean, sum or integrated, standard deviation (STD) and coefficient of variation (CoV) as well as climate variables. The fortnightly NDVI data were geo-referenced and averaged to monthly; annual NDVI indicators were derived for each pixel; their temporal trends were determined by linear regression (t-test, significance level, $P = 0.05$) and mapped to depict spatial changes. A negative slope of linear regression indicates a decline of green biomass and a positive slope, an increase – except for STD and CoV which indicate trends in variability.

Monthly grids of rainfall for the period 1980-2002 were geo-referenced and re-sampled to the same spatial resolution as the NDVI (8km) using neighbourhood statistics. Spatial pattern and temporal trend of rainfall for each pixel were determined by regression and statistical analysis using SPSS 12.0.1 for Windows, which was also used for correlation and confidence analyses.

Hot spots identified according to their negative trends of biomass and rain-use efficiency were masked by the mapped urban extents and irrigated areas.

3   RESULTS

3.1   NDVI indicators of land degradation and improvement

Minimum NDVI: The lowest value that occurs in any one year (annual) - which is usually at the end of the dry season. Variation in minimum NDVI may serve as a baseline for other parameters.

Maximum or peak NDVI: Represents the maximum green biomass. The large spatial variations reflect the diverse landscapes and climate.

Maximum-minimum NDVI: The difference between annual maximum and minimum NDVI reflects annual biomass productivity for areas with just one growing season – as in the North China case study - but may not be meaningful for areas with bimodal rainfall such as Kenya.

Sum or integrated NDVI: The sum of fortnightly NDVI values for the year most nearly integrates annual biomass productivity.

Standard deviation (STD): NDVI standard deviation is the root mean square (RMS) deviation of the NDVI time series values (annual) from their arithmetic mean. It is a measure of statistical dispersion, measuring the spread of NDVI values.

Coefficient of variation (CoV): CoV can be used to compare the amount of variation in different sets of sample data. NDVI CoV images were generated by computing for each pixel the standard deviation (STD) of the set of individual NDVI values and dividing this by the mean (M) of these values. This represents the dispersion of NDVI values relative to the mean value.

Temporal trends: The long-term trends of the indicators of biological productivity may be taken as indicators of land degradation (where the trend is declining) or land improvement (where the trend is increasing). A positive change in the value of a pixel-level CoV over time relates to increased dispersion of values, not increasing NDVI; similarly, a negative CoV dispersion – which is the case over nearly the whole country - means decreasing dispersion of NDVI around mean values, not decreasing NDVI. The trend in CoV may reflect land cover change.

3.2   Spatial patterns and trends in biomass productivity

3.2.1   Trends in NDVI indicators

The trends in all NDVI indicators for each pixel, determined by the slope of the linear regression equation are summarised in Table 1.

Table 1.   Statistics of NDVI indicators in Kenya

NDVI indicators	NDVI values			Pixels (%)		% NDVI change/year			Δ NDVI/year		
	min	max	mean	+	-	+	-	mean	+	-	mean
Minimum	0	0.782	0.213	62.1	37.9	1.089	0.759	0.392	0.0023	0.0018	0.0007
Maximum	0.002	0.997	0.497	79.2	20.8	0.240	0.100	0.170	0.0012	0.0006	0.0008
Max-Min	0.0001	0.667	0.298	78.1	21.9	1.914	0.741	1.329	0.0057	0.0026	0.0038
Mean	0.001	0.846	0.329	73.0	27.0	0.979	0.377	0.615	0.0024	0.0011	0.0014
Sum	0.013	10.154	3.946	79.0	21.0	0.993	0.378	0.700	0.0271	0.0116	0.0188
STD	0.048	0.158	0.096	74.0	26.0	1.901	0.797	1.197	0.0015	0.0008	0.0009
CoV	0.16	0.668	0.301	67.0	33.0	1.291	1.074	0.507	0.0058	0.0047	0.0023

In Kenya over the period of 1981-2003, there was an overall increase in values for all NDVI indicators.

3.2.2   Spatial-temporal trends in annual sum NDVI

Figure 2 depicts 23-year mean annual sum NDVI over the period 1981-2003 at pixel level. The trends over the period 1981-2003 are depicted in Figure 3. The spatial pattern of the multi-year mean biomass productivity coincides very well with the agro-ecological zones defined by Somboek and others (1982, Figure 2b).

Biomass increased over the 23 years across 79% of the country but decreased over 21% (Table 1, Figure 3a and b); for the country as a whole, the 23-year trend was upwards (Figure 4); but relative and absolute decreases in biomass occurred across much of the cropped area, particularly where cropping has extended into marginal lands.
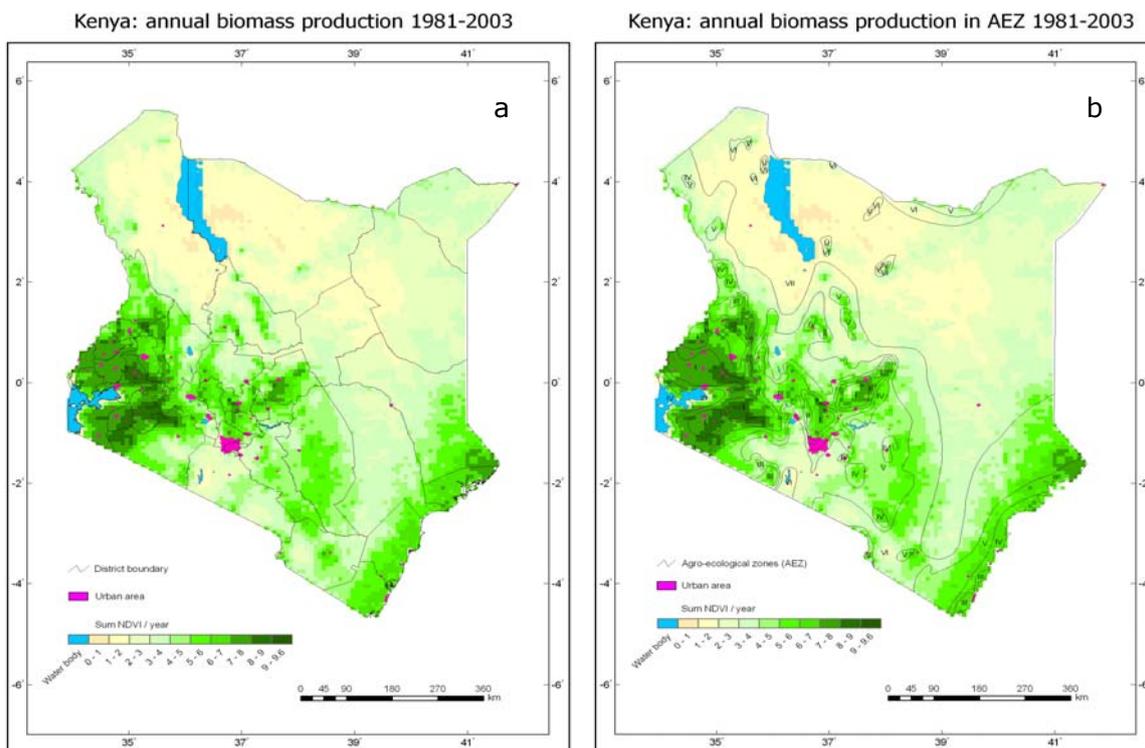
Figure 2.   Kenya: spatial pattern of annual biomass productivity 1981-2003
            a – relative to administrative districts, b – relative to agro-ecological zones
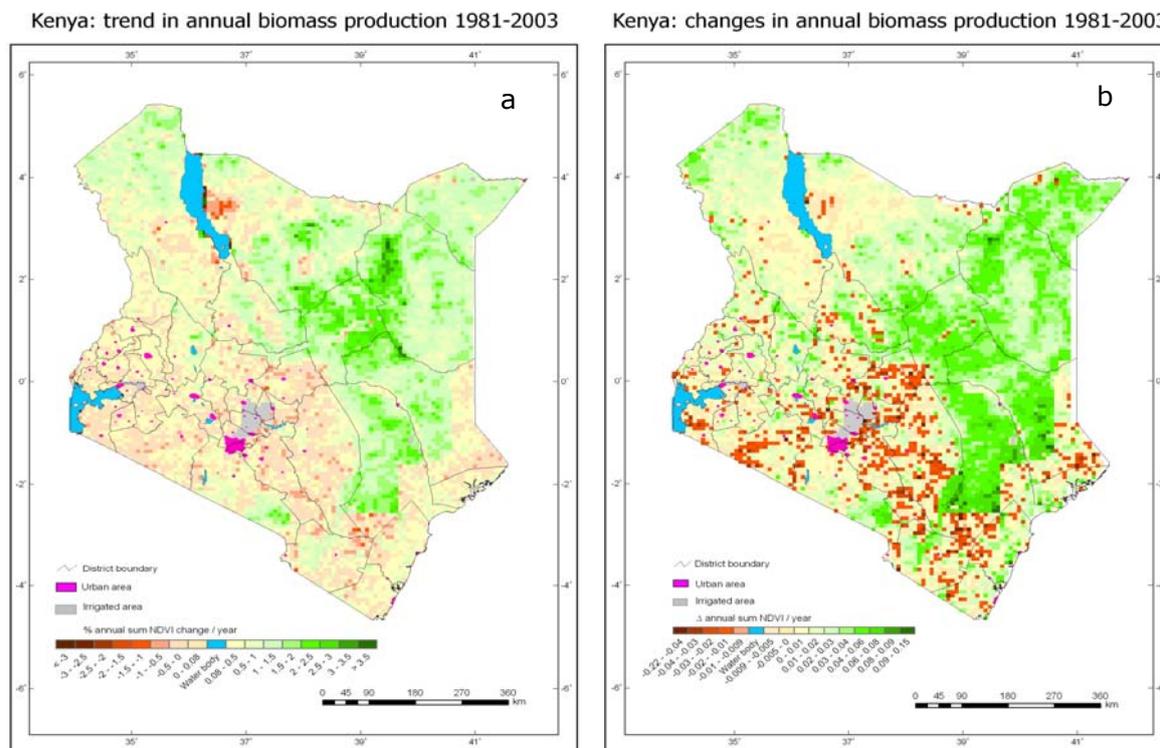
Figure 3.   Kenya: changes in annual biomass productivity 1981-2003
            a – percentage change, b – absolute change
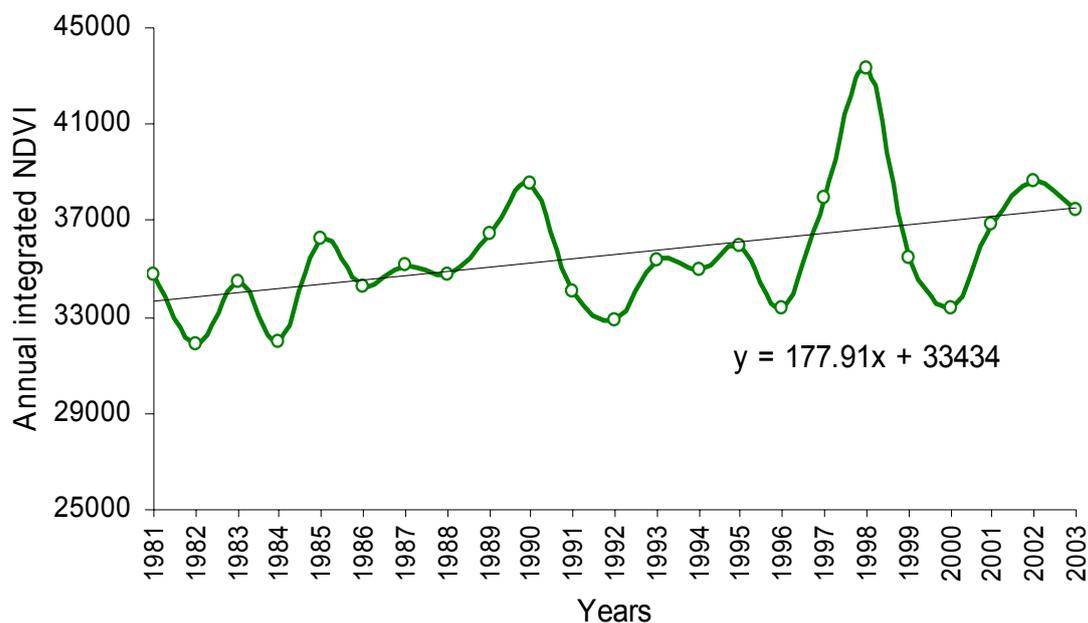
Figure 4.   Kenya: spatial integrated annual sum NDVI 1981-2003

