The use of the Normalized Difference Vegetation Index (NDVI) to assess land degradation at multiple scales: a review of the current status, future trends, and practical considerations

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Executive summary

This report examines the scientific basis for the use of remotely sensed data, particularly Normalized Difference Vegetation Index (NDVI), primarily for the assessment of land degradation at different scales and for a range of applications, including resilience of agro-ecosystems. Evidence is drawn from a wide range of investigations, primarily from the scientific peer-reviewed literature but also non-journal sources. The literature review has been corroborated by interviews with leading specialists in the field [7].

The use of continuous time series of global NDVI data, based on the NOAA AVHRR sensor, developed rapidly in the early 1990s. Since then, the data processing and the techniques for analyses of the data have improved significantly. Techniques for data quality screening, geometric correction, calibration between sensors, atmospheric and solar zenith corrections, cloud screening, and data mosaicking have become operational and resulted in several databases of global NDVI data of high quality that are freely accessible over the Internet. The spatial resolution of these datasets range from coarse (8 – 1 km) to medium (250 m) resolution.

Even if there is no alternative to remotely sensed data for global and continental scale monitoring of vegetation dynamics, the technique is not without weaknesses. The report reviews the use of NDVI for a range of themes related to land degradation. Land cover change, including deforestation, has been detected quantitatively even though the drivers are elusive [3.1]. Drought monitoring and early warning systems use NDVI data and have developed fully operational systems for data dissemination and analysis [3.2]. Desertification processes at the global, continental and sub-continental scale have been studied intensively in the last two decades with a key finding that most of the world's drylands show a trend of increasing NDVI. The interpretation of the causes and implications of that greening trend is still a matter of discussion [3.3]. Soil erosion have been studied at national and sub-national level, primarily using NDVI derived from data of medium to high spatial resolution, such as Modis 250 m and Landsat 30 m resolution [3.4]. Salinization of soils have been studied using a wide range of remotely sensed data but the detection and monitoring of salinization is more experimental than for other forms of land degradation [3.5]. Monitoring of vegetation burning is an area where NDVI has been widely used for three purposes: to assess the risk of fire in terms of fire-fuel load; detection and monitoring of fire; mapping burned areas; as well as monitoring vegetation recovery after fire [3.6]. NDVI has been used to facilitate mapping and monitoring of biodiversity loss, even though species composition cannot be assessed [3.7]. Soil carbon is an important indicator of land productivity that been studied by means of NDVI, both as a standalone measure and as input to ecosystem models. Studies have shown a high agreement between NDVI based and ground based estimates [3.8].

Part of the ToR of the report was to assess the potential of NDVI for monitoring of agro-ecosystem resilience. Resilience is a concept with a broad range of definitions. In its original form, the ability to recover from disturbance or stress, ecosystem resilience can be assessed to a certain degree by combining NDVI with ancillary data, such as rainfall, often described as a hysteresis curve [3.9].

Even if NDVI is by far the most commonly used vegetation index, other indices have been proposed and used for global scale studies, such as two types of the Enhanced Vegetation Index (EVI). These indices are reviewed and compared with NDVI. The 3-band EVI is subject to certain technical problems and the 2-band EVI is highly correlated with NDVI. The conclusion that NDVI is the preferred index for operational monitoring is thus strengthened by the comparison [2.3].

Interpretation of trends and patterns of NDVI data cannot automatically be interpreted in terms of land degradation and improvements. The report highlights a number of issues that must be considered for operational use of NDVI for land degradation monitoring [4].

NDVI is sometimes considered to become saturated for dense vegetation (Leaf Area Index >1) which is incorrect. The reason for the asymptotic relationship between NDVI and LAI is because all visible photons are absorbed at high LAI. In fact this confirms that NDVI represents photosynthetic capacity and primary production rather than LAI [4].

Distinction between land degradation/improvement and the effects of climate variation is an important and contentious issue. There is no simple and straightforward way to disentangle these two effects. Rain Use Efficiency (RUE), calculated by dividing NDVI by rainfall, is used in the GLADA method to separate human action from natural variation. Even if theoretically sound, there are both technical and scientific problems with this approach. The technical problems are related to the mismatch of scale between climate data (most often point based) and NDVI (spatially continuous). Spatial interpolation of point observations is highly problematic, at least for short time periods. The scientific problems are concerned with the contextual relationship between vegetation and rainfall. The following rule of thumb can be applied: Where vegetation dynamics are strongly driven by rainfall, i.e. in drylands, declining (RUE) is correlated with land degradation. In humid areas, where vegetation is not as strongly driven by variations in rainfall, NDVI in itself is strongly correlated with vegetation dynamics and may be taken as a proxy for land degradation and improvement provided that potential false alarms are accounted for [4, 5.2].

The accessibility and reliability of datasets is crucial for operational monitoring. The report reviews 14 of the most important datasets of NDVI, and 6 climate databases that potentially can be used in combination with NDVI data. The most widely used dataset and also the most rigorously tested one is the GIMMS and its most recent version the GIMMS3g (Global Inventory for Mapping and Modelling Studies). It contains continuous data coverage from August 1981 to the present at 15-days intervals. It is also the only dataset that is continuously updated with new data. The GIMMS3g is accessible free of charge over the Internet. Since 2000 NDVI data are available from both AVHRR (at 8 km resolution) and MODIS (1000-250 m resolution). Normally they are highly correlated but the report recommends to use MODIS data as the benchmark [8].

For monitoring at national, sub-national and project levels, the report recommends the use of nested approaches in which coarse resolution data, such as AVHRR NDVI at 8 km resolution are combined with other remotely sensed data that offer higher spatial resolution ranging from 0.5m to 250m and better spectral and radiometric resolution. These data, calibrated against the long-term but coarse resolution AHVRR database, can be used to elucidate reasons for changes in the coarse-resolution NDVI signal (such as forest destruction or other land-use change, habitat fragmentation or soil erosion) and for national, sub-national reporting, and project monitoring [9].

A combined approach - analyzing spatial patterns and temporal trends in the coarse-resolution imagery, zooming in for greater detail using fine-resolution NDVI supplemented by systematic information on climate, terrain and land cover, and spot checks with very high resolution commercial satellite imagery - can contribute to the assessment of agro-ecosystem resilience. Targeted research is needed to establish exact procedures for such monitoring applications [9].

Even if NDVI data are easily accessible and free of charge, successful land degradation monitoring requires adequate technical, institutional and skilled human resources. Such capacity, however, can probably be built effectively at existing regional and/or national centers [10]. With such capacity, NDVI can be used for cost effective and reliable national reporting on several of the UNCCD core indicators [11.1] and potentially also as input to a revised GEF resource allocation method, at least after some further testing on real data [11.2].

To conclude, a substantial body of peer-reviewed research lends unequivocal support for the use of coarse-resolution time series of NDVI data for studying vegetation dynamics at global, continental and sub-continental levels. There is compelling evidence that these data are highly correlated with biophysically meaningful vegetation characteristics such as photosynthetic capacity and primary production that are closely related to land degradation and to agroecosystem resilience. The GIMMS3g dataset that now contains continuous data coverage since August 198, is the most reliable, used and cited database as well as the only database that is up-to-date, free-of-charge and will be continued for the foreseeable future.

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List of Acronyms

ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
CIESIN	Center for International Earth Science Information Network
CRU	Climatic Research Unit, University of East Anglia
EVI	Enhanced Vegetation Index
EUE	Energy Use Efficiency
FAO	Food and Agriculture Organization of the United Nations
FASIR	Fourier-Adjusted, Sensor & Solar zenith angle corrected, Interpolated, Reconstructed
GEF	Global Environment Facility
GDP	Gross Domestic Product
GIMMS	Global Inventory for Mapping and Modeling Studies
GLADA	Global Assessment of Land Degradation and Improvement
GOME-2	Global Ozone Monitoring Experiment–2
GOSAT	Greenhouse gases Observing SATellite
HANTS	Harmonic ANalysis of Time Series
IRS	Indian Remote Sensing
LADA	Land Degradation Assessment in Drylands
LAI	Leaf Area Index
LTD	Long-Term Data Record
LUE	Light-Use Efficiency
LULCC	Land Use and Land-cover Change
MERIS	MEdium Resolution Imaging Spectrometer
MODIS	Moderate Resolution Imaging Spectroradiometer
MVC	Maximum Value Composition
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NOAA	National Oceanic and Atmospheric Administration
NPP	Net Primary Productivity
PAL	Pathfinder AVHRR Land
REDD	Reducing Emissions from Deforestation and Forest Degradation
RESTREND	Residual Trend
RUE	Rain-Use Efficiency
RUSLE	Revised Universal Soil Loss Equation
SCIAMACHY	SCanning Imaging Absorption spectroMeter for Atmospheric CHartographY
SLM	Sustainable Land Management
SOC	Soil Organic Carbon
SOTER	Soil and Terrain Database
SPOT–VGT	Satellite Pour l'Observation de la Terre - Végétation
STAR	System for Transparent Allocation of Resources
UNCCD	United Nations Convention to Combat Desertification
UNEP	United Nations Environmental Programme
UNFCCC	United Nations Framework Convention on Climate Change
VASClimO	Variability Analyses of Surface Climate Observations

1 Introduction

The global demand for food is expected to rise steeply as a result of burgeoning population, shifting dietary preferences, and food wastage, while increasing demands for renewable energy are competing with food production (Hubert et al. 2010). In 2009, the FAO estimated that we must increase the global food production by 70% to meet demands in 2050 (FAO 2009). But this figure is questioned and seen as an underestimation, which further underlines the urgency of global food provisioning (Tilman 2010, Tilman et al. 2002), particularly in the light of the revised World Population Prospects 2012 predicting significantly higher population increase than earlier projections, especially for many countries in sub-Saharan Africa (UN 2013). Further, accelerating climate change is projected to have severe impacts on crop productivity over large parts of the globe (Porter et al. 2014). The combination of increasing water scarcity, as a result of climate warming, and increasing competition across sectors is likely to cause dramatic situations in terms of food and water security in many regions (Strzepek and Boehlert 2010). At the same time "business as usual is not an option". This was the stern message from the International Assessment of Agricultural Science and Technology (IAASTD) when it was presented by its chairman Bob Watson in 2008. By this he meant that agriculture does not deliver what we need – food security for all – instead it undermines the global environment in terms of land degradation, greenhouse gas emission, pollution of soils, rivers, lakes and oceans, and reducing biodiversity (Foley et al. 2011). The threat to food security represents a planetary emergency that demands a variety of creative solutions and policies at global, regional and local levels. One of the most urgent responses to this situation is measures to stop and reverse land degradation. But such solutions are currently hampered by the lack of reliable data as well as methods for collecting such data. This report is a review of the state-of-the-art of remote sensing techniques for assessing land degradation and improvements.

1.1 Land degradation in the UNCCD and GEF

Land degradation has been highlighted as a key development challenge by the UNCCD, the Convention on Biodiversity, the Kyoto Protocol on global climate change, and the Millennium Development Goals (United Nations 2011, UNEP 2007). The GEF was designated a financial mechanism for the UNCCD in 2003; through establishment of its Land Degradation focal area the GEF aims to arrest land degradation, especially desertification and deforestation by support to sustainable land management (SLM). SLM implements agricultural practices that maintain vegetative cover, build up soil organic matter, make efficient use of input such as water, nutrients and pesticides efficiently, and minimize off-site impacts (Bierman *et al.* 2014).

Both the UNCCD and the GEF use land cover to monitor land degradation and implementation of SLM. Likewise, the trend in land cover is a key indicator of progress in meeting the UNCCD's Strategic Objective 2: to improve the condition of affected ecosystems (UNCCD decision 22/COP.11). For the GEF, achievement of the overall goal of the Land Degradation focal area is measured through "*change in land productivity*" using, as a proxy, net primary productivity NPP which is estimated through remotely sensed normalized difference vegetation index (NDVI) screened for drought effects using rain-use efficiency RUE. To measure the impact of interventions, GEF-funded SLM projects should report on changes in land cover (GEF 2014). The same approach has also been used to allocate resources from the land degradation focal area of the GEF; other things being equal, countries suffering from serious land degradation, as measured as change in NDVI, are allocated more funds than those with lesser measurable evidence of land degradation.

Recent improvements and the longer time series of the fundamental NDVI dataset call for a review of indicators for measuring the implementation of the Convention and the GEF's allocation of resources to combat land degradation, as well as for measuring the impacts of its SLM projects.

1.2 Concepts, processes and scales of land degradation

Land is defined as the "*ensemble of the soil constituents, the biotic components in and on it, as well as its landscape setting and climatic attributes*" (Vlek *et al.* 2010). Land degradation a composite concept that has been defined in many and various ways. Indeed, it is a concept as much as a process, defined in various ways by researchers and institutions in this field. This could partly be as a result of the diversity of processes of land degradation in type, scale, time, and extent; the processes are well known but not always fully understood. According to Warren (2002), land degradation is a very contextual phenomenon and cannot "be judged independently of its spatial, temporal, economic, environmental and cultural context". This ambiguity makes it hard to establish measurable indicators, remotely sensed or otherwise.

Stocking and Murnaghan (2000) describe land degradation as a composite term that "*has no single readily-identifiable feature, but instead describes how one or more of the land resources (soil, water, vegetation, rocks, air, climate, and relief) has changed for the worse*" (Figure 1). Land degradation has also been recognized with a more utilitarian definition: "*the aggregate diminution of the productive potential of the land, including its major uses (rain-fed, arable, irrigated, rangeland, forest), its farming systems (e.g. smallholder subsistence) and its value as an economic resource*. (Haigh 2002)" This definition highlights deterioration in the biological productive potential of the land, *i.e.* the entire geo-ecological system which includes soils, climate, biodiversity, topography, and land use. The key message conveyed by this definition is akin to that conveyed by the Millennium Ecosystem Assessment's definition of land degradation, "*the reduction in the capacity of the land to perform ecosystem goods, functions and services that support society and development*" (MEA 2005). According to UNEP (2007), "*land degradation is the long-term loss of ecosystem function and services, caused by disturbances from which the system cannot recover unaided"*. This definition conveys two important messages: the resilient properties of landscapes and their constituent parts; and the need for intervention if and when disturbances cause the resilience thresholds are breached.

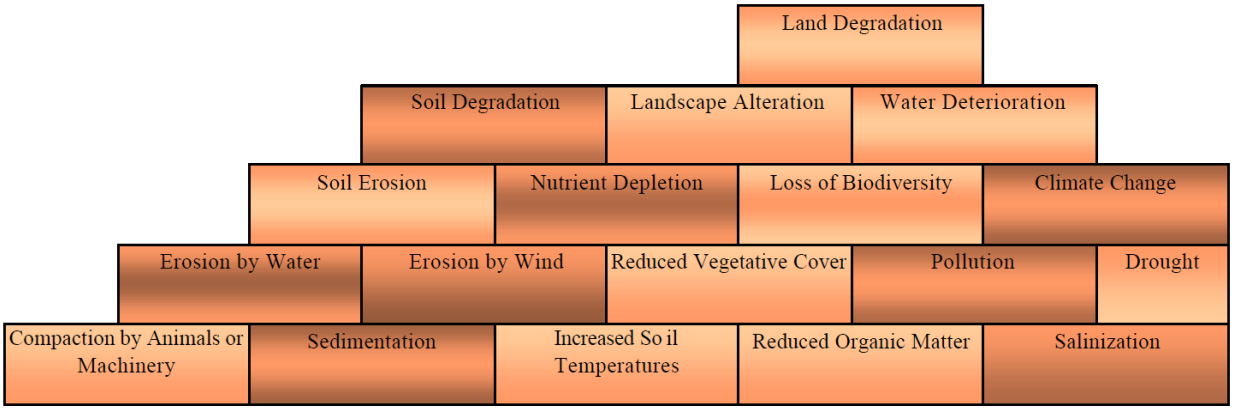

Figure 1 The complexity of processes that constitute land degradation (Stocking and Murnaghan 2000).

Degradation may also be considered in terms of specific components of the land that are affected. For example, vegetation degradation implies reduction in productivity, declining species diversity and degeneration in the nutritional value of plant populations for the faunal biota. And soil degradation implies deterioration in soil quality and fertility. Such changes may be brought about by many factors (erosion, pollution, deforestation, and others). Again, land degradation may be considered in respect

of its physical aspects, referring to changes in the soil composition, especially loss of soil organic matter, and structure, such as compaction or crusting and waterlogging; chemical, pertaining to changes in the soil chemistry's chemical make-up as a result of leaching, salinization or acidification; and biological degradation referring to reduction of soil biodiversity.

Estimations of the extent and severity of land degradation has varied substantially. The only agreement has been that all global estimates have rested on very poor data (Hassan et al. 2005). The Millennium Ecosystem Assessment reported estimates between 70% and 10% of drylands globally being affected by land degradation and concluded with '*medium certainty that some 10-20% of the drylands are suffering from one or more forms of land degradation. And the livelihoods of millions of people … are affected*' (Hassan et al. 2005). These figures where however not based on a systematic assessment of empirical data.

In order to overcome this uncertainty barrier GEF/UNEP/FAO initiated the LADA project (Land Degradation in Drylands) which adopted the approach used by Bai and others (Bai et al. 2008). Based on the analysis of a 30-year time series of global NDVI data in combination with gridded climate data, Bai *et al*. (2008) reported that about 20% of cultivated land, 30% of forests and 10% of grasslands are degrading. Many studies have reported increasing severity and extent of land degradation in many parts of the world but estimates tend to be highly method-specific (see Annex 1 and Annex 2).

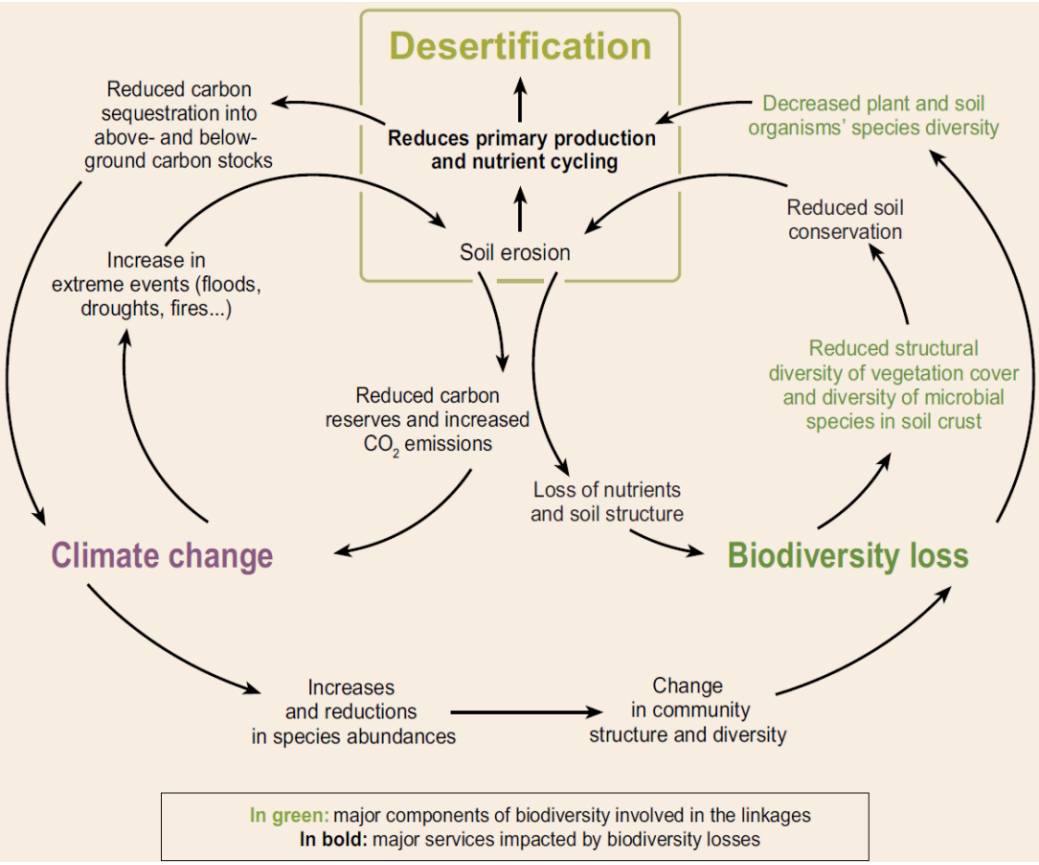

Figure 2 Linkages and Feedback Loops among Desertification, Global Climate Change, and Biodiversity Loss (MEA 2005)

Land degradation can be caused by local human activities and biophysical processes as well as by activities and processes that are not tied to the local human or physical landscape (Figure 2). Local activities that contribute to land degradation include mining, unsustainable farming practices,

overgrazing, pollution from industrial and non-industrial sources, and landscape modification. Hoekstra *et al.* (2005) argue that land degradation resulting from human conversion of natural habitats is most extensive in tropical dry forests (69% converted in SE Asia), temperate broadleaf and mixed forests, temperate grasslands and savannas (>50% lost in North America), and Mediterranean forest and scrub. Human activities responsible for land degradation go beyond farming practices, deforestation, and other direct human interactions with the land (Hoekstra *et al.* 2005). UNEP (2012a) and MEA (2005) see the causes of desertification (nefarious land degradation affecting people in arid and semi-arid regions) ranging from international economic activities to unsustainable land-use practices by local communities. It has also been observed that processes such as dryland degradation may be exacerbated by climate change (Cowie *et al.* 2011).

1.3 Assessment of resilience of agroecosystems

No less than land degradation, resilience is an ambiguous term (Thorén and Persson 2014) subject to scientific and political debates (Walker *et al.* 2004). In his seminal paper in 1973, Holling writes: '*Resilience determines the persistence of relationships within a system and is a measure of the ability of these systems to absorb change of state variable, driving variables, and parameters, and still persist* (Holling 1973). Perrings (1998) offered a more open definition: '*in its broadest sense, resilience is a measure of the ability of a system to withstand stresses and shocks – its ability to persist in an uncertain world*' and interdisciplinary scientists interested in coupled social and ecological systems (SESs) have incorporated the idea into their thinking, as expressed by Adger: '*The ability of human communities to withstand external shocks or perturbations to their infrastructure, such as environmental variability or social, economic or political upheaval, and to recover from such perturbations'* (Adger 2000).

Renschler *et al.* (2010) have argued that environmental and ecosystem resources might be used as indicators of ability of the ecological system to return to or near pre-shock or pre-event states. The strong correlation of NDVI with above ground NPP makes this index a useful indicator of ecosystem resilience. In a study aimed at exploring the concepts and application of theories of general resilience, Walker *et al.* (2014) identified twelve components of general resilience in five catchments in south eastern Australia. These components include diversity (which be identified and measured by processes including vegetation clearing, forest fires, floods, and drought); connectivity, modularity, and reserves in ecological systems (Walker *et al.* 2014) which can be identified and measured by earth observation methods, including land use and land cover change assessments. In the context of monitoring land degradation using remotely sensed data, we would prefer a more precise definition of resilience that can be operationalised by something measurable. A central concept in ecological resilience is a system's ability to absorb and recover from disturbance or stress; this may be depicted by a hysteresis curve (Kinzig *et al.* 2006), Figure 3.

