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Review

Assessing Land Degradation and Desertification Using Vegetation Index Data: Current Frameworks and Future Directions

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Abstract: Land degradation and desertification has been ranked as a major environmental and social issue for the coming decades. Thus, the observation and early detection of degradation is a primary objective for a number of scientific and policy organisations, with remote sensing methods being a candidate choice for the development of monitoring systems. This paper reviews the statistical and ecological frameworks of assessing land degradation and desertification using vegetation index data. The development of multi-temporal analysis as a desertification assessment technique is reviewed, with a focus on how current practice has been shaped by controversy and dispute within the literature. The statistical techniques commonly employed are examined from both a statistical as well as ecological point of view, and recommendations are made for future research directions. The scientific requirements for degradation and desertification monitoring systems identified here are: (I) the validation of methodologies in a robust and comparable manner; and (II) the detection of degradation at minor intensities and magnitudes. It is also established that the multi-temporal analysis of vegetation index data can provide a sophisticated measure of ecosystem health and variation, and that, over the last 30 years, considerable progress has been made in the respective research.

Keywords: land degradation; desertification; NDVI; NPP; multi-temporal; trend analysis; RESTREND; RUE; UNCCD

1. Introduction

The United Nations Convention to Combat Desertification (UNCCD), ratified by 195 countries, identifies land degradation and desertification as one of the most pressing environmental concerns of our times [1,2]. Furthermore, the UN Conference on Sustainable Development ("Rio + 20") has called for a target of "zero net land degradation", whereby the rate of deteriorating lands would be counterbalanced by the rate of land improvement. These political frameworks, whilst admirable, require sound scientific evidence for effective implementation [3]. However, in spite of political and scientific recognition of the importance of land degradation, current estimates of its extent and severity are highly unreliable and spurious. The often quoted statistics that 15% of the Earth's surface and 60% of drylands are degraded [4], are acknowledged as qualitative and unsubstantiated [5,6]. These estimates, based on coarse resolution expert opinions, are not suitable for policy making or for scientific investigations into the potential remediation of degraded lands [7].

The timely and early detection of degradation processes is necessary to prevent the continuing deterioration of land condition. The lack of authenticated evidence on the magnitude of desertification has led to questions over the very existence of a global degradation problem [8,9], with large-scale studies frequently at odds with plot and field-scale studies [10,11]. There is a pressing need, therefore, for accessible and accurate measurements on the extent of degradation and desertification for policy, natural resource management and scientific research needs [7,12]. Given the temporal nature of land degradation, it is paramount that measurements adhere to the principles of repetitiveness, objectivity and consistency [13]. These requirements, combined with the size of the land occupied by semi-arid regions and the degree of development of many vulnerable nations, make Earth Observation (EO)-based systems a candidate choice for establishing monitoring networks [14,15]. So far, the most frequently utilised method employing EO datasets is trend analysis of vegetation index data, most commonly the Normalised Difference Vegetation Index (NDVI), as a proxy for Net Primary Production (NPP).

Land degradation and desertification is a complex area of scientific research. This complexity partly arises from an open discussion on the definition of what actually constitutes degradation. This confusion occurs due to the interdisciplinary nature of desertification, encompassing geographical, ecological, meteorological and social perspectives, all of which can have regionally specific interpretations [16]. Early observations, provided by European foresters in 1930's West Africa, classified desertification as the consequence of desert boundary displacement [17]. This viewpoint was later adapted to cover a variety of mechanisms that would result in a detrimental impact upon "the physical, chemical or biological status of land which may also restrict the land's productive capacity" [18]. Quantifying desertification by measurements of vegetation productivity and cover has led to long running debates concerning both the acknowledgment and inference of climatic influence on semi-arid ecosystems, with the UNCCD acknowledging that degradation can result from "various factors including climate variations and human activities" [1]. For a comprehensive review of the various definitions and their contexts see reviews by [5,6,19]. For the purpose of this article, we follow the definition used by the Millennium Ecosystem Assessment [20], which refers to land degradation as "the reduction in the capacity of the land to perform ecosystem goods, functions and services that support society and development", and to desertification as the same process in arid and semi-arid environments (collectively, the drylands). Hence, we use the terms desertification and degradation interchangeably. This definition considers the ability of land to support primary production as key ecosystem service, and its adoption implies that a reduction in the measured NPP at a site can potentially be viewed as land degradation [21]. This notion forms the theoretical framework on which the majority of EO-based assessments of degradation are founded, e.g., [14,15,22]. The potential of vegetation index variation as a measure of ecosystem health has been acknowledged for nearly 30 years [23], yet in spite of this simple concept, the subject has become extremely controversial within the scientific literature [11,24,25]. This controversy prevents the realisation of land degradation early warning and monitoring systems, which have been postulated for some time [15].

In this paper, we review the theoretical and statistical frameworks used for assessing land degradation with vegetation indices with a view to clarify current understandings and to highlight avenues for future research. Our specific objectives are to provide:

– a brief review of the origin of NDVI and the association of multi-temporal analysis in an land degradation framework;
– an evaluation of the current methods used to assess degradation and desertification through vegetation indices;
– an assessment of how these methods integrate into the wider debates on the mechanisms and processes of land degradation.

