Chapter 9
Assessing Drivers of Vegetation Changes in Drylands from Time Series of Earth Observation Data

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Abstract This chapter summarizes methods of inferring information about drivers of global dryland vegetation changes observed from remote sensing time series data covering from the 1980s until present time. Earth observation (EO) based time series of vegetation metrics, sea surface temperature (SST) (both from the AVHRR (Advanced Very High Resolution Radiometer) series of instruments) and precipitation data (blended satellite/rain gauge) are used for determining the mechanisms of observed changes. EO-based methods to better distinguish between climate and human induced (land use) vegetation changes are reviewed. The techniques presented include trend analysis based on the Rain-Use Efficiency (RUE) and the Residual Trend Analysis (RESTREND) and the methodological challenges related to the use of these. Finally, teleconnections between global sea surface temperature (SST) anomalies and dryland vegetation productivity are illustrated and the associated predictive capabilities are discussed.

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C. Kuenzer et al. (eds.), *Remote Sensing Time Series*, Remote Sensing and Digital Image Processing, DOI 10.1007/978-3-319-15967-6_9

9.1 Introduction

The United Nations Convention to Combat Desertification (UNCCD) definition of desertification, or dryland degradation (used synonymously) is:

> land degradation in arid, semi-arid and dry sub-humid areas resulting from various factors, including climatic variations and human activities" followed by "land degradation" means reduction or loss, in arid, semi-arid and dry sub-humid areas, of the biological or economic productivity and complexity of rainfed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from land uses or from a process or combination of processes, including processes arising from human activities and habitation patterns (UNCCD homepage, www.unccd.int).

This definition implies that change in vegetation productivity is a key indicator (but not the only one) of land degradation. Furthermore, vegetation productivity is of great economic importance because crop and livestock production is the most essential economic activity in many arid and semi-arid regions. Moreover, primary production is an important element in dryland key supporting ecosystem services, as defined by the Millennium Ecosystem Assessment (MEA) Desertification Synthesis (Adeel and World Resources Institute 2005). Therefore, spatially and temporally consistent, long-term data on changes and trends in vegetation productivity are of great interest for the assessment of environmental conditions and their trends in dryland regions. Earth Observation (EO) satellite data provide the only suitable means of temporally and spatially consistent global scale data, covering the last three decades (Prince 2002).

According to Adeel and World Resources Institute (2005), at least 10–20 % of drylands are already degraded and a recent publication from the UNCCD (UNCCD-secretariat 2013) states that global assessments indicate an increase in the percentage of highly degraded land area from 15 % in 1991 to 25 % by 2011. Many reputable sources rank desertification among the greatest environmental challenges today and a major impediment to meeting basic human needs in drylands (MEA & UNCCD). It is, however, also underlined that more elaborate studies are needed to identify where the problems occur and what is their true extent. This chapter introduces different EO-based methods for monitoring indicators of land degradation and to gain insight into the driving mechanisms of observed changes in vegetation productivity.

9.2 Inferring Causes for Observed Changes

Trends in vegetation productivity may be related to climatic as well as non-climatic causes of change (e.g. management), and it is obviously of great policy relevance to better understand the drivers and causal mechanisms of observed productivity trends. There is good correspondence between EO-based vegetation dynamics and precipitation in most dryland areas (Fig. 9.1) which is not surprising since

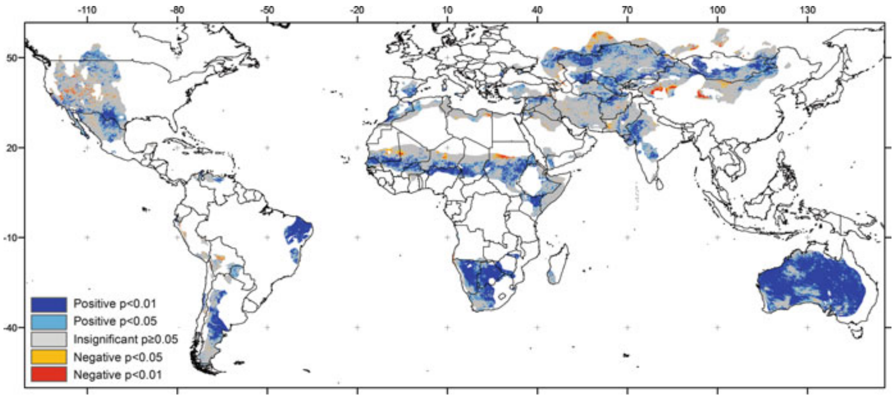

Fig. 9.1 Significance of linear correlation between annual integrated GIMMS3g NDVI and annual summed CMAP precipitation 1982–2010 for dryland areas (hyper-arid not included). CMAP precipitation has been resampled to match the spatial resolution of the GIMMS3g NDVI

vegetation growth is primarily water constrained in these areas (Nemani et al. 2003). However, large dryland regions of non-significant correlation between rainfall and vegetation growth can also be observed.

Different datasets of precipitation exist for continental to global scale analysis based on a combination of rain gauge measurements and a variety of different satellite observations (Huffman et al. 2009; Huffman et al. 2007; Xie and Arkin 1997). Three different products have been used in this chapter (GPCP (Global Precipitation Climatology Project), CMAP (CPC Merged Analysis of Precipitation) and TRMM (Tropical Rainfall Measuring Mission)) and are summarized in Table 9.1.

