Assessment of land degradation:a case study in Kenya using NASA GIMMS

Dent, D. L.*; Bai, Z.G.

ISRIC – World Soil Information, PO Box 353, 6700 AJ Wageningen, The Netherlands

Abstract

Biomass is an integrated measure of productivity; its deviance from the norm may indicate land degradation or improvement. Biomass can be assessed by the normalized difference vegetation index (NDVI) derived from satellite data. 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 part of 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 NDVI data and decadal precipitation. ArcGIS algorithms were used to calculate various biomass indicators; temporal trends were determined by regression at annual intervals and mapped to depict spatial changes. In Kenya over the period of 1981-2003, biomass increased over about 78% of the land area and decreased over 21% - but the decrease has been across the most productive areas, the high-rainfall zones. A declining trend of biomass is strongly correlated with the cropped area and, in particular, the extension of cropping into marginal lands. To assess whether this trend represents land degradation or declining rainfall, we calculated rain-use efficiency, the ratio between green biomass (NDVI) and rainfall, which may be a more robust indicator of land degradation. The trends are similar but rain-use efficiency shows sharpest decline in two areas: the drylands around Lake Turkana and the whole of Kitui District in Eastern Province.

1. Introduction

Land degradation is believed to be a severe and widespread problem (UNCED 1992, UNEP 2006) but there is no authoritative, global measure. The only harmonized assessment, the *Global Assessment of Human-induced Soil Degradation* (Oldeman *et al.* 1991) is a map of perceptions - the kinds and degree of degradation - not a measure of degradation and now out-of-date; land degradation and perceptions have moved on. There is pressing need for an up-to-date, quantitative, reproducible assessment to support policy development for food and water security, environmental integrity, and economic development. This is now under way within the FAO/UNEP program Land Degradation in Drylands to identify: 1) the status and trends of land degradation, 2) *hotspots* suffering extreme constraints or at severe risk and their counterpoint – areas 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. Global satellite data, in particular the normalized difference vegetation index (NDVI - the difference between reflected near-infrared and visible wavebands divided by the sum of these two wavebands), enable measurement of changes in biomass. NDVI has a strong linear relationship with the fraction of photosynthetically active radiation absorbed by the plant (Asrar *et al.* 1984, Sellers *et al.* 1997); many studies have shown strong correlation between NDVI and vegetation cover (e.g. Purevdoj *et al.* 1998) and above-ground net primary productivity (Paruelo *et al.* 1997). It has been applied in studies of to land degradation from the field scale (1:10 000) to the degree of generalization

* Corresponding author 'phone + 31 317 471715; fax: + 31 317 471700; E-mail: David.Dent@wur.nl

required for national action or international policy development (1:1 million to 1:5 million) e.g. Tucker *et al.* 1991, Bastin *et al.* 1995, Stoms and Hargrove 2000, Wessels *et al.* 2004, Singh *et al.* 2006). Local norms may be established by stratifying the land area according to climate, soils and terrain, and land use/vegetation; deviance may then be calculated.

Here we present several NDVI indicators and analyse trends over a 23-year period (1981-2003) using the GIMMS dataset with information on climate and land use from Kenya (Fig. 1). More than 80 percent of Kenya is dryland. The pressure of burgeoning population without investment in soil and water conservation threatens irreversible land degradation; loss of rural livelihoods; and water supplies to urban areas, hydro-power and irrigation schemes.

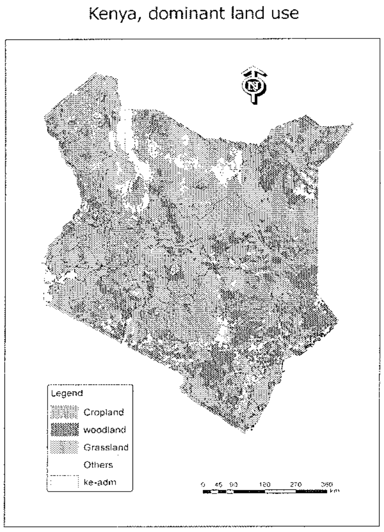

Fig. 1: Kenya, dominant land use types (FAO 2005)

2. Data and analysis

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 *et al.* 2004). The accuracy of GIMMS is proven to be suitable for a global assessment and it is compatible with MODIS and SPOT data (Brown *et al.* 2006).

