Received: 16 August 2016 | Revised: 6 September 2017 | Accepted: 28 November 2017
DOI: 10.1002/ldr.2871

RESEARCH ARTICLE

WILEY

Phases or regimes? Revisiting NDVI trends as proxies for land degradation

Marcos Horacio Easdale[1,2] | Octavio Bruzzone[1,2] | Paul Mapfumo[3] | Pablo Tittonell[1,4]

[1] Instituto Nacional de Tecnología Agropecuaria (INTA), EEA Bariloche, Bariloche, Río Negro, Argentina

[2] Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), Patagonia Norte, Argentina

[3] Department of Soil Science and Agricultural Engineering, University of Zimbabwe, Harare, Zimbabwe

[4] Farming Systems Ecology Group, Wageningen University, Wageningen, The Netherlands

Correspondence
M. H. Easdale, Instituto Nacional de Tecnología Agropecuaria (INTA), EEA Bariloche, Av. Modesta Victoria 4450 (8400), Bariloche, Río Negro, Argentina.
Email: easdale.marcos@inta.gob.ar

Funding information
Ministerio de Ciencia, Tecnología e Innovación Productiva, Grant/Award Number: PICT 2015-929; Instituto Nacional de Tecnología Agropecuaria, Grant/Award Number: PATNOR-1281103

Abstract

One of the main challenges in land degradation assessment is that a rigorous and systematic approach to addressing its complex dynamics is still missing. The development and application of operative tools at regional and global scales remain a challenge. Land degradation is usually defined as a long-term decline in ecosystem function and productivity. Due to its temporal and spatial resolution as well as data availability, the use of time series of spectral vegetation indexes obtained from satellite sensors has become frequent in recent studies in this field. Slope of linear trends of the normalized difference vegetation index is usually considered an accurate indicator and is widely used as a proxy for land degradation. Yet this method is built on a number of simplifying conceptual and methodological assumptions that prevent capturing more complex dynamics, such as cyclic or periodic behaviors. Our aim was to examine the limitations associated with using linear normalized difference vegetation index trends as proxies for land degradation by comparing outcomes with an alternative methodological procedure based on wavelet autoregressive methods. We explored these issues in 5 case studies from Africa and South America. We observed that trend explained a marginal portion of total temporal variability, whereas monotonic functions, such as linear trends, were unable to capture dynamics that were non-unidirectional, resulting in misinterpretation of actual trends. Wavelet autoregressive method results were encouraging as a step towards the application of more accurate methods to provide sound scientific information of land degradation and restoration.

KEYWORDS

desertification, MODIS, time series analysis, variability, wavelets

1 | INTRODUCTION

Land degradation is a major concern both in scientific and political arenas (Sadeghravesh, Khosravi, & Ghasemian, 2016; Torres, Abraham, Rubio, Barbero-Sierra, & Ruiz-Pérez, 2015). Monitoring systems are at the core of demands to better support decision-making and to assess the impact of interventions (Vogt et al., 2011). There is a need for operational methods and tools to assess the state and dynamics of land degradation at regional and global scales, able to provide updated information using low-cost data, for long-term series and across spatial scales. Land degradation is usually defined as a long-term decline in ecosystem function and productivity, which may be assessed using series of satellite sensed data such as the normalized difference vegetation index (NDVI; Bai, Dent, Olsson, & Schaepman, 2008). NDVI trend is widely used as proxy for land degradation (Bai et al., 2008; Metternicht, Zinck, Blanco, & Del Valle, 2010; Wessels et al., 2007) and most frequently computed as the slope of a linear regression of NDVI time series (Anyamba & Tucker, 2005; Eckert, Hüsler, Liniger, & Hodel, 2015; Fensholt et al., 2012; Gaitán, Bran, & Azcona, 2015; Vlek, Bao Le, & Tamene, 2008; Yin, Udelhoven, Fensholt, Pflugmacher, & Hostert, 2012). However, we argue that linear trend is too simplistic both from theoretical and methodological perspectives and that it may lead to misinterpreting—mask or exaggerate—prevailing land degradation dynamics.

A conceptual discussion regards whether significant slopes refer to a system phase of a state at dynamic equilibrium or if it refers to a shift towards a new state or regime change (Hastings & Wysham, 2010; López, Cavallero, Brizuela, & Aguiar, 2011). Because the initial status is often unknown, a positive slope may be thought to represent either a recovery from drought (Vicente-Serrano et al., 2013), greening trends as a function of both climatic and nonclimatic factors (Xiao & Moody, 2005), a response to other disturbances such as fire events (Diaz-Delgado, Salvador, & Pons, 1998; Gouveia, Bastos, Trigo, &

DaCamara, 2012; Riaño et al., 2002), or a permanent land-use change generating higher primary productivity than the previous situation, such as afforestation (Li, 2015; Vasallo, Dieguez, Garbulsky, Jobbágy, & Paruelo, 2012). A negative slope, on the other hand, might represent a downwards trend due to either a long-lasting drought (Anyamba & Tucker, 2005), more abrupt shocks such as volcanic ash fallout (de Schutter et al., 2015), or permanent disturbances such as land use change, for example, resulting in a decrease of irrigated areas (Gumma et al., 2015). Both phases and regime shifts are confounded in the same process when NDVI changes are depicted by a linear trend. From a methodological perspective, linear regression is by definition a monotonic function, which means that it is either entirely increasing or decreasing. There is no option for a change in the trend, and therefore a significant positive or negative slope means invariably a regime change, which cannot be differentiated from a state phase.

We state that operative tools to assess land degradation through studying NDVI changes should be able to capture system dynamics by emphasizing the possibility of a cyclic behavior and not only a one-direction process. Methods are needed that are sensitive both to monotonic changes as a potential reference of regime shifts and to nonmonotonic changes as depicted by cyclic dynamics, which can be constituted by different phases. Our objective was to examine the limitations associated with using linear NDVI trends as proxies for land degradation, by comparing outcomes with an alternative methodological procedure based on the use of wavelet autoregressive methods (WARM). The study was guided by two questions: (a) how much variability from temporal NDVI information is explained by the trend? and (b) can we distinguish between cyclic and monotonic change? We explored these issues in five case studies that included drylands, rainforest and humid areas: (a) NE and (b) SE Zimbabwe, (c) W Kenya–E Uganda, (d) N Argentina–S Bolivia, and (e) NW Patagonia (Argentina).

2 | MATERIAL AND METHODS

2.1 | Case studies

We selected five regional case studies based on the following criteria: (a) contrasting biomes including deserts, arid and semiarid rangelands, rainforests, and ecological gradients within the area considered (soil types, altitude, and rainfall), (b) different land uses such as cultivated land, livestock, and pastoralism, (c) different continents (South America and Africa), (d) a latitudinal gradient from Equator 0° to 39° S, v) different climate regimes. These were also sites where the authors of this paper have worked extensively and have first-hand knowledge on and for which ground information is amply available.

The case study area of NE Zimbabwe is an area characterized by coexistence of two dominant, contrasting soil types: granitic sands (5–10% clay content) and red clay soils (35% clay), defining different plant productivity potential (Figure 1). Native vegetation is

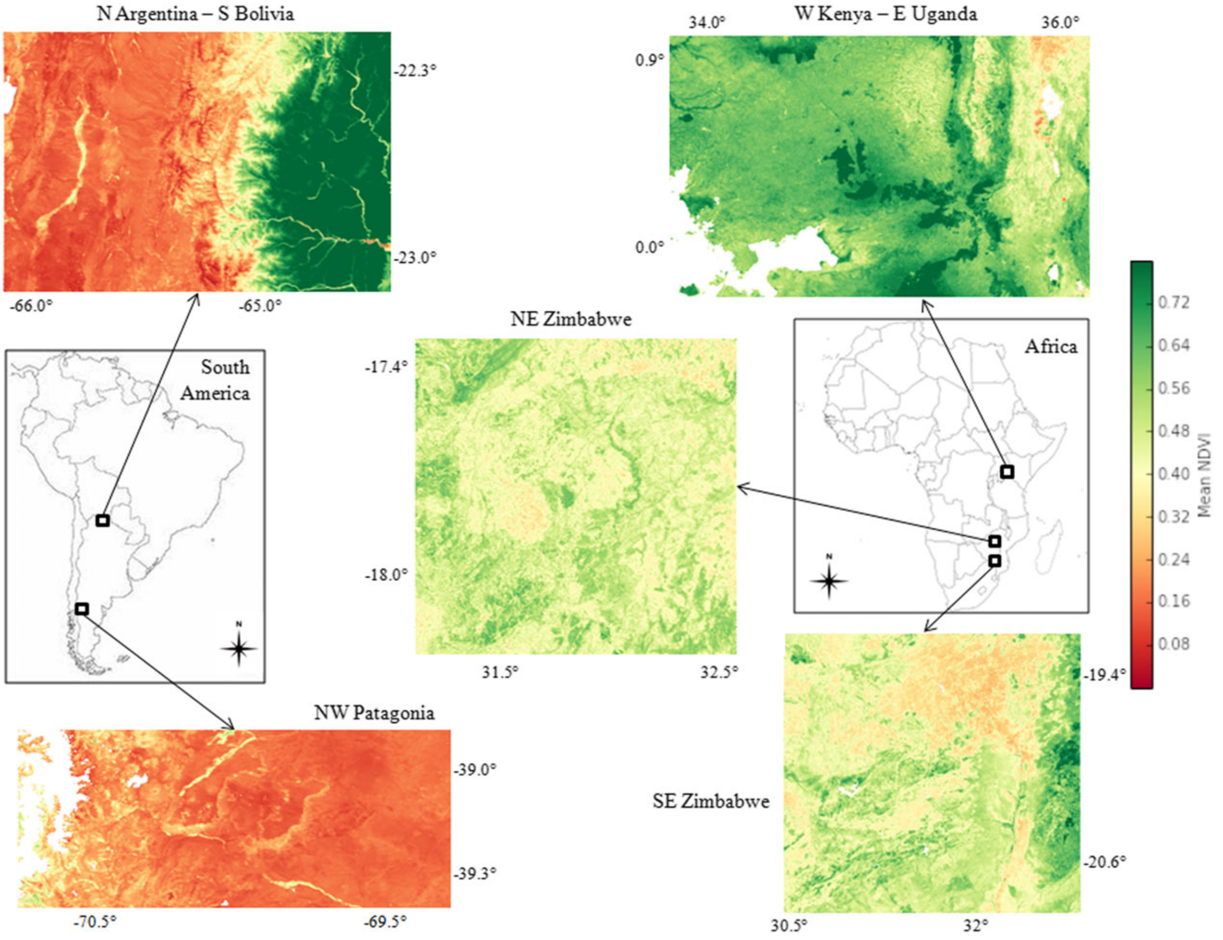

FIGURE 1 Mean normalized difference vegetation index (NDVI) of case study areas located in Africa: NE and SE Zimbabwe, and W Kenya–E Uganda, and in South America: N Argentina–S Bolivia and NW Patagonia (Argentina) [Colour figure can be viewed at wileyonlinelibrary.com]