Although the focus of this review is the assessment of degradation and desertification in drylands, the frameworks discussed are by no means exclusive to this subject or environment, and are in many cases equally applicable to more wide-ranging global environmental change studies [26].

2. NDVI: Origin and Data

NDVI is expressed as:

$$\boldsymbol{NDVI} = (\boldsymbol{NIR} - \boldsymbol{RED}) \, / \, (\boldsymbol{NIR} + \boldsymbol{RED}) \tag{1}$$

where NIR and RED are reflectance values in the near-infrared and red wavebands, respectively. Thus, values range between −1 and 1 with an NDVI < 0 indicating cloud or water and >0.7 dense canopy coverage. There is some confusion over the exact origin of the NDVI. Although frequently cited as the original record, both Deering [27] and Rouse Jr *et al.* [28] used the *transformed* vegetation index (TVI = SQRT(NDVI + 0.5)), *not* the NDVI. A number of ecology and spectroscopy studies through the late 1960s and 1970s used NDVI, with the original paper remaining elusive [29–31]. In light of this confusion, the NDVI is most commonly credited to Tucker [32] who compared field biomass data with various band combinations obtained from handheld spectroradiometer readings.

NDVI is not a direct measure of vegetation or biomass, hence, it is not directly translatable into NPP. However, there is a considerable volume of literature reporting a close coupling between NDVI and *in-situ* NPP measurements [23,33–35]. For a full review of the advantages and limitations of vegetation index usage in dryland regions refer to Eisfelder *et al.* [36] and references therein. A key limitation of NDVI in regions of sparse biomass is the influence of soil interference, thus it is not advisable to apply NDVI in regions with an average value of NDVI < 0.1.

Time series analysis of NDVI can be applied using any system capable of measuring reflectances in the red and near infrared reflectance bands. However, long-term studies encounter data consistency and availability issues from a number of factors, including solar zenith angle, volcanic aerosols, sensor degradation and sensor compatibility. As such, analyses commonly utilise pre-processed datasets corrected for these issues (Table 1). The longest source of imagery available is obtained from the Advanced Very High Resolution Radiometer (AVHRR) sensor. Developed datasets include the 1981–2001 Pathfinder AVHRR Land-record (PAL) [37], the 1981–2006 Global Inventory Modelling and Mapping Studies (GIMMSg) [38], and the 1981–2011 GIMMS3g [39] at 8 km resolutions A recent European consortium have merged AVHRR data with SPOT imagery generating a 5 km (1981–1998) and 1 km (1998–2012) product [40]. The AVHRR-derived datasets, in particular the GIMMS and GIMMS3g products, continue as the most popular record, due to the unparalleled time span, in spite of the increasing availability of higher resolution products, such as SPOT (1 km), MERIS (1 km) and MODIS (500 m), all of which feature reduced time-spans. A comprehensive review of the available NDVI data sets is given in Pettorelli [41].

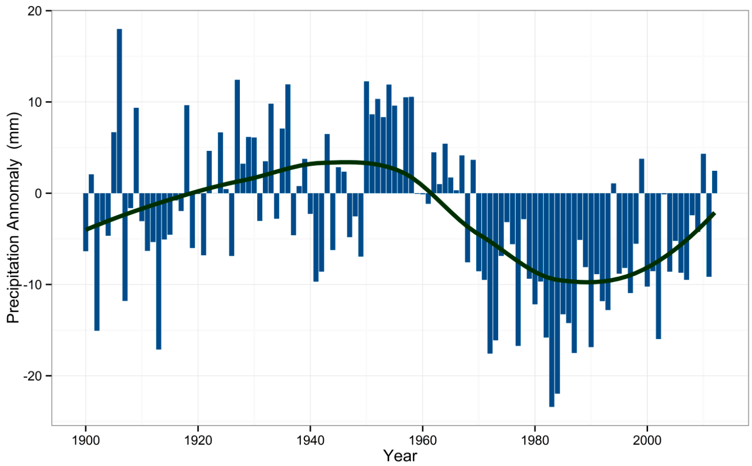
Table 1. A summary of commonly utilised Normalised Difference Vegetation Index (NDVI) datasets.

Name	Sensor	Time-Span	Time-Step	Resolution
Pathfinder (PAL)	AVHRR	1981–2001	10-day	8 km
Global Vegetation Index GVI)	AVHRR	1981–2009	7-day	4 km
Land Long Term Dara Record (LTDR)	AVHRR	1981–2013	Daily	5 km
Fourier-Adjusted, Sensor and Solar zenith angle corrected, Interpolated, Reconstructed (FASIR)	AVHRR	1982–1998	10-day	0.125°
GIMMS	AVHRR	1981–2006	15-day	8 km
GIMMS3G	AVHRR	1981–2011	15-day	8 km
S10	SPOT-Vegetation	1998+	10-day	1 km
EM10	ENVISAT-MERIS	2002–2012	10-day	1/1.2 km
SeaWiFS	SeaWiFS	1997–2010	Monthly	4 km
MOD (MYD)13 A1/A2	Terra (Aqua) MODIS	2000+	16-day	500 m/1 km
MOD13 (MYD)A3			Monthly	1 km
MOD13 (MYD)C1/C2			16-day/ Monthly	5.6 km
MOD13 (MYD) Q1			16-day	250
MEDOKADS	AVHRR	1989+	Daily	1 km