We used GIMMS data from July 1981 to December 2003, along with decadal rainfall from the CRU TS 2.1 dataset (Mitchell 2004) and information on land cover from air photo interpretation (Fig.1, FAO 2005). ArcGIS Spatial Analyst and ERDAS IMAGINE modules were used to calculate biomass indicators: NDVI minimum, maximum, maximum-minimum, mean, sum, and coefficient of variation (CoV). The fortnightly NDVI data were averaged to monthly; annual NDVI indicators were derived for each pixel; their temporal trends were determined by linear regression (significance level = 0.05) and mapped to depict spatial changes. A negative slope of linear regression indicates a decline of green biomass and positive, an increase – except for CoV which indicates trends in variability.

3. Results

3.1 NDVI indicators

The values of the NDVI indicators are summarised in Table 1. Temporal trends for each pixel, determined by the slope of the linear regression equation, are classed as *no change* (slope <0.0001 and >-0.0001), *increase* (positive slope ≥0.0001), and *decrease* (negative slope ≤-0.0001).

Table 1: Statistics of NDVI indicators

NDVI indicators	NDVI values			No change	Increase	Decrease
	minimum	maximum	mean	No. (%)	No. (%)	No. (%)
Minimum	0	0.782	0.213	530 (6)	5402 (60)	3164 (35)
Maximum	0.002	0.997	0.497	231 (3)	7126 (78)	1739 (19)
Max-min	0.0001	0.667	0.298	206 (2)	6977 (77)	1913 (21)
Mean	0.001	0.846	0.329	410 (5)	6462 (71)	2224 (25)
Sum	0.013	10.154	3.946	33 (0.4)	7123 (78)	1940 (21)
NDVI CoV	0	0.366	0.301	13 (0.1)	19 (0.2)	9064 (99.7)

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

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

Maximum-minimum NDVI: The difference between annual maximum and minimum NDVI reflects biomass production for areas with just one growing season but may not be appropriate for areas with bimodal rainfall.

Sum or integrated NDVI: The sum of fortnightly NDVI values for the year most nearly integrates biomass production. The trend over 23 years increased over 78% of the country but decreased over 21%, largely in the better watered areas (Fig. 2 a, b). For the country as a whole, the 23-year trend was upwards (Fig. 3).

Coefficient of variation (CoV): CoV can be used to compare the amount of variation in different sets of sample data. 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 over. A positive change in the value of a pixel-level CoV over time relates to increased dispersion of values, not increases 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 trends in CoV may reflect land cover change.

