Chapter 3
Applications of NDVI for Land Degradation Assessment

In the late 1960s, several researchers began using red and near-infrared reflected light to study vegetation (Pearson and Miller 1972). In the late 1960s, ratios of red and near-infrared light were used to assess turf grass condition and tropical rain forest leaf area index (Birth and McVey 1968; Jordan 1969). Compton Tucker was the first to use it for determining total dry matter accumulation, first from hand-held instruments (Tucker 1979), and then from NOAA AVHRR satellite data (Tucker et al. 1981, 1985), demonstrating that the growing season integral of frequent NDVI measurements represented the summation of photosynthetic potential as total dry matter accumulation. Starting in July 1981, a continuous time series of global NDVI data at a spatial resolution of 8 km has been available from the AVHRR instrument mounted on NOAA weather satellites. Soon, researchers realized the value of NDVI time-series remote sensing (Goward et al. 1985; Justice et al. 1985; Townshend et al. 1985; Tucker et al. 1985). This early work was the spur for development of the higher-resolution Moderate-Resolution Imaging Spectroradiometer (MODIS) instrument. The application of satellite NDVI data has blossomed into many fields of natural resources investigation (see Annex 1). One particular appeal of remote sensing in the study of large geographic areas, or at multiple times over the year(s), is the potential for cost savings (Pettorelli 2013). We examine the use of NDVI in research on land-use and land-cover change, drought, desertification, soil erosion, vegetation fires, biodiversity monitoring and conservation, and soil organic carbon (SOC).

3.1 Land-Use and Land-Cover Change

Land cover is the observed (bio)physical cover on the earth's surface (Di Gregorio 2005). In a strict sense, it should be limited to the description of vegetation and artificial (man-made) features on the land surface, but land-use and land-cover change (LULCC) is a general term used to refer to the human modification of the

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earth's terrestrial surface (Bajocco et al. 2012). Mankind has modified land and land cover for thousands of years to obtain food, fuel, fiber, and other materials, but current rates and intensities of LULCC are far greater than ever before (Lambin et al. 2003; Mayaux et al. 2008). The quantity and quality of vegetation cover are an important controls on the evolution landscapes, their resilience or degradation (Symeonakis and Drake 2004), and the quality of environmental services.

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

3.2 Drought and Drought Early Warning

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

NDVI and associated vegetation indices have been used to detect and investigate meteorological, hydrological, and agricultural droughts worldwide. Strictly speaking, NDVI is most useful for detecting and investigating drought effects on the vegetation cover, in this case agricultural droughts. Generally, meteorological (dry weather patterns) and hydrological (low water supply) droughts would not be detected by NDVI before they impact the vegetation cover. The exception in this case may be hydrological drought, if the analysis includes water level in plant matter. NDVI has been used by several studies of the Sahelian drought (see Annex 1) an example is the investigation of the persistence of drought in the Sahel in the period 1982–1993 (Anyamba and Tucker 2012). Another study combined anomalies of El Niño Southern Oscillation (ENSO) indices and NDVI anomalies to construct an ENSO-induced drought onset prediction model for northeast Brazil using multiple linear regression (Liu and Juárez 2001). The normalized difference water index (NDWI) is a sister index calculated from the 500-m SWIR band of MODIS that has been used in drought studies (Chen et al. 2005; Delbart et al. 2005; Jackson et al. 2004; Gao 1996). Mishra and Singh (2010) argue that NDWI may be a more sensitive indicator than NDVI for drought monitoring, but its developer (Gao 1996) emphasized that the index is: *complementary to, not a substitute for NDVI*.

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

3.3 Desertification

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

In detecting the status and trend of desertification, researchers have built on the relationship between NDVI and biomass productivity that has been well established in the literature (Jensen 2007; Purkis and Klemas 2011). These initiatives are greatly helped by the continuous global NDVI time series of vegetation that has been available since the early 1980s. The UNCCD fostered increased interest in desertification research, especially with regard to the Sahel which was by that time experiencing a wet period, captured by satellite imagery, analyzed using NDVI time series, and described as a *greening of the Sahel* (Olsson et al. 2005). The following studies used NDVI time series to investigate temporal and spatial patterns of the Sahel's greenness and rainfall variability as well as their interrelationships (Herrmann et al. 2005; Hickler et al. 2005). Herrmann et al. (2005) and Olsson et al. (2005) concluded that while increased rainfall was the main reason for greening, there were also a number of hypothetical human-induced changes superimposed on the climatic trend-changes such as improved agricultural practices, as well as migration and population displacement. Besides documenting the close coupling of rainfall and vegetation response in the Sahel, Anyamba and Tucker (2005) pointed out that current greener conditions are still not as green as those that prevailed from 1930 to 1965. Together, these studies and many that have followed (see Annexes 1 and 2) demonstrate the opportunities offered by NDVI as a proxy for vegetation response to rainfall variability, especially in arid and semiarid ecosystems. Herrmann et al. (2005) also demonstrated the possibility of using NDVI as a proxy for environmental response to management.

