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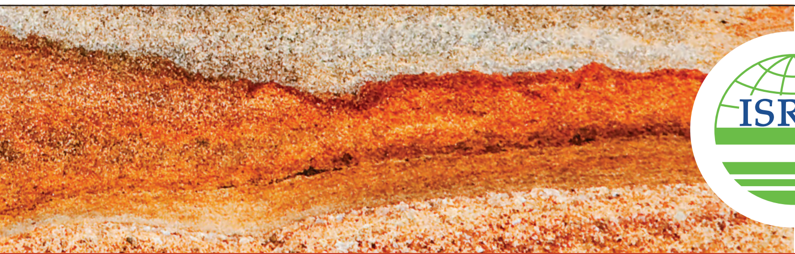
Towards mapping global soil degradation



ISRIC World Soil Information

ISRIC Report 2012/02

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Global changes of remotely sensed greenness and simulated biomass production since 1981

Towards mapping global soil degradation

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ISRIC Report 2012/02

Wageningen, 2012

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Citation
Z.G. Bai, J.G. Conijn, P.S. Bindraban and B. Rutgers, 2012. *Global changes of remotely sensed greenness and simulated biomass production since 1981; Towards mapping global soil degradation*. Wageningen, ISRIC, ISRIC Report 2012/02. 34 pp.; 10 fig.; 57 ref.

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Contents

List of acronyms and abbreviations

AVHRR	Advanced Very High Resolution Radiometer
CRU	Climate Research Unit, University of East Anglia
EMD	Empirical Mode Decomposition
ESA	European Space Agency
FAO	Food and Agriculture Organization of the United Nations, Rome
F_{PAR}	Fraction of absorbed Photosynthetically Active Radiation
GIMMS	Global Inventory Modelling and Mapping Studies, University of Maryland
GLADA	Global Assessment of Land Degradation and Improvement
GLASOD	Global Assessment of Human-Induced Soil Degradation
GMAO	The Global Modeling and Assimilation Office
HANTS	Harmonic Analyses of NDVI Time-Series
IMAGE-GLOBIO	Integrated Model to Assess the Global Environment - Global Biodiversity Model
ISRIC	International Soil Reference Information Centre
JRC	European Commission Joint Research Centre
LADA	Land Degradation Assessment in Drylands
LAI	Leaf Area Index
Landsat ETM+	Land Resources Satellite, Enhanced Thematic Mapper
LINPAC	A LINtul model for Perennial and Annual Crops
LUS	Land Use Systems, FAO
MOD17A3	MODIS 8-Day Net Primary Productivity data set
MODIS	Moderate-Resolution Imaging Spectroradiometer
MVC	Maximum Value Composite
NDVI	Normalized Difference Vegetation Index
NOAA	The US National Oceanic and Atmospheric Administration
NPP	Net Primary Productivity
PBL	Netherlands Environmental Assessment Agency
RUE	Rain-Use Efficiency
SZA	Solar Zenith Angle
TBW	Total annual production of biomass
WISE	A harmonized Dataset of Derived Soil Properties for the World
WOCAT	World Overview of Conservation Approaches and Technologies

1 Background

1.1 The need for a new assessment

The global food- and eco-system will encounter unprecedented pressures over the next few decades, as agricultural production must increase by 70-100% to feed over 9 billion people by 2050. This is further compounded by the growing demand for non-food items such as biofuels and biomaterials. There is compelling evidence, however, that the productive capacity of cropland is degrading. Estimates of the rate at which this is happening, globally, and the costs incurred in terms of productivity and economic losses, and how this impacts on food security are extremely variable and uncertain because of (i) uncertainties in underlying information; (ii) lack of an objective definition of land degradation; (iii) methodological weaknesses to relate changes in productivity to land degradation or other variables (e.g. climate or management) and (iv) different system boundaries used in different estimates (types of land degradation accounted for; inclusion or not of off-site effects) (Pimentel *et al.*, 1995; Trimble & Crosson, 2000; Lal, 2007; Wilkinson & McElroy, 2007; Sonneveld & Dent, 2007; Telles *et al.*, 2011). Even at the local level, it is still a challenge to quantitatively assess the effects of soil degradation on crop yields (WOCAT, *http://www.wocat.net/*). As a consequence, land degradation appears to be underemphasized on national and international policy agendas (Nkonya *et al.*, 2011) and the investments required to safeguard future food security are unknown.

Land degradation is a phenomenon that leads to the decline in productivity of agro-based goods and ecosystems services. Yet, land can be used for a range of other functions like urbanisation and industry for instance, which are considered valuable but not contributing to agro-ecological functions. Balancing different functions is at the heart of any decision related to land use, certainly so as it affects people most that rely directly on land resources for their livelihoods.

If interpreted appropriately, up-to-date quantitative information about land degradation can support policy decision making on balancing such needs, including food and water security, economic development, environmental integrity and resource conservation. However, rather than doing this by the conventional approach of classifying areas affected by degradation and then determining its impacts, which incurs loss of information and fruitless discussions about class boundaries, a more integrated approach appears to be more promising. This would aim at the assessment of changes in land attributes which, through the use of mechanistic models and supported by empirical findings could then be translated in changes in ecosystem functioning or goods and services (e.g. agricultural productivity, carbon storage, water regulation). This integrated approach is followed in a comprehensive modelling exercise 'IMAGE-GLOBIO' by PBL Netherlands Environmental Assessment Agency with explicit attention to the relation between economic activities and biodiversity.

Land may degrade due to a wide range of activities including changes in land use, unbalanced nutrient management, inappropriate soil tillage leading to erosion, salinization due to inappropriate irrigation or reduced precipitation etc. The productivity of land, *i.e.* the amount of biomass that can be produced, is affected by degradation. Yet, the relation between 'land degradation' and 'biomass productivity' is not straightforward and needs accurate understanding of soil processes in relation to climate, plant growth and management. Higher level integration through the 'IMAGE-GLOBIO' approach will advance this primary relation between ecosystems/biodiversity, land productivity, economic development and poverty. The scope of this research relates specifically to land degradation and biomass productivity.

1.2 Indicators

Land degradation may be defined as a long-term loss of ecosystem function and productivity caused by disturbances from which the land cannot recover unaided (Bai *et al.*, 2008a,b). It may be measured by the change in net primary productivity (NPP – the difference between the rate at which the plants in an ecosystem produce useful chemical energy and the rate at which they use some of that energy during respiration); deviation from the norm may be taken as an indicator of land degradation or improvement. As a proxy, the remotely sensed normalized difference vegetation index (NDVI, or greenness) has been shown to be related to biophysical variables that control vegetation productivity and land/atmosphere fluxes (Hall *et al.*, 2006) such as: leaf area index (Myneni *et al.*, 1997), the fraction of photosynthetically-active radiation absorbed by vegetation (Asrar *et al.*, 1984), and NPP (Alexandrov & Oikawa, 1997; Rasmussen, 1998a, b). It has also been used to estimate vegetation change, either as an index (Anyamba & Tucker, 2005; Olsson *et al.*, 2005) or as one input to dynamic vegetation models (Nemani *et al.*, 2003; Seaquist *et al.*, 2003; Fensholt *et al.*, 2006). Consistent time-series data at spatial resolutions from 20m to 8km (Brown *et al.*, 2006) enable analysis and generalization.