3.2 Spatial patterns, biomass and rainfall

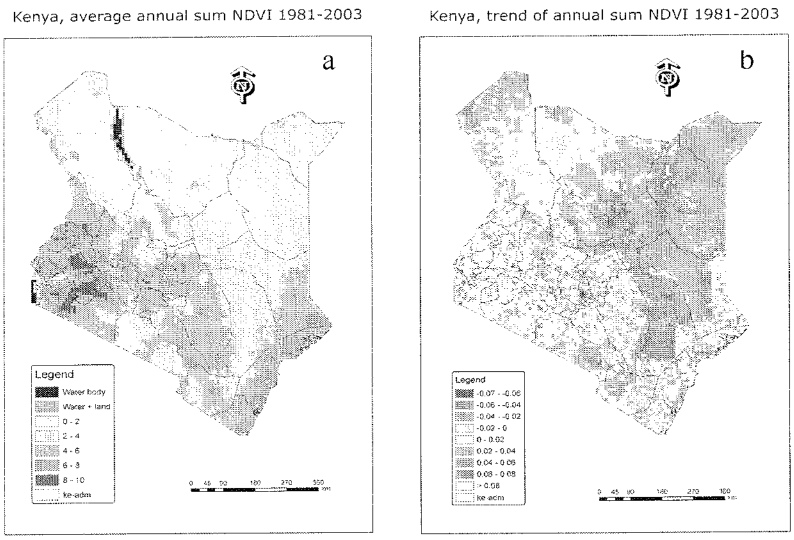

Fig. 2: Spatial pattern (a) and temporal trend (b) of biomass 1981-2003

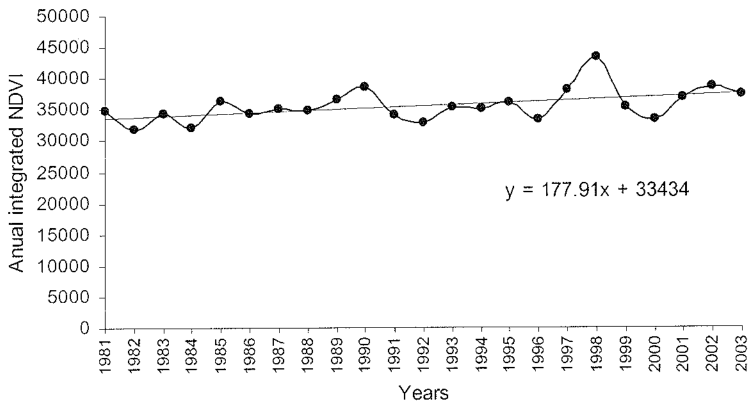

Fig. 3: Spatial integrated annual NDVI 1981-2003

In Kenya, there is a strong coincidence between declining biomass and cropland (Fig. 1), especially, with the expansion of cropland into dryer, marginal areas.

But production depends on rain as well as soil. Mean biomass (Fig. 2a) essentially reflects the mean annual rainfall (Fig.4a) *which has fluctuated significantly*, both spatially (Fig.4b) and cyclically over the period (Fig. 5). Rainfall increased over about 80% of the country and decreased over 20% (Fig. 4b); over Kenya as a whole, rainfall increased over the period (Fig. 5).

The overall trend of rainfall is up, so is the overall trend of biomass, although the correlation for Kenya as a whole is weak (Fig. 6).