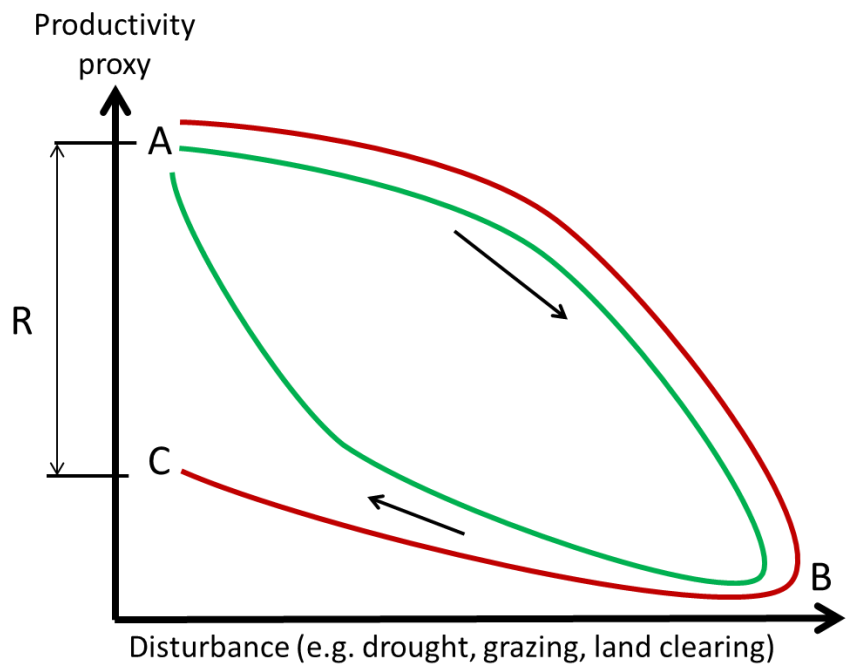

Figure 3 The principle of hysteresis. At point A, before the stress, productivity is high. As the stress increases, productivity declines to a point B where the stress is reduced. As the stress is reduced, productivity increases. A fully resilient system (green curve) will spring back to its original state (A). A less-resilient system (red curve) will only recover to point C. The resilience of the system, R, is related to the distance between A and C, the lower the value, the higher the resilience.

A resilient system subject to stress, such as drought for example, may reduce its productivity as long as the stress persists but, then, return to its pre-stress productivity. If the system is not sufficiently resilient, it will not regain its pre-stress productivity. The Sahel is an example of resilience at a grand scale. Since the 1980s, long time-series of NDVI data have been used extensively in the study of land degradation in the Sahel (Fensholt *et al.* 2013, Anyamba and Tucker 2005, Hickler *et al.* 2005, Prince *et al.* 1998), confirming a general pattern of recovering vegetation.

The interpretation of the recovery of vegetation *vis-à-vis* the resilience of such systems must however be approached with caution. This is because the state of an ecosystem is not only defined by its overall bioproductivity, but also by the vegetation composition as well as the ecosystem services it offers. It therefore follows that the stability of positive trends in bioproductivity (an aspect of ecosystem dynamics that can be captured by the time-series analysis of NDVI data) may not necessarily report the resilience of such systems. Recent studies relating long-term NDVI trends to ground observations in Senegal show that positive NDVI trends do not systematically indicate positive developments, neither in terms of the composition of the vegetation cover, which showed impoverishment even in the greening areas (Herrmann and Tappan 2013), nor in terms of human well-being (Herrmann *et al.* 2014).

NDVI is proposed as a measure of *land cover status* - one of the eleven impact indicators recommended in the UNCCD Minimum set of Impact Indicators"; its purpose (Orr 2011) is to "*monitor land degradation in terms of long-term loss of ecosystem primary productivity and taking into account effects of rainfall on NPP*". The DPSIR (Driving Force – D; Pressure - P; State - S; Impact - I; Response - R) is a general framework for organizing information and reporting about state of the environment. First developed by the Organization for Economic Cooperation and Development (OECD) in the 1980s, this framework is currently being applied in a range of fields and projects, including those of the UNCCD and GEF (Orr 2011). The DPSIR is also the methodological

framework used by UNEP in its Global Environment Outlook (GEO) reports at global, regional, and national levels (UNEP 2012a). The state variables are pointers to the condition of the system (including bio-physical factors/processes), as well as trends (environmental changes) which may be naturally or human-induced (Vacik *et al.* 2007, Orr 2011). NDVI can be useful in the evaluation of vegetation cover, carbon stocks, and land condition (Orr 2014) which may provide resilience indicators.

2 The potential for assessment of land degradation by remote sensing

Given the diversity of the biophysical and socio-economic processes involved, the types, extent and severity of land degradation cannot be encapsulated by a few simple measures (Stocking and Murnaghan 2000). In the assessment of land degradation or changes in land productivity, two complementary approaches may be distinguished:

1. An assessment of historic trends in land degradation or changes in land productivity, in which past changes are examined;
2. An assessment of future trends, in which scenario building and projections are made of expected changes in land degradation or land productivity based on defined scenarios.

For a comprehensive assessment, monitoring and mapping of land degradation, four main themes need to be explored, including:

1. Causes of degradation - the drivers, mostly man-made such as agricultural practices, overgrazing, deforestation, industrial activities such as mining.
2. Type of degradation - the nature of the process driving decline in land quality or productivity. For example drought, salinization, and wind or water erosion.
3. Degree of degradation - classified in degrees of severity, such as light, moderate, strong and extreme
4. Extent of degradation - the total area affected

2.1 Normalized Difference Vegetation Index (NDVI)

The last half century has seen the development and use of different remotely sensed vegetation indices. The basic assumption behind the development and use of these indices is that some algebraic combination of remotely-sensed spectral bands can reveal valuable information such as vegetation structure, state of vegetation cover, photosynthetic capacity, leaf density and distribution, water content in leaves, mineral deficiencies and evidence of parasitic shocks or attacks (Jensen 2007, Liang 2005). The algebraic combination of spectral bands should therefore be sensitive to one or more of these factors. Conversely, a good vegetation index should be less sensitive to factors that affect spectral reflectance such as soil properties, atmospheric conditions, solar illumination, and sensor viewing geometry (Jensen 2007, Liang 2005, Purkis and Klemas 2011).

The structure of leaves, evolved for photosynthesis, determines how vegetation interacts with sunlight. Two processes occur within leaves: absorption and scattering of sunlight. Plant pigments (chlorophyll and carotenoids) and liquid water absorb specific wavelengths of light. Scattering is caused by the internal structure of leaves, where the leaf interior is a labyrinth of air spaces and irregularly shaped water-filled cells. Internal scattering of light is caused by differences in the refractive index between air and water-filled cells, and internal reflections from irregularly shaped cells. Green leaves absorb strongly in the blue and red regions, and less so in the green region, hence their green colour (Jensen 2007). No absorption occurs from the upper limit of our vision at 700nm out to beyond 1300nm where liquid water begins to absorb strongly (Figure 4). No absorption means higher levels of reflectance from green vegetation (Tucker and Garratt 1977).

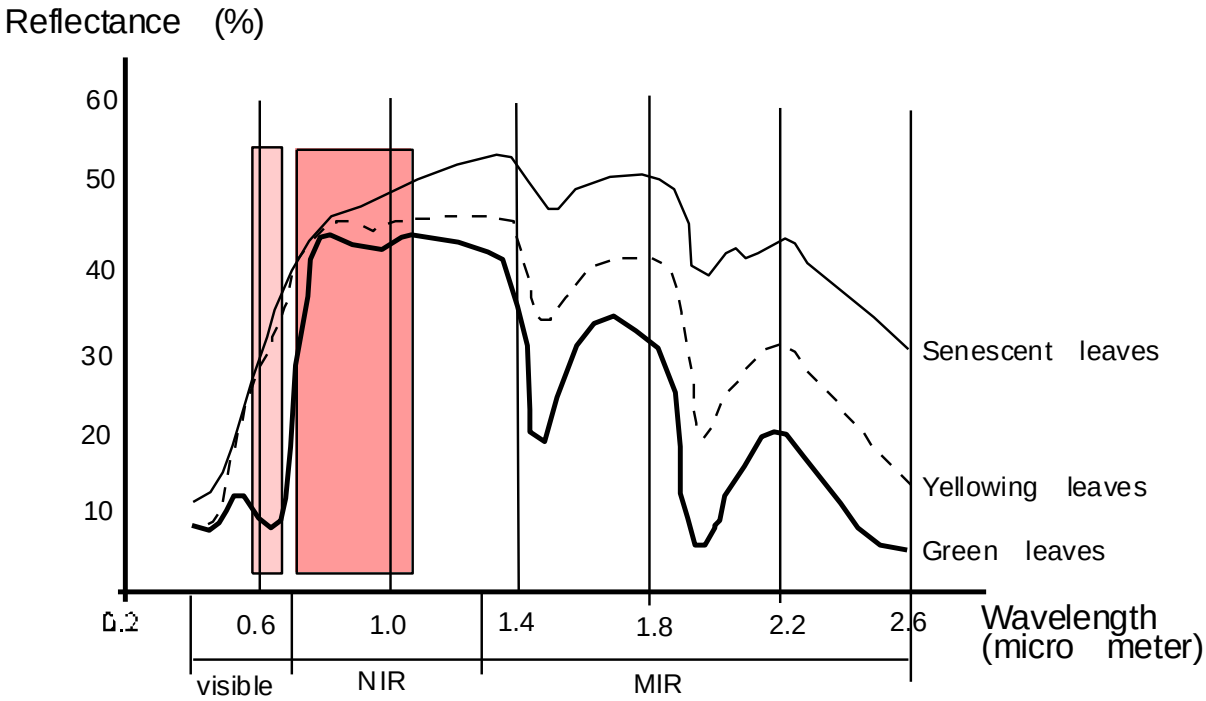

Figure 4 Spectral response characteristics of vegetation at three stages of development. The spectral bands of the most commonly used sensor for NDVI studies, NOAA AVHRR, is superimposed on the spectral response curve. Chlorophyll contained in a leaf has strong absorption at 0.45 µm and 0.67 µm and high reflectance in the near-infrared (0.7 – 1.1 µm). In the shortwave-IR, vegetation displays three absorption features that can be related directly to the absorption of water contained within the leaf.

The normalized difference vegetation index (NDVI), (Equation 1) is the ratio of the difference between the near-infrared band (NIR) and the red band (R) and the sum of these two bands (Rouse Jr *et al.* 1974).

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad \textit{Equation 1}$$

where NIR is reflectance in the near-infrared band and RED is reflectance in the visible red band. The NDVI algorithm takes advantage of the fact that green vegetation reflects less visible light and more NIR, while sparse or less green vegetation reflects a greater portion of the visible and less near-IR. NDVI combines these reflectance characteristics in a ratio so it is an index related to photosynthetic capacity. The range of values obtained is between −1 and +1. Only positive values correspond to vegetated zones; the higher the index, the greater the chlorophyll content of the target.

NDVI has been used to identify and interpret a range of phenology metrics that describe periodic plant life-cycle events and how these are influenced by seasonal and inter-annual variations in climate and habitat (see the Applications of NDVI for Land Degradation Assessment in Section 3; Annex 1; and Annex 2). So the duration of photosynthetic activity (identified using NDVI) can be interpreted to indicate the length of the growing season; time of maximum NDVI corresponds to time of maximum photosynthesis; seasonally integrated NDVI indicates photosynthetic activity during the growing season; and the rate of change in NDVI may indicate speed of increase or decrease of photosynthesis. These metrics are influenced by several characteristics of the vegetation. One of the most important in remote sensing is the leaf area index (LAI) which refers to the projected area of leaves per unit of ground area (Ross 1981).

2.2 Remote sensing features that characterize NDVI-based assessments of land degradation

Potential for the use of normalized difference vegetation index (NDVI) as a proxy for land productivity (one of the indicators of the state of land degradation) is based on numerous and rigorous studies that have identified a strong relationship between NDVI and NPP (Prince and Goward 1995, Vlek *et al.* 2010, Field *et al.* 1995), (also see the discussion on Key Issues in the Use of NDVI for Land Degradation Assessment in Section 5). Remotely sensed data products derived from satellite measurements come in several bands of the electromagnetic spectrum (see the main features of image products from the different sensors in Annex 5). NDVI and related indices use bands in the visible and infrared wavelengths. When using satellite-derived products, it is important to consider sensor and image characteristics such as: image size, region of the earth from which images are acquired, spatial resolution, number of bands and wavelengths detected, spectral characteristics of the bands concerned, frequency of image acquisition, date of origin of the sensor (Strand *et al*. 2007). Another important consideration when using satellite-derived products is the time of acquisition of such data (time of the day, or season in question). Such temporal differences may give rise to alterations such as such as shadows (depending on the time of the day) or phonological differences (depending on the season) that may affect the quality of the data. Remote sensing products rarely meet all requirements for image size, spatial and temporal resolution, and availability. There is always need for trade-offs (Purkis and Klemas 2011, Strand *et al.* 2007). Images with large path width have low spatial resolution, lower data volume and shorter temporal resolutions – so they tend to have a longer time series from which long-term changes can be observed. With the large path width of low-resolution imagery, large areas can be covered and analyzed by a few images. On the other hand, high spatial-resolution is associated with a smaller path width large data volumes, and longer temporal resolution; this demands greater resources in data storage, manipulation and analysis. Also, most high-resolution datasets are pricey - beyond the reach of many potential users outside the research community of the satellite launching program or country (see Annex 7 on current costs of some satellite data products). In general, high spatial resolution data are helpful for fine-scale assessments and analysis at local level, while medium spatial resolution data are useful at a regional or, even, project scale. At a continental or global scale, coarse spatial resolution data support archives of long time series and are preferred for many NDVI-based assessments and analyses. Long time series simplify the use of remote sensing to assess land degradation and monitor changes (Albalawi and Kumar 2013, Anyamba and Tucker 2012, Bai et al. 2008, Cook and Pau 2013, de Jong et al. 2011b, Shalaby and Tateishi 2007, Symeonakis and Drake 2004, Townshend et al. 2012).

2.3 Other vegetation indices closely related to NDVI

One of the earliest attempts at separating green vegetation from the soil background using the NIR/Red ratio was carried out by Pearson and Miller (1972). Since then, many and various vegetation indices have been developed, tested, modified and used for vegetation-related studies worldwide. These include Leaf Area Index (LAI), per cent vegetation cover, green leaf biomass, fraction of absorbed photosynthetically active radiation (fAPAR), photosynthetic capacity, and carbon dioxide fluxes (Albalawi and Kumar 2013, Liang 2005, Purkis and Klemas 2011). More than 150 vegetation indices have appeared in the literature although few have been systematically tested (Bennett *et al.* 2012, Verrelst *et al.* 2006, Higginbottom and Symeonakis 2014). Vegetation indices derived from satellite data are one of the principal sources of information for monitoring and assessment of the Earth's vegetative cover (Gilabert *et al.* 2002). We direct readers to these references for background information on vegetation indices and focus our attention on the normalized difference vegetation index and related vegetation indices.

2.3.1 Indices closely related to NDVI

The *Enhanced Vegetation Index* (EVI) (Equation 2) is a modification of NDVI with a soil adjustment factor, L, and two coefficients, C_1 and C_2 which describe the use of the blue band in correction of the red band for atmospheric aerosol scattering. C_1, C_2, and L, are coefficients that have been empirically determined as 6.0, 7.5, and 1.0, respectively. EVI was developed by the MODIS Land Discipline Group for use with MODIS data to decouple the canopy background signal and reduction in atmospheric influences (Huete *et al.* 2002, Jensen 2007). However, subsequent work with the EVI has resulted to two scientific controversies resulting from use of this index (Morton *et al. 2014,* Saleska *et al. 2007),* that question the use of this index. Because of this controversy, NDVI is always preferred over EVI. Furthermore, it has been difficult to inter-calibrate the EVI between or among different instruments because the surface reflectance uncertainty of the blue band is high for dense green vegetated areas. Eric Vermote (Personal communication 2014) has found the MODIS blue surface reflectance from dense green vegetation to be on the order of 3%-4% with an absolute surface reflectance uncertainty of ±2-±3%. For this reason, the VIIRS vegetation index science team has proposed discontinuing the three-channel EVI and replacing it with a substitute two-channel EVI that is a modified NDVI (Equation 3 and Equation 4). This was first proposed by Jaing *et al.* (2008).

$$EVI = 2.5 * \frac{(NIR - RED)}{(NIR + C_1 * RED - C_2 * BLUE + L} \qquad \textit{Equation 2}$$

2.3.2 Comparing NDVI to EVI

Here, we discuss only those vegetation indices for which current and freely available global data sets exist. The contenders are NDVI, the 3-channel Enhanced Vegetation Index of Huete *et al.* (2002) and the 2-channel Enhanced Vegetation Index of Jiang *et al.* (2008).

The three-channel EVI will be discontinued for VIIRS because of problems with the calibration of the blue band (blue surface reflectance from dense green vegetation is ±2-3%); problems with sub-pixel clouds, aerosols, and snow; the fact that MODIS data are atmospherically corrected; and the realization that the blue band is very highly correlated to the red band for vegetation. The three-channel EVI has been replaced by a two-channel EVI (Jiang *et al.* 2008). Figure 5 shows the three-channel EVI sensitivity to aerosols, smoke, sub-pixel clouds and snow. It also shows the very high correlation between the blue and red surface reflectances from vegetated areas which therefore adds no new information to this index.

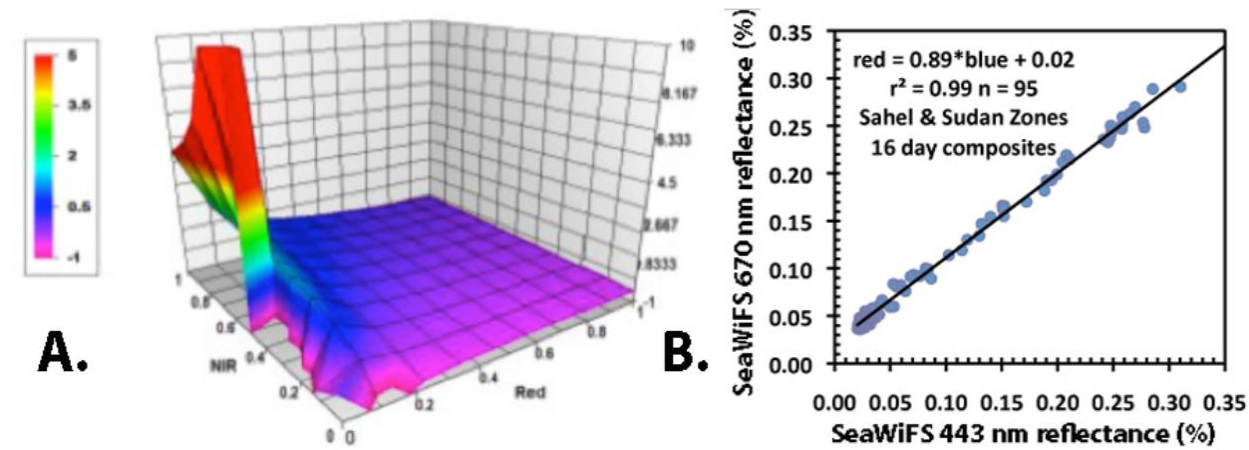

Figure 5 The 3-channel blue, red, near-infrared EVI vegetation index suffers from not being atmospherically-resistant and is very sensitive to high blue-band surface reflectance. (A) shows the erroneous 3-channel EVI values from sub-pixel clouds, smoke, aerosols, and snow. (B) shows the

very high correlation between the blue and red bands for vegetated areas. Information theory tells us that highly correlated variables do not increase the variance explained together over using just one of the variables.

Because of the problems with the EVI3's blue band illustrated in Figure 5a, the MODIS 3-channel EVI products were frequently produced with a two-channel red and near-infrared 'soil-adjusted vegetation index' or SAVI substitute algorithm depending on circumstances. Thus MODIS 3-channel EVI data were, in practice, a combination of 3-channel and 2-channel products and not the same numerical product everywhere all the time. For these reasons, we propose to use the NDVI.

The 2-channel EVI proposed by Jiang *et al.* (2008) (Equation 3) is very similar to NDVI and is directly related to the NDVI and gives more weight to the near-infrared band.

$$EVI2 = 2.5*(NIR - Red)/(NIR + 2.4*Red + 1) \qquad \textit{Equation 3}$$

What, then is the advantage of the EVI2 over the NDVI? Multiplying each side of Equation 3 by (NIR+RED)/(NIR+RED) or 1.0 and rearranging terms gives Equation 4:

$$EVI2 = NDVI * 2.5 * (NIR - Red)/(NIR + 2.4 * Red + 1) \qquad \textit{Equation 4}$$

The NDVI and EVI2 are very similar, with the NDVI being directly related to primary production, and the EVI2 being more heavily weighted to mapping leaf area index in very dense plant canopies (Figure 6).

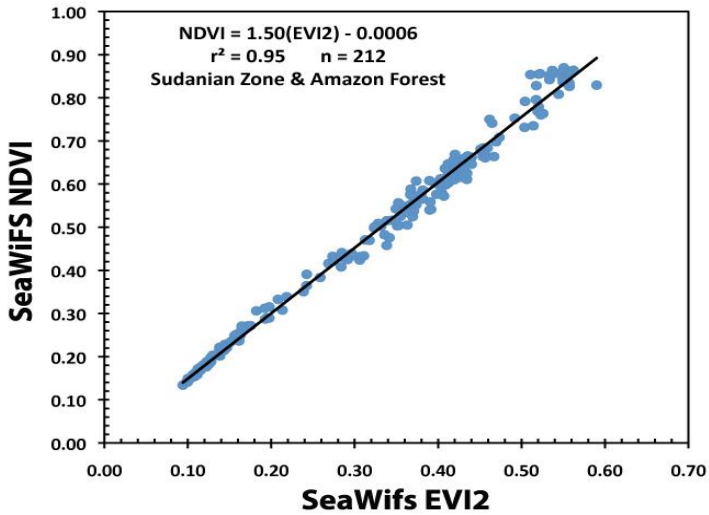

Figure 6 A NDVI and EVI2 comparison using SeaWiFS data from the Sudanian Zone of Africa combined with similar data from the Central Amazon for 212 points. Note the very high degree of similarity between the NDVI and the 2-channel EVI.

Quantitative inter-comparability between or among similar satellite instruments is important because a global analysis at 8 km spatial resolution using data over 33 years can identify specific areas of possible land degradation which then can be investigated in more detail with much higher spatial resolution time series data from MODIS at 250m. Fortunately, NDVI with only two channels lends itself to quantitative inter-comparability among similar satellite instruments (Figure 7).

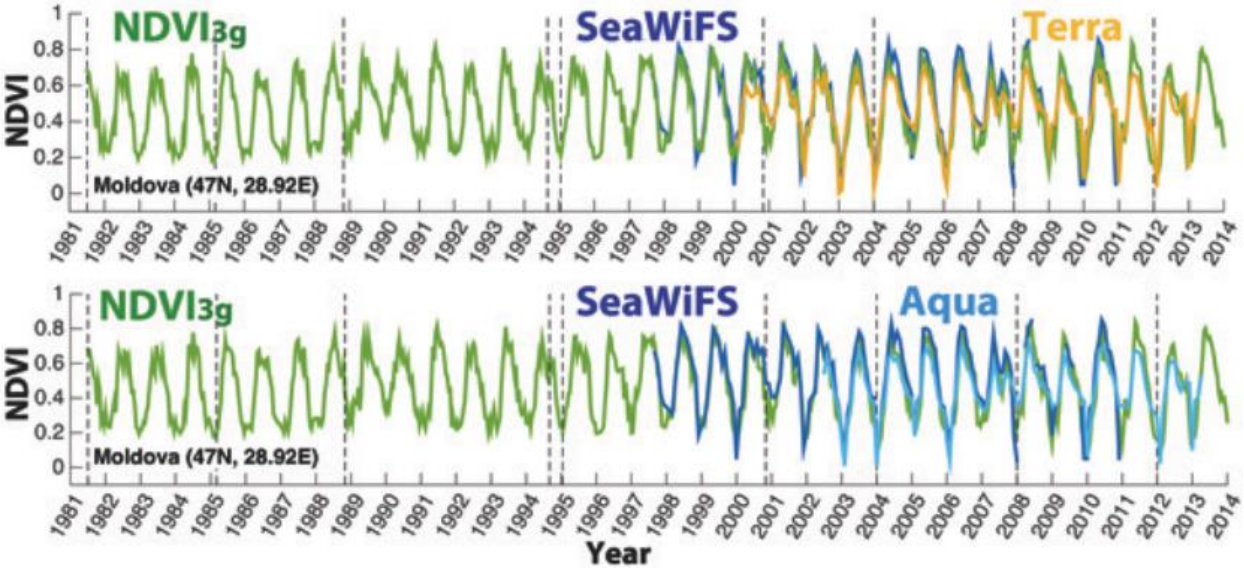

Figure 7 Comparison of NDVI data from eight different AVHRR instruments at nine times from 1981 to 2014 (noted by the vertical dashed lines) to NDVIs from SeaWiFS for 1997-2010, Terra MODIS from 2000 to 2013, and Aqua MODIS from 2002 to 2013. T NDVI time series from these four sources are very similar. There are currently three AVHRR instruments operating, two with MetOps and one with NOAA, and one in storage awaiting launch on MetOps-3 in 2016. There is an excellent chance that we will have a 35-40 year NDVI record from the AVHRR instruments.

