Chapter 5
Key Issues in the Use of NDVI for Land Degradation Assessment

5.1 NDVI, NPP, and Land Degradation

A substantial body of research has established the correlation between NDVI and aboveground biomass, and knowledge of the theoretical basis for using satellite-derived NDVI as a general proxy for vegetation conditions has advanced (Mbow et al. 2014; Pettorelli et al. 2005; Sellers et al. 1994). Reduction of primary productivity is a reliable indicator of the decrease or destruction of the biological productivity, particularly in drylands (Wessels et al. 2004; Li et al. 2004). NPP expressed in g of C m^{-2} $years^{-1}$ and quantifies net carbon fixed by vegetation. According to Cao et al. (2003), NPP is "the beginning of the carbon biogeochemical cycle," defined mathematically as in Eq. (5.1):

$$\mathrm{NPP} = f\left(\mathrm{NDVI, PAR, fPAR, aPAR, LAI}\right) \tag{5.1}$$

where fPAR is the fraction of absorbed photosynthetic active radiation, aPAR is the absorbed photosynthetic active radiation, and LAI is the leaf area index. Changes in NPP or, rather, its proxy NDVI induced by land degradation can be measured using a range of remote sensing techniques so remote sensing has become an essential tool for global, regional, and national studies of land degradation (Anyamba and Tucker 2012; Bai et al. 2008; Bajocco et al. 2012; de Jong et al. 2011b; Field et al. 1995; Horion et al. 2014; Le et al. 2014; Prince and Goward 1995). Many approaches have been developed to estimate NPP, notably the Global Production Efficiency Model (GLO-PEM) (Prince and Goward 1995), the Light-Use Efficiency (LUE) Model (Monteith and Moss 1977), the Production Efficiency Approach (Goetz et al. 1999; Goward and Huemmrich 1992), and the Sim-CYCLE (Ito and Oikawa 2002). And models have been developed to estimate NPP directly from remotely sensed NDVI at a global scale. Running et al. (2004) offered Eq. (5.2):

$$\mathrm{NPP} = \Sigma\left(\varepsilon \times \mathrm{NDVI} \times \mathrm{PAR} - \mathrm{R}_{lr}\right) - \mathrm{R}_{g} - \mathrm{R}_{m} \tag{5.2}$$

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where ε is the conversion efficiency; PAR is photosynthetically active radiation; R_{lr} is 24-h maintenance respiration of leaves and fine roots; R_g is annual growth respiration required to construct leaves, fine roots, and new woody tissues; and R_m is the maintenance respiration of live cells in woody tissues. Drawing on this relationship, Bai et al. (2008) adopted an empirical relationship to translate NDVI trends to NPP trends for their proxy global assessment of land degradation (Eq. 5.3):

$$\mathrm{NPP}_{\mathrm{MOD17}}\left(kg\ \ C\ \ ha^{-1}\mathrm{year}^{-1}\right) = 1106.37 \times \Sigma\mathrm{NDVI} - 564.55 \tag{5.3}$$

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

5.2 NDVI, RUE, and Land Degradation

The concept of rain-use efficiency (RUE), coined by Le Houerou (1984), is the ratio of aboveground NPP to annual precipitation. It tends to decrease with increase in aridity and potential evapotranspiration (Purkis and Klemas 2011; Symeonakis and Drake 2004; Le Houerou 1984). It has been observed that RUE is generally lower in degraded lands than in non-degraded lands (Symeonakis and Drake 2004); Fensholt et al. (2013) contend that RUE is “a conservative property of the vegetation cover in drylands, if the vegetation cover is not subject to non-precipitation related land degradation.” Nonetheless, the use of RUE as an indicator for land degradation has been hotly contested on the grounds of methodology, differences in scale, and ecological contexts (Dardel et al. 2014; Fensholt et al. 2013; Wessels 2009; Fensholt et al. 2012; Wessels et al. 2007).

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

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

RUE itself has been used as a proxy for land degradation (Safriel 2007; Symeonakis and Drake 2004) where RUE, itself, is not negatively correlated with rainfall. To stress the need for decoupling of precipitation and NDVI correlation in

RUE estimation and land degradation assessments, Fensholt et al. (2013) use the term *nonprecipitation-related land degradation*. This decoupling can be partly achieved by replacing annual ∑NDVI (a variable commonly and erroneously) used in RUE computations by a *small NDVI integral* that covers only the rainy season (not the whole year) and counting only the growth in NDVI in relation to some reference level. When this approach is applied to the African Sahel, Fensholt et al. (2013) find that positive RUE trends dominate most of the Sahel, which suggests that *nonprecipitation-related land degradation* is not widespread in the region.