represented by the Miombo woodland, a savannah-type ecosystem, and agricultural activities include large-scale commercial (mostly on clay soils) and smallholder (mostly on sandy soils) maize-based production with strong livestock interactions. Under smallholder systems, cattle herds typically graze in communal areas. Average annual rainfall is 810 mm, ranging from >1,000 mm yr^{-1} in the country's Eastern Highlands to ~800 mm in the central watershed. The country's rainfall generally decreases from NE to SW. The case study area of SE Zimbabwe spans a semiarid W–E gradient of decreasing altitude and annual rainfall, from 900 to 400 mm (Figure 1). The area is dominated by smallholder subsistence farming with cattle and goats as the main livestock activity and irrigated sugar cane along the flood plains of the Save river.

The case study area in W Kenya and E Uganda comprises one of the most densely populated regions of sub-Saharan Africa (up to 1,000 inhabitants per square kilometer in some places; Figure 1). It encompasses humid and subhumid highlands west of the rift valley where soils are deep and relatively fertile (Nitosols and Luvisols), and rainfall is bimodal (1,100 to 1,800 mm), allowing two cropping seasons per year. Smallholder subsistence maize farming dominates, coexisting with rainfed sugar cane, dairy to the south and cotton to the west. Remnants of the original Congolese-type tropical forest remain within national parks and protected areas.

The case study of N Argentina and S Bolivia includes a great W–E biophysical gradient in terms of altitude (from the Andean range above 3,500 m.a.s.l. to plains and valleys located at 400 m.a.s.l.) and annual rainfall from less than 100 to 1,000 mm (Figure 1). This gradient includes the biomes of the Puna dryland on the Western side dominated by grass-shrub steppes and smallholder pastoralism, with crop production in local valleys. The Yungas tropical rainforest is located towards the East of the gradient.

Finally, the case study of NW Patagonia is located also in a W–E biophysical gradient in terms of altitude (from 2,000 to 400 m.a.s.l.) and rainfall (from 1,000 to 200 mm yr^{-1}), but mostly dominated by grass-shrub and shrub-grass steppes from the Patagonian Western District and Monte Austral ecological regions, respectively (Figure 1). Local meadows with very high productivity are frequent towards the Western sector but represent less than 3% of the total area, which are used for livestock production. Smallholder transhumant pastoralism dominates, with goat husbandry in mixed herding with sheep and cattle.

2.2 | Data source

We used the 16-day composite MODIS images (MODIS13Q1 product) for the series February 2000–February 2016, which were obtained from the USGS Earth Resources Observation and Science Data Center. The pixels from the selected study areas (i.e., 250 m × 250 m of spatial resolution) were uploaded from MODIS mosaics with Python-GDAL library (Geospatial Data Abstraction Library, GDAL Development Team [2015]) and then clipped by means of a point-inside-polygon routine from the Matplotlib library of Python programming language (Hunter, 2007). This procedure automatically detects if whatever of the four corners of the pixel is found inside the polygon of the study area or whichever of the corners of the study area is found inside a given pixel. For these cases, the pixel is then considered inside the study area. The sequence of clipped MODIS images were piled up into a space-time cube (i.e., a three-dimensional matrix comprised by longitude, latitude, and time). Hence, we obtained the temporal sequence for each pixel along the last dimension of that matrix (i.e., time). In order to avoid further distortion, data were not reprojected, keeping the sinusoidal projection provided by the original MODIS mosaics.

NDVI was derived from MODIS images, which was calculated with the following equation (Rouse, Haas, Schell, & Deering, 1973):

$$NDVI = (\rho NIR - \rho R)/(\rho NIR + \rho R) \tag{1}$$

where ρNIR and ρR are the surface reflectances centered at 858 nm (near-infrared) and 648 nm (visible) portions of the electromagnetic spectrum, respectively.

2.3 | Data preprocessing

Because NDVI is a continuous finite variable, we assumed that the NDVI error followed a logit-normal distribution (i.e., a statistical distribution whose logit transform follows a normal distribution, Ashton, 1972).

Before fitting the NDVI time series, data were logit-transformed in order to use a normal likelihood function. Because NDVI is a value between −1 and 1, but values lower than 0 do not have a biological meaning, we treated it in a similar way as a proportion between 0 and 1. Logit transformation also avoids the use of the more complex Beta distribution as a likelihood function. Instead, we used a normal function, which is also simpler in interpretation in terms of mean and variance. A second benefit was to avoid dealing with meaningless values (i.e., estimated values larger than 1 or lower than zero).

After the transformation of NDVI data, we centered the series by removing the mean. Because the values lower than zero had no biological meaning, they were treated as missing values (i.e., values below zero mean snow cover, clouds, water, or rocks). If a pixel in the data stack consisting of *xy* NDVI layers contained more than 20 negative values, it was discarded from the analysis. After this procedure, most of the discarded pixels corresponded to borders of water bodies and top of the mountains.

2.4 | Trend estimation methods

2.4.1 | Simple linear regression

Linear trend of NDVI time series was used in this article as an example of a monotonic function. We estimated the interannual NDVI trend using a linear regression of series of annual integral NDVI (NDVI-I). The NDVI-I was calculated as the weighted sum of the 23 annual data (16-day composites) divided by the fraction of the year that each composite occupied (i.e., because the last composite which corresponds to December occupies a shorter time span of 13 or 14 days, instead of 16 days). This process resulted in series of 16 NDVI-I data per pixel, which were used to perform simple linear regression analysis. After performing the regression, the pixels were classified according to the sign and the significance of the slope ($\alpha = 0.05$). Hence, pixels with negative significant slope were classified as *decreasing* (red pixels) and pixels with positive significant slope as *increasing* (green pixels). Pixels with nonsignificant slope were classified as *no trend* (white pixels). The linear regression was performed using the statsmodels library for statistical analysis from Python (Seabold & Perktold, 2010).

2.5 | WARM model

2.5.1 | Filter description

Instead of using the most common wavelet transformation (discrete or continuous), we chose an alternative via a sparse transform through the matching pursuit (MP) algorithm with time frequency dictionaries (Mallat & Zhang, 1993). MP decomposes any signal into a weighted sum of time-frequency dictionaries, which most commonly are Gabor atoms (Demanet & Ying, 2007). These atoms are periodical trigonometric functions (e.g., a cosine function) multiplied by a Gaussian window. Here, the periodic function was centered in the Gaussian window so that the maximum of the window coincided with a maximum of the cosine (or minimum, depending on the amplitude sign).

The MP method consists of an iterative greedy selection of best-matching function from a list of randomly generated atoms (Mallat & Zhang, 1993). We used the maximum likelihood criterion to choose the best fitting atom. After one atom is selected, a new atom is added, and this procedure is repeated until the information explained by the dictionary reached a certain level considered satisfactory. We choose the Akaike information criterion (Akaike, 1974) as a stopping rule for the iterative selection of Gabor atoms. Instead of using the standard MP, we choose the Orthogonal MP (OMP) in which all the coefficients (including those of the previously selected atoms) are updated. This procedure reduced the information shared between atoms and gave us more parsimonious results. After each iteration, we further refined the calculation of the parameters of the Gabor atom, to increase the likelihood function. We performed this step using a random optimization procedure (Matyas, 1965).

Finally, at the end of the OMP procedure, we ran an autoregressive model with conditional heteroscedasticity to check for autocorrelation of errors, because we found that the NDVI data contained nonconstant variance. As in the previous steps, all the coefficients of the Gabor atoms and of the autoregressive model with conditional heteroscedasticity model were updated via random optimization. The order of the model AR was increased stepwise until the AIC value began to increase, while the heteroscedasticity coefficients were kept into order one, because we found in preliminary studies that higher orders made the fitting procedure unnecessarily complex.

2.6 | Trend estimations

After fitting the WARM model, we had a series of periodic functions whose shared information was minimal, whose fitting was corrected by autocorrelation of errors and whose residuals were Gaussian white noise (i.e., any two values are statistically independent no matter how close they are in time; Marmarelis, 2012). Those atoms contained information on periodic variability of different frequency of the NDVI time series. Some atoms contained a trigonometric function whose wavelength was longer than the length of the time series (16 years), because the trend (i.e., the long term variation of the mean on a time series) is indistinguishable from very low frequency phenomena, we considered these atoms to be the ones containing the trend component of the NDVI time series. These were considered the trend atoms.