A decreasing trend in NDVI does not necessarily indicate land degradation, nor does an increasing trend necessarily indicate land improvement. Biomass depends on several factors including: climate - especially fluctuations in rainfall, sunshine, temperature and length of growing season; land use; large-scale ecosystem disturbances such as fires; and the global increase in nitrate deposition and atmospheric carbon dioxide. To interpret NDVI trends in terms of land degradation or improvement, we have to eliminate false alarms, in particular those arising from climatic variability and land use change. Globally, this can be done for climate, for which a century's consistent data are available (Bai *et al.*, 2008a), but global time series are not yet available for land use which has to be examined case-by-case.

Total biomass production (TBW) can serve as an integral indicator that accounts for the impact of climate variables, including temperature and rainfall, in interaction with crop and soil properties. The combination of satellite-based estimation of NDVI and calculated TBW based on long-term series of climatic data and constant crop and soil properties is used in this study to disentangle the likely impact of climate from other causes on the observed trends in NDVI.

NDVI is a ratio of red and near-infrared light reflected by the Earth's surface. To provide a more tangible measure of land degradation, the NDVI in this study is correlated to net primary productivity (NPP) using MODIS (moderate-resolution imaging spectroradiometer) NPP data (Running *et al.*, 2004) for the overlapping period 2000-2006.

1.3 Research objective

This research is a component of PBL project on the Biodiversity, Ecosystem Services and Development (Biodiversiteit, ecosysteemdiensten en ontwikkelingsvraagstukken). The ultimate goal of the PBL project is to gain a quantitative understanding of the interrelations between ecosystem degradation and economic development, particularly with regard to food- and water security in developing countries.

The ultimate goal of this research component of the PBL project is to develop a quantitative methodology to relate soil degradation to biomass production and assess the loss of productivity world-wide due to soil degradation.

The objective of the research described in this report is to quantify trends in land degradation and biomass productivity over the past three decades and discuss the findings in order to identify future research avenues to better identify the causes and/or further refine the approach.

2 Data and methodology

2.1 NDVI

The Normalized Difference Vegetation Index (NDVI) is calculated from the red (RED) and near-infrared (NIR) light reflected by the Earth's surface, *i.e.,* NDVI = (NIR-RED)/(NIR+RED), and is used as a measure of vegetation or greenness. The NDVI data used in this study are produced by the Global Inventory Modelling and Mapping Studies (GIMMS) group from measurements made by the AVHRR radiometer on board of the US National Oceanic and Atmospheric Administration satellites (US-NOAA) (Tucker *et al.*, 2004; Pinzon *et al.*, 2007). The fortnightly images at 8km-spatial resolution, derived from daily 4 km global area coverage are corrected for view geometry, volcanic aerosols, and other effects not related to vegetation cover(Tucker *et al.*, 2005). The maximum-value-composite (MVC) technique is used to remove bias caused by atmospheric conditions (Holben, 1986). Orbital drift correction is performed using an empirical mode decomposition (EMD) transformation method of Pinzon *et al.* (2005) removing common trends between time series of solar zenith angle (SZA) and NDVI. Orbital decay and changes in NOAA satellites affect AVHRR data but processed NDVI data have been found to be free of trends introduced from these effects (Kaufmann *et al.*, 2000). No atmospheric correction is applied to the GIMMS data except for volcanic stratospheric aerosol periods (1982–1984 and 1991–1994) (Tucker *et al.*, 2005); some uncertainty still remains, especially in hazy and cloudy conditions (Nagol *et al.,* 2009). To remove any residual cloud effects or other outliers, the Harmonic Analysis of NDVI Time-Series (HANTS) algorithm (Verhoef *et al.*, 1996; Roerink *et al.*, 2000; Wit & Su, 2005) has been applied to smoothen and reconstruct the NDVI time-series (Jong *et al.*, 2011); the HANTS-reconstructed data from July 1981 to December 2006 was employed in this study.

2.2 TBW

Total annual production of biomass (TBW) was calculated for each year in the period 1981-2006 with the crop model LINPAC (Conijn *et al.*, 2011; Jing *et al.*, 2011) and refers to the rain-fed production level, *i.e.* optimum management but not irrigated, ample nutrient availability and free from pests, diseases and weeds. The model has a time step of one day and calculates daily biomass increase based on crop characteristics, soil and weather data: including soil texture, soil depth, soil water holding capacity, radiation, temperature, precipitation, vapour pressure and wind speed. Daily soil water availability and (evapo)transpiration following from a soil water balance calculation, and daily leaf area growth are intermediary variables. Accumulation of daily biomass production over the season leads to total biomass production and yield. Prior to the biomass calculation, the suitability of each location for cropping is checked per year as function of temperature, soil water availability and crop characteristics leading to calculated sowing and harvesting dates of all crop cycles in a year. For annual crops the number of cycles per year ranges from 0 to an assumed maximum of three and is found by 'fitting' temperature sum requirements of a crop into the period of suitable growing days per year (see also Conijn *et al.*, 2011). For perennial vegetation the plant growth period equals the period of suitable growing conditions. For this study two runs were separately executed to calculate the biomass production of an annual and a perennial vegetation and TBW has been found by combining the results of the two runs on the basis of the crop land fraction (f_{crop}) in each location:

$$TBW = f_{crop} * TBW_{annual} + (1 - f_{crop}) * TBW_{perennial}$$

if $TBW_{annual} = 0$, then $TBW = TBW_{perennial}$; if $TBW_{perennial} = 0$, then $TBW = TBW_{annual}$.

Time series of gridded weather data (monthly averages/totals) from the Climate Research Unit (CRU, 2011) were used as input with a resolution of 30x30 arc-minutes. Daily values are calculated by a random distribution function for precipitation and by linear interpolation for the other climate variables. Soil characteristics were obtained from the ISRIC-WISE v1.0 database (Batjes, 2006) in combination with the Digital Soil Map of the World from FAO with a resolution of 5x5 arc-minutes (FAO, 1996). The land use map of Erb *et al.* (2007) was used to estimate the crop land fraction with a resolution of 5x5 arc-minutes. The annual crop has been approximated by taking the characteristics of a wheat/maize crop as input (wheat for temperate and maize for tropical regions) and those of Miscanthus to represent the perennial vegetation. Some parameters were adapted to ensure that in locations with short growing seasons (*e.g.* in dry or cold climates) vegetation types with shorter growth cycles compared to wheat, maize or Miscanthus could also be simulated.

Because soil and crop characteristics are kept constant, the impact of changes in climate over time on biomass production can be estimated.