It has been shown that dryland areas across the globe, on average have experienced an increase in greenness during the satellite record, from 1981 till present (Fig. 9.2, previous chapter). However, similar increases in greenness over the last three decades in the same or different regions may have widely different explanations (Fensholt et al. 2012; Mao et al. 2013) including driving mechanisms of both climate and human induced changes in land use and land cover. Mao et al. (2013) estimated satellite-derived relative change in annual LAI (leaf area index) from the years 1982 to 2009 at the global scale and found a South-to-North asymmetry in the trends coinciding with trends in temperature over the same period. Precipitation patterns were found to decrease this asymmetric-latitudinal LAI trend, with strong local effects. By combining EO data analysis with model simulations it was found that positive and negative vegetation trends in dryland areas were primarily driven by changes in climate, with positive trends dominating. de Jong et al. (2013a) used an additive spatial model with 0.5° resolution, including climate-associated effects and influence of other factors such as land use change to separate possible drivers of observed changes. They attributed just above 50 % of the spatial variance in global productivity to changes in climate variables.

Table 9.1 Precipitation datasets used in this chapter and their main characteristics

Satellite product	CPC Merged Analysis of Precipitation (CMAP)	Global Precipitation Climatology Project (GPCP)	Tropical Rainfall Measuring Mission (TRMM)
Spatial resolution	2.5 × 2.5°	2.5 × 2.5°	0.25 × 0.25°
Spatial coverage	Global	Global	Latitude: 50 N – 50 S
			Longitude: 180 W – 180 E
Temporal resolution	Monthly	Monthly	Aggregated to monthly (from 3 hourly)
Temporal coverage	1979–present	1979–present	1998–present
Sensors included	GPCC rain gauge,	SSM/I emission,	SSM/I,
	IR-based GOES precipitation index,	SSM/I scattering,	Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E),
	OLR precipitation index, Microwave Sounding	IR-based Goddard Earth Observing System (GEOS) precipitation index,	Advanced Microwave Sounding Unit-B (AMSU-B),
	Unit (MSU),	Television and Infrared	Infrared (IR) data from the international constellation of geosynchronous earth orbit (GEO) satellites, Gauge,
	SSM/I scattering,	Observation Satellite Operational Vertical Sounder (TOVS)-based estimates,	GPCC,
	SSM/I emission,	Outgoing longwave radiation (OLR) precipitation index, GPCC,	Climate Assessment and Monitoring System (CAMS).
	National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis.	Global Historical Climate Network (GHCN, produced by NOAA) and CAMS.	
Download address	ftp://ftp.cpc.ncep.noaa.gov/precip/cmap/monthly	http://www1.ncdc.noaa.gov/pub/data/gpcp/v2/sat_gauge_precip	http://daac.gsfc.nasa.gov/data/datapool/TRMM/
References	Xie and Arkin (1997)	Adler et al. (2003)	Huffman et al. (2007)

The relative importance of precipitation, air temperature and incoming solar radiation for vegetation growth across the globe has been mapped by (Nemani et al. 2003) showing regions of different climatic dominant limiting factors. Areas primarily constrained by precipitation occupied approximately 50 % of the global

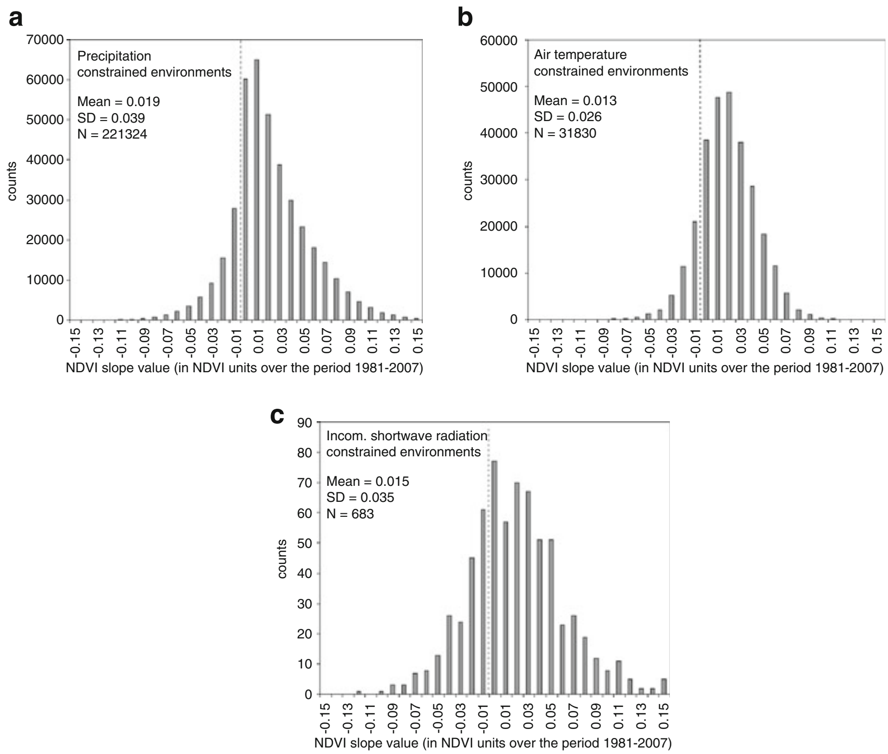

Fig. 9.2 Histograms of the NDVI slope in semi-arid areas from July 1981 to December 2007 in environments constrained by, (**a**) precipitation, (**b**) air temperature and (**c**) incoming shortwave radiation. Dashed vertical line represents NDVI trend values of 0 (NDVI units over the total period 1981–2007). Note the different scale on the y-axis value for each sub-plot due to the different number of pixels in each category

semi-arid areas, 7 % by air temperature and <1 % by incoming shortwave radiation (the remaining 42 % of semi-arid pixels were not characterized by a single predominant driver) (Fensholt et al. 2012). The NDVI trend coefficients of these three categories of potential climatic constraints to plant growth for semi-arid areas across the globe (Fig. 9.2a–c) were found to be positive on average for all three constraints (mean NDVI trend coefficients of 0.019, 0.013, and 0.015 for precipitation, air temperature, and incoming shortwave radiation, respectively). This implies that current generalizations, claiming that land degradation is ongoing in dryland areas worldwide (Adeel and World Resources Institute 2005; UNCCD Secretariat 2013) are not supported by the most recent satellite based analysis of vegetation greenness (being closely related to the key indicator of biological productivity).

