Can linear trend analyses of NDVI time series data truly detect land degradation? Simulations may provide the answer.

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Abstract – There has been a recent proliferation of remote sensing-based trend analysis for monitoring regional desertification. These show contradictory results. All of them claim to have been "validated" through expert interpretation, in the absence of sufficient field data. We suggest that such an approach is not sufficiently rigorous. Therefore, we demonstrate an approach which simulates land degradation so that the intensity, rate and timing of the reduction in NDVI can be controlled, in order to quantitatively evaluate the ability of methods to detect these known changes. The results show that linear trend analysis is rather insensitive to previously observed levels of NDVI reduction due to degradation in the well-studied communal lands in the Lowveld of South Africa. The period of investigation, has a large but rather unpredictable influence on the linear trends. This casts doubts over the ability of linear trend analysis, to detect relatively subtle, slowly-developing degradation in semi-arid rangelands.

Keywords: AVHRR, NDVI, desertification, land degradation, linear trends, monitoring, simulation, South Africa

1. INTRODUCTION

Desertification (or land degradation in dry areas) can be defined a persistent loss of ecosystem services (MA, 2005), building on earlier definitions based on reduced biological productivity (UNCCD, 1994). Many studies have used multi-year, coarse resolution (≥1 km) satellite data to monitor changes in the duration and amount of green vegetation cover, as a proxy for changes in primary productivity for the purposes of assessing land degradation (Bastin et al., 1995; Diouf and Lambin, 2001; Nicholson et al., 1998; Prince et al., 1998; Prince and Justice, 1991; Tucker et al., 1991a; Tucker et al., 1991b; Wessels et al., 2007). The indices based on reflectance in the visible and near-infrared spectra (e.g. Normalized Difference Vegetation Index, NDVI) have been shown to correlate with plant biomass, leaf area and primary production (Huete et al., 2002). The Advanced Very High Resolution Radiometer (AVHRR) sensors have collected nearly thirty years of data available for monitoring land degradation. However, monitoring and detecting desertification in this way has become a controversial topic. The methods for identifying desertification from satellite and rainfall data are fiercely debated in the scientific literature (Bai et al., 2008; Hein and de Ridder, 2006; Prince et al., 2007; Veron et al., 2006; Wessels, 2009).

The basic problem is that different trend assessments, based on similar time series of satellite vegetation index data, lead to conflicting answers in terms of which areas are showing negative trends (Bai et al., 2008; Hein and de Ridder, 2006; Hellden and Tottrup, 2008; Prince et al., 2007; Wessels, 2009). There is furthermore a general lack of suitable field data spanning the duration of the satellite time-series (1980's to present), effectively precluding the quantitative evaluation of the methods (Fensholt et al., 2009; Hellden and Tottrup, 2008; Wessels et al., 2007). Most of the studies have therefore resorted to "validating" trend analysis maps through the use of regional expert opinion or by invoking ancillary data sets and publications. We suggest that such an approach is not sufficiently rigorous.

Therefore, we propose an approach which simulates land degradation so that the intensity, rate and timing of the reduction in NDVI (vegetation production) expected from land degradation can be controlled, in order to quantitatively evaluate the ability of linear trend analysis methods to detect these known changes. The duration of the assessment period is also varied. The approach would enable basic questions to be addressed, such as: how intense, rapid and prolonged must the reduction in NDVI be before a statistically significant negative trend can be inferred?

We demonstrate the approach for a semi-arid region in the north-east of South Africa, the Lowveld, which encompasses both protected areas and areas of documented degradation (Hoffman and Todd, 2000). Previous research in the area has demonstrated that the sum of 10-day maximum NDVIs measured over the growth season (October to April) was 10 - 20% lower in degraded rangelands than in undegraded areas and that this difference did not decrease in years of high rainfall (Wessels et al., 2007; Wessels et al., 2004).