2.3 MODIS NPP

MODIS (Moderate-Resolution Imaging Spectro-Radiometer) MOD17A3 is a dataset of terrestrial gross and net primary productivity, computed at 1-km resolution at an 8-day interval with daily MODIS land cover, F_{PAR}/LAI and global GMAO surface meteorology at 1km for the global vegetated land surface (Heinsch *et al.*, 2003; Running *et al.*, 2004; Zhao *et al.*, 2005; Zhao & Running, 2010). The dataset produces gross primary production of vegetation every day, and sums to net primary production, essentially vegetation growth, at the end of the year. The NPP data have been validated in various landscapes (Fensholt *et al.*, 2004; 2006; Gebremichael & Barros, 2006; Turner *et al.*, 2003; 2006) indicating that the calculated NPP are reliable at the regional scale (Zhao *et al.*, 2005; 2006). The MOD17A3 is continuously produced and available till 2010; the improved MOD17A3 from 2000 through to 2006 which matches the available HANTS-reconstructed NDVI dataset is used in this study to indicate non-vegetated areas for which NPP is assumed zero and to correlate with NDVI.

2.4 Analytical method

The fortnightly NDVI data were averaged to monthly, then aggregated to an annual scale, expressed as annual sum NDVI (ΣNDVI), ranging from 0 to 12, unitless. Annual sum NDVI indicator is computed pixel-by-pixel for a calendar year from the first of January to the end of December, and taken to represent annual accumulated greenness. Multi-year mean values for each pixel were calculated for the two indices (ΣNDVI, TBW) over the period 1981-2006; their temporal trends were calculated for each pixel by linear regression at an annual interval. Both mean values and trends were mapped globally to depict spatial patterns. A negative slope of linear regression indicates a decrease of ΣNDVI and calculated biomass production (TBW) and a positive slope, an increase. Positive and negative slopes of both indices were compared at a pixel level and mapped to illustrate differences in temporal trends. Absolute changes of ΣNDVI and TBW per pixel during 1981–2006 are presented by the estimated slope values and subsequently, percentage changes have been calculated relative to the mean value of the whole period, *i.e.*, 100(slope/multi-year mean). The resolution of NDVI is resampled to 5x5 arc-minutes to match that of the TBW.

Linear regression was also applied to illustrate the relation between (1) NPP as function of ΣNDVI and (2) ΣNDVI as function of TBW, taking the mean pixel values of all relevant pixels world-wide, *i.e.* from vegetated areas (according to the MODIS NPP data set).

3 Result and discussion

3.1 ΣNDVI

Globally, annual sum NDVI (ΣNDVI, or greenness) increased by 2.8 per cent over the period 1981-2006 (*P*<0.001), revealing an overall greening of the World-wide (Fig. 1). However, there are major regional differences. Figures 2 to 4 depicts the spatial patterns of 26-year mean annual ΣNDVI and trends over the period 1981-2006.

The patterns of greenness are in line with general perceptions and land cover map (JRC, 2003, See Appendix I) with rainforests near the equator (dark green indicating high ΣNDVI) and low ΣNDVI values near the fringes of deserts and polar areas. The changes in greenness (Fig. 3) suggest a general decline in areas with high ΣNDVI and improvements in some fringes of deserts such as in the Sahel and the Kalahari, The eastern part of the Indian continent, Inner Turkey, Northern America, Siberia and Western Australia. Relative changes are large where mean value of ΣNDVI is low, but these patterns remain visible when changes are expressed in absolute terms (Fig. 4).

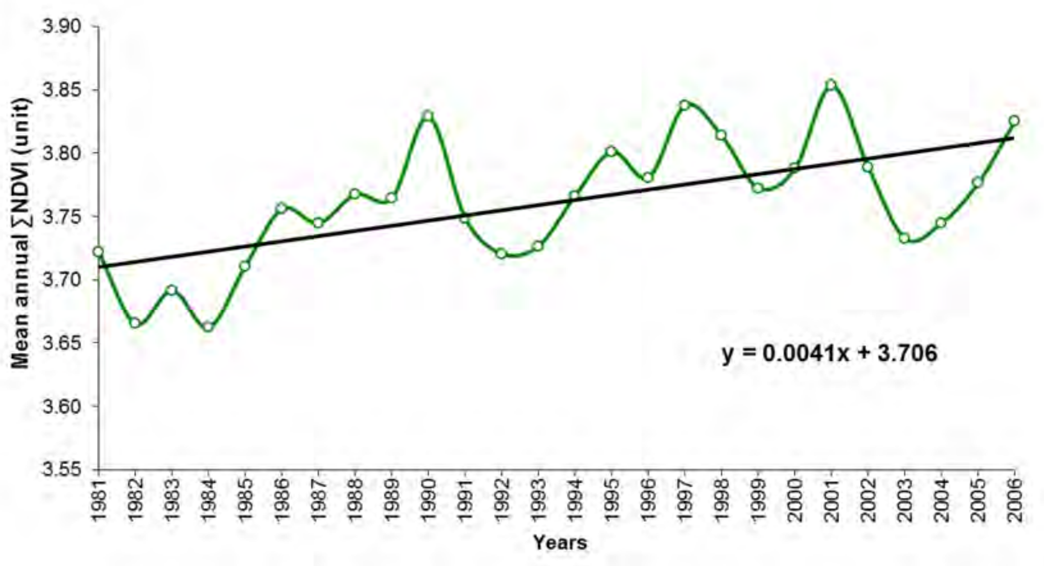

Figure 1.
Trend of total mean annual sum NDVI during 1981-2006 for the whole World.

