MONITORING AND ASSESSING LAND DEGRADATION TO SUPPORT SUSTAINABLE DEVELOPMENT

A BACKGROUND TO THE USE OF THE LAND DEGRADATION MONITORING TOOLBOX – TRENDS.EARTH

GEF-LAND DEGRADATION MONITORING PROJECT | GUIDANCE

CONSERVATION INTERNATIONAL
GLOBAL ENVIRONMENT FACILITY
INVESTING IN OUR PLANET
VITAL SIGNS
LUND UNIVERSITY
NASA

Assessing Land Degradation to Support Sustainable Development

A background to the use of the land degradation monitoring toolbox – Trends.Earth

GEF-Land Degradation Monitoring Project | Guidance

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For additional information on the project see http://vitalsigns.org/gef-ldmp.

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LIST OF ACCRONYMS

AMP	Amplitude
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
CBD	Convention on Biodiversity
CBO	Community-Based Organizations
COP	Convention of Parties
DN	Digital Number
DUR	Duration
EOSN	End of Season – NDVI
EOST	End of Season – Time
ESA	European Space Agency (ESA)
ETM	Enhanced Thematic Mapper
EUROSEM	European Soil Erosion Model
FAO	Food and Agriculture Organization of the United Nations
FuDSEM	Fuzzy-based Dynamic Soil Erosion Model
GDP	Gross Domestic Product
GEF	Global Environment Facility
IRS	Indian Remote Sensing Satellites
LDN	Land Degradation Neutrality
LULCC	Land Use and Land Cover Changes
MAXN	Maximum NDVI
MAXT	Time of Maximum
MERIS	MEdium Resolution Imaging Spectrometer
MODIS	Moderate Resolution Imaging Spectroradiometer
NCSA	National Capacity Self-Assessment
NDVI	Normalized Difference Vegetation Index
NGO	Non-governmental organizations
NOAA	National Oceanic and Atmospheric Administration
NPP	Net primary productivity
RUE	Rain Use Efficiency
SDG	Sustainable Development Goals
SOSN	Start of Season – NDVI
SOST	Start of Season – Time
SPOT	Satellite pour l'observation de la Terre
SWAT	Soil and Water Assessment Tool
SWIR	NIR and Short Wave InfraRed
TIN	Time Integrated NDVI
UNFCCC	United Nations Framework Convention on Climate Change
UNEP	United Nations Environmental Programme
UNCCD	United Nations Convention to Combat Desertification
USLE/RUSLE	Revised Universal Soil Loss Equation
WEPP	Water Erosion Prediction Project

I. INTRODUCTION

1. INTRODUCTION

The United Nations Convention to Combat Desertification (UNCCD) defines land degradation as "any reduction or loss in the biological or economic productive capacity of the land resource base. It is generally caused by human activities, exacerbated by natural processes, and often magnified by and closely intertwined with climate change and biodiversity loss" [1]. This definition stresses the functional attribute of land. Manifestations of land degradation can be many, and depend on the type of land cover, land use, nature of cause of degradation, and the natural environment within which the land degradation is occurring. Ponce-Hernandez [2] identified some of the manifestations of land degradation in drylands. These include reduced productivity of desired plants; undesirable alterations in the biomass and the diversity of micro and macro flora and fauna (soil biodiversity); accelerated soil physical, chemical and biological deterioration; undesirable alterations in ecosystem services; and increased hazards for human occupancy. Degradation may be also understood in terms of specific components of the land that are affected by the process. For example, vegetation degradation may imply a reduction in biomass productivity; decrease in plant species diversity; or degeneration in the nutritional value of plant populations for the faunal biodiversity supported by that landscape. On the other hand, soil degradation may indicate deterioration in soil quality and fertility as a result of physical, chemical or biological damage; loss of organic matter; changes in soil structure, chemistry and biology. Such changes may be brought about by numerous factors, such as erosion, pollution, deforestation, and others.

At the turn of the century, it was estimated that about 2.6 billion people were affected by land degradation and desertification in more than one hundred countries - meaning over 33% of the earth´s land surface [3]. Annual income foregone globally in the areas affected by desertification alone amounts to about US$ 42 billion each year [4]. From an environmental standpoint, land degradation triggered an estimated total loss of 9.56 × 108 tons of carbon from 1981 and 2003, which amounts to $48 billion in terms of lost carbon fixation [5]. At a country level, the cost of land degradation may range from 1% up to about 10% of the agricultural gross domestic product (GDP) for various countries worldwide [5].
The African continent is one of the regions that are most widely affected by land degradation [6-8]. Besides being the most vulnerable region in the world to degradation, the African continent is also the most severely affected region. It is estimated that desertification affects about 45 % of the continent's land area, with about 55 % of the affected area at high or very high risk of further degradation [7]. In their assessment of the economic cost of land degradation in East Africa, Kirui and Mirzabaev (2015) estimated that degradation affected 51%, 41%, 23%and 22% of land area in Tanzania, Malawi, Ethiopia and Kenya respectively. Regarding the cost of this degradation to national GDP, this represented about 14%, 7%, 23%, and 5%, of GDP in Tanzania Malawi, and Ethiopia Kenya, respectively [6]. Such high levels of degradation are detrimental to ecosystems and the services they support, such as agricultural production, biodiversity conservation, water conservation and purification, and a host of others. Despite the severity of the situation, the conditions seem to be getting worse, and urgent action needs to be taken to address the problem of land degradation. Nkonya and others [7] estimate that by 2030, inaction on soil erosion may lead to a total annual loss of nitrogen, phosphorus and potassium (NPK) nutrients of about 4.74 million tons/year, worth approximately USD 72.40 billion purchasing power parity (PPP) in present value for the continent. They estimate this to be equivalent to USD 5.09 billion PPP per year [7].

Among global and regional development and environmental institutions, land degradation is a phenomenon of immense weight for both present and future sustainable development prospects. Land degradation has been highlighted as a key development challenge in main international conventions such as the United Nations Convention to Combat Desertification, the Convention on Biodiversity (CBD), the Kyoto Protocol on global climate change and the Millennium Development Goals.

II. CAPACITY BUILDING TO SUPPORT LAND DEGRADATION ASSESSMENTS AND MONITORING

2. CAPACITY BUILDING TO SUPPORT LAND DEGRADATION ASSESSMENTS AND MONITORING

An expert consultation organized by the United Nations Convention to Combat Desertification (UNCCD), Convention on Biodiversity (CBD), United Nations Framework Convention on Climate Change (UNFCCC), Food and Agriculture Organization of the United Nations (FAO), and the Global Environment Facility (GEF[1]) observed that adequate national capacities for using appropriate data and methods to assess and monitor land degradation could be achieved within a relatively short space of time. These could be in technology transfers and capacity building in the use of Earth observation and geospatial information; the use of consistent methodologies and data sets; data interpretation and validation at the national level; and the use of derived assessments to guide national land policies and international reporting. Bellamy and Hill [9] identified five main types of capacities required to meet and sustain global environmental objectives. Below is an extract:

1. STAKEHOLDER ENGAGEMENT

- A sense of readiness is necessary from all parties involved, including at the political level, to achieve and sustain global environmental objectives.
- Achieving environmental sustainability necessitates the engagement of stakeholders, which in turn is predicated on their level of awareness and understanding, as well as having the skills to take action.
- Non-governmental organizations (NGOs) and Community-Based Organizations (CBOs) must be fully engaged to reach marginalized communities, who in turn engage civil society stakeholders.
- Best practice methodologies are needed to engage stakeholders.
- The National Capacity Self-Assessment (NCSA) process was innovative, benefitting from broad and interactive participation of stakeholders, which made the assessments highly relevant.

2. INFORMATION MANAGEMENT AND KNOWLEDGE

- Although not complete, environmental information exists. However, the capacities to access and manage this information, including coordination with other management information systems remain weak.
- There is a need to incorporate traditional/ indigenous knowledge into the environmental management information system.

3. ORGANIZATIONAL CAPACITIES

- Many countries lack clarity in their organizational set-up to adequately finance environmental management.

4. ENVIRONMENTAL GOVERNANCE

- Many countries continue to lack a comprehensive and adequate set of environmental policies, with missing or unenforced legislative and regulatory instruments that further hinder environmental management.

5. MONITORING AND EVALUATION

- Countries are monitoring and evaluating their projects, but the knowledge that is generated is not being adequately used in decision-making processes.

This document and its associated training contribute to addressing gaps in the first, second and fifth categories of capacities for countries in relation to land degradation assessments and monitoring. It will strengthen local capacity to generate, access, and use information and knowledge for evaluation and monitoring of land degradation. This outcome aligns with the GEF 6 Land Degradation Focal Area Strategy[2].

III. PURPOSE OF THIS DOCUMENT

3. PURPOSE OF THIS DOCUMENT

This document is developed within the framework of the Global Environment Facility (GEF) Project titled: Enabling the use of global data sources to assess and monitor land degradation at multiple scales[3]. The project has as objective to provide guidance, methods and a toolbox for assessing and monitoring status and trends of land degradation using remote sensing technology, which can be employed to inform land management and investment decisions as well as to improve reporting to the UNCCD and the GEF.

The main aim of this document is to develop the capacity of countries in the application of tools and recommended approaches for land degradation assessment using remote sensing. To this end, this document is designed to provide a condensed set of referral resources with much of what is needed as background knowledge in assessing and monitoring land degradation using data from Earth observation. It provides a theoretical background to understanding land degradation; the importance of vegetation condition as a proxy for identifying trends in land condition; the use of geospatial techniques to assess and monitor degradation; and the implications of such results for national and sub-national land degradation policies. The current manual also aims to provide the guidance requested by the UNCCD on how to combine earth observation with national data and field surveys for the purpose of assessing land degradation. However, this guidance is also useful in monitoring and reporting on land degradation neutrality (LDN) if linked to the LDN scientific conceptual framework and applied at the different steps of LDN monitoring and reporting.

HENCE, THIS DOCUMENT WILL:

- **a -** Review the current understanding of land degradation and its importance for sustainable development, especially within the African context;
- **b -** Offer a theoretical background to the current scientific knowledge of the importance of vegetation to environmental resources and ecosystem services;
- **c -** Provide an appraisal of relationship between vegetation condition and land degradation;
- **d -** Provide guidance for reporting of key indicators of land condition for GEF and UNCCD (productivity, land cover, soil carbon);
- **e -** Provide a manual for the use of the Trends. Earth for assessing vegetation condition as a proxy for land degradation or improvement.

Trends.Earth is a decision support tool for the assessment and monitoring of vegetation condition. Together with the Trends.Earth toolbox, this document is intended to address the urgent need for accurate information about the trends and extent of land degradation to assist sub-national, national and international efforts in designing appropriate interventions that will ensure the sustainability of livelihoods in affected environments. This document and its associated tools should serve as a primary resource for identifying cold and hotspots of vegetation changes and so guide targeted efforts at identifying causes and responses to degradation as well as the impacts of land degradation on local livelihoods.

[1] Framework and Guiding Principles for a Land Degradation Indicator: To monitor and report on progress towards target 15.3 of the Sustainable Development Goals, the strategic objectives of the Rio Conventions and other relevant targets and commitments. Outcomes of the Expert Meeting Washington, DC February 26, 2016. Draft for Consultation

[2] The goal of the Land Degradation Focal Area Strategy is to: "contribute to arresting and reversing current global trends in land degradation, specifically desertification and deforestation."
See GEF-6 Programming Direction: https://www.thegef.org/sites/default/files/documents/GEF-6 Programming Directions.pdf

[3] More on this project can be found here: https://www.thegef.org/project/enabling-use-global-data-sources-assess-and-monitor-land-degradation-multiple-scales.

IV. TARGET AUDIENCE

4. TARGET AUDIENCE

This document and its associated tools are intended as a resource that provides guidance on methods, and the use of a toolbox for assessing and monitoring status and trends in land degradation using remote sensing technology. Its goal is to inform land management and investment decisions as well as improve reporting to the UNCCD and the GEF. The primary target audience is, therefore, national stakeholders involved in the assessment, monitoring of vegetation and land condition at the national and sub-national scale, and contributing to national reporting requirements on indicators of land condition for GEF and UNCCD.

The document also stands to benefit many other stakeholders that are not directly involved in GEF and UNCCD reporting. These include people who may want to directly assess and monitor vegetation condition at multiple national and sub-national scales, such as environmental or natural resource managers and policymakers. The vast scope of this material and its associated tool makes it ideal for training in a host of disciplines that involve the understanding of land use and land cover changes and their implications on environmental resources, ecosystem services, and sustainable development.

Yam Farm, Okwabena. © Benjamin Drummond

V. A REFRESHER ON REMOTE SENSING

5. A REFRESHER ON REMOTE SENSING

5.1 PASSIVE AND ACTIVE REMOTE SENSING

We make the broad distinction between two kinds of remote sensing techniques, passive and active sensing systems. Passive remote sensing uses the naturally existing radiation, such as visible light, near infrared (NIR) or thermal infrared (TIR). The sensing systems measure the amount of reflected or emitted such radiation. Most operational remote sensing systems operate in this mode. In active remote sensing, the sensing system itself emits pulses of radiation and detects the reflected (back-scatter) pulse as a way to investigate properties of the surface from where the pulse was reflected. Radar is the most common technique for active remote sensing; Active remote sensing will not be the focus of this report.

5.2 RADIATION THEORY

Every physical body/object which has a temperature above the absolute zero (i.e. -273○C) emit electromagnetic radiation, the warmer the body, the more radiation is emitted. The wavelength of the emitted radiation also changes with temperature. This is illustrated by the electromagnetic (EM) spectrum (Figure 1).

The part of the EM spectrum which is of interest to passive remote sensing for the purpose of land degradation studies is primarily the visible part with wavelengths between about 400 and 800 nm (or 0.4 – 0.8 µm).

The relationships between the temperature of the emitting body, the amount of radiation, and the wavelength are described by Planck's law of radiation, illustrated by two graphs in Figure 2.

Figure 2. Illustrating Wien's Law of Displacement. The red line (y-scale to the left) shows the EM spectrum of the Sun (about 5800 K) while the green line (y-scale to the right) shows the EM spectrum of the Earth (about 300 K).

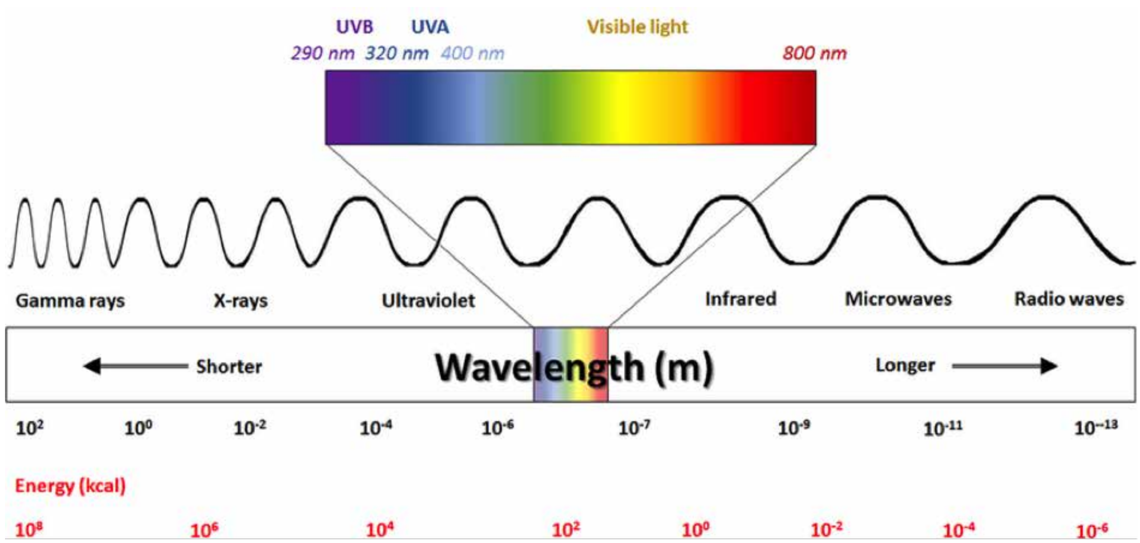

Figure 1. The electromagnetic spectrum.

Note that the wavelengths of the emission curves are very different. The relationship between the temperature of the radiative body and the wavelength of the radiation maximum ("λmax)" is described by a simple formula, the Wien's Law of Displacement. Wien's displacement law states that there is an inverse relationship between the wavelength of the peak of the emission of a black body and its temperature. It is presented as:

$$\lambda max = b / T \qquad \text{Equation 1}$$

where λmax is the peak wavelength in meters, T is the temperature of the blackbody in Kelvins (K), and b is a constant of proportionality, called Wien's displacement constant and equals 2.90×10^{-3} m-K (meter-Kelvins).

For optical wavelengths, it is often more convenient to use the nanometer in place of the meter as the unit of measure. In this case, $b = 2.90 \times 10^{6}$ nm-K. For infrared wavelengths, we use the micron (μ) or micrometer (μm).

In this case, b = 2900 μm-K. Hence according to Wien's displacement law, the hotter an object is, the shorter the wavelength at which it will emit most of its radiation, and, further, that the wavelength for maximum or peak radiation power is found by dividing Wien's constant by the temperature in Kelvins. The peak of each curve moves to the left (shorter λ) as temperature goes up.

It follows that the radiation maximum of the Sun (temperature about 5800 K) corresponds to visible green light (2900/5800 = 0.5 μm) while the radiation maximum of the Earth (assume 300 K) is close to 10 μm, which is in the thermal IR radiation part of the EM spectrum.

5.3 RADIATION INTERACTION WITH THE ATMOSPHERE

Radiation interaction with the atmosphere
The radiation from the sun is the primary source of radiation used in passive remote sensing systems.

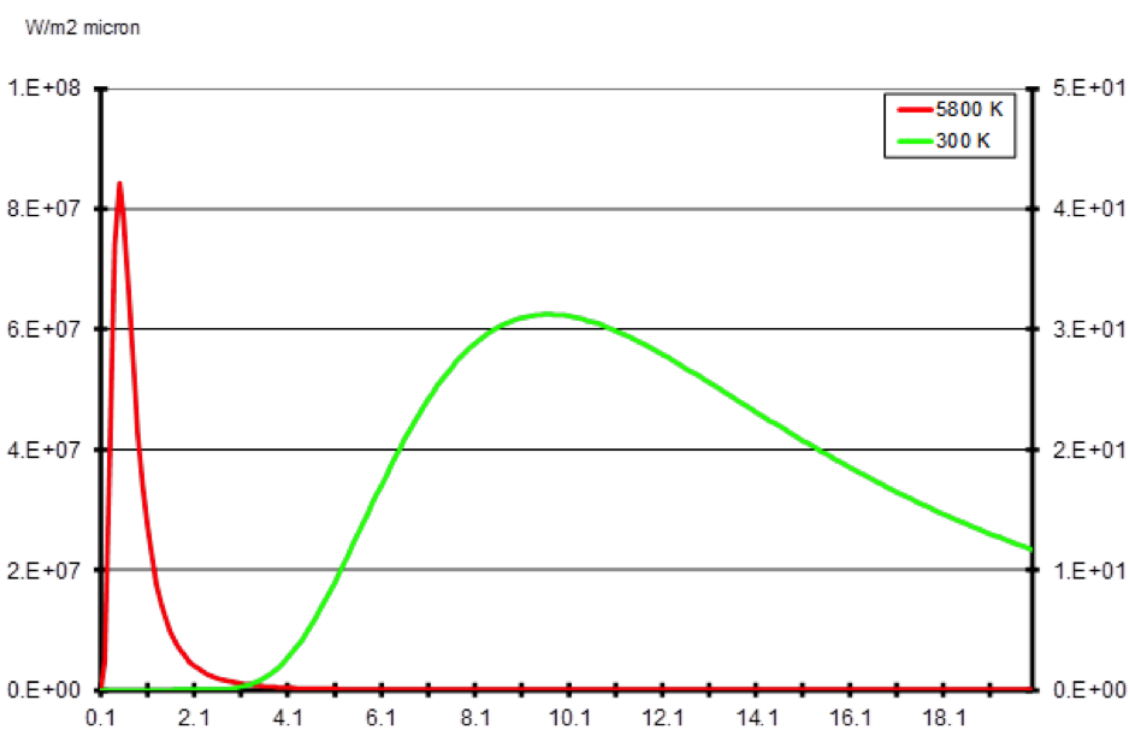

Figure 2. Illustrating Wien's Law of Displacement.