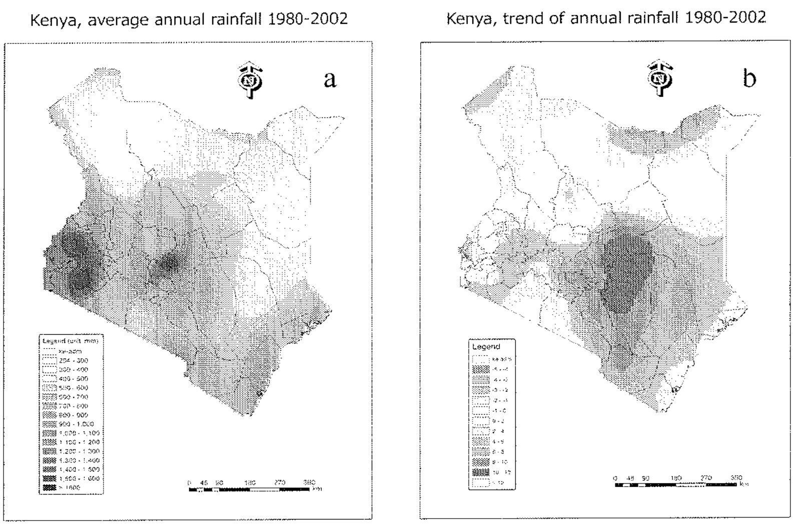

Fig. 4: Spatial pattern (a) and temporal trend (b) of annual rainfall 1980-2002

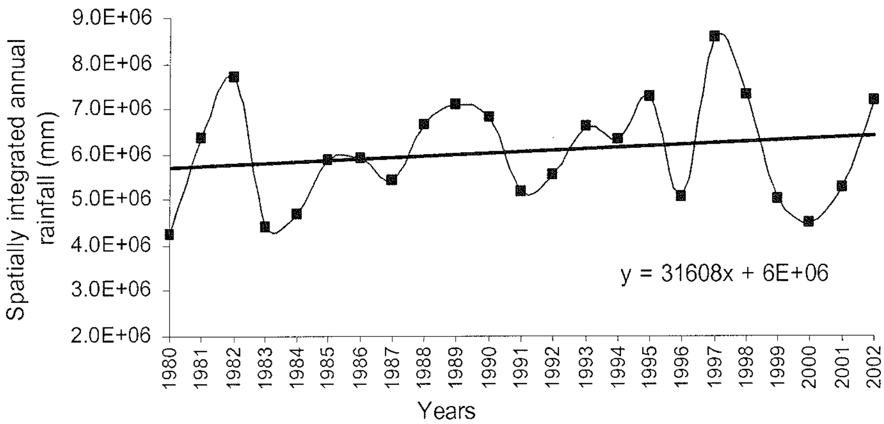

Fig. 5: Spatially integrated annual rainfall 1980-2002

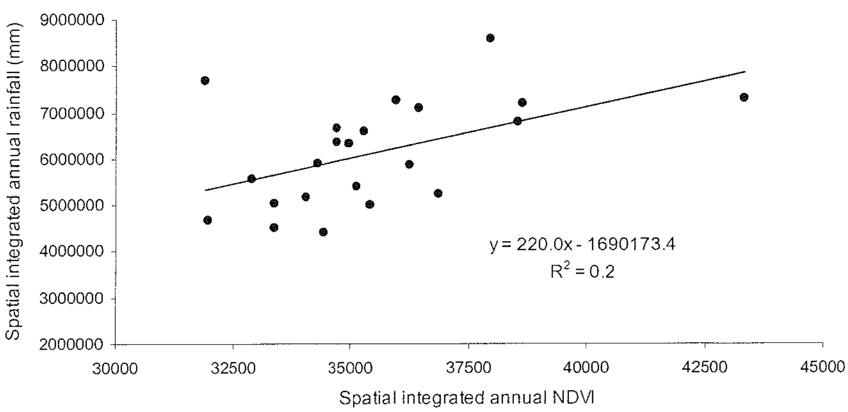

Fig. 6: Relationship between annual sum NDVI (all pixels) and annual rainfall (all pixels). Each dot represents one year.

3.3 Spatial patterns rain-use efficiency

A reduction in biomass does not necessarily mean land degradation. Biomass fluctuates according to variation in rainfall, phenology, and changes in land use - which may or may not be related to the land degradation. Rain-use efficiency (RUE), the ratio of net primary productivity to rainfall, overcomes this problem by expressing production per drop of rain. Although RUE is systematically lower in ecosystems subject to drought stress, it is also lower in degraded drylands than in equivalent non-degraded areas (Le Houerou 1984) - so deviation from the normal value of RUE may indicate land degradation or improvement.

In an earlier study in NW China (Bai *et al.* 2005), we found that values for rain-use efficiency calculated from NDVI, *which values are easy to obtain*, were comparable to those calculated from net primary productivity, which are not easy to obtain. For this study, we calculated rain-use efficiency as the ratio between annual integrated NDVI and annual rainfall – Fig. 7a and b.

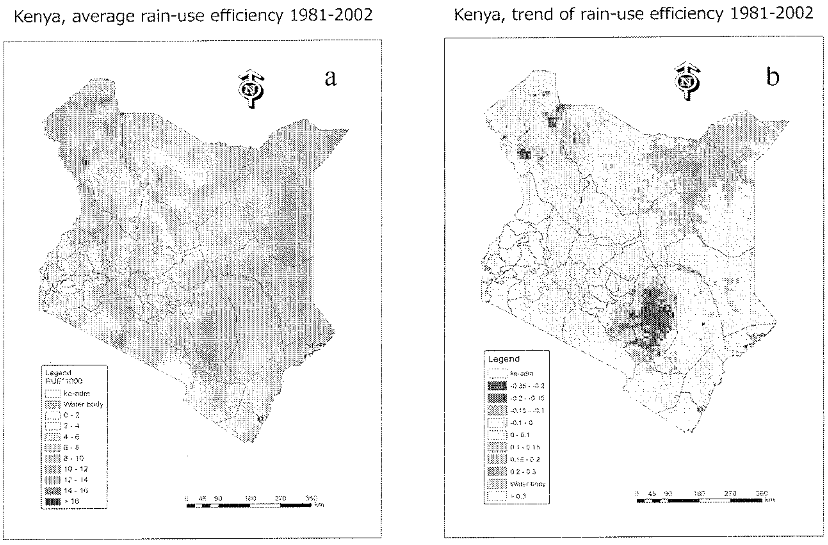

Fig. 7: Spatial pattern (a) and temporal trend (b) of rain-use efficiency derived from integrated NDVI

Rain-use efficiency picks out two land degradation hotspots: the drylands around Lake Turkana and the sub-humid cropland of Eastern Province from Meru south to Machakos, including the the whole of Kitui District. In the drylands, production has declined from a low base; the hotspot in the eastern croplands represents decline in an area of much higher potential.