3. Background of Multi-Temporal Analyses

The use of NDVI for assessing desertification originates in the Sahel region of sub-Saharan Africa, which experienced a prolonged reduction in rainfall between 1960 and 1990 (Figure 1), with particularly severe droughts in 1973, 1984 and 1990 [42]. These droughts represent the most dramatic climatic shift on modern record and resulted in widespread famine across the region [42]. This ecological and meteorological transition was viewed as the consequence of anthropogenic desertification, supporting the "expanding deserts" paradigm [17,43,44]. Desertification was understood to result from human alteration of land-atmosphere interactions (Figure 2) [45]. Reduced vegetation cover, initiated by increased grazing pressures [46,47], was postulated to increase localised albedo and temperature, in turn reducing regional rainfall leading to further vegetation cover loss [48,49]. Thus, an increased anthropogenic pressure was attributed as the major driver of regional climate and land cover processes [50]. This was in agreement with studies demonstrating the impact of intensive grazing on surface reflectance across the Negev-Sinai border [51–53]. Conclusions regarding an expanding Sahara and encroaching dune systems, such as those proposed by Lamprey [44] and Stebbing [17], were heavily cited in both scientific publication and media outlets [54]. More recent research heavily challenged this viewpoint and paradigm [5,55–57]. A number of studies in the Sudano-Sahelian region combined field surveys with aerial photography and multi-temporal NDVI. These studies revealed little expansion of the Sahara, and a relatively minor human footprint when compared to the climatic signal [55–57]. Other regional-scale analyses [54,58] reinforced this conclusion, casting serious doubt on the expanding deserts paradigm [6]. The study of Tucker [58] was a seminal study in demonstrating the potential of EO for long-term regional-scale ecosystem studies. In combination with other studies in the tropics [59,60], Tucker [58] demonstrated the potential to apply time-series analysis on EO imagery for monitoring and assessing ecosystem processes.

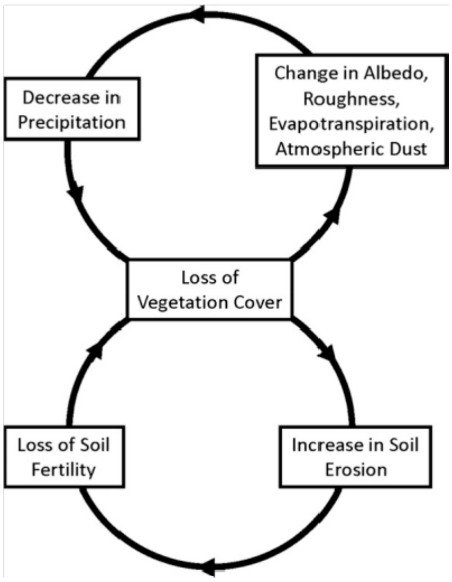
Figure 1. Time Series of the Sahel Precipitation Anomaly Index. Anomalies are with respect to the 1950–1979 period (Data source: [61]).



The demonstration of the potential of multi-temporal NDVI imagery [58], coupled with the development of pre-processed long-term data sets [37], resulted in an increase in the application of time-series analysis using NDVI. In the Sahel, a greening trend was observed by numerous studies [62–65]. Herrmann *et al.* [63] used the residual trend method (see Section 4) in combination with trend analysis on 19 years of monthly NVDI data to conclude that the region was, in general, greening with only localised degradation present. This analysis was reinforced by Huber *et al.* [64] on an extended NDVI data set, in conjunction with soil moisture estimates, with similar conclusions. Process-based ecosystem-modelling studies reported an agreement between the observed NDVI patterns and climate model-based estimates [66], with little influence from population or grazing pressures [67]. Growing season NDVI was found to have increased by 0.09 units from 1981–2007 [64], although a reduction in the rate of greening was noted around 2000 [68].This greening trend was found to be consistent across semi-arid regions globally, traditionally viewed as the hot-spots of land degradation [9,69,70]. With comparable desert boundary variation also noted in Asian drylands [71,72].

Greening was found to occur through two mechanisms: a lengthening of the growing season through earlier springs and delayed senescence and an increase in the maximum amplitude of NDVI [70,73,74]. Evidence of increased vegetation productivity accompanied a revised view of the cause of Sahelian rainfall fluctuations. Modelling studies revealed that the desiccation-vegetation feedback loop, theorised by Charney [48], had been greatly exaggerated [5]. Regional rainfall variation is primarily related to external drivers, principally sea surface temperature in the low-latitudes [75] but also northern hemisphere volcanic aerosol emissions [76], with localised vegetation-atmospheric interactions playing a minor role [75]. The majority of vegetation greening, in the Sahel and globally, can be attributed to increased precipitation over the past 30 years [77]. However, the question of human influence on semi-arid ecosystems remains highly controversial [14,78]. Furthermore, the sensitivity of trend methods to detecting degradation processes has been questioned [21]. Claims that current precipitation patterns may be disguising wide-spread degradation [11,21] require urgent investigation. The consequences of this degradation would be severe when dry periods return to degrading or degradation-prone localities.

Figure 2. Representation of the positive feedback loop for desertification [45].