9.2.1 Precipitation Controlling Observed Vegetation Changes in the Sahel

The Sahel is one of the world's largest dryland areas bordering the Sahara Desert to the north. Sahel has been referred to as the region of largest global rainfall anomalies during the last century (Nicholson 2000), suffering from recurrent droughts and large inter-annual variations in vegetation productivity. The grasslands of the Sahel constitute the basis for livestock production and the livelihoods of millions of people. Since the 'Sahel drought' of the 1970s and early 1980s, this zone has been described as a hotspot of land degradation, threatened both by recurrent droughts (Nicholson 2000) and by human overuse, e.g., through overgrazing (Hulme 2001; Lamb 1982) which is in contrast to more recent EO findings (Anyamba and Tucker 2005; Eklundh and Olsson 2003; Fensholt and Rasmussen 2011; Herrmann et al. 2005; Prince et al. 1998; Rasmussen et al. 2001). The productivity of the semi-natural grasslands of the Sahel is to a considerable extent controlled by precipitation. Recent analyses of trends in precipitation based on rain gauge measurements (Lebel and Ali 2009), as well as on global precipitation datasets (Fensholt and Rasmussen 2011; Fensholt et al. 2013; Huber et al. 2011) show that precipitation has increased in the Sahel since the mid-1980s. Thus the greening, observed in the field and by use of time series of satellite images, is not surprising. Linear regression analysis of GIMMS3g (Global Inventory Monitoring and Modeling System) NDVI (Normalized Difference Vegetation Index) against the CMAP (CPC Merged Analysis of Precipitation) precipitation (Xie and Arkin 1997) was conducted by Fensholt et al. (2013) for the period 1982–2010 (Fig. 9.3). An overall strong linear correlation between growing season integrated NDVI and precipitation is observed for the Sahel with 65.1 and 47.7 % of the pixels analysed being significantly positively correlated ($p < 0.05$ and 0.01, respectively).

9.2.2 Assessing Drivers of Observed Changes Based on Rain-Use Efficiency

If the greening in drylands is predominantly an effect of increased precipitation, it could be argued that this may disguise continued degradation caused by other factors, such as excessive cultivation and overgrazing. Over the last decades several studies have attempted to eliminate the effect of rainfall change (by a normalization procedure) on biological productivity, to better isolate the impact of non-rainfall related changes, e.g. human impacts (Evans and Geerken 2004; Prince et al. 1998; Wessels et al. 2007). This is sought to be captured by the concept of Rain-Use Efficiency (RUE), defined as the ratio of ANPP (aboveground net primary productivity) to annual precipitation (Le Houérou 1984, 1989; Prince et al. 1998). Consequently, changes in RUE have been suggested as an integral measure for evaluating

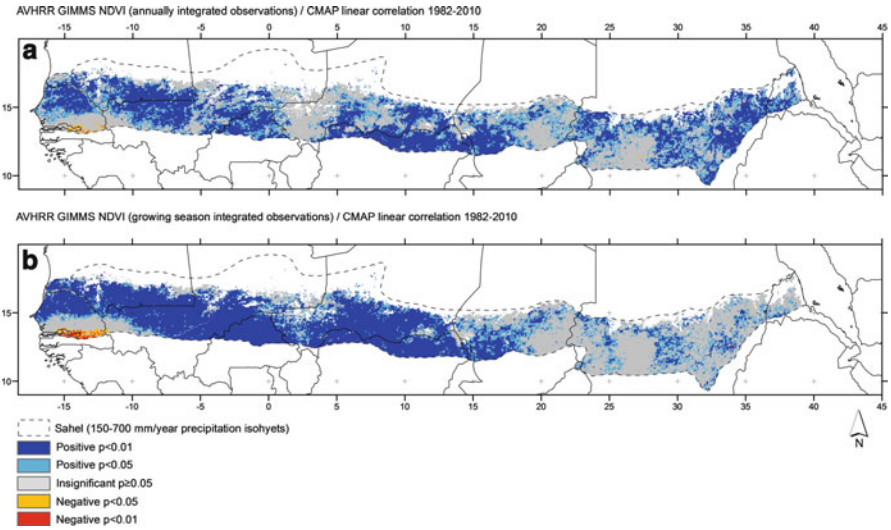

Fig. 9.3 Significance of correlation between GIMMS3g NDVI and precipitation from CMAP (Table 9.1) 1982–2010 for (**a**) Annually integrated NDVI (**b**) growing season integrated NDVI. CMAP precipitation has been resampled to match the spatial resolution of the GIMMS3g NDVI

land degradation and desertification and a number of authors have attempted to assess non-precipitation related land degradation – or the reverse – in global drylands. Time series of RUE have been estimated wholly or partly from satellite remote sensing or using only ground measurements (Bai et al. 2008; Hein and de Ridder 2006; Hein et al. 2011; Prince et al. 1998, 2007).