2. MATERIALS AND METHODS

2.1 Study area

The study area is located in savannas in the north-eastern part of South Africa (Fig. 1). The area is especially suited for the simulation of land degradation, since the apartheid-era "homelands", now communal-tenure areas, are juxtaposed with areas under conservation, such as the 2 million ha Kruger National Park (Pollard et al., 2003). The former homelands are densely settled, impoverished and are widely agreed to represent a degraded state with respect to soil erosion, grazing potential, and fuel wood resources (Hoffman and Todd, 2000; Twine, 2005). They are generally characterized by high livestock numbers, principally cattle and goats, at 3-4 times the recommended stocking rates (Shackleton, 1993). For the simulation analysis, four areas containing 999, 420, 693 and 928 AVHRR pixels respectively were located inside the park (Fig. 1), on the same granite-derived soils as occurs in the communal areas, with similar rainfall.

2.2 1km AVHRR data

Local Area Coverage (LAC) (1.1 x 1.1 km resolution) data from the AVHRR sensor have been received daily at the CSIR Satellite

Application Centre in South Africa, since 1985 (for details see (Wessels et al., 2004)). Due to the failure of NOAA-13, data were not available for 1994. The time series were processed up to June 2003 after which AVHRR/NOAA 16 became unstable.

NDVI summed over the growth season (ΣNDVI) is widely used as a proxy for net primary production (NPP) due to its positive relationship with fraction of absorbed photosyntheticaly active radiation (Fensholt et al., 2009; Hellden and Tottrup, 2008; Myneni and Williams, 1994; Prince, 1991). ΣNDVI has also been shown to be correlated with end of growing season herbaceous biomass in Kruger National Park (R2 = 0.42-0.76) (Wessels et al., 2006). The 10-day maximum value NDVI composites were summed for each pixel in the over the growing season, October to April (ΣNDVI, n=16, July 1985 to June 2003).

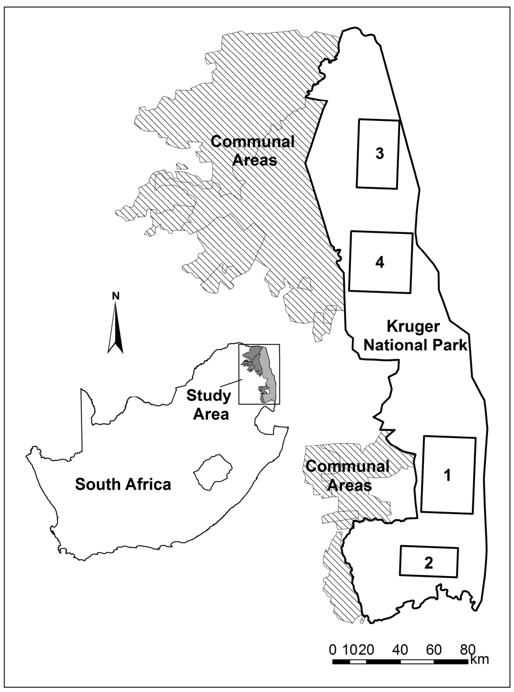

Figure1. The study area in the Lowveld of South Africa containing the communal areas and Kruger National Park with four areas within which degradation was simulated.

2.3 Simulated land degradation

Land degradation was simulated by introducing reductions in the AVHRR ΣNDVI according to the following scheme (91 unique combinations):

1. Five intensity levels (10, 15, 20, 30, 40% reduction in ΣNDVI)
2. Seven rates of development (the specified degradation intensity was phased in linearly over 1-7 years, after which the reduction was maintained until the end of the time series).
3. Sixteen start-dates for degradation (years 1-16).

A single simulation example is given in Fig. 2. Furthermore, the effect of time series length and assessment periods were simulated by excluding either the first or last three years of the simulated time series before calculating the trend.

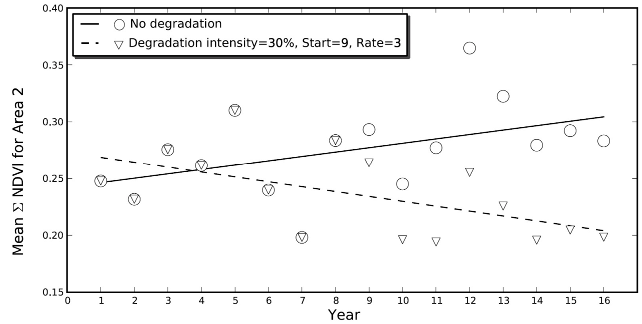

Figure 2. Example of original ΣNDVI time series for Area 2 and the same time series containing simulated degradation with intensity of 30%, starting in year 9 at rate of 3 years.