When the radiation is emitted from the sun, it travels through outer space more or less unaffected until it reaches the atmosphere. In the atmosphere, the radiation is subject to two main processes, scattering, and absorption.

In Figure 3 we show a schematic illustration of radiation from the sun (short wave radiation SWR) entering the atmosphere and hits the surface of the earth. Here some of the radiation is reflected back into space, again through the atmosphere, in the form of reflected SWR, which is the radiation measured up by common RS satellites, such as Landsat and MODIS. Some of the SWR hitting the surface of the Earth is absorbed rather than reflected. The absorption heats up the surface which results in increased emission of radiation, according to Planck's law of radiation. This is illustrated as the long wave radiation (LWR) where the wavelength is much longer (Figure 2). We call these wavelengths Thermal Infrared radiation (TIR). When detected by a RS system, this can be used to measure the surface temperature of earth provided that the emissivity of the surface is known.

When radiation from the sun moves through the atmosphere, it is subject to two processes with great importance for remote sensing, absorption and scattering (Figure 3). One reason why these processes are so important for remote sensing is that these processes are highly wavelength specific. Absorption is the process by which solar radiation is absorbed by gases, such as water vapor, ozone and carbon dioxide (CO2), and particles (aerosols) and the result is heating of the atmosphere. Some gases absorb radiation very strongly at particular wavelength intervals, such as water vapor. Scattering is the process by which radiation bounces on particles and the direct solar radiation becomes diffuse. In summary absorption and scattering makes the atmosphere less transparent at some wavelength intervals and more transparent in others, so called atmospheric windows. Figure 4 shows how transparent the atmosphere depending on wavelength and the most important gases absorbing radiation at different wavelengths. Scattering is less wavelength specific, but affects primarily the short wavelengths, i.e. visible blue light and shorter wavelengths.

In Figure 4 it is clear that visible light, i.e. 0.4 – 0.7 µm, corresponds to an atmospheric window, while the near-infrared area is characterized by several wavelength intervals with high absorption by water vapor. The absorption means that there is less energy to be sensed which limits the use of these wavelengths for remote sensing. On the other hand, these absorption bands can be useful for assessing the moisture content of the atmosphere and to some extent vegetation.

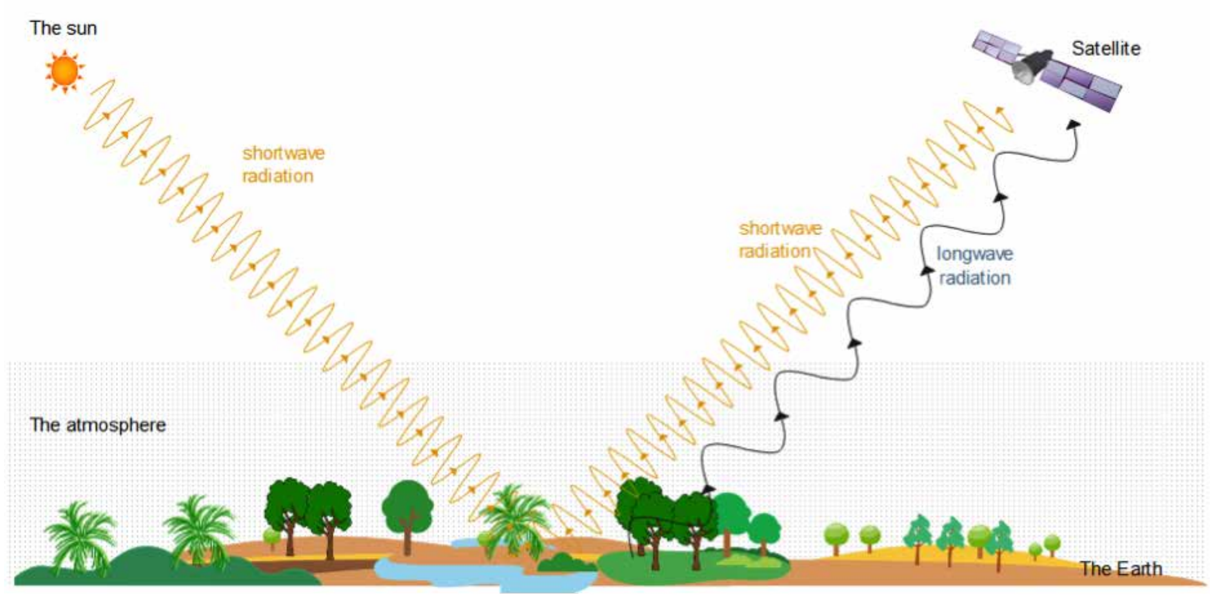

Figure 3. Radiation transfers between the sun, Earth and satellites.

5.4 RADIATION INTERACTION WITH THE SURFACE OF THE EARTH

After passing through the atmosphere, the solar radiation hits the surface of the Earth. Some of the radiation is reflected back into space which means that the wavelengths are the same as the original solar radiation (SWR in Figure 3), but some radiation is absorbed and contributes to heating the surface. The warming of the surface of the Earth then results in radiation of long-wave radiation back into space according to Planck's law and Wien's law of displacement (LWR in Figure 3).

The reflectance is highly wavelength dependent, which is used by remote sensing to infer much information about the surface from where the reflectance comes. In Figure 5 is shown how three different surfaces, soil, vegetation, and water, reflects light (visible – intermediate IR).

By sensing the reflected solar radiation in different wavelength bands, as shown in Figure 5, it is possible to infer many important characteristics about the surface, particularly about vegetation. The life process of green vegetation is photosynthesis by which the green plants use water and nutrients (from the soil), carbon dioxide (from the atmosphere), and energy from the sun to build biomass. The energy absorbed by the green plants (by the chlorophyll) is primarily red visible light (about 0.5 µm), hence a dip in the reflectance curve in Landsat band 3. The green plants also reflect highly in the near-IR part of the spectrum (band 4 in Landsat series 1 through 7, and band 5 in Landsat 8). This particular phenomenon (various combinations of the red and near-IR bands) is harnessed to construct vegetation indices such as the normalized difference vegetation index - NDVI (see further below).

5.5 REMOTE SENSING DATA

The most common platform to measure the reflected solar (or emitted LWR) radiation is a satellite. The satellites are either circling the Earth in near-polar orbits, i.e all orbits converge over the poles, or placed in a geostationary position above a certain place on the globe. The polar orbits are often sun-synchronous which means that the local time of satellite passage is always the same – an important prerequisite for un-biased image data. Such orbits are usually between 700 and 800 km above the Earth, while geostationary orbits are more precise (35780 km) where the Earth's gravity and the centrifugal force balance ("Newton's cannonball").

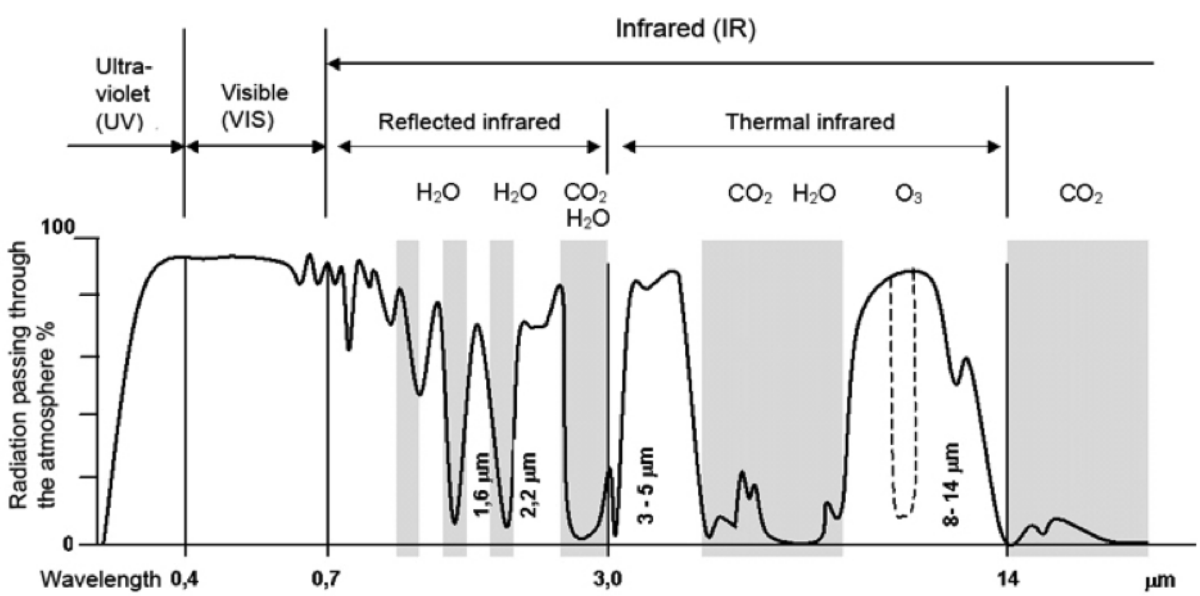

Figure 4. The transmission of radiation through the atmosphere (Burai 2012[4]).

[4] Applied remote sensing. Available here: http://www.tankonyvtar.hu/hu/tartalom/tamop412A/2010-0010_02_Applied_Remote_Sensing/adatok.html

Satellites in polar orbits takes about 100 minutes to complete one orbit around the Earth, during which time it continuously senses the radiation coming from the ground (during the night-pass only emitted radiation). Thus it takes several days to cover the Earth completely. In geostationary orbits, the satellite can continuously sense half of the Earth, although the resolution deteriorates to infinity at the edges.

The data from the satellites are continuously transmitted to ground receiving stations, where the data is processed in terms of geometry and various radiometric corrections, in order to prepare the data for analysis. Two groups of characteristics contribute to differentiate satellite data, especially with respect to their use for the study of land change phenomena. These include different characteristics of resolutions, and the nature of information contained in the data (spectral, textural and contextual information), (see also Table 1).

5.6 DATA RESOLUTIONS

SPATIAL RESOLUTION refers to the size on the ground of one pixel. This varies from under 1 m for ultra-high resolution (e.g. Quickbird) to several kilometers (e.g. the Advanced Very High Resolution Radiometer - AVHRR). Most operational satellite systems have either a spatial resolution of 0.25 – 1 km (MODIS) or 10-30 m (Landsat or Spot). In principle, continuous time series data are usually of coarser spatial resolution than single images.

SPECTRAL RESOLUTION refers to the number of wavelength bands the satellite uses to measure the radiation coming from Earth. Pan-chromatic data do not separate the measured radiation into spectral bands, but use just one broad band, often corresponding to visible light (compare with a B/W photography). Multi-spectral data have divided the measurement of radiation into two or more spectral bands (see Figure 5).

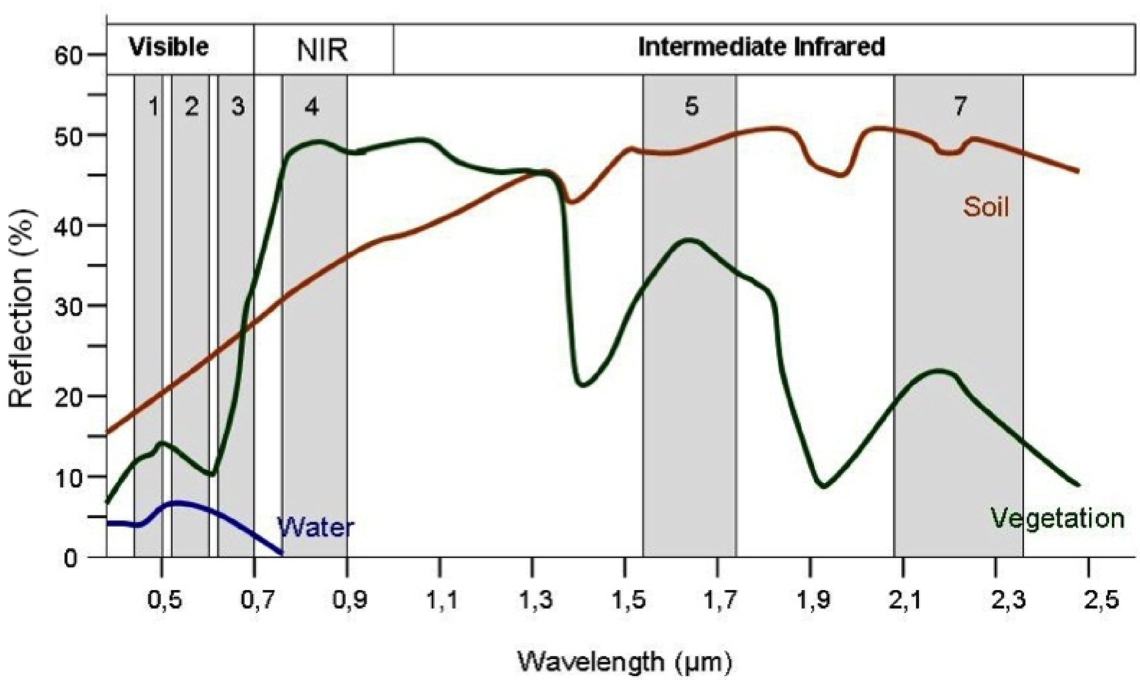

Figure 5. Spectral reflectance of three surfaces, green vegetation, soil and water. The spectral bands of Landsat 7-8 have been superimposed.

TEMPORAL RESOLUTION is the amount of time, expressed in days, that elapses before a satellite revisits a particular point on the Earth's surface (at nadir, i.e. directly under the satellite). In principle, the higher the spatial resolution the coarser the temporal resolution. The tradeoff between spatial and temporal resolution can be compensated by having two or more satellites operating simultaneously, tilting the instrument sideways, or having a wide swath angle. For analyzing processes over time it is crucial to use continuous time series.

RADIOMETRIC RESOLUTION refers to the sensitivity of the sensing system to quantify the incoming radiation in digital levels, often expressed as bits (1 bit = 2 levels; 8 bits = 256 levels, 10 bits = 1028 levels, 12 bits = 4096 levels). Many of the older sensing systems, such as Landsat and AVHRR used only 8 bits, while new sensors use up to 12 bits (e.g. Sentinel).

When we analyze the remotely sensed data we can distinguish between three types of information we can make use of: spectral, textural, and contextual.

5.7 INFORMATION CONTAINED IN THE DATA

SPECTRAL INFORMATION (spectral bands and combinations, vegetation indices) refers to information in each and every pixel, regardless of the surrounding. This kind of information is analyzed and used according to bio-physical principles, for example the link between the process of photosynthesis and radiation physics, and radiation characteristics of clear and turbid water, etc. Time series of data are particularly useful for analyze bio-geo-physical processes, such as land degradation.

TEXTURAL INFORMATION is the information we get from analyzing each pixel in relation to its neighborhood. For example speckle in an image may indicate small-scale farming while the absence may indicate range land. In forested regions, smooth areas may indicate intact forests while speckle may indicate selective and/or illegal logging.

CONTEXTUAL INFORMATION refers to the information we can infer from the image coupled with ancillary information, for example digital map data or local knowledge about the ground conditions.

There are many types of Earth Observation (EO) data with a wide range of potential uses. In Table 1 we summarize some of the most important remote sensing missions, categorized by their potential field of application.

Trends.Earth uses two main datasets for computing trajectories of NDVI – data from the Modis Moderate Resolution Imaging Spectroradiometer (MODIS) and Advanced Very High Resolution Radiometer (AVHRR) sensors. The MODIS vegetation indices are produced on 16-day intervals and at spatial resolutions of 250m, 500m, and 1000m. The NDVI products of this dataset (like the enhanced vegetation index – EVI produced by the same mission) is derived from atmospherically-corrected reflectance in the red, near-infrared, and blue wavebands. Trends.Earth uses both MODIS Terra and MODIS Aqua for different process. Data from the AVHRR sensor onboard the National Oceanic and Atmospheric Administration (NOAA) polar-orbiting weather satellites is also a valuable source of NDVI time-series. Trends.Earth offers the choice of using this data as an alternative to MODIS data. NDVI data from AVHRR are composites put together to obtain nearly cloud-free images showing maximum greenness at a spatial resolution of 1km. Given its daily temporal resolution, AVHRR data are used to generate NDVI-based images of the planet's land surface on a regular basis, making it possible to assemble image series that portray seasonal and annual changes of vegetation globally.

For over 35 years, Compton J. Tucker and colleagues have been working on developing NDVI imageries from the AVHRR data [10, 11]. Through the framework of the Global Inventory Monitoring and Modeling System (GIMMS) project, this data has been systematically corrected for calibration, view geometry, volcanic aerosols, and other effects not related to vegetation change. The result has been carefully assembled and updated into what is today a 3rd generation of this data archive – the GIMMS NDVI3g [12].

TABLE 1

SUMMARY OF SOME COMMONLY AVAILABLE REMOTE SENSING DATASETS, THEIR POTENTIAL USES, SPATIAL AND TEMPORAL RESOLUTIONS, AS WELL AS THE TIME PERIOD COVERED.

EO VARIABLE	MISSION/ SENSOR	DATASET / PRODUCT[b]	SPATIAL RESOLUTION	TEMPORAL RESOLUTION	AVAILABILITY
SURFACE TEMPERATURE	MODIS	MOD11	1 - 5.6 km	Daily-Monthly	2000 -
	AVHRR	Thermal IR	4 - 8 km	Daily-Monthly	1981 -
	ASTER	Thermal IR	90 m	Periodic/on request	2000 -
	Meteosat	Thermal IR	3/5 km	Every 15 minutes	1997 -
	LANDSAT	Thermal IR	60 - 120 m	Periodic, 5-16 days	1982 -
PRECIPITATION	TRMM/TMPA		0.25 Degrees	3 hours	2008 -
	Var.	RFE	8 km	10 day	
FLOODING	MODIS	MOD09, reflectance	250 - 500 m	Daily - Weekly	2000 -
	LANDSAT	Thermal	60 - 120 m	Periodic, 5-16 days	1982 -
SOIL MOISTURE	AMSR-E/AQUA	Passive microwave	25 km	Daily	2002 -
	SMAP	Passive/active microwave	1 - 10 km	2 - 3 days	2015 - 2018
VEGETATION & LAND COVER HIGH SPATIAL DETAIL, IMPACTS OF EXTREME EVENTS	LANDSAT	TM, EMT+, OLI	30 m	Periodic, 5-16 days	1982 -
	SPOT	HRV/HRVIR/HRG	2.5 - 20 m	Periodic/on request	1986 -
	Ikonos, Quickbird, GeoEye		0.5 - 1 m	Periodic/on request	2000 -
	SENTINEL-2[a]		10 - 60 m	3-5 days	2015 -
VEGETATION & LAND COVER. LOW SPATIAL DETAIL, TEMPORAL DYNAMICS	MODIS	MOD09 Reflectance	250 - 500	Daily - Weekly	2000 -
	SPOT/VEGETATION		1 km	10 - day composites	1998 -
	AVHRR	GIMMS	8 km	15 - day composites	1982 -
	MODIS	MDC12 land cover	0.5 - 5.6 km	Annual	2000 -
	MODIS	MOD44 veg. change	250 m	3 - month	2000 - 2013

VI. MONITORING VEGETATION USING EARTH OBSERVATION

6. MONITORING VEGETATION USING EARTH OBSERVATION

Vegetation is a vitally important component in almost every terrestrial ecosystem. As photosynthesizing organisms, green plants convert solar energy into biomass and form the foundation of all terrestrial food chains. Vegetation influences the energy balance at the earth's surface as well as within the atmospheric boundary layer, contributing to the mitigation of extremes of local climate. Vegetation produces oxygen required by most organisms while sequestering carbon from the atmosphere; helps hold soil in place and by so-doing soil development over time, and provides habitat and food for many organisms thereby contributing to the sustenance of biodiversity. Given these vital roles in most ecosystems, vegetation is a fundamental component in the regulation of various biogeochemical cycles, such as water, carbon, and nutrients. Vegetation directly contributes to the social well-being and economic development of communities by providing direct resources (such as timber, food, medicines) as well as indirect services (such as watershed protection, protection from mass movements, and a range of other ecosystem services). Vegetation is also a source of spiritual and cultural experiences to many peoples and cultures in Africa and different parts of the world.