The basic assumption involved in the use of RUE is that NPP (net primary productivity) is proportional to (or at least linearly related to, see below) precipitation in the absence of human-induced land degradation. If this assumption of proportionality does not hold, the normalization for precipitation, which is the basis for the use of RUE is not successful (Prince 2002) and the use of RUE to detect non-precipitation related land degradation will become biased by changes in precipitation. Several papers have questioned this proportionality. It is well known that for increasing amounts of rainfall, the importance of water availability will at some point decrease (Prince et al. 2007) violating the assumption of proportionality between productivity and precipitation. An important question is whether the transition from water being the primary constraint for vegetation growth into other factors such as nutrients and incoming solar radiation, is observed for dryland areas. Using ground data from a variety of semi-arid rangelands in the Sahel and elsewhere, (Hein and de Ridder (2006), Hein et al. (2011)), as well as Hein (2006) argued that at high precipitation levels RUE will tend to decrease in dryland areas, because other production factors than water availability become limiting. The interval of annual precipitation in which proportionality may be assumed is debated and varies with vegetation, soil and climate. Hein et al. (2011) cited Breman and

Dewit (1983) for the statement that the proportionality breaks down at/above around 300 mm of rainfall per year.

Hein and de Ridder (2006) further argued that RUE will also decrease in areas of very low precipitation because most of the precipitation will evaporate and thus not be available for vegetation. Thus, they suggested that a quadratic or cubic relationship between productivity and precipitation should replace the assumption of proportionality for dryland areas. Prince et al. (2007) however challenged this interpretation with respect to the lack of an ecological justification. Other publications based on *in situ* measurements suggest that biome-specific RUE values should be applied depending on the rainfall regime (Huxman et al. 2004; Paruelo et al. 1999; Ruppert et al. 2012). However, Hu et al. (2010) concluded that inter-annual variation in RUE is not correlated with precipitation at the site level from a large dataset of *in situ* observations from dryland areas in China. The hypothesis of a constant of RUE for different species/rainfall regimes has implications for interpreting values of EO-based (Earth Observation) RUE in both the temporal and spatial domain since RUE values might not be directly inter-comparable across space for drylands receiving different amounts of rainfall (Prince et al. 1998). Also, if the amount of rainfall for a given pixel changes towards wetter or dryer conditions over time, this will have implications for the interpretation of RUE if a non-proportional relation between productivity and precipitation exists.

Based on annually integrated NDVI and annual precipitation (Fensholt and Rasmussen (2011), Fensholt et al. (2013)) demonstrated that for most pixels in the Sahel there is no proportionality, but sometimes a linear relation between ΣNDVI (seasonal or annual) and annual precipitation exists (as in Fig. 9.3). Proportionality is mathematically defined as the relationship of two variables whose ratio is constant, and unless the linear relationship between the vegetation metric and precipitation crosses the origin (0,0) of the Cartesian coordinate plane, proportionality is not obtained. It is argued that this lack of proportionality undermines the general use of satellite-based RUE time series as a means of identifying non-precipitation related land degradation (Fensholt et al. 2013), Veron et al. (2005). The specific data pre-processing of EO-based metrics for vegetation productivity have implications for the proportionality between productivity and precipitation and will therefore impact on the degradation/recovery assessment results obtained when using RUE. Fensholt et al. (2013) studied the sensitivity of the RUE approach to the EO-based proxies used (Fig. 9.4). Annually summed AVHRR GIMMS3g NDVI was shown to be linearly related to annual precipitation but no proportionality was found, thereby making a normalisation impossible (the inability of RUE to normalise for variability in precipitation is obvious from a remaining high per-pixel temporal correlation between RUE and precipitation). The results show significant negative trends in RUE (Fig. 9.4a) (primarily western and central Sahel). If substituting annually summed AVHRR GIMMS3g NDVI with a different vegetation productivity metric (the growing season integrated NDVI) in the RUE calculation (Fig. 9.4b), proportionality between productivity and precipitation was attained for the majority of pixels in the Sahel allowing for a successful use of RUE (no correlation between RUE and precipitation). The use of a growing season

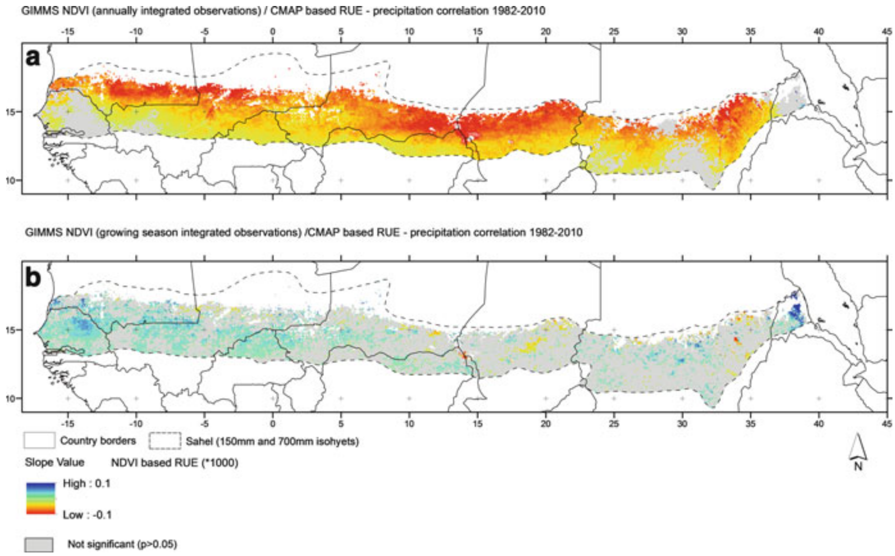

Fig. 9.4 RUE linear trends 1982–2010 based on (**a**) Annual sums of AVHRR GIMMS3g NDVI. (**b**) Growing season integrals of AVHRR GIMMS3g NDVI. Both productivity estimates are divided by annual sums of precipitation from GPCP (Table 9.1) to obtain Rain-Use Efficiency (RUE). GPCP precipitation has been resampled to match the spatial resolution of the GIMMS3g NDVI

integral of NDVI, which does not violate proportionality, produces very different results in trends of RUE, with the majority of pixels being characterised by significant positive RUE trends across the entire Sahelian belt. Clearly, this example illustrates that widely different conclusions concerning drivers of observed changes in vegetation trends and land degradation in the Sahel may be obtained depending on the vegetation parameterization approach used for the RUE analysis. Care must be taken that the assumed precipitation normalisation is in fact successful; otherwise trends in RUE will be nothing but a simple reflection of the trend in the precipitation dataset or perhaps other factors controlling NPP.