3.2.3   Spatial-temporal trend in annual maximum NDVI

The pattern of annual maximum biomass productivity (Figure 5) reflects the diverse landscapes and climate and is well characterised by the agro-ecological zones (Figure 5b). Over the 23-year period, annual peak biomass increased over 79 per cent of the area and decreased across 21 per cent (Figure 6a, b). Apparent decreases in both relative and absolute changes in annual peak biomass were found across cropland (Kitui District of Eastern province, Nakuru, Southern Baringo and North-western Narok District of Rift Valley province) and woodland and forest (e.g. in the Lamu of Coast province and South-eastern Garissa of North-eastern Province) - Figure 6a, b.
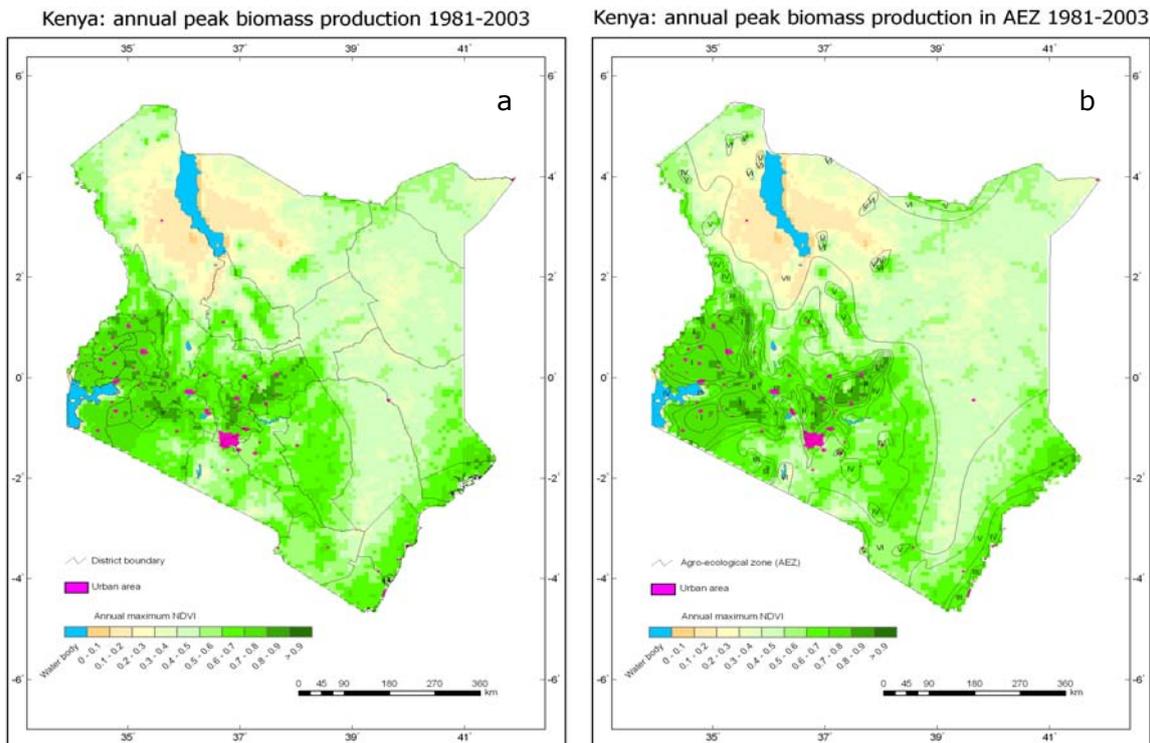
Figure 5.   Kenya: spatial patterns of annual peak biomass productivity 1981-2003
            a – in different districts, b – in different agro-ecological zones
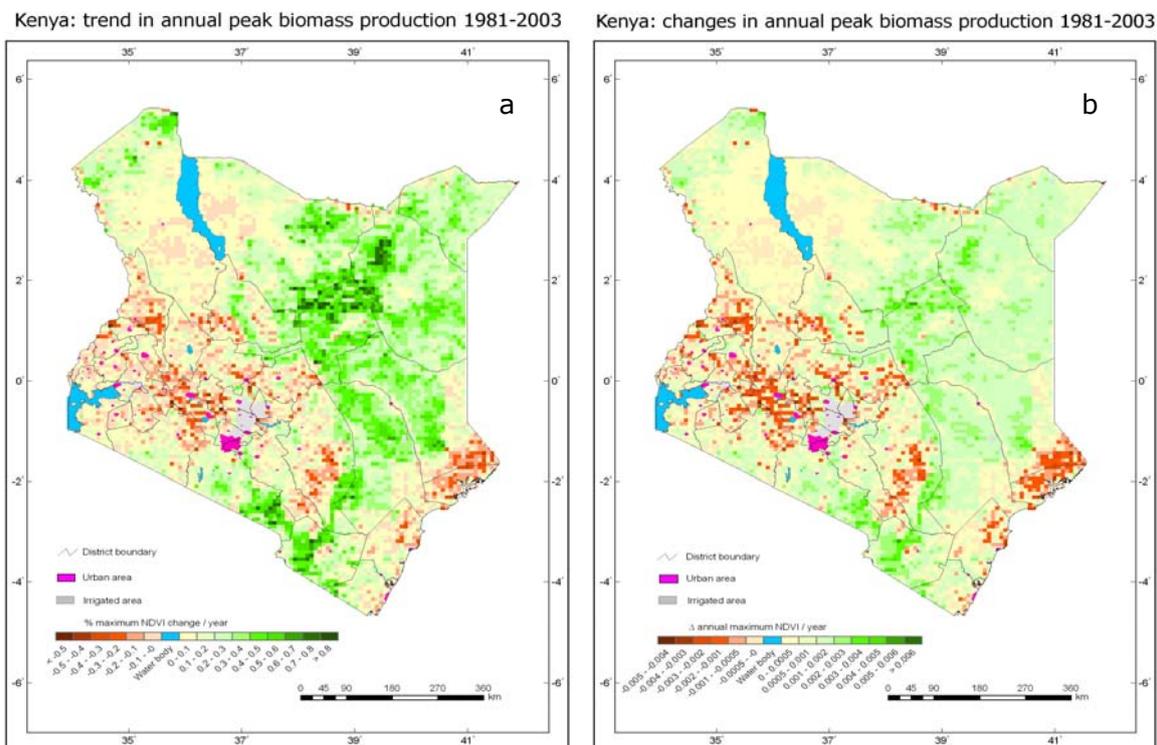
Figure 6.   Kenya: changes in annual peak biomass productivity 1981-2003
            a – percentage; b – absolute values

3.3 Spatial patterns: biomass and rainfall

3.3.1 Annual biomass and precipitation

Biomass fluctuates according to rainfall, stage of growth and changes in land use, as well as land quality. In Kenya, there is a strong coincidence between declining biomass and cropland (compare Figures 1 and 3), especially with the expansion of cropland beyond the high-rainfall zones.