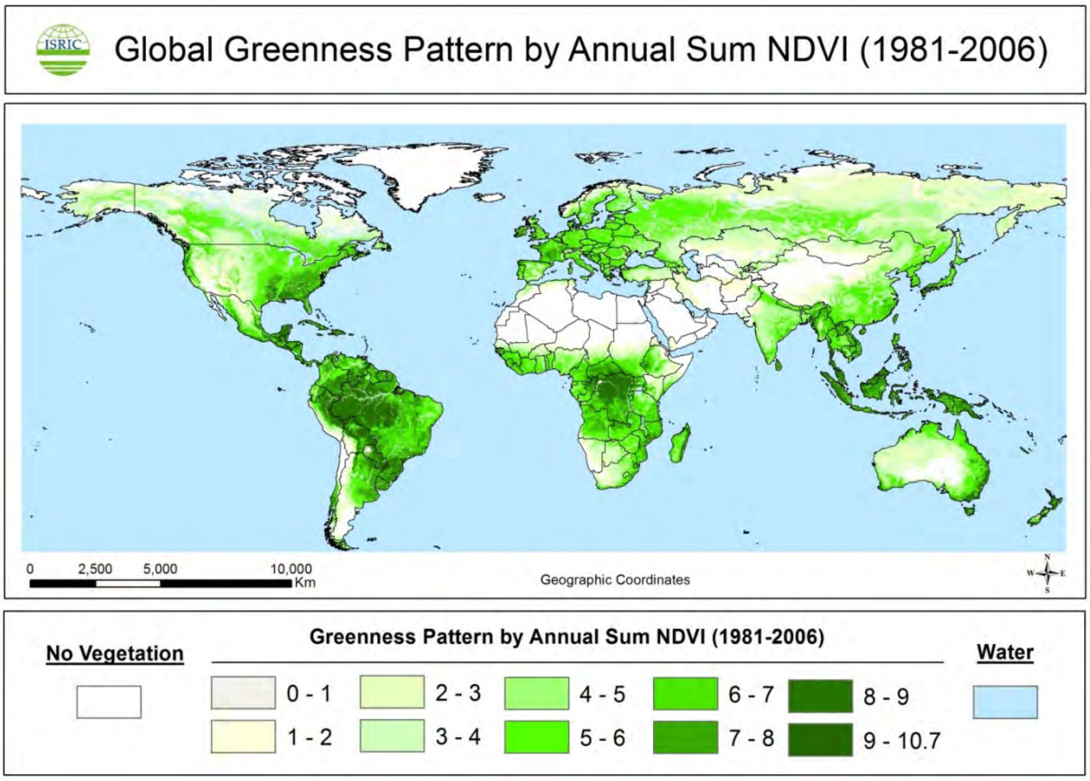

Figure 2.
Global pattern of mean annual sum NDVI (ΣNDVI) for the period 1981–2006.

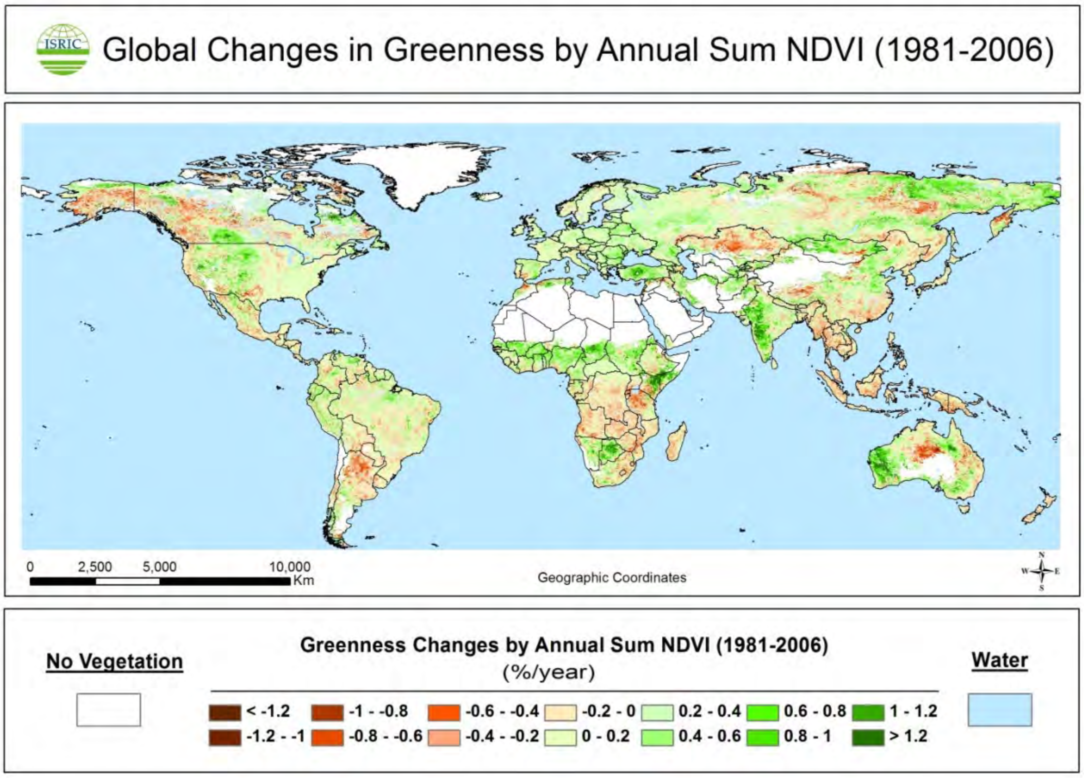

Figure 3.
Global pattern of percentage changes of ΣNDVI for the period 1981–2006.

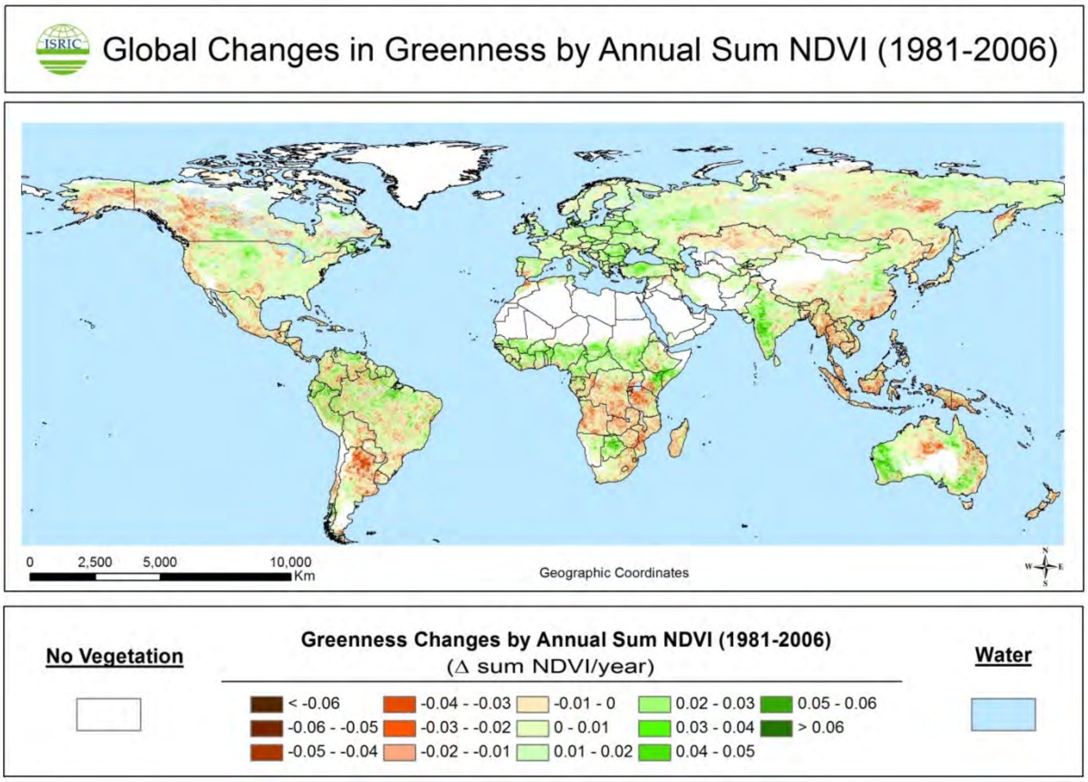

Figure 4.
Global pattern of absolute changes of ΣNDVI for the period 1981-2006.

3.2 TBW

Figures 5 to 7 show the spatial patterns of the mean, percentage and absolute changes of calculated rain-fed biomass production of annual and perennial vegetation combined (TBW).