6.1 NDVI AS AN INDICATOR OF VEGETATION CONDITION

The last half century has seen the development and use of various vegetation indices. The underlying assumption behind the design and use of these indices is that some algebraic combination of remotely-sensed spectral bands can reveal valuable information such as vegetation structure, the state of vegetation cover, leaf density and distribution, the water content in leaves, mineral deficiencies and evidence of parasitic shocks or attacks [13]. 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 reflectances such as soil properties, atmospheric conditions, solar illumination, and sensor viewing geometry [13, 14]. Plants have adjusted their internal and external structure to perform photosynthesis.

This structure and its interaction with electromagnetic energy have a direct influence on how leaves and canopies appear spectrally when recorded using remote sensing instruments. A majority of vegetation has a maximum spectral reflectance in the infrared (Figure 6). Reflectance is influenced by the presence of pallisade cells and spongy mesophyll. Pallisade cells comprise of chloroplasts with chlorophyll pigment. The chlorophyll absorbs most red and blue incident light and reflects approximately 20% of the green light incident upon it.

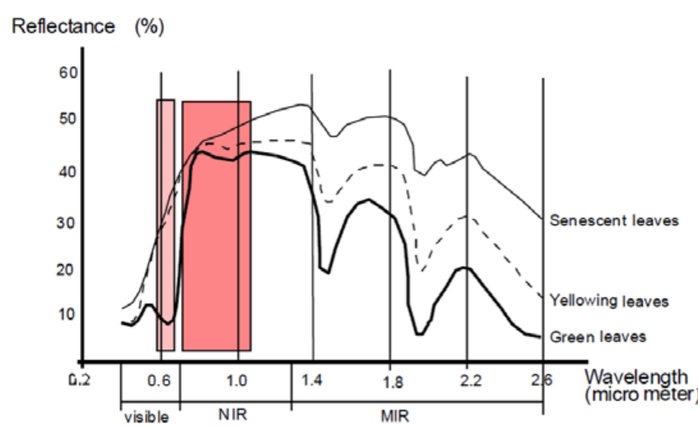

Figure 6. Spectral response characteristics of vegetation at three stages of development[5].

[5] 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 (Yengoh et al. 2015).

In a typical green leaf, the near-IR reflectance increases dramatically in the region from 0.7-1.2 µm (about 76% in 0.9 µm). The reasons that healthy plant canopies reflect so much near-IR energy are that the leaf already reflects 40-60% of incident near-IR energy from spongy mesophyll, and the remaining 45-50% of the energy transmitted through the leaf and can be reflected once again by leaves below it. The NDVI formula is presented as:

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad \text{Equation 2}$$

Where NIR is reflectance in the near infrared band and RED is reflectance in the visible red band.

The NDVI algorithm takes advantage of this fact that green vegetation reflects less visible light and more near-IR, while sparse or less green vegetation reflects a greater portion of the visible and less near-IR. The NDVI algorithm combines these reflectance characteristics in a ratio, thereby a useful index of photosynthetic activity. The range of values obtained by the NDVI is between −1 and +1. Only positive values correspond to vegetated zones and the higher the index, the more the chlorophyll content of the target.

6.2 NDVI AS A PROXY FOR LAND DEGRADATION

Safriel (2007) outlines that vegetation cover is the most common indicator of the state of the land. It, therefore, follows that changes in the quantity, quality, and distribution of vegetation can point to shifts in the ability of ecosystems to support communities with a range of resources and ecosystem services. This can also point to changes in the capacity of the natural environment to function as it used to, for example, contribute to biogeochemical cycling and support biodiversity. Assessing and monitoring vegetation changes (in cover, composition, structure, and function) can, therefore, serve as a means of understanding the state, health, and quality of environmental resources and services in an area.

The potential for the use of NDVI as a proxy for land productivity (one of the indicators of the state of land degradation) is based on studies that have identified a strong relationship between NDVI and net primary productivity (NPP) [15-17]. The indicators of land degradation vary with the type of land degradation being examined, severity of the land degradation (LD) process, and spatial extent of the LD. For instance, the most common indicators of desertification are changing vegetation and land use, drought, soil, erosion, and urbanization [18]. The potential for the use of NDVI as a proxy for land productivity (one of the indicators of the state of land degradation) is based on studies that have identified a strong relationship between NDVI and NPP [15-17]. Multi-temporal datasets provided by satellites simplify the use of remote sensing imagery and techniques to assess the extent of indices relevant for LD assessments as well as monitor changes of such indices over time. The datasets available for such analysis are variable in image resolutions (spatial, spectral, and radiometric resolutions), spatial coverage, temporal resolution, and cost. Image resolutions can range from low (AVHRR) to medium (Landsat TM, Landsat MSS, OLI, and IRS-I, ISS-II), and high (SPOT, IKONOS, QuickBird, GeoEye- 1, Worldview-1, and WorldView-2).

6.3 IMAGERY CHARACTERISTICS OF NDVI-BASED ASSESSMENTS

Remotely sensed products derived from satellite imagery come in several spectral bands, each of which corresponds to a specific wavelength range in the electromagnetic spectrum. For applications driven by NDVI and related indices, bands in the visible and infrared wavelengths are most commonly used. In using satellite-derived products for a range of environmental applications, it is important to consider some sensor and image characteristics. These include image size; the region of the earth from which images are acquired; spatial resolution of the images; the number of bands and wavelengths detected; spectral characteristics of the bands concerned; frequency of image acquisition; date of origin of the sensor [19].

For most environmental applications, remote sensing products tend not to perfectly meet all requirements for image size, spatial and temporal resolutions, as well as availability. There is therefore always need for tradeoffs between some of these characteristics [14, 19]. Images with large swath tend to be associated with low spatial resolutions, lower data volumes, and shorter temporal resolutions. They, therefore, tend to have a longer archive of consistent data series from which long-term changes can be assessed. With the large path width of low-resolution images, large spatial areas of the earth can be covered and analyzed on one or few images. High spatial resolution data, on the other hand, tends to cover a smaller swath, is associated with large data volumes, and has longer temporal resolutions. High spatial resolution data, therefore, demands greater resources in data storage, manipulation, and analysis. Also, most high-resolution datasets tend to be more expensive and out of the reach of many potential users outside the research community of the satellite launching program or country. In general, high spatial resolution data (such as from IKONOS, GeoEye, and QuickBird) are helpful for fine-scale assessments and analysis local level, while medium spatial resolution data (such as from Landsat TM and Terra ASTER) are useful at a regional scale. At a continental or global scale, coarse spatial resolution data (such as from AVHRR and MODIS) support archives of long time series and are preferable for some NDVI-based assessments and analysis [14, 19].

Multi-temporal datasets provided by satellites simplify the use of remote sensing imagery and techniques to assess the extent of indices relevant for LD assessments. They also expand the boundaries of possibilities for monitoring changes of such indices over time [18, 20-26]. The datasets available for such analysis are variable in resolutions (spatial, spectral, temporal, and radiometric resolutions), spatial coverage and cost. Image resolutions can range from low (NOAA-AVHRR) to medium (Landsat TM, Landsat MSS, and IRS-I, ISS-II), and high (SPOT, IKONOS, QuickBird, GeoEye- 1, Worldview-1, and WorldView-2).

Efforts are being made to permit the integration of datasets of different spatial and temporal resolutions, such as to harvest benefits implicit in the various resolution scales. An example is the addition of the panchromatic band (has significant spectral width, with much of the visible and near-infrared portion of the electromagnetic spectrum, and high spatial resolution) to some sensors to achieve higher spatial resolutions. This is the case with the panchromatic band (15 meters) on the Landsat 7 ETM+ sensor in which other bands are 30 meters or greater. By incorporating the panchromatic band with other bands, the visual sharpness of the image can be enhanced [19].

6.4 DATA DEVELOPMENTS IN NDVI-BASED LAND DEGRADATION ASSESSMENTS

While coarse spatial resolution datasets have substantial value at the global scale, they lack satisfactory thematic and spatial detail desirable for habitat assessments at the level of individual countries, smaller regions and local settings for finer resolution assessments, such as vegetation species distribution studies or high-quality forest-change monitoring. The role of mapping, monitoring, and assessments at the national and subnational level is performed on the most part using moderate resolution sensors, such as the Moderate Resolution Imaging Spectroradiometer (MODIS) with spatial resolutions of 250m – 1000 m, as well as Landsat, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Satellite pour l’observation de la Terre (SPOT HRV), and Indian Remote Sensing Satellites (IRS) with spatial resolutions from 15 to 60 meters. Newer, high-resolution optical sensors (5 meters or less) such as IKONOS, Quickbird, OrbView, and GeoEye currently provide enough spatial and spectral detail to discriminate between individual trees and in some cases species [27].

Even though moderate and high-resolution remotely-sensed data offer better opportunities for land degradation assessment and related studies and policy-making at the country, sub-regional and local levels, some of the data (especially high-resolution imagery) is cost-prohibitive regarding data acquisition and handling for many national governments and research institutions [27]. The use of Landsat family of products for land use and land cover change assessments and monitoring has consistently increased since its launch in the early 1970s. This increase is owed mainly to Landsat having a relatively fine resolution for land use change studies, the temporally consistent nature of the dataset, as well as its global coverage [26].

The potential for using free data in the assessment and monitoring of environmental change (principally forest cover change) at the global level has been demonstrated for Landsat products [26]. Kim et al. [28] examined and proposed solutions to the key challenges to creating global products of forest cover and cover change at Landsat resolutions. Among some of these challenges are the processes and tools for atmospheric correction, proper calibration coefficients, working with different phenologies[6] between compilations, terrain correction, proper accuracy assessment, and the automation of land cover characterization and change detection [26]. This study demonstrates the potential for existing datasets to support robust assessments of some forms of land degradation, provided sufficient care is taken to address known limitations.

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[6] Phenology is the science of the relations between climate and periodic biological phenomena, as the migrations and breeding of birds, the flowering and fruiting of plants, etc.

VII. USING VEGETATION TO ASSESS CHANGES IN ENVIRONMENTAL CONDITIONS

7. USING VEGETATION TO ASSESS CHANGES IN ENVIRONMENTAL CONDITIONS

An understanding of the changes in vegetation conditions that are associated with environmental factors is essential in knowing how vegetation can be used as a proxy for assessing and monitoring land condition over space and time. The timing and recurrence of plant life cycle events are driven by environmental factors for natural systems, such as conserved forests and other natural vegetation formations not being affected by human activity, but also mediated by human factors in managed systems, such as crop cultivation zones.

7.1 CONTRIBUTIONS TO CHANGES IN SPECTRAL CHARACTERISTICS OF VEGETATION

As a result of human and natural influences, vegetation undergoes changes from one place to another and from one time to the other. These changes can alter the spectral properties of vegetation, and therefore have the potential to be assessed using data and methods of earth observation. Spatial changes in NDVI may reflect differences or changes in the types of species, the presence of stressed vegetation in an area of similar vegetation type, or even differences in weather conditions. Temporal changes on the other hand tend to reflect changes in factors that vary over time, some recurring in regular intervals and others not. These could include changes in seasons, stages in the crop cycle, as well as human factors such as vegetation harvesting. Changes in vegetation that can be monitored using earth observation have been categorized into four general categories [29, 30]:

ABRUPT CHANGES result from disturbance events that have the potential of transforming a landscape, at least in the short-term. These include activities such as logging, deforestation, agricultural expansion, and the burning of vegetation using fire. Such events may radically alter the spectral properties of the land surface and will be easily noticeable on satellite imagery.

SEASONAL CHANGES follow cyclical intra-annual and interannual patterns of phenology in predictable and mostly repeatable patterns of green-up and senescence (see Table 2 and Figure 11 for an annual breakdown of plant phenological cycles). Phenological changes can also have marked impacts on spectral characteristics of the vegetation. Their repeatability offers the potential for identification of breaks in the predictable pattern if there is a disturbance in the vegetation.

GRADUAL CHANGES are subtle within-state changes taking occurring in vegetation communities. These tend not to be related to normal phenological cycles. Within-state changes can include changes in plant communities related to natural succession, grazing pressure, and climate-induced biome shifts. They also include changes associated with vegetation damage caused by insects and disease, drought and storms [31, 32].

SHORT-TERM INCONSEQUENTIAL VEGETATIVE CHANGES refer to events that cause vegetative spectral changes not perceived as having long-term ecological importance. An example of such events would include rain-fall events that affect spectral properties of the soil background wind that affects leaf angles during the time of data acquisition.

7.2 TIME-SERIES IN ENVIRONMENTAL CHANGE STUDIES

A time series refers to a collection of observations of quantitative data items (observations) obtained through repeated measurements over time (see the example in Figure 7). Such a series of data points is therefore indexed in a successive time order (hours, days, weeks, months, years). It is standard practice for a time-series sequence to be taken at successive equally spaced points in time, making it a sequence of discrete-time data. Time series data can be generated for a broad range of analysis in almost all scientific disciplines. The most common use of remotely sensed time-series imagery is for temporal trajectory analysis, in contrast to bi-temporal change detection [33]. In the case of assessing and monitoring land degradation using environmental proxies, NDVI is used as the dependent variables for the establishment of change trajectories.

There are mainly two different types of time-series: a stock series, and a flow series. A stock series is a measure of certain attributes (value or quantity) at a point in time (such as the number of farms in fallow, or the rate of unemployment). A flow series is a measure of activity over a given period (such as rainfall in days of the week; NDVI in months of the year; or stream flow rate in years of the decade). The main difference between a stock and a flow series is that flow series are more likely to be affected by effects related to calendar events. For example, the rainy season (which is associated to increases in vegetation activity in arid and semi-arid environments) tends to be a clearly determined period in the annual calendar of many areas. Both the stock and the flow series can be seasonally adjusted using the same seasonal adjustment process. Seasonal adjustment is the process of estimating and then removing systematic and calendar related influences from a time series. It is important to seasonally adjust observed data because seasonal effects can conceal the true underlying movement in the series.

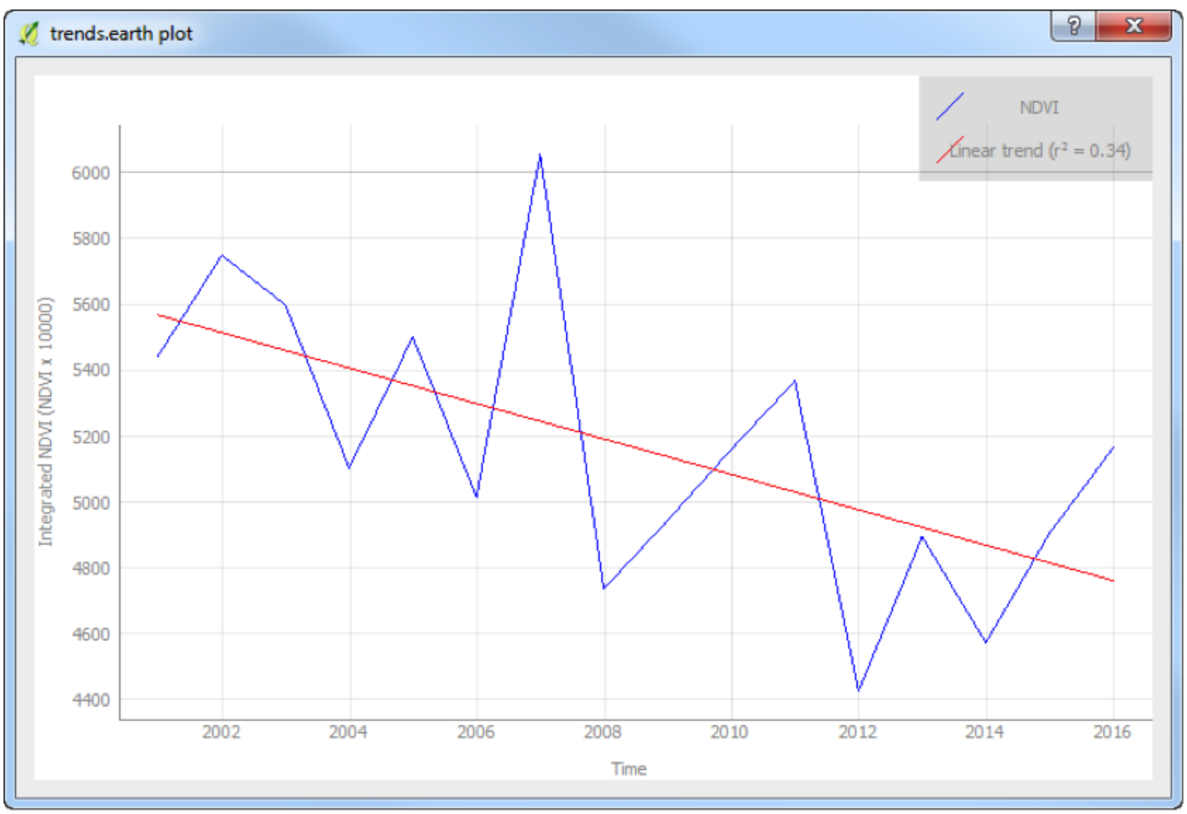

Figure 7. Trends.Earth extract of NDVI time-series of a rice field in Western Kenya. The data is derived from MODIS (MOD13Q1) 250-meter images at 16-day intervals for a single pixel.

Seasonal effects can also conceal some non-seasonal characteristics that may be of interest to analysts. While important, seasonal adjustment should be used after careful contemplation. When a time series is dominated by the trend or irregular components, it is nearly impossible to identify and remove what little seasonality is present. In such a case, seasonally adjusting a non-seasonal series is impractical, and will often introduce an artificial seasonal element into the series.

Time series are important because they can be used to identify and analyze the characteristic patterns of behavior or performance over time. They can, therefore, serve to add the historical perspective of the variable being investigated into the current estimates, as well as perform forecasts into the future of such a variable.

A time series can be decomposed into four components (see Figure 14 for illustrations): the secular trend (smooth long-term direction), cyclical trend (data exhibit rises and falls that are not of fixed period); the seasonal (systematic, calendar related changes) and the irregular (unsystematic, short-term fluctuations, also known as residuals).

THE SECULAR TREND is the long term pattern of a time series. A trend can be positive or negative depending on whether the time series exhibits an increasing long term pattern or a decreasing long term pattern. The secular trend can be either linear or nonlinear (i.e. exponential or quadratic)

A CYCLICAL COMPONENT is any pattern showing an up and down movement around a given. Cyclical variations are therefore quasi-regular fluctuations around the long-term trend. These can last for periods longer than a calendar year and are commonly found in business cycles. The duration of each cycle depends on the type of business or industry being studied.

