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The Sensitivity and Response of Terrestrial South American Vegetation to Interannual Climatic Variability Induced by the ENSO

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ABSTRACT. The sensitivity of vegetation to climatic variations operates over a range of spatio-temporal scales. Whilst comprehensive and extensive studies that involve the spatial changes in terrestrial systems using remotely sensed data have been undertaken, only a few investigations have focused on temporal change in these systems. In this study econometric time-series modelling techniques were applied to National Oceanographic and Atmospheric Administration Advanced Very High Resolution Radiometer Normalized Difference Vegetation Index data sets in order to evaluate the resistance and resilience of terrestrial South American vegetation to the interannual El Niño Southern Oscillation perturbations. Lags between vegetation response and the El Niño Southern Oscillation perturbations are identified and quantified. The results indicate that the terrestrial vegetation loses its sensitivity to El Niño Southern Oscillation perturbations in the post 1993 period. This hypothesis is investigated further using stochastic Auto Regressive Integrative Moving Average model simulation techniques.

Keywords: Climatic perturbation, lag, resistance and resilience, sensitivity, remote sensing

1. Introduction

Terrestrial ecological systems are subjected constantly to climatic perturbations. The vegetation component takes an active role in the regulation of the equilibrium of terrestrial systems by the processes of ‘resistance’, which is the ability to absorb disturbances without changing its basic structure, and ‘resilience’, which is the characteristic return time to equilibrium following a perturbation (Pimm, 1984). The sensitivity and rapidity of vegetation response to these perturbations operate over a range of spatio-temporal scales (Nielson, 1993). Delays in vegetation response are influenced by phenology (or seasonality) and are more dependent on the timing and the length of the perturbations rather than magnitude (Wellens, 1997). Provision of information on the state of vegetation pre- and post-climatic perturbations is a critical starting point for analysing changes in the dynamics of terrestrial systems (Shimabukuro et al., 1997).

The El Niño Southern Oscillation (ENSO) is the largest known global climate variability signal on interannual time scales. It is a quasi-periodical fluctuation between warm El Niño and cold La Niña states of the Pacific sea surface temperatures and has a recurrence oscillation period of approximately 2 to 7 years (Philander, 1990). The Southern Oscillation Index (SOI), which is defined as the sea level pressure difference between the eastern and western Pacific, is now used widely as an indicator of the strength and phase of the ENSO cycle (Rasmusson, 1985). El Niño and La Niña events are denoted respectively by negative and positive trends in the SOI. Whilst the largest ENSO signature exists in and over the tropical Pacific, it also affects global atmospheric circulation on a wider scale through the so-called “teleconnection” effects (Diaz & Kiladis, 1992; Xue & Shukla, 1997; Dawson & O’Hare, 2000). Therefore, a global understanding of ENSO impacts on terrestrial ecosystems is necessary.

Existing analytical models, which are based primarily on mathematical simulations of sea surface temperature anomalies, have been criticised for failing to incorporate processes of terrestrial vegetation components (Cramer & Fischer, 1996). This can be attributed to logistical problems associated with the *in-situ* collection of data related to these components at regional to global scales. Arguably the only feasible approach is the intensive and extensive use of remote sensing instruments, which provide information at the required spatio- temporal scales (Eva & Lambin, 1998; Graetz, 1990). A sensor of particular interest is the National Oceanographic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) which provides data suitable for monitoring terrestrial vegetation dynamics (Cracknell, 1997). Data recorded by this sensor are used to calculate the Normalized Difference Vegetation Index (NDVI), a mathematical combination of radiation flux recorded in the red and near infrared portion of the electromagnetic spectrum (Perry & Lautenschlager, 1984). NDVI is a sensitive indicator of the condition of green vegetation (Justice et al., 1985; Yang et al., 1998) and can be used as a surrogate measure of the response of vegetation to climatic disturbances (Li & Kafatos, 2000, Myneni et al., 1996). Previous studies have identified

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interannual NDVI variability signals associated with the ENSO (Eastman & Fulk, 1993; Anyamba & Eastman, 1996; Myneni et al., 1996; Li & Kafatos, 2000). A common criticism of these studies, however, is that whilst establishing spatial relationships between vegetation trends and ENSO forcing, quantitative evidence that climate variation affects vegetation phenology or productivity is rarely provided due mainly to persistent orbital and atmospheric artefacts in the satellite sensor record (Holben et al., 1996; Privette et al., 1995). These factors cause apparent decreases in the vegetation greenness, which impede a quantitative interpretation of the NDVI time series. For example, anomalies in the image products have been reported during the 1991/92 period due to extensive atmospheric interference which resulted in low NDVI values (Asner et al., 2000). Whilst these effects are partially accounted for in the Pathfinder record through a temporal routine of maximum value compositing (James & Kalluri, 1994), the technique has a tendency to universally decrease the NDVI (Tanre et al., 1992). Therefore, further research is necessary to minimize and quantify the effects of non-biological artefacts in the NOAA AVHRR satellite data (Asner et al., 2000).