The VIIRS instrument now flying on the NASA-NOAA *NPOESS Preparatory Project* polar-orbiting meteorological satellite will continue to deliver NDVI and two-channel EVI data through 2030 and beyond on the NASA-NOAA Joint Polar Satellite System (JPSS) five satellites (JPSS-1 through JPSS-5). The 3-channel EVI will be discontinued.

We conclude that NDVI has fewer problems than the 3-channel EVI because can be inter-calibrated more easily with only two bands and will be replaced by the EVI2 from the NPP and JPSS-1 to JPSS-5 satellites. We choose to use the standard NDVI to identify land degradation because it is directly related to photosynthetic. However, when EVI2 data are available we and others will evaluate this vegetation index for land degradation also. Excellent NDVI data are available from MODIS and this forms the foundation of our work because we require 250 m NDVI data for disaggregation (Huete et al. 2002). We stress all of our proposed land degradation NDVI work must also use MODIS NDVI data from 2000 to 2014 to confirm 8 km NDVI3g data from the same time period.

3 Applications of NDVI for land degradation assessment

In the late 1960s, several researchers began using red and near-infrared reflected light to study vegetation (Pearson and Miller 1972). In the late 1960s, ratios of red and near-infrared light to assess turf grass condition and tropical rain forest leaf area index (Birth and McVey 1968, Jordan 1969). Compton Tucker was the first to use it for determining total dry matter accumulation, first from hand-held instruments (Tucker 1979), and then from NOAA AVHRR satellite data (Tucker et al. 1985, Tucker et al. 1981), demonstrating that the growing season integral of frequent NDVI measurements represented the summation of photosynthetic potential as total dry matter accumulation. Starting in July 1981, a continuous time series of global NDVI data at a spatial resolution of 8kmhas been available from the AVHRR instrument mounted on NOAA weather satellites. Soon, researchers realized the value of NDVI time-series remote sensing (Goward *et al.* 1985, Justice *et al.* 1985, Townshend *et al.* 1985, Tucker *et al.* 1985) and this early work was the spur or development of the higher-resolution Moderate Resolution Imaging Spectroradiometer (MODIS) instrument, and the

application of satellite NDVI data has blossomed into many fields of natural resources investigation (see Annex 1). We examine the use of NDVI in research on land use and land-cover change, drought, desertification, soil erosion, vegetation fires, biodiversity monitoring and conservation, and soil organic carbon.

3.1 Land Use and Land-cover Change (LULCC)

Land cover is the observed (bio)physical cover on the earth's surface (Di Gregorio 2005). In a strict sense, it should be limited to the description of vegetation and artificial (man-made) features on the land surface but land-use and land-cover change (LULCC) is a general term used to refer to the human modification of Earth's terrestrial surface (Bajocco et al. 2012). Mankind has modified land and land-cover for thousands of years to obtain food, fuel, fibre and other materials but current rates and intensities of LULCC are far greater than ever before (Lambin *et al.* 2003, Mayaux *et al.* 2008). The quantity and quality of vegetation cover are an important controls on the evolution landscapes, their resilience or degradation (Symeonakis and Drake 2004), and the quality of environmental services.

Substantial research effort has been invested in the use of NDVI to assess the location and extent of land use and land cover change (Diouf and Lambin 2001, Mas 1999, Stow et al. 2004, UNEP 2012b, Veldkamp and Lambin 2001, Yuan and Elvidge 1998). Scales of application range from global studies of land cover classification and mapping (DeFries and Townshend 1994, Friedl *et al.* 2002, Hansen *et al.* 2000, Turner and Meyer 1994), through regional and national scales (Lambin and Ehrlich 1997, Sobrino and Raissouni 2000, Stow *et al.* 2004) to very localized studies (Shalaby and Tateishi 2007, Sternberg *et al.* 2011, Yuan and Elvidge 1998, Lunetta *et al.* 2006). Horion *et al.* (2014) used long-term trends in dry-season minimum NDVI to assess changes in tree cover in the Sahel; dry-season minimum NDVI was found to be uncorrelated with dry grass residues from the preceding growing season or with seasonal fire frequency and timing over most of the Sahel, so the NDVI parameter can be used as a proxy for assessing changes in tree cover in such ecosystems. While land use and cover change can serve as pointers to the existence (or absence) of land degradation, care must be taken in interpreting the results of such studies. Veldkamp and Lambin (2001) warn about the need to distinguish between the location and quantity of change, as well as the causes of such changes. For example, while NDVI can help in identifying deforestation, its rate and area affected, the underlying drivers are often far away in space and time (Veldkamp and Lambin 2001). And there are many cases where land cover change as detected by NDVI time series does not necessarily lead to degradation but may rather be considered beneficial (Lambin *et al.* 2003, Shalaby and Tateishi 2007).

3.2 Drought and drought early warning

Drought generally refers to a substantial decline in the amount of precipitation received over a prolonged period (Mishra and Singh 2010). Droughts occur in practically all climatic zones and are recognized as a severe hazard to the environment and development (Sivakumar and Stefanski 2007). In terms of land degradation, droughts cause loss of water availability and quality, and declining primary production which increases the vulnerability of the land to erosion and disturbed riparian habitats, with potential loss of biodiversity (Mishra and Singh 2010, Zargar *et al.* 2011).

The NDVI and associated vegetation indices have been used to detect and investigate meteorological, hydrological and agricultural droughts worldwide. Strictly speaking, the NDVI is most useful for detecting and investing drought effects on the vegetation cover, in this case agricultural droughts. Generally, meteorological (dry weather patterns) and hydrological (low water supply) droughts would not be detected by the NDVI before they impact the vegetation cover. The exception in this case may be hydrological drought, if the analysis includes water level in plant matter. The NDVI has been used by several studies for the study of the Sahelian drought (see Annex 1). An example of such studies

include that carried out to investigate the persistence of drought in the Sahel in the period 1982-1993 (Anyamba and Tucker 2012). Another study combined anomalies of El Niño Southern Oscillation (ENSO) indices and NDVI anomalies to construct an ENSO-induced drought onset prediction model for northeast Brazil using multiple linear regression (Liu and Juárez 2001). The normalized difference water index (NDWI) is a sister-index calculated from the 500-m SWIR band of MODIS that has been used in drought studies (Chen *et al.* 2005, Delbart *et al.* 2005, Jackson *et al.* 2004, Gao 1996). Mishra and Singh (2010) argue that NDWI may be a more sensitive indicator than NDVI for drought monitoring, but its developer (Gao 1996) emphasized that the index is: "*complementary to, not a substitute for NDVI*".

NDVI has also been used widely in attempts to develop famine early warning systems, such as the FEWS NET which is an operational system for dissemination of data related to food production and availability globally. The system uses NDVI data from both NOAA AVHRR and MODIS operationally. The system was preceded by rigorous testing of the ability of NDVI to detect areas of imminent food shortages (Henricksen and Durkin 1986, Hutchinson 1991, Quarmby et al. 1993). A main finding was that NDVI in combination with relevant climate data have a very strong potential for forecasting crop failure.

3.3 Desertification

Beginning in the 1970s, the international community recognized that land degradation/desertification was an economic, social and environmental problem, and began a process which ultimately resulted in the creation of the UN Convention to Combat Desertification (CCD). The convention defines desertification as "*land degradation in arid, semi-arid, and dry sub-humid areas resulting from various factors, including climatic variations and human activities*" (UNCCD 1994). Some studies report that desertification poses a serious global threat, affecting both developed and developing countries (Grainger 2013): others report that drylands have been greening, and caution against broad generalizations (Fensholt *et al.* 2012). Since the 1980s, remote sensing has been used extensively in the study of desertification in different parts of the world (Erian 2005, Fensholt et al. 2013, Karnieli and Dall'Olmo 2003, Nkonya et al. 2011, Symeonakis and Drake 2004, UNEP 2012b, Olsson et al. 2005, Tucker and Nicholson 1999). While studies in the 1980s demonstrated the value of the NDVI for tracking vegetation dynamics, a clear relationship between NDVI, biomass accumulation (especially in the Sahel) and the many variables which interact with them was not fully understood (Herrmann and Sop 2015). Most studies simply referred to vegetation trends and embed their hypotheses and findings in the larger debate on desertification. Beyond showing changes in bioproductivity, the interpretation of those trends was rather speculative. Today, notwithstanding the significant advances in knowledge of these processes, desertification remains a difficult process to assess given the complex relationship between biomass and ecosystem health (Herrmann and Sop 2015). More recently, there have been a several studies linking remotely sensed trends to ground observations (Brandt et al. 2014, Dardel et al. 2013, Herrmann and Tappan 2013). Examples of such recent developments in the understanding of desertification also include the use of land productivity dynamics in constructing a World Atlas on Desertification - WAD (see Annex 2).

In detecting the status and trend of desertification, researchers have built on the relationship between NDVI and biomass productivity that has been well established in the literature (Jensen 2007, Purkis and Klemas 2011). These initiatives are greatly helped by the continuous global NDVI time series of vegetation that has been available since the early 1980s. The UNCCD fostered increased interest in desertification research, especially with regard to the Sahel which was by that time experiencing a wet period, captured by satellite imagery, analyzed using NDVI time-series, and described as a "*greening*

of the Sahel" (Olsson *et al*. 2005). Following studies used NDVI time series to investigate temporal and spatial patterns of the Sahel's greenness and rainfall variability as well as their inter-relationships (Herrmann *et al.* 2005, Hickler *et al*. 2005). Herrmann *et al.* (2005) and Olsson *et al.* (2005) concluded that while increased rainfall was the main reason for greening, there were also a number of hypothetical human-induced change superimposed on the climatic trend, such as improved agricultural practices, as well as migration and population displacement. Besides documenting the close coupling of rainfall and vegetation response in the Sahel, Anyamba and Tucker (2005) pointed out that current greener conditions are still not as green as those that prevailed from 1930 to 1965. Together, these studies and many that have followed (see Annex 1and Annex 2) demonstrate the opportunities offered by NDVI as a proxy for vegetation response to rainfall variability, especially in arid and semi-arid ecosystems. Herrmann *et al.* (2005) also demonstrated the possibility of using NDVI as a proxy for environmental response to management.

3.4 Soil erosion

Erosion is the displacement of materials like soil, mud and rock by gravity, wind, water, or ice. The most common agents of soil erosion are water and wind (Foth 1991); their effects may be on-site (where soil detachment and transportation occurs), or off-site (where eroded soil is deposited). In soil erosion studies, the NDVI is commonly used in conjunction with soil-erosion estimation models such as the Fuzzy-based dynamic soil erosion model (FuDSEM), the Revised Universal Soil Loss Equation (USLE/RUSLE), the Water Erosion Prediction Project (WEPP), the European Soil Erosion Model (EUROSEM), and the Soil and Water Assessment Tool (SWAT) (Prasannakumar et al. 2012, Zhou et al. 2008). Mulianga *et al.* (2013) in Kenya, and Ai *et al.* (2013) in China Terra-MODIS derived NDVI is used to characterize the state of the ecosystem (spatial and temporal heterogeneity of the vegetation conditions), and as one of the input parameters for estimating the potential of erosion using fuzzy-set theory. In a study of the effect of vegetation cover on soil erosion in the Upper Min River watershed in the Upper Yangtze Basin, China, Zhou *et al.* (2008) used NDVI as a land-management factor (an input into the RUSLE model) representing the effect of soil disturbing activities, land cover and vegetation productivity on soil erosion. A similar study also using NDVI as a land cover management factor to determine the vulnerability to erosion of soils was carried out in a forested mountainous sub-watershed in Kerala, India (Prasannakumar *et al.* 2012). In such studies, NDVI proved to be a useful indicator of land cover condition and a reliable input into models of soil dynamics.

In most soil erosion research, the NDVI data come from Landsat TM/ETM (Thematic Mapper/Enhanced Thematic Mapper) with a spatial resolution of 30m (Ai *et al.* 2013, Chen *et al.* 2011) or MODIS with a spatial resolution of 250m (Fu *et al.* 2011, Mulianga *et al.* 2013). These data are generally used in conjunction with a digital elevation model with a spatial resolution of 30m (Ai *et al.* 2013, Fu *et al*. 2011, Mulianga *et al.* 2013, Prasannakumar *et al*. 2012).

3.5 Soil Salinization

Salinity is salt in the wrong place, affecting water quality, uptake of water and nutrients by plants, and breaking up roads and buildings. It occurs naturally in drylands and areas prone to tidewater flooding but is often exacerbated by poor soil and water management (Zinck and Metternicht 2008). A quarter of global cultivated land is saline and one third is sodic (high in adsorbed sodium) but salinity can vary significantly, even over short distances. While soil salinization is a global problem, the phenomenon is more extensive in dry regions than in humid ones (Zinck and Metternicht 2008). Salinity is plain to see at the soil surface and has been mapped from air photos and Landsat visible-light imagery. However, most of the salt is deep in the regolith and it's hard to isolate the effects of soil salinity on vegetation from the effects of other factors (Lobell *et al.* 2010).

Assessment employs a combination of methods including airborne and ground-based electromagnetic induction (EM), field sampling and solute modeling (Farifteh *et al.* 2006, Dent 2007). Airborne EM measures salt in three dimensions to a depth of 300m: passive sensors like AVHRR and other NDVI methods cannot see below the surface but this has not deterred users - *e.g.* Platonov *et al.* (2013) investigated whether the values of maximum multi-annual NDVI reflected the degree of soil salinity within agricultural areas of Syr Darya province of Uzbekistan. The study found that by calculating the maximum multi-annual NDVI values from satellite images, one can create more spatially detailed soil salinity maps using two methods: the pixel-based and the average for fields (Platonov et al. 2013). NDVI was reported to be one of the best band combinations estimating soil salinity for some crops, such as alfalfa and corn, but not for others such as cantaloupe or wheat (Eldeiry and Garcia 2010). On the other hand, in a study that evaluated the use of multi-year MODIS imagery in conjunction with direct soil sampling to assess and map soil salinity at a regional scale in North Dakota and Minnesota, Lobell et al. (2010) found that the enhanced vegetation index (EVI) for a 7-year period outperformed the NDVI in showing a strong relationship with soil salinity. Nonetheless, the NDVI has been used to study top-soil salinity conditions at the local and regional scales in different geographical settings. One may wonder the extent to which such studies can be generalized when surface occurrences are so variable from season-to-season and year-to-year and vegetation effects so variable (Metternicht and Zinck 2003). Nearly all the salt – and salt movement - is deep underground: this is a case where NDVI is not a suitable technique.

3.6 Vegetation burning

Fire is a common occurrence in many parts of the world. Wild fires in forests, savannas, mountain regions and other ecosystems are integral to the evolution of some of these systems; periodic fires are important in maintaining many grassland, shrub steppe, and savanna ecosystems (Mitchell and Roundtable 2010). On the other hand, fires (wild or man-made) give rise to soil erosion, greenhouse gas emissions, soot, and bad air quality, and diminish biodiversity, soil water retention capacity and soil structure (Purkis and Klemas 2011). Within the latter context, fires may therefore constitute a form of land degradation.

Satellite remote sensing has been used for modeling and mapping a variety of ecosystem conditions associated with fire risks, potential, and management. These include fire-fuel mapping risk estimation (De Angelis *et al.* 2012), fire detection, post-fire severity mapping, and ecosystem recovery from fire stress. Besides the detection of active fires, remote sensing is also used to assess and quantify the spatial and temporal variations of changes of vegetation cover in areas affected by fires. Here, NDVI images of pre-fire and post-fire are essential for estimating the amount of areas affected, especially when supported by techniques of supervised classification. Lanorte *et al.* (2014) used NDVI time-series to monitor vegetation recovery after disturbance by fire at two test sites in Spain and Greece. A similar study by Leon *et al.* (2012) used MODIS NDVI to monitor post-fire vegetation response in New Mexico. Their study outlined the potential of using NDVI to monitor the recovery vegetation cover after fire disturbance (Leon et al. 2012). NDVI is also used to determine phenological information of the area affected (Chuvieco *et al.* 2004, Díaz-Delgado *et al.* 2003). In pre-burn analysis, this information can be used to calculate and map fire fuel availability as well as potential economic and ecological losses likely to result from such fires. In post-burn analysis, NDVI can be used in fire severity mapping, to assess ecological recovery from fires (Malak and Pausas 2006, Díaz-Delgado *et al.* 2003), to estimate carbon emissions resulting from the fire episode, and environmental impact assessment (Isaev *et al.* 2002).

Besides the NDVI, studies of vegetation fires make use of related vegetation indices such as the Modified Soil adjusted Vegetation Index (MSAVI), Enhanced Vegetation Index (EVI) and the Foliar

Moisture Index (FMI) (Wang *et al.* 2010) and, also, indices specific to this field such as the Nomalized Burn Ratio (NBR), NBR Change Index (dNBR) and the Normalized Thermal Index (NTI) (Wang *et al.* 2010). Vegetation fire research makes use of an array of satellite sensors: MODIS, ASTER, Advanced Land Imager (ALI), AVHRR, Landsat 5 TM, Landsat 7 ETM+, Spot 4 and 5, Quickbird-2, and IKONOS-2. For most tasks involving the use of NDVI such as fuel mapping, vegetation classification, and post-fire burn area and severity assessment and mapping, the main sensors are AVHRR, MODIS, Landsat 5 TM, and Landsat 7 ETM+ (see Annex 1).

3.7 Soil organic carbon

The absorption of carbon by land-based ecosystems goes some way towards offsetting worldwide fossil fuel emissions (Mishra and Singh 2010, Piao *et al.* 2009, Bernoux and Chevallier 2014). Soil organic carbon is also increasingly recognized as an excellent indicator to monitor the status and functioning of soils – hence progressively recommended in various international initiatives for monitoring soil quality (Bernoux and Chevallier 2014). In the 1980s and 1990s, for example, 10 – 60% global carbon emissions were offset through this process. While the global pattern and sources of sinks is imperfectly understood (Piao *et al.* 2009), it is well accepted that vegetation plays an important role in carbon sequestration.

Vegetation data based on NDVI have been instrumental in the assessment and monitoring of key global biomes (see Annex 1). The first pan-tropical biomass map was developed through MODIS-GLAS data fusion in 2011 (Saatchi *et al.* 2011). The outcome of this initiative has been a benchmark map of biomass carbon stocks in support of REDD assessments at both project and national scales. NDVI has been used in regional studies of soil organic carbon (SOC). Together with terrain attributes, climate data, land use data, and bedrock geology data, NDVI data were used to predict the SOC pool for seven states in the Midwestern United States (Mishra et al. 2010). In another study, NDVI data were used as an input into the Carnegie-Ames-Stanford Approach (CASA) terrestrial ecosystem model to estimate losses of SOC resulting from wind erosion in China (Yan et al. 2005). In investigating changes in soil organic C and total N in the Hexi corridor, China, a significant correlation was found between NDVI and SOC, as well as NDVI and N (Pan *et al.* 2013).

3.8 Biodiversity monitoring and conservation

High rates of biodiversity loss threaten to breach planetary boundaries (Rockström *et al.* 2009). A growing body of knowledge is developing around the tools and techniques for assessing and predicting ecosystem responses to global environmental changes (Pettorelli *et al.* 2014, Pettorelli *et al.* 2005, Yeqiao 2011). In mapping and studying protected lands, for example, Yeqiao (2011) notes that satellite remote sensing can provide wide-ranging geospatial information at various spatial scales, temporal frequencies, spectral properties and spatial contexts. While traditional approaches to measuring species richness provide detailed local data but it is hard to up-scale this information; and while traditional approaches to measuring species richness provide useful information on small spatial scales, such methods are in their application spatially constrained to large geographical areas (Duro *et al*. 2007). Remote sensing tools (with NDVI playing an important role) offer opportunities for such large area descriptions of biodiversity in a systematic, repeatable and spatially exhaustive manner (Duro *et al.* 2007, Turner *et al.* 2003).

NDVI plays an important role in the development of land cover maps – an important tool in the *direct approach* or *first-order analysis* of species occurrence (Turner *et al.* 2003). Depending on the scale, biome and ecosystem in question, land cover maps provide implicit or explicit data on the composition, abundance and distribution of individual or assemblages of species (Duro *et al.* 2007, Pettorelli *et al.* 2014, Turner *et al.* 2003). Data derived from vegetation productivity, in association with other environmental parameters (climatic and geophysical) are statistically related to species

abundance or occurrence data (Duro *et al.* 2007). One example includes the use of AVHRR-derived NDVI to explain the spatial variability of species richness of birds at a quarter degree spatial resolution in Kenya. The study found a strong positive correlation between species richness and maximum average NDVI (Oindo *et al.* 2000). NDVI also contributes to the *indirect approach* to measuring species composition, abundance and distribution. Different aspects of vegetation condition (derived from vegetation indices such as NDVI) contribute to the mapping of environmental variables which, provide indications (through biological principles) of species composition, abundance and distribution (Duro *et al.* 2007, Pettorelli *et al.* 2014). A high resource abundance (indicated by high NDVI values derived from NOAA/AVHRR satellite imagery) was used to explain the occurrence and distribution of the devastating locust specie *Schistocerca gregaria* in Mauritania (Despland *et al.* 2004).

3.9 Monitoring ecosystem resilience

The NDVI use in vegetation monitoring and assessment is aimed at improving our understanding, predictions and impacts of disturbances such as drought, fire, flood and frost on global vegetation resources (Pettorelli *et al.* 2014, Pettorelli *et al.* 2005). The use of the NDVI to monitor vegetation and plant responses to environmental changes at the level of trophic interactions constitutes one of the main uses of the NDVI in nature and conservation research. The application of the NDVI as a resilience indicator has been applied in numerous studies, such as reported by Díaz-Delgado *et al.* (2002), Simoniello *et al.* (2008), Cui *et al.* (2013). Diaz-Delgado *et al.* (2002) used NDVI values derived from Landsat imagery to assess the recovery of Mediterranean plant communities after recurrent fire disturbances between the periods 1975 and 1993. The study concluded (among other things) that the use of time-series NDVI and other imagery products can be useful in understanding the resilience of Mediterranean plant communities and post-fire vegetation dynamics over large regions and long time periods (Díaz-Delgado *et al.* 2002). Simoniello *et al.* (2008) characterized the resilience of Italian landscapes using a time series of NDVI trends to estimate mean recovery times of vegetation to different levels of anthropic pressure. They concluded that with 8 km AVHRR-NDVI data and remote sensing techniques, substantial details on vegetation cover activity (pointers to its resilience) at local scale could be captured, even in ecologically complex territories such as that of the Italian peninsula (Simoniello *et al.* 2008).