THE SEASONAL COMPONENT is present when a pattern exists to indicate that a series is influenced by seasonal factors (such as season of the year). Seasonality is always of a fixed and known period and can be identified by regularly spaced peaks and troughs in a time-series, which have a consistent direction and approximately the same magnitude relative to the trend.

THE IRREGULAR COMPONENT is what remains after the seasonal and trend components of a time series have been estimated and removed. It is also called the residual. The irregular component results from short-term fluctuations in the series, which are neither systematic nor predictable. In a highly irregular series, these fluctuations can dominate movements, which will mask the trend and seasonality of the series.

7.3 ASSESSING ENVIRONMENTAL CHANGES USING TIME-SERIES IMAGERY

Before embarking on the task of assessing and reporting changes using any sources of data and methodologies, it is important to clearly define what is and would be understood as a change in the context being studied. What may be agreed upon as change may sometimes be contextual, and even in some cases controversial. This is especially the case for the definition and interpretation of changes that are supposed to indicate the direction of socioeconomic or cultural well-being of communities. A holistic approach to arriving at a working definition that involves all stakeholders associated with the phenomenon being studied is therefore advisable.

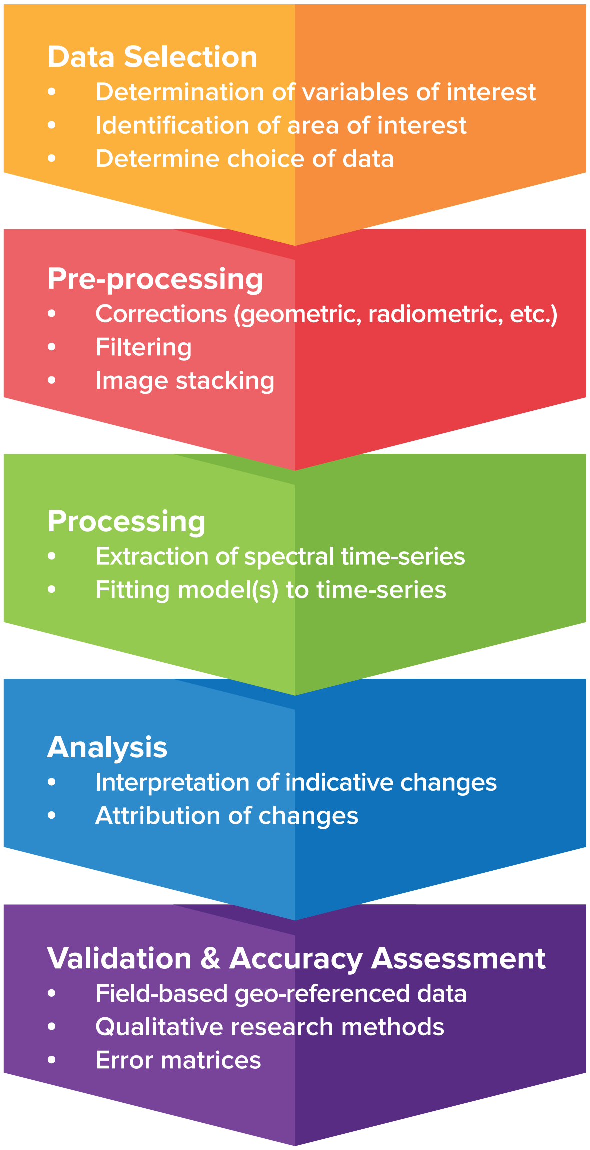

Figure 8. The general process flow for deriving and analyzing NDVI time-series for land cover change studies.

7.4 DATA SELECTION

The initial step involves making selections of images that are suitable for and can be used to respond to the task in question (Figure 8). Many considerations go into determining the choice of data utilized for any time-series studies of land cover changes or vegetation dynamics. Among some of the most important considerations are the resolutions (temporal, spatial, and radiometric) of the data.

Data spacing considerations are important, as different applications of time series analysis may demand different spacing options for acquired data. Some analyses require equally spaced data (for example the period of annual peak phenology), while others can deal with the entire acquisition record of usually unequally spaced time series. Applications of earth observation data for land cover change assessments have to consider several sensor and image characteristics:

1. **SPATIAL RESOLUTION** refers to the size of the smallest feature that can be detected by a satellite sensor or displayed in an image. This is limited by the pixel size which, in turn, depends on the instantaneous field of view of the sensor (a measure of the ground area viewed by a single detector element at a given instant). Therefore, a high-resolution image that reveals fine detail is one with a small pixel size, and a low-resolution image has large pixels that reveal only coarse features. When using satellite imagery for change detection analysis, the image pixel is the fundamental unit of analysis and is used to detect and measure changes without taking into considering the spatial context.
2. **TEMPORAL RESOLUTION** refers to the time between images during which a particular area can be recorded. For instance, the re-visit time for SeaWiFS is 2 days, 16 days for Landsat TM, 26 days for SPOT, and 35 days for IKONOS. Some NDVI applications can make do with data of long temporary resolutions; others, such as the development of early warning systems for the sudden loss of habitat from phenomena such as wild fires or illegal logging may require daily or weekly acquisitions.
3. **IMAGE SIZE** refers to the area covered by a single image, defined by the path width and the distance of the satellite along its path. Path widths range from as little as 8km to 2000km.

4. **IMAGE AVAILABILITY** is a critical consideration; access to affordable sources of data of the correct spatial and temporal resolutions determines the scope of any assessment. Notwithstanding the numerous satellite image types and sources, only a few are suitable for the assessment of many environmental phenomena at the country scale, due either to high costs or the data archive being too small.

Multi-temporal datasets are essential for the assessment and monitoring of land degradation [18, 20, 22, 26]. For most environmental applications, the available remotely-sensed products rarely meet all the above requirements, so trade-offs have to be made between some of these characteristics. A large path width of low spatial resolution means that large areas can be covered with one or few images, so the volume of data is modest. These systems generally have a long archive of consistent data from which long-term changes can be assessed. On the other hand, data of high spatial-resolution are associated with a smaller path width, longer return period, and a large volume of data that demands substantial data storage, manipulation, and analysis. These datasets also tend to be pricey - out of reach of most potential users outside the research community of the satellite launching program or country. High-spatial-resolution data (IKONOS, GeoEye, QuickBird, Worldview-1 and 2) find application in fine-scale assessments.

Examples include application in precision farming. Medium spatial resolution data such as Landsat TM and Terra ASTER are used at the regional scale. Coarse-spatial-resolution data like AVHRR and MODIS support archives of long time series that are invaluable for NDVI-based assessments from the national to global scale. To achieve the best of all possible worlds, efforts have been made to integrate datasets of different spatial and temporal resolution. For example by adding the panchromatic band (much of the visible and near-infrared portion of the electromagnetic spectrum with 15m resolution) on the Landsat 7 ETM+ sensor in which other bands are 30m or greater, the visual sharpness of the image is enhanced.

7.5 PRE-PROCESSING OF IMAGE DATA

After the desired set of data has been selected, several steps of initial processing are required to make the data fit for use in the analysis (Figure 8). A time-series derived from satellite imagery contains a combination of seasonal, gradual and abrupt ecosystem changes occurring in parallel within the data. It also contains noise introduced by the sensing environment, geometric errors, atmospheric scatter, clouds [34], and many other phenomena that need to be taken care of to get the data into a pristine format for good analysis. Pre-processing of data involves a number of tasks geared toward taking care of these errors and “noise” in the data. Such pre-processing may involve many established practices. The ultimate aim of pre-processing images is to enhance the quality of the image data by reducing or eliminating radiometric and geometric errors caused by internal and external conditions that were present when the image was being captured.

When a sensor on board a spacecraft or aircraft observes electromagnetic energy reflected by a body on the ground surface, this energy is influenced by factors such as the sun’s azimuth, haze, aerosols, ground elevation, etc. The electromagnetic radiation can be described as having some “noise,” which makes it different from energy that would be observed from the body, and much shorter distances.

Radiometric correction involves removing sensor or atmospheric ‘noise’, to obtain the real irradiance or reflectance. This can lead to the modification of digital number (DN) values to account for “noise” originating from the intervening atmosphere between the sensor and the ground surface, the sun-sensor geometry, as well as errors and gaps on the sensor itself.

Images can be geometrically distorted either as a result of internal distortion arising from the geometry of the sensor, or external distortion caused by the shape of the object or the geometry of the surface in which it is observed.

These distortions can result in misalignment between the actual image coordinates and the coordinates to which the image will be projected and used. Geometric correction is the process of establishing the relationship between the image coordinate system and the geographic coordinate system using resources such as the calibration data of the sensor, measured data of position and altitude, ground control points, and atmospheric condition when the image was taken. The goal of geometric correction is to avoid geometric distortions from a distorted image.

After the various corrections have been performed on data, the steps that follow depend on the type of analysis for which the images will serve. For analysis such as land cover classifications that may require a lot of visual assessment and user input, the images are enhanced to improve the visual appearance of objects in the images. The number of image enhancement techniques are many [35]. However, some of the common ones include image reduction, image magnification; contrast adjustments, band rationing, transect extraction, spatial filtering, Fourier transformations, principal components analysis, and texture transformation. The goal of image enhancement procedures is to improve the visual interpretability of any image by increasing the apparent distinction between the features in the scene.

This objective is to derive an image from the original image that increases the potential for visually interpreting more information from the data [35]. Enhancement operations are normally applied to image data after the appropriate restoration procedures have been performed. This is especially the case with procedures for removing noise. Noise removal is an important precursor to most enhancements procedures. Besides these enhancement techniques, data for pixel-by-pixel time series analysis may include the application of specific filters to smooth raw data. Different filters are used to achieve different tasks in these processes.

7.6 DATA ANALYSIS

Time series analysis involves methods for analyzing time series data to extract meaning and other characteristics of the data. Digital image processing relies primarily on the radiance of image picture elements (called pixels) for each band. The radiance in each pixel is then translated into a DN. This is a gray scale intensity ranging from the lowest intensity (black) of 0 to the highest intensity which depends on the bit size of the pixel. For example, for an 8-bit image, the maximum intensity value will be 255 (or white); 65535 for a 16-bit image; 16777215 for a 24-bit image. A DN for a specific band will indicate the intensity of the radiance at that wavelength.
When using time-series data to analyze vegetation activity, there are some questions we are interested in at the conceptual level. We may want to know:

- Is there a discernible trend in vegetation activity, and how significant is this trend? In other words, do the measurements tend to increase (or decrease) over time?
- Is there seasonality, meaning that there is a regularly repeating pattern of highs and lows related to calendar seasons?
- Are there irregular values that fall outside the general trending pattern of the vegetation? In other words, are there cases of very positive or very negative performance of vegetation (indicated by outliers on the regression line)?
- Are there any abrupt changes to either the level of the series or the variance?

For statistical analysis of multi-decadal time series (especially with climate related variations of interest), the most common statistical parameters that are derived from time series on a per pixel basis are: mean, minimum/maximum, standard deviation, variability, anomalies, turning points, and trends [36]. NDVI values of these statistical parameters can be used to examine the time series (Figure 9).

PHENOLOGICAL PROPERTIES: A multi-annual series of vegetation activity comprises several annual cycles concatenated to form such a series. Each annual cycle of vegetation activity has phenological characteristics and terms specific to understanding and assessing them. The United States Geological Survey has compiled a summary of these terms, which include most aspects of plant phenological activities as well as their associated implications for the interpretation of NDVI data. Together these terms (Table 2) are defined regarding the phenological the assessment and monitoring of vegetation using NDVI.

TIMESAT is a software package developed by Per Jonsson and Lars Eklundh for analyzing time-series of satellite sensor data [37]. The software investigates the seasonality of satellite time-series data and their relationship with dynamic properties of vegetation [37-39]. These seasonality parameters include (a) beginning of season, (b) end of season, (c) length of season, (d) base value, (e) time of middle of season, (f) maximum value, (g) amplitude, (h) small integrated value, (h+i) large integrated value (see Figure 10).

TIMESAT is open source software, provides three different smoothing functions to fit time-series data (asymmetric Gaussian, double logistic and adaptive Savitzky–Golay filtering) as well as a user-defined weighting scheme to be applied in the smoothing process.

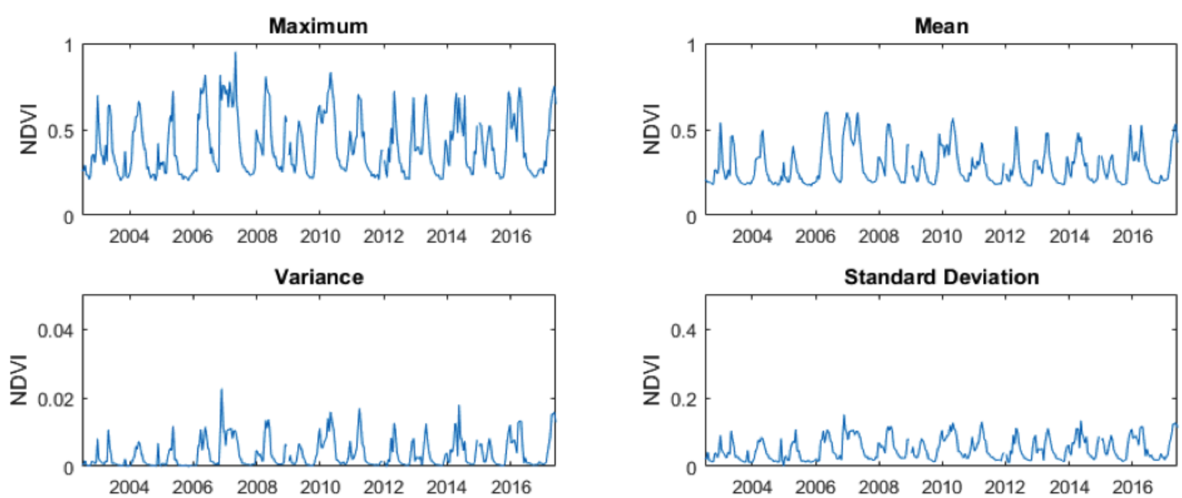

Figure 9. NDVI statistics for an area in Boka Dovu, outside Arusha, Tanzania. This is summary statistics for 81 pixels of MODIS (MOD13Q1) 250-meter resolution at 16-day intervals.

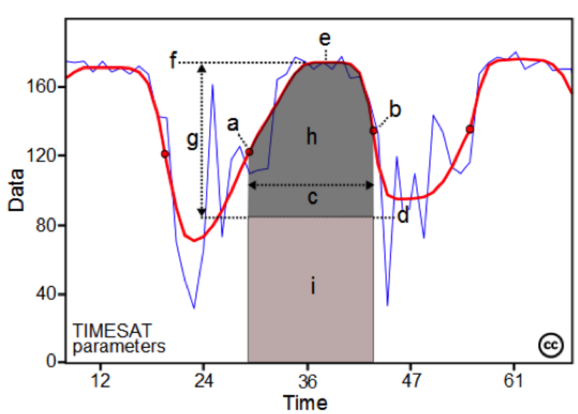

Figure 10. Seasonality parameters generated by a TIMESAT run. Source: TIMESAT web page at: http://web.nateko.lu.se/timesat/timesat.asp

TABLE 2.

INTERPRETATION OF ANNUAL PHENOLOGY DATA[7]

ACRONYM	PHENOLOGICAL INTERPRETATION	DESCRIPTION
SOST: START OF SEASON - TIME	Beginning of measurable photosynthesis in the vegetation canopy	Day of year identified as having a consistent upward trend in time series NDVI
SOSN: START OF SEASON – NDVI	Level of photosynthetic activity at the beginning of measurable photosynthesis	NDVI value (baseline) identified at day of year identified as a consistent upward trend in time series NDVI
EOST: END OF SEASON – TIME	End of measurable photosynthesis in the vegetation canopy	Day of year identified at the end of a consistent downward trend in time series NDVI
EOSN: END OF SEASON – NDVI	Level of photosynthetic activity at the end of measurable photosynthesis	NDVI value corresponding with the day of year identified at the end of a consistent downward trend in time series NDVI
MAXT: TIME OF MAXIMUM	Time of maximum photosynthesis in the canopy	Day of year corresponding to the maximum NDVI in an annual time series
MAXN: MAXIMUM NDVI	Maximum level of photosynthetic activity in the canopy	Maximum NDVI in an annual time series
DUR: DURATION	Length of photosynthetic activity (the growing season)	Number of days from the SOST and EOST
AMP: AMPLITUDE	Maximum increase in canopy photosynthetic activity above the baseline	Difference between MAXN and SOSN
TIN: TIME INTEGRATED NDVI	Canopy photosynthetic activity across the entire growing season	Daily (interpolated) integration of NDVI above the baseline for the entire duration of the growing season

[7] Source: USGS: https://phenology.cr.usgs.gov/methods_metrics.php

LINEAR REGRESSION: A linear regression of the annual integrals NDVI data is one of the most common trend analysis methods used to investigate trends in vegetation dynamics. In this procedure, linear trends are estimated by regressing the data as a function of time on the pixel(s) of interest (Figure 12). Trends are a common feature of time series data. Using regression, we can model and forecast the trend in time series data by including t=1,…,T,t=1,…,T, as a predictor variable:

$$y_t=\beta_0+\beta_1 t+\varepsilon_t.$$

A linear regression analysis results in an equation of a regression trend line that explains the relationship between NDVI values and time for the cells of interest.

A positive slope would indicate an increasing trend while a negative slope indicates a decreasing trend. It is the a common procedure to check for the significance of slopes using a significance test with a predetermined confidence level, to understand how strong the positive or negative trend is. When investigating land degradation, the mere presence of the negative trend in NDVI may not directly indicate the manifestation of degradation. Many factors can contribute to negative trends in NDVI. For example, in agricultural ecosystems, changes in crop type may contribute to a negative trend, which may not necessarily mean land degradation.

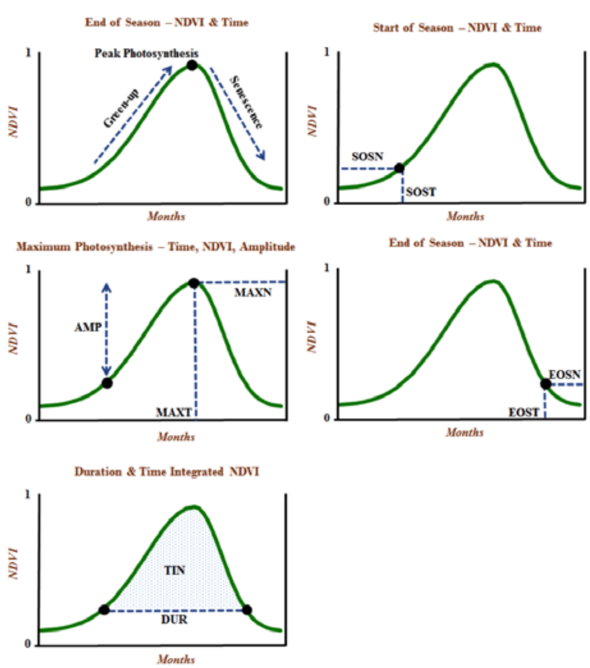

Figure 11. Illustration of vegetation cycle showing key phenological metrics. See Table 2 on page 39 for the interpretation of acronyms.