Mean annual biomass productivity (represented by sum NDVI in Figure 2) essentially reflects the mean annual rainfall (Figure 7a). But *rainfall has fluctuated significantly*, both spatially (Figure 7b and c) and cyclically over the period (Figure 8). Statistics show a moderate correlation between NDVI and annual rainfall:

$$\text{Rainfall [mm year}^{-1}] = 59.85 * (\text{annual sum NDVI}) + 350.8 \qquad [1]$$

$$(r = 0.53, n = 9096, P<0.001)$$

Rainfall increased over about 80 per cent of the country (with an annual rate of 0.75 per cent or 4.7mm) and decreased over 20 per cent (average rate of 0.26 per cent or 1.3mm) (Figure 7b and c). In particular, rainfall increased across in East-Central Kenya. For Kenya as a whole, rainfall increased at an average of 0.55 per cent or 3.5mm per year over the period (Figure 8); biomass also increased although the correlation for Kenya as a whole is only moderate (equation [1], Figure 9).

3.3.2 Annual peak biomass (maximum NDVI) and yearly maximum rainfall

The spatial pattern of annual precipitation (Figure 10a) is very similar to the pattern of annual peak biomass productivity (Figure 5a, b). However, the declining trend of annual maximum rainfall over 1980-2002 was not followed by biomass productivity in the cropped areas but in the forest and woodland in the Lamu of Coast province and in the dry grassland of North Kenya (comparing Figures 6a, b to Figure 10b, c).
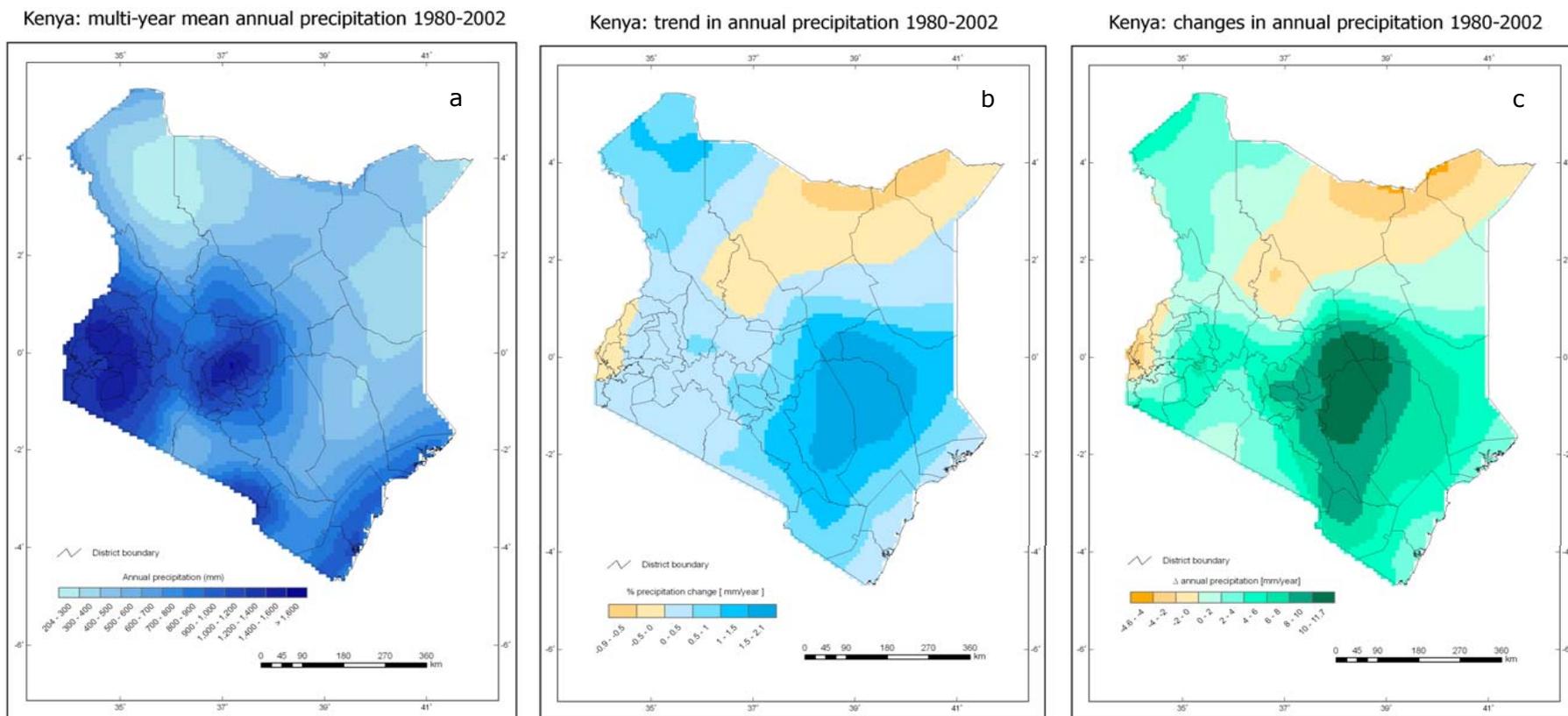
Figure 7.   Kenya: annual rainfall 1980-2002
spatial pattern (a) and temporal trends (b – percentage change, c – absolute change)
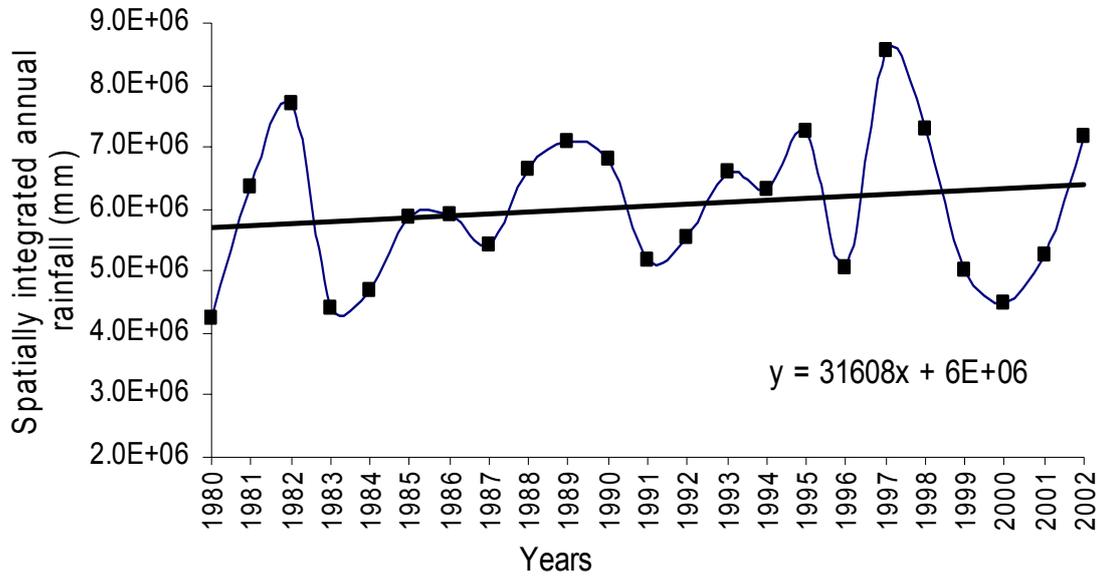
Figure 8.   Spatially integrated annual rainfall 1980-2002
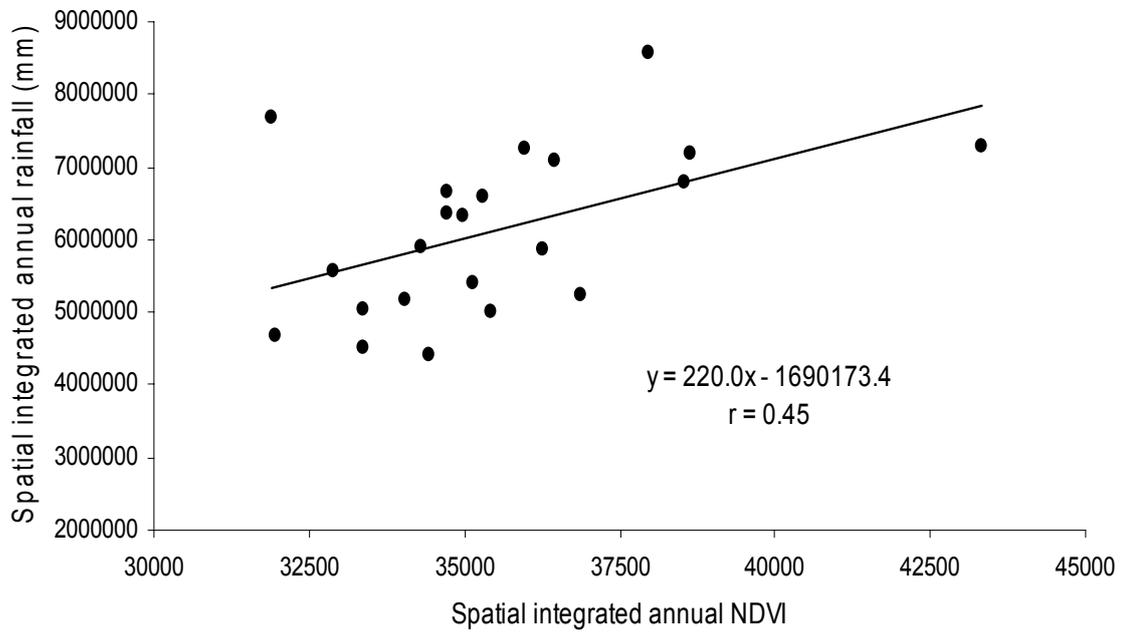
Figure 9.   Relationship between annual sum NDVI (all pixels) and annual precipitation (all pixels)
            Each dot represents one year
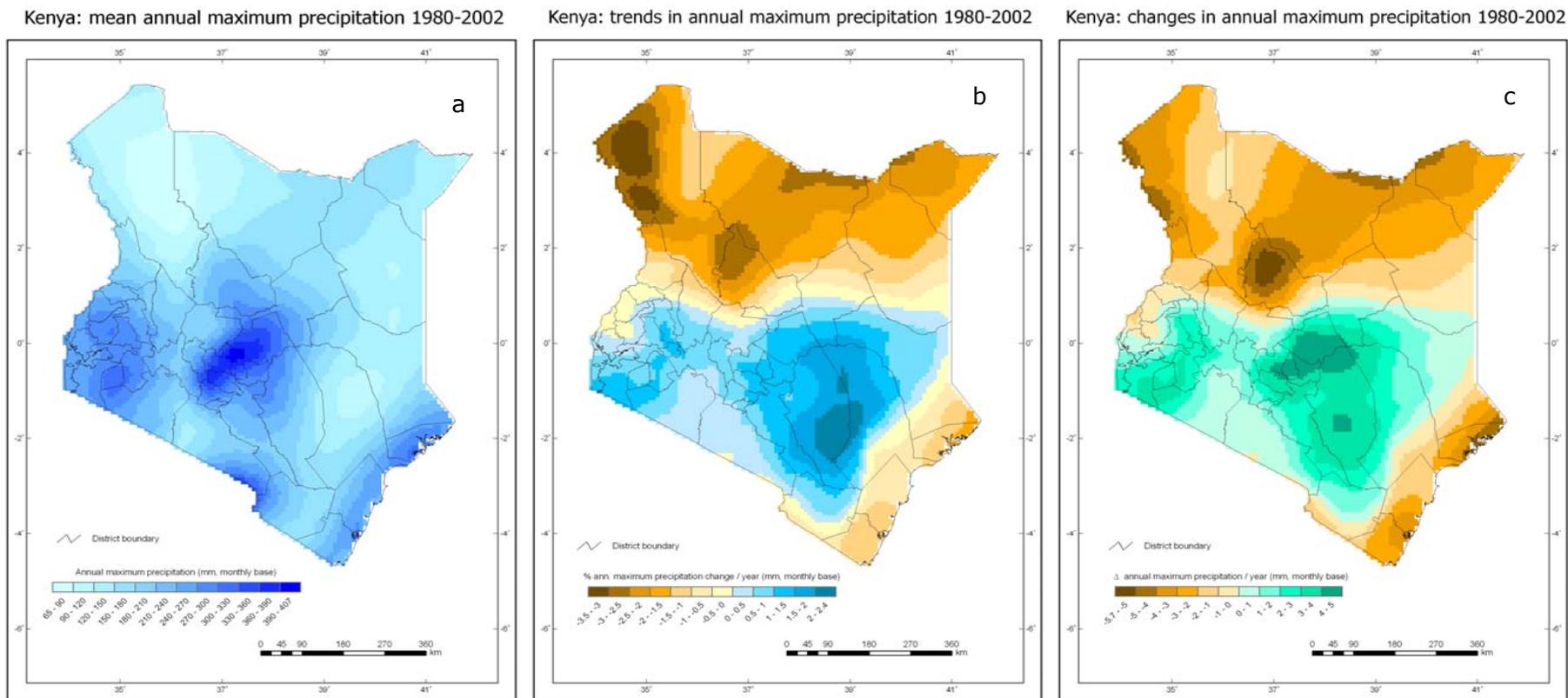
Figure 10. Kenya: annual maximum rainfall 1980-2002
Spatial pattern (a) and temporal trends (b – percentage change, c – absolute change) on a monthly basis