Cui *et al.* (2013) used Landsat TM and Landsat MSS time-series data to characterize land cover status as a proxy for measuring ecosystem resilience. They observed that the state of Southern African ecosystems and their response to a climatic shock (dry conditions) could be quantified in terms of vegetation amount and heterogeneity (Cui *et al.* 2013). Gibbes *et al.* (2014) used 28-year of AVHRR-MODIS NDVI time series data in conjunction with global gridded monthly time series of modeled rainfall to determine the resilience of ecological systems in the Kavango-Kwandu-Zambezi catchments. Besides highlighting the explicit vegetation-precipitation linkages across this highly vulnerable region, the study underlined the important role played by precipitation in modulating conditions of the savanna ecosystems (Gibbes *et al.* 2014). Another method of the application of NDVI to assess the resilience of ecosystems involves comparing stable-state NDVI trends to post-disturbance (from events such as such as fire, flooding, and hurricanes) NDVI trends to determine differences in ecosystem productivity across spatial-temporal scales (Renschler *et al.* 2010). These studies confirm the ability of remote sensing derived NDVI, in combination with rainfall data, to detect land degradation processes that can be related to the resilience of ecosystems and landscapes.

4 Limits to the use of NDVI in land degradation assessment

During the past half century, NDVI has been widely used for vegetation mapping and monitoring as well as in the assessment of land-cover and associated changes. This is because remotely-sensed

satellite-derived datasets provide spatially continuous data (data that are not sampled at individual points) and yield time-series signatures from which temporal patterns, trends, variations and relationships may be derived (Jacquin *et al.* 2010). This has not prevented people from misusing the NDVI - care should be exercised in the use of any scientific methodology.

As a spectral index of vegetation, NDVI provides the most direct quantification of the fraction of photosynthetically active radiation (fPAR) that is absorbed by vegetation (Running *et al.* 2004) (Figure 8 and Figure 10). The convenience of satellite-derived NDVI and techniques of remote sensing for monitoring vegetation cover and assessing vegetation condition has been demonstrated at spatial scales from local to global and in diverse fields of environmental studies:

- Desertification (Olsson *et al.* 2005, Sternberg *et al.* 2011, Tucker and Nicholson 1999, Wessels *et al.* 2004, Symeonakis and Drake 2004)
- Drought assessment and monitoring (Anyamba and Tucker 2012, Bandyopadhyay and Saha 2014, Karnieli *et al.* 2010, Liu and Juárez 2001)
- El-Nino impacts on ecosystems (Liu and Juárez 2001)
- Monitoring and assessment of regional to global changes in land-cover and land use (Achard *et al.* 2007, Bradley and Mustard 2008, Cook and Pau 2013, Field *et al.* 1995, Lambin and Ehrlich 1997, Prince and Goward 1995, Rouse Jr *et al.* 1974)
- Ecosystem health and services (Pettorelli *et al.* 2014, Zhang *et al.* 2013, Bai *et al.* 2013).

Nonetheless, the use of NDVI to discriminate directly between degraded and non-degraded area can be challenging, both in implementation and interpretation (see Section 5). In a study in which non-degraded and degraded areas in north-eastern South Africa, both exposed to identical rainfall regimes, were paired and monitored along 16 growth seasons, Wessels *et al.* (2004) concluded that, in some cases, degraded areas were no less stable than non-degraded areas. This is a call for caution in properly contextualizing land degradation assessments based on NDVI, NPP or RUE-derived indices (see Key Issues in the use of NDVI for Land Degradation Assessments in Section 5). It is our recommendation in this report that all NDVI studies use MODIS NDVI data as the benchmark. If identical NDVI trends between or among different NDVI data sets are not found, something is incorrect and it is not the MODIS NDVI data. This study insists that all NDVI3g land surface studies be compared to MODIS NDVI data from the overlap period (see Figure 9). Failure to perform this inter-comparison can only lead to confusion.

Other issues also need to be considered in the use of NDVI for land degradation assessments:

- *The contentious issue of NDVI saturation at higher LAIs*: It has been argued that the NDVI signal from tropical evergreen forests is saturated so that there is a low signal: noise ratio. This is reported to occur when NDVI is related to LAI through a linear or exponential regression model (Schlerf *et al.* 2005). We are using NDVI as a surrogate for photosynthetic capacity. When photosynthetic capacity is at a maximum, there will be no change in NDVI because there is no change in photosynthetic capacity - because all visible photons have been absorbed. This is not saturation because primary production or photosynthesis is driven by light absorption. When there is no more light to be absorbed in high leaf density situations, photosynthesis is at a maximum and cannot increase (Figure 8). Furthermore, integrated NDVI is directly related in a linear fashion to integrated fluorescence (Figure 10). If NDVI saturation was correct, the relationship in Figure 10 would not occur.

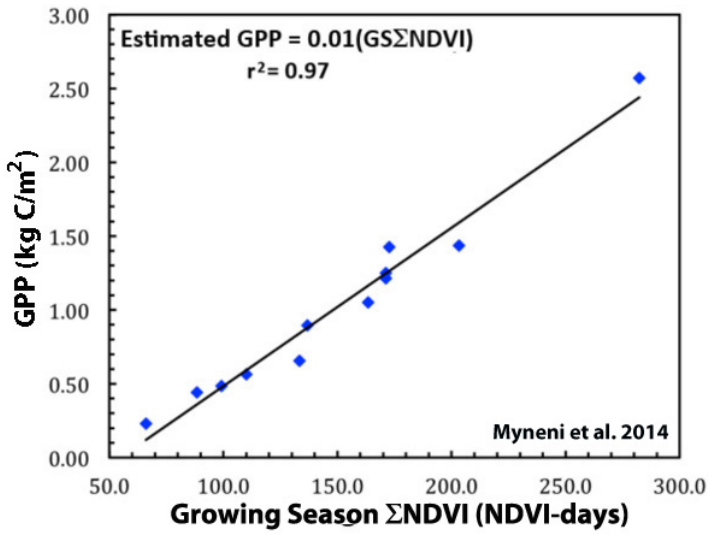

Figure 8 Comparison between integrated gross primary production from 12 flux towers and integrated NDVI from MODIS Terra for the respective growing seasons where the flux towers were situated. This demonstrates the strong relationship between NDVI and primary production which is directly related to chlorophyll abundance and energy absorption (Myneni et al. 1995, Myneni R. B. et al. 2014). There is no saturation of NDVI with respect to photosynthetic capacity (also see Figure 10).

- Caution is needed in the use of vegetation indices to estimate LAI because there is no unique relationship between LAI and any particular vegetation index, but rather a set of relationships, each depending on the architecture of the plants in question (Haboudane *et al.* 2004). A LAI of a grass canopy cannot be compared to the same LAI of a broadleaf forest—the former has vertical leaves and the latter has horizontal leaves. NDVI is directly related to primary production and energy absorption (Myneni *et al.* 1995) and not to LAI.
- *It's hard to separate the effects of climate from the effects of land degradation:* Wessels *et al.* (2007) used the trend of residuals (RESTREND) to distinguish human-induced land degradation from the effects of rainfall variability. GLADA's empirical screening using RUE identified much the same patterns as RESTREND and has the advantage that it translates to NPP for economic analysis (see discussion in Section 5). Conijn *et al.* (2013) disentangled climate from other factors affecting NDVI by modelling biomass production independently according to crop characteristics and global data for climate, soils and land use. Combining NDVI trends and modelled changes in biomass yields four scenarios: a) positive ∑NDVI and positive biomass change - greening might be explained by improving weather; b) positive ∑NDVI and negative biomass - in spite of worsening weather, greenness has increased thanks to management or atmospheric fertilization; c) negative ∑NDVI and positive biomass - greenness declines against a trend of expected increase, so land degradation or land use change has outweighed favourable weather; and d) negative ∑NDVI and negative biomass – declining greenness may be explained by worsening weather (Conijn *et al.* 2013). Whether the benefits of clearer separation of the climatic drivers is worth the substantial effort required is debatable, bearing in mind that the spatial variability of rainfall in drylands makes interpolation of the sparse point measurements problematic and the limitations of biomass modelling using a limited number of vegetation types and pre-defined management. It is no easier to verify changes in calculated biomass using independent data than to verify changes in NDVI.

- *Cloudiness:* The traditional approach of dealing with cloud cover has been to use Maximum Value Composites (MVC) (Holben 1986) which minimizes cloud contamination, reduces directional reflectance and off-nadir viewing effects, minimizes sun-angle and shadow effects, and minimizes aerosol and water-vapour effects. MVC requires that a series of original daily observations of multi-temporal geo-referenced satellite data be processed into NDVI images pixel-by-pixel. Each NDVI value is inspected and only the highest value is retained for each pixel location to eventually form part of an MVC image. MVC has been used in the production of the GIMMS NDVI 8 km dataset (Tucker *et al.* 2005). This compositing approach was necessary because the needed atmospheric variables were not present in the early part of this record for explicit corrections. To avoid time series bias, the same processing approach has been applied to the entire 1981 to 2014 NDVI3g data set.

  This and any other compositing procedure may give rise to bias if a single false high is registered (Pettorelli *et al.* 2005). All compositing approaches may underestimate photosynthetic capacity under cloudy conditions, high aerosol situations, and the presence of snow cover. To eliminate these possibilities of bias, de Jong *et al.* (2011a) used the HANTS algorithm to remove residual cloud effects by applying Fourier analysis complemented by detection of outliers that were replaced by a filtered value. Comparison of global NDVI trends using the HANTS-reconstructed data with the original GIMMS data showed no measurable difference (de Jong *et al.* 2011a). This approach identifies the high frequency "noise" components in NDVI time series data sets and removes them. All vegetation index data sets suffer from these problem and are easily corrected using the techniques of Jong *et al.* (2011a).
- *Autocorrelation nullifies trend analysis:* Autocorrelation (whereby any individual value is influenced by the preceding values) is avoided by using annual ∑NDVI rather than the fortnightly GIMMS values, but this entails a loss of information; for example, we cannot analyze subtly changing seasonal responses of the NDVI signal that may indicate the nature of any degradation. De Jong *et al.* (2011a) applied the non-parametric Mann-Kendall model that is unaffected by autocorrelation to GIMMS NDVI data, and normalized the data for seasonal variations in phenology rather than calendar years (which should be better in the Southern hemisphere where growing seasons do not fall neatly within the calendar year). Linear regression measures annual accumulated photosynthetic activity while Mann-Kendall measures the photosynthetic intensity of the growing season. Each has its own advantages but the close similarity of the patterns of greening and browning revealed by the two models suggests that both are robust.
- *Direct assessment of some land degradation processes:* As discussed in Section 3.5, there are constraints in using NDVI to identify and map soil salinity: most of the salt remains below the soil surface so it cannot be detected on satellite images (Farifteh *et al.* 2006); surface salinity is very dynamic and its detection can be blurred by vegetation and other surface features (Metternicht and Zinck 2003). The effects of sodicity and soil acidity are also impossible to distinguish from other limitations on the growth and productivity of vegetation.
- *Measurement of land degradation using NDVI trends underestimates the problem:* Farming everywhere is running down stocks of soil organic matter that supplies plant nutrients, maintains infiltration, available water capacity and resilience against erosion, and fuels soil biodiversity. Over the last century, 60% of soil and biomass carbon has been lost through land use change. Chernozem, the best arable soils in the world, have lost 30-40% cent of their organic carbon yet they yield abundantly till a tipping point is reached and then the system flips – like the American Dust Bowl in the 1930s (Krupenikov *et al.* 2011). NDVI data do show that heavy use of fertilizer across much of China, the Indo-Gangetic Plain, Europe, the

American mid-West and southern Brazil is no longer accompanied by increasing production but may be concealing soil degradation.

5 Key issues in the use of NDVI for land degradation assessment

5.1 NDVI, NPP and Land Degradation

A substantial body of research has established the correlation between NDVI and above-ground biomass and knowledge of the theoretical basis for using satellite-derived NDVI as a general proxy for vegetation conditions has advanced (Mbow *et al.* 2014, Pettorelli *et al.* 2005, Sellers *et al.* 1994). Reduction of primary productivity is a reliable indicator of the decrease or destruction of the biological productivity, particularly in drylands (Wessels *et al.* 2004, Li *et al.* 2004). NPP is expressed in g of C m^{-2} yr^{-1}, quantifies net carbon fixed by vegetation. According to Cao *et al.* (2004), NPP is "the beginning of the carbon biogeochemical cycle"; defined mathematically defined as in Equation 5:

$$NPP = f(NDVI, PAR, \mathrm{fPAR}, \mathrm{aPAR}, \mathrm{LAI}) \qquad \textit{Equation 5}$$

where fPAR is the fraction of absorbed photosynthetic active radiation, aPAR the absorbed photosynthetic active radiation and LAI is the leaf area index. Changes in NPP or, rather, its proxy NDVI induced by land degradation can be measured using a range of remote sensing techniques so remote sensing has become an essential tool for global, regional and national studies of land degradation (Anyamba and Tucker 2012, Bai *et al.* 2008, Bajocco *et al.* 2012, de Jong *et al.* 2011b, Field *et al.* 1995, Horion *et al.* 2014, Le *et al.* 2014, Prince and Goward 1995). Many approaches have been developed to estimate NPP, notably the Global Production Efficiency Model (GLO-PEM) (Prince and Goward 1995), the Light Use Efficiency (LUE) Model (Monteith and Moss 1977), the Production Efficiency Approach (Goetz *et al.* 1999, Goward and Huemmrich 1992), and the Sim-CYCLE (Ito and Oikawa 2002). And models have been developed to estimate NPP directly from remotely sensed NDVI at a global scale. Running *et al.* (2004) offered Equation 6:

$$NPP = \Sigma(\varepsilon * NDVI * PAR - R_{lr}) - R_g - R_m \qquad \textit{Equation 6}$$

where ε is the conversion efficiency; PAR is photosyntheticaly active radiation; R_{lr} is 24-hour maintenance respiration of leaves and fine roots; R_g is annual growth respiration required to construct leaves, fine roots, new woody tissues; R_m is the maintenance respiration of live cells in woody tissues. Drawing on this relationship, Bai *et al.* (2008) adopted an empirical relationship to translate NDVI trends to NPP trends for their proxy global assessment of land degradation (Equation 7):

$$NPP_{MOD17}(\mathrm{kg\ C\ ha^{-1}}\ year^{-1}) = 1106.37 * \Sigma NDVI - 564.55 \qquad \textit{Equation 7}$$

where NPP_{MOD17} is the annual mean NPP derived from MODIS MOD17 Collection 4 data and sum NDVI is the 4-year (2000–2003) mean annual sum NDVI derived from GIMMS.

5.2 NDVI, RUE and Land Degradation

The concept of rain use efficiency (RUE), coined by Le Houerou (1984) is the ratio of above-ground NPP to annual precipitation. It tends to decrease with increase in aridity and potential evapotranspiration (Purkis and Klemas 2011, Symeonakis and Drake 2004, Le Houerou 1984). It has been observed that RUE is generally lower in degraded lands than in non-degraded lands (Symeonakis and Drake 2004); Fensholt *et al.* (2013) contend that RUE is "a conservative property of the vegetation cover in drylands, if the vegetation cover is not subject to non-precipitation related land degradation". Nonetheless, the use of RUE as an indicator for land degradation has been a hotly

contested on the grounds of methodology, differences in scale and ecological contexts *(*Dardel *et al. 2014, Fensholt et al.* 2013, Wessels 2009, Wessels *et al.* 2012, Wessels *et al.* 2007).

In the short-term, vegetation reacts to natural rainfall variation so RUE needs to be examined over the long-term to exclude false alarms (Nkonya *et al.* 2011). The common practice in estimating RUE is to use summed NDVI as an EO-based proxy for NPP (Fensholt *et al.* 2013) but the nature of the relationship between ΣNDVI and annual precipitation (proportionality, linearity, or non-linearity) has been seen as an important consideration when estimating satellite-based RUE time-series (Fensholt and Rasmussen 2011). In semi-arid landscapes, where livestock farming is predominant, degradation from overgrazing often results in decreased or changes in the composition of vegetation communities and reduced rain-use efficiency (Diouf and Lambin 2001).

Using satellite-based ΣNDVI and annual precipitation, Fensholt & Rasmussen (2011) demonstrated that there is no proportionality, but sometimes a linear relation, between ΣNDVI and annual precipitation for most pixels in Sahel. The authors argue that this undermines the generalized use of satellite-based RUE time-series as a means of detecting non-precipitation related land degradation.

RUE itself has been used as a proxy for land degradation (Safriel 2007, Symeonakis and Drake 2004) where RUE, itself, is not negatively correlated with rainfall. To stress the need for decoupling of precipitation and NDVI correlation in RUE estimation and land degradation assessments, Fensholt *et al.* (2013) use the term "*non-precipitation related land degradation*". This decoupling can be partly achieved by replacing annual ∑NDVI (a variable commonly and erroneously) used in RUE computations by a "*small NDVI integral*" that covers only the rainy season (not the whole year) and counting only the growth in NDVI in relation to some reference level. When this approach is applied to the African Sahel, Fensholt *et al.* (2013) find that positive RUE-trends dominate most of the Sahel, which suggests that "*non-precipitation related land degradation*" is not widespread in the region.

While RUE can be used to normalize the effects of rainfall variability in the vegetation productivity signal when interpreting degradation trends (Landmann and Dubovyk 2014), the interpretation of RUE should be put in the proper environmental and land use context; *e.g.* RUE is closely related to the scale of observation (Prince *et al.* 1998) and is not valid for land-use systems that show no rainfall–vegetation productivity correlations (Bradley and Mustard 2008). Given these caveats, the usefulness of RUE as a stand-alone indicator of vegetation productivity is limited. Another approach is through normalized cumulative RUE differences (CRD). The computation uses normalized monthly RUE with a *Z*-score normalization to correct for high outliers in the rainfall data (Landmann and Dubovyk 2014). Using 250m MODIS NDVI data, this approach was employed to map vegetation productivity loss over eastern Africa between 2001 and 2011 (Landmann and Dubovyk 2014). The study concluded that 3.8million ha of land experienced vegetation loss over the period, with an accuracy assessment of 68% agreement between the rainfall-corrected MODIS productivity decline map and all reference pixels discernable from Google Earth and the Landsat-derived map and an accuracy of 76% for deforestation. The study concluded that under high land use intensities, the CRD showed a good potential to discern areas with '*severe*' vegetation productivity losses.

Dardel *et al.* (2014) used RUE residuals derived from linear regression as an indicator of ecosystem resilience in the Gourma region in Mali. This study made use of data from long-term field observations of herbaceous vegetation mass and GIMMS-3g NDVI data to estimate ANPP, RUE, and the ANPP residuals over the period 1984–2010. Counter-intuitively, an increased run-off coefficient was observed over the same period of stable RUE. In Burkina Faso, an increase in discharge of rivers was first observed despite a reduction in rainfall - the "*Sahelian Paradox*" described in 1987 (Albergel 1988). Dardel *et al.* 2014 coined the term the "*second Sahelian Paradox*" to refer to the

"*divergence of these two indicators of ecosystem resilience (stable RUE) and land degradation (increasing run-off coefficient)*" (Dardel *et al.* 2014).

5.3 Separating the effects of other causes of NDVI Changes

Vegetative cover is a measurable indicator of ecosystem change but the performance of vegetation depends on many micro- and macro-environmental factors (especially climate). Changes in vegetation reflect changes in both the natural factors that influence vegetation growth and performance, as well as human influences. Hence, whereas NDVI can be a good indicator of NPP, separating the effects of climate variability on NDVI changes from those of land degradation is a challenge (Vogt *et al.* 2011). Different approaches, as described hereafter have been used in recent studies.

One of the most popular techniques of application of NDVI in the assessment and monitoring of desertification is through the analysis of time series NDVI images. In NDVI time series analysis, linear models may be used to best fit the cyclic vegetation variation into a line (Equation 8). The slope of the line can then be used to deduce the direction of vegetation variation (decrease or increase), as well as the strength of variation from the steepness of the trend line (for example, no change, minimal, moderate, or severe change). In this case, the NDVI linear model will be:

$$NDVI_t = a \ . \ t + NDVI_0 \qquad \textit{Equation 8}$$

where a is the trend, $NDVI_0$ is constant and t is time.

Evans and Geerken (2004) used linear regression on NDVI time-series and rainfall to discriminate between the NDVI signal attributable to climatic conditions and that to human influence. The difference between the observed maximum NDVI and the regression-predicted maximum NDVI (referred to as residuals) was calculated pixel-by-pixel to identify the climate signal (the effect of precipitation) (Evans and Geerken 2004). Once the climate signal is identified and removed from the trends in vegetation activity, the remaining vegetation variations are attributed to human activities. Positive trends in the vegetation represent areas of vegetation recovery while negative trends constitute human-induced degradation of vegetation cover. RESTREND involves regressing ΣNDVI from annual precipitation and then calculating the residuals - the difference between observed ΣNDVI and ΣNDVI as predicted from precipitation (Fensholt *et al.* 2013, Wessels *et al.* 2012, Wessels *et al.* 2007). RUE and RESTREND were compared using AVHRR NDVI from 1985-2003 and modelled NPP from 1981-2000 to estimate vegetation production in South Africa (Wessels *et al.* 2007). The study found that RUE was not a reliable indicator of land degradation. RESTREND was found to offer better prospects but the study cautioned on the need for local level investigations to identify the cause of negative trends. In a later study Wessels *et al.* (2012) concluded that the RESTREND approach in fact also has shortcomings, since the calculation of the residual NDVI is based on the assumption of a strong linearity between NDVI and rainfall over time; a relation which in the case of degradation during the period of analysis will be altered and thereby compromising the reliability of the RESTREND calculation.

Popastin *et al.* (2008) proposed the use of geographically weighted regression (GWR) between NDVI and precipitation for identifying the human induced signal in NDVI time series data. Using this method, the GWRs will describe the expected (predicted) NDVI for any particular climate signal. Deviations from the regression line by the observed NDVI would indicate vegetation changes that are attributable to stimuli other than climate (Propastin *et al.* 2008). Positive deviations indicate vegetation improvements while negative deviations indicate declining in vegetation condition.

5.4 Abrupt Changes

Linear trends are easy to calculate and in the early years of satellite NDVI this was the only feasible approach. However, contrasting trends can balance out so it is important to ensure that the necessary assumptions for the determination of linear trends are met for each analysis. Citing De Beurs *et al.* (2005), Higginbottom and Symeonakis (2014) list them as: (1) independence of the dependent variable, (2) normality in the model residuals, (3) consistency in residual variance over time, and (4) independence in residuals. Where there is need to separate NDVI time series into linear trend, seasonal components and errors, non-linear NDVI time series models are used (Erian 2005). Key components of such non-linear models (Equation 9) would usually include a linear trend, stochastic component, external variables, periodic components (in terms of cycles and periodic trends), and white noise (Erian 2005, citing Udelhoven 2005).

Equation 9

$$NDVI_t = \alpha + \beta_1 \bullet t + \left(\sum_{i=1}^{NoOfLags} \beta_i NDVI_{t-i} \right) + \left(\sum_{j=1}^{NoOfX} \sum_{k=1}^{NoOfLags} \beta_{jk} X_{jk} \right) + \left(\sum_{m=1}^{NoOfHarm} a_m \cos \bullet 2\pi \frac{1}{P_m} \bullet t + b_m \sin 2\pi \frac{1}{P_m} \bullet t \right) + \varepsilon$$

Constant | Linear trend | Stochastic component | External variables | Periodic components (cycles, long periodical trends) | White noise

The more than 30 years of NDVI record now available reveal many breaks of trend, even reversals. The Breaks for Additive Season and Trend (BFAST) approach has been developed to detect and capture these NDVI trend changes (de Jong *et al.* 2011c, Verbesselt *et al.* 2010a, Verbesselt *et al.* 2010b). The algorithm combines the decomposition of time series into seasonal, trend, and remainder component with methods for detecting changes. An additive decomposition model is used to iteratively fit a piecewise linear trend and a seasonal model (Haywood and Randall, 2008). According to De Jong *et al.* (2012), the general form of the model is Equation 10:

$$Y_t = T_t + S_t + e_t : t \in T \qquad \textit{Equation 10}$$

where, at time t (in the time series T), Y_t is the observed NDVI value, T_t is the trend component, S_t the seasonal component en et the remainder component which contains the variation beyond what is explained by T_t and S_t. Using this method (Equation 10), De Jong *et al.* (2011a) mapped the global distribution of greening to browning or vice versa; about 15% of the globe witnessed significant trend shifts within the period studied. Common change detection methods average out this mixed trend effect, underestimating the trend significance (de Jong et al. 2011c).