2.4 Linear trend analysis

Degradation is expected to result in a statistically-significant negative slope in the ΣNDVI –time regression (Anyamba and Tucker, 2005; Fensholt et al., 2009; Hellden and Tottrup, 2008; Olsson et al., 2005; Wessels et al., 2007). The ordinary least-squares (OLS) regressions between the ΣNDVI versus time (1-16 growing seasons) were applied per pixel to each of the combinations of intensity, start and rate. The slope of the regression, and the associated p-value were the primary analysis outputs.

3. RESULTS

The most negative slope of the 91 combinations was reported per area and intensity in Table 1. For each degradation intensity and area, the fraction the 91 combinations where more than 25% of the pixels in an area reached a statistically significant ($p \leq 0.05$) negative slope was calculated (Table 1).

3.1 Degradation intensity

Without the introduction of simulated degradation there was an overall positive trend in ΣNDVI in all four the areas (Table 1) (e.g. Fig. 3, top panel). A 20% degradation had to be introduced before a negative slope developed in two of the areas (area 1 and 2), although the slope was not significant in more than 25% of the pixels in these areas (Table 1). It required a 30% degradation intensity before all four areas showed a negative slope and a 40% degradation intensity before more than 25% of pixels in all four areas had statistically significant negative slopes (Table 1).

3.2 Rate and timing of degradation

The influence of the rate of degradation depended on when the degradation was started relative to the middle of the time series. When started before the middle of the time-series, the rate had the largest influence on the slope when the rate was the slowest. After the middle of the time series, the relationship between the rate and the slope was the opposite, i.e., the rate had the smallest influence on the slope when it was the slowest (Fig. 3, 2 center panels).

The slopes were the most negative and significant when the degradation started in the middle of the time series and these negative slopes decreased as the degradation was introduced towards the beginning and end of the time series (Fig. 3, bottom panel). Overall the trends were the most negative (reported in

Table 1) when the degradation was introduced within one year and in the middle of the time series.

Table 1. The most negative median slope in ΣNDVI resulting from of 91 combinations of intensity, start and rate of simulated degradation, for each area (1-4), and the fraction of the 91 combinations where more than 25% of the pixels in an area reached a statistically significant negative slope ($p \leq 0.05$).

		ΣNDVI all growing seasons N=16	
Degradation intensity (%)	area	Most negative median slope	Fraction >25% significant
0	1	1.29	0.00
0	2	0.98	0.00
0	3	1.34	0.00
0	4	1.26	0.00
10	1	0.62	0.00
10	2	0.27	0.00
10	3	0.75	0.00
10	4	0.67	0.00
20	1	-0.06	0.00
20	2	-0.45	0.00
20	3	0.16	0.00
20	4	0.09	0.00
30	1	-0.75	0.21
30	2	-1.17	0.51
30	3	-0.43	0.00
30	4	-0.49	0.00
40	1	-1.43	0.58
40	2	-1.88	0.73
40	3	-1.01	0.25
40	4	-1.07	0.32

3.3 Length of the observed time series and period of assessment

When 3 years at the beginning of the time series were excluded, stronger negative slopes developed. In contrast, when years at the end of the time series were excluded, weaker negative slopes developed, since less of the time series contained the fully phased-in reductions in ΣNDVI.