3.4   Rain-use efficiency

Long-term reduction in biomass may indicate land degradation but biomass also fluctuates according to rainfall, stage of growth, and changes in land use. Rain-use efficiency (RUE), the ratio of net primary productivity to precipitation, addresses this problem by expressing production per unit of rainfall. RUE is systematically lower in ecosystems subject to drought stress, but it is also lower in degraded drylands than in equivalent non-degraded areas (Le Houérou 1984, 1988, 1989; Snyman 1998; Illius and O'Connor 1999; O'Connor and others 2001). Wessels and others (2007) point out that RUE varies greatly between years – this is also evident in our data – but we judge that the long-term trend is a useful indicator of land degradation and improvement. The combined trends of biomass and rain-use efficiency may be a more robust indicator of land degradation or improvement than crude biomass, *and these indicators can be derived from available global datasets.*

In North China, Bai and others (2005) demonstrated that values for rain-use efficiency calculated from NDVI, *which are easy to obtain*, were comparable with those calculated from measurements of net primary productivity, which values are not easy to obtain. For Kenya, rain-use efficiency was calculated as the ratio between annual integrated NDVI and station-observed annual rainfall on a yearly time-step.

Figure 11 shows the spatial pattern and temporal trend of rain-use efficiency in Kenya over 1981-2002: rain-use efficiency actually increased over most of the country but two areas stand out as *hot spots* of declining productivity and declining rain-use efficiency: the drylands around Lake Turkana and a swath of cropland in Eastern Province from Meru south to Machakos, including the whole of Kitui district.

In the drylands, productivity has declined from a low base. Livelihoods in these areas are always precarious and the *hot spot* coincides with today's famine amongst the Turkana nomads (McVeigh 2006). The *hot spot* in the eastern croplands represents decline in an area of much higher potential.

Figure 12 depicts the trends in rain-use efficiency for, respectively, sites of stable trend (Kakamega in the Lake Victoria catchment), decrease (Kitui, Eastern Province), and increase (Buna, Northeastern Province). Locations of the sites are shown on the front cover of this report.
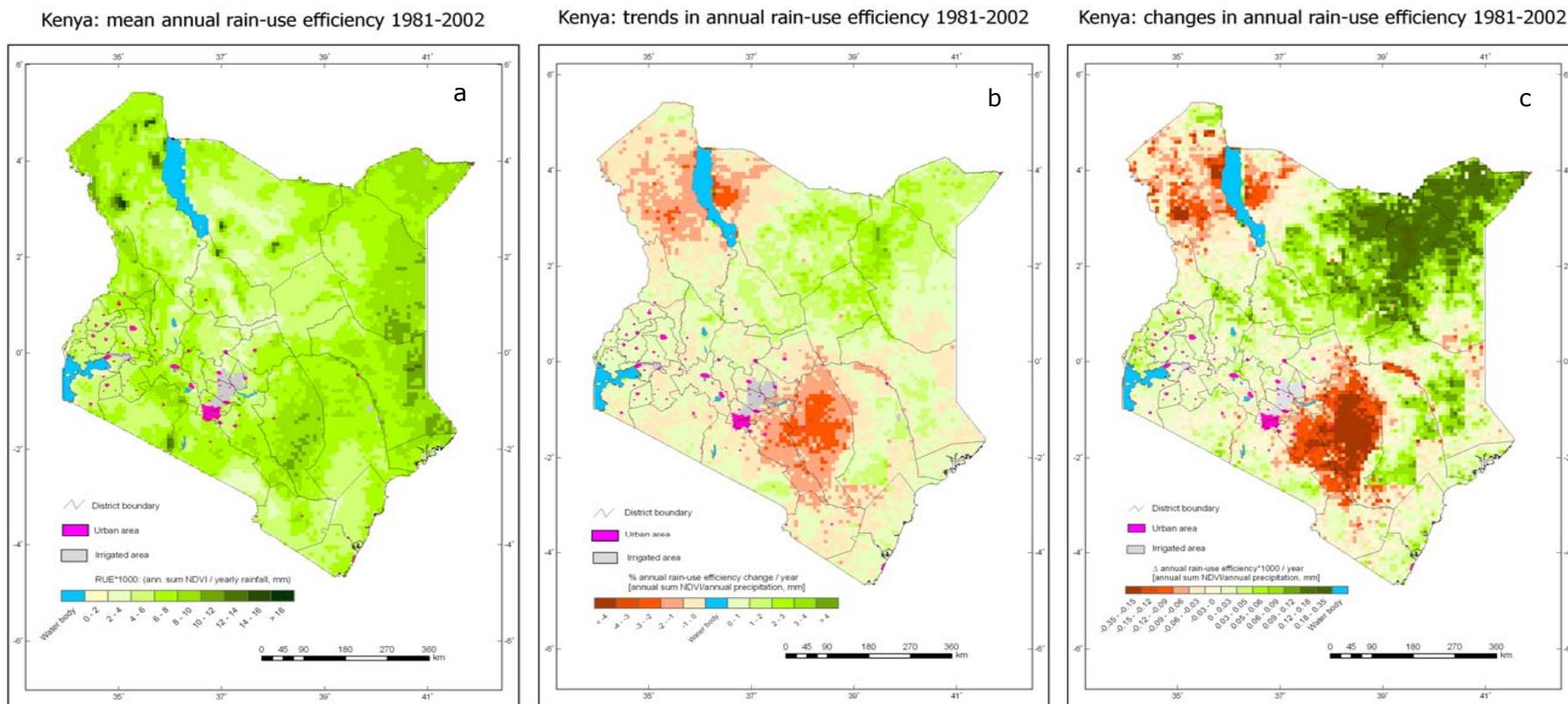
Figure 11. Kenya: rain use efficiency
Spatial pattern (a) and temporal trend (b – percentage changes, c – absolute changes)
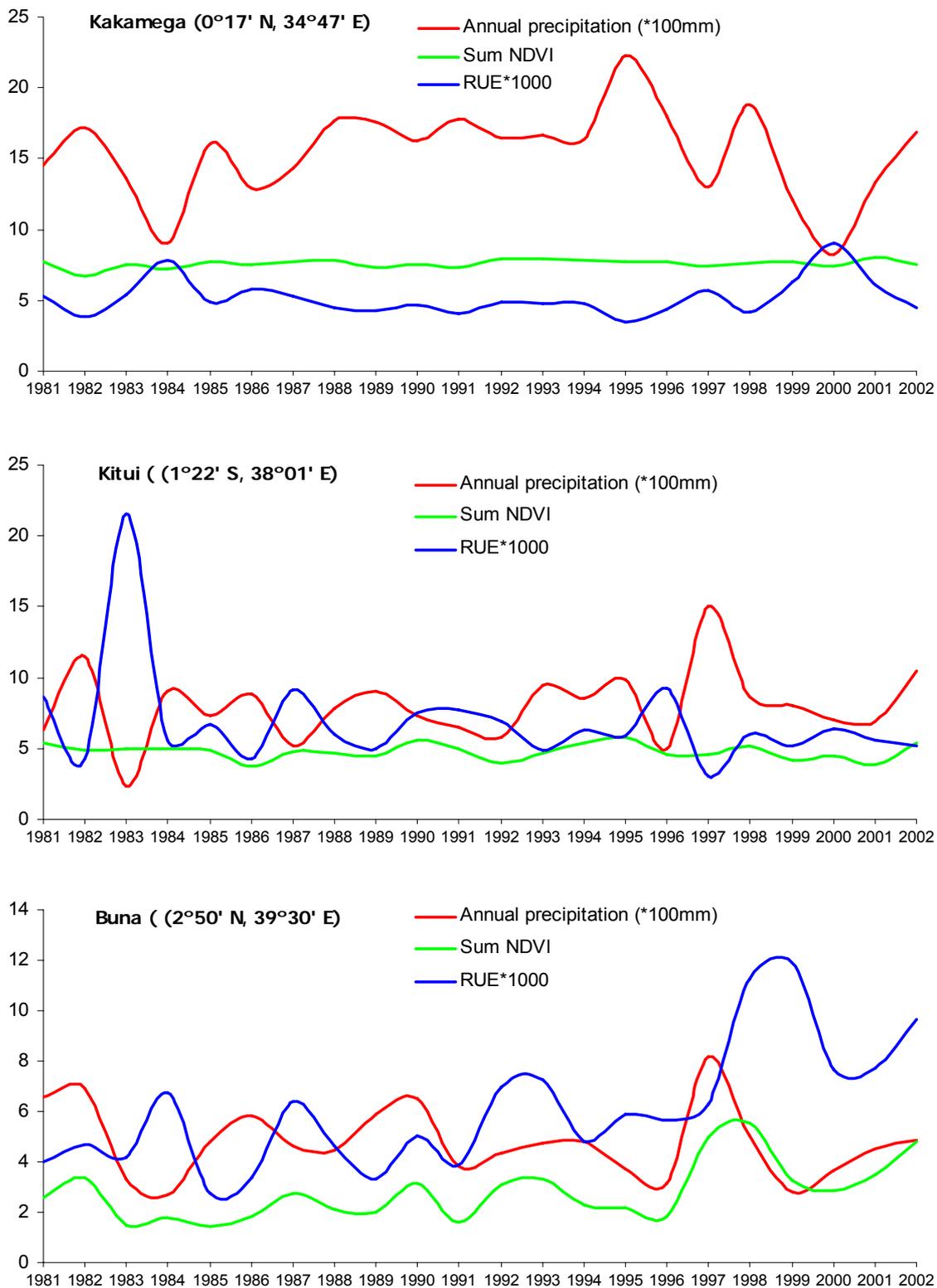
Figure 12. Contrasting trends of rain-use efficiency with biomass and rainfall