Mapping the mean TBW clearly illustrates the effect of climatic conditions on the calculated capacity to produce biomass in the world (Fig. 5). Dark green colours are found in areas of tropical rain forests and light green dominate near dry and cold climates. In deserts and very cold areas a zero biomass production is calculated (white colour), because these conditions are too harsh for vegetation to survive. In the calculation for this study, irrigation has not been taken into account which means that current irrigated production areas will not emerge as green areas, such as the Nile Delta. The patterns are comparable to those of Figure 2.

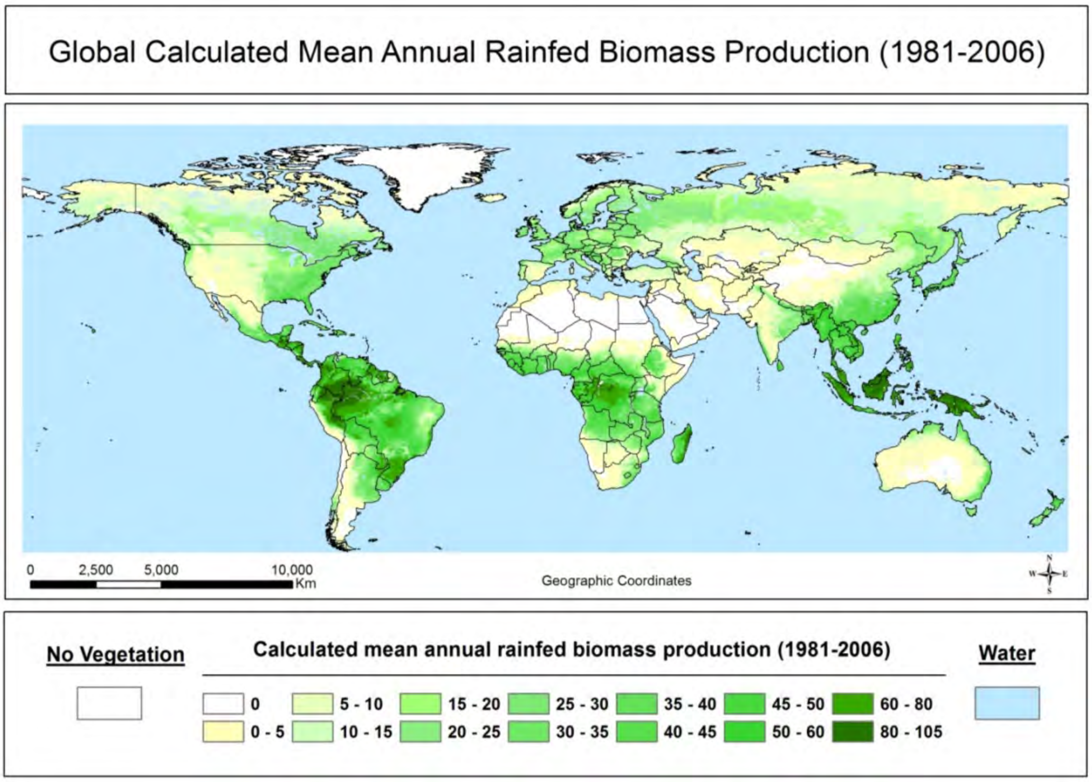

Figure 5.
Calculated mean annual rain-fed biomass production TBW for the period 1981-2006 (tonne dry matter ha^{-1} y^{1}).

The changes in biomass production over the period 1981-2006 show some marked declines in areas like France, the Baltic region, Chile, Western USA, Northern China, Northern India and Eastern Australia (Figs. 6-7). These changes suggest that, over the past three decades, the weather conditions in these areas have developed unfavourably for biomass production.

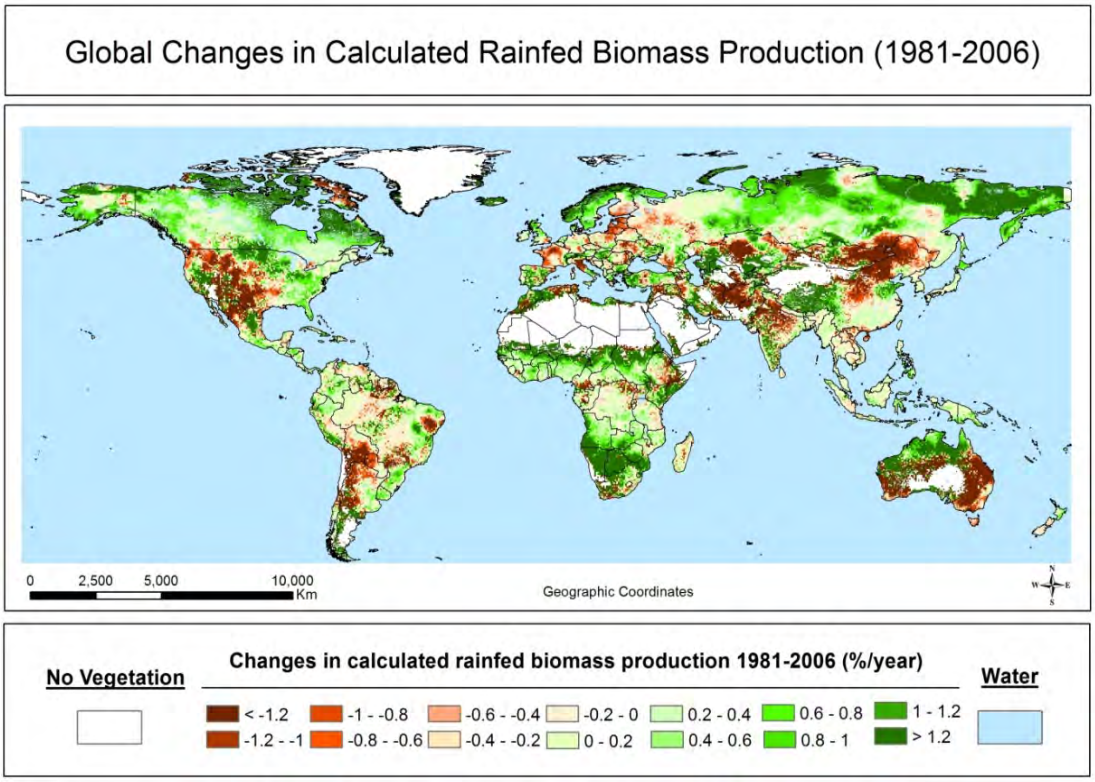

Figure 6.
Percentage changes of calculated rain-fed biomass production TBW for the period 1981-2006.