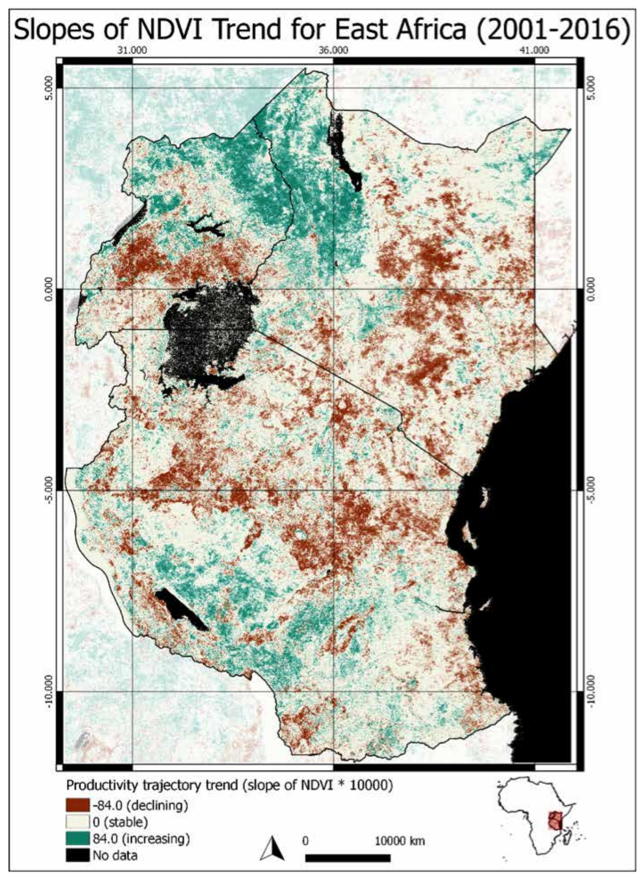

Figure 12. Slopes of NDVI trends for three countries of East Africa (Kenya, Tanzania, and Uganda) for the period 2000-2016. The data is derived from MODIS (MOD13Q1) 250-meter images at 16-day intervals.

SEASONAL TREND ANALYSIS: Seasonal trend analysis is used to identify trends in the essential character of the seasonal cycle while rejecting noise and short-term variability seasonal cycle. Eastman et al. [40] explain its mechanics and use at length. The process is based on a two-stage analysis of the time-series. In the first step, harmonic regression is applied to each year of images in the time series to extract an annual sequence of overall greenness and the amplitude and phase of annual and semi-annual cycles [41]. In these greenness parameters, amplitude 0 represents the annual mean NDVI or overall greenness for each year; amplitude 1 represents the peak of annual greenness, and phase 1 denotes the timing of annual peak greenness, represented by the position of the starting point of the representative sine wave of annual greenness. An increase in the phase angle means a shift in the timing to an earlier time of the year, while a decrease in the phase angle indicates a shift in the timing to a later time of the year. Eastman et al. [41] identified that values of phase image potentially range from 0 to 359, such that each 30° indicates a shift of approximately one calendar month. In the second step, trends over years in the greenness parameters were analyzed using a Theil–Sen median slope operator. This process is robust to short-term inter-annual variability up to a period of 29% of the length of the series [40].

MONOTONIC MANN-KENDALL TREND ANALYSIS: The monotonic Mann-Kendall trend analysis is a nonparametric trend indicator computing the degree to which a trend is consistently decreasing or increasing [42]. The trend test determines whether the data increases or decreases between two subsequent data points (pair-wise combinations of values) in time and values an increment of 1 and a decrement of - 1. The resulting Mann-Kendall statistic is therefore the relative frequency of decreases minus the relative frequency of increases and ranges from -1 to 1. A positive trend will indicate that the data increases more often than they decrease over time and vice versa (Figure 13). While the simple linear regression tends to be sensitive to outliers, the Mann-Kendall trend test is resistant to them [42].

THEIL-SEN SLOPE (TS): The Theil-Sen (TS) procedure is a rank-based, nonparametric statistical method for calculating the median of the slopes between pair-wise combinations over time, and can tolerate up to approximately 30% noisy input observations without influencing the trend estimate [43, 44]. The Thiel-Sen is robust against seasonality, non-normality and serial dependence [43, 44]. It is used to quantify the temporal trends in the NDVI time series. The Theil-Sen procedure is therefore effective for determining trends in a noisy series as it performs multiple estimates of the slope derived from all pairs of observations [43, 44].

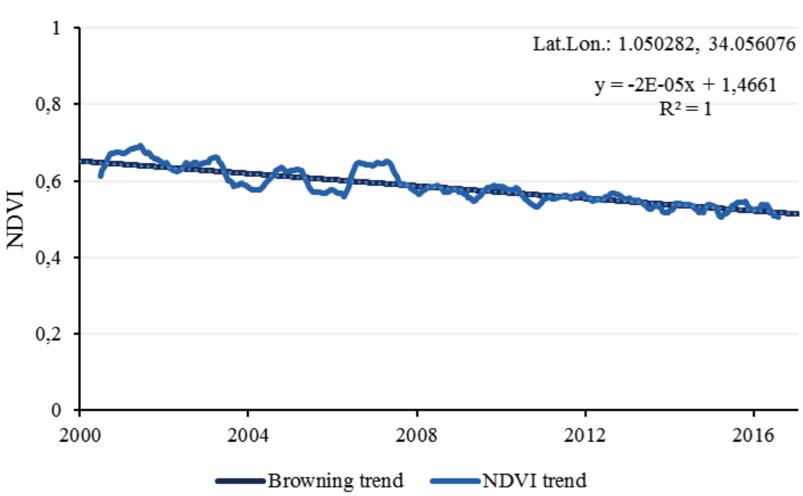

Figure 13. Browning trend of an intensively farmed valley in the east of Uganda. The data is of raw NDVI values for a single 250-meter pixel from MODIS (MOD13Q1) at 16-day intervals.

BREAKS FOR ADDITIVE SEASONAL AND TREND (BFAST): Long-term NDVI trend calculations, such as derived from OLS or Mann-Kendall analyses show the overall trend of vegetation of the entire study period. Through this analysis, one cannot understand if there have been episodes of vegetation performance that did not follow the general trend of the entire series. In other words, the analysis may want to know if the vegetation has had periods when the trends were different from the general pattern presented by the long-term picture. Have there been breaks in the general trend observed? A break in a time series trend indicates changes between positive and negative trends within a period of analysis period [45]. BFAST [29, 46] has emerged as one of the most useful tools for examining breaks in time-series. BFAST[8] integrates the decomposition of time series into trend, season, and remainder components (Figure 14 and Figure 15).

The process iteratively estimates the time and number of abrupt changes within time series and characterizes change by its magnitude and direction [29, 46]. The BFAST package in R has enabled the possibility to classify the trends using the following classes: monotonic increase; monotonic decrease; monotonic increase - with positive break; monotonic; decrease - with negative break; interruption - increase with negative break; interruption - decrease with positive break; reversal - increase to decrease; reversal - decrease to increase (Figure 15).

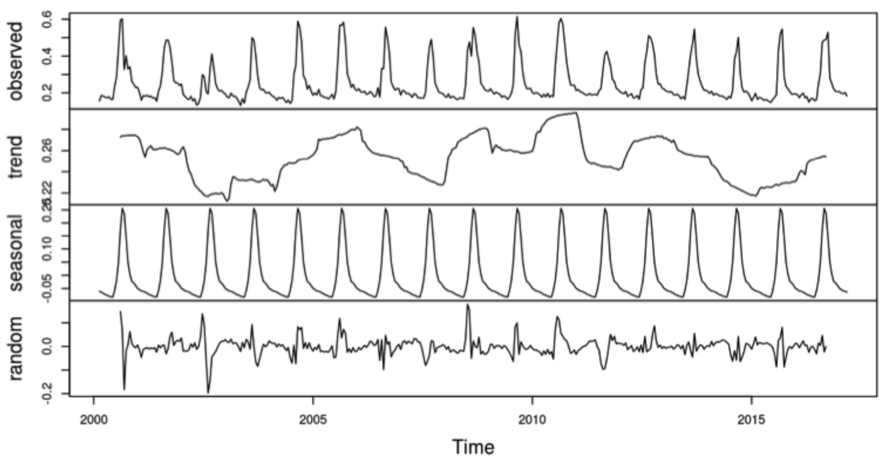

Figure 14. Decomposition of additive time-series using BFAST into principal components (trend, seasonal and random) for a six-hectare heavily grazed area in Dodji, Senegal. The data is derived from MODIS (MOD13Q1) 250-meter images at 16-day intervals.

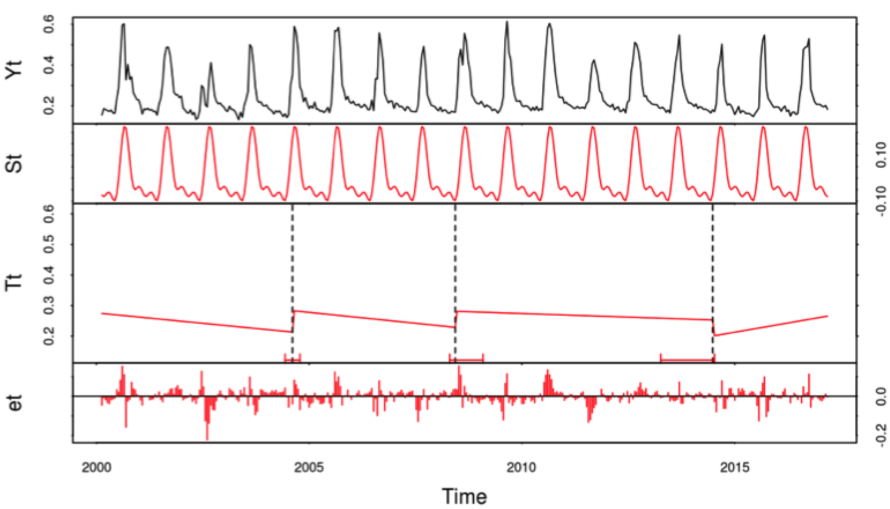

Figure 15. The BFAST plot for Dodji in Senegal. Yt = original data; St = fitted seasonal component; Tt = trends with breakpoints; and et = remainder (estimated noise).

[8] The BFAST package for implementation in the R environment (http://bfast.r-forge.r-project.org) has been developed by the Laboratory of Geo-Information Science and Remote Sensing, Wageningen University. Description by Jan Verbesselt (http://www.wur.nl/en/Persons/Jan-Verbesselt.htm): The BFAST package provides generic functionality for continuous change monitoring, trend analysis, and near-real time disturbance detection of any kind of disturbance or change process (gradual e.g. forest degradation to more abrupt like deforestation, droughts). The methods can be applied to any series of satellite images going from for example MODIS, Landsat, Rapid Eye, or RADAR data (see papers below). Besides that generic change detection functions bfast for time series segmentation, or bfastmonitor for near-real time monitoring can be applied to any kind of time series like for example rainfall, temperature, or dendrochronology series.

RAIN USE EFFICIENCY[9] (RUE): The concept of rain use efficiency (RUE) was first coined by Le Houerou (1984). RUE is the ratio of above-ground NPP to annual precipitation [47-49] and tends to decrease with increase in aridity and potential evapotranspiration [25, 49]. Since NPP is the rate of carbon dioxide fixation by vegetation after losses through vegetation respiration [21], NPP is therefore closely related to NDVI. Given that RUE is calculated by expressing NPP as a ratio of annual precipitation, the reason why RUE has been widely used as a proxy for the assessment of land degradation becomes apparent. RUE has been used to assess LD at field level, regional, level, national and global levels. It has been observed that RUE is generally lower in degraded lands than in un-degraded lands [25]. Fensholt et al. [48] notes 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 issue. This contestation is attributed to methodological approaches, differences in scale and ecological contexts [47, 48, 50-52]. Since vegetation reacts in the short-term to natural variations, RUE needs to be examined over the long-term to exclude false alarms [5]. The common practice in estimating RUE is to use summed NDVI as an EO-based proxy for NPP [48]. The nature of the relationship between ΣNDVI and annual precipitation (proportionality, linearity, or nonlinearity) has been seen as an important consideration when estimating satellite-based RUE time-series [53]. 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 [54].

RUE continues to be one among many preferred approaches of separating the effects of rainfall (natural) from anthropogenic impacts on vegetation productivity and the detectability of land degradation. The scientific consensus on its application and interpretation is as of yet not fully achieved [47, 55].

Residual Trend Analysis (RESTREND): RESTREND involves regressing ΣNDVI from annual precipitation and then calculating the residuals - the difference between observed ΣNDVI and ΣNDVI as predicted from precipitation [48, 51, 56]. The two methods were tested (RUE and RESTREND), using AVHRR NDVI from 1985-2003 and modeled NPP from 1981-2000 to estimate vegetation production in South Africa [56]. The study found that RUE was not as reliable an indicator of land degradation as RESTREND. While RESTREND was found to offer better prospects, the study cautioned on the need for local level investigations to identify the cause of negative trends [56].

Even though the RESTREND technique has proven to be useful for estimating RUE, it is urged that its effectiveness would be robust for pixels for which there is a high linear correlation between ΣNDVI and annual precipitation – in other words, where rainfall is the dominant factor controlling ΣNDVI [57]. It has also been noted that since positive and negative residual trends can result from natural ecological processes, the RESTREND technique can be appropriate for problem identification at a regional scale, while causes of negative trends at the local level would be more appropriately identified by local investigations [56].

[9] In Trends.Earth,the analysis of both RUE and Pixel RESTREND is done using on the one hand either MODIS or AVHRR data for NDVI, and a choice of precipitation datasets as the explanatory dataset. These precipitation datasets include: (i) The Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks- Climate Data Record (PERSIANN-CDR) provides daily rainfall estimates at a spatial resolution of 0.25 degrees in the latitude band 60S - 60N from 1983 to the near-present; (ii) The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) is a 30+ year quasi-global rainfall dataset. Spanning 50°S-50°N (and all longitudes), starting in 1981 to near-present; (iii) The Global Precipitation Climatology (GPCP) which provides precipitation estimates on a 1-degree grid over the entire globe for the period October 1996 – present; (iv) The Global Precipitation Climatology Centre (GPCC) monthly precipitation dataset from 1901-present is calculated from global station data; (v) ECMWF's ERA I data for volumetric soil water layer data; and (vi) NASA's Moderate-Era Retrospective Analysis for Research and Applications (MERRA 2) data.

7.7 VALIDATION

The accuracies of change detection using remote sensing depend on many factors. Jiangya [33] identifies some of the key determinants of change detection accuracies to be the availability and quality of ground reference data, precise geometric registration and calibration or normalization, the complexity of landscape and environment, methods or algorithms used, skills and experience of the analyst, as well as time and cost restrictions. Other determinants include spectral, spatial, and temporal characteristics of the multi-date imagery and the types of processes affecting land change dynamics.

Ground truth is a term used in various fields to refer to information provided by direct observation (i.e. empirical evidence) as opposed to information provided by inference. In remote-sensing, ground-truthing describes the process of verifying satellite image information and results of analysis with what is already known about the location on the ground. Our definition of ground-truthing within the context of this report builds heavily on direct on-site assessments for triangulating and interpreting results of remotely sensed data[10]. Ground-truthing is the process of verifying, by direct observation, or determination through other forms of on-the-ground validation (through surveys or interviews) something that is hypothesised, assumed or inferred. See section 10 for some methods of triangulating and validating results of remotely sensed data analysis using other research methods.

Ground-truth information is often referred to as "reference data," involves the collection of measurements or observations about objects, areas or phenomena that are being remotely sensed[11]. Tom Server outlines two main uses of ground-truth information: the data can aid in the interpretation, analysis and validation of the remotely sensed data; and, such information helps in understanding the socioeconomic forces behind land cover modifications due to human activities. Ground-truthing is an expensive exercise as it involves travel (sometimes over long distances and difficult circumstances), as well as a host of logistical and equipment costs. It is also time consuming, and may involve a lengthy process of negotiating access to the locations or communities of interest.

This may be especially true for rural areas and smallholder farming communities as well as other land resource users that are not used to researchers asking them about their livelihood activities. Proper negotiation and access is needed to reduce the potential for suspicion among local communities. In describing sources of data to support remote sensing ground-truthing activities, Nicholas M. Short used the fulfilment of criteria such as multistage, multilevel, multisensory, multispectral, mutitemporal, multisource and multiphase[12]. It would be desirable to obtain ground-truthing data to validate vegetation change analysis that meets the criteria of multitemporal - obtained at different times; multisource - should come from many relevant, but not necessarily interrelated, sources; and multiphase - data may be correlated with one another and with other types of remote sensing data.

[10] There are specialized studies and guides for triangulating, assessing, and reporting land degradation at field level. See for example the work of Michael A. Stocking and Niamh Murnaghan (2001) Handbook for field assessment of land degradation. More on approaches, tools and technologies for supporting decision making on sustainable land management practices can be found in the vast array or resources provided by the World Overview of Conservation Approaches and Technologies (WOCAT). This initiative is recognized by the UNCCD secretariat as the primary recommended database for UNCCD best practices on sustainable land management (SLM) technologies. Tools such as questionnaires that can be used in the validation of desktop-based of land degradation studies at field and landscape level can also be found within the WOCAT resource base https://www.wocat.net/.

[11] Find a practical example of ground truthing described by NASA scientist Tom Sever here: https://weather.msfc.nasa.gov/archeology/peten_groundtruth.html

[12] Read more on the characteristics of ground-truthing data on Section 13 of the online book by Nicholas M. Short, titled: Remote Sensing and Image Interpretation & Analysis (http://priede.bf.lu.lv/GIS/.Descriptions/RST/TofC/toc1.shtml).

VIII. USE OF NDVI-BASED ASSESSMENTS FOR SOME COMMON LAND CONDITIONS IN AFRICA

8. USE OF NDVI-BASED ASSESSMENTS FOR SOME COMMON LAND CONDITIONS IN AFRICA

While LD is a global phenomenon that affects about 30-40% of the global land surface [21] some regions and biomes are more prone to degradation than others are. Some major influences of land cover changes are climatic conditions, geomorphological processes such as soil erosion, ecological processes such as vegetation succession, human land use that leads to alterations in land cover and changes the speed of some geomorphological processes are examples [58]. Others include inter-annual climate variability, climate changes, natural disasters, changes in the composition of biodiversity and associated prey-predator relationships, and well as modifications in the trophic chains and interactions in ecosystems [59].

About 65% of agricultural land in Africa has suffered some form of physical and chemical degradation resulting from human activities and climate variability [60, 61]. Human activities and climate variability are responsible for the degradation of more than 30% of the continent's pastureland, about 19% of its forests and some of its water resources [60-62]. Drivers of land degradation are many and diverse (see Table 3). The scale, severity, and impact of land degradation on the environment and people will depend on many factors. These include the type of degradation, its location and size, and in many cases its perception, and efforts made by human populations to address the phenomenon. A number of direct and indirect drivers can explain land degradation (Table 3).

Local activities that contribute to LD include mining, unsustainable farming practices, overgrazing, pollution from industrial and non-industrial sources, and landscape modification, among many others. Land degradation resulting from the human conversion of natural habitats are most extensive in tropical dry forests (69% converted in SE Asia), temperate broadleaf and mixed forests, temperate grasslands and savannahs (> 50% loss in North America), and Mediterranean forests, woodlands and scrub [63]. Human activities responsible for LD go beyond farming practices, deforestation, and other direct human interactions with the land. The causes of desertification (a process of land degradation affecting people in arid and semi-arid climates) to include international economic activities to unsustainable land use practices of local communities [18].

The impact of degradation tends to be more severe in areas with high incidences of poverty. Poor populations usually have smaller resource margins to cope with adversity. They, therefore, tend to have lower capacities to deal with the direct consequences of land degradation, such as a decline in the provision of ecosystem services and environmental resources on which they may be depending. In Africa, where a majority of the population depends on crop and livestock production for livelihood, land degradation may have substantial impacts on the socio-economic well-being of entire communities and even countries.

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TABLE 3.

CATEGORIZING DRIVERS OF LAND DEGRADATION. SOME OF THE FACTORS THAT MAY UNDERLIE THE PROCESSES THAT ARE REVEALED BY SATELLITE IMAGERIES – TO BE EXAMINED BY COMPLEMENTARY RESEARCH PROCESSES TO EARTH OBSERVATION.