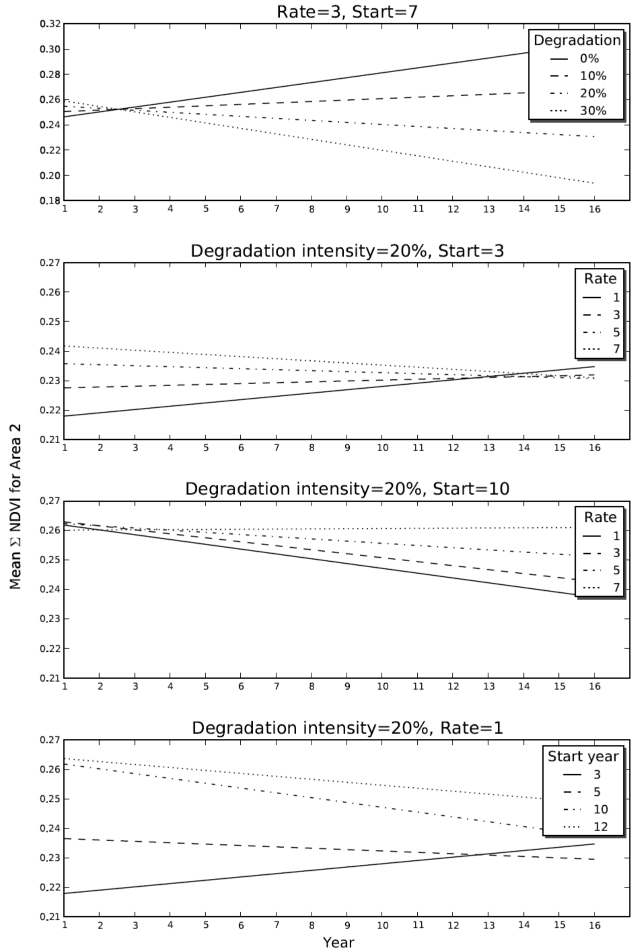

Figure 3. Example of trends in ΣNDVI resulting from various combinations of simulated degradation intensity, rate (in years) and start of degradation.

4. DISCUSSION

For this study area, which is fairly representative of the semi-arid environments in which much desertification monitoring is undertaken, a 30-40% reduction in ΣNDVI was required before a statistically significant negative slope could be detected in at least 25-50% of the pixels (Figs 3 and 7). Such a large reduction in ΣNDVI can result from radical land cover transformation, such as deforestation or expansion in cultivated areas - but the reductions associated with the early stages of rangeland degradation (where there is some hope of remediation) are much more subtle. Even in the worst cases of apparent land degradation in our study area, the difference in AVHRR ΣNDVI between degraded and non-degraded areas was 10 - 20% (Wessels et al., 2007; Wessels et al., 2004). Although linear trend analysis may be able to identify extreme degradation (30% reduction in ΣNDVI lasting several years), by the time degradation is that advanced there may be limited opportunity to implement mitigating measures.

This casts doubts over the ability of linear trend analysis, applied to the AVHRR NDVI, to detect relatively subtle, slowly-developing degradation in semi-arid rangelands – precisely the circumstances and techniques which have been most widely applied in the literature (Anyamba and Tucker, 2005; Fensholt et al., 2009; Hellden and Tottrup, 2008; Olsson et al., 2005; Wessels et al., 2007). The simulations demonstrated that using a significantly negative linear trend as an indicator confounds magnitude, timing and rate of degradation within a given period of assessment, which complicates its interpretation as a mapped indicator of degradation. Degradation which starts close to the beginning or end of the time series is especially difficult to detected with linear trend techniques (Wessels et al., 2007) (Figure 3). The period of assessment has a large influence on the detection of linear trends. This alerts us to the fact that an assessment of trends is only applicable to a particular period and that trends may change notably within three years. The start of the time series in almost all studies is determined by the beginning of the satellite data record, in this case 1985. The initial years of the time series have a strong influence on trend assessments, especially since they are often implicitly treated as the reference (pre-degradation) period (Veron et al., 2006). Therefore, starting or ending the period of investigation 3 years earlier or later results in contrasting trends, thus severely complicating year-to-year land degradation monitoring. The exact period of assessment thus has a large but unpredictable influence on the detected trends.

Although this paper does not yet present a solution for the detection of land degradation, it proposed a change in the mode of investigation. We suggest that studies should first undertake the simulation approach outlined here to establish the robustness of their approach before raising either alarm or false hope. In the mean time important policy and management decisions should not be based on the anecdotal validation of regional trend maps.

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