After finding the trend atoms, we calculated the ratio between the information contained by the trend and the total information of the time series, as the generalized coefficient of determination (Cox & Snell, 1989) of the trend-only model.

Trend atoms contained a periodical function which is longer than the time series. This function had one minimum and one maximum value within the span of the time series. Hence, the trend was not necessarily monotonic and therefore its minimums and/or maximums could be found anywhere in the time series. In order to classify different kinds of trends, we used as a rule the location of the maximum value with respect to the location of the minimum value in the time series. We defined four classes: (a) *Increasing* (In, the maximum occurred after the minimum, and minimum was located at the end of the time series), (b) *Decreasing* (Dc, the minimum occurred after the maximum, and maximum was located at the end of the time series), (c) *Recovering* (Rc, decreasing time series whose minimum occurred before the end of the time series, and after the minimum a change in the trend direction occurred), and (d) *Relapsing* (Rl, increasing time series whose maximum occurred before the end of the time series, and after the maximum a change in the trend direction occurred; Figure 2). For the purpose of this paper, increasing and decreasing patterns obtained with the WARM model were treated as monotonic trends as in the cases of the simple regression method. On the other hand, recovering and relapsing trends were considered as functions that described different cycle phases.

2.7 | Test of methods

We analyzed the outcome of both methods in two well-documented areas located in North Patagonia, Argentina. The aim was to test if the four classes of trend from the WARM model could be differentially identified from those obtained by the simple linear regression. The selected areas represented two contrasting situations in terms of environmental disturbance and land-use change. On the one hand, we selected a representative pixel from a grass-shrub steppe located in Pilcaniyeu Experimental Station of the National Institute for Agricultural Technology (INTA, in Spanish; 41.0083 S, 70.5796 W), where a massive ash fallout from the eruption of the Puyehue-Cordón Caulle volcanic complex took place in June 2011 (Collini et al., 2013). The ash deposits significantly affected the dynamics of rangelands in the following months (Figure 3a). On the other hand, we selected a representative pixel of a land-use change process which involved a shrubland clearing in an arid region followed by forest plantation under irrigation (39.3687 S, 69.0393 W). Due to several problems with water availability and the irrigation system, after the year 2015, the afforestation could not be adequately irrigated and hence it was abandoned (Figure 3B).

3 | RESULTS

The WARM model did provide different outcomes in comparison with the simple linear regression method in the case studies used for testing

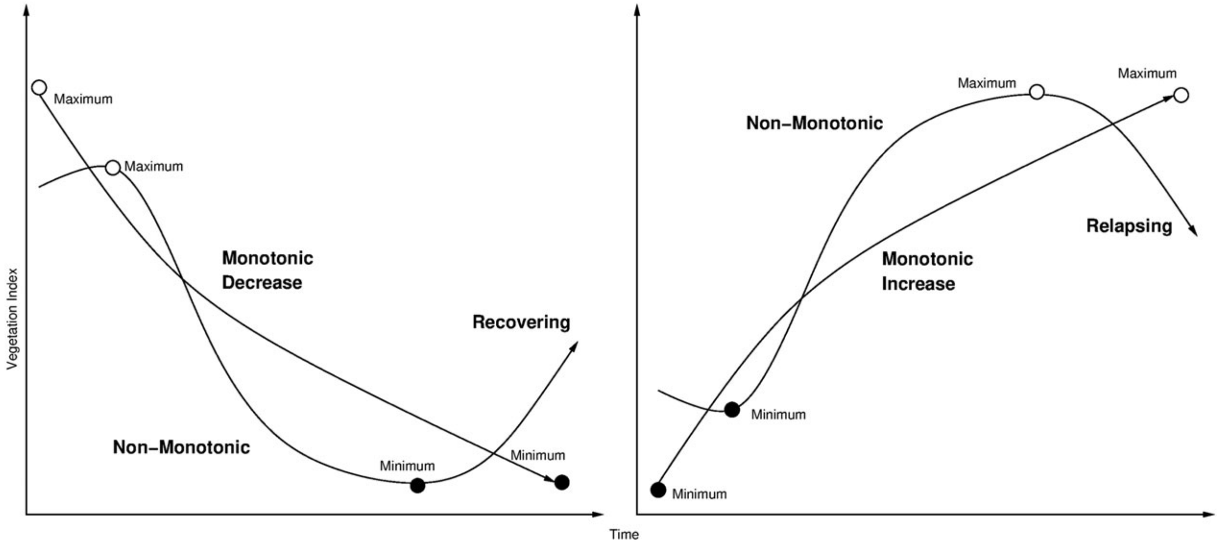

FIGURE 2 Classification of trends in monotonic and nonmonotonic functions according to the position of the last maximum or minimum value: (a) decreasing and recovering and (b) increasing and relapsing, respectively

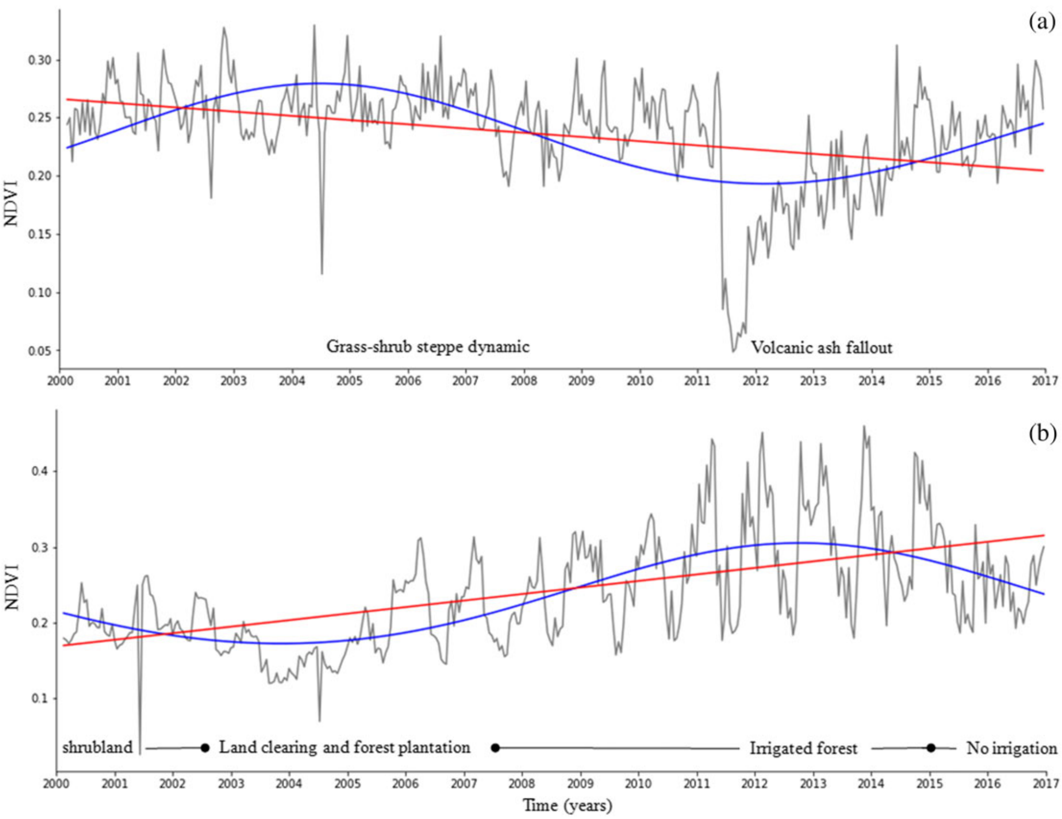

FIGURE 3 Trends obtained from the simple linear regression method (red line) and wavelet autoregressive method model (blue line) of normalized difference vegetation index time series in two selected areas from North Patagonia, Argentina: (a) a grass-shrub steppe that faced an ash fallout from a volcanic eruption (41.0083 S, 70.5796 W) and (b) a shrubland clearing followed by forest plantation under irrigation, which was not irrigated in last 2 years of the time series due to problems with water availability and irrigation system (39.3687 S, 69.0393 W). Statistics for linear trends: (a) slope = −0.0036, R^2 = 0.30, *p* value = .021; (b) slope = +0.0086, R^2 = 0.64, *p* value = .0001 [Colour figure can be viewed at wileyonlinelibrary.com]

the models. The WARM model identified a recovering trend of the grass-shrub steppe affected by volcanic ash fallout, whereas the linear regression trend recorded a statistically significant decreasing pattern (Figure 3a). As well, the WARM model identified a relapsing trend of the afforested land for which irrigation was interrupted at the end of the time series, whereas the linear regression trend recorded a statistically significant increasing pattern (Figure 3B). These results demonstrate the sensitivity of WARM model to differentially capture

TABLE 1 Aggregated results obtained from the wavelet autoregressive method (WARM) model and simple linear regression method

Method	Variable	Regional study areas: N Argentina–S Bolivia	NW Patagonia, Argentina	W Kenya–E Uganda	SE Zimbabwe	NE Zimbabwe
WARM model	Trend (explained variability[a]; %)	2.10	7.43	2.59	3.22	0.80
	1.Decreasing (%)[b]	1.25	0.92	1.58	22.83	7.60
	2.Recovering (%)[b]	13.58	54.91	18.73	41.47	16.29
	3.No trend (%)[b]	37.88	39.98	45.48	31.51	60.65
	4.Relapsing (%)[b]	40.80	6.37	23.12	3.89	14.30
	5.Increasing (%)[b]	4.39	1.26	8.50	0.30	1.16
	Monotonic change (%)[b] (increasing + decreasing)	5.64	2.18	10.08	23.13	8.76
	Cyclic change (%)[b] (recovering + relapsing)	54.38	61.28	41.85	45.36	30.59
Simple linear regression method	6.Linear decreasing (%)[b]	3.31	36.46	6.16	27.25	7.20
	7.No trend (%)[b]	52.15	57.44	77.42	71.55	82.70
	8.Linear increasing (%)[b]	44.54	6.10	16.42	1.20	10.10
	Monotonic change (%)[b] (linear increasing + linear decreasing)	47.85	42.56	22.58	28.95	17.3

[a]Percentage of total variability.