CATEGORY OF DRIVERS	SPECIFIC DRIVERS OF LAND DEGRADATION
DIRECT DRIVERS	Excessive use of chemicals
	Inappropriate waste disposal
	Insufficient drainage
	Overgrazing
	Shortening of elimination of fallow periods
	Poor land management
	Deforestation
	Overexploitation of wood cover
	Use of fire on landscapes for different reasons
	Poor irrigation practices
	Introduction of non-native herbivores
	Pollution and other industrial causes
	Waterlogging
	Cultivation of marginal lands
INDIRECT DRIVERS	Population growth
	Limited availability of land associated with poor land management
	Poor land tenure and tenancy systems
	Short-term economic pressures on small-holder farmers limit adoption of conservation methods
	Limited economic resources restrict investment in land management
NATURAL	Strong rains
	Floods
	Strong winds
	Climatic variations and changes
	Mass movements
	Droughts
	Pest infestations of above ground biomass

8.1 LAND USE AND LAND COVER CHANGES (LULCC)

Land cover is the observed biophysical cover on the earth's surface [64]. In a strict sense, it should be limited to the description of vegetation and artificial (human-made) features on the land surface. Accordingly, areas where the surface consists of bare soil or bare rock outcrops are land itself rather than land-cover [64]. While the inclusion of water surfaces in the definition of land-cover has remained a contentious issue, the scientific community usually includes these features within the term, giving land-cover a broader definition than would otherwise be in a strict definition.

Land-use and land-cover change (LULCC) is a general term used to refer to the human modification of Earth's terrestrial surface [65]. While human modification of land and land-cover to obtain food, fuel, fiber and other materials have been occurring for thousands of years, current rates and intensities of LULCC are far greater than ever in history [66, 67]. Such LULCCs are having unparalleled changes in ecosystems and environmental processes (with potential to contribute to or accelerate LD) at local, regional and global scales, such as climate change, biodiversity loss and the pollution of water, soils and air [62, 65]. According to Townsend et al. (2014), among all forms of land cover changes, forest cover change regarding "deforestation is one of the most significant because of the magnitude of the resultant transformations in biophysical and ecological properties."

LULCCs emerge from interactions among and between components of coupled human-environmental systems. LULCC result from multi-scale drivers and proximate factors of land degradation, and are a function of combined socioeconomic systems and environmental systems [68]. Interest in the assessment of LULCC has therefore been picked up within international conventions such as the UNFCCC, CBD and UNCCD. This interest now features in major international assessments such as the Millennium Assessment, the FAO Global Forest Resources Assessment, and the Global Monitoring for Food Security.

Mayaux et al. [67] identified five main attributes of LULCC: (1) the nature of changes observed; (2) temporal permanence of these changes; (3) direction of change; (4) direction; (5) intensity and spatial distribution of changes. Land-cover changes may vary significantly on the temporal scale - hence the landscape may be affected for a few days (floods), some weeks (vegetation fires), a year (biomass density in the Sahel belt), a few years (deforestation), or for a longer period (urbanization) [67]. A majority of these changes have been known to affect vegetation.

The quantity and quality of vegetation cover is an important determinant in the evolution of the landscape, it degradation [25], and quality of environmental services landscapes can provide. Changes in vegetation cover, for example, is one of the key causal factors in causing other forms of land degradation such as drought, soil erosion and desertification [25]. Changes in vegetation cover (through deforestation for example) contribute to atmospheric greenhouse gas buildup in the atmosphere and can negatively affect biodiversity [69]. Vegetation cover is the main components of the terrestrial biosphere [70] and is a good indicator of global change, and time-series measurements of vegetation can be used as proxies for understanding the dynamics of processes occurring on the earth's surface [14].

Vegetation change is also an important indicator of the health of ecosystems and a good proxy to the vulnerability of the land to different forms of degradation [23, 53, 71, 72]. At local or regional scales, the modification or conversion of vegetation can have significant consequences to soil quality, soil and wind erosion, sediment transport and deposition, land productivity and local biodiversity. At the global scale, large-scale changes in vegetation cover can affect global biogeochemical cycles; contribute to climate variability; and the loss of biodiversity at the global scale.

8.1.1 NDVI IN LULCC ASSESSMENTS

Substantial research effort has been invested in the use of NDVI in assessing the location and extent of land use and land cover change at all spatial scales [54, 62, 73-76]. In fact, one of the most common uses of NDVI has been in the assessment of land cover changes. Since the early days of development and refinement of the index, its use in evaluation and monitoring of land cover change (especially in land uses related to vegetation dynamics) has been very popular. The application of NDVI in land cover studies has been carried out at different scales. At the global level, NDVI has been used for land cover classifications and mapping [77-80]. This has also been done at regional and national scales [74, 81, 82]. Localized studies applying NDVI for land cover research have also been carried out [24, 76, 83, 84]. While several approaches have been used to determine vegetation cover from NDVI, two main techniques stand out. That using the scaled NDVI or N* (proposed by Choudhury *et al*. 1994), defined as:

$$N^* = \frac{NDVI - NDVI_0}{NDVI_5 - NDVI_0} \qquad \text{Equation 3}$$

where $NDVI_S$ is the value of NDVI at 100% vegetation cover ($N^* = 1.0$) and $NDVI_0$ is the value for bare soil ($N^* = 0$). The second method involves estimating a linear relationship between green vegetation cover (V_c) and NDVI by measuring vegetation cover in the field and comparing it to satellite NDVI data [85, 86]. The regression relationship found and applied by Symeonakis and Drake (2010) in their study that monitored desertification and land degradation over sub-Saharan Africa was:

$$V_c = 1.33 + 131.877\ NDVI \qquad \text{Equation 4}$$

with fit statistics of $R^2 = 0.73$, $F = 241.63$, and $p = 4.26 * 10^{-27}$.

To assess changes in Sahelian tree cover, Horion et al. (2014) used long-term trends in dry season minimum NDVI derived from SPOT-VGT, MODIS Terra, and the AVHRR-derived GIMMS dataset as a proxy tree cover. The time-series of dry season minimum NDVI were found to be uncorrelated to dry grass residues from the preceding growing season and to seasonal fire frequency and timing over most of the Sahel [71]. This study suggests that minimum NDVI can be used as a proxy for assessing changes in tree cover in such arid and semi-arid ecosystems [71]. Some global hotspots of land cover changes are associated with major forms of degradation. These include areas such as Asia, which currently has the greatest concentration of areas of rapid, large-scale deforestation and dryland degradation [87]. It also includes Brazil's Amazon basin, which is a major hotspot of tropical deforestation and associated species depletion [87]. In regions of the European continent such as Siberia, increased logging is contributing to substantial forest degradation [87].

While land use and cover change can serve as pointers to the existence (or non-existence) of LD, care must be taken in interpreting the results of such studies. Veldkamp and Lambin (2001) caution on the need to distinguish between the location and quantity of change, as well as the causes of such changes. For example, while the use of NDVI can help in identifying the existence of deforestation (its rate and area affected), the underlying drivers of this phenomenon (with potentially huge outcome for land degradation) tend to be often remote in space and time, involve macroeconomic transformations and policy changes that may be operating at a higher hierarchical level [75]. It must also be noted that cases may exist where land cover change may not necessarily lead to degradation, but rather be considered as positive for the landscape [24, 66].

The availability of free data series with global coverage which dates back to the 1980s offers the opportunity for research into the long-term, spatially distributed dynamics of vegetation over large geographical areas [16].

Four main earth observation sensors are commonly used for global land cover mapping. These include: NOAA-AVHRR (spatial resolution of 1 km, 5 spectral bands); SPOT-Vegetation (spatial resolution of 1 km, 4 spectral bands); Terra or Aqua-MODIS (spatial resolution of 0.25 km / 0.5 km / 1 km, 36 spectral bands); and Envisat-MERIS (spatial resolution of 0.3 km, 15 spectral bands) [14]. While a majority of global and regional scale studies have initially been heavily based on the time series of NDVI derived from the NOAA's AVHRR, increasingly, the use of data from SPOT-VEGETATION, the NASA's MODIS, and the ESA's MERIS is gaining ground [53, 88].

8.2 DESERTIFICATION

The United Nations Environmental Programme (UNEP) took steps in 1992 to address the problem of encroaching deserts into adjoining regions by adopting the Convention to Combat Desertification, and designating the year 2006 as the International Year of the Desert and Desertification. One of the first steps of the UNCCD was to develop a definition of desertification as "land degradation in arid, semi-arid, and dry sub-humid areas resulting from various factors, including climatic variations and human activities" [89]. Desertification is a serious global threat, affecting both developed and developing countries [90].

Since the 1980s, remote sensing has been extensively used in the study of desertification in different parts of the world [5, 25, 48, 62, 91-94]. These studies have largely used a variety of vegetation indices derived from satellite products to study properties of vegetation (in semi-arid or arid environments), such as biomass productivity, leaf area index, total dry matter accumulation, and annual net primary productivity. The African Sahel (a semi-arid belt that straddles Africa from the Atlantic to the Red Sea) is particularly susceptible to protracted rainfall shortages [90, 95]. One such prolonged shortage began in 1968 and was responsible for the deaths of between 100,000 and 250,000 people [95].

In desertification research, NDVI has been used to (a) detect the status and trends of desertification, (b) categorize areas according to their severity of desertification, and (c) to identify or measure the effects of policies and actions on desertification [59].

8.2.1 NDVI IN DESERTIFICATION ASSESSMENTS

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 [14, 72]. This relationship has formed the basis for the application of satellite information (especially NDVI) in the detection, monitoring, and assessment of biomass dynamics worldwide. The initiatives are greatly helped by the availability of continuous global time series of vegetation, available since the early 1980s (De Jong et al., 2012).

It can be argued that the 1990s saw increased interest in desertification research, especially with regards to the African Sahel. In this decade, the African Sahel experienced an anomalously high rainfall, a feature that was captured by satellite imagery, analyzed using NDVI time-series, and coined in reports as a "greening of the Sahel" [93]. Follow-up studies used NDVI time series to investigate temporal and spatial patterns of the African Sahel's greenness and rainfall variability as well as their interrelationships [96, 97]. Herrmann et al. [96] concluded that while rainfall was the dominant causative factor for the increase in greenness, there was hypothetically a human-induced change superimposed on the climate trend. Anyamba and Tucker [98] used NDVI to identify close coupling of rainfall and a greening vegetation response in the African Sahel ecosystem.

They also underlined that when these changes are seen within the context of the long-term climate history of the African Sahel, the greener conditions are still far below the wetter conditions that prevailed in this ecosystem from 1930 to 1965.

Together, these studies (and many that have come after them) reinforced the substantial opportunities that the use of NDVI offered as a proxy for vegetation response on the land surface to precipitation variability (especially in arid and semi-arid ecosystems of the world). Herrmann et al. [96] also demonstrated the possibility of using NDVI as a proxy of environmental response to management. The effect of this management factor (usually denoted as "C" in models) has been included in some studies of environmental change [99].

8.3 SOIL EROSION

Erosion is defined as the displacement of earth solids (such as soil, mud, and rock) by the agents of currents such as the wind, water, or ice by downward movement in response to gravity [100]. The most common forms of erosion globally are by water and the wind [101]. Natural rates of soil erosion are low unless the surface of the ground is exposed directly to the wind and rainwater. Rates of erosion depend on several landscape factors such as soil texture, the gradient of slope and land cover; climatic factors such as the amount, as well as intensity and duration of rainfall and wind speeds. Human factors of land use (deforestation, soil tillage) and landscape modification (surface and underground water management) can also significantly contribute to influencing rates of erosion [100].

Effects of soil erosion can be on-site (where soil detachment and transportation occurs), or off-site (places where the eroded soil is deposited). On-site impacts of soil erosion include a reduction in soil quality as a result of the loss of the nutrient-rich upper soil layers, reduction the infiltration of water into the soil and decline in its water-holding capacity [102]. Soil quality and fertility decline resulting from erosion currently constitutes a major global problem and is a severe long-term threat to the sustainability of world agricultural productivity [100]. Off-site impacts of soil erosion may include the accumulation of sediments and agricultural pollutants in watercourses, leading to the silting up of dams, disruption of the ecosystems of lakes with potential for loss of biodiversity, and contamination of drinking water and downstream watercourses [102]. All of these constitute substantial environmental and socioeconomic problems in areas affected and warrant the investment of significant financial, technical and technological resources to address them.

Soil erosion is critical because it can lead to the loss of the surface, organic horizons of the soil – the horizon that contains most of the soil's organic material, and an exchange medium for transferring nutrients from the soil to plants [59]. Beside leading to a decrease in the productivity of affected areas, soil erosion also has the potential of reducing rates of infiltration of water into the soil, increasing sediment transfer to waterways or lower lying ecosystems that may suffer damage as a result.

8.3.1 NDVI IN SOIL EROSION ASSESSMENTS

In soil erosion studies, NDVI tends to be used in conjunction with other classical soil erosion estimation models, such as the fuzzy-based dynamic soil erosion model (FuDSEM), the Revised Universal Soil Loss Equation (USLE/RUSLE), Water Erosion Prediction Project (WEPP), European Soil Erosion Model (EUROSEM), Soil and Water Assessment Tool (SWAT) [103]. In Mulianga et al. [104] and Ai et al. [105], NDVI is used to both 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 in Kenya and China respectively using fuzzy-set theory and decision-making processes. In other cases, NDVI is used as a management factor - representing the effect of soil-disturbing activities, plants, crop sequence and productivity level, soil cover and sub surface biomass on soil erosion. This is the case in the study of the effect of vegetation cover on soil erosion in the Upper Min River watershed in the Upper Yangtze Basin, China [99]. It is also used as a land cover management factor (input into the RUSLE) model to determine the vulnerability of soils in a forested mountainous sub-watershed in Kerala, India to erosion [103].

NDVI for a majority of soil erosion research tends to be derived from Landsat TM/ETM (Enhanced Thematic Mapper) data with a spatial resolution of 30 m [105, 106] or Moderate Resolution Imaging Spectroradiometer (MODIS) data with a spatial resolution of 250m [104, 107]. These data are generally used in conjunction with Digital Elevation Model with a spatial resolution of 30 m [103-105, 107].

8.4 DROUGHT

Drought generally refers to a substantial decline in the amount of precipitation received over a prolonged period [108]. Droughts occur in practically all climatic zones and are recognized as an important environmental and developmental hazard, especially in the face of growing global water demand and climate change [4]. Droughts vary in severity and duration and may be associated with some effects that are immediate while others may be delayed [108, 109]. Some of its effects may also be directly observable, while others are insidious and difficult to either attribute, measure or decouple from the effects of other environmental causes [109]. Droughts can affect both surface and groundwater resources, leading to reduced flows, availability, and supply for human and ecosystem needs. Regarding land degradation, droughts can lead to deteriorated water quality, the decline in primary productivity of ecosystems which increases their vulnerability to agents such as erosion, and disturbed riparian habitats with the potential loss of biodiversity [108, 109].

Four main classes of droughts are commonly known [108]. These include meteorological drought which is a lack of precipitation over a region for a period of time. Hydrological drought refers to a period with inadequate surface and subsurface water resources for established water users of a given resources management system. Agricultural drought refers to a period with declining soil moisture and resulting crop failure without any reference to surface water resources. The socio-economic drought which is associated with a failure of water resources systems to meet water demands and thus associating droughts with supply of and demand for an economic good (water).

Droughts can affect ecosystems both ecologically and socioeconomically. In the short term, drought can decrease biomass yield for humans and forage availability for wildlife and livestock. Over extended periods, droughts have the potential of decreasing surface and sub-surface water supplies, robbing soils of their protective vegetal cover and exposing them to erosion, and driving the die-out of native plant and some animal species. Droughts are expected to increase in frequency, severity, and extent in the near future [110].

8.4.1 NDVI IN DROUGHT ASSESSMENTS

Studies have made use of NDVI (and associated vegetation indices) in detecting and investigating meteorological, hydrological and agricultural droughts in different parts of the world. An example of this is the use of NDVI anomaly[13] to identify the persistence of drought in the Sahel between 1982-1993 with a signature large-scale drought period during 1982-1985 [20]. Another method entailed combining 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 [111]. Lastly, by combining NDVI anomaly and Rainfall Anomaly Index in analyzing the spatial and temporal trend, prevalence, severity level and persistence of meteorological and vegetative drought in Gujarat, India [112]. The most common space-borne sensor for investigating and analyzing both meteorological and vegetative drought is the NOAA–AVHRR where both the NDVI (reflectance bands) and Land Surface Temperature (thermal bands) are used [20, 92, 113]. A sister-index that has been used in drought studies is the normalized difference water index (NDWI) [114]. The NDWI is derived from the NIR and short wave infrared (SWIR) channels that reflect changes in both the water content and spongy mesophyll in vegetation canopies [114]. It is defined as:

$$\mathrm{NDWI}=\frac{(\rho(0.86\mu m)-\rho(1.24\mu m))/}{(\rho(0.86\mu m)+(\rho(1.24\mu m))} \qquad \text{Equation 5}$$

where $\rho(\lambda)$ is apparent reflectance, and λ is wavelength. $\rho(\lambda)$ is equal to $\pi\, L(\lambda)/[\cos(\theta 0)\, E0(\lambda)]$ with $L(\lambda), \theta 0$, and $E0(\lambda)$ being the measured radiance, the solar zenith angle, and the solar irradiance above the earth's atmosphere respectively.

NDWI (calculated from the 500-m SWIR band of MODIS) has been used to detect and monitor the moisture condition of vegetation canopies over large areas [115-117]. Mishra and Singh [108] argue that NDWI may be a more sensitive indicator than NDVI for drought monitoring because NDWI is more sensitive to both desiccation and wilting of the vegetative canopy. While acknowledging the sensitivity of NDWI to changes in liquid water content of vegetation canopies, the developers of NDWI [114] are keen to stress that the index is: "complementary to, not a substitute for NDVI."

8.5 NATURE CONSERVATION

Among some of the human activities that threaten to breach planetary boundaries are anthropogenic contributions to climate change, ocean acidification, reduction of the stratospheric ozone layer, accelerated and unsustainable global freshwater use, high rates at which biological diversity loss, and large-scale changes land use [118]. These human activities lead to environmental changes that affect the distribution and dynamics of vegetation, animal populations, the systems they support, and the services to provide [119]. A growing body of knowledge is developing the tools and techniques of assessing and predicting ecosystem responses to these global environmental changes. In mapping and studying protected lands, for example, Yeqiao [120] notes the diversity of geospatial information that satellite remote sensing stands to provide is wide ranging. Such diversity can be seen in the different spatial scales (high spatial resolution, large area coverage), different temporal frequencies (daily, weekly, monthly, annual observations), different spectral properties (visible light, near infrared, microwave), and with spatial contexts (immediate adjacent areas of protected lands vs. broader background of land bases) [120]. In this knowledge development, the spatial component that links ecology, biogeography, environmental science, and satellite remote sensing is increasingly playing an important role [121].

The fusion of disciplines required to achieve optimum outcomes in the development and use of satellite remote sensing in biodiversity research, nature conservation and the sustainable use of natural resources is however still at its infancy [121]. Notwithstanding, several studies have demonstrated the potential of satellite remote sensing in a number of fields of biodiversity and nature conservation research [27, 120, 122, 123].