In arid regions, vegetation, and therefore NDVI, is highly correlated to rainfall [79], thus any variation in rainfall affects the NPP. Although temperature variation is also important in many regions [72,80]. Therefore, in order for any long-term permanent degradation to be detected, it is necessary to remove the influence of a precipitation trend. A number of methods have been proposed that aim to accomplish this. Le Houerou [81] originally proposed the ratio of NPP to rainfall, the Rain-Use Efficiency (RUE), as an ecosystem indicator. It was suggested that arid lands would produce around 4 kg-dry matter/ha/year/mm rainfall, and that a reduced RUE indicated land degradation. Further analysis revealed that RUE values varied between regions [82,83]. Consequently, temporal variation in RUE was proposed as an indicator of degradation [22]. Prince *et al.* [22] investigated the regional RUE of the Sahel from 1982–1994, using seasonally integrated NDVI as a proxy for NPP. This analysis revealed little temporal variation in RUE across the region, thus indicating a consistent ecosystem dynamic through periods of droughts. However, the application of RUE as an indicator of land degradation has become highly controversial [24,78,84]. An explanation of the limitations and assumptions of RUE is given in Section 4. Statistical methods to separate NDVI from rainfall trends have also been proposed; these include the RESidual TRENDds (RESTREND) method [85,86] and the Precipitation Marginal Response (PMR) [87]. These methods both focus on detecting a shift in the statistical relationship between rainfall and NDVI. The proposed degradation mechanism is comparable to RUE: as degradation occurs, the usage of precipitation shifts, whereas meteorologically-induced degradation relationships stay constant [85,86,88].

4. Trend Analysis Frameworks

4.1. NDVI Trend Analysis

Time series techniques can be grouped into parametric and non-parametric methods. The application of these techniques on EO imagery has become a contentious issue due to the inherent limitations and assumptions; an overview of the most commonly used ones, is given below.

Linear trend analysis applies a linear regression model to quantify change in the dependent variable, y (*i.e.*, NDVI) against an independent variable, x (*i.e.*, time). The direction and magnitude of change from this model thus explains the change in NDVI over the period analysed. This test has a number of assumptions that must be met in order to be considered robust [89]:

(1) independence of the dependent variable;
(2) normality in the model residuals;
(3) consistency in residual variance over time;
(4) independence in residuals.

In addition to spatial autocorrelation functions present [90,91], memory effects in dryland systems make inter- and intra-annual NDVI values strongly correlated [92–94]. Thus, assumption one above and, commonly, four, are unlikely to be met. The consistency in residual variance is heavily influenced by anomalous and outlier values, such as those caused by hemispheric climatic oscillations [21], and may also be breached.

The Theil-Sen trend is a non-parametric trend estimation technique. Functionally similar to linear least squares regression, it operates on non-parametric statistics and is not dependent upon the assumptions of linear regression. Trends are estimated using the median values and are therefore less susceptible to noise and outliers, with a robust trend estimated with up to ~29% noise across the data [95,96].

The Mann-Kendall test measures the monotonicity or consistency of a trend [97]. The test is a cumulative value of the instances of increases or decreases from a pairwise comparison, with values of +1 indicating a continually increasing and −1 a continually decreasing trend. Although robust against the assumption of linear regression, the trend is susceptible to producing low values for time series with a strong overall change but moderate annual fluctuations.

4.2. Differences between Trends, Datasets and Sensors

A number of studies have compared the results obtained from applying a variety of trend methods [8,70]. Results indicate that although the trend estimations differ, there is rarely a major difference between results with both direction and magnitude consistent across methods. For global semi-arid regions, Fensholt *et al.* [8] compared Mann-Kendall and linear regression models, finding a mean difference of 0.039 and −0.019 for positive and negative trends and maximum differences of 0.285 and 0.158 with standard deviations of 0.037 and 0.029, respectively. A comparison of trend estimation, for a pixel in the Sudanese Sahel, is shown in Figure 3.

A majority of studies use NDVI data sets derived from the AVHRR sensor (Table 1). As a meteorological sensor the AVHRR was not designed for terrestrial ecosystem applications [98], thus a number of issues are inherent. For example, the near-infrared waveband (Channel 2) overlaps with a region of strong atmospheric water vapour absorption, influencing the resulting NDVI values. Unlike modern sensors such as MODIS and SPOT, AVHRR does not possess ancillary bands that allow for the detection of atmospheric conditions. Thus, a range of processing is applied to raw AVHRR imagery in the preparation of NDVI records. The PAL and GIMMS/3 g records do not apply atmospheric correction, instead using maximum value compositing (MVC) of Top of Atmosphere (TOA) values to preserve the original data patterns [38,39,99]. However, comparison with the LTDR, which possess an atmospheric correction procedure, highlights the residual error that may remain within the GIMMS data due to this omission, particularly in regions with high Aerosol Optical Thickness (AOT) [100]. Furthermore, aging of the AVHRR carrying satellite results in a shift in the equatorial crossing time of the sensor, referred to as orbital drift. Orbital drift can, without reliable correction, influence NDVI values and computed trends, for a location specific quantification of orbital drift effects on AVHRR data see Nagol *et al.* [101]. Comparisons of the various AVHRR-derived datasets (PAL, GIMMS/3g, LTDR, FASIR) display regionally varying levels of agreement. For the Iberian peninsula, Alcaraz-Segura *et al.* [102] found good spatial agreement between the PAL, LTDR and FASIR datasets, with the GIMMS-derived trends differing. A similar observation was identified in South America where the GIMMS data failed to identify trend highlighted by PAL and FASIR records [103]. In the USA and Mexico, records displayed good correlation, however, trend estimates did vary particularly in dryland areas [104]. In a global-scale analysis, Beck *et al.* [105] compared the four AVHRR-derived records with Landsat and MODIS imagery. Consistency in trends was identified for Australia and central Asia, with divergent trend estimates in Africa, South America and the Sahel [105].