[b]Percentage of the total pixels included in each study area.

dynamics that were nonunidirectional and where a simple regression method would record monotonic patterns.

Results of the time series analysis differed substantially between methods for all five case studies in Africa and South America, even though the input data were the same. Trend estimated by the linear regression method recorded many more pixels with no significant slopes (i.e., above 50% for all study cases), whereas the WARM model recorded less area without significant trend, which means a higher capacity to discriminate trend patterns (Table 1). For example, a relevant proportion of pixels without significant linear trend was discriminated as recovering and/or relapsing in W Kenya–E Uganda (Figure 4b) and NE and SE Zimbabwe (Figures 5b and 6b).

Monotonic changes recorded by the simple linear regression method were mostly described as cyclic phases across all case studies with the WARM model. For example, many linear increasing and decreasing trends (Figures 7a and 8a) were recorded as relapsing and recovering, respectively (N Argentina–S Bolivia, Figure 7b; NW Patagonia, Figure 8b). Decreasing and increasing trends estimated by

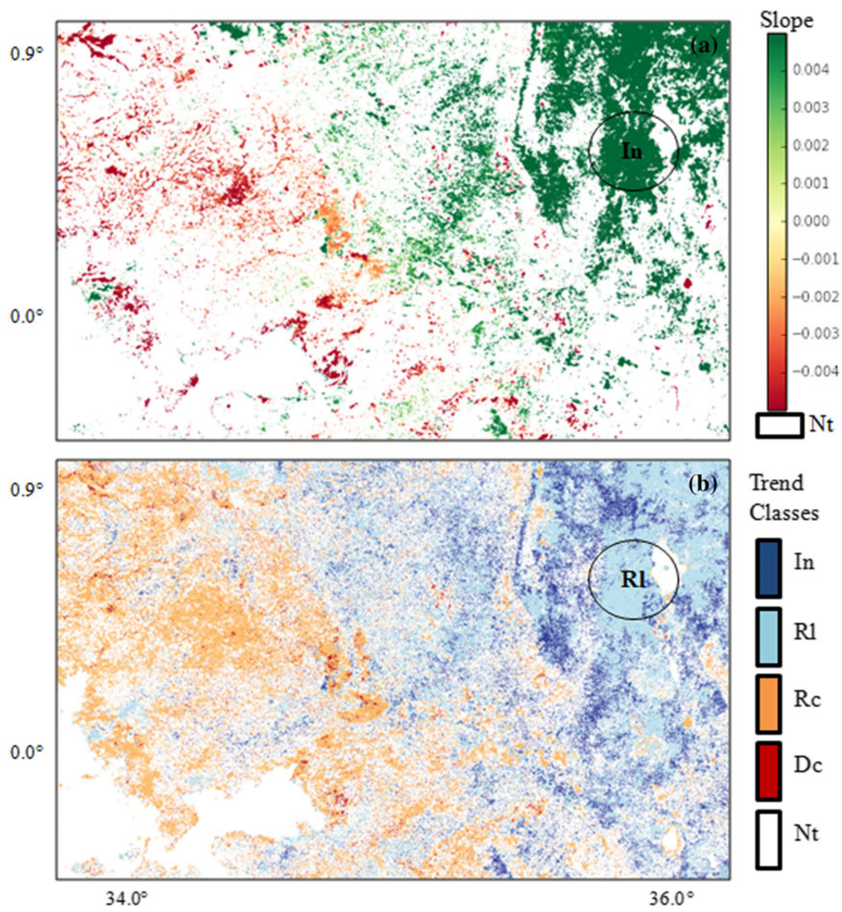

FIGURE 4 Case study area of W Kenya–E Uganda, Africa: (a) slope of the linear trend and (b) classes of trends obtained from the wavelet autoregressive method (WARM) model (see Figure 2). Circles exemplify a similar zone with (a) increasing trend and (b) relapsing trend, obtained from simple linear regression method and wavelet autoregressive method model, respectively. Dc = decreasing; In = increasing; Nt = nonsignificant trend; Rl = relapsing; Rc = recovering; α = 0.05 [Colour figure can be viewed at wileyonlinelibrary.com]

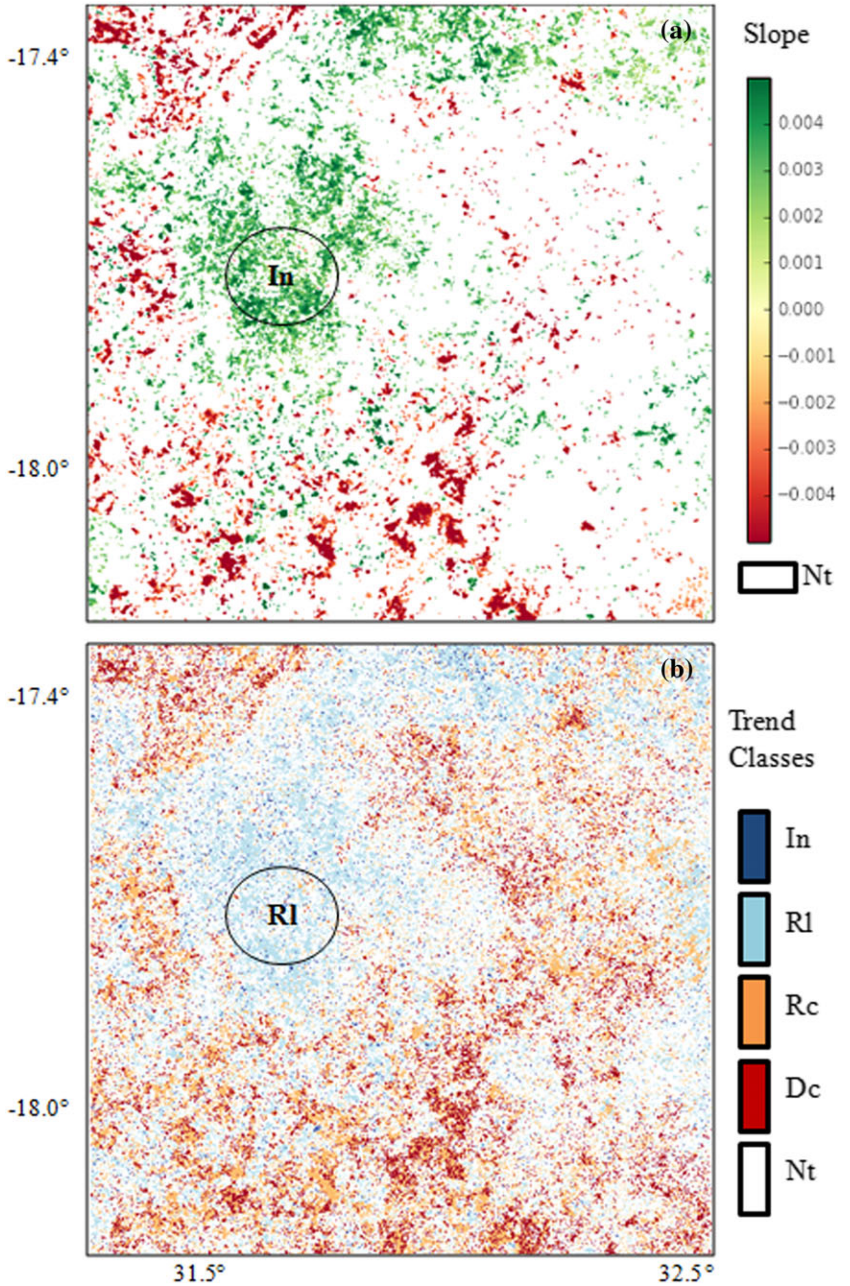

FIGURE 5 Case study area of NE Zimbabwe, Africa: (a) slope of the linear trend and (b) classes of trends obtained from the wavelet autoregressive method (WARM) model (see Figure 2). Circles exemplify a similar zone with (a) increasing trend and (b) relapsing trend, obtained from simple linear regression method and WARM model, respectively. In = increasing; Rl = relapsing; Rc = recovering; Dc = decreasing; Nt = nonsignificant trend; α = 0.05 [Colour figure can be viewed at wileyonlinelibrary.com]

the WARM model represented less than 10% of pixels in most cases, reaching 23% in the case of SE Zimbabwe (Table 1). In other words, most case studies recorded decreasing or increasing trends for less than 10% of the total spatial area, whereas cyclic change was significant for a minimum of one third to as much as two thirds of the total spatial area, for all case studies.

To illustrate the main differences between both methods, we highlighted areas with contrasting results for each case study. For example, zones that were classified as having decreasing trends and could then be associated with a potential degradation process with the linear method (Dc, Figures 6a, 7a, 8a) were instead classified as recovering with the WARM model (Rc, Figures 6b, 7b, 8b). These differences exemplified the need for caution when interpreting NDVI changes over time. On the other hand, zones that were identified by the monotonic function as significantly increasing (In, Figures 4a, 5a, 7a) were classified as relapsing by the nonmonotonic function (Rl, Figures 4b, 5b, 7b). This refers to a shift in the orientation of the trend within the same analyzed time. Hence, whereas a greening pattern can be inferred in the first option, a phase change can be emphasized in the second.

A noteworthy result to be highlighted from our analysis of these five regional case studies, spanning a wide diversity of biophysical situations, is that trend explained less than 8% of total temporal variability of NDVI time series, whereas in most cases, it was below 3% (Table 1).