6 Development of land degradation assessments

Early assessments of land degradation like the Global Assessment of Soil Degradation (GLASOD) (Oldeman *et al.* 1990) were based on compilations of expert opinion. They are unrepeatable and systematic data show them to be unreliable (Sonneveld and Dent 2009). Under the FAO/UNEP program *Land Degradation in Drylands (LADA)*, Bai *et al.* (2008) undertook a global assessment of land degradation and improvement (GLADA) by analysis of linear trends of climate-adjusted GIMMS NDVI data. GLADA, the first quantitative assessment of global land degradation (de Jong 2010) aimed to identify and delineate "*hot spots of land degradation, and their counterpoint - bright spots of land improvement*" (Bai *et al.* 2008). The study revealed that about 24% of the global land area was affected by land degradation between 1981 and 2003. Humid areas accounted for 78% of the global degraded land area while arid and semiarid areas accounted for only 13%. Cropland and rangelands

accounted for 18% and 43% respectively, of the 16% of global land area where the NDVI increased. The authors observed a positive correlation between population density and NDVI but, also, a correlation between poverty and land degradation. They emphasized that NDVI cannot be other than a proxy for land degradation and that it reveals nothing about the kind of degradation or the drivers (Bai *et al.* 2008).

Potential false alarms caused by drought cycles and rising global temperatures were removed by screening the data using rain-use efficiency (RUE) and energy-use efficiency (EUE). RUE was estimated from the ratio of the annual sum NDVI to annual rainfall calculated from the VASClimO station-observed monthly rainfall data gridded to 0.5^{o} latitude/longitude (Beck *et al.* 2005); EUE was represented by the ratio of NDVI and accumulated temperature calculated from the CRU dataset (Jones and Harris 2013, Mitchell and Jones 2005). The sequence of operations was:

1. Areas where biomass productivity depends on annual rainfall were identified as those with a significant positive relationship between NDVI and rainfall. In these areas, years of below-normal rainfall exhibit below-normal NDVI and also, usually, increased RUE. Where there is decreasing NDVI but steady or increasing RUE, the loss of productivity was attributed to drought and these areas were masked. Where both NDVI and RUE declined, something else is happening and these areas were included in the next stage of analysis.
2. For the remaining areas where productivity is not limited by rainfall and, also, for those with a positive relationship between productivity and rainfall but declining RUE, greening and browning trends were calculated as *RUE-adjusted NDVI*. Similarly, EUE was used to separate trends caused by rising temperatures, the net result being a *climate-adjusted NDVI.*
3. Urban areas were masked (this makes little difference to the global results -0.5% for the identified degrading land and 0.2% for improving land). Irrigated areas were not masked; the separation of areas of positive and negative correlation with rainfall effectively separates wetlands, irrigated areas and areas with surplus rainfall from the areas - where unadjusted NDVI is a good measure of degradation and improvement. Humid areas have not been masked; unadjusted NDVI was used for all of those areas where RUE is *not* appropriate.
4. The T–test was used to test the significance of the linear regression; class boundaries were defined for 90, 95 and 99% levels.
5. To arrive at a measure amenable to economic analysis, NDVI trend was translated into gain or loss of NPP by correlation with MODIS 8-day NPP data (Running *et al.* 2004) for the overlapping period (2000–2006).
6. Several indices of land degradation and improvement were compared with land cover, land use, and landform. Land use change is a main driver of land degradation so it would be useful to undertake analysis of NDVI against change in land use and management but there are no corresponding time series data for land use or land cover. GLC2000 (Bartholomé and Belward 2005) global land cover and Land use systems of the World (FAO 2013) were used for preliminary comparison with NPP trends.
7. Soil and terrain: A global soil and terrain database at scale 1:1 million-scale was compiled using the 90m-resolution SRTM digital elevation model and a dataset of key soil attributes for the LADA partner countries (ISRIC 2008b, ISRIC 2008a). Correlations between land degradation and soil and terrain were investigated in country studies.
8. Population, urban areas and poverty indices: The CIESIN Global Rural-Urban Mapping Project provides data for population and urban extent, gridded at 30 arc-second resolution (CEISIN 2004). Sub-national rates of infant mortality and child underweight status and the gridded population for 2005 at 2.5 arc-minutes resolution (CEISIN 2007) were compared with indices of land degradation.

The picture revealed by GLADA was against received wisdom which reckoned that degradation was worst in the Sahel, the Amazon rain forest and, more generally, in drylands. But the Sahel, Amazon and drylands mainly showed increases in climate-adjusted NDVI. The areas hardest hit appeared to be Africa south of the Equator, Southeast Asia, the Pampas and Chaco regions in South America, North-central Australia and swaths of the high-latitude forest belt extending across North America and Siberia. The identification of increases in the Amazon by Bai *et al.* (2008) must be questioned in the light of more recent studies by Morton *et al.* (2014). It has been shown that the apparent greening of Amazon forests revealed in optical remote sensing data is due to seasonal changes in NIR reflectance – an artifact of variations in sun-sensor geometry (Morton *et al.* 2014). The picture is different again when the same analysis is applied to the extended GIMMS3g dataset for 1981-2011, the differences are not just because of the longer run of data but because of changes in GIMMS data-processing to correct better for the periodic replacement of AVHRR sensors (especially AVHRR 2 to AVHRR 3). Importantly, the processing of the latest GIMMS dataset does no assume stationarity (no overall change in NDVI) but, rather, reveals the underlying trends (Pinzon and Tucker 2014).

7 Experts' opinions on the use of NDVI for land degradation assessment

Methodological issues were raised by Wessels (2009) regarding use of NDVI in the GLADA assessment, chiefly the interpretation of RUE outside arid and semi-arid regions, growing season differences between the northern and southern hemisphere and their implications for calendar year summations of NPP, and issues of scale in the interpretation of AVHRR NDVI vs. MODIS NPP relationships. He also maintained that the RESTREND technique provided a more dependable alternative. In response, Dent *et al.* (2009) clarified that RUE was not being used as an indicator of land condition but simply to separate NDVI trends caused by drought in those areas where biomass potential is directly related to rainfall, essentially drylands. Regarding seasonal differences in growing season between the northern and southern hemispheres, there was no difference in the long-term trends when the hydrological year was used for the southern hemisphere. And, finally, the RESTREND approach was also applied to the GLADA data and showed no significant difference with the RUE-adjusted NDVI approach; the choice of the RUE-adjusted NDVI was made on account of its simplicity and amenability to economic evaluation (Dent *et al.* 2009).

7.1 NDVI – rainfall proportionality, an important consideration

A methodological weaknesses that might seem to question the applications of RUE in the Bai *et al.* (2008) study (as with many studies in this area) has to do with the lack of consideration given to the effect of lack of proportionality in the use and interpretation of RUE (computed from NDVI-derived NPP) as a proxy for identifying areas of land degradation. The theoretical basis for the concept of RUE assumes proportionality between NPP (as indicated by NDVI) and rainfall (Le Houerou 1984) meaning that a fixed ratio (RUE) exists despite changes in rainfall over time. In relationship between these two variables, NDVI and rainfall are forced to intercept at zero to meet the assumption of proportionality with changes in the rainfall (Dardel et al. 2014, Fensholt and Rasmussen 2011, Verón et al. 2005). The theoretical assumption of proportionality is important in understanding the functioning of the relationship between these two variables (rainfall and NDVI). Recent studies have shed light on the importance of considering proportionality in the use of RUE derived from relationship between NPP (derived from NDVI) and rainfall (Dardel et al. 2014, Fensholt and Rasmussen 2011). The practical application of the relationship between NDVI and rainfall does not lead to generally robust results characterised by proportionality between variables. One of the main reasons for this lack of robustness is that NDVI is never zero – NDVI is always slightly positive, even on bare soils (Verón et al. 2005, Fensholt and Rasmussen 2011). The assumption of a linear relationship between NDVI and rainfall will also not to be applicable in cases where vegetation

growth requires a certain threshold of rainfall (Dardel et al. 2014), as tends to be the case in many areas of the tropical savannah with a distinct rainy and dry season. The result in both cases (either on bare soils or in places where a threshold of rainfall is required for vegetation growth to be triggered) is that a linear relation between NDVI and rainfall might exist but no proportionality. This means that RUE is in fact not able to normalise vegetation productivity for varying rainfall and consequently RUE calculated in this case is sensitive to changes in rainfall over both space (will artificially trend to infinity values (Dardel et al. 2014)) and time (Fensholt and Rasmussen 2011, Fensholt et al. 2013). The result of the RUE dependency on rainfall in a time-series analysis will be that "*significant trends will emerge if rainfall undergoes temporal changes within this range of values*" (Dardel et al. 2014, Fensholt and Rasmussen 2011, Fensholt et al. 2013). If overlooking this fundamental inefficiency of RUE to normalise for rainfall changes in the case where proportionality between variables are absent, the direct use of RUE for trend analysis (or indirect use when masking out pixels due to a certain trend in RUE) will lead to misleading interpretations. As a precaution not to include cases of pixels with such artificial trends simply reflecting a change in the rainfall regime rather than land degradation, Fensholt and Rasmussen (2011) restricted their analysis of trends in Sahelian rain-use efficiency to using only cases (1) where no per-pixel temporal correlation between annual RUE and rainfall was found and (2) where estimates of growing season ΣNDVI and annual rainfall correlation were statistically significant ($p<0.05$).

7.2 Building on the GLADA assessment

Recent studies have used different approaches to assess land degradation at different scales, some using the GLADA methodology at different scales. Bajocco *et al.* (2012) summed NDVI values on a pixel basis recorded for each year between 2000 and 2002, and computed the mean annual ΣNDVI to represent a surrogate for the total annual biomass production of the Mediterranean region. Le *et al.* (2014) used the long-term trend of inter-annual mean NDVI) over the period 1982–2006 to delineate land degradation hotspots but cautioned that the use of proxies is subject to uncertainties which need to be understood and addressed. De Jong *et al.* (2011a) also made use of the GIMMS NDVI data to analyze global greening and browning, using three approaches: a linear model corrected for seasonality; a seasonal non-parametric model; and analyzing the time-series according to vegetation development stages rather than calendar days. The trends found using the linear model approach corrected for seasonality were very close to those identified by Bai *et al.* (2008) applying a linear model to yearly mean values but there was a substantial difference in results from the different models a cautionary reminder of the importance of putting results within the context of the methods applied, and of providing adequate metadata to aid interpretation and understanding of the results. De Jong *et al.*2011 also used the Harmonic Analysis of NDVI Time-Series (HANTS) algorithm to remove residual cloud effects by applying Fourier analysis complemented by detection of outliers that were replaced by a filtered value. Comparison of global NDVI trends using the HANTS-reconstructed data with the original GIMMS data shows no measurable difference - so GLADA is unaffected by cloud cover. Chinese researchers have made use of the GIMMS database and the GLADA methodology for several countrywide studies. In the process, some new indices were developed, such as the Sensitivity Index - the degree of reaction of NDVI to rainfall change in specific rainfall regions (see China's experiences on the usefulness of GLADA in Annex 4 and Annex 3 discussion recent developments with GLADA).

Nkonya *et al.* (2013) used the first difference econometric approach in studying the global extent of land degradation and its human dimensions. NDVI trends were used to represent land degradation or improvement and the NDVI-derived global land cover change was overlain with poverty distribution to better understand the connection between land degradation and poverty. The study found consistencies with Bai *et al.* (2008) in the relationship between severe poverty and decrease in the

NDVI in some, but not all parts of Africa. In a rigorous analysis of greenness in semi-arid areas, world-wide, using AVHRR GIMMS data from 1981–2007, Fensholt *et al.* (2012) found that semi-arid areas are, on average, greening but similar increases in greenness over the study period may have broadly different explanations and cautioned against general assertions of on-going land degradation in semi-arid regions.

8 Main global NDVI datasets and databases

Coarse-spatial-resolution datasets are invaluable at the global scale but they lack the thematic and spatial detail required for habitat assessments at the country level and for finer resolution assessments such as vegetation species distribution or high-quality forest-change monitoring. Mapping, monitoring and assessments at the national and sub-national level are performed using moderate-resolution sensors such as Landsat, ASTER, SPOT HRV, and IRS with spatial resolutions from 15 to 60m. Newer, high-resolution optical sensors (5m or better) provide enough spatial and spectral detail to discriminate between individual trees and, in some cases, species but high-resolution imagery is prohibitively costly (see Annex 7) for many national governments and research institutions (Strittholt and Steininger 2007).

8.1 Main NDVI datasets

Significant research effort has been invested in processing satellite sensor data into NDVI. The most common sensor used in these initiatives is the AVHRR sensor on board the NOAA satellites to produce global scale NDVI datasets. The development of these datasets by different research groups usually involves the use of diverse schemes, protocols and algorithms for corrections and processing (Scheftic *et al. 2014)*. As a result, the environmental change community currently has a range of datasets that may be used for a variety of applications (Table 1).

Table 1 Commonly utilized Normalized Difference Vegetation Index (NDVI) datasets (Modified from Higginbottom and Symeonakis 2014)

Name	Sensor	Time-span	Time-step	Resolution
Pathfinder (PAL)	AVHRR	1981–2001	10-day	8 km
Global Vegetation Index GVI)	AVHRR	1981–2009	7-day	4 km
Land Long Term Dara Record (LTDR)	AVHRR	1981–2013	Daily	5 km
Fourier-Adjusted, Sensor and Solar zenith angle corrected, Interpolated, Reconstructed (FASIR)	AVHRR	1982–1998	10-day	0,125°
GIMMS	AVHRR	1981–2006	15-day	8 km
GIMMS3G	AVHRR	1981–2014	15-day	8 km
S10	SPOT-Vegetation	1998+	10-day	1 km
EM10	ENVISAT-MERIS	2002–2012	10-day	1/1,2
SeaWiFS	SeaWiFS	1997–2010	Monthly	4 km
MOD (MYD)13 A1/A2	Terra (Aqua)	2000+	16-day	500 m/1 km
MOD13 (MYD)A3			Monthly	1 km
MOD13 (MYD)C1/C2			16-day/Monthly	5,6 km
MOD13 (MYD) Q1	MODIS		16-day	250 m
MEDOKADS	AVHRR	1989+	Daily	1 km

The most widely used global NDVI datasets are the Global Inventory for Mapping and Modeling Studies (GIMMS); NOAA/NASA Pathfinder (PAL); the Long Term Data Record (LTD); and the Fourier-Adjusted, Sensor and Solar zenith angle corrected, Interpolated, Reconstructed (FASIR) adjusted (NDVI) (see Annex 1).

The *Global Inventory for Mapping and Modeling Studies (GIMMS)* dataset is the most updated global time-series NDVI product (Fensholt and Proud 2012). It has a temporal resolution of two weeks (24scenes/year) and a spatial resolution of approximately 8km. The GIMMS NDVI3g data set (Pinzon and Tucker 2014), now comprises more than 33 years of data corrected for instrument calibration, variations in solar angle and view zenith angle, stratospheric aerosols from major volcanic eruptions, and other effects not related to vegetation change. Cloud and haze effects are minimized by taking the highest fortnightly value within composite 8km blocks of pixels (Holben 1986).

The *NOAA/NASA Pathfinder (PAL) NDVI* dataset was created from the PAL 8km daily product(Green and Hay 2002, James and Kalluri 1994). The PAL 8km daily data were spatially re-sampled, based on maximum NDVI values from AVHRR Global Area Coverage data which have a minimal resolution of 4km (De Beurs and Henebry 2005, James and Kalluri 1994). The PAL Global 10-day composite NDVI product is part of the Pathfinder Land data set archived at the Goddard Earth Sciences, Distributed Active Archive Center (GES-DAAC)(Green and Hay 2002). The dataset has been corrected for changes in sensor calibration, ozone absorption, Raleigh scattering and sensor degradation after pre-launch calibration, and have been normalized for changes in solar zenith angle (James and Kalluri 1994). The dataset is not continually being processed and data after 1999 are not accessible online at the website of GES-DAAC of the Goddard Space Flight Center.

Long Term Data Record (LTD) is a global daily dataset of 0.05° (about 5km ground spatial distance) developed by the NASA-funded LTDR Project. The dataset is currently at its 4th version and available for the period 1981-2013 from the reprocessing of the N07-N18 AVHRR data (Pedelty *et al.* 2007). The current version includes records from the processing of data from NOAA-16 and NOAA-17 lengthening the LTDR records from AVHRR to 2013.

The Fourier-Adjusted, Sensor and Solar zenith angle corrected, Interpolated, Reconstructed (FASIR) adjusted NDVI datasets are products of the International Satellite Land-Surface Climatology Project, Initiative II (ISLSCP II) data collection, developed to provide a 17-year satellite record of monthly changes in the photosynthetic activity of terrestrial vegetation for use in general circulation climate models and biogeochemical models (Sellers *et al.* 1994, Sietse 2010). The NDVI collections are provided in data files at spatial resolutions of 0.25, 0.5 and 1.0 degree latitude/longitude. FASIR adjustments concentrated on reducing NDVI variations arising from atmospheric, calibration, view and illumination geometries and other effects not related to actual vegetation change (Sietse 2010).

The *Moderate-Resolution Imaging Spectrometer (MODIS)* is an extensive program using sensors on two satellites (both the Terra and Aqua satellites) that each provide complete daily coverage of the earth. Started in January 2000, the MODIS sensor provides vegetation indices (NDVI and EVI) produced globally on 16-day intervals at 3 resolutions (250, 500 and 1000 m). The MODIS NDVI data are fully consistent spatially and temporally with AVHRR NDVI products (Tucker et al. 2005). Comparisons between AVHRR and MODIS NDVI products over a wide range of vegetation types have shown a very high correlation, $r > 0.9$ according to (Gallo et al. 2005). See also Figure 9. A complete collection of MODIS Land products can be accessed freely online either from USGS or NASA sites (see Annex 7).

8.2 Quality-related considerations

The potential for using free data for assessment and monitoring of environmental change (principally forest cover change) at the global level has been most clearly demonstrated for Landsat products (Townshend *et al.* 2012). The key challenges for creating global products of forest cover and cover change are the processes and tools for atmospheric correction, proper calibration coefficients, working with different phenologies between compilations, terrain correction, proper accuracy assessment, and the automation of land cover characterization and change detection (Townshend *et al.* 2012). Most of the commonly used datasets mentioned above (such as the PAL, GIMMS, LTDR, and the FASIR) have undergone many evaluations and inter-comparisons on a range of criteria (Beck *et al.* 2011, Fensholt and Proud 2012).

Beck *et al.* (2011) undertook a global intercomparison of the four AVHRR-NDVI datasets (PAL, GIMMS, LTDR, FASIR) against Landsat imagery for the period 1982-1999, finding significant differences in trends for almost half of the total land surface. The PAL and the LTDR (Version 3) datasets lacked calibration; GIMMS had the best calibration and was the most accurate in terms of temporal change. In a study investigating whether vegetation trends derived from NDVI and phenological parameters are consistent across products, Yin *et al*. (2012), compared GIMMS and SPOT-VGT derived NDVI. Strong similarities were found in inter-annual trends and, also, in trends of the seasonal amplitude and annual sum NDVI but significant disagreements were observed in NDVI-derived trends based on phenological parameters such as amplitude (maximum increase in canopy photosynthetic activity above the baseline), and integral of NDVI (canopy photosynthetic activity across the entire growing season) (Yin *et al.* 2012). These correspond to seasonal vegetation cycles between GIMMS and SPOT VGT. The study attributed these discrepancies to variables such as land cover and vegetation density. Such discrepancies highlight the need for the use of appropriate and rigorous pre-processing when working with data from different remote sensing systems.

8.3 Precipitation Data Sets

Various precipitation datasets are used in combination with NDVI data in many earth science applications. Among the most widely used of these datasets are the Modern Era-retrospective Reanalysis for Research and Applications (MERRA), Interim Reanalysis (or ERA-Interim Reanalysis), Global Precipitation Climatology Project (GPCP), Africa Rainfall Climatology, and the VASClimO (Table 2).

Table 2 Commonly used precipitation datasets for earth science and environmental applications.

Precipitation Data	Time Span & Scale	Reference
NASA MERRA	1979-present at 0.5° × 0.5°	Rienecker *et al.* 2011
ERA-Interim	1979-present at 80 km	Dee *et al.* 2011
GPCP	1979-2012 at 1.0° × 1.0°	Huffman *et al.* 2009
African Rainfall Climatology	1983-2013 at 0.1° × 0.1°	Novella *et al.* 2013
VASClimO	1951-2000 at 0.5°, 1.0°, and 2.5°	Beck *et al.* 2004, Schneider et al. 2008
TRMM	1997-present at 0.25° × 0.25°	Gentemann *et al.* 2004

The *Modern Era-retrospective Reanalysis for Research and Applications (MERRA)* is a NASA re-analysis for the satellite era using the Goddard Earth Observing System Data Assimilation System Version 5 numerical weather and climate model The Project focuses on historical analyses of the hydrological cycle on a broad range of weather and climate time scales and places the NASA EOS suite of observations in a climate context. This data set has a spatial resolution of 0.5° x 0.5° from 1979 to the present (Rienecker *et al.* 2011).

The *Interim Reanalysis* (or ERA-Interim Reanalysis) output comes from the European Centre for Medium Range Weather Forecasts. It is a global atmospheric reanalysis from 1979, continuously updated in real time through the present with a spatial resolution of 80km (Dee *et al.* 2011).

The *Global Precipitation Climatology Project (GPCP)* version 2.2 is a blend of precipitation gauge data and satellite data taking advantage of the strengths of each data type. These data are 1° x 1° and run from 1979 to 2012 (Huffman *et al.* 2009). Tropical Rainfall Monitoring Mission or TRMM data form the basis of the GPCP data set and are blended with station data to improve the rainfall accuracies.

The *Africa Rainfall Climatology* version 2 is a gridded, daily 30-year (1983–2013) precipitation dataset at 0.1° × 0.1° spatial resolution produced by NOAA's Climate Prediction Center (Novella and Thiaw 2013), produced using an operational rainfall estimation algorithm now updated to Rainfall Estimates Version 2 (Novella and Thiaw 2013).

The *VASClimO* is a global data set of station-observed precipitation produced by gridding 9343 homogeneity-checked station time-series of precipitation for the period 1951–2000 (Rudolf *et al.* 2005). It provides a globally gridded total monthly precipitation from January 1951 to December 2000 at three resolutions: 0.5° × 0.5°, 1.0° × 1.0°, and 2.5° × 2.5° and is updated by the GPCC full-data re-analysis product version 4 (Schneider *et al.* 2008).

Tropical Rainfall Measurement Mission (TRMM) datasets is obtained by active and passive microwave measurements derived by instruments onboard the Tropical Rainfall Measuring Mission's (TRMM) Microwave Imager (TMI). Besides measuring rain rates, the TMI can also measure sea surface temperature (SST), ocean surface wind speed, columnar water vapor, and cloud liquid water. TRMM is a joint program between NASA and the National Space Development Agency of Japan (Gentemann *et al.* 2004).

9 Country-level use of satellite products to detect and map land degradation processes

For ecological studies and environmental change research, Petrorelli *et al.* (2005) distinguish two main groups of satellite products: a) long-term NDVI data sets including the coarse scale (8–16km resolution) NOAA–AVHRR time-series extending from 1981 to the present and the small-scale Landsat–TM dataset extending from 1982; use of Landsat products for land use and land cover change has been growing because Landsat has a relatively fine resolution for land use change studies and wave bands extending across the visible, near-infrared, shortwave infrared spectrum (Townshend *et al.* 2012); and b) finer scale but short-term NDVI time-series datasets which include MODIS–TERRA (250–1000m resolution) extending from 2000 to the present, and the 1 km to 300 m resolution SPOT–VGT dataset extending from 1998 to the present. However, these data are not available free of charge (see Annex 7).