3.5   Net primary productivity

Net primary productivity (NPP) is the rate at which vegetation in an ecosystem fixes CO_2 from the atmosphere (gross primary productivity, GPP) minus the rate at which the vegetation returns CO_2 to the atmosphere through respiration. It is an important ecosystem process removing carbon dioxide from the atmosphere and converting it to biomass including food, fibre and wood, but also because it creates environments suitable for human inhabitation (Zhao and others 2005). Land degradation inevitably reduces the biomass productivity.

Net primary productivity can be measured in the field or estimated by remote sensing (NPP is directly correlated with NDVI, see Running and Nemani 1988, Potter and others 1993, Paruelo 1997, Prince and others 1998, Symeonakis and Drake 2004, Wang and others 2004). We have used both methods.

3.5.1   NDVI and field-measured NPP

Net primary productivity of grassland in Kenya was obtained for 1981-2003 from sum NDVI using a simple regression model calibrated with the data for net primary productivity of savanna grassland in Nairobi National Park from 1984 to 1994 - measured by monitoring monthly dynamics of live biomass and dead matter, above and below ground, together with monthly litter bag estimates of decomposition rates above and below ground (Kinyamario 1996). Correlations of monthly or annual sum NDVI to the field measured NPP parameters over the period of 1984-1994 are listed in Table 2.

The following linear regression model was used to convert NDVI to NPP for grassland in Kenya:

NPP (DM, ton ha^{-1} y^{-1}) = 2.498 * (annual sum NDVI) + 2.477   [2]

(n = 11, r = 0.77, P <0.05)

Where NPP is the field-measured net primary productivity and DM is dry organic matter.

The converted 23-year mean annual biomass productivity for the grassland is shown in Figure 13a. Taking the converted 23-year mean annual NPP as default value, percentage and absolute changes in the grassland biomass productivity over the period of 1981-2003 were computed (Figure 13b and c).

Net primary productivity increased over 86 per cent of grassland with an average rate of 0.36 per cent per year and decreased over 14 per cent with a mean change rate of 0.09 per cent. For Kenyan grassland as a whole, the NPP increased with an average rate of 0.30 per cent per year over the 23-year period (Figure 14, Table 3, confidence level = 95 per cent).

Table 2.   Correlation between NDVI and biomass (g/m$^{2)}$)

NDVI	Biomass	Correlation	Coefficient (r)	Sample
Monthly	Monthly AGbiomass	y = 47.227x + 119.45	0.085	98
Annual sum	Annual AGbiomass	y = 276.87x - 29.229	0.676	11
Monthly	Monthly AGtotmatter	y = -68.995x + 691.89	0.067	98
Annual sum	Annual AGtotmatter	y = 1329x - 523.32	0.910	11
Monthly	Monthly ANPP	y = 16.151x + 106.86	0.020	17
Annual sum	Annual ANPP	y = 289.84x - 257.99	0.982	10
Monthly	Monthly NPP (ANPP+BNPP)	y = 53.875x + 137.97	0.041	24
Annual sum	Annual NPP (ANPP+BNPP)	y = 249.8x + 247.67	0.765	10