4 | DISCUSSION

Trend estimations from remote sensing time series data gained consensus to be used as proxies for land degradation. In particular, trend is frequently defined by the slope of a linear regression of NDVI time series, which was considered in this paper as an example of a monotonic function. Here, we showed through a range of case studies that there

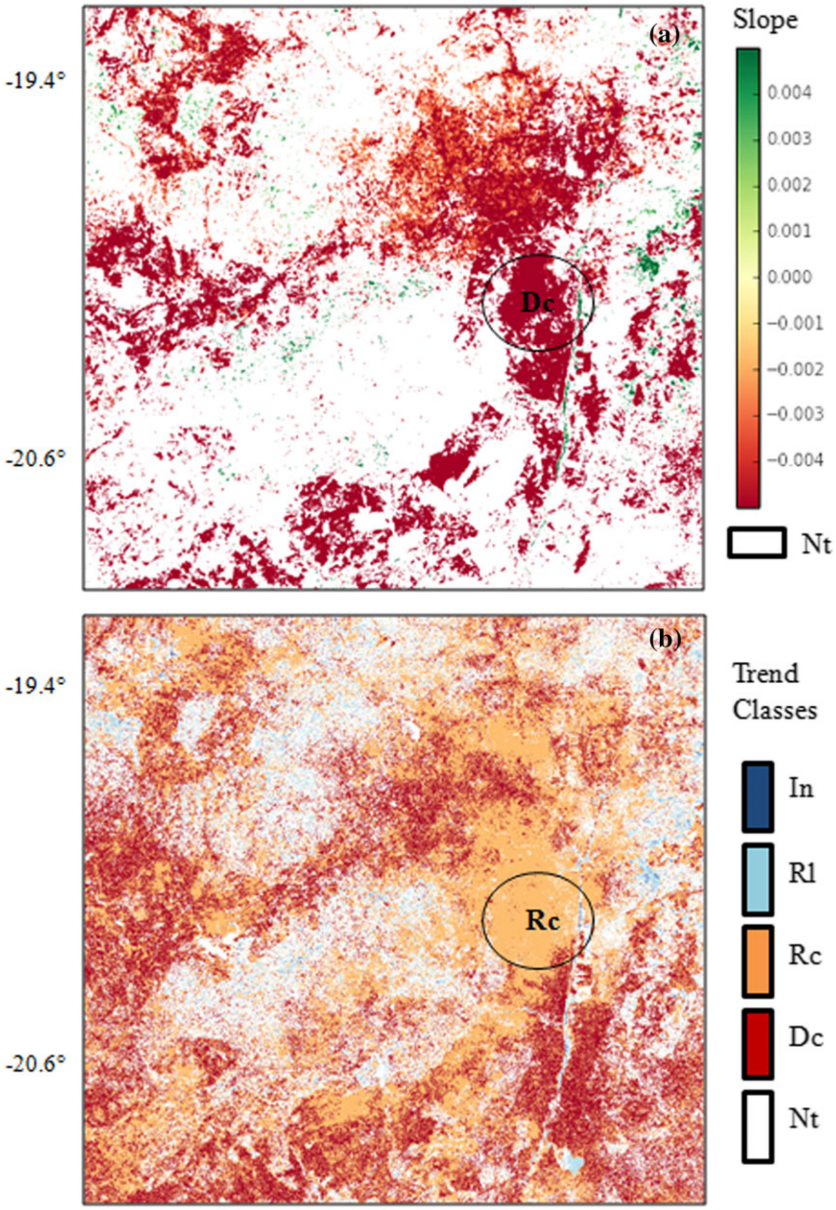

FIGURE 6 Case study area of SE Zimbabwe, Africa: (a) slope of the linear trend and (b) classes of trends obtained from the wavelet autoregressive method (WARM) model (see Figure 2). Circles exemplify a similar zone with (a) decreasing trend and (b) recovering trend, obtained from simple linear regression method and WARM model, respectively. In = increasing; Rl = relapsing; Rc = recovering; Dc = decreasing; Nt = nonsignificant trend; α = 0.05 [Colour figure can be viewed at wileyonlinelibrary.com]

are three main limitations with this approach. First and foremost, trend explained a marginal portion of the temporal information that is contained in NDVI time series, barely less than 3% in most cases (Table 1). Second, the monotonic characteristic of linear functions prevents us from considering the more complex dynamics of ecosystems, in terms of periodic or cyclic changes, which was corroborated in all case studies (Figures 3--8). Finally, WARM model was much more sensitive to different kinds of trends as measured by monotonic and nonmonotonic functions than linear method, and a higher proportion of spatial patterns was described as cyclic change (Table 1).

Ecosystems are complex and adaptive systems (Levin, 1998), which fluctuate in a state or regime in dynamic equilibrium under similar conditions (Folke et al., 2004). Because ecosystems are exposed to perturbations or disturbance factors, a system will be often pushed away from the steady state, but it will tend to return to the original situation due to feedback processes (Holling, 1973), if a threshold was not surpassed (Groffman et al., 2006; Figure 3a). During this kind of stressful circumstances, there is a lag response on the output of the ecosystem in reaction to present and past inputs or perturbations, and the trajectory return to the equilibrium point may differ from the one adopted during the outward movement (Beisner, Haydon, & Cuddington, 2003; Gallopín, 2006). This phenomenon is known as hysteresis (Tittonell, 2014; Tittonell et al., 2012). The results of this article suggest that linear NDVI trend is intended to describe a complex system using a very simple tool without taking into account these complex dynamics of ecosystems.

One of the current challenges in applied ecology and environmental sciences is the tremendous gap between the wide theoretical consensus around complex dynamic of ecosystems and some methodological proposals aimed at tackling this complexity. The foundations of this gap are too frequently based on the dominant mindset that supports the usage of averages, normal distributions, and linear relationships to describe spatial or temporal differences, instead of time series analyses (Easdale & Bruzzone, 2015). Land degradation assessment based on NDVI monotonic trends is a relevant example to illustrate this problem. Many studies aimed at analyzing global or regional land degradation are supported by the argument that trends can be adequately tackled and explained by monotonic functions (Anyamba & Tucker, 2005; Beck et al., 2011; de Jong, de Bruin, de Wit, Schaepman, & Dent, 2011; Eckert

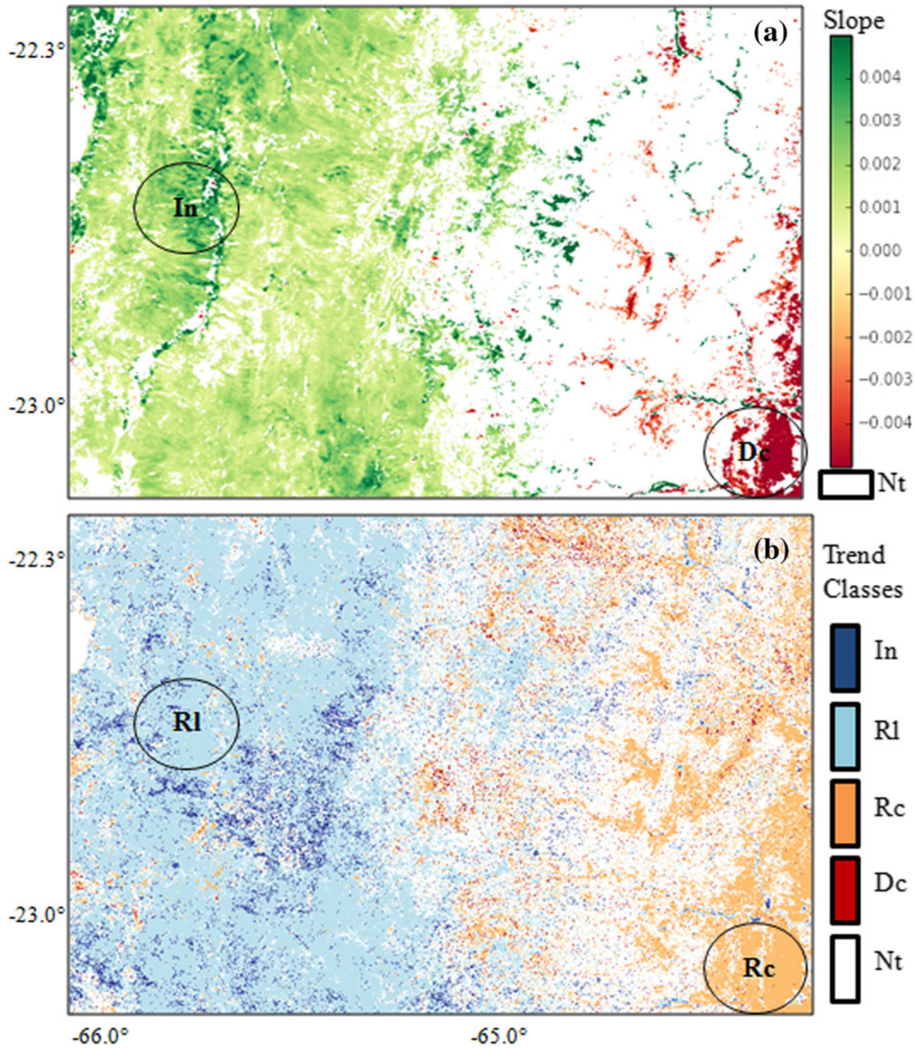

FIGURE 7 Case study area of N Argentina–S Bolivia, South America: (a) slope of the linear trend and (b) classes of trends obtained from the wavelet autoregressive method (WARM) model (see Figure 2). Circles exemplify a similar zone with (a) increasing and decreasing trends and (b) relapsing and recovering trends, obtained from simple linear regression method and wavelet autoregressive method model, respectively. In = increasing; Rl = relapsing; Rc = recovering; Dc = decreasing; Nt = nonsignificant trend; α = 0.05 [Colour figure can be viewed at wileyonlinelibrary.com]

et al., 2015; Fensholt et al., 2012; Gaitán et al., 2015; Luo, Tang, Zhu, Di, & Xu, 2016; Miao, Yang, Chen, & Gao, 2012; Omuto, Balint, & Alim, 2014; Saha, Scanlon, & D'Odorico, 2015; Vlek et al., 2008; Yin et al., 2012). The main implication of this position is that it is not possible to consider neither states at dynamic equilibrium with a range of luctuation nor hysteresis, becoming then a major limitation of linear NDVI trends for land degradation studies. The main consequence of this methodological pitfall is the promotion of alarmist conclusions associated with regime shifts such as desertification as measured by significant negative slopes or even the opposite situation with regard to greening patterns as measured by significant positive slopes, which may not be the correct circumstances (Figure 3). Recent research emphasizes some limitations of monotonic methods and trend analyses based on remote sensing vegetation index data for the detection of land degradation (de Jong et al., 2011; Wessels, van den Bergh, & Scholes, 2012) and the need to move forward in the analysis of nonlinear vegetation change (Jamali, Seaquist, Eklundh, & Ardö, 2014).