3.4 Soil Erosion

Erosion is the displacement of materials like soil, mud, and rock by gravity, wind, water, or ice. The most common agents of soil erosion are water and wind (Foth 1991); their effects may be on-site (where soil detachment and transportation occurs) or off-site (where eroded soil is deposited). In soil erosion studies, NDVI is commonly used in conjunction with soil-erosion estimation models such as the fuzzy-based dynamic soil erosion model (FuDSEM), the Revised Universal Soil Loss Equation (USLE/RUSLE), the Water Erosion Prediction Project (WEPP), the European Soil Erosion Model (EUROSEM), and the Soil and Water Assessment

Tool (SWAT) (Prasannakumar et al. 2012; Zhou et al. 2008). Mulianga et al. (2013) in Kenya and Ai et al. (2013) in China, used Terra-MODIS-derived NDVI to characterize the state of the ecosystem (spatial and temporal heterogeneity of the vegetation conditions), and as one of the input parameters for estimating the potential of erosion using fuzzy-set theory. In a study of the effect of vegetation cover on soil erosion in the Upper Min River watershed in the Upper Yangtze Basin, China, Zhou et al. (2008) used NDVI as a land-management factor (an input into the RUSLE model) representing the effect of soil disturbing activities, land cover, and vegetation productivity on soil erosion. A similar study, also using NDVI as a land-cover management factor to determine the vulnerability to erosion of soils, was carried out in a forested mountainous sub-watershed in Kerala, India (Prasannakumar et al. 2012). In such studies, NDVI proved to be a useful indicator of land-cover condition and a reliable input into models of soil dynamics.

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

3.5 Soil Salinization

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

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

3.6 Vegetation Burning

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

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

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

3.7 Soil Organic Carbon (SOC)

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

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

3.8 Biodiversity Monitoring and Conservation

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

NDVI plays an important role in the development of land-cover maps—an important tool in the *direct approach* or *first-order analysis* of species occurrence (Turner et al. 2003). Depending on the scale, biome, and ecosystem in question, land-cover maps provide implicit or explicit data on the composition, abundance, and distribution of individual or assemblages of species (Duro et al. 2007; Pettorelli et al. 2014; Turner et al. 2003). Data derived from vegetation productivity, in association with other environmental parameters (climatic and geophysical), are statistically related to species abundance or occurrence data (Duro et al. 2007; Pettorelli 2013). One example is the use of AVHRR-derived NDVI to explain the spatial variability of species richness of birds at a quarter degree spatial resolution in Kenya, finding a strong positive correlation between species richness and maximum average NDVI (Oindo et al. 2000). NDVI also contributes to the *indirect approach* to measuring species composition, abundance, and distribution. Different aspects of vegetation condition (derived from vegetation indices such as NDVI) contribute to the mapping of environmental variables which provide indications (through biological principles) of species composition, abundance, and distribution (Duro et al. 2007; Pettorelli et al. 2014). A high resource abundance (indicated by high NDVI values derived from NOAA/AVHRR satellite imagery) was used to explain the occurrence and distribution of the devastating locust specie *Schistocerca gregaria* in Mauritania (Despland et al. 2004).

3.9 Monitoring Ecosystem Resilience

The 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 (Pettorelli et al. 2005, 2014). The use of the NDVI to monitor vegetation and plant responses to environmental changes at the level of trophic interactions constitutes one of the main uses of the NDVI in nature and conservation research. The application of the NDVI as a resilience indicator has been applied in numerous studies, such as reported by Díaz-Delgado et al. (2002), Simoniello et al. (2008), and Cui et al. (2013). Diaz-Delgado et al. (2002) used NDVI values derived from Landsat imagery to assess the recovery of Mediterranean plant communities after recurrent fire disturbances between the periods 1975 and 1993. They concluded (among other things) that the use of time-series

NDVI and other imagery products can be useful in understanding the resilience of Mediterranean plant communities and postfire vegetation dynamics over large regions and long time periods (Díaz-Delgado et al. 2002). Simoniello et al. (2008) characterized the resilience of Italian landscapes using NDVI trends to estimate mean recovery times of vegetation to different levels of anthropic pressure. They concluded that with 8-km AVHRR-NDVI data and remote sensing techniques, substantial details on vegetation cover activity (pointers to its resilience) at local scale could be captured, even in ecologically complex territories such as that of the Italian peninsula (Simoniello et al. 2008).

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