Our approach to assessment of land degradation using satellite data depends on observing changes in total seasonal photosynthesis or primary production through time at continental scales, with the ability to disaggregate to national and district-level scales when required. This is necessary because all actions to halt land degradation must be implemented at the national or sub-national scale. NDVI data exist globally at 8km since 1981 from the AVHRR and at 250 m from MODIS since 2000. This study recommends that all 8 km NDVI3g analyses should be complimented by comparisons to MODIS NDVI 250 m data for their overlap periods (Figure 9).

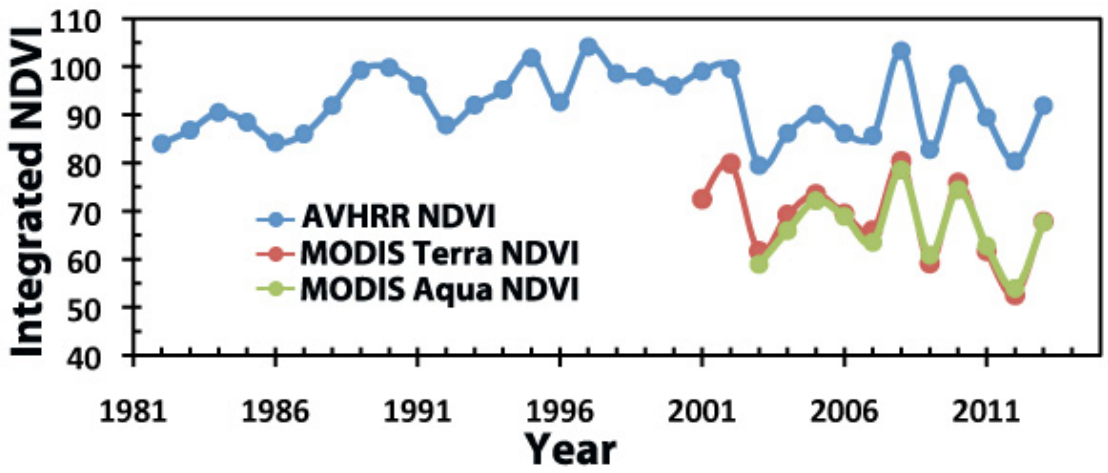

Figure 9 Integrating NDVI values is directly related to gross primary production over the growing season for an area in Moldova. We have taken the NDVI values from Figure 8 and numerically integrated them from the first of March to the end of October for 1981 to 2013 for the GIMMS NDVI3g dataset, for 2001-2013 for MODIS Terra NDVI, and for 2003 to 2013 for the MODIS Aqua NDVI data. Note very similar behaviour in integrated NDVI values (NDVI-days). There appears to be a break point between 2002 and 2003.

The possibility of using other sources of primary-production data. We could also possibly use the MODIS-derived net primary production product (MOD17) (Running *et al.* 2004) or chlorophyll fluorescence from the Greenhouse Gases Observing Satellite (GOSAT), the SCanning Imaging Absorption SpectroMeter for Atmospheric CHartographY (SCIAMACHY), or the Global Ozone Monitoring Experiment–2 (GOME-2) instruments (Joiner *et al.* 2013, Joiner *et al.* 2012), are alternative products to map and monitor land primary production. The MODIS NPP product is a global-modeled output product and, like many global products, performs less well when disaggregated to the national and district levels; its driving variables are not available at resolutions <1km. The fluorescence products from SCIAMACHY, GOSAT, and GOME-2 satellites appear to be very useful for measuring primary production; SCIAMACHY data collection begun in early 2002 at a spatial resolution of 30 x 60 km (Gottwald *et al.* 2006); GOSAT data start in 2009 and are 10 x 10km in spatial resolution (Joiner *et al.* 2011); GOME-2 data start in late 2006 and have a nadir spatial resolution of 0.5^{o} x 0.5^{o} (Joiner *et al.* 2013).

The large spatial scale of these data is because fluorescence measurements are made within several Fraunhoffer lines that are only 1 Angstrom or 0.1nm wide so it is necessary to collect fluorescence data over large areas to get enough photons for an adequate signal to noise ratio. These coarse spatial scales make disaggregation to the sub-national difficult. Recent studies by Joiner and a member of our team - Tucker (*submitted*), have shown that the time integral of fluorescence is linearly and very highly correlated to the NDVI time integral (Figure 10). The NDVI advantage for land degradation studies is that land degradation can be studied over 33+ years with the GIMMS3g data set at 8km and for fifteen years at 250m from MODIS NDVI with the potential to downscale with NDVI data at 30m from Landsat and at 1m from commercial satellite data.

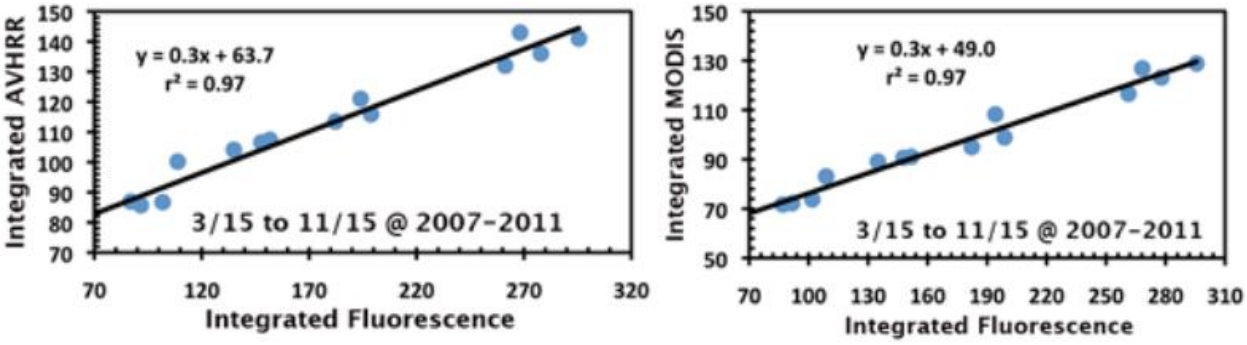

Figure 10 Integrated AVHRR and MODIS NDVI compared to GOME-2 chlorophyll fluorescence for the Russian wheat growing areas of 51°-56°N x 40°-54°E, 47°-53°N x 54°-60°E, and 50°-57°N x 60°-72°E from March 15 to November 15 of 2007 to 2011. Three areas over five years provide a sample size of 15 (Yoshida et al. 2014). This figure contradicts the allegations that NDVI saturates and supports our use of the NDVI as being directly related to primary production.

At present, there is insufficient time history of fluorescence to assess land degradation for these reasons: (1) Although SCIAMACHY fluorescence data started in 2002 their spatial resolution is 30 x 60 km which is very coarse resolution; (2) Fluorescence data from GOME-2 start in 2006 and from GOSAT in 2009 so we don't have enough time history to detect land degradation trends using these data. Twenty years on, satellite fluorescence data may be another tool for quantifying land degradation over large areas at a coarse scale but, for the present, there is no alternative to NDVI in land degradation assessment.

10 Challenges to the use of NDVI in land degradation assessments

Technological Barriers: Currently, most global datasets useful for environmental applications are archived in databases that can be accessed using the internet. These include the GIMMS, NOAA-PAL, LTD, and FASIR datasets. There are also free on-line data service platforms for executing pre-processing operations (such as data smoothing, spatial and temporal sub-setting, mosaicing and re-projection) of MODIS time series vegetation indices (such as NDVI and EVI) on request. Currently, the internet speed for many regions of the developing world remains too slow to enable effective access to these datasets or on-line processing.

Technical capacity: NDVI is a relatively simple index to compute and use in a number of environmental assessments (Liang 2005). However, when it comes to land degradation assessment, the use of NDVI can be problematic, both in implementation and interpretation (Wessels *et al.* 2004). Therefore, the analysts need to be properly equipped with the intellectual and technical skills to contextualize the problems of land degradation for particular cases and the interaction of key variables (NDVI, NPP or RUE derived indices) in the process.

Institutional and Policy Barriers: Effective use of satellite remote sensing products and technologies for a range of environmental assessments at the national level requires an appropriate institutional and policy framework. At the national level, this means the creation and effective management of a geo-information infrastructure that enables the decentralization of information management through integration of geographic information and remote sensing systems. The level of integration could vary, depending on the set-up of the country's administrative zones, the nature of land degradation being assessed, and the distribution of geo-information services in the country.

Barriers to effective knowledge management, decision support, and continuity: Given the complex array of environmental and socio-economic processes involved in land degradation (Figure 1), there is need for an effective system of knowledge and information management. Information has to flow

between and across sectors (such as agriculture, nature conservation, and other forms of land uses) for a proper interpretation of the distribution and trends of NDVI signals. A meaningful assessment of historic trends in land degradation or changes in land productivity requires continuity in the system of data collection, analysis, presentation and activities related to each dataset or process. In many developing countries, frequent changes of government constitute a major constraint on the implementation of some programs and projects - ongoing policies, programs, and projects are often abandoned – creating a knowledge and continuity gap that may prove difficult to fill when these programs and projects are re-launched.

Economic and Financial Barriers: While the most popular NDVI datasets for regional, national and global applications from major archives are free, effective access, processing and use require some investment. The level of investments required depend on the scale of operations envisaged. While many governments in poor countries may lack the financial resources to put in place the full range of investments required for optimal access and use of existing NDVI databases, the costs of key investments in the sector are diminishing. This is especially true of hardware, some software, and internet service costs. Investment in a professional and technical cadre is a bigger, longer-term issue but home-grown expertise is essential if there is to be national ownership of the issue and the results of any assessment.

11 Recommendations for future application of NDVI

11.1 In the Convention National Reporting

As discussed in the Introduction, both the UNCCD and the GEF use land cover to monitor land degradation. The UNCCD progress indicators (formerly known as impact indicators) should show progress made in achieving long-term benefits for people living in areas affected by desertification, land degradation and drought, for affected ecosystems, and for the global environment. At its eleventh session the COP adopted a refined set of six progress indicators (decision 22/COP.11, see Annex 6) which will be used for the first time during the second leg of the fifth reporting process in 2016. Recommendations were made to the latest Conference of the Parties of the UNCCD (ICCD/COP(11)/CST/2) for refinements to the provisionally adopted set of impact indicators (Annex 6).

The findings of this report have implications for all three Strategic Objectives (SOs) of the UNCCD: SO-*1to improve the living conditions of affected populations*; SO-2 *to improve the conditions of affected ecosystems*; and SO-3 *to generate global benefits through effective implementation of the UNCCD* (Table 3). Monitoring of drought using NDVI and NDWI could have implications for trends in access to safe drinking water (SO-1). It has been clearly shown that NDVI is a reliable measure of photosynthetic capacity and thus for monitoring trends in land cover and productivity of the land (SO2). NDVI can also support reporting on global benefits related to trends in carbon stocks and biodiversity (SO3), as shown in other sections of this report (also see the use of remote sensing derived land productive capacity dynamics for the new World Atlas of Desertification – Annex 2). In addition, reporting on these indicators should ideally be harmonized with reporting to the UNFCCC on carbon stocks and to the CBD on biodiversity indicators.

Table 3 UNCCD core indicators for national reporting.

Indicator	Potential use of NDVI
Strategic objective 1: To improve the living conditions of affected populations	
SO1-1: Trends in population living below the relative poverty line and/or	*Not applicable*

income inequality in affected areas	
SO1-2: Trends in access to safe drinking water in affected areas	NDVI could be combined with the Normalized Difference Water Index (NDWI) to monitor drought, and be linked to water use of land-use systems (see Section 3.2 and Annex 1).
Strategic objective 2: To improve the condition of affected ecosystems	
SO2-1: Trends in land cover	NDVI is the best tested vegetation index with the longest time series for monitoring of land cover trends (33 years), which compensates for the low resolution (Section 8). However, care needs to be exercised in interpretation of the results and the drivers of change (Annex 2).
SO2-2: Trends in land productivity or functioning of the land	The relationship between NDVI and biomass productivity has been well established in the literature, and NDVI can be used to estimate land productivity and monitor such productivity over time (Annex 2)
Strategic objective 3: To generate global benefits through effective implementation of the UNCCD	
SO3-1: Trends in carbon stocks above and below ground	NDVI can be used together with higher resolution data to estimate trends in carbon stocks for e.g. REDD and SOC assessments (see Section 3.7 and Annex 1).
SO3-2: Trends in abundance and distribution of selected species	NDVI can be used to monitor habitat fragmentation and connectivity which are crucial in affecting the abundance and distribution of species (see Section 3.1 and Annex 1).

11.2 In a Revised GEF Resource Allocation Methodology

Land cover is used as an indicator for all three GEF focal areas affected by the System for Transparent Allocation of Resources (STAR) that calculates country-specific allocations from each focal area[1]:

Land Degradation - the latest Global Benefit Index (GBI) for the Land Degradation (LD) Focal Area was designed to take into account three key factors in accordance with GEF mandate for financing: 1) the need for controlling and preventing land degradation in the context of land-based production systems; 2) the challenge of combating desertification in the drylands, including the need for adaptation to drought risks; and 3) the need to address livelihoods of vulnerable populations. Proxy indicators were derived for each of these factors based on available data.

With regard to factor 1), a quantitative estimate of land area (in km^2 or as per cent of territory) affected by LD was used as a proxy indicator for "*loss of ecosystem function and productivity*". The indicator was derived by Bai *et al.* (2008) using NDVI. Each country's share of the global total area affected was calculated for use in the GBI. The three indices were assigned weights as follows: 60 percent to dryland area, 20 percent to rural population, and 20 percent to land area affected. The resulting algorithm is as follows:

GBILD = (0.2*global share of land area affected) + (0.6*proportion of dryland area) + (0.2*proportion of rural population)

Climate Change – for its land-use, land-use change and forestry (LULUCF) component it uses forest cover in hectares and absolute change in forest cover, as reported by countries to FAO. NDVI could potentially be used to strengthen this index as NDVI is strongly correlated with vegetation dynamics in humid areas.

[1] GEF/POLICY: PL/RA/01, March 14 2013: System for Transparent Allocation of Resources (STAR).

Biodiversity – this index uses distribution of terrestrial eco-regions, including threatened eco-regions as monitored by WWF. Also here, the use of NDVI could improve data quality if it is used consistently.

Trends in NDVI could thus become an important part of a land cover indicator that cuts across three GEF focal areas and is used as a proxy for productivity, carbon stocks and biodiversity. With regard to the Land Degradation focal area, a revised GEF STAR should be based on all the six core indicators identified for the UNCCD Strategic Objectives (see Table 3 and Annex 6). However, with a more robust application of NDVI based on recent advances, this index might be given a greater weight in a revised STAR, as it can contribute to monitoring of five of the UNCCD indicators if applied consistently and using the most reliable datasets.

12 Conclusion

This report examines the scientific basis for the use of remotely sensed data, particularly NDVI, in land degradation assessments at different scales and for a range of applications. It draws on evidence from a wide range of investigations, primarily from the scientific peer-reviewed literature but also non-journal sources.

Research in land degradation based on satellite remote sensing currently makes use of a wide variety of datasets of different geographical scales, spatial, spectral and temporal resolutions. The availability of free data of continuous land surface observations from medium to coarse spatial resolution satellite sensors continues to support a range of ecosystem models and environmental applications. At the global level however, a few of these datasets stand out. In the context of NDVI-based potential for land degradation assessment, the AVHRR-derived GIMMS dataset is the most widely used product. In the short to medium term, the quality control required to make this dataset a transparent source for a range of environmental applications is guaranteed. In the same light, continuous updates to the archive to extend it well beyond 33 years will enhance the potential for this data to be used to identify longer term trends and trend components in terrestrial ecosystem studies.

The GLADA approach, which was based on an earlier version of GIMMS, has been widely adopted. Several studies have used the same and later versions of the GIMMS dataset, with or without the GLADA approach, to investigate an array of environmental issues. Many caveats raised initially, some of which were flagged by GLADA itself, have been dealt with. As new methods are developed in data analysis and computers become more efficient in processing information, more questions that draw on the relationship between NDVI, RUE, EUE and NPP may be explored. These questions could address ever-growing (and in some cases emergent) concerns on issues such as the resilience of ecosystems, the coupling of socio-ecological systems, as well as new horizons in environmental assessment and management. The GLADA approach and NDVI data archives offer the potential for assessment of the performance of different policy options and can inform the implementation of the UNCCD and the allocation of resources from its financial mechanism, the GEF.

As a tool, NDVI and related indices as well as the GLADA approach still continue to have limitations. Beyond some of the technical weaknesses associated with implementation and interpretation, there are barriers to their effective use for national assessments. We note that, over recent years, hardware components as well as some software to support the use of NDVI in national assessments have become more accessible. Notwithstanding the fall in costs of hardware and software, there is need for national services to be staffed by personnel with the appropriate technical expertise. This is necessary for many reasons, including the ability to ask the right questions and use the appropriate tools and depth of analysis in answering them, and the ability to produce end-products that meet international standards for cross-country comparisons.

NDVI continues to be valid for measuring and reporting on some of the key strategic objectives of the UNCCD and has the appropriate qualities for use as an indicator for a number of indices.

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Annex 1 - Inventory of some global and sub-global remote sensing based land degradation assessments

Scale	Land degradation domain	Time range	Data	Main findings
Senegal	Land cover change & human well-being	1982-2008	GIMMS	Interpreting satellite-derived greening as an improvement of environmental conditions that may translate into more stable livelihoods and greater well-being of populations in the area may not always be justified (Herrmann et al. 2014).
Mali	Ecosystem resilience in relation to ANPP, RUE, & ANPP	1984-2010	GIMMS-3g	There is a divergence of two key indicators of ecosystem resilience: a stable RUE and increasing run-off coefficient – condition termed "the second Sahelian paradox" (Dardel et al. 2014)
Amazon	Land cover change & global environmental implications	2000-2012	MODIS	The Amazon forest has declined across an area of 5.4 million km2 since 2000 as a result of reductions in rainfall. If drying continues in this region, global climate change may be accelerated through associated feedbacks in carbon and hydrological cycles (Hilker et al. 2014).
Italy	Land use & land cover change	1984-2010	Landsat TM	Total regional forest cover increased by 19.7%, consistent with National Forest Inventory data. Considerable forest expansion also occurred on degraded soils in drought-prone Mediterranean areas (Mancino et al. 2014).
Senegal	Land use land cover change & environmental conditions	1982-2008	AVHRR	The interpretation of satellite-derived greening trend as an improvement or recovery is not always justified. This can be the case in terms of the composition of the vegetation cover, which may show impoverishment even in the greening areas (Herrmann and Tappan 2013).
China	Soil organic carbon & salinization	2011	Landsat TM	Significant decrease in soil organic C and total N contents were observed with increasing salinity. Soil organic C and total N contents had significant positive correlations with the NDVI (Pan et al. 2013).
World	Trends & drivers of greenness in semi-arid areas	1981-2007	GIMMS-g	Current generalizations claiming that land degradation is ongoing in semi-arid areas worldwide are not supported by the satellite based analysis of vegetation greenness (Fensholt et al. 2012).
West Africa	Soil erosion, & land productivity	1982–2003	GIMMS	Multi-pronged assessment strategies offers better insights into different processes involved in land degradation (Le et al. 2012).
World	Vegetation greening & browning trends	1981–2006	GIMMS	Models confirm prominent regional greening trends identified by previous studies (de Jong et al. 2011).
South Africa	Biodiversity monitoring & conservation	1995-2006	GIMMS	Change in productivity driven by rainfall as well as that caused by elephant populations have ramifications for biodiversity and also impacts on biodiversity (Hayward and Zawadzka 2010).
USA	Biodiversity monitoring & conservation	2005	MODIS	There is a significant positive correlation between species compositional dissimilarity matrices and NDVI distance matrices. Remotely sensed NDVI can be a viable tool for monitoring species compositional changes at regional scales (He et al. 2009).
China	Desertification & land surface conditions	1980, 1990, & 2000	Landsat MSS & TM/ETM+	Human activities might explain the expansion of desertification from 1980-1990. Conservation activities were the main driving factor that induced the reversion of desertification from 1990 to 2000 (Xu et al. 2009).
Zimbabwe	Land use, land cover change &	2000-2005	MODIS	About 16% of the country was at its potential production. Total loss in productivity due to land degradation stood at

	degradation			about 13% of the entire national potential. Most of the degradation was caused by human land use, concentrated in the heavily-utilized, communal areas (Prince et al. 2009).
Sahel	Desertification & drought – changing trends	1982-1999	PAL	A consistent trend of increasing vegetation greenness that may be attributed to increasing rainfall; but also factors, such as land use change and migration (Olsson et al. 2005).
Sahel	Drought & vegetation dynamics	1981-2003	AVHRR	The current trends of recovery in the Sahel are still far below the wetter conditions that prevailed in the region from 1930 to 1965. Current trend patterns therefore only reflect a gradual recovery from extreme drought conditions that peaked during the 1983–1985 period (Anyamba and Tucker 2005).
South Africa	Ecosystem resilience & stability of landscapes	1985-2003	AVHRR	While degraded areas were no less stable or resilient than non-degraded area, the productivity of degraded areas, per unit rainfall, was consistently lower than non-degraded areas. Degradation impacts tend to be reflected as reductions in productivity that varies along a scale from slight to severe (Wessels et al. 2004).
Global	Vegetation growth & NPP	1982-1999	PAL / GIMMS	Global changes in climate have reduced several critical climatic constraints to plant growth, leading to a 6% increase in global NPP (Nemani et al. 2003).
China	Vegetation dynamics & variations in NPP	1981-2000	AVHRR	Increase in NPP of about 0.32% per year and decrease in net ecosystem productivity between the 1980s and 1990s due to global warming (Cao et al. 2003).
Spain	Vegetation burning & recovery	1994	Landsat TM & MSS	There are different patterns of post-fire recovery based on dominant plant species, severity of burn, and a combination of both factors (Díaz-Delgado et al. 2003).

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Annex 2 - Use of remote sensing derived land productive capacity dynamics for the new World Atlas of desertification (WAD)

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1 Background and rationale

The European Commission‘s Joint Research Centre of the (JRC), together with UNEP and supported by a global network of international research institutions and experts, are developing the new World Atlas of Desertification (WAD)
Monitoring and assessing land degradation dynamics involves increasingly most relevant information extracted from time series of satellite observations globally. The dynamics of the earth’s standing vegetation biomass is considered a valid approximation of overall land system productive capacity dynamics and thus also reflecting the underlying ecologic conditions and possible constraints for primary productivity, such as soil fertility, water availability, land use/management etc., and hence related to land degradation. In fact, reduction or loss of land productive capacity, mostly biological and/or economical is one common denominator in the various definitions that are used for land degradation.

The currently longest available satellite observation datasets with global coverage at 1km resolution, from e.g the SPOT VGT sensor, have a continuous frequent temporal sampling over a long enough period, 15 years now, that makes it possible to extract proxy information on the phenology and seasonal productivity for each 1km^2 area on earth to compile a global land productivity dynamics layer. Even longer continuous time series with more than 30 years continuity are available through the GIMMS NDVI product dating back as far as to 1981, however with the limitation of the spatial resolution to 8x8 km pixels. This resolution may be well suitable for the analysis of broader land-atmosphere interaction but may imply stronger limitations for monitoring and assessing the human-ecosystem interactions primarily through land use at landscape level. These operate and function typically at smaller land units as can be typically depicted at the spatial resolution of GIMMS. Nevertheless, the length of this NDVI time series raises interest to consider also ways to combine it with higher resolution products for enhanced analysis.

2 Methodology for time series processing and analyses

Building on numerous studies that use time series of remotely sensed vegetation indices (e.g. NDVI, Fapar) as base layer, we expand this set of variables by calculating phenological metrics from time series of the vegetation index. De-convolution of the original time series into phenological metrics yields additional information on various aspects of vegetation/land cover functional composition in relation to dynamics of ecosystem functioning and land use (Ivits et al., 2012a). This can provide a quantitative basis to monitor such information on ecosystem dynamic equilibrium and change, envisaged to provide users with an independent measure on how ecosystems respond to external impacts, be it human induced or natural variability (Ivits et al., 2012b).