Y = NPP, x = NDVI
AGbiomass: above-ground live biomass
AGtotmatter: above-ground total matter (AGbiomass, standing dead, litter)
ANPP: above-ground net primary productivity (calculated)
BNPP: below-ground net primary productivity (calculated)
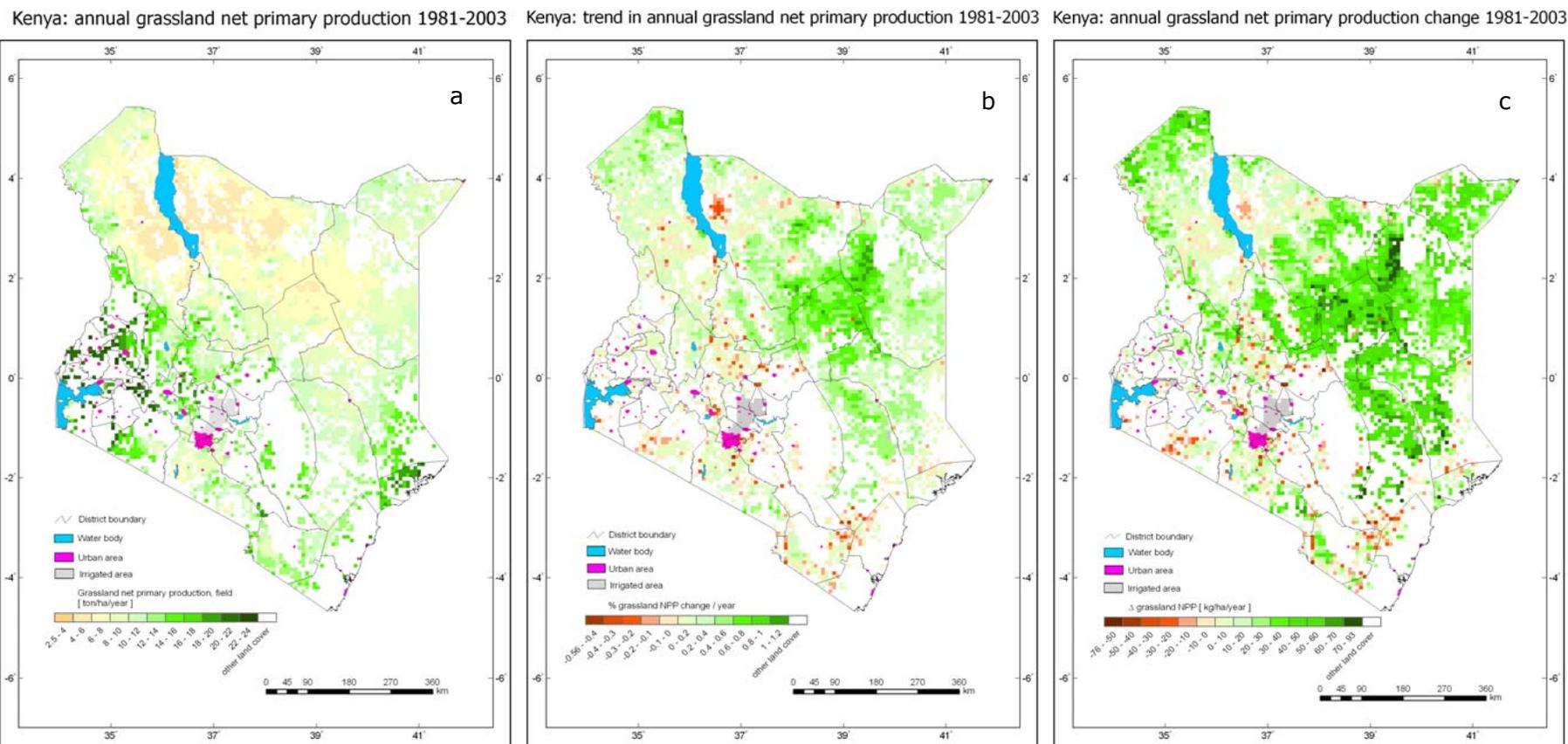
Figure 13. Kenya: grassland NPP pattern and loss 1981-2003
a – multi-year mean, b – percentage change, c – absolute change
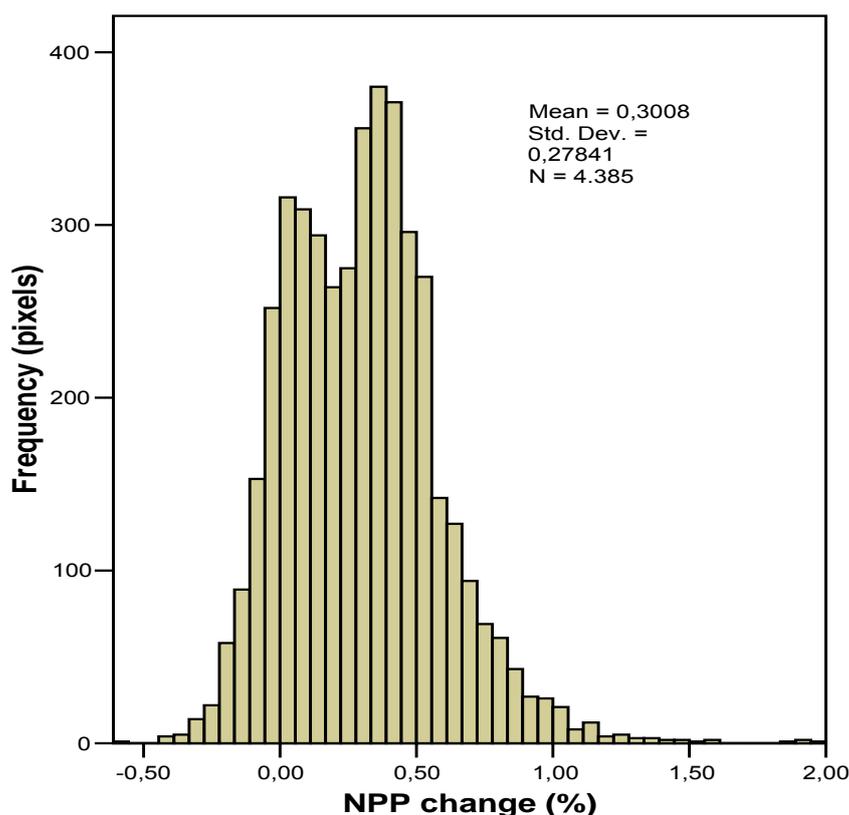
Figure 14. NPP change in Kenyan grassland

3.5.2 Remotely sensed NPP and converted NPP using NDVI-Field Measured Model

There are hardly any field-measured data for NPP for the various land use types in Kenya. The gap may now be filled by remote sensing: MODIS 8-day NPP data, derived from moderate-resolution imaging spectroradiometer measurements at 1-km resolution at an 8-day interval. This is the first regular, near-real-time dataset for repeated monitoring of vegetation primary productivity (Heinsch and others 2003). The 8-day NPP was computed from the product of PAR, f_{APAR} (fraction of absorbed photosynthetically active radiation) and conversion efficiency coefficients obtained from other MODIS products (MOD15A2) and ancillary data (biome properties lookup table). Globally, the MOD17 NPP is comparable to the Ecosystem Model–Data Intercomparison NPP data set, and global total MODIS GPP and NPP are inversely related to the observed atmospheric CO_2 growth rates and the multivariate ENSO index, indicating that MOD17 is reliable (Zhao and others 2005, 2006). The dataset has been validated and evaluated in various landscapes (e.g. Fensholt and others 2004, 2006; Gebremichael and Barros 2006; Turner and others 2003, 2006). See, also, the overview by Justice and others (2002).

For comparison with the locally measured grassland NPP, units for MOD17 NPP data (g C m^{-2} year^{-1}) were converted into dry organic matter (ton DM ha^{-1} year^{-1}), taking 1.0 g carbon being equivalent to 2.2 g oven-dry organic matter (ORNL NAAC, http://www-eosdis.ornl.gov/NPP/html_docs_grass_dict.html).   Four-year   (2000-

2003) mean annual grassland NPP derived from MOD17A3 at 1-km resolution were derived and are shown in Figure 15.
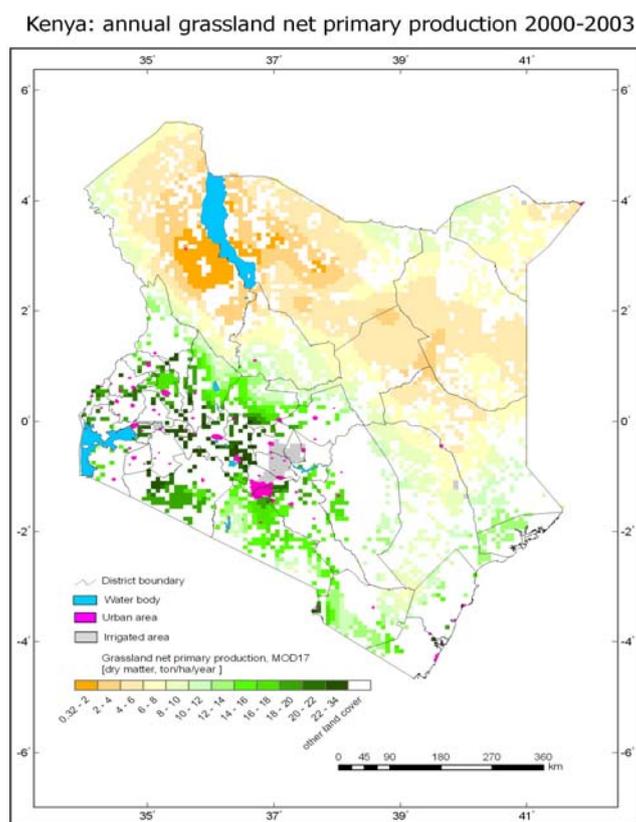
Figure 15. Kenya: Four-year mean annual grassland NPP derived from MOD17

The spatial pattern of grassland biomass production derived from MOD17A3 is similar to the converted NPP using NDVI-Field Measured Model [2] (Figures 15 and 13a). Statistics indicate a high correlation:

$$NPP_{MOD17} \text{ [DM, ton ha}^{-1} \text{ year}^{-1}] = 1.27*NPP_{Field-NDVI} - 5.67 \qquad [3]$$

(r = 0.76, n = 4600, P<0.005)

Where NPP_{MOD17} is net primary productivity derived from remote sensing, $NPP_{Field-NDVI}$ is net primary productivity converted by the field measured NPP – NDVI Model [2]. DM is dry organic matter. Error or uncertainty in the regression model [3] is: slope (1.27) ± 0.025; intercept (-5.67) ± 0.28.

The regression model [3] indicates that 1) both MOD17A3 NPP product and the Field Measurement-NDVI model can be used to convert the NDVI values to NPP; 2) the trend in NDVI over the period of 1981-2003 can be employed to calculate loss of biomass production over the period.

3.5.3   Remotely sensed NPP and NDVI

Figure 16 shows four-year mean annual MODIS NPP 2000-2003 at 1-km resolution, fderived from the MOD17 data for each land use type in Kenya. The spatial pattern of the remote sensed NPP is similar to that represented by annual integrated NDVI (Figure 2) but shows finer details.

The four-year annual mean NPP was re-sampled into 8-km resolution by neighbourhood statistics; the four-year mean annual sum NDVI over the same period (2000-2003) was calculated; correlation between the two raster data for all land cover types in Kenya is very high:

NPP_{MOD17} [DM, ton ha^{-1} year^{-1}] = 3.498 * $NDVI_{sum}$ − 3.516   [4]

(r = 0.85, n = 9096, P<0.001)

Where NPP_{MOD17} is annual net primary productivity derived from MOD17, $NDVI_{sum}$ is a four-year (2000-2003) mean annual sum NDVI derived from GIMMS, DM is dry organic matter. Error or uncertainty in the regression model [4] is: slope (3.498) ± 0.044; intercept (-3.516) ± 0.192.

Taking the four-year mean annual NPP as the norm, annual biomass productivity for Kenya and trend in annual integrated NDVI over a 23-year period (1981-2003) as deviation, the percentage and absolute changes in net primary productivity were calculated and depicted in Figure 17. The derived changes in NPP for each dominant land cover types are listed in Table 3.