8.5.1 NDVI IN NATURE CONSERVATION RESEARCH

While traditional approaches to measuring species richness do provide useful information, such methods are spatially constrained in their application to large geographical areas [124]. Tools of remote sensing offer opportunities for such large area descriptions of biodiversity in a systematic, repeatable and spatially exhaustive manner [123, 124]. NDVI plays a major role in the developing of land cover maps – an important tool in the "direct approach" or "first-order analysis" of species occurrence [123]. Depending on the scale and 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 [121, 123, 124]. Data derived from vegetation productivity, in association to other environmental parameters (climatic and geophysical), are statistically related to species abundance or occurrence data [124]. An example includes the use of NDVI to explain the expansion of roe deer in the Scandinavian peninsula [125]. NDVI also contributes to the "indirect approach" of measuring species composition, abundance, and distribution. Different aspects of vegetation condition (derived from vegetation indices such as NDVI) contribute to the environmental variables which when assessed, provide indications (through biological principles) of species composition, abundance, and distribution [121, 124]. A high resource abundance (indicated by high NDVI values) was used to explain the occurrence and distribution of the devastating locust species Schistocerca gregaria in Mauritania and on the Red Sea coast [122].

[13] The Land Component of Copernicus Programme (http://land.copernicus.eu/global) defines NDVI anomaly as the deviation of the NDVI value from the 10-year average (avgNDVIdt) for the same period: aNDVIt = NDVIt – avgNDVIdt. A positive anomaly means an NDVI above the average and can be interpreted as a good or very good productivity period and/or an early growing season, and inversely for a negative value.

The use of NDVI to monitor vegetation and plant responses to environmental changes at the level of trophic interactions constitutes one of the main uses of NDVI in nature and conservation research. The use of NDVI 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 [119, 121]. Vegetation data has been instrumental in the assessment and monitoring of the conditions of some important global biomes. For example, MODIS data has been critical for the monitoring of tropical biomass [126]. The first pan-tropical biomass map was developed MODIS-GLAS[14] data fusion by Saatchi et al. [126]. This initiative represented a "benchmark" map of biomass carbon stocks in support of REDD[15] assessments at both project and national scales. Two main groups of satellite products are important for ecological studies and environmental change research [119]. The first group comprises the long-term NDVI datasets, including the coarse scale (8–16 km resolution) NOAA–AVHRR time-series extending from 1981 to the present and the small-scale Landsat–Thematic Mapper (TM) dataset extending from 1984 to 2003. The second group is made up of the better quality, but short-term NDVI time-series datasets, which include the MODIS–TERRA (250–1000 m resolution) extending from 2000 to the present, and the high resolution (up to a few meters resolution) SPOT–VGT dataset extending from 1998 to the present.

One of the most significant advances in remote sensing over the last two decades has been the development of hyperspectral sensors and software to analyze the resulting image data. Hyperspectral sensors contain bands with narrow wavelengths compared to multispectral sensors, which contain bands with broad wavelengths. Hyperspectral data, therefore, provides a significant enhancement of spectral measurement capabilities for investigating the more subtle differences in vegetation types at the species level and with greater accuracies [127].

[14] GLAS refers to Geosceince Laser Altimeter System

[15] Reducing Emissions from Deforestation and Forest Degradation (REDD+: http://www.unredd.net/about/what-is-redd-plus.html) is a mechanism developed by Parties to the United Nations Framework Convention on Climate Change (UNFCCC). It creates a financial value for the carbon stored in forests by offering incentives for developing countries to reduce emissions from forested lands and invest in low-carbon paths to sustainable development.

IX. EFFORTS AT ASSESSING VEGETATION DYNAMICS

9. EFFORTS AT ASSESSING VEGETATION DYNAMICS

9.1 OTHER VEGETATION INDICES CLOSELY RELATED TO NDVI

The Difference Vegetation Index (DVI) is probably the simplest of the vegetation indices. Besides being able to distinguish between soil and vegetation, DVI is sensitive to the amount of vegetation. DVI (Equation 6) does not deal with the difference between reflectance and radiance caused by the atmosphere or shadows. DVI is defined as [128]:

$$DVI = NIR - RED \qquad \text{Equation 6}$$

NIR is reflectance in the near infrared band, and RED is reflectance in the visible red band. Within virtually the same range of simplicity as the DVI, is the Simple Ratio (SR) or Ratio Vegetation Index (RVI). Birth and McVey first described it in 1968 [129]. RVI (Equation 7) is indeed one of the most widely used vegetation index given that the common practice in remote sensing is the use of band ratios to eliminate various albedo effects. The ratio of NIR to red as the vegetation component of an image scene is at the very basis of RVI. The output of RVI computation is high for vegetation and low for soil, ice, and water. RVI is capable of indicating the amount of vegetation while reducing the effects of atmosphere and topography. RVI is defined as [129]:

$$\mathrm{RVI} = \frac{NIR}{RED} \qquad \text{Equation 7}$$

NIR is reflectance in the near infrared band and RED is reflectance in the visible red band. Most vegetation indices rely in the existence of a "soil-line" in red and NIR wavelength space [13]. The soil-line is a principal axis of soil spectral variation extending outward from the origin with increasing brightness. Given that most of the soil spectra fall on or close to the soil-line, and since the intercept of such a line is close to the origin, RVI and NDVI values of bare soils (ratios) will be nearly identical for a wide range of soil conditions [13, 130].

The soil-Adjusted Vegetation Index (SAVI) is based on NDVI and was proposed by Huete [130]. SAVI (Equation 8) is a transformation technique to minimize soil brightness from spectral vegetation indices involving red and NIR wavelengths (principally NDVI and the Perpendicular Vegetation Index). The main feature of the transformation comprises shifting the origin of reflectance spectra plotted in NIR-red wavelength space to account for first-order soil-vegetation interactions and differential red and NIR flux extinction through vegetated canopies [13, 130].

$$SAVI = \frac{NIR - RED}{(NIR + RED + L)} * (1+L) \qquad \text{Equation 8}$$

L is the coefficient that should vary with vegetation density (ranging from 0 for very dense vegetation cover to 1 for very sparse vegetation cover). It follows therefore that if L = 0, the SAVI = NDVI. A shortcoming of SAVI is that we rarely know the vegetation density, making it difficult to optimize this index [13]. To solve this chicken-and-egg problem of needing to know the vegetation cover before calculating the vegetation index, which is what gives you the vegetation cover, a modification to SAVI was proposed by Qi et al. [131], the Modified-SAVI (MSAVI). In MSAVI (Equation 9), the L-factor is dynamically adjusted using the image data. In an assessment of MSAVI on cotton fields, Qi et al. [131] found that MSAVI resulted in greater vegetation sensitivity as defined by a "vegetation signal" to "soil noise" ratio.

$$MSAVI(1+L) = \frac{R_{NIR} - R_{red}}{(R_{NIR} + R_{red} + L)} \qquad \text{Equation 9}$$

L= 1 - (2 x slope x NDVI x WDVI). WDVI (Equation 10) is the Weighted Difference Vegetation Index which is functionally equivalent to PVI. It is calculated as: WDVI = NIR - (slope x RED)

$$WDVI = R_{nir} - R_{vis}\left(\frac{Rs_{vis}}{Rs_{nir}}\right) \qquad \text{Equation 10}$$

Developed by the MODIS Land Discipline Group and proposed for use with MODIS Data, the *Enhanced Vegetation Index (EVI)* is a modification of the 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 [72]. The key advantage of the EVI algorithm is the decoupling of the canopy background signal and a reduction in atmospheric influences [72, 132]. Huete et al. [132] demonstrated that the EVI (Equation 11) has an improved sensitivity to high biomass and does not saturate as easy as the NDVI.

Equation 11

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

One important challenge which faced in using the vegetation indices which attempt to minimize the effect of a diverse soil background is an increase in the sensitivity to variations in the atmosphere [131, 133]. To address this problem, efforts have been made to develop vegetation indices that are less sensitive to different aspects of atmospheric contamination. The Soil and Atmospherically Resistant Vegetation Index (SARVI) is a variant of NDVI, which attempts to address this problem (Equation 12).

Equation 12

$$SARVI = (1 - L) . (R_{800} - R_{rb})/(R_{800} + R_{rb} + L)$$

where $R_{rb} = R_y - y . (R_b - R_r)$

The technique entails prior correction for molecular scattering and ozone absorption of the blue, red, and near-infrared remote sensor data [72, 134]. So Rx is reflectance values with prior correction for molecular scattering and ozone absorption and is a constant used to stabilize the index to variations in aerosol content [13, 72, 134]. Huete et al. [134] proposed it by integrating the L function from SAVI and a blue band normalization to derive a soil and atmospherically resistant vegetation index (SARVI) that corrects for both soil and atmospheric noise.

9.2 CLASSIFICATION OF VEGETATION INDICES

Attempts have been made to classify vegetation indices in the literature [13, 135-137]. The types of classifications tend to be determined by the use for which the vegetation indices will be put. In studying the sensitivity of vegetation indices to sensor illumination and viewing geometry, Verrelst et al. [137] classified vegetation indices into four groups. Broadband greenness indices are measures of the overall quality of photosynthetic material in vegetation. Narrowband greenness indices measure of the overall quantity and quality of pigment content in vegetation. Light use efficiency indices are measures of the efficiency with which vegetation can use incident light for photosynthesis. Lastly, leaf pigment indices represent measures of stress-related pigments present in vegetation [137]. NDVI, SAVI, EVI and SRI are examples of broadband indices while DVI, RVI, TSAVI and MSAVI are examples of narrowband indices [137, 138]. Regarding application, Bullock and Jewitt [138] argue that narrowband greenness indices can offer more fine-tuned measures of the overall quantity and vigor of green vegetation than the broadband greenness. This is mainly because narrowband greenness vegetation indices use reflectance measurements in the red and near-infrared regions to sample the “red edge” portion of the reflectance curve [138].

Jackson and Huete [135] classify VIs into two groups. These include slope-based and distance-based vegetation indices. Slope-based VIs are arithmetic combinations that focus on the contrast between the spectral response patterns of vegetation in the red and near-infrared portions of the electromagnetic spectrum [136]. The main objective of slope-based indices is to report the state and abundance of vegetation [136]. Distance-based vegetation indices, on the other hand, are heavily based on the bi-spectral plot of red versus infrared reflectance. They measure the degree of vegetation present by estimating the difference of any pixel’s reflectance from the reflectance of bare soil (the soil-line in the bi-spectral plot) [13, 135, 136]. Distance-based vegetation indices are crafted principally to cancel the effect of soil brightness in cases where vegetation is sparse, and pixels contain a mixture of green vegetation and soil background such as arid and semi-arid environments [136]. Examples of different groups of indices are reported in Silleos et al. [136]. In addition to slope- and distance-based vegetation indices, Verrelst et al [137] include the group of indices that are derived from orthogonal transformation techniques. These include Principal Component Analysis (PCA) and the Green Vegetation Index (GVI) of the Kauth-Thomas Tasseled Cap Transformation.

X. METHODS THAT COMPLEMENT THE USE OF REMOTE SENSING FOR LAND DEGRADATION RESEARCH

10. METHODS THAT COMPLEMENT THE USE OF REMOTE SENSING FOR LAND DEGRADATION RESEARCH

The advantages of using remote sensing technology in land degradation assessment are many. They include time-saving, wide areal coverage, possibilities of revisiting analysis, saving projects and data to facilitate long term monitoring. The availability of free data series with global coverage which dates back to the 1980s offers the opportunity for research into the long-term, spatially distributed dynamics of vegetation over large geographical areas [16]. Coarse and medium spatial resolution satellite images are well suited for the task of detecting and monitoring vegetation cover dynamics over time because they provide consistent, valuable and repeatable measurements at a spatial scale, which is appropriate for detecting the effects of many processes that cause degradation of the vegetation cover. Remote sensing techniques, therefore, offer the possibilities of accessing areas that may otherwise be difficult or expensive to access through other means. Because of the diversity of scales, that techniques of RS offer, the availability of rich global datasets of landscapes, land use and other aspects of human interactions with natural resources, remote sensing techniques are increasingly used to monitor a range of human activities at different scales and over different time periods [59].

Notwithstanding their importance, remote sensing techniques are not as efficient at identifying drivers of land condition as they are in identifying potential areas where the land condition has changed or is undergoing change. To move beyond identifying locations, extent, and trends of changes in land condition, other tools of scientific investigation need to complement remote sensing techniques, data, and tools. Increasingly, researchers combine the use of vegetation indices (chiefly NDVI) and other geospatial techniques with other methods of data collection in integrated methodologies when assessing the extent, severity, and trends in land degradation. An understanding of the causes and potential consequences of land degradation or improvement is needed to enable one to identify what types of research methods may contribute to the triangulation[16] of remote sensing data, tools and methods in understanding land condition (Table 4).

10.1 FOCUS GROUPS

A focus groups consist of a small number of people (often 10 or less) brought together to participate in a guided discussion of a specific topic or set of related topics by a moderator (Figure 16). The discussion focuses on and follows a pre-determined focus group moderator's guide [140, 141]. Focus groups provide insights into how people think and provide a deeper understanding of the phenomena being investigated [141]. Focus groups could serve different purposes in the assessment and monitoring of land degradation.

EXPLORATION: Focus groups can be used to probe into people's perceptions of land status, condition, and trends. The investigator may be interested in understanding how people perceive land degradation in a particular community.

PARTICIPATORY PLANNING: In understanding the impact of land degradation and potential solutions, an investigator may want to involve local communities in identifying issues and seeking solutions. Focus groups can serve as a forum for such engagements.

SYSTEMATIC RESEARCH: Focus groups are tools of data collection in their own right. Methodologies for collecting and analyzing focus group data have been developed, and can be applied in the field of land use and land cover changes, as well as land degradation.

EVALUATION: Focus groups would serve as fora for assessing the outcome of interventions in land degradation management. As a community, the researchers will have the opportunity of generating in-depth data on the results of land degradation interventions on a range of community services, as well as community perceptions of success.

TABLE 4.

METHODS THAT COMPLEMENT THE USE OF REMOTE SENSING FOR LAND DEGRADATION ASSESSMENTS AND MONITORING

SPATIAL SCALE	PROCESSES/FEATURES BEING ASSESSED	COMPLEMENTARY METHODS	POTENTIAL SYSTEMS OF INTEREST
FIELD OR FARM	• Land degradation types; extent; severity, causes, impacts; risks • Land condition land cover change; biodiversity;	• Field surveys; • Focus groups; • Interviews; • Models; • Field measurements; • Participatory mapping	• Land (farm, grazing); • Soil; • Surface hydrology; • Biodiversity
SUB-NATION AND NATIONAL	• Land degradation types; extent; severity, causes, impact; risks • Land condition land cover change; biodiversity; • National carbon budgets • National land-based SDG targets • Ecotourism potentials	• Field surveys; • Focus groups; • Interviews; • Models; • Field measurements • Participatory mapping • Pilot sites • GPS sampling	• Land (farm, grazing, conserved lands); • Soil; • Surface hydrology; • Biodiversity • Ecosystems • Agroecological zones

[16] The idea of triangulation builds on the notion that looking at something from multiple points of view improves accuracy. Triangulation of method mixes the qualitative and quantitative research approaches and data. Research approaches that combine both tend to be richer and more comprehensive, and can uncover insights that may not have been evident from using only one of the methods 139. Neuman, L.W., *Social research methods: Qualitative and quantitative approaches*. 2002.

Interview of a farmer in Morogoro, Tanzania using a structured questionnaire.

All in-depth key-informant interview of land users in Kisumu, Western Kenya.

Focus group sessions with agriculturalists and other land users in Boyo Division, North West Region of Cameroon.

Figure 16. Processes of qualitative data collection that can be used to complement results from remotely sensed data.

10.2 KEY INFORMANT INTERVIEWS

Key informant interviews involve intensive individual interviews with a single respondent a small number of those surveyed (up to about 2 or 3) to explore their perspectives on a particular issue (Figure 16). Such interviews are particularly useful when an investigator has limited knowledge about a situation and wants to get preliminary ideas from the participants. This form of data collection can also be used to dig deeper into a specific topic of interest, thereby gathering data from "key informants" that is especially knowledgeable of the situation. Key informants could include community leaders, local practitioners, professionals, policy-makers, or residents with first-hand knowledge about the community. Key informant interviews tend to be in-depth and loosely structured, allowing freedom for both the interviewer and the interviewee to explore additional points and change direction, if necessary [140]. In studies of land use, land cover changes, and land degradation, key informants that may be considered (depending on the particular area of focus) would include farmers, grazers, and users of land-based natural resources (such as firewood, timber, and non-timber forest products). Leaders of agricultural and natural resources support groups, land resource professionals and policy makers in the natural resources and agricultural sectors will also be very useful key informants.

10.3 COMMUNITY MAPPING AND PARTICIPATORY GIS

Participatory mapping is a map-making process that attempts to make visible the association between land and local communities by using the commonly understood and recognized language of cartography [142]. Participatory GIS, on the other hand, is the practice of gathering and recording spatial data using traditional methods such as interviews, questions, focus groups with members of local communities [143]. Participatory mapping and GIS builds on the premise that local inhabitants possess expert knowledge of their local environments that can be expressed in a geographical framework, which is easily understandable and universally recognized.

Participatory maps are planned around a common goal and a strategy for use and are often made with input from an entire community in an open and inclusive process [143]. The more open and inclusive the process of mapping, the more the final map will reflect the collective experience of the group producing the map. In land degradation assessments and monitoring projects, community mapping and participatory GIS can be used to create maps that represent land and resource use patterns, identify areas that have or are undergoing changes in the major land degradation indicators, and identify areas of hazards. Community mapping and participatory GIS can also provide data on community values and perceptions of different forms and severity of land degradation, as well as information on traditional knowledge and practices related to land condition. Communities can serve as extremely valuable stakeholders in providing data for assessments or monitoring of land use changes and for the development of alternative scenarios for landscapes they occupy and operate within[17].

10.4 OBSERVATION

Most aspects of land degradation and their outcomes can have physical manifestations on the land, landscapes, or on the human activities that are supported by these landscapes. Such manifestations could include the visible presence of soil erosion, gully formation, or the poor performance of crops in agricultural fields. Observing and relating these phenomena to other forms of data and analysis can therefore be a useful process in triangulating research evidence. Observation is a research method in which the researcher gains physical access to the community in which he/she is investigating, with the purpose of developing an understanding of the physical, social, cultural, and economic contexts in which study participants live [140, 144]. Through participant observation, researchers can also uncover factors essential for a thorough understanding of the research problem but that were unknown when the study was designed.

In land degradation research, these could include key aspects of land status, such as the severity of a particular form of degradation, main contributing factors to land condition, and insights into the future of land use in a given community. During observations, some biophysical indicators may serve as pointers to the land condition, the degree of degradation, and possible trends (Figure 17). These observations can be further investigated during complementary research processes such as focus groups, key informant interviews, or cross-referenced with satellite-derived data sources and analysis. Such observations may include:

VEGETATION CONDITION: degree of vegetation cover; numbers of trees per unit area and kinds; vegetation quality; and evidence of recent community interactions with vegetation cover, such as deforestation (see Figure 17).

SOIL CONDITION: degree of exposure to the soil to elements of erosion; evidence of water erosion (in sheets, rills, and gullies); evidence of wind erosion such as loose soil particles in a windy environment or atmospheric haze of dust comprising fine mineral and organic soil particles that contain most of the soil nutrients.

WATER RESOURCES: the presence of small aquatic biodiversity in surface waters; presence or absence of visible pollutants on surface waters (such as a film of oil waste on the surface); evidence of pollution by domestic and industrial activities, sources of domestic water supply and water availability.

10.5 SURVEYS

Survey research involves the practice of collecting information from a sample of individuals through their responses to questions [145]. This practice can involve the use of different types of data collection instruments. The main survey instrument tends to be a structured questionnaire for the collection of purely quantitative data. There can also be the use of semi-structured questionnaires for the collection guided open-ended questions [146].