Comparisons between sensor datasets are a common method of quality assurance for AVHRR-derived NDVI records. The MODIS sensor is considered the most accurately calibrated and atmospherically corrected NDVI record available. Therefore, comparing the MODIS products with overlapping AVHRR-derived data can highlight issues present with the older AVHRR records. A global comparison of MODIS and GIMMS NDVI trends, for dryland regions was, undertaken by Fensholt *et al.* [8]. Trend values show high correlations (0.8>) for most semi-arid regions; however, areas bordering the arid zone with sparse vegetation were lower indicating spurious NDVI in these localities. This was in agreement with earlier work which identified that MODIS-GIMMS correlations were higher in the humid regions of the Sahel, compared to the arid areas [65].

4.3. Detecting Structural and Real-Time Change

Trend breaks. All of the methods detailed above establish a trend detailing the change in NDVI over time; this represents a simplification of what may be a highly complex chronology of shorter duration trends [106,107]. Analysing the overall trend, particularly with long time series, may be misleading as contrasting trends can potentially balance out. Verbesselt *et al.* [107] proposed that NDVI change can be classified in three components: seasonal/cyclic changes, gradual variation, and abrupt or sudden changes. Within this outline, they developed the Breaks for Additive Season and Trend (BFAST) algorithm, which disaggregates an NDVI time-series into three constituents: seasonal variation, trends, and noise [107]. By allowing the detection of multiple shorter duration trends, a better understanding of the temporal drivers of NDVI can be obtained. de Jong *et al.* [106] implemented the BFAST algorithm on the global GIMMS NDVIg archive. Semi-arid regions were identified as being highly variable in trend direction and magnitude, partly due to the impact of hemispheric climatic oscillations [68,106]. It was highlighted that dryland regions frequently displayed abrupt greening spells followed by periods of gradual browning.

Real-Time Change Detection

The detection of historic trends and shifts in vegetation productivity is very useful to scientific inquiry, and may serve to inform land management policies to mitigate degradation drivers. However, historic trends are of limited value to contemporary management, as considerable reductions must first materialise (see Section 5.2). Thus, real-time or near real-time detection is necessary to inform policy makers at the earliest possible opportunity. This objective, *i.e.*, the identification of real-time environmental disturbance, is shared by a number of environmental applications, such as food security [108], deforestation [109] and epidemiology [110]. The challenge of being able to identify real-time disturbance is in distinguishing a genuine trend from the seasonal trend and noise components. White and Nemani [111] demonstrated that phenological change could be forecast by comparing a user-defined threshold against the historical variability found within clustered phenoregions. The setting of arbitrary user-defined thresholds encounters difficulty when there are complex land cover transitions or frequent periods of high instability, adding a significant cost to application [112]. To overcome this issue, Verbesselt *et al.* [112] proposed a pixel-level disturbance detection approach, based on the historical time-series of each individual pixel. For each pixel, a stable "history" period is automatically determined and disturbances are compared to this regime [112]. This approach proved suitable for detecting drought-induced disturbance but was not so successful in removing background noise.

4.4. Removing Precipitation Influence

As previously mentioned, Rain Use Efficiency (RUE) is the quotient value of NPP to corresponding precipitation [22,81]. It has been proposed that degradation reduces the precipitation usage of an area, as overland flow and runoff increase with reduced vegetation cover and density. Thus, a reduced RUE can be indicative of land degradation, independent of climatic effects [22]. This mechanism is based on two key assumptions: (1) linearity in the response of NDVI/NPP to increased precipitation; and (2) an independence of RUE to fluctuation in its constituents [65]. The well reported linear relationship between NPP and rainfall in drylands [79] can potentially be compromised when tail events for both rainfall and NPP occur. At high precipitation amounts, factors other than rainfall become limitations to NPP, and increases in precipitation do not induce further productivity [79]. At very low precipitation there may be no vegetation present resulting in RUE values approaching infinity. This is further exacerbated by the positive intercept caused by soil reflectance [65]. At low biomass levels the vegetation is unable to prevent runoff and infiltration from occurring, thus subsequently low RUE will be observed. Rainfall increases may potentially drive an increase in both RUE and biomass, rendering RUE irrelevant as a detrending technique [84]. However, this interpretation has been criticised as being limited to sites with anomalous precipitation regimes [24,113,114]. RUE values have been demonstrated to correlate with inter-annual precipitation fluxes [65,88]. However, it is statistically questionable to test for dependence between RUE and rain as they are not independent [115]. Fensholt *et al.* [116] proposed the use of a seasonality subtracted "small integral" of NDVI, as opposed to the full growth season integral, which could mitigate against correlations with rainfall, provided linearity assumptions are satisfied.