Kenya: four-year mean annual NPP 2000-2003

Kenya: four-year mean annual NPP in AEZ 2000-2003
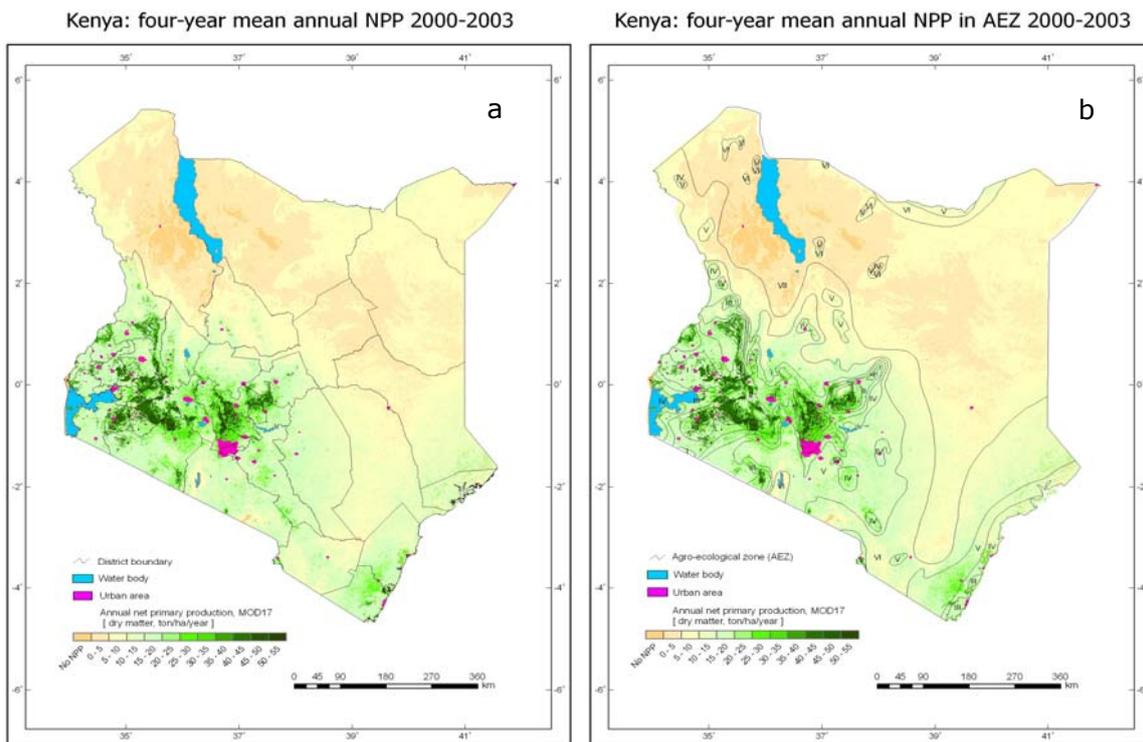
Figure 16. Kenya: Four-year mean annual NPP derived from MOD17
a – relative to administrative districts, b – relative to agro-ecological zones

Kenya: trend in annual net primary production 1981-2003

Kenya: change in annual net primary production 1981-2003
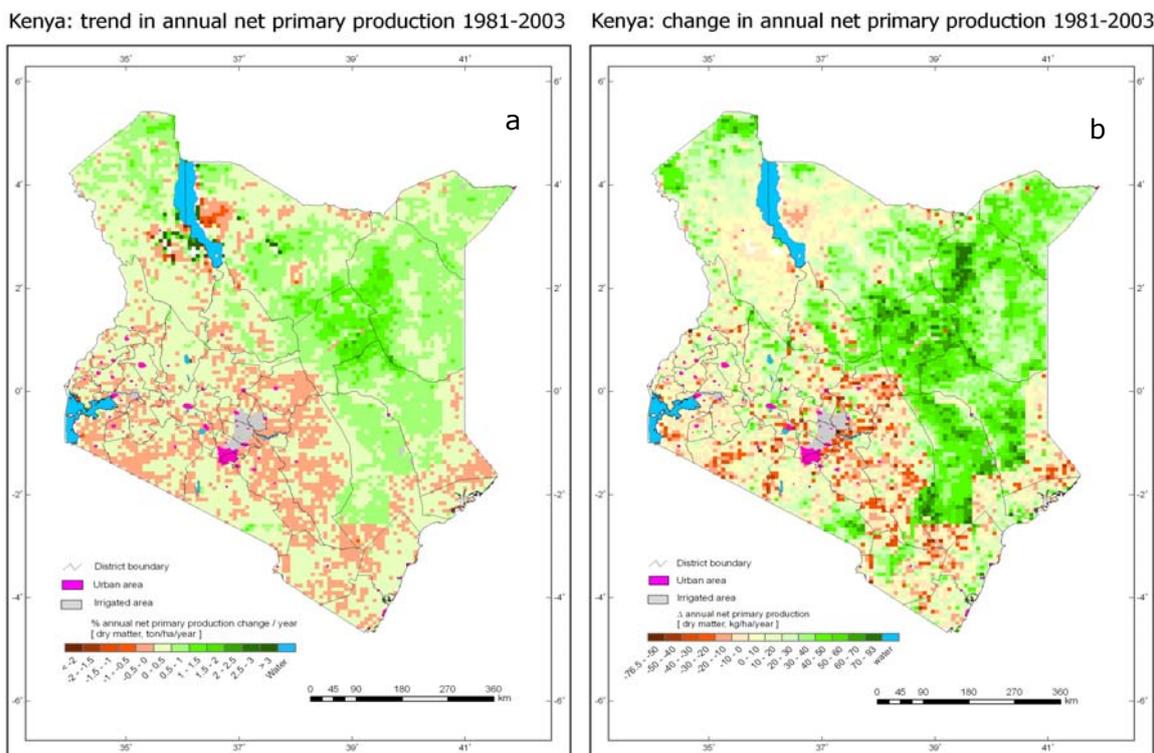
Figure 17. Kenya: changes in net primary productivity 1981-2003
a – percentage change, b – absolute change

Table 3.   Changes in net primary productivity for dominant land cover types, 1981-2003 in
           Kenya

Land cover	Pixels (%)		% NPP change/year			Δ NPP [DM, kg ha^{-1} year^{-1}]		
	+	-	+	-	average	+	-	average
Grassland	86	14	0.36	0.09	0.30	32.3	10.5	26.5
Cropland	58	42	0.09	0.07	0.02	15.4	12.9	3.4
Forest & woodland	80	20	0.42	0.09	0.32	31.0	12.3	22.2

During the period, net primary productivity overall increased in all land cover types:
grassland, cropland, and forest and woodland. But across 40 per cent of cropland it
decreased – on average by 13 kg per hectare per year.

3.6   *Hot spots* of land degradation

Across the country, 17 per cent of the land has suffered both declining net primary
productivity and declining rain-use efficiency over 1981-2003. These areas may be
identified as *hot spots* of land degradation (Figure 18).
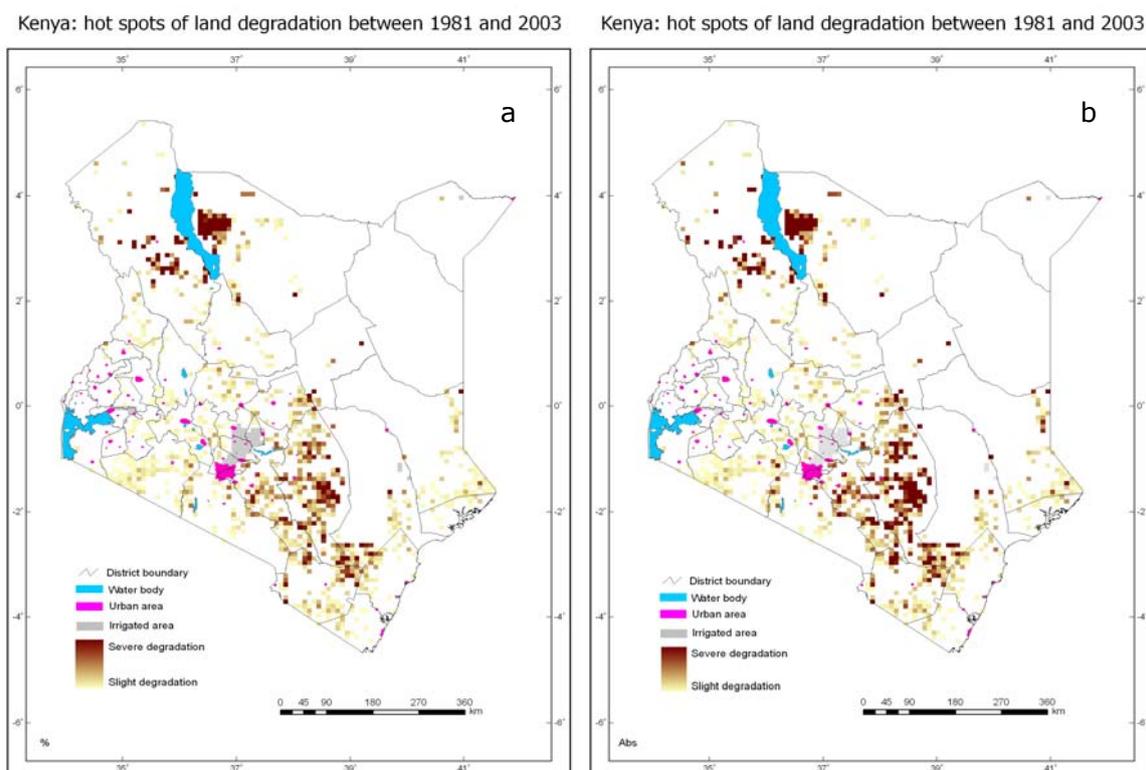
Figure 18. Kenya: areas with both declining NPP and declining RUE 1981-2003
           a - percentage change, b - absolute change

3.7 Analysis of *hot spots*

Working is continuing on the statistical and spatial relation between biomass trends, soils, land use and social and economic data to characterise the *hot spots* and to divine the drivers of land degradation.