Whereas there are many methodological and operational advances of focusing on the relationships between climatic drivers and vegetation structure and responses in the face of degradation processes (Gaitán et al., 2013; Nemani et al., 2003; Verón & Paruelo, 2010), there are still difficulties to fully discriminate effects of climate from effects of human-induced land degradation (Wessels et al., 2007). Indeed, measures of land degradation based on NDVI trends underestimate the problem because the downward rate of change of some ecosystem services or natural capital stocks such as soil organic matter, nutrient cycling, or available water capacity may be comparatively higher (Nezomba, Mtambanengwe, Tittonell, & Mapfumo, 2015; Yengoh, Dent, Olsson, Tengberg, & Tucker, 2014). In addition to these major challenges, we emphasize that NDVI trend explains a very low portion of the total temporal variability (often less than 3%—cf. Table 1), given the current available length of remote sensing data.

The use of remote sensing is increasingly valuable for terrestrial ecologists tackling vegetation dynamics, wildlife movement patterns, climate change impacts, land-use change and ecosystem services assessments (Pettorelli et al., 2005; Smith et al., 2014). However, the use of NDVI to discriminate between degraded and nondegraded areas is still challenging both in terms of implementation and interpretation

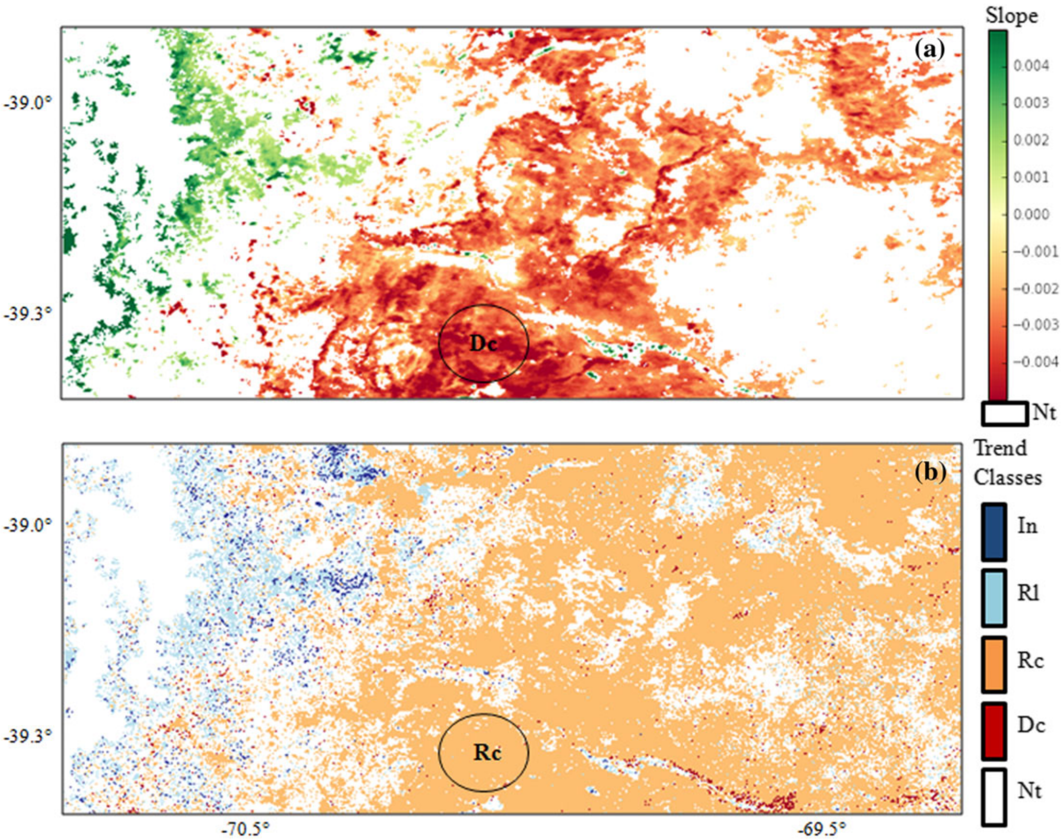

FIGURE 8 Case study area of NW Patagonia, Argentina, South America: (a) slope of the linear trend and (b) classes of trends obtained from the wavelet autoregressive method (WARM) model (see Figure 2). Circles exemplify a similar zone with (a) decreasing trend and (b) recovering trend, obtained from simple linear regression method and wavelet autoregressive method model, respectively. In = increasing; Rl = relapsing; Rc = recovering; Dc = decreasing; Nt = nonsignificant trend; α = 0.05 [Colour figure can be viewed at wileyonlinelibrary.com]

(Yengoh et al., 2014). One of the main issues that need to be considered is that NDVI is directly related to energy absorption but not to leaf area index (LAI), which means that there are several relationships between LAI and vegetation indices. The overall relationship can be expressed as a function of amount of photosynthetically active vegetation or chlorophyll content and other canopy characteristics such as leave/plant structure (Haboudane, Miller, Pattey, Zarco-Tejada, & Strachan, 2004). In addition, the issue of NDVI saturation at higher LAIs (Wang, Adiku, Tenhunen, & Granier, 2005) reduces accuracy in many highly productive zones. A solution to this problem is choosing vegetation indices that saturate less with high vegetation cover such as the enhanced vegetation index (Wang, Liu, & Huete, 2002). On the other hand, many scholars alert on the need to deal with noise components of time series due to cloudy conditions, high aerosol situations, presence of snow cover, sun-sensor-surface viewing geometries, calibration, digital quantization errors, and sensor degradation (Hird & McDermid, 2009; Kaufmann et al., 2000; Tanré, Holben, & Kaufman, 1992; Viovy, Arino, & Belward, 1992).

Further research is needed to separate NDVI time series into other different components such as low and high frequency domains as measures of periodic components, stochastic components, and white noise (Hird & McDermid, 2009; Jakubauskas, Legates, & Kastens, 2001; Verbesselt, Hyndman, Newnham, & Culvenor, 2010). The identification of phases and states is also dependent on the length of the temporal window used to perform the analysis (Yengoh et al., 2014). A temporary disturbance may be seen as a change of state or a regime shift when the window of time is short, as shown in the case of a grass-shrub steppe dynamics facing sudden volcanic ash fallout (Figure 3a). On the other hand, a too long window of time blurs out most perturbations. Then, in trend analysis of satellite remote sensing data such as NDVI which are based on monotonic functions, what is commonly assumed to be a new state or regime shift as measured by significant slopes may often be no more than a state phase that depicts recurrent phenomena in ecosystem dynamics (Table 1). In other words, the result of confusing regime shifts with plain stochastic noise (Doney & Sailley, 2013) or red noise which is dominated by low-level frequencies and is positively self-correlated (Rudnick & Davis, 2003).

4.1 | A brief comparison of methods

Simple linear regression method, as an example of a monotonic function, is simple and easy and offers straightforward outcomes. However, results are simplistic and do not provide sound scientific information of current dynamics (Figure 3). The WARM model was sensitive to discriminate both monotonic and nondirectional dynamics and recorded less area without significant trend, which means a higher capacity to discriminate trend patterns. Hence, results of monotonic functions are already included among the potential outcomes of WARM model, with the additional advantage of capturing nonmonotonic patterns. We acknowledge however that model development and implementation is more laborious, and some of the results obtained may be less intuitive at first glance.

Finally, none of both methods may be expected to provide accurate information on land degradation or restoration, basically because trend explained a minor proportion of temporal NDVI variability (Table 1). In this regard, we suggest that trend analysis should be integrated into other frequency domain analysis of time series such as interannual and intraannual cycles and perturbations (Hastings & Wysham, 2010) and complemented with explanatory variables such as climatic data and land-use information, which may provide more complete pictures of changes in NDVI dynamics. The WARM model has potential to be used in this direction. As well, other alternative methods for the analysis of nonlinear vegetation change such as polynomials (Jamali et al., 2014) or breakpoints detection in time series (Verbesselt et al., 2010) highlight the need to move forward in this theme. Future research is needed to advance in the identification of different components of temporal variability, key changes, or dynamic thresholds which may provide evidences that need to be supported by ground data. At this stage of development, we conclude that results obtained in this paper are encouraging as a step towards more accurate ways of assessing land degradation process using remote sensing data.