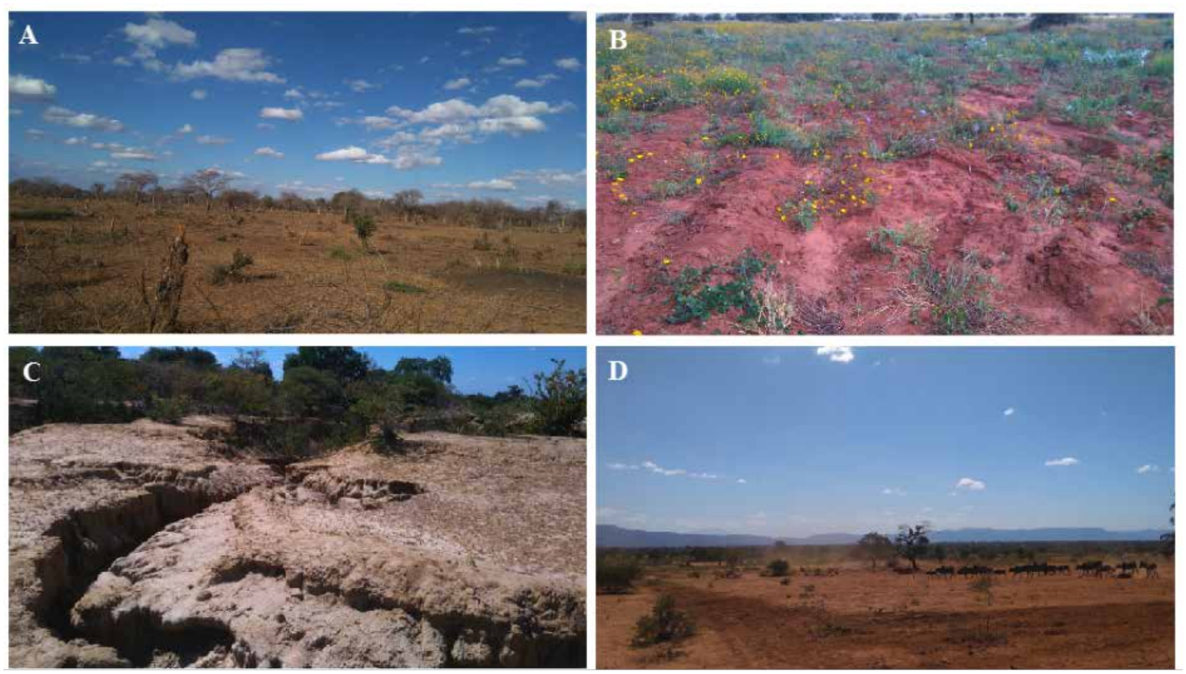

Figure 17. Examples of directly discernible features of land condition during field observations in central districts of Tanzania. A - Recent deforestation in Ndaleta; B - Land that is poorly protected from erosional forces after bean harvest in Simanjiro; C - Gullying in Masange; D - Overgrazed area suffering from wind erosion in Pahi. Note the dust swirl at the center of the image.

[17] The International Fund for Agricultural Development (IFAD) offers best practices for participatory mapping. The resources can be found The resources can be found here: https://www.ifad.org/documents/10180/d1383979-4976-4c8e-ba5d-53419e37cbcc

The use of both practices may give rise to mixed research methods [146, 147]. The survey instrument can be served in different ways. It can be a written document that is completed by the person(s) being surveyed, an online questionnaire, a face-to-face interview, or a telephone interview.

Surveys can be used in different aspects of land degradation research. A *baseline survey*[18] can be used as a starting point for monitoring of changes in land use, land cover, and land status. A baseline survey will provide a comprehensive characterization of conditions of the land (using carefully crafted indicators) for a specific year that would serve as a benchmark for future measurements, comparisons, and reference. A trend survey can be used to track progress on activities. In land degradation studies, such activities may be those undertaken to address an underlying land use problem or a land condition. Trends surveys tend to be less comprehensive than baseline surveys. Event-based surveys are used to capture the manifestation of a particular happening at a particular point in time. A rapid deforestation of a watershed may prompt an event-based survey to assess some of the immediate issues surrounding the event. These may include questions such as: Who has been responsible? What are the immediate consequences of the deforestation? What can be done in the immediate term to mitigate the situation? What considerations should be addressed by long-term efforts to address the issues associated with the event?

10.6 REFLECTIONS ON COMPLEMENTARY SOURCES OF DATA ON LAND DEGRADATION RESEARCH

The organization of research and data collection, as well as the decision on which types of complementary sources of data that can be used to assess and monitor land degradation will depend on the goals of the land degradation project, as well as on the purpose of research type.

Each data collection method has its strengths and weaknesses that have to be considered when designing the project (Table 5).

An important contributing factor to the type of method used to complement earth observation based analysis of land degradation is the kind of research that is being carried out by the investigator. There are different categories of classification of research types. For example, research can be classified according to the mode of data collection (continuous and ad hoc research); the type of data collected and used (qualitative and quantitative research); and the source of the data (primary and secondary research). A common classification is based on how the research inquiry is carried out (exploratory, descriptive and explanatory research). Exploratory, descriptive and explanatory research practices are applicable in land degradation research at different scales. It must be noted that these categories are not mutually exclusive, they are a matter of emphasis. As any research study will change and develop over time, you may identify more than one purpose.

10.6.1 EXPLORATORY RESEARCH

The goal of exploratory research is to identify key issues and key variables for a particular line of inquiry. The researcher may be in need of this knowledge to enable him/her test the feasibility of a more extensive study, determine the best methods to be used in a subsequent study, or even refine research questions to reflect the situation on the ground better. Methods that may be used to carry out an exploratory research may include a literature search, conducting focus groups and interviews. An example of an exploratory research in land degradation may involve studies that seek to sample land users' opinions on land use practices.

[18] A baseline survey is an example of a cross-sectional survey. Cross-sectional surveys are used to gather information on a population at a single point in time. Longitudinal surveys involve gathering information over a period of time or from one point in time up to another, with the aim of collecting data and examining the changes in the data gathered. Trend studies are an example of longitudinal surveys.

TABLE 5.

STRENGTHS AND WEAKNESSES OF METHODS THAT CAN BE USED TO COMPLEMENT RESULTS FROM THE ANALYSIS OF REMOTELY SENSED DATA ON LAND CONDITION AND TRENDS

METHODS	STRENGTH	WEAKNESSES
OBSERVATION	• Allows for insight into contexts, relationships, behavior. • Can provide information previously unknown to researchers that are crucial for project design, data collection, and interpretation of other data	• Time-consuming. • Documentation relies on memory, personal discipline, and diligence of researcher. • Requires conscious effort at objectivity because method is inherently subjective -
KEY INFORMANT INTERVIEWS	• Stimulates detailed responses with nuances and contradictions. • Gets at interpretive perspective - connections and relationships on the main issues of interest • Detailed and rich data can be gathered on each topic as the interviewer can explore each topic freely • Can easily be combined with other research techniques	• A great amount of time required to arrange and conduct interviews and primary data collection. • Takes time to select good informants and build trust • Could be expensive, with costs of arranging and conducting interviews, traveling. • Potential for interviewer bias • The information derived may be difficult to quantify.
FOCUS GROUPS	• Elicits information on a range of norms and opinions in a short time. • Group dynamic stimulates conversation, reactions	• Not as efficient in covering an issue in-depth compared to key informant interviews. • The potential for moderator bias as moderators can significantly influence the outcome of a focus group discussion.
SURVEY	• Surveys can produce a large amount of data in a short time for a relatively low cost. • Flexible and can be administered in different formats • Yields many responses • Data are generalizable if the sampling is carefully chosen.	• Can be time-consuming • Securing a high response rate to a survey can be hard to control (low response rates) • Captures what people say they think and believe but not necessarily how they behave in real life • - The data from the process are likely to lack details or depth on the topic.

10.6.2 DESCRIPTIVE RESEARCH

The goal of descriptive research is to provide an accurate description of observations of phenomena or an issue [148]. The desire of the researcher, in this case, is to provide as much information as possible on the phenomena of matters in question. To achieve depth and accuracy, proper planning is indispensable. Descriptive research seeks to answer questions related to Who? What? Where? When? How? How many? Hence as part of the planning process, questions to be addressed may include: What is going to be described? How will the description be achieved? What limits of description should be applied to the study (for example temporal, spatial delimitations)? What units and indicators should be used? The description could be measures, analyses, forecasts, etc. Quantitative analysis of primary and secondary data, observations, interviews, surveys, questionnaires are commonly used methods in descriptive research. In the last decade, there have been several attempts at understanding the status and trends of land degradation in Africa. This is an example of a descriptive research endeavor.

10.6.3 EXPLANATORY RESEARCH

Also known as causal research, this research type seeks to identify the extent and nature of cause-and-effect relationships as well as explain the patterns of interrelationships between variables that influence a particular situation or outcome [148]. The goal of explanatory research would be to provides an understanding of the relationships that exist between variables affecting phenomena, or influencing an outcome. It could also be aimed at assessing the impacts of specific changes on existing practices or norms, processes, etc. The collection and use of primary data through a variety of methods are common in explanatory research. Studies that seek to understand the relationships between land use and land cover changes on land degradation are examples of explanatory research efforts.

Mikumi National Park, Africa, Tanzania. © Benjamin Drummond

XI. SUSTAINABLE DEVELOPMENT GOALS (SDGS) AND LAND DEGRADATION INDICATORS

11. SUSTAINABLE DEVELOPMENT GOALS (SDGS) AND LAND DEGRADATION INDICATORS

The 2030 global sustainable development agenda adopted by the United Nations General Assembly in 2015 includes 17 new Sustainable Development Goals (SDGs) together with 169 targets[19]:

Goal 1.	End poverty in all its forms everywhere
Goal 2.	End hunger, achieve food security and improved nutrition and promote sustainable agriculture
Goal 3.	Ensure healthy lives and promote well-being for all at all ages
Goal 4.	Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all
Goal 5.	Achieve gender equality and empower all women and girls
Goal 6.	Ensure availability and sustainable management of water and sanitation for all
Goal 7.	Ensure access to affordable, reliable, sustainable and modern energy for all
Goal 8.	Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all
Goal 9.	Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation
Goal 10.	Reduce inequality within and among countries
Goal 11.	Make cities and human settlements inclusive, safe, resilient and sustainable
Goal 12.	Ensure sustainable consumption and production patterns
Goal 13.	Take urgent action to combat climate change and its impacts
Goal 14.	Conserve and sustainably use the oceans, seas and marine resources for sustainable development
Goal 15.	Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss
Goal 16.	Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels
Goal 17.	Strengthen the means of implementation and revitalize the Global Partnership for Sustainable Development

[19] United National General Assembly: Transforming our world : the 2030 Agenda for Sustainable Development. United Nations General Assembly available here: http://www.un.org/ga/search/view_doc.asp?symbol=A/RES/70/1&Lang=E, [Accessed December 1, 2015].

The assessment and monitoring of land degradation stand to contribute to three main SDGs. These include:

- 2.4 - By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality
- 15.2 - By 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally
- 15.3 - By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought, and floods, and strive to achieve a land degradation-neutral world

The achievement of the above targets falls within the framework of goals set by a number of global and regional initiatives and programs to halt and reverse land degradation as well as restore degraded ecosystems. Of particular interest is the desire of the UNCCD to meet Target 15.3 to achieve LDN[20] by 2030 [149].

This document and its associated methodologies and toolbox contribute in enabling national stakeholders to perform monitoring and assessment of land degradation in support of established national land-based SDG priorities. It provides standardized global datasets to test the three land-based indicators at national and subnational levels. It assists countries in the planning and implementation of step-wise approaches in land degradation assessment and monitoring which involve identifying, mapping and quantifying land degradation hotspots and trends. Through such support, countries can then proceed to identify land management options that can stop or reverse these negative trends (actions that contribute to achieving LDN). They can also proceed with reviewing existing national action programs and identifying the mix of financial, scientific and administrative and land management options that can contribute to addressing the identified trends in land degradation hotspots; and in setting realistic national LDN targets.

11.1 REPORTING OF KEY INDICATORS FOR UNCCD AND GEF (PRODUCTIVITY, LAND COVER, SOIL CARBON)

Both the UNCCD and the GEF use land productivity, land cover and carbon stocks below and above ground to monitor land degradation and report on progress to combat it. The UNCCD progress indicators (formerly known as impact indicators) 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 Convention of Parties (COP) adopted a refined set of six progress indicators (Decision 22/COP.11). Table 6 includes guidance for use of NDVI for these indicators earlier reported by Yengoh et al., (2015):

Both the UNCCD and GEF also plan to use the indicator subset of land productivity, land cover and carbon stocks below and above ground to monitor and report on LDN, which is discussed next.

[20] The United Nations Convention to Combat Desertification (UNCCD, 2016) defines land degradation neutrality as “a state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystems”. The goal of LDN is described by the UNCCD as being to “to maintain or even improve the amount of healthy and productive land resources over time and in line with national sustainable development priorities.” It sees LDN as a target “that can be implemented at local, national and even regional scales,” through two complementary pathways of action: sustainable land management and ecosystem restoration. LDN is a globally agreed target that can serve to galvanize action to address land degradation by providing clear targets that facilitate tracking progress, or the lack of progress in meeting land improvement goals. The UNCCD adopted a set of three land-based progress indicators, which will become central to reporting on progress towards LDN: Tier 1: trends in land cover; Tier 2a: Trends in land productivity or the functioning of the land; and Tier 2b: Trends in carbon stock above and below ground.

TABLE 6.

UNCCD PROGRESS 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 INCOME INEQUALITY IN AFFECTED AREAS	Not applicable.
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.
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. However, care needs to be exercised in interpretation of the results and the drivers of change.
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.
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 soil organic carbon assessments.
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.

11.2 LAND DEGRADATION NEUTRALITY FRAMEWORK

Achieving LDN requires an approach that provides decision-makers with the means to balance potential gains and losses in terms of intent (capturing the expected outcomes of land use and management decisions in such a way that favours neutrality) and results (evaluating the impact of those decisions). The LDN framework therefore includes the vision (intended outcomes of LDN), the frame of reference (baseline) against which achievement is measured, the mechanism for neutrality (counterbalancing anticipated negative changes with actions planned to deliver gains, and tracking the cumulative effect of land use decisions), achieving neutrality (preparing for and pursuing LDN), and monitoring neutrality (evaluating progress and achievement of LDN). Figure 18 illustrates the key elements of the scientific conceptual framework for LDN and their interrelationships, detailed in this report.

The target at the top of Figure 18 expresses the vision of LDN, emphasizing the link between human prosperity and the natural capital of land – the stock of natural resources that provides flows of valuable goods and services. The balance scale in the centre illustrates the mechanism for achieving neutrality: ensuring that future land degradation (losses) is counterbalanced through planned positive actions elsewhere (gains) within the same land type (same ecosystem and land potential). The key point of the scale depicts the hierarchy of responses: avoiding degradation is the highest priority, followed by reducing degradation and finally reversing past degradation. The arrow at the bottom of the diagram illustrates that neutrality is assessed by monitoring the LDN indicators relative to a fixed baseline. The arrow also shows that neutrality needs to be maintained over time, through land use planning that anticipates losses and plans gains. Adaptive management applies learning from interim monitoring to inform mid-course adjustments to help ensure neutrality is achieved, and maintained in the future.

Monitoring achievement of neutrality will quantify the balance between the area of gains and area of losses, within each land type across the landscape. The LDN indicators are the same UNCCD global indicators discussed above: land cover (land cover change), land productivity (net primary production) and carbon stocks (soil organic carbon).

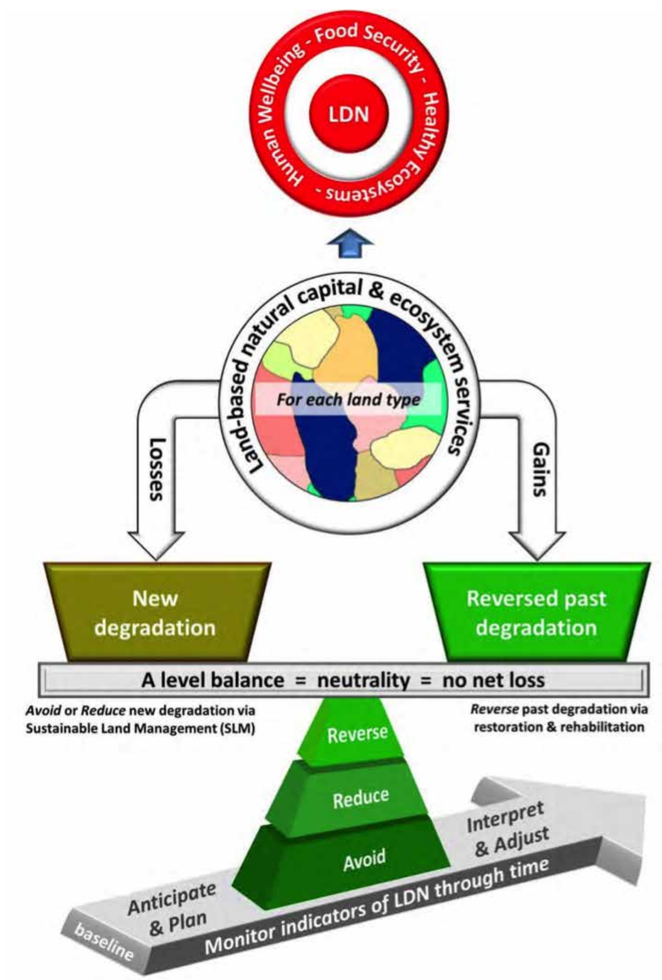

Figure 18. Key elements of an LDN scientific conceptual framework [150].

11.3 MONITORING AND REPORTING OF LDN

The guiding principles for monitoring and reporting on SDG target 15.3 were developed by an Expert Meeting held in Washington in March 2016, organized by the UNCCD, FAO, and STAP of the GEF. In 2017, the Commonwealth Scientific and Industrial Research Organisation (CSIRO) developed Good Practice Guidance for the assessment and monitoring of SDG indicator 15.3.1[21]. This guidance document has been used to develop methodologuies for the assessment of land degradation indicators in the Trends.Earth toolbox.

The principles for assessment and monitoring land degradation are similar to the 2006 Intergovernmental Panel on Climate Change Guidelines (for national greenhouse gas inventories[22]) with regards to estimation methods at three levels of detail: from Tier 1 (the default method) to Tier 3 (the most detailed method):

TIER 1: Earth observation, geospatial information and modelling

TIER 2: Statistics based on estimated data for administrative or natural boundaries

TIER 3: Surveys, assessments and ground measurements

From these guiding principles, more technical good practice guidance will need to be needed so that countries can:

1. Set Baselines to determine the initial status of the sub-indicators in absolute values. This would include: 1) the preparation of base land cover information which builds on standard land cover ontology; 2) the establishment of a baseline for land productivity (such as NPP/NDVI); and 3) the establishment of a baseline for carbon stocks, above and below ground, with an emphasis on soil organic carbon below ground and building on the IPCC's work on carbon above ground.
2. Detect Change in each of the sub-indicators, including the identification of areas subject to change and their validation or evaluation by a participatory national inventory of land degradation, particularly where change in two or three of the sub-indicators coincide or overlap spatially.
3. Derive Indicator 15.3.1 by summing all those areas subject to change, whose conditions are considered negative by national authorities (i.e., land degradation) while using the Framework in their measurement and evaluation of changes within each sub-indicator and their combination.
4. Use national data, to the greatest extent possible, to derive the sub-indicators and other relevant indicators and information at the country level covering bio-physical, governance and socio-economic conditions as well as the status of land resources. National data can be collected through existing sources (maps, databases, reports) and including participatory inventories on existing land management systems and their characteristics.

[21] CSIRO, 2017. Good Practice Guidance. SDG Indicator 15.3.1: Proportion of land that is degraded over total land area. September 2017.

[22] Found here: http://www.ipcc-nggip.iges.or.jp/public/2006gl/pdf/0_Overview/V0_1_Overview.pdf.

XII. REFERENCES

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