Data to hand include the GLC 2000 land cover (Figure 19) as well as the FAO (2005) analyses for 2000 and 1990; soil and terrain data at scale 1:1 million derived from KENSOTER (Batjes and Gicheru 2004) (Figure 20); and household socio-economic survey data from CEEPA (http://www.ceepa.co.za/).
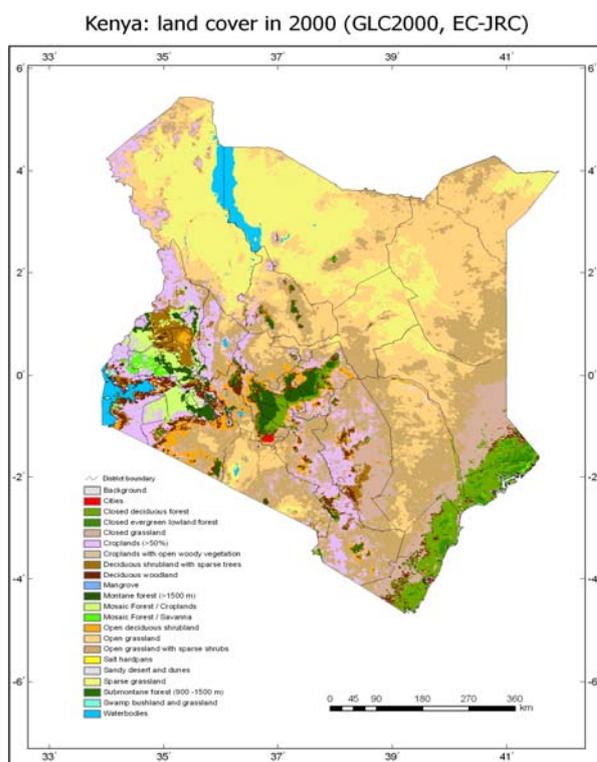
Figure 19. Kenya: land cover in 2000
(EC-JRC, 2003)
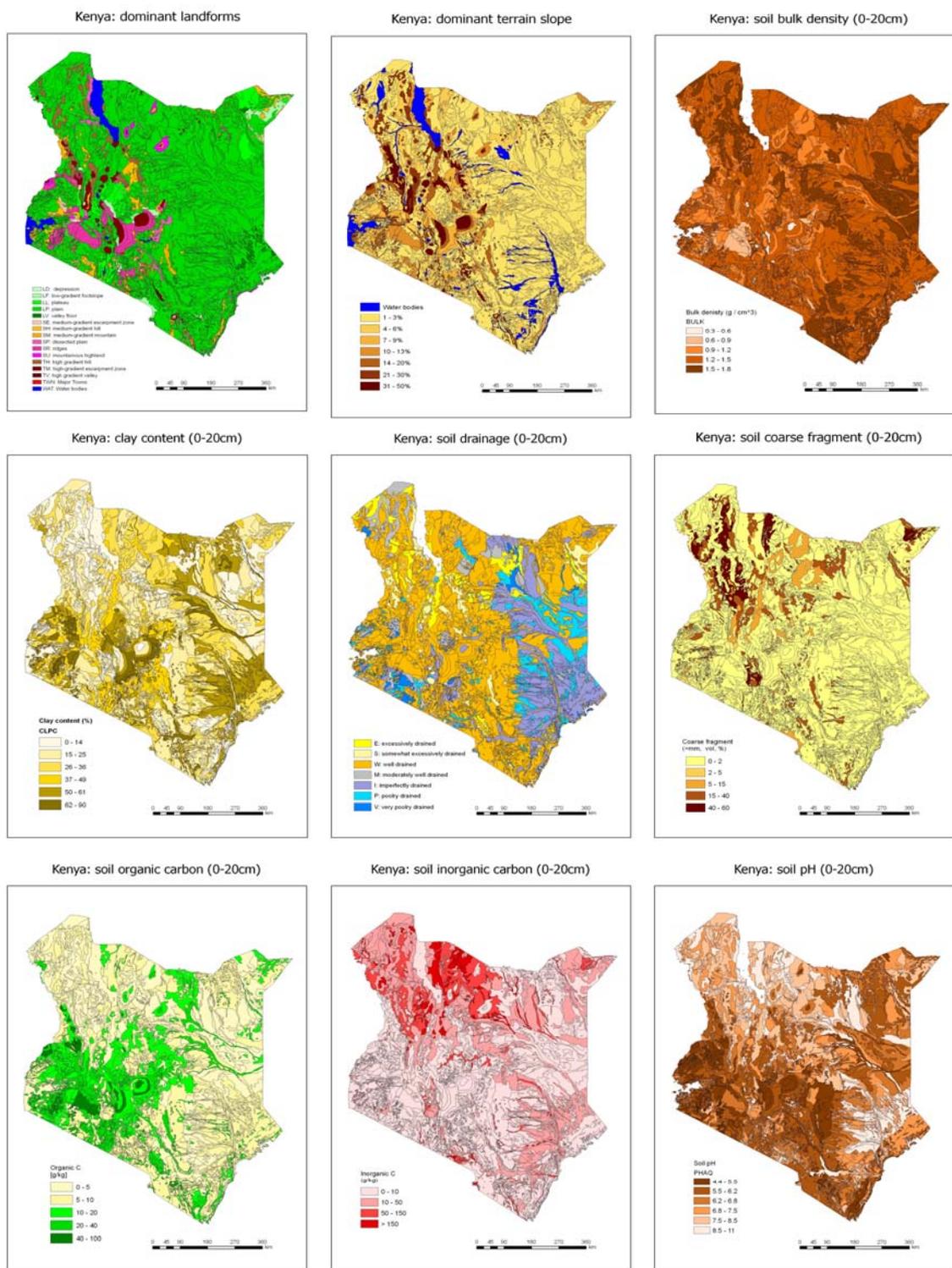
Figure 20. Soil and terrain components and derived properties for dominant soils in Kenya
          (Batjes and Gicheru 2004)

4 SUMMARY AND CONCLUSIONS

- Remote sensing of biomass indicators may indicate *hot spots* of land degradation. Combination of the biomass trend with rain-use efficiency trend is a more robust indicator of land degradation than crude biomass in those places where productivity is constrained by rainfall.

- Interpretation is not straightforward; the various NDVI patterns must be followed up by fieldwork to establish the actual conditions on the ground.

- The consistent, spatial data for biomass also enable a statistical examination of other data for which we do not have continuous spatial coverage – such as spot measurements of soil attributes, and socio-economic data that may reveal the drivers of land degradation. Provided these other data are geo-located, they can be scaled against the continuous biomass trends.

- The data from a defined, recent period enable us to distinguish between the legacy of historical land degradation, which may be irreversible, and degradation that is taking place now. For many purposes, it is more important to address present-day land degradation.

For Kenya:

- Green biomass and net primary productivity increased overall in all main land use types (cropland, grassland, and forest and woodland) over the period of 1981-2003, but hardly at all in cropland.

- Forty per cent of cropland suffered a *decrease* in NPP; 30 per cent of cropland suffered a *decrease* in both net primary productivity and rain-use efficiency which, provisionally, we may identify as land degradation. Much of this degradation has followed the expansion of cropping into marginal lands.

- Significant *hot spots* are also identified in the semi-arid grasslands around Lake Turkana

Note: the output of GLADA depends on the quality of the input data as much as on quality of the analysis. The GIMMS dataset is physical data, already corrected for known physical aberrations. The VASClimO 1.1 and CRU TS 2.1 dataset are compiled from the best available meteorological station data but for many areas these are sparse and have gaps of some years; in such cases, a relaxed interpolation has been used to create the global grid. Land cover data are interpretations by classification of satellite imagery and it is arresting to note the difference between the FAO (2005) land cover data that we have used in this study and the LC2000 data (Figure 19) which provide global coverage.

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ABBREVIATIONS

AGbiomass	Above-Ground Live Biomass
AGtotmatter	Above-Ground Total Matter (AGbiomass, standing dead, litter)
ANPP	Above-Ground Net Primary Productivity
APAR	Absorbed Photosynthetically Active Radiation
AVHRR	Advanced Very High Resolution Radiometer
BNPP	Below-Ground Net Primary Productivity
CEEDA	Centre for Environmental Economics and Policy in Africa
CoV	Coefficient of Variation
CRU TS	Climate Research Unit, Time Series
EMDI	Ecosystem Model–Data Intercomparison
ENSO	El Niño/Southern Oscillation Phenomenon
FAO	Food and Agriculture Organization of the United Nations
F_{APAR}	Fraction of Absorbed Photosynthetically Active Radiation
GIMMS	The Global Inventory Modelling and Mapping Studies
GLADA	Global Assessment of Land Degradation and Improvement
GLASOD	Global Assessment of Human-Induced Soil Degradation
GLCN	Global Land Cover Network
GPCC/DWD	The Global Precipitation Climatology Centre/the German Met Service (DWD)
GPP	Gross Primary Production
KENSOTER	Soil and Terrain database of Kenya
LADA	Land Degradation Assessment in Drylands
MOD15A2	MODIS 8-Day Net Photosynthesis
MOD17A3	MODIS 8-Day Net Primary Productivity
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
NPP	Net Primary Productivity
ORNL	Oak Ridge National Laboratory
PAR	Photosynthetically Active Radiation
RUE	Rain-Use Efficiency
SOTER	Soil and Terrain Database
SPOT	SPOT vegetation
SRTM	Shuttle Radar Topography Mission
UNCCD	United Nations Convention to Combat Desertification
UNCED	United Nations Conference on Environment and Development
UNEP	United Nations Environment Programme
VASClimO1.1	Variability Analyses of Surface Climate Observations