5 | CONCLUSIONS

Land degradation is frequently assessed through monotonic functions applied to NDVI trends. Here, we challenged this approach by showing its limitations at capturing more complex land dynamics than those described by linear trends. The main conclusions that arise from comparison time series analysis methods are that (a) trend explained a marginal portion of the temporal information that is contained in NDVI time series, and (b) the monotonic characteristic of linear functions prevents us from considering the more complex dynamics of ecosystems, in terms of periodic or cyclic changes. With regard to the first issue, we stress the need for caution in the usage of NDVI trends as proxies to land degradation. To overcome the limitations identified in the second issue, the WARM model proposed in this paper allows distinguishing between monotonic and nondirectional trend patterns in NDVI dynamics, even within the still short length of the time series currently available for land degradation studies. Results are encouraging as a step towards the application of more accurate tools to provide sound scientific information of land degradation and restoration. Yet further research is needed to better understand the influence of external drivers such as climate, environmental, or land-use change and internal ecological dynamics (or likely some combination) in such cyclic patterns of NDVI. These scientific challenges still need a shift in the focus from dominant approaches based on *average thinking* towards *dynamic thinking* in research on land degradation and restoration.

ACKNOWLEDGMENTS

This research was funded by Instituto Nacional de Tecnología Agropecuaria (INTA, PATNOR-1281103) and Ministerio de Ciencia, Tecnología e Innovación Productiva Argentina (PICT 2015-929). We thank suggestions from anonymous reviewers and editor-in-chief which significantly enhanced key aspects of this paper and overall readability.

ORCID

Marcos Horacio Easdale http://orcid.org/0000-0003-1097-5242

REFERENCES

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723. https://doi.org/10.1109/TAC.1974.1100705

Anyamba, A., & Tucker, C. J. (2005). Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981 to 2003. *Journal of Arid Environments*, *63*(3), 596–614. https://doi.org/10.1016/j.jaridenv.2005.03.007

Ashton W.D. 1972. The logit transformation: With special reference to its uses in bio-assay. Griffin's Statistical Monographs & Courses, 32. Charles Griffin, London UK, 88 pp.

Bai, Z. G., Dent, D. L., Olsson, L., & Schaepman, M. E. (2008). Proxy global assessment of land degradation. *Soil Use and Management*, *24*(3), 223–234. https://doi.org/10.1111/j.1475-2743.2008.00169.x

Beck, H. E., McVicar, T. R., van Dijk, A. I., Schellekens, J., de Jeu, R. A., & Bruijnzeel, L. A. (2011). Global evaluation of four AVHRR–NDVI data sets: Intercomparison and assessment against Landsat imagery. *Remote Sensing of Environment*, *115*(10), 2547–2563. https://doi.org/10.1016/j.rse.2011.05.012

Beisner, B. E., Haydon, D. T., & Cuddington, K. (2003). Alternative stable states in ecology. *Frontiers in Ecology and the Environment*, *1*(7), 376–382. https%3A%2F%2Fdoi.org%2F10.1890%2F1540%26hyphen%3B9295(2003)001%5B0376%3AASSIE%5D2.0.CO%3B2

Collini, E., Osores, M. S., Folch, A., Viramonte, J. G., Villarosa, G., & Salmuni, G. (2013). Volcanic ash forecast during the June 2011 Cordón Caulle eruption. *Natural Hazards*, *66*(2), 389–412. https://doi.org/10.1007/s11069-012-0492-y

Cox, D. R., & Snell, E. J. (1989). *The analysis of binary data*. London: Chapman & Hall.

Demanet, L., & Ying, L. (2007). Wave atoms and sparsity of oscillatory patterns. *Applied and Computational Harmonic Analysis*, *23*(3), 368–387. https://doi.org/10.1016/j.acha.2007.03.003

Diaz-Delgado, R., Salvador, R., & Pons, X. (1998). Monitoring of plant community regeneration after fire by remote sensing. In L. Trabaud (Ed.), *Fire management and landscape ecology* (pp. 315–326). Fairfield: International Association of Wildland Fire.

Doney, S. C., & Sailley, S. F. (2013). When an ecological regime shift is really just stochastic noise. *Proceedings of the National Academy of Sciences USA*, *110*(7), 2438–2439. https://doi.org/10.1073/pnas.1222736110

Easdale, M. H., & Bruzzone, O. (2015). Anchored in 'average thinking' in studies of arid rangeland dynamics–The need for a step forward from traditional measures of variability. *Journal of Arid Environments*, *116*, 77–81. https://doi.org/10.1016/j.jaridenv.2015.02.006

Eckert, S., Hüsler, F., Liniger, H., & Hodel, E. (2015). Trend analysis of MODIS NDVI time series for detecting land degradation and regeneration in Mongolia. *Journal of Arid Environments*, *113*, 16–28. https://doi.org/10.1016/j.jaridenv.2014.09.001

Fensholt, R., Langanke, T., Rasmussen, K., Reenberg, A., Prince, S. D., Tucker, C., … Epstein, H. (2012). Greenness in semi-arid areas across the globe 1981–2007—An earth observing satellite based analysis of trends and drivers. *Remote Sensing of Environment*, *121*, 144–158. https://doi.org/10.1016/j.rse.2012.01.017

Folke, C., Carpenter, S., Walker, B., Scheffer, M., Elmqvist, T., Gunderson, L., & Holling, C. S. (2004). Regime shift, resilience, and biodiversity in ecosystem management. *Annual Review of Ecology, Evolution, and Systematics*, *35*, 557–581. https://doi.org/10.1146/annurev.ecolsys.35.021103.105711

Gaitán, J. J., Bran, D., Oliva, G., Ciari, G., Nakamatsu, V., Salomone, J., … Maestre, F. T. (2013). Evaluating the performance of multiple remote sensing indices to predict the spatial variability of ecosystem structure and functioning in Patagonian steppes. *Ecological Indicators*, *34*, 181–191. https://doi.org/10.1016/j.ecolind.2013.05.007

Gaitán, J. J., Bran, D. D., & Azcona, C. (2015). Tendencia del NDVI en el período 2000–2014 como indicador de la degradación de tierras en Argentina: Ventajas y limitaciones. *AGRISCIENTIA*, *32*(2), 83–93.

Gallopín, G. C. (2006). Linkages between vulnerability, resilience, and adaptive capacity. *Global Environmental Change*, *16*(3), 293–303. https://doi.org/10.1016/j.gloenvcha.2006.02.004

Gouveia, C. M., Bastos, A., Trigo, R. M., & DaCamara, C. C. (2012). Drought impacts on vegetation in the pre- and post-fire events over Iberian Peninsula. *Natural Hazards and Earth System Sciences*, *12*, 3123–3137. https://doi.org/10.5194/nhess-12-3123-2012

Groffman, P. M., Baron, J. S., Blett, T., Gold, A. J., Goodman, I., Gunderson, L. H., … Poff, N. L. (2006). Ecological thresholds: The key to successful environmental management or an important concept with no practical application? *Ecosystems*, *9*(1), 1–13. https://doi.org/10.1007/s10021-003-0142-z

Gumma, M. K., Kajisa, K., Mohammed, I. A., Whitbread, A. M., Nelson, A., Rala, A., & Palanisami, K. (2015). Temporal change in land use by irrigation source in Tamil Nadu and management implications. *Environmental Monitoring and Assessment*, *187*, 4155. https://doi.org/10.1007/s10661-014-4155-1

Haboudane, D., Miller, J. R., Pattey, E., Zarco-Tejada, P. J., & Strachan, I. B. (2004). Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. *Remote Sensing of Environment*, *90*(3), 337–352. https://doi.org/10.1016/j.rse.2003.12.013

Hastings, A., & Wysham, D. B. (2010). Regime shifts in ecological systems can occur with no warning. *Ecology Letters*, *13*, 464–472. https://doi.org/10.1111/j.1461-0248.2010.01439.x

Hird, J. N., & McDermid, G. J. (2009). Noise reduction of NDVI time series: An empirical comparison of selected techniques. *Remote Sensing of Environment*, *113*(1), 248–258. https://doi.org/10.1016/j.rse.2008.09.003

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, *4*, 1–23.

Hunter, J. D. (2007). Matplotlib: A 2d graphics environment. *Computing in Science and Engineering*, *9*(3), 90–95.

Jakubauskas, M. E., Legates, D. R., & Kastens, J. H. (2001). Harmonic analysis of time-series AVHRR NDVI data. *Photogrammetric Engineering and Remote Sensing*, *67*(4), 461–470.

Jamali, S., Seaquist, J., Eklundh, L., & Ardö, J. (2014). Automated mapping of vegetation trends with polynomials using NDVI imagery over the Sahel. *Remote Sensing of Environment*, *141*, 79–89. https://doi.org/10.1016/j.se.2013.10.019

de Jong, R., de Bruin, S., de Wit, A., Schaepman, M. E., & Dent, D. L. (2011). Analysis of monotonic greening and browning trends from global NDVI time-series. *Remote Sensing of Environment*, *115*(2), 692–702. https://doi.org/10.1016/j.rse.2010.10.011

Kaufmann, R. K., Zhou, L., Knyazikhin, Y., Shabanov, N. V., Myneni, R. B., & Tucker, C. J. (2000). Effect of orbital drift and sensor changes on the time series of AVHRR vegetation index data. *IEEE Transactions on Geoscience and Remote Sensing*, *38*(6), 2584–2597. https://doi.org/10.1109/36.885205

Levin, S. A. (1998). Ecosystems and the biosphere as complex adaptive systems. *Ecosystems*, *1*, 431–436. https://doi.org/10.1007/s100219900037

Li, X. (2015). Afforestation areas from the grain for green program. In X. Cui, W. Zhu, X. Xu, & X. Li (Eds.), *Land-use changes in China. Historical reconstruction over the past 300 years and future projection*. Singapore: World Scientific Publishing Co.

