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et al. 1991) is a map of perceptions - the kinds and degree of degradation - not a measure of degradation and now out-of-date; land degradation and perceptions have moved on.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. Purevdojr et al. 1998) and above-ground net primary productivity (Partuelo 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)](image)

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 $\geq 0.0001$), and decrease (negative slope $\leq -0.0001$).

Table 1: Statistics of NDVI indicators

<table>
<thead>
<tr>
<th>NDVI indicators</th>
<th>NDVI values</th>
<th>No change</th>
<th>Increase</th>
<th>Decrease</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>minimum</td>
<td>maximum</td>
<td>mean</td>
<td>No. (%)</td>
</tr>
<tr>
<td>Minimum</td>
<td>0</td>
<td>0.782</td>
<td>0.213</td>
<td>530 (6)</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.0002</td>
<td>0.997</td>
<td>0.497</td>
<td>231 (3)</td>
</tr>
<tr>
<td>Max-min</td>
<td>0.0001</td>
<td>0.667</td>
<td>0.298</td>
<td>206 (2)</td>
</tr>
<tr>
<td>Mean</td>
<td>0.001</td>
<td>0.846</td>
<td>0.329</td>
<td>410 (5)</td>
</tr>
<tr>
<td>Sum</td>
<td>0.013</td>
<td>10.154</td>
<td>3.946</td>
<td>33 (0.4)</td>
</tr>
<tr>
<td>NDVI CoV</td>
<td>0</td>
<td>0.366</td>
<td>0.301</td>
<td>13 (0.1)</td>
</tr>
</tbody>
</table>

*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

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).
Kenya, average annual rainfall 1980-2002

Kenya, trend of annual rainfall 1980-2002

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.

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 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