A different use of RUE as a measure of land degradation has been suggested by (del Barrio et al. 2010). The RUE values for each site and date were rescaled according to the upper and lower bounds of the VI (vegetation index)/precipitation point scatter to calculate the performance of RUE for a given landscape location to a reference potential conditions (i.e. maximum RUE observed) for this landscape type. However, the reference values depend on the actual observations, and assume that some areas are in their potential condition and others are fully degraded. It could also be that the RUE of a given pixel as compared to a reference landscape will be dependent on local soil variability and topographic conditions.

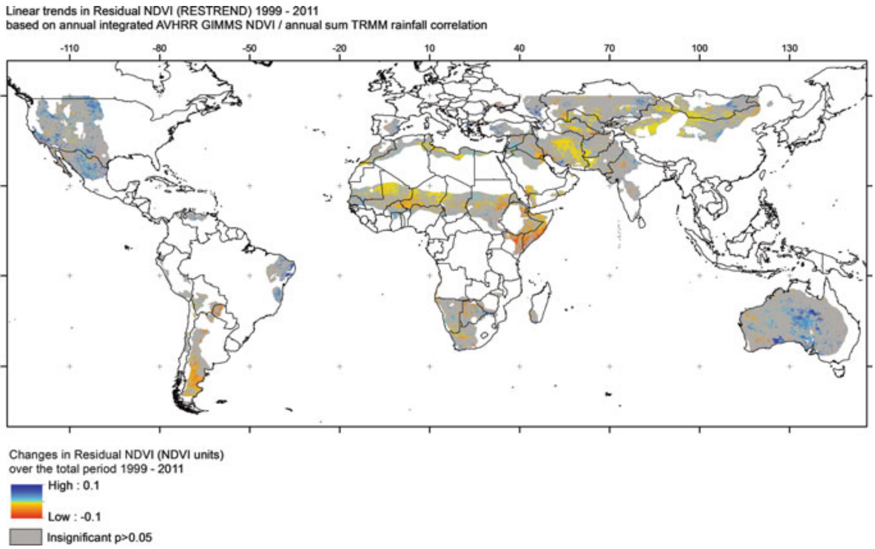

Fig. 9.5 Linear trends in Residual NDVI (RESTREND) 1999–2011. The residuals were estimated from linear regressions between annual integrated AVHRR GIMMS3g NDVI and annual summed TRMM (Table 9.1) rainfall. TRMM precipitation has been resampled to match the spatial resolution of the GIMMS3g NDVI

9.2.3 Assessing Drivers of Observed Changes Using the Residual Trends Productivity Approach

A different approach, called Residual Trend Analysis (RESTREND), has been developed in an attempt to distinguish rainfall-related variations and trends from human-induced land degradation (Archer 2004; Evans and Geerken 2004; Wessels et al. 2007). Following this method, per-pixel ΣNDVI (seasonal or annual) is regressed against annual precipitation, as with RUE, and then residuals are calculated for each site/time point from the best-fit linear regression for all sites. These residuals are then plotted against time to detect any temporal trends in deviations from the potential (as estimated by the best-fit regression). Just as with RUE, RESTREND seeks to expose factors other than precipitation, including a human-induced change (Herrmann et al. 2005; Huber et al. 2011; Wessels et al. 2007) that affect NPP.

In Fig. 9.5 AVHRR GIMMS3g NDVI was regressed against satellite-measured precipitation data from TRMM (Tropical Rainfall Measuring Mission; latitudinal coverage: 50 N-50S) from 1999 to 2011 and then used in a RESTREND analysis. Mixed patterns of increasing and decreasing trends of residual NDVI can be observed, with large negative values in eastern Africa and southern America and mainly positive trends in Australia and northern America.

9.2.4 Limitations/Challenges for RUE and RESTREND Approaches

Instead of assuming proportionality or linearity between precipitation and productivity for the use of RUE as being criticised by Hein and de Ridder (2006) and Hein et al. (2011) it was suggested by Fensholt et al. (2013) to restrict the analysis applicable to the RUE approach to regions or pixels for which proportionality can be shown to exist from remotely sensed data. This allows for maintaining the basic simple notion of RUE (as formulated by Le Houérou (1984)) as a means of normalizing for the effect rainfall on vegetation productivity and also helps in defining the limits within which RUE should be applied, i.e. to regions where rainfall is the primary constraint to vegetation growth. For a given pixel, however, in the case of severe ongoing land degradation in the middle part of the time series being studied, the linearity between rainfall and productivity may decline. This may be captured in the RUE time series as gradual changes that may reverse over time involving a trend break. Hence, if one applies strict statistical criteria at the per-pixel level there is a risk of excluding pixels from the analysis that are in fact the ones showing signs of human-induced land degradation. It is therefore suggested to apply the statistical requirement of a significant correlation between precipitation and vegetation productivity to be fulfilled at the regional level by a zonation/stratification of the per-pixel relation.