López, D. R., Cavallero, L., Brizuela, M. A., & Aguiar, M. R. (2011). Ecosystemic structural–functional approach of the state and transition model. *Applied Vegetation Science*, *14*(1), 6–16. https://doi.org/10.1111/j.1654-109X.2010.01095.x

Luo, H., Tang, Y., Zhu, X., Di, B., & Xu, Y. (2016). Greening trend in grassland of the Lhasa River Region on the Qinghai-Tibetan Plateau from 1982 to 2013. *The Rangeland Journal*, *38*(6), 591–603.

Mallat, S. G., & Zhang, Z. (1993). Matching pursuit with time-frequency dictionaries. *IEEE Transactions on Signal Processing*, *41*(12), 3397–3415. https://doi.org/10.1109/78.258082

Marmarelis, V. (2012). *Analysis of physiological systems: The white-noise approach*. Springer Science & Business Media 488 pp.

Matyas, J. (1965). Random optimization. *Automation and Remote Control*, *26*(2), 246–253.

Metternicht, G., Zinck, J. A., Blanco, P. D., & Del Valle, H. F. (2010). Remote sensing of land degradation: Experiences from Latin America and the Caribbean. *Journal of Environmental Quality*, *39*, 42–61. https://doi.org/10.2134/jeq2009.0127

Miao, C. Y., Yang, L., Chen, X. H., & Gao, Y. (2012). The vegetation cover dynamics (1982–2006) in different erosion regions of the Yellow River Basin, China. *Land Degradation and Development*, *23*, 62–71. https://doi.org/10.1002/ldr.1050

Nemani, R. R., Keeling, C. D., Hashimoto, H., Jolly, W. M., Piper, S. C., Tucker, C. J., … Running, S. W. (2003). Climate-driven increases in global terrestrial net primary production from 1982 to 1999. *Science*, *300*(5625), 1560–1563. https://doi.org/10.1126/science.1082750

Nezomba, H., Mtambanengwe, F., Tittonell, P., & Mapfumo, P. (2015). Point of no return? Rehabilitating degraded soils for increased crop productivity on smallholder farms in eastern Zimbabwe. *Geoderma*, *239*, 133–145. https://doi.org/10.1016/j.geoderma.2014.10.006

Omuto, C. T., Balint, Z., & Alim, M. S. (2014). A framework for national assessment of land degradation in the drylands: A case study of Somalia. *Land Degradation and Development*, *25*, 105–119. https://doi.org/10.1002/ldr.1151

Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J. M., Tucker, C. J., & Stenseth, N. C. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in ecology & evolution*, *20*(9), 503–510. https://doi.org/10.1016/j.tree.2005.05.011

Riaño, D., Chuvieco, E., Ustin, S., Zomer, R., Dennison, P., Roberts, D., & Salas, J. (2002). Assessment of vegetation regeneration after fire through multitemporal analysis of AVIRIS images in the Santa Monica Mountains. *Remote Sensing of Environment*, *79*, 60–67. https://doi.org/10.1016/S0034-4257(01)00239-5

Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1973). Monitoring vegetation systems in the Great Plains with ERTS. In: Third ERTS Symposium, NASA SP-351 I, pp. 309–317.

Rudnick, D. L., & Davis, R. E. (2003). Red noise and regime shifts. *Deep-Sea Research I*, *50*, 691–699. https://doi.org/10.1016/S0967-0637(03)00053-0

Sadeghravesh, M. H., Khosravi, H., & Ghasemian, S. (2016). Assessment of combating-desertification strategies using the linear assignment method. *Solid Earth*, *7*(673–683), 2016. https://doi.org/10.5194/se-7-673-2016

Saha, M. V., Scanlon, T. M., & D'Odorico, P. (2015). Examining the linkage between shrub encroachment and recent greening in water-limited southern Africa. *Ecosphere*, *6*(9), 156. https://doi.org/10.1890/ES15-00098.1

de Schutter, A., Kervyn, M., Canters, F., Bosshard-Stadlin, S. A., Songo, M. A., & Mattsson, H. B. (2015). Ash fall impact on vegetation: A remote sensing approach of the Oldoinyo Lengai 2007–08 eruption. *Journal of Applied Volcanology*, *4*(1), 1–18. https://doi.org/10.1186/s13617-015-0032-z

Seabold, S., & Perktold, J. (2010). Statsmodels: Econometric and statistical modeling with python. In Proceedings of the 9th Python in Science Conference, Texas, USA, pp. 57–61.

Smith, A. M., Kolden, C. A., Tinkham, W. T., Talhelm, A. F., Marshall, J. D., Hudak, A. T., … Gosz, J. R. (2014). Remote sensing the vulnerability of vegetation in natural terrestrial ecosystems. *Remote Sensing of Environment*, *154*, 322–337. https://doi.org/10.1016/j.rse.2014.03.038

Tanré, D., Holben, B. N., & Kaufman, Y. J. (1992). Atmospheric correction against algorithm for NOAA-AVHRR products: Theory and application. *IEEE Transactions on Geoscience and Remote Sensing*, *30*(2), 231–248. https://doi.org/10.1109/36.134074

Tittonell, P. (2014). Livelihood strategies, resilience and transformability in African agroecosystems. *Agricultural Systems*, *126*, 3–14. https://doi.org/10.1016/j.agsy.2013.10.010

Tittonell, P., Scopel, E., Andrieu, N., Posthumus, H., Mapfumo, P., Corbeels, M., … Mkomwa, S. (2012). Agroecology-based aggradation-conservation agriculture (ABACO): Targeting innovations to combat soil degradation and food insecurity in semi-arid Africa. *Field Crops Research*, *132*, 168–174. https://doi.org/10.1016/j.fcr.2011.12.011

Torres, L., Abraham, E. M., Rubio, C., Barbero-Sierra, C., & Ruiz-Pérez, M. (2015). Desertification research in Argentina. *Land Degradation & Development*, *26*(5), 433–440.

Vasallo, M. M., Dieguez, H. D., Garbulsky, M. F., Jobbágy, E. G., & Paruelo, J. M. (2012). Grassland afforestation impact on primary productivity: A remote sensing approach. *Applied Vegetation Science*, *16*, 390–403. https://doi.org/10.1111/avsc.12016

Verbesselt, J., Hyndman, R., Newnham, G., & Culvenor, D. (2010). Detecting trend and seasonal changes in satellite image time series. *Remote Sensing of Environment*, *114*(1), 106–115. https://doi.org/10.1016/j.rse.2009.08.014

Verón, S. R., & Paruelo, J. M. (2010). Desertification alters the response of vegetation to changes in precipitation. *Journal of Applied Ecology*, *47*(6), 1233–1241. https://doi.org/10.1111/j.1365-2664.2010.01883.x

Vicente-Serrano, S. M., Gouveia, C., Camarero, J. J., Beguería, S., Trigo, R., López-Moreno, J. I., … Sanchez-Lorenzo, A. (2013). Response of vegetation to drought time-scales across global land biomes. *Proceedings of the National Academy of Sciences USA*, *110*, 52–57

Viovy, N., Arino, O., & Belward, A. S. (1992). The Best Index Slope Extraction (BISE): A method for reducing noise in NDVI time-series. *International Journal of Remote Sensing*, *13*(8), 1585–1590.

Vlek, P., Bao Le, Q., & Tamene L. (2008). Land decline in Land Rich Africa—A creeping disaster in the making. Rome, Italy: CGIAR Science Council Secretariat.

Vogt, J. V., Safriel, U., Von Maltitz, G., Sokona, Y., Zougmore, R., Bastin, G., & Hill, J. (2011). Monitoring and assessment of land degradation and desertification: Towards new conceptual and integrated approaches. *Land Degradation and Development*, *22*, 150–165. https://doi.org/10.1002/ldr.1075

Wang, Z., Liu, C., & Huete, A. (2002). From AVHRR-NDVI to MODIS-EVI: Advances in vegetation index research. *Acta Ecologica Sinica*, *23*(5), 979–987.

Wang, Q., Adiku, S., Tenhunen, J., & Granier, A. (2005). On the relationship of NDVI with leaf area index in a deciduous forest site. *Remote Sensing of Environment*, *94*(2), 244–255. https://doi.org/10.1016/j.rse.2004.10.006

Wessels, K. J., Prince, S. D., Malherbe, J., Small, J., Frost, P. E., & VanZyl, D. (2007). Can human-induced land degradation be distinguished from the effects of rainfall variability? A case study in South Africa. *Journal of Arid Environments*, *68*(2), 271–297. https://doi.org/10.1016/j.jaridenv.2006.05.015

Wessels, K. J., van den Bergh, F., & Scholes, R. J. (2012). Limits to detecting of land degradation by trend analysis of vegetation index data. *Remote Sensing of Environment*, *125*, 10–22.

Xiao, J., & Moody, A. (2005). Geographical distribution of global greening trends and their climatic correlates: 1982–1998. *International Journal of Remote Sensing*, *26*(11), 2371–2390.

Yengoh, G. T., Dent, D. L., Olsson, L., Tengberg, A., & Tucker, C.. (2014). The use of the normalized difference vegetation index (NDVI) to assess land degradation at multiple scales: A review of the current status, future trends and practical considerations. Springer, USA. https://doi.org/10.1007/978-3-319-24112-8

Yin, H., Udelhoven, T., Fensholt, R., Pflugmacher, D., & Hostert, P. (2012). How normalized difference vegetation index (NDVI) trends from Advanced Very High Resolution Radiometer (AVHRR) and Système Probatoire d'Observation de la Terre VEGETATION (SPOT VGT) time series differ in agricultural areas: An inner Mongolian case study. *Remote Sensing*, *4*, 3364–3389. https://doi.org/10.3390/rs4113364

How to cite this article: Easdale MH, Bruzzone O, Mapfumo P, Tittonell P. Phases or regimes? Revisiting NDVI trends as proxies for land degradation. *Land Degrad Dev*. 2018;29:433–445. https://doi.org/10.1002/ldr.2871