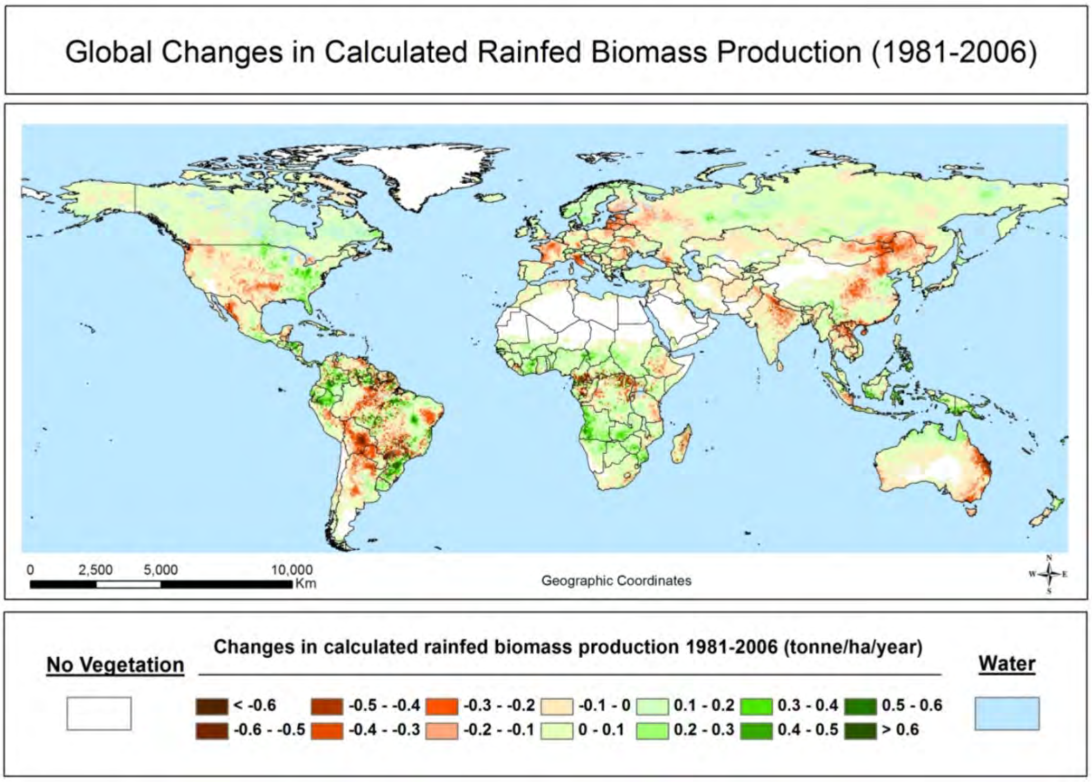

Figure 7.
Absolute changes of calculated rain-fed biomass production TBW for the period 1981-2006.

3.3 Comparing trends of ΣNDVI and TBW

The changes in ΣNDVI and TBW are illustrated by a 4-color map of the world at 5 by 5 arc-minutes resolution depicting combinations of positive and negative changes. Any change below 5% over the analysed period of 26 years is masked white so that only the larger changes will appear on the map (Fig. 8). The following tentative explanation of the different combinations can be given:

a. Positive ΣNDVI and positive TBW change. The improved greenness (ΣNDVI) might be totally or partly explained by improved weather conditions as these are the cause for the increase in TBW. A relatively low positive ΣNDVI change and high positive TBW change could even indicate that deteriorating conditions of *e.g.* soil and land use have had a negative effect on the vegetation, but have been masked by the larger positive effect of climatic changes.
b. Positive ΣNDVI and negative TBW change. Worsening climatic conditions decreased TBW but rather than an expected negative effect on ΣNDVI, the greenness has improved. This is possibly caused by favourable interventions like irrigation, fertilization, increasing atmospheric CO_2 concentrations, deposition of reactive nitrogen, or reforestation. Hence favourable human interventions or natural changes could have caused these combined trends.
c. Negative ΣNDVI and positive TBW change. The greenness declines against a trend of expected positive change from climatic conditions. It is likely then that other factors such as deforestation or severe soil degradation have had a larger impact on the productivity.
d. Negative ΣNDVI and negative TBW change. The decline in greenness may have resulted (partly) from worsening climatic conditions. Here a stronger decline in ΣNDVI over TBW could also indicate a worsening of soil conditions or land use change, like deforestation.

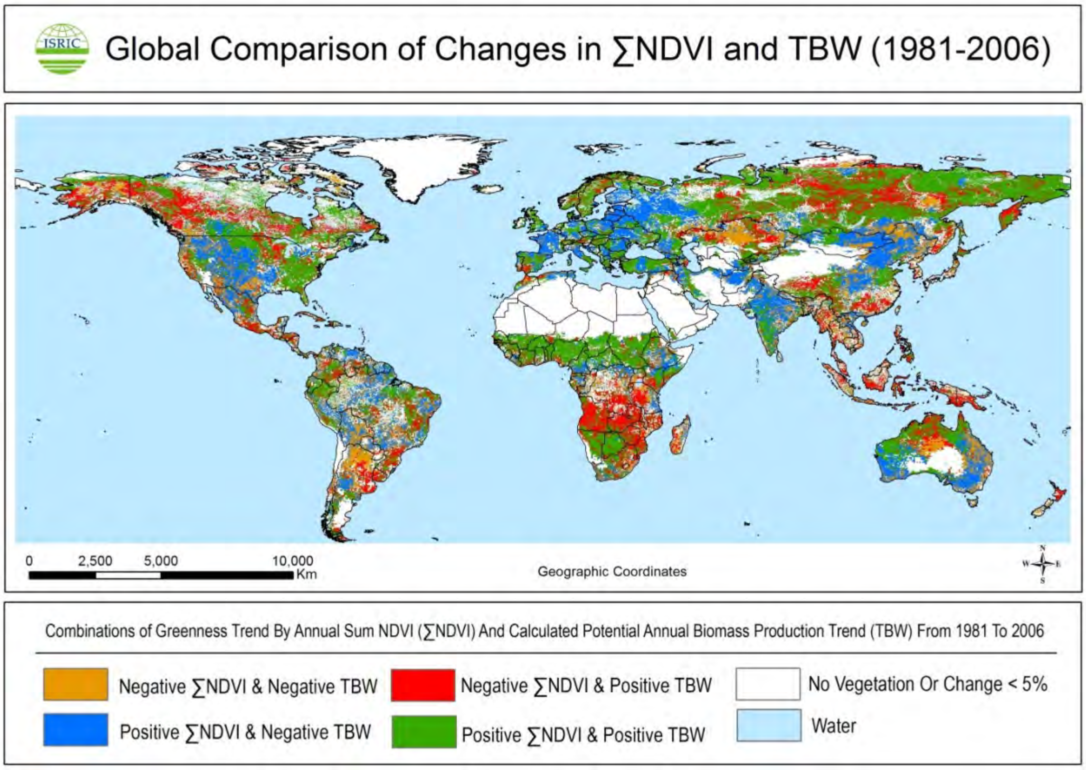

Figure 8.
Global illustration of areas with positive or negative change in greenness (ΣNDVI) and climate-related capacity to produce biomass (TBW) during 1981 to 2006. Pixels (5 by 5 arc-minutes) with low change rates of both variables (less than 5% for the entire period) are not shown.