Figure 3. Comparison of linear and Theil Sen regression slopes for a pixel in the Sahel.

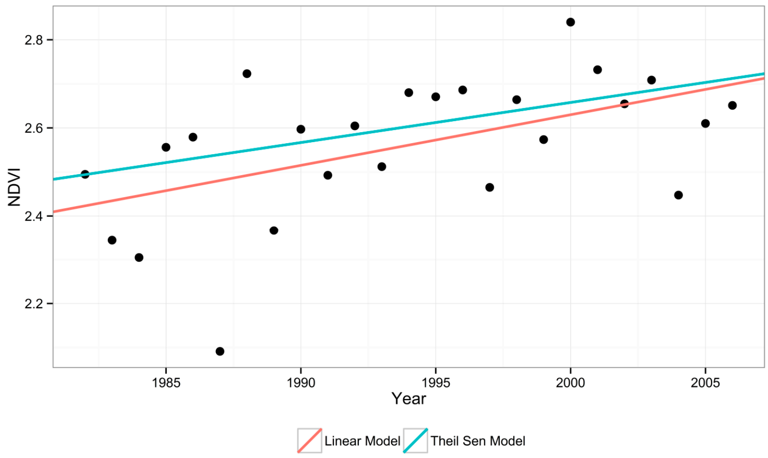
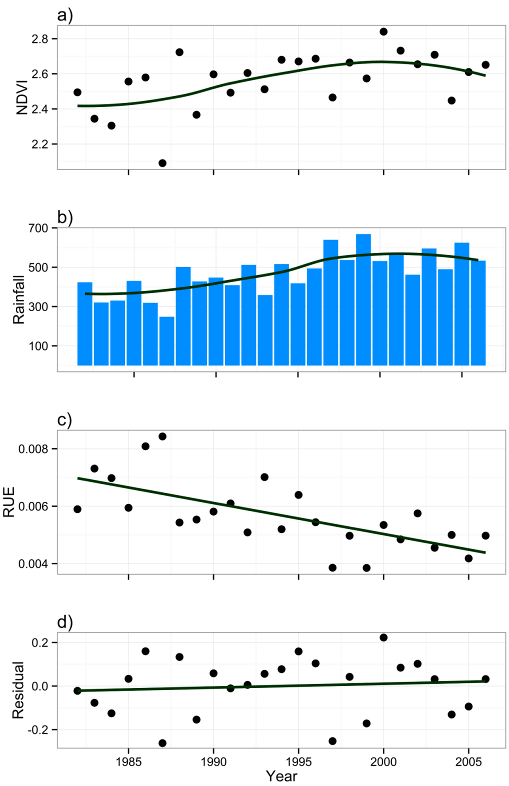


Figure 4. Comparison of the Rain Use Efficiency and residual trends for a pixel in the Sahel.



The Residual Trends (RESTREND) method compares the response of an NDVI time-series to a predicted response. The predicted response is generated by calculating a regression between NDVI values and precipitation [85,86]. The residuals from this regression are then subjected to a trend analysis. A positive trend in residuals indicates an increasing NDVI signal compared to the precipitation trend (land improvement), whereas a negative trend indicates a declining NDVI per precipitation unit (degradation). By implementing a statistical rather than a quotient method, this approach avoids the limitations of RUE with regards to linearity and dependence [88]. A comparison of RUE and RESTREND is shown in Figure 4, note the negative RUE trend induced by high rainfall at the end of the time series.

The Precipitation Marginal Response (PMR) quantifies the slope of a linear regression between NPP/NDVI and rainfall, thus describing the sensitivity of NPP to rainfall fluxes by expressing the change in the dependent variable (NDVI) per unit of precipitation [87,117].

5. Relating Time-Series Frameworks to Degradation Processes

All trend analysis assessments are based on the foundation that comparable sites, when subjected to degradation, will display reduced photosynthetic production, and thus NDVI [35,118]. This represents a symptomatic approach, as the mechanism of land degradation is irrelevant, provided a reduction in NPP materialises [13]. Thus, the two key assumptions of these methods are, firstly, that degradation consistently materialises as a reduction in NPP, and secondly, that NDVI variation is capable of capturing this reduction. These issues are reviewed below.