The resulting remote sensing derived spatial layers are then combined with ancillary bio-physical and socio-economic information in order to flag areas that actually show signals of

actual land degradation. This includes attributions to different levels of intensity and probability of major causes, which will include major land degradation/desertification issues and the associated land use transitions considered in the WAD. They are summarized below (Sommer et. al., 2011):

1. Overuse of agricultural land, intensification, inappropriate agricultural practices/non-SLM, increased soil erosion
2. Increase in intensive irrigation, overuse of water resources, salinization
3. Grazing mismanagement, overgrazing and decreasing NPP in rangelands, soil degradation, sand encroachment
4. Deforestation
5. Increased aridity or drought
6. Socio-economic issues, changes in population distribution and density, rural migration/land abandonment, urban sprawl
7. Uncontrolled expansion of mineral mining and industrial activities, extensive air and water pollution by waste materials, soil loss by contamination

Analysis of long-term changes and current efficiency levels of vegetative or standing biomass are combined into land-productivity dynamics according to figure 1 below. According to this scheme the evaluation proceeds as follows:
Analysis of long-term changes and current efficiency levels of vegetative standing biomass are combined into land productive capacity dynamics. Output from both the Long-Term Change Map was combined with start levels at begin of the time series, the state change of productivity and with a relative productivity map based on the principles of Local Net Scaling approach (Prince et al., 2009), relating all pixels within an Ecosystem Functional Unit (Ivits et. al., 2012a) to the productivity of the best performing samples of that respective unit.

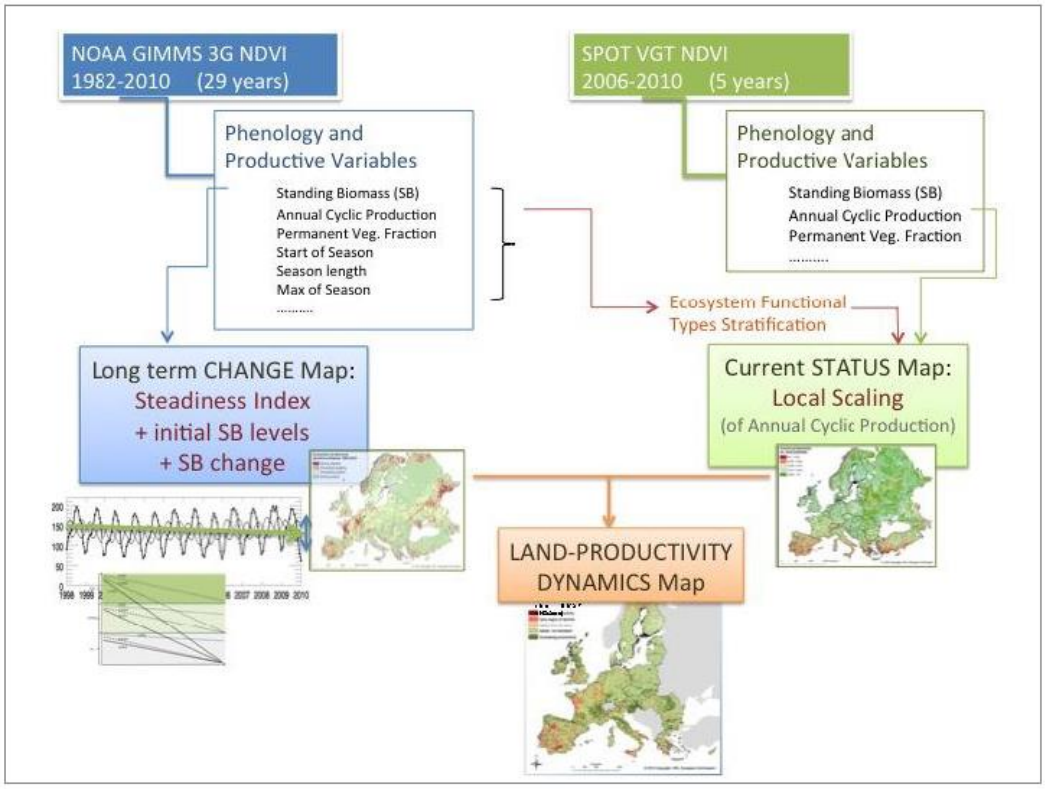

Figure 1: General scheme for the calculation of the land-productivity dynamics

Figure 1: Processing scheme for deriving land productive capacity dynamics from the remote sensing time series (note that the approach was applied both to NOAA GIMMS 3G NDVI (Cherlet et al., 2013) as indicated above and also to 15 years SPOT VEGETATION NDVI 1999 to 2013)

This processing chain has been applied at global levels and results in 5 classes indicating areas of negative, positive change or stability of land productive capacity dynamics (see figure 2 below). The classes are interpreted as indicator of change or stability of the land's apparent capacity to sustain its dynamic equilibrium of primary productivity during the given observation period., which is now further analysed in relation to available information on land cover/use and environmental change relevant to the issues listed in table 1 above.

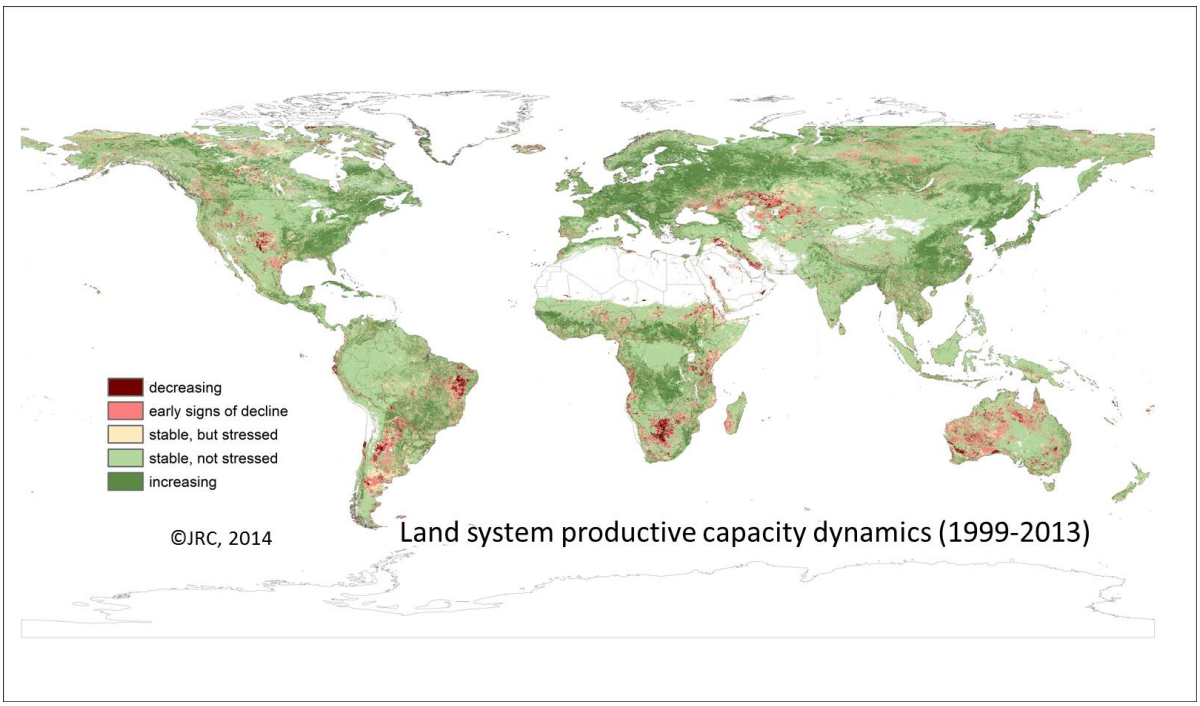

Figure 2: Global map of land system productive capacity dynamics derived from SPOT VEGETATION 15 year time series (1999-2013)

3 Preliminary findings and conclusions

This product should not be seen as a direct map of global land degradation, but as a globally mapped indicator which should be further evaluated in an integrated interpretation framework as proposed by the WAD or possibly also as outlined by the UNCCD ad hoc expert group (AGTE) for the new set of progress indicators.

Therefore, the land system productive capacity data are now further analyzed and evaluated in relation to available information on land cover/use and environmental change relevant to the issues listed in table 1 above.

An example such as potential agricultural overexploitation of land is given below for Nigeria in figure 3. Convergence of evidence is elaborated for interpreting the land productive capacity in the light of identifying and mapping on-going critical land use system transformations. Areas where the dynamics are decreasing are mostly areas where a number of land stress factors are coinciding that potentially are threats to a sustained use of the land and are highlights for further analysis. Stress factors can be natural e.g. drought, or human induced such as over extraction of soil nutrients by demanding crops depending on irrigation as shown below.

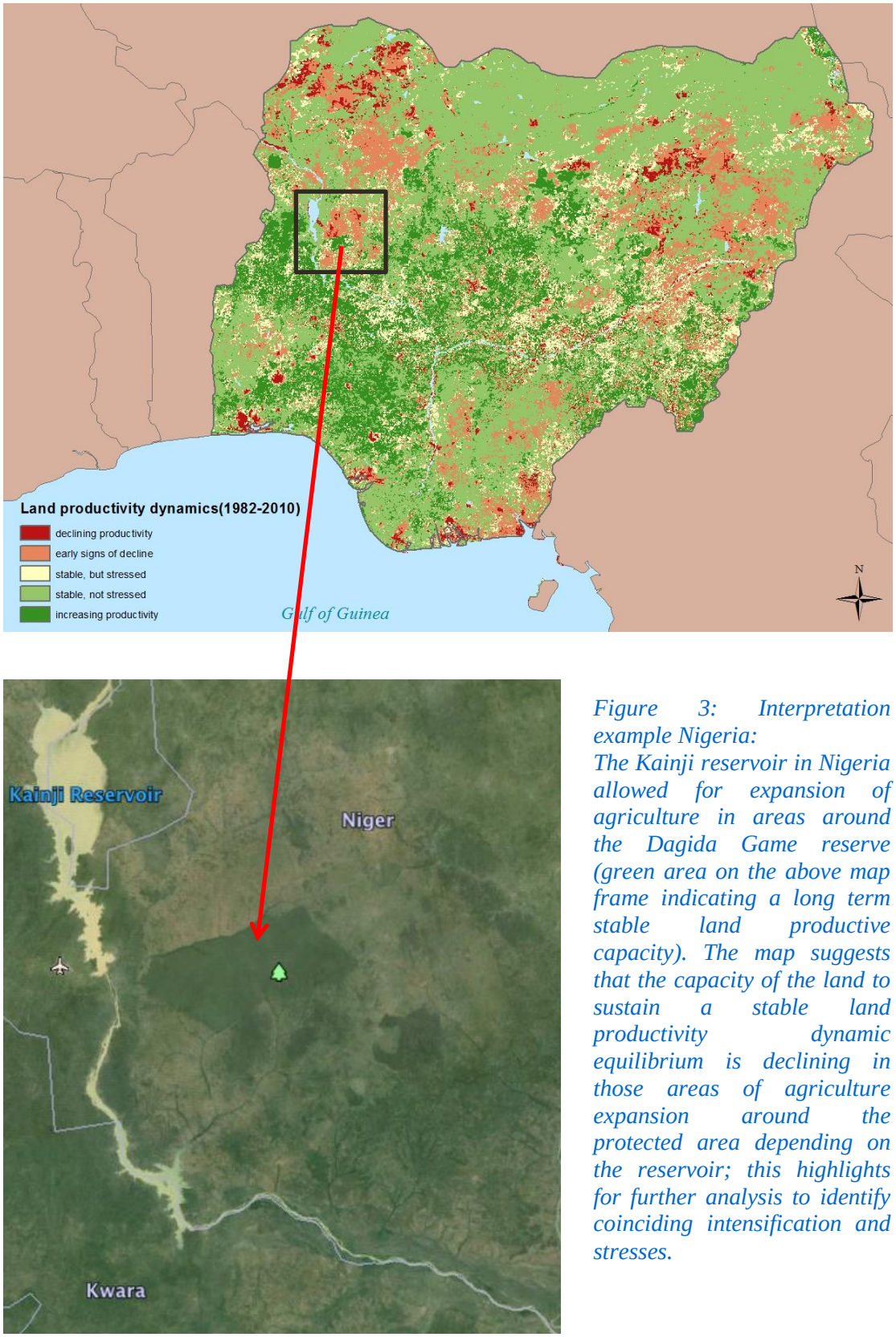

Figure 3: Interpretation example Nigeria:
The Kainji reservoir in Nigeria allowed for expansion of agriculture in areas around the Dagida Game reserve (green area on the above map frame indicating a long term stable land productive capacity). The map suggests that the capacity of the land to sustain a stable land productivity dynamic equilibrium is declining in those areas of agriculture expansion around the protected area depending on the reservoir; this highlights for further analysis to identify coinciding intensification and stresses.

A broader statistical analysis and evaluation is also underway but needs to be carefully framed and integrated with the data and information provided within the thematic WAD chapters.
Nevertheless some general observations of observed trends and patterns, here from the 15 year time series, appear coherent with other studies.
While excluding land areas with no significant vegetal primary productivity, i.e. hyper-arid, arctic and very-high altitude mountain regions from statistics, it is evident that indications of decreasing land system productive capacity can be observed globally. About 20% of the land surface, involving all vegetation cover types, are showing signs of decreasing land system productive capacity. Only 19.52% of the considered vegetal productive land surface is cropland, of which 18.55% show clearly decreasing trends or early signs, while for the rest of non-cropland 19.88% are affected, which however accounts for 80% of the overall area with declining land system productive capacity. Considering that strong efforts and resources are committed to maintain agricultural land productive and the fact that there are clear limitations to further expansion of croplands these figures are an issue of concern. The huge semi-natural and rangeland areas affected (approx. 18 million sqkm), however, highlight the enormous dimension of the critical dynamically changing ecological conditions worldwide.
The picture gets way more differentiated when breaking down the statistics to continental, regional and sub-regional levels. As mentioned before, when entering into this necessary exercise the increased use of additional thematic information for setting-up a more stratified analytical approach is strongly recommended, though way more time consuming and cumbersome.
Nevertheless, when just looking at croplands at continental level we notice substantial differences in the dimension/extension of potentially critical areas, which will require careful consideration and definitely more in-depth analysis.
In Africa about 20.6% of the considered land surface is cropped of which 21.7% show signs of decreasing land productive capacity. The relative proportion of concerned cropland is similar than the one of semi-natural/rangelands areas. This is above global average but not extremely. In turn surprisingly South America with about 21.4% cropland shows a much higher percentage of potentially affected croplands, up to 31.9%, also proportionally clearly higher than for semi-natural/rangelands areas (25.84%).
Europe is the continent with the relatively highest extension of croplands, i.e. about 32%, of which 15.75% may be confronted with critical developments of land productive capacity, especially in the south of Eastern Europe but also the Iberian Peninsula, which is proportionally higher than for other land cover/land use types (10.3%).

While human factors will need to be further analysed rather in a stratified at regional to sub-regional level, first analyses at global level dealt with the correlation of some spots of decreasing productive capacity in the shorter time series product (i.e. 15 years 1999 to 2013) against actual global drought monitoring data. These revealed strong correlations of areas in southern Africa (between Botswana, Namibia and South-Africa), North-eastern Brazil and Australia-Oceania with recent events of recurrent droughts. In this respect it will be also a clear issue in the WAD to analyse more in depths possible differences of dynamics between drylands and non-drylands.

Issues of uncertainty of remote sensing time series derived products as function of length of the time series, spatial and spectral characteristics will also need to be better addressed. It could be recommended that scientific groups developing monitoring products should join forces for example by addressing these issues in a kind of ensemble analysis aiming at ways to take benefit from combinations of longer time series and higher spatial detail, thus stimulating additional options and criteria for generating new elements of convergence of evidence.

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Annex 3 - Developments with GLADA

1 A different view of the world

The picture is different again when the same analysis is applied to the extended GIMMS3g dataset for 1981-2011(Figure 1); the differences are not just because of the longer run of data but because of changes in GIMMS data-processing to correct better for the periodic replacement of AVHRR sensors (especially AVHRR 2 to AVHRR 3) (Pinzon and Tucker 2014). The original procedure for matching the data from successive AVHRR instruments (as one satellite replaced another) introduced biases because it assumed stationarity, i.e. it was assumed that there was no underlying trend. We now know that there are complex long-term trends in the data. Re-processing of the whole dataset has removed the biases and better reveals the underlying trends. Changes like this in the fundamental data do nothing for their credibility but we are confident that the fundamental data are now much improved.

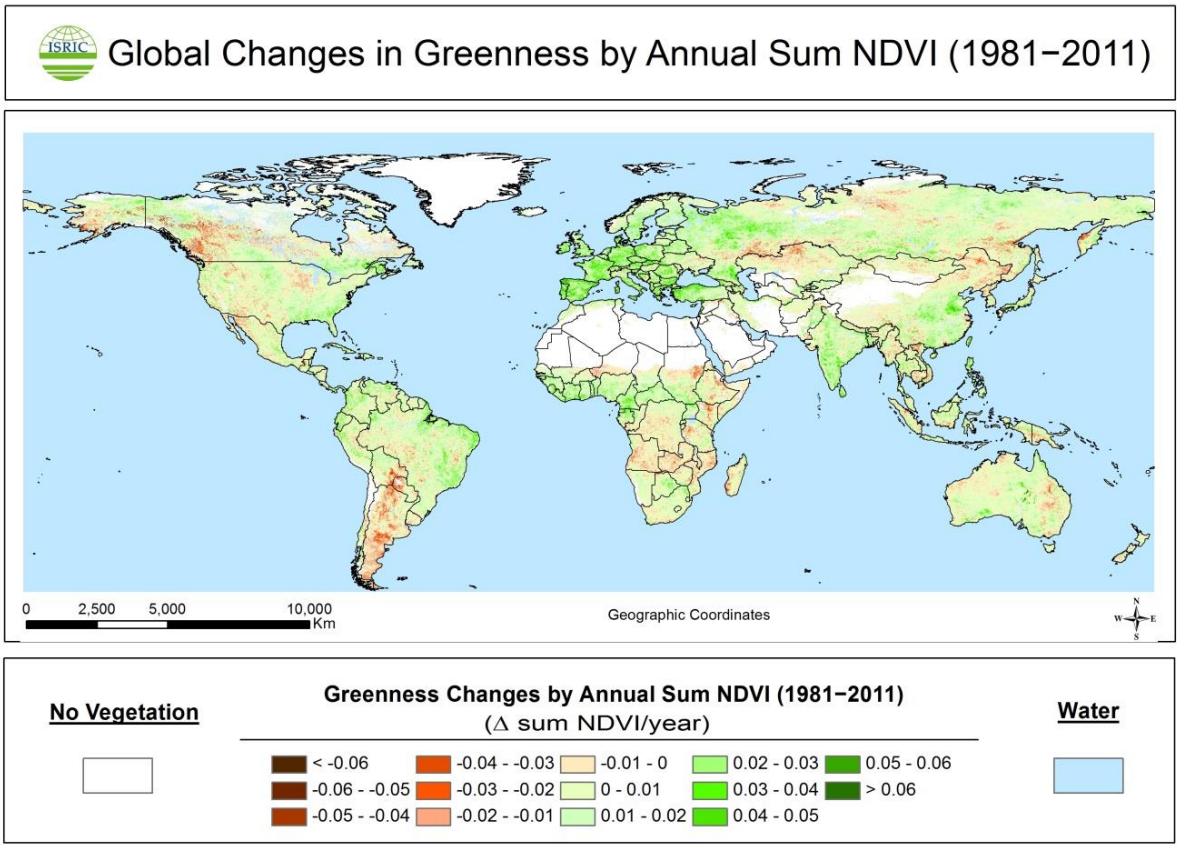

Figure 1 Global change in NDVI, 1981-2011

The GLADA methodology applied to the new dataset provides unequivocal answers to our original policy questions:

- *Land degradation is a global issue* with 22% of the land degrading over the last thirty years, representing a loss of net primary production of some 150 million tons of carbon but a loss of soil organic carbon orders of magnitude more.
- *The areas hardest hit* are Africa, especially south of the Equator with an arm of degradation extending north to the Ethiopian highlands and two outliers in the Sahel - the Nile provinces of Sudan and Koulikoro Province, Mali; the Gran Chaco, Pampas and Patagonia;

southeast Asia; the grain belt from the Ukraine eastwards through Russia to Kazakhstan; the Russian far east and northeast China; and swaths of high-latitude forest.

- *All kinds of land use are afflicted.* Cropland comprises 13% of the global land area but makes up 15% of the total degrading land; rangeland makes up 29% of the land but 42% of degraded land; forest is also over-represented, occupying 23% of the land area but 37% of the degrading area.
- *Comparison of rural population density with land degradation shows no simple pattern*; taking infant mortality and the percentage of young children who are underweight as proxies for poverty, there is some correlation but we need a more rigorous analysis.
- *Fourteen per cent of the land surface has been improving over the period.*

2 Changing trends

The longer time series now reveals significant changes in trend over the last thirty years. Linear trend analysis is a blunt instrument but, working with the GIMMS 2g (1981-2007) dataset, de Jong *et al.* (2011) used the Breaks for Additive Seasonal and Trend (BFAST) algorithm to analyze changes of trend. They found that most parts of the world have experiences periodic changes of trend, even reversals (de Jong et al. 2011). This is important for interpretation of longer term trends where diverging trends may balance out, for instance in China where a significant break in trend was identified around 1996. Figure 2 illustrates persistent and expanding degradation in Tibet and the southwestern provinces; a dramatic increase in degradation across the northeast; and a loss of impetus in many intensively farmed areas in spite of the increasing application of synthetic fertilizer from 7 million tons in 1977 to more than 58 million tons in 2012 (National Bureau of Statistics 2013). Over the period 1981-1996, 1.8% of the country suffered degradation but 17.5% was improving (80.7% showed no significant change or was barren): between 1996 and 2011, 12.6% of the land was degrading and only 10% showed improvement (77.4% no change or barren).

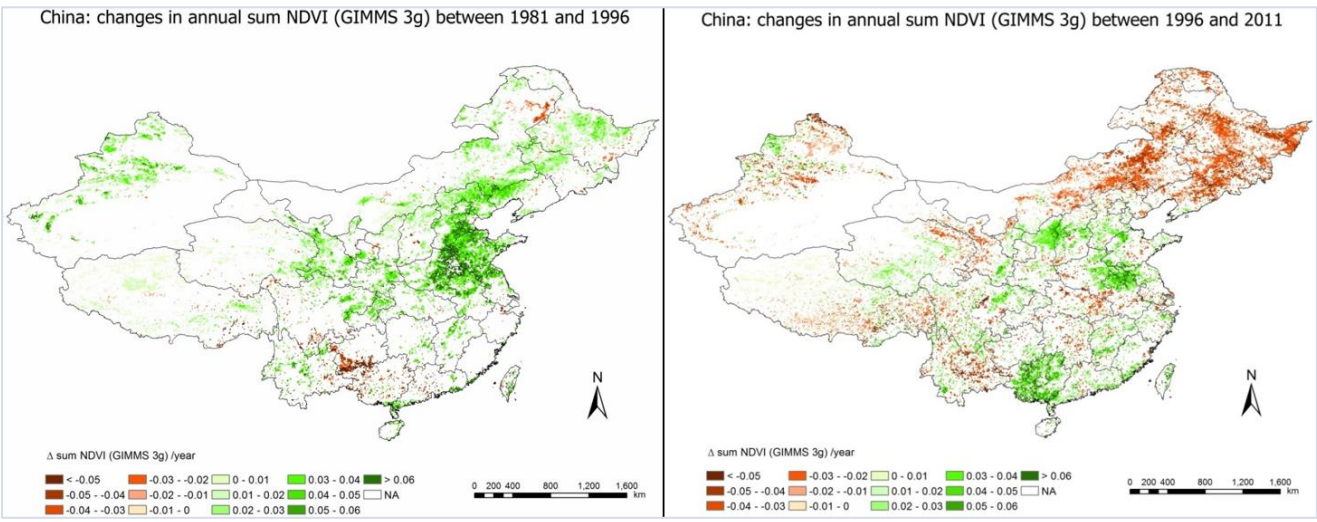

Figure 2 China: changes in annual sum NDVI 1981-96 (a) and 1996-2011 (b)

In more detail, trend analysis for the southern provinces of Guangdong, Guangxi, Hunan, Jiangxi and Fujian, which exhibit a general improvement over the last thirty years, shows cyclically declining NDVI at the beginning of the time series but a reversal of the trends after about 1995 (Figure 3) which may be attributed to the take-up of the Grain-for-Green initiative (Cao et al. 2009, Bai and Dent 2014).