Figure 8 clearly shows that most pixels in the world have changes that exceed our 5% threshold for at least one of the two indices (excluding large deserts and very cold areas, like Greenland) and that in many regions the coloured pixels are grouped into larger areas. Positive changes in both ΣNDVI and TBW (green) feature in the Sahel region, the Kalahari, Russia, Northern Australia and Eastern parts of USA. Also the Southern part of India and south east Europe, including Turkey experience improving conditions.

The positive changes in ΣNDVI combined with negative in TBW (blue) in north-east Europe, Northern China, Northern India, the mid-western part of USA and southern Australia tend to have been positively influenced by human interventions despite the fact that weather conditions reduced the productivity.

Negative changes in ΣNDVI combined with positive in TBW (red) in parts of Africa, Indonesia, Canada, Alaska and Siberia suggesting deforestation, soil degradation or other causes that deteriorated the productivity despite improved weather conditions.

Both negative ΣNDVI and negative TBW are found in Kazakhstan, North China, the Chaco in Northern Argentina, and Western Australia suggest that these regions have been experiencing worsening conditions either climatic change or management of soil use.

3.4 Relations between ΣNDVI, TBW and NPP

Figure 9 shows the relation between mean values of annual ΣNDVI and NPP for the period 2000–2006 at spatial resolution of 4.36 by 4.36 arc-minutes for all data points and for 1% random sampling of all data. While these variables are significantly correlated ($r^2 = 0.7$), the graph clearly indicates that a straightforward conversion of ΣNDVI into NPP by the linear regression cannot be justified:

$$NPP = 1.26 * \Sigma NDVI - 1.53 \qquad (n = 2{,}450{,}665;\ r^2 = 0.70) \qquad (1)$$

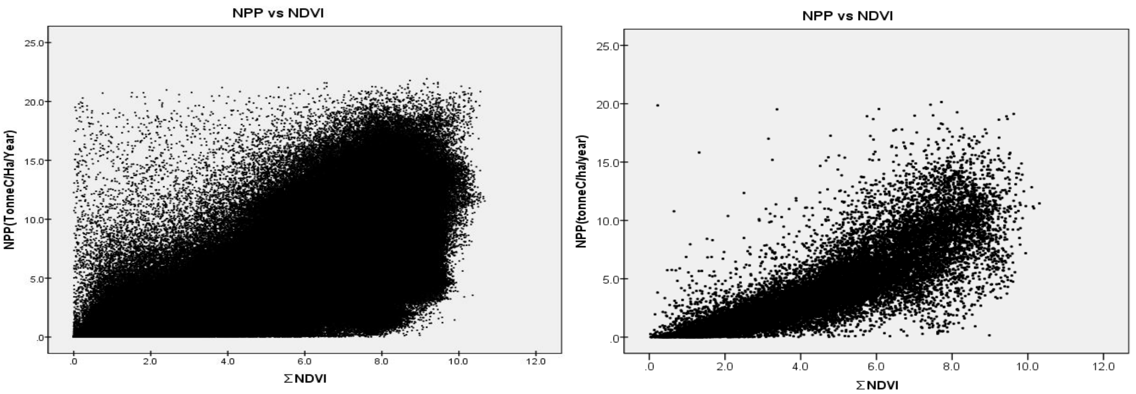

Figure 9.
Scatter plot of the relation between ΣNDVI and NPP: left - all data; right - 1% of the all data sampled randomly.

Nonlinear correlations between ΣNDVI and NPP and other factors affecting this relation need to be identified for any sensible conversion.

Figure 10 shows the relation between annual ΣNDVI and square root of TBW for the period 2000–2006 at spatial resolution of 5 by 5 arc-minutes for all data points and for 1% randomly sampling of all data.

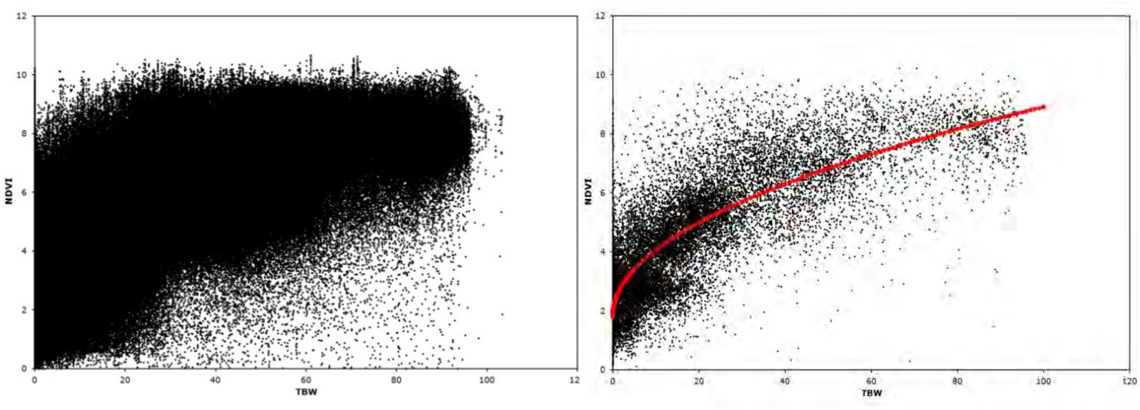

Figure 10.
Scatter plot of the relation between TBW and ΣNDVI (only vegetated pixels were selected): left - all data; right - 1% of the all data sampled randomly, including the regression line from equation 2, based on all data.

The regression coefficients of the correlation between ΣNDVI and the square root of TBW is given below in equation (2) and their estimated standard errors are 0.0019 and 0.00042, respectively, for the intercept and the slope.

$$\sum NDVI = 0.71 * \sqrt{TBW} + 1.80 \qquad (n = 1,727,651;\ r2 = 0.62) \qquad (2)$$

Although the percentage variance accounted for is 62%, the variation of the data relative to the regression line still remains high (Fig. 10). The use of the square root of TBW in equation (2) indicates that the relation between ΣNDVI and TBW is curve-linear and that the increase of ΣNDVI as function of TBW decreases at higher levels of TBW. This curvature could be explained because NDVI values are not likely to increase much further once the canopy is closed (depending on the crop at a Leaf Area Index (LAI) of about 3-5), while the rate of biomass production has been found to continue to increase up to LAI values of 6-8 (Myneni *et al.*, 2002; Jones & Vaughan, 2010). A straight line between ΣNDVI and TBW gave a lower percentage accounted for and also a much higher estimation of the intercept with a value of 3.00. This intercept gives the value for ΣNDVI at TBW = 0 and theoretically should approach the mean ΣNDVI of non-vegetated areas, which equals circa 1.1.

In the study of Global Assessment of Land Degradation and Improvement (GLADA) (Bai *et al.*, 2008a, b), rain-use efficiency (RUE) was used to adjust NDVI change over 1981-2003 due to changes in rainfall, and temperature, *i.e.,* RUE-adjusted NDVI approach, and the adjusted changes in NDVI were translated to net primary production using MODIS data for the overlapping period 2000-2003 for an economic analysis. However, this adjustment has limitations in areas where surplus rainfall occurs and does not take rainfall distribution and other weather variables into account.