5.1. Does Land Degradation Initiate a Decline in NPP?

The assumption that land degradation reduces the NPP of a site is dependent upon the underlying mechanism. A reduction in vegetation cover, whilst species composition and diversity is maintained, will materialise as a reduction in NPP [10]. However, a common degradation mechanism affecting dryland regions is encroachment of woody shrub species into grasslands. This process results in an increase in bare ground coverage coupled with increased runoff and alterations of soil C and N stocks [45,119]. Nevertheless, shrubland encroachment does not necessitate a reduction in NPP. Thus, the analysis of the seasonal maximum or annual integral of NDVI is unlikely to detect this process successfully. However, shrubs species, and encroachment, do exhibit a number of distinct eco-hydrological responses, which may be exploited by an NDVI-based analysis. Shrubs species are, in general, perennial plants and manage to survive the dry season. Mitchard and Flintrop [120] mapped woody and shrub biomass in African Savannahs, using the dry season maximum NDVI. The results of this analysis agreed with collated field data of shrub encroachment and forest degradation, although the authors stipulate that the results should be viewed with caution due to the technical issue with dry season NDVI [120]. The ability of shrub species to support deeper root networks also influences their usage of precipitation. Williamson *et al.* [121] investigated the species-specific response of NDVI to preceding precipitation events. Grassland species reported the highest relationships for concurrent precipitations, whereas shrubland relationships were notably improved when the previous years were included [121]. Verón and Paruelo [87] highlighted the potential of variation in the rainfall-NDVI co-efficient (the precipitation marginal response) as a potential indicator of species composition variation. It should be noted that shrub encroachment is not universally accepted as a component of land degradation [122]. Nevertheless, the associated reduction in pastoral resource that accompanies an increase in shrub coverage makes it a commonly perceived degradation process in many regions, and is thus included herein. In addition to the commonly acknowledge process of shrub encroachment an impoverishment of woody vegetation species has also been reported [123]. Herrmann and Tappan [123] and Herrmann *et al.* [124] compared Senegalese vegetation trend maps with archive photography and focus group meetings with local inhabitants. Results indicated that NDVI derived-greening trends did not necessarily correlate with users perceptions of vegetation improvement. In some locations a decrease in tree coverage and a shift to drought tolerant shrub species was reported, irrespective of changes in population and land usage. Interestingly, opposing results were found for an area of the Sahel in Mali, where an increase in cultivation and tree cover was identified [125].

In summary, a variety of NDVI-based methods have been designed and tested, but validation of results, and hence the suitability of NDVI-based methods to assess degradation, remains limited

5.2. Can NDVI Trends Capture a Reduction in NPP?

The ground truthing and validation of products generated by remote sensing is a critical methodological stage. However, the validation of trend analyses is inherently problematic. It is rarely feasible to validate 30-year trends with a large spatial footprint. In addition, there are few biomass-sampling sites with a spatial scale suitable for validating coarse resolution pixels and even fewer sites with a continuous record dating back to the early 1980s. Here, we summarise the existing literature on comparisons of long-term biomass data with vegetation index values and trends, and discuss alternative methods of validation, such as qualitative validation and simulation analysis.

Wessels *et al.* [35] compared a 533-site, 19-year biomass dataset with an AVHRR-derived NDVI record for the Kruger National Park, South Africa. This comparison produced generally favourable correlations for the NDVI/biomass relationships, with an average R^2 of 0.42 capturing the majority of inter-annual variability. Sites with low correlations were attributed to the heterogeneous land cover resulting in mixed pixels, poorly represented by the biomass samples [35]. A number of Sahelian localities have been subjected to long-term observation under the African Monsoon Multidisciplinary Analysis—Coupling the Tropical Atmosphere and the Hydrological Cycle (AMMA-CATCH) programme. Two of these sites, *i.e.*, Gourma, located in northern Mali (data from 1984–2011) and Fakara in southern Niger (data from 1994–2011), were assessed against long-term GIMMS3g NDVI time-series trends [126]. At both sites, field data agreed with the direction and magnitude of the corresponding NDVI trend, with respective correlation co-efficients of 0.74 and 0.41. The co-efficient for Fakara becomes 0.59 when an outlier for 2010 is omitted [126]. The lower values obtained for Fakara were attributed to a mixed agro-pastoral land use pattern, when compared to the predominantly pastoral land use identified at the Gourma site [126]. The issue of localised land use/cover patterns resulting in mixed pixels was also noted by Brandt *et al.* [127]. This was partially rectified by utilising a higher-resolution NDVI product (Geoland V1 at 5 km resolution), which revealed patterns obscured by the GIMMS3g data. However, attempts to document localised factors for regional analysis proved problematic due to the large variety of land use/cover conditions present [128]. In the absence of long-term biomass records, a number of studies have used qualitative comparisons to validate trend outputs. Wessels *et al.* [88] compared rainfall-corrected NDVI trends, using RESTREND, to a national land survey output, with an acceptable level of agreement between the two outputs. Further qualitative validation was undertaken by Evans and Geerken [85], who used field study surveys and visual interpretation of Landsat imagery to validate degradation assessments for Syrian drylands. Both of these studies relied on a generally high level of agreement between outputs and the validation data to assess the reliability of applied methods. Studies that attempt large-scale regional [64,65] or global [8,14] assessments, frequently rely on even less robust validations and focus on the linkages of hot-spots with environmental change narratives postulated by field studies. Although commonplace, studies utilising qualitative validation methods have been highly criticised. Wessels *et al.* [21] highlighted that this process does not sufficiently assess the accuracy and sensitivity of methodologies to variable start-dates and intensities of degradation.

A recent alternative to the approaches above is simulation analysis, which tests the sensitivity of methods by artificially altering a dataset prior to analysis, thus a technique is assessed against a known baseline. This approach has been used to test the responsiveness of time-series segmentation methods aiming to decompose noisy data series [107,112,129] prior to the application on a global time-series [68,106]. The advantage of the simulation approach is that the intensity and duration of a shift can be determined, and the response of the applied analysis directly compared [130]. A land degradation simulation assessment was implemented by Wessels *et al.* [21], where a variety of start-date and intensity land degradation simulations were applied to 1 km-NDVI data covering the Kruger National Park, to represent the degradation of a non-degraded baseline. This study revealed that an NDVI reduction of 20%–40% was required to identify a significant negative trend in the region, using either RESTREND or a number of other trend techniques [21]. Thus, the majority of trend techniques employed [8] would be capable of detecting only the most severe of degradation processes, and would therefore not be useful as a degradation early-warning system [21]. Comparable simulation experiments were used to test the sensitivity of RUE in the Sahel region [115]. Here a degradation of >20% was found to be detectable, provided it did not occur at the start or end period of analysis.