Also the use of the RESTREND approach for assessing human induced influence of vegetation changes is based on linearity between rainfall and productivity. For pixels for which a high linear correlation between ΣNDVI (annual/seasonal) and annual precipitation exists, meaningful estimations based on the RESTREND technique is feasible. If, however, for a given pixel a weak relation between ΣNDVI and annual rainfall exists, this approach is of little use, because the uncertainty caused by estimating the NDVI residuals increases proportionally. As pointed out by Wessels et al. (2012) this is likely to happen for a scenario, as above, where human-induced land degradation starts in the middle of a time series. A simulated degradation intensity ≥ 20 % was shown to cause an otherwise strong relationship between NDVI and rainfall to break down, thereby making the RESTREND an unreliable indicator of land human induced degradation.

A way to minimize the effects of fitting only one linear regression for the whole time-series is the identification of gradual or abrupt changes in the RUE time series using change detection method such as Breaks For Additive Seasonal and Trend (BFAST) (Verbesselt et al. 2010a, b). As described in the previous chapter, the basic principle of the BFAST algorithm is the decomposition of a time series into seasonal, trend, and remainder components, coupled with the detection of abrupt changes in both the trend and seasonal components. BFAST enables the detection of trend changes within EO time series assuming that nonlinearity can be approximated by piecewise linear models. This type of analysis can provide valuable information on the occurrence of trend changes, as well as on the timing and

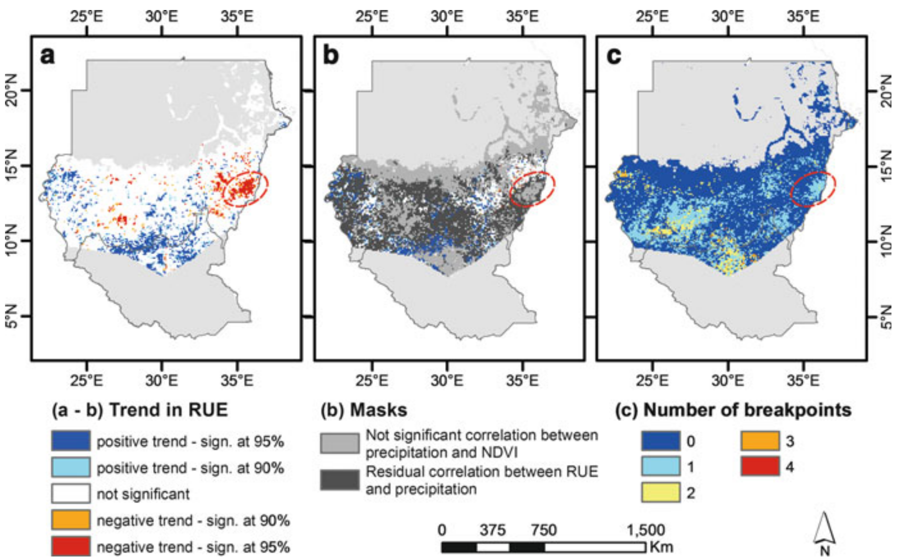

Fig. 9.6 (**a**) Direction and significance of 1982–2011 trends in RainUse Efficiency derived from the GIMMS3g NDVI and the GPCP yearly totals for dryland areas of Sudan. Non vegetated areas were masked out (*light grey*). (**b**) As in (a) but superimposed by pixels being masked due to lack of correlation between rainfall and NDVI (*medium grey*) and residual correlation between RUE and rainfall (*dark grey*). (**c**) Number of break points in Rain-Use Efficiency identified by BFAST between 1982 and 2011

magnitude of related break points in the time series (de Jong et al. 2012, 2013b; Verbesselt et al. 2012). Land degradation assessment based on a joint analysis of both long-term trends and abrupt changes in precipitation and vegetation time series should therefore be more accurate as they will not be solely based on diagnosis of long-term linear changes in ecosystem efficiencies but will also use more accurate information on potential abrupt changes observed either in climate or in the vegetation traits.

An example of the application of BFAST to address the issues of the RUE and RESTREND approaches for land degradation assessment is an analysis for Sudan (Fig. 9.6). Sudan is characterised by widespread and rapidly accelerating environmental degradation, which is sufficiently severe to be amongst the factors triggering tensions and conflicts (United Nations Environment Programme. 2007). This example is based on the growing-season NDVI integral derived from the GIMMS3g archive (1981 to the present) used as proxy for vegetation productivity and annual precipitation from the Global Precipitation Climatology Project (GPCP) (Table 9.1). Figure 9.6a shows the trends in RUE without taking into consideration that there are large areas of the semi-arid Sudan where the preconditions for using RUE are not fulfilled (lack of linearity between vegetation productivity and precipitation and/or residual correlations between RUE and precipitation are observed) (Fig. 9.6b). However, breaks in the RUE time series detected by the BFAST

(Fig. 9.6c) indicate that for many pixels (e.g. the region highlighted with a red circle) the linearity assumption on which the RUE approach is based upon is not fulfilled because of a distinct breakpoint within the period of analysis. Therefore the rejection of these pixels based on a too strict statistical criteria of linearity may actually lead to disregarding some of the regions that are most vulnerable and most seriously hit by land degradation.

9.3 Assessment of the Roles of Climate on Anomalies of Dryland Vegetation Productivity

9.3.1 Combining Dynamic Global Vegetation Models and EO Data

Recent studies based on process-based modelling approaches (Dynamic Global Vegetation Models; DGVM's) have attempted to disentangle the climate and human effects on the Sahelian greening (Hickler et al. 2005; Seaquist et al. 2009) and greening at the global scale (Mao et al. 2013). The use of DGVM's like the LPJ (Lund-Potsdam-Jena) (Sitch et al. 2003) allows studying the causes for current and historical variability and trends in vegetation productivity of global drylands when comparing against time series of EO data for the same period (Hickler et al. 2005). DGVM's provide the potential vegetation properties and modelling includes atmospheric CO_2 fertilization, nitrogen/phosphorous deposition and land use and land cover change (not accommodated in EO-based Light Use Efficiency (LUE) approaches) as well as dryland resilience in the context of disturbance processes from human influence like bush fires. Discrepancies between modelled and EO-based observed productivity have therefore been used as means of inferring information of drivers of changes (Seaquist et al. 2009). Combining process-based ecosystem models with high-temporal resolution remote sensing using data assimilation offers an interesting way forward adding insights about the patterns and mechanisms driving observed vegetation dynamics at these spatial scales; yet it remains an underutilized avenue of research (Seaquist et al. 2012).