This study, conducted for the extended period of 1981-2006, advanced the RUE-adjusted approach by using a soil-crop model (LINPAC) which includes both weather and soil properties to estimate rain-fed biomass production and can be used to adjust NDVI due to changes in climate. The above-illustrated relations of NDVI to TBW and NPP after further verification can help to ultimately estimate losses of biomass production due to soil degradation.

However, there are some caveats when applying these methodologies globally:

1) The NDVI signal can be saturated at closed vegetation canopy (Ripple, 1985). This implies that NDVI is more sensitive for cropland and rangeland than for forest; however, it is still useful for forests because the canopies of many forests *e.g.,* deciduous forest and pine in the world are not closed (Illera *et al.*, 1996; Wang *et al.*, 2004; 2005);
2) The large spatial variability of rainfall in dry lands makes interpolation of point measurements problematic, and weather observation stations are sparse in many of these areas with considerable uncertainties in gridded climate data as a result.
3) TBW has been calculated for a limited number of vegetation types and with predefined management level. E.g. irrigation has not been taken into account and in irrigated areas the effects of climate will be different from the calculated results.

4 Conclusions

PBL – the Netherlands Environmental Assessment Agency - uses a higher level integration approach through the 'IMAGE-GLOBIO' model to relate land degradation to biomass productivity, and further, to economic activities and biodiversity. However, the assessment of the impacts of land degradation on biomass productivity is not straightforward and needs accurate understanding of soil processes in relation to climate, plant growth and management. To support the approach of PBL, ISRIC and PRI-WUR have jointly analysed the global patterns and trends in greenness (represented by ΣNDVI) and simulated annual biomass production (TBW). Decreasing levels of ΣNDVI could indicate land degradation but should be adjusted first by a correction with other causes of change in ΣNDVI, such as changes in climate.

Overall ΣNDVI, as a proxy for greenness of the world, increased with circa 1% per decennium during 1981-2006. This rate is statistically significant with $p < 0.001$ and may also be relevant, *e.g.* in relation to CO_2 fixation by the world's vegetation. More research is needed to quantify the effects.

The global spatial patterns of ΣNDVI and TBW appeared similar, but the temporal changes were different leading to distinct areas where (a) both increased, (b) both decreased, (c) an increase in ΣNDVI was linked to a decrease in TBW and (d) vice versa. Because changes in simulated TBW are only caused by changes in weather, comparison of the trends in ΣNDVI and TBW have been used to qualitatively describe the impact of climate changes on changes in ΣNDVI. If a decline in ΣNDVI can be explained by a negative trend in climatic conditions, it is not an indication for land degradation, while at the other hand, an increase in ΣNDVI does not necessarily exclude land degradation if climatic conditions have improved.

The relations of NPP as function of ΣNDVI and ΣNDVI as function of TBW have been established by linear regression and a considerable amount of variation could be explained ($R^2 > 60\%$). Still, the scatter plots of both seem to reveal a large variation around the regression line, as can be concluded by visual check, which indicates that the calculations of NPP and ΣNDVI are surrounded by much uncertainty. Investigating possible co-variables of the relationships, e.g., vegetation type, climatic zone, etc., might lead to more precise results.

In this study we have developed a methodology that can be used to estimate the impact of land degradation on biomass production. This methodology can be applied globally with a high spatial resolution and can therefore contribute very well to answer PBL's questions but needs further refinement, verification and should be extended with non-climate related causes of changes in land productivity. In the next chapter we give some suggestions for a follow-up to advance the methodology further to the needs of PBL.

5 Recommendations to advance the analysis

The current analysis shows some interesting features with regards to the trends in changing productivity and possible causes. Yet, for more conclusive findings, refinement of the current methodology is suggested. We would like to suggest the followings as follow up:

A. Finalizing the assessment of climatic effects on change in NPP

A global map of NPP change during 1981-2006, corrected for effects of changes in climate, will be developed. To obtain this in a scientifically sound way, first the relation between NPP and NDVI should be studied in more detail, especially related to the form of this relationship (linear, curve-linear, saturation-type, etc.) and whether different equations should be used for different parts of the world (e.g. depending on climatic conditions, growing season length, type of vegetation, etc.). The form of the relation(s) between NPP and NDVI can also be used for the relation between NDVI and TBW. Ultimately, the derivative of the relation of NDVI as function of TBW can be used to 'adjust' NDVI for climate-related effects and the climate-adjusted NDVI can be used to calculate climate-adjusted NPP change. This will be illustrated in a global map with a 5x5 arc-minute resolution.

B. Verification of the observed/calculated trends with independent data

The observed trends of NDVI and TBW will be verified for selected areas where 'field' data have been observed in the past. First the existing map of NDVI/TBW changes already obtained by excluding grid cells with less than 5% change over 1981-2006 will be adjusted to exclude those areas which are not statistically significant (by using a student's t-test with e.g. 90% confidence level). The resulting map will be used to select areas and compare with information 'on-the-ground'. Such information could be obtained for instance from existing projects and databases on soil degradation, such as WOCAT (World Overview of Conservation Approaches and Technologies, http://www.wocat.net/) and regional/national experts. This will be done as much as possible for all four combinations of positive and negative trends for both NDVI and TBW to verify the four divergent situations as depicted in Figure 8. A second aspect of verification will be performed by comparing the NPP data from MODIS with the calculated TBW for the same period (2000-2006). Theoretically, TBW data, illustrating the capacity to produce biomass, should be higher than NPP. The ratio of NPP and TBW (*i.e.* NPP as fraction of TBW) will be calculated and spatially checked for inconsistencies. Other literature data will be investigated too and if necessary, TBW data can be improved.

C. Further explanation of NPP change to distinguish soil degradation from other causes

The climate-adjusted NPP change can not only be attributed to soil degradation. Other changes may have affected the NPP and other data with a global spatial coverage will be studied that can be used as source to further disentangle the NPP change into a number of underlying causes, including soil degradation. Possible options are: geo-referenced changes in land use, fertiliser use, irrigation, abandoned agricultural areas, atmospheric N deposition, large flooding areas, etc. The effect of atmospheric CO_2 rise on productivity increase will be another part of this study and should be investigated as function of site conditions that co-determine how much of the CO_2 increase affects biomass productivity. It will be checked where the change in CO_2 can significantly have affected the NPP change during the period with available data (1981-2006). Linkage of the NPP changes to the socio-economic data could also be explored.

Acknowledgements

This work is part of PBL (Netherlands Environmental Assessment Agency) project M/500214: Biodiversity, ecosystem services and development (biodiversiteit, ecosysteemdiensten en ontwikkelingsvraagstukken). We thank Maurits van den Berg, Ben ten Brink and Michel Bakkenes for advice and discussions.

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Appendix I.
The global land cover for the year 2000 (JRC, 2003)