A number of studies have proposed that additional analyses using higher resolution imagery, such as the Landsat and SPOT satellites, would be well suited to provide further localised information on trends observed [63,131,132]. Comparisons of Landsat and AVHRR-based trends have revealed generally similar patterns [131], with further analysis demonstrating that vegetation estimates derived from Landsat imagery all display similar trend patterns [133]. Recent progress in applying time-series analysis on Landsat imagery stacks has demonstrated the potential for observing land use/cover variation at high spatial and temporal resolution [134–137]. In addition, the ability to generate large-area compositing techniques from multiple Landsat scenes [138,139], offers new opportunities for multi-scale analyses to improve on the relationships between land use/cover change and NDVI trends on multiple spatial and temporal scales.

An important consideration of remote sensing studies is the resolution and scale of imagery used [140]. Higher resolution imagery will better identify local issues and trends, particularly in heterogeneous areas [128,131]. This advantage must be balanced with the more generalised large-scale view undertaken a large number of studies, where observing local factors is not a primary objective [8,14]. NDVI-based studies have historically been limited to the coarse-resolution preprocessed datasets details above (Table 1); this has limited the discussion of the impacts of altering the scale upon trend estimations.

Recent developments in the provision of both free and pre-processed Landsat data [141,142] may lead to an increased focus on higher-resolution sensor data, therefore the impact of varying pixel size on trend estimation should be a research priority prior to the undertaking analysis.

6. Conclusions and Outlook

Land degradation and desertification are important issues to both ecological and social research. The need for a quantitative, repeatable methodology to assess land degradation and desertification reliably is more pressing than ever before. EO data offer the only viable method for large-scale assessments, and despite the continued controversy over the techniques used, considerable progress has been made over the last 30 years. This review has identified two key prerequisites to the establishment of degradation and desertification monitoring and early warning systems. Firstly, methodologies must be subject to a standardised and robust validation in order for policy makers and planners to have confidence in results; secondly, degradation at minor intensities or early stages must be detectable in order for preventive action to be taken before irreversible damage occurs.

The validation of trend analysis would ideally be undertaken by robust comparisons with field biomass data covering a comparable spatial and temporal scale. However, this is rarely possible. The need for using remotely sensed vegetation data is related to this very issue and a major concern is the requirement for consistency between studies. This could potentially be achieved through a standardised comparison with whatever long-term data exist. The proposed Global Drylands Observing System (GDOS) [143,144] would be a critical precursor to this. Alternatively, the simulation experiments proposed by Wessels *et al.* [21] and Verbesselt *et al.* [112] offer clear potential for the development of consistent and repeatable methodologies [115], which could be aided by the transition to open-source statistical programs. The availability of packages such as BFAST [107] and Greenbrown [130] demonstrates the potential for such a transition.

The early detection of land degradation, particularly at low intensities represents a major limitation on the usability of degradation early-warning and monitoring systems. The application of structural and real-time change detection represent the greatest progress on this issue, but further work is still required. Bayesian statistics, whereby model assumptions are based on prior knowledge, may also be beneficial for identifying deviation form expected trajectories.

The land degradation monitoring community may also benefit from the experiences of deforestation observation projects, which have acknowledged the importance of local stakeholders and end-users for efficient development [145,146]. The use of volunteered information and photographs for validation of land cover maps could be of value as an additional data source in regions with limited long-term field data. The monitoring of desertification is meaningless if not integrated with local end-users. The traditional top-down approach of researchers developing products leads to a lack of connection between the intended users and the design procedure, and may not be suitable for handling the wide variety of local issues [145]. Software tailored for land degradation, comparable to the CLASlite (Carnegie Landsat Analysis System-lite) program, which allows end-users to access information and development methodologies to map deforestation and forest cover, would be of advantageous [147]. However, technological limitations in many developing regions may hamper the uptake of such technology [148].

It should be cautioned that NDVI analysis is best suited as one component of a multi-faceted methodology. The multiple symptoms and drivers of land degradation provide a number of opportunities for quantitative assessment using EO [149,150]. It is through the combination of these indicators that a holistic assessment of land degradation can be achieved [15,151]. In addition, NDVI-based analyses only consider the biomass of an ecosystem; this falls short of fully appreciating the wide range of ecosystem services and local uses that may be present [152]. Degradation assessments cannot be achieved through a biomass or Carbon stock assessment alone, as it is the usage and flow of biomass/Carbon that provide benefit to the biosphere [153]. Land degradation and desertification prevention and remediation efforts should also consider local stakeholder usage and ecosystem functions in order to promote poverty alleviation and environmental health objectives in synchrony [154].

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Author Contributions

Thomas Higginbottom is the main author who initiated the idea and wrote the manuscript; Elias Symeonakis provided review and comment.

Conflicts of Interest

The authors declare no conflict of interest.

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