In sum: remote sensing of biomass indicators can identify hotspots of land degradation. Interpretation is not straightforward and the various NDVI patterns should be followed up to establish the actual conditions on the ground.

Acknowledgements

We thank C.J. Tucker, J.E. Pinzon and M.E. Brown for access to the GIMMS datasets and Felix Rumbold for providing the EC-JRC-MARS-FOOD precipitation data. We are indebted Michael Schaepman for concept development and to ISRIC colleagues J Hunting, for the assistance in ArcGIS, and VWP van Engelen and GWJ van Lynden for discussions.

References

Asrar, G.M., Fuchs, M., Kanemasu, E.T., Hatfield, J.L., 1984. Estimating absorbed photo-synthetically active radiation and leaf area index from spectral reflectance in wheat. Agronomy Journal 87, 300-306.

Bastin, G.N., Pickup, G., Pearce, G., 1995. Utility of AVHRR data for land degradation assessment - a case study. International Journal of Remote Sensing 16, 651-672.

Brown, M.E., Pinzon, J.E., Didan, K., and others, 2006. Evaluation of the consistency of long-term NDVI time series derived from AVHRR, SPOT-Vegetation, SeaWIFS, MODIS and LandSAT ETM+, IEEE Transactions Geoscience and Remote Sensing (in press).

FAO, 2005. Agricultural trend analysis using satellite remote sensing data: a case study – Kenya by Ilaria Rosati. Rome, June 2005.

Le Houerou, H.N., 1984. Rain-use efficiency: a unifying concept in arid-land ecology. Journal of Arid Environments 7, 213-247.

Oldeman, L.R., Hakkeling, R.T.A., Sombroek, W.G., 1991. World map of the status of human-induced soil degradation: an explanatory note, second revised edition. ISRIC, Wageningen, and UNEP, Nairobi.

Paruelo, J.M., Epstein, H.E., Lauenroth, W.K., Burke, I.C., 1997. ANPP estimates from NDVI for the central grassland region of the United States. Ecology 78, 953-958.

Purevdoj, Ts., Tateishi, R., Ishiyama, T., Honda, Y., 1998. Relationships between percentage vegetation cover and vegetation indices. International Journal of Remote Sensing 19, 3519-3535.

Sellers, P., Randall, D.A., Betts and others, 1997. Modeling the exchanges of energy, water and carbon between continents and the atmosphere. Science 275, 502-509.

Singh, D., Meirelles, M.S.P., Costa, G.A., and others, 2006. Environmental degradation analysis using NOAA/AVHRR data. Advances in Space Research 37, 720-727.

Stoms, D.M., Hargrove, W.W., 2000. Potential NDVI as a baseline for monitoring ecosystem functioning. International Journal of Remote Sensing 21, 401-407.

Tucker, C.J., Dregne, H.E., Newcomb, W.W., 1991b. Expansion and contraction of the Sahara Desert from 1980-1990. Science 253, 299-301.

Tucker, C.J., Pinzon, J.E., Brown, M.E., 2004. Global Inventory Modeling and Mapping Studies (GIMMS) Satellite Drift Corrected and NOAA-16 incorporated Normalized Difference Vegetation Index (NDVI), Monthly 1981-2002. The University of Maryland.

UNCED, 1992. Managing fragile ecosystems: combating desertification and drought. Agenda 21, Chapter 12. United Nations Conference on Environment and Development Available online at: (http://www.un.org/esa/sustdev/documents/agenda21) (5 August 2005).

UNEP, 2006. Global Environmental Outlook GEO-4, UN environmental programme, Nairobi.

Wessels, K.J., Prince, S.D., Frost, P.E., Van Zyl, D., 2004. Assessing the effects of human-induced land degradation in the former homelands of northern South Africa with a 1 km AVHRR NDVI time-series. Remote Sensing of Environment 91, 47-67.