9.3.2 Sea Surface Temperature and Vegetation Productivity Teleconnections

Vegetation productivity across different dryland regions is known to be affected locally by changes in precipitation as discussed in the previous sections. The causes of inter-annual precipitation variability has also been related to variability in regional climate driven by SST patterns. In the African Sahel, the reasons for the large inter-annual and decadal fluctuations in rainfall are still not entirely understood, but early works by (Folland et al. (1986), Lamb (1978), Palmer 1986) found a relationship (teleconnection) with regional and global SST conditions. Sahelian precipitation and SST patterns have been related to the ENSO (El Nino Southern Oscillation) and NAO (North Atlantic Oscillation) (Biasutti et al. 2008; Palmer 1986; Shanahan et al. 2009; Ward 1998). Relationships between precipitation and SST have been found also in the Pacific (Caminade and Terray 2010; Janicot et al. 1998; Mohino et al. 2011), the Indian Ocean (Bader and Latif 2003; Giannini et al. 2003; Lu 2009) and the Mediterranean (Philippon et al. 2007; Raicich et al. 2003; Rowell 2003).

In the Sahel, the importance of SST on precipitation is still unclear. While several studies have reported limited correlations (Anyamba and Eastman 1996; Anyamba and Tucker 2005; Anyamba et al. 2001; Philippon et al. 2007; Propastin et al. 2010), others have shown stronger relationships (Camberlin et al. 2001; Oba et al. 2001; Ward 1998). Oba et al. (2001), attributed large parts of the inter-annual variation of vegetation productivity during the 1980s to the NAO. Wang (2003), on the other hand, did not find a consistent relationship. Other studies (e.g. Brown et al. (2010)) have found significant relationships individually between the Pacific Decadal Oscillation (PDO) and two phenological metrics of NDVI (start of season and seasonal integrated NDVI) in West Africa but a limited influence of the Indian Ocean Dipole (IOD). However, although Williams and Hanan (2011), found the IOD and the Multivariate ENSO Index (MEI) to be related to rainfall individually, (when taken together) interacting effects of the two indices removed the correlations.

Direct relationships between SST and vegetation measurements from AVHRR time series have also been demonstrated. For example, Huber and Fensholt (2011) studied the direct correlations between the Sahelian dryland vegetation variability and large-scale ocean–atmosphere phenomena causing changes in SST patterns. It was concluded that over the last 3 decades, significant correlations existed between global climate indices/SST anomalies and Sahelian productivity, however with different characteristics in western, central and eastern Sahel. Whereas the vegetation productivity in the western Sahel could be associated with SST for large oceanic areas of the Pacific, the Atlantic as well as the Indian Ocean (Fig. 9.7), for the eastern Sahel only small areas in the Atlantic were found to be significantly related to dynamics in NDVI.

Overall, these large scale climate indices and especially SST anomalies for specific ocean areas were found to have predictive power expressed by a statistically significant relation between northern latitude winter/spring SSTs and summer vegetation productivity in the Sahel (Fig. 9.8). This time lag of several months could be of immense importance for forecasting annual vegetation productivity in this region and possibly in other dryland areas across the globe, home to the world's poorest populations.

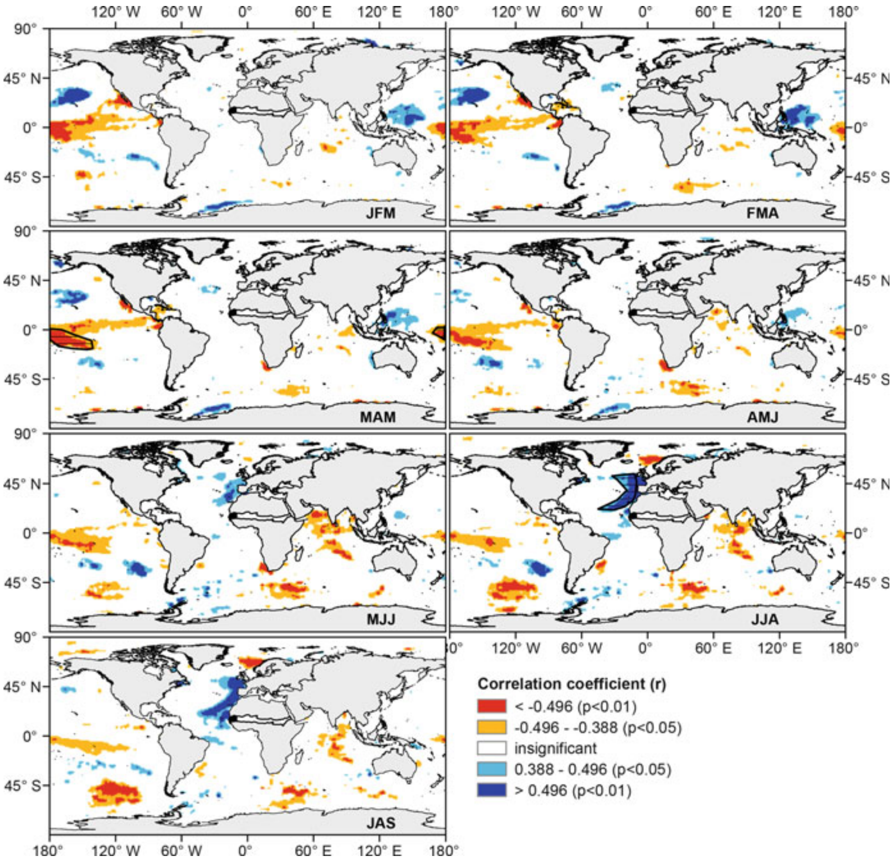

Fig. 9.7 Maps of significant correlation coefficients ($p < 0.05$) between the Sahel NDVI anomaly index (based on July–September NDVI (JAS)) for the West African Sahel sub-region and mean SST anomalies from 1982 to 2007 for different intra-annual time lags (e.g., correlation between JAS NDVI anomalies and JFM (January–March) SST anomalies)