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

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

5.3 Separating the Effects of Other Causes of NDVI Changes

Vegetative cover is a measurable indicator of ecosystem change, but the performance of vegetation depends on many micro- and macro-environmental factors (especially climate). Changes in vegetation reflect changes in both the natural factors that influence vegetation growth and performance, as well as human influences.

Hence, whereas NDVI can be a good indicator of NPP, separating the effects of climate variability on NDVI changes from those of land degradation is a challenge (Vogt et al. 2011). Different approaches, as described hereafter, have been used in recent studies.

One of the most popular techniques of application of NDVI in the assessment and monitoring of desertification is through the analysis of time-series NDVI images. In NDVI time-series analysis, linear models may be used to best fit the cyclic vegetation variation into a line (Eq. 5.4). The slope of the line can then be used to deduce the direction of vegetation variation (decrease or increase), as well as the strength of variation from the steepness of the trend line (e.g., no change, minimal, moderate, or severe change). In this case, the NDVI linear model will be

$$\mathrm{NDVI}_t = a \cdot t + \mathrm{NDVI}_0 \tag{5.4}$$

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

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

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

5.4 Abrupt Changes

Linear trends are easy to calculate, and in the early years of satellite NDVI, this was the only feasible approach. However, contrasting trends can balance out so it is important to ensure that the necessary assumptions for the determination of linear trends are met for each analysis. Citing De Beurs and Henebry (2005), Higginbottom and Symeonakis (2014) list them as (1) independence of the dependent variable, (2) normality in the model residuals, (3) consistency in residual variance over time, and (4) independence in residuals. Where there is need to separate NDVI time series into linear trend, seasonal components, and errors, nonlinear NDVI time-series models are used (Erian 2005). Key components of such nonlinear models (Eq. 5.5) would usually include a linear trend, stochastic component, external variables, periodic components (in terms of cycles and periodic trends), and white noise (Erian 2005, citing Udelhoven and Stellmes 2007).

$$NDVI_t = \underbrace{\alpha}_{\text{Constant}} + \underbrace{\beta_1 \bullet t}_{\text{Linear trend}} + \underbrace{\left(\sum_{i=1}^{NoOfLags} \beta_i NDVI_{t-i} \right)}_{\text{Stochastic component}} + \underbrace{\left(\sum_{j=1}^{NoOfX} \sum_{k=1}^{NoOfLags} \beta_{jk} X_{jk} \right)}_{\text{External variables}} + \underbrace{\left(\sum_{m=1}^{NoOfHarm} a_m \cos\bullet 2\pi \frac{1}{P_m} \bullet t + b_m \sin 2\pi \frac{1}{P_m} \bullet t \right)}_{\substack{\text{Periodic components} \\ \text{(cycles, long periodical trends)}}} + \underbrace{\varepsilon}_{\text{White noise}} \tag{5.5}$$

The more than 30 years of NDVI record now available reveal many breaks of trend, even reversals. The Breaks for Additive Season and Trend (BFAST) approach has been developed to detect and capture these NDVI trend changes (de Jong et al. 2011c; Verbesselt et al. 2010a; Verbesselt et al. 2010b). The algorithm combines the decomposition of time series into seasonal, trend, and remainder component with methods for detecting changes. An additive decomposition model is used to iteratively fit a piecewise linear trend and a seasonal model (Haywood and Randall, 2008). According to De Jong et al. (2012), the general form of the model is Eq. (5.6):

$$Y_t = T_t + S_t + e_t : t \in T \tag{5.6}$$

where, at time t (in the time series T), Y_t is the observed NDVI value, T_t is the trend component, and S_t is the seasonal component and the remainder component which contains the variation beyond what is explained by T_t and S_t. Using this method (Eq. 5.6), De Jong et al. (2011a) mapped the global distribution of greening to browning or vice versa; about 15 % of the globe witnessed significant trend shifts within the period studied. Common change detection methods average out this mixed trend effect, underestimating the trend significance (de Jong et al. 2011c).