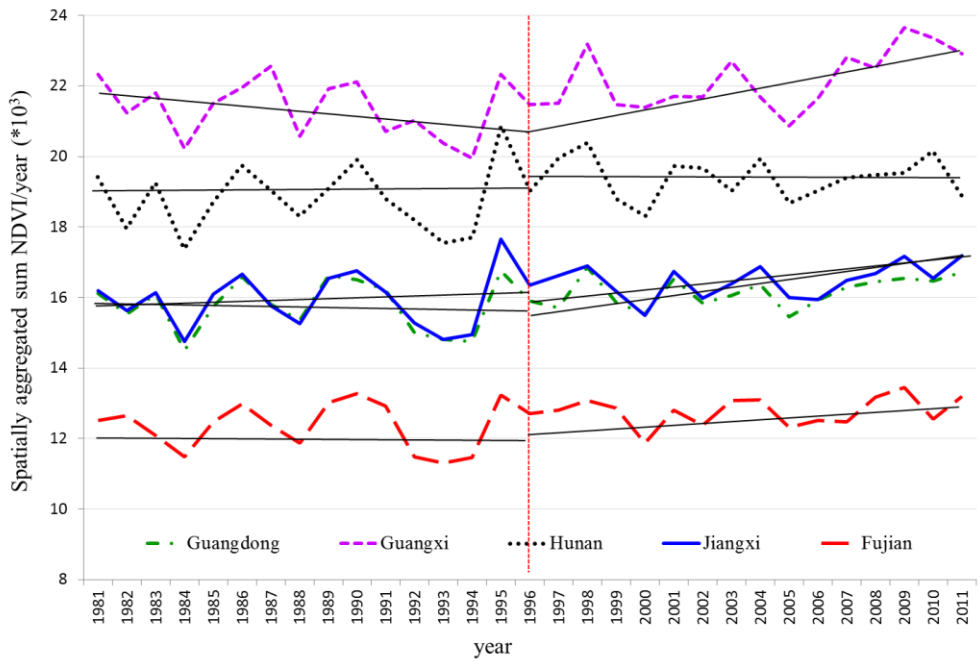

Figure 3 China: NDVI trends in five southern provinces 1981-2011

Chinese researchers have also made use of the GIMMS NDVI database and the GLADA methodology for a number of countrywide studies. In the process, some new indices have been developed, such as the Sensitivity Index - the degree of reaction of NDVI to rainfall change in specific rainfall regions were developed (see Appendix 4).

3 Making allowance for terrain, soil and land use

We might expect resilience against land degradation to depend on terrain, the kind of soils, land use and management. Bai and Dent. (2014) used the SRTM digital elevation model and ChinaSOTER at scale 1:1 million to assess the effects of soils and terrain on land degradation and improvement. Figure 4 depicts the relative departure of each pixel from the trend of its SOTER unit, separating the impact of soil and terrain from other factors and giving a picture of land degradation and improvement at the landscape scale - where most land use and management decisions are taken.

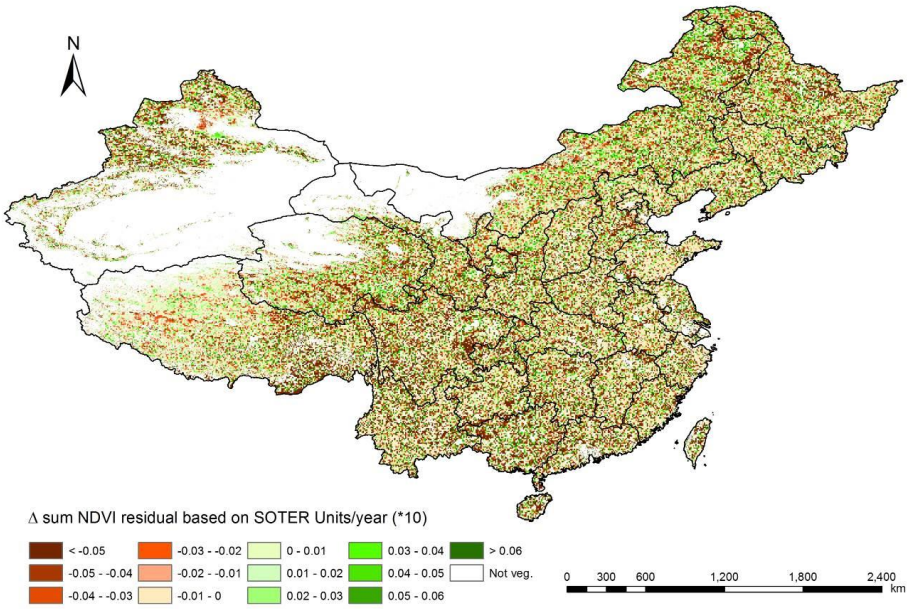

Figure 4 Trends of NDVI residuals from SOTER units, 1981–2011

This analysis examines land degradation and improvement at the landscape scale, where most land use decisions are actually taken, and shows which parts of the landscape are doing better and which are doing worse than the landscape as a whole – so it is a pointer to specific places where remedial action may be needed. Use with finer resolution data such as MODIS NDVI would be useful for national-level reporting and for assessment of policy and project impacts on the ground.

Analysis of land degradation in terms of land use and management is more problematic because no two consecutive land use surveys have used the same classification.

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Annex 4 - China's experiences on the usefulness of GLADA

Zhang Kebin[1]

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1. Introduction

Based on the practice and experience of the LADA program, the proposed standard method for global assessment of drylands using the GLADA methodology is a good decision and choice. The bedrock of the GLADA approach is the use of NDVI as the basic indicator, enabling consistency and comparability. Assessment methods for land degradation assessment at the national level (LADA - national) have adopted a layered approach whereby a comprehensive analysis incorporating social information can be conducted on various environments so as to broaden the perspective of people when observing land degradation.

Rightly embracing the fundamentals of GLADA and the LADA-national approach, GLADIS leads to the improvement and enhancement of GLADA and, from this point of view, GLADIS is applicable to and ready for the assessment on global land degradation in the following step. The Chinese team believes that, GLADIS can be used as a basic method for such assessment at not only the global level but, also, at the national level for countries with a large land area, including China. Of course, at the national level, the remote sensing data should be at an appropriate resolution.

Certainly, the methodology needs constant improvement so as to make the assessment more realistic. For example, according to the GLADA assessment, since the early 1980s subsequent years have witnessed land degradation in both in arid areas and, also, increasing appearance of hot spots of degradation in more humid areas. This is the case in China but we cannot tell whether it is a coincidence or the result of methodological problems.

NDVI is affected by various factors such as climate (rainfall), soil, kind of tillage and so on. Fluctuations in climate (especially those of rainfall) often lead to fluctuations in NDVI. Especially in arid areas, a high sensitivity of vegetation to rainfall always results in fluctuations of NDVI according to those of rainfall. In this case, NDVI changes do not mean that the quality or long-lasting production potential of land has changed accordingly; that is to say, the land quality exhibits no degradation or improvement. So, if we rely solely on the change of NDVI as an indicator of land degradation, such judgment possibly may draw out wrong assessment conclusions. So to eliminate the interference of rainfall fluctuations, GLADA employs the concept of RUE.

When testing the GLADA assessment against China's actual situation and an analysis of the impact of rainfall on NDVI, it is found that the actual situation is complicated; rainfall has a great impact on NDVI but this impact is not homogeneous - it reduces gradually as rainfall increases. In fact, with rainfall reaching a certain level, the impact of increasing rainfall on NDVI gradually weakens until, in the humid area with abundant rainfall, the impact of fluctuation of rainfall on the change in NDVI becomes very small, even negligible. If RUE is still used as an indicator of land

degradation in these humid areas then we are not certain that it is appropriate. [Editor's comment: There appears to be some misunderstanding here. GLADA uses RUE to mask drought effects only in those areas where there is a direct correlation between NDVI and rainfall - essentially this applies to drylands. In humid areas (and irrigated areas) NDVI is used unmodified as a proxy for biological productivity.]

For this consideration, combining with the actual situation in China, and through an analysis of the relation between NDVI and rainfall, we have tried to determine the quantitative impact of rainfall on NDVI under different rainfall conditions (*i.e.* different regions), so as to use different corrective factors for different area according to actual rainfall when eliminating the impact of rainfall on NDVI, so that it is more scientific to use NDVI as an assessment indicator for land degradation, and also to supplement the GLADA method.

2. Data

GIMMS-8KM-NDVI data: The Chinese team used the GIMMS 2g dataset of NOAA-AVHRR NDVI 15-days synthesized data from July 1981 to September 2006 (a total of 26 years). This study uses the average value of the two fortnightly data points as a monthly value and the annual accumulated NDVI value is the sum of 12 monthly values. Data resolution is 8km.

Rainfall data: The rainfall data come from the China National Meteorological Information Center which stores and shares historical and real-time meteorological data; all data passing a quality test are re-compiled. The rainfall data used in this study include 26 years measured data from 707 meteorological stations in mainland China from 1981 to 2006. The time period of rainfall data matches the time period of NDVI data.

3. The relation between NDVI and rainfall

Figure 1 shows the relationship between annual sum NDVI and annual rainfall observed from 707 meteorological stations in China from 1981 to 2006:

- There is a close relation between NDVI and rainfall
- The relation between NDVI and rainfall is not homogeneous but, nonetheless direct
- In areas with low rainfall, the rainfall has the strongest impact on NDVI and the data are tightly aligned around the best-fitted curve. With increasing rainfall, the impact of rainfall on NDVI falls away and the correlation also gradually weakens.

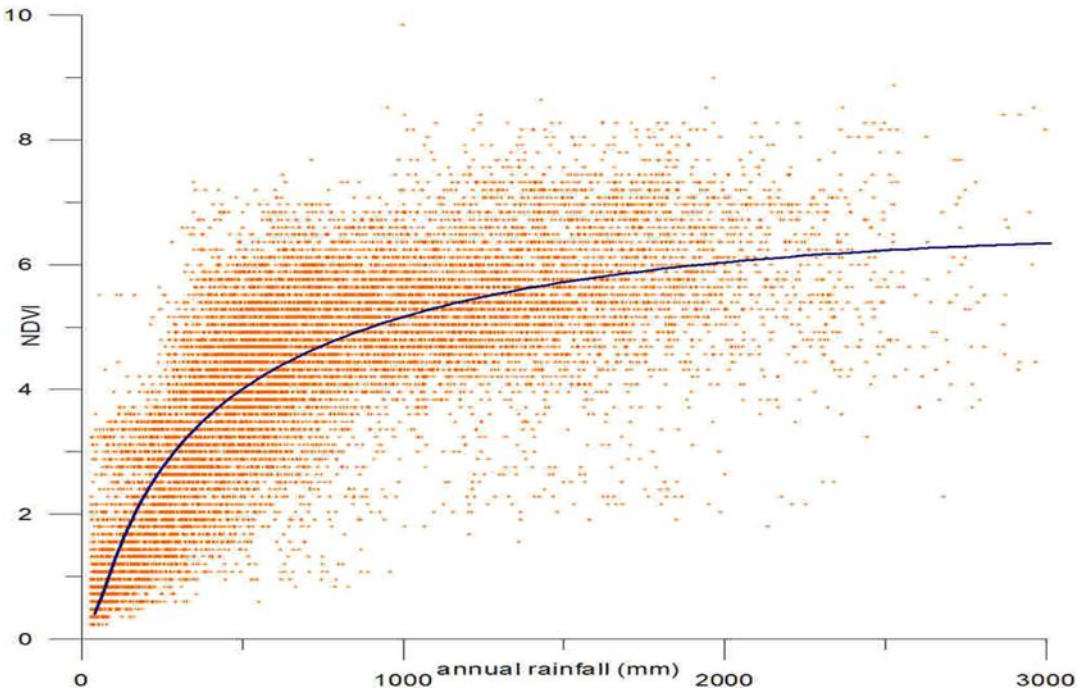

Figure1. Best-fit curve between NDVI accumulated value and annual rainfall

Definition and calculation of the sensitivity index: In order to express this close relation between NDVI and rainfall, we have derived a sensitivity index of NDVI to rainfall (Ns) (in short, Sensitivity Index). The Chinese team also defined the Sensitivity index as the rate of NDVI change with rainfall change by sensitivity index of NDVI to rainfall in the following mathematical expression:

$$N_s = \frac{0.0424 - 0.01313 \times \log_{10} \mathrm{NR_a} - 0.01176 \times \log_{10}^2 \mathrm{NR_a}}{\mathrm{NR_a} \times \ln 10}$$

The sensitivity index quantitatively reveals the rate of change of NDVI with the change of rainfall under any rainfall conditions. More importantly, the sensitive index may be used as the parameter for eliminating the impact of rainfall on NDVI in the assessment of land degradation.

4. Future studies

More studies should be carried out on the relationship of NDVI and rainfall.

Appendix 5 - Main features of image products from the different sensors

***(Source: Xie et al. 2008)*.**

Products (sensors)	Features	Vegetation mapping applications
Landsat TM	Medium to coarse spatial resolution with multispectral data (120 m for thermal infrared band and 30 m for multispectral bands) from Landsat 4 and 5 (1982 to present). Each scene covers an area of 185 × 185 km. Temporal resolution is 16 days.	Regional scale mapping, usually capable of mapping vegetation at community level.
Landsat ETM+ (Landsat 7)	Medium to coarse spatial resolution with multispectral data (15 m for panchromatic band, 60 m for thermal infrared and 30 m for multispectral bands) (1999 to present). Each scene covers an area of 185 km × 185 km. Temporal resolution is 16 days.	Regional scale mapping, usually capable of mapping vegetation at community level or some dominant species can be possibly discriminated.
SPOT	A full range of medium spatial resolutions from 20 m down to 2.5 m, and SPOT VGT with coarse spatial resolution of 1 km. Each scene covers 60 × 60 km for HRV/HRVIR/HRG and 1000 × 1000 km (or 2000 × 2000 km) for VGT. SPOT 1, 2, 3, 4 and 5 were launched in the year of 1986, 1990, 1993, 1998 and 2002, respectively. SPOT 1 and 3 are not providing data now.	Regional scale usually capable of mapping vegetation at community level or species level or global/national/regional scale (from VGT) mapping land cover types (i.e. urban area, classes of vegetation, water area, etc.).
MODIS	Low spatial resolution (250–1000 m) and multispectral data from the Terra Satellite (2000 to present) and Aqua Satellite (2002 to present). Revisit interval is around 1–2 days. Suitable for vegetation mapping at a large scale. The swath is 2330 km (cross track) by 10 km (along track at nadir).	Mapping at global, continental or national scale. Suitable for mapping land cover types (i.e. urban area, classes of vegetation, water area, etc.).
AVHRR	1-km GSD with multispectral data from the NOAA satellite series (1980 to present). The approximate scene size is 2400 × 6400 km	Global, continental or national scale mapping. Suitable for mapping land cover types (i.e. urban area, classes of vegetation, water area, etc.).
IKONOS	It collects high-resolution imagery at 1 m (panchromatic) and 4 m (multispectral bands, including red, green, blue and near infrared) resolution. The revisit rate is 3–5 days (off-nadir). The single scene is 11 × 11 km.	Local to regional scale vegetation mapping at species or community level or can be used to validate other classification result.
QuickBird	High resolution (2.4–0.6 m) and panchromatic and multispectral imagery from a constellation of spacecraft. Single scene area is 16.5 × 16.5 km. Revisit frequency is around 1–3.5 days depending on latitude.	Local to regional scale vegetation mapping at species or community level or used to validate vegetation cover extracted from other images.
ASTER	Medium spatial resolution (15–90 m) image with 14 spectral bands from the Terra Satellite (2000 to present). Visible to near-infrared bands have a spatial resolution of 15 m, 30 m for short wave infrared bands and 90 m for thermal infrared bands.	Regional to national scale vegetation mapping at species or community level.

AVIRIS	Airborne sensor collecting images with 224 spectral bands from visible, near infrared to short wave infrared. Depending on the satellite platforms and latitude of data collected, the spatial resolution ranges from meters to dozens of meters and the swath ranges from several kilometers to dozens of kilometers.	At local to regional scale usually capable of mapping vegetation at community level or species level. As images are carried out as one-time operations, data are not readily available as it is obtained on an 'as needs' basis.
Hyperion	It collects hyperspectral image with 220 bands ranging from visible to short wave infrared. The spatial resolution is 30 m. Data available since 2003.	At regional scale capable of mapping vegetation at community level or species level.

Annex 6 - UNCCD core indicators for national reporting: ICCD/COP(11)/CST/2

Proposed refinements to the provisionally adopted set of impact indicators			
Indicator	*Metrics/Proxies*	*Description*	*Potential data source/Reference methodology*
Strategic objective 1: To improve the living conditions of affected populations			
Trends in population living below the relative poverty line and/or income inequality in affected areas	**Poverty severity (or squared poverty gap)** *or* **Income inequality**	Takes account of both the distance separating the poor from the poverty line and the inequality among the poor Alternative to the poverty severity metric for those countries where poverty is no longer an issue; strategic objective 1 has in this sense already been reached	World Bank methodology[a, b] OECD* methodology[c]
Trends in access to safe drinking water in affected areas	**Proportion of population using an improved drinking water source**	An improved drinking water source is defined as one that is protected from outside contamination through household connection, public standpipe, borehole, protected dug well, protected spring, rainwater, etc.	WHO/UNICEF* Joint Monitoring Programme for Water Supply and Sanitation methodology[d]
Strategic objective 2: To improve the condition of ecosystems			
Trends in land cover structure	**Vegetative land cover structure**	Intended as the distribution of land cover types of greatest concern for land degradation (excluding artificial surfaces) by characterizing the spatial structure of vegetative land cover; it should include and specify natural habitat classes	Sourced from products like GlobCover*e*, *f* or finer-resolution products under development (Gong et al., 2013); and following established land cover classifications (e.g. FAO/ UNEP LCCS*[g])
Trends in land productivity or functioning of the land	**Land productivity dynamics**	Based on long-term fluctuations and current efficiency levels of phenology and productivity factors affecting standing biomass conditions	New World Atlas of Desertification methodology;[h] update foreseen every five years
Strategic objective 3: To generate global benefits through effective implementation of the UNCCD			
Trends in carbon stocks above and below ground	**Soil organic carbon stock** *to be replaced by* **Total terrestrial system carbon stock** *once operational*	Intended as the status of topsoil and subsoil organic carbon Including above- and below-ground carbon	Sourced from e.g. the GTOS* portal[i] To be streamlined with the GEF*-financed UNEP* Carbon Benefits Project[j,k]

Trends in abundance and distribution of selected species *(potentially to be replaced by an indicator measuring trends in ecosystem functional diversity once system understanding and data production allows)*	**Global Wild Bird Index**	Measures average population trends of a suite of representative wild birds, as an indicator of the general health of the wider environment	Following the indicator guidance provided for and to be streamlined with the CBD* process*l*, [m]

*Abbreviations:
CBD - Convention on Biological Diversity
FAO - Food and Agriculture Organization of the United Nations
GEF - Global Environment Facility
GTOS - Global Terrestrial Observing System
LCCS - Land Cover Classification System
OECD - Organisation for Economic Co-operation and Development
UNEP - United Nations Environment Programme
UNICEF - United Nations Children's Fund
WHO - World Health Organization

a <http://web.worldbank.org/WBSITE/EXTERNAL/TOPICS/EXTPOVERTY/EXTPA/0,,contentMDK:20242881~isCURL:Y~menuPK:492130~pagePK:148956~piPK:216618~theSitePK:430367,00.html>.
b <http://siteresources.worldbank.org/INTPA/Resources/tn_measuring_poverty_over_time.pdf>.
c <http://www.oecd.org/els/soc/43540354.pdf>.
d <http://www.wssinfo.org/>.
e <http://due.esrin.esa.int/globcover/>.
f <http://www.gofcgold.wur.nl/sites/gofcgold_refdataportal.php>.
g <http://www.fao.org/docrep/003/X0596E/X0596e00.htm>.
h <http://wad.jrc.ec.europa.eu/>.
i <http://www.fao.org/gtos/tcoDAT.html>.
j <http://carbonbenefitsproject-compa.colostate.edu/>.
k <http://www.unep.org/climatechange/carbon-benefits/Home/tabid/3502/Default.aspx>.
l <http://www.unep-wcmc.org/wild-bird-index_568.html>.
m <http://www.bipindicators.net/WBI>.

Annex 7 - Current cost[1] of selected satellite imagery

Type	Years	Bands	MS (m)	Pan (m)	Scene size (km)	Cost (km^2)
CORONA http://www.nro.gov/history/csnr/corona/factsheet.html	1960-1972	1	—	08-feb	17 x 232	$30 per scene
Landsat 4-5 MSS http://landsat.usgs.gov/about_landsat5.php	1982-1999	4	80	—	170 x 185	Free
Landsat 4-5 TM http://landsat.usgs.gov/about_landsat5.php	1982-2012	7	30	—	170 x 185	Free
Landsat 7 ETM+ http://landsat.usgs.gov/about_landsat7.php	1999-present	8	30	15	170 x 185	Free
Landsat 8 http://landsat.usgs.gov/landsat8.php	2013-present	8	30	15	170 x 185	Free
GIMMS and GIMMS3g http://ecocast.arc.nasa.gov/data/pub/gimms/	1981-present	1	8,000	-	Continuous global	Free
MODIS http://modis.gsfc.nasa.gov/data/	1999-present	36	250, 500, 1000		Continuous global	Free
SPOT 1-3 http://www.geo-airbusds.com/en/143-spot-satellite-imagery	1986-1997	3	20	10	60 x 60	$1,200 per scene
SPOT 4 http://www.geo-airbusds.com/en/143-spot-satellite-imagery	1998-2013	4	20	10	60 x 60	$1,200 per scene
SPOT 5 http://www.geo-airbusds.com/en/143-spot-satellite-imagery	2002-present	4	10	2.5 / 5	60 x 60	$2,700 per scene
SPOT 6-7 http://www.geo-airbusds.com/en/143-spot-satellite-imagery	2012-present	4	6	1.5	60	$5.15
IKONOS https://www.digitalglobe.com/	1999-present	4	4	1	11.3	$10
QuickBird https://www.digitalglobe.com/	2001-2014	4	2.4	0.6	16.8	$16
Pléiades 1A-1B http://www.geo-airbusds.com/pleiades/	2011-present	4	2	0.5	20	$13
WorldView-1 https://www.digitalglobe.com	2007-present	1	—	0.46	17.6 x 14	$13

WorldView-2 https://www.digitalglobe.com	2009-present	8	1.84	0.46	16.4	$29
WorldView-3 https://www.digitalglobe.com	2014-present	28	1.24	0.31	13.1	-

MS = Multispectral resolution
Pan = Panchromatic resolution
Scene size = the total coverage of the scene, or the maximum swath width (if just a single number)

[1]This info was put together in September 2014. Prices are only estimates based on online sources, but prices may be lower with certain sales outlets, and academic discounts can range from 20-30%. http://rmseifried.com/2014/09/19/satellite-imagery-types-resolution-and-pricing/