9.4 Summary

The United Nations Convention to Combat Desertification (UNCCD) definition of desertification (degradation in dryland areas) implies that change in vegetation productivity is a key indicator (but not the only one) of land degradation. Spatially and temporally consistent, long-term data on vegetation productivity is therefore of great interest for the assessment of changes in environmental conditions in dryland regions and Earth Observation (EO) satellite data provide the only suitable means of consistent monitoring of changes at the global scale.

Current generalizations, claiming that land degradation is ongoing in dryland areas worldwide are not supported by recent satellite based analysis of vegetation and this chapter introduced some of the most widely used methods of inferring

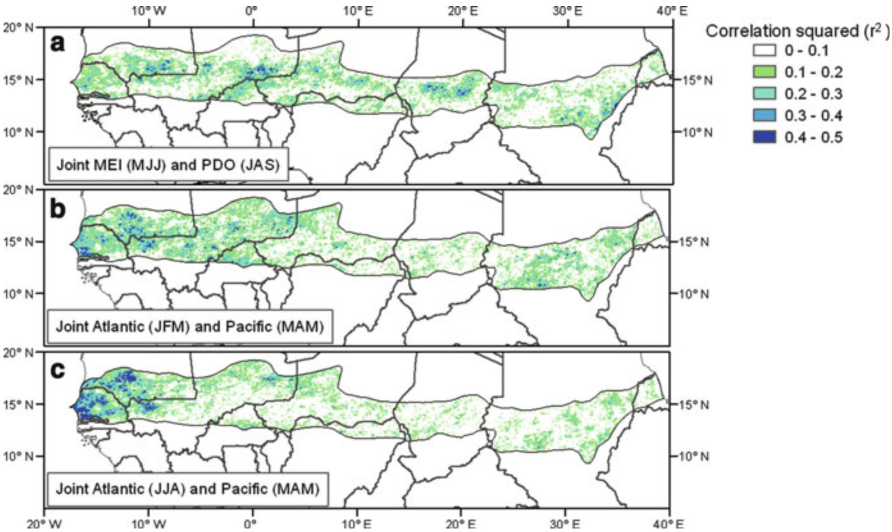

Fig. 9.8 Maps of joint explained variance (r^2) from partial correlation analysis of July-September (JAS) NDVI anomalies and (**a**) the Multivariate ENSO Index (MEI) averaged over May–July (MJJ) and the Pacific Decadal Oscillation (PDO) averaged over July–September (JAS), (**b**) the SST indices extracted from the Atlantic and Pacific for January–March (JFM) and March–May (MAM), respectively, and (**c**) the SST indices extracted from the Atlantic and Pacific for June–August (JJA) and March–May (MAM), respectively

drivers of dryland vegetation changes observed from remote sensing time series data. Trends in vegetation productivity may be related to climatic as well as non-climatic causes of change (e.g. management), and it is of great policy relevance to better understand the drivers and causal mechanisms of observed productivity trends. However, one of the main challenges in dryland vegetation research remains resolving and disentangling the impact from climate and human induced land use change respectively. A strong coupling between EO-based vegetation dynamics and precipitation and/or temperature was found in most dryland areas but also large regions of non-significant correlation between rainfall/temperature and vegetation growth was observed pointing towards human influence on vegetation from changes in land use practices.

The Sahel (being one of the world's largest dryland areas) has suffered from recurrent droughts and large inter-annual variations in vegetation productivity over recent decades. Sahel was used here as a showcase for two interrelated methods of detecting the impact of non-rainfall related changes on vegetation; the concept of RUE (Rain-Use Efficiency) and the RESTREND approach. Both approaches however are based on the assumption of a strong per-pixel linear relationship between rainfall and productivity (over time) that might be compromised in the case of escalating land degradation during the period under study. Rather than fitting only one per-pixel linear regression for the whole time-series, it is suggested here to combine a change detection method such as BFAST (Breaks For Additive Seasonal and Trend) (see previous chapter) for identification of time series breakpoints in combination with RUE/RESTREND approaches to overcome the problem of the assumption of long-term rainfall/vegetation linearity that might be incompatible with the manifestation of degradation.

Finally, global sea surface temperature (SST) anomalies (caused by large-scale ocean–atmosphere phenomena) were shown to be teleconnected to regional scale vegetation productivity in the Sahel, thereby being important for an improved understanding of inter-annual changes in the Sahelian dryland productivity. Large scale climate indices and especially SST anomalies for specific ocean areas were found to have predictive power for the vegetation productivity in the Sahel and the existence of a time lag of several months between SST anomalies and vegetation productivity provides an important basis for forecasting annual vegetation productivity in this region and possibly in other dryland areas across the globe.

Acknowledgements This book chapter is written within the frame of the project entitled Earth Observation based Vegetation productivity and Land Degradation Trends in Global Drylands. The project is funded by the Danish Council for Independent Research (DFF) Sapere Aude programme.

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