The aim of this paper is to evaluate the temporal sensitivities of South American terrestrial vegetation to ENSO forcing, with specific focus on the El Niño events that occurred in 1982/83, 1986/87, 1991/92 and 1997/98. This paper presents a simple, yet mathematically sound, quantitative estimation of vegetation response. It differs from previous work (e.g. Li & Kafatos, 2000; Asner et al., 2000) in those inter-relationships between vegetation response and ENSO perturbations are analysed using econometric time series modelling techniques as opposed to existing methods of spatial analysis and digital image processing. Remotely sensed inputs for time series model simulation of vegetation dynamics is a unique aspect of this investigation.

2. Study Area and Data Sets

The study was based on a transect across South America (corresponding to 6 °S), which passes through the largest extent of the Amazon Basin. Along the transect the following vegetation cover types can also be identified: marginal xerophytic vegetation on the Peruvian coast, cloud forests of the Andes, central Amazon primary forest, Brazilian Cerrados, Caatinga, anthropogenically induced plantations and Brazilian coastal forests. The timing and intensity of seasons in these different vegetation types differ according to their physiological composition, each contributing to the temporal processes of the terrestrial system as a whole. The following data sets were used for the analysis:

- Two sets of NDVI image products derived from the AVHRR sensor deployed on NOAA satellites. The NDVI data sets were produced as part of the NOAA/NASA Pathfinder AVHRR Land (PAL) program and are available in the public domain (http://www.daac.gsfc.nasa.gov/):

  (a) Coarse monthly NDVI products with a spatial resolution of 1 degree x 1 degree (or 110 km x 110 km), covering the period from October 1981 to December 1992.

  (b) Finer 8km by 8km NDVI image products for the period of November 1981 to December 1999.

- Monthly Southern Oscillation Index (SOI) data computed by the Climatic Research Unit at the University of East Anglia (Kyle et al., 1998). This is used as an indicator of the ENSO activities and as a surrogate for sea surface temperature or the climatic variability over the period of concern.

3. Methods

3.1. Signal Processing

Time series NDVI data were constructed using the monthly mean values for all pixel locations across the transect to produce a smoothed data set which minimises the effects of variations in land cover types, topographic conditions and localised climate patterns. Thus the data were given a coarser linear-spatial context to enable clear detection and description of large-scale terrestrial processes (Anyamba, 1994). It was hypothesised that interannual deviations in vegetation response to climate are attributable directly to ENSO forcing. Interannual signals in the NDVI and SOI data were extracted using time series modelling techniques. First, a seasonal decomposition model was applied to the series to filter out the seasonal noise:

$$y_t = TR_t + SN_t + CL_t + IR_t \qquad (1)$$

where y_t is the observed value of the time series in period t; TR_t, SN_t, CL_t and IR_t are defined respectively as trend, seasonal, cyclical and irregular factors with an additive nature. In theory, the model adds the seasonal adjustments to the seasonally adjusted series to obtain correspondence with the observed values and the results are then used to remove the seasonal effect from the time series (Cleveland & Devlin, 1988).

To facilitate the clear depiction of interannual signals, irregularities in the seasonally decomposed time series were exponentially smoothed using the ‘Winters’ model that incorporates a memory decay component based on past history of the data (Janacek & Swift, 1993):

$$y_t = (b_0 + b_t t) + SN_t + e_t \qquad (2)$$

where b_0 and b_1 are model parameters; SN_t is the seasonal factor; e_t is an exponential function. This model incorporates the assumptions that the time series data exhibit non-linearity and require seasonal adjustment on interannual scales (Janacek & Swift, 1993).

3.2. Assessment of Vegetation Resistance

Delay times between vegetation responses to ENSO perturbations are expected due to the process of resistance. Hence, the length of the time lag can be used as an indicator of the magnitude of vegetation resistance. The lag, measured using a cross-correlation model, was assumed to be the phase difference between the processed (signal extracted) series, with the SOI considered as the independent or driving variable and NDVI the dependant variable. Cross-correlation is a measure of the similarities or the shared properties between two signals. Applications of this function include cross-spectral analysis and delay measurements (Ifeachor & Jervis, 1993). The cross-correlation $P_{xy}(L)$ of two sample populations *x* and *y* as a function of the lag is calculated as:

$$P_{xy}(L)=\frac{\sum_{k=0}^{N-L-1}(x_k-\bar{x})(y_{k+L}-\bar{y})}{\sqrt{(\sum_{k=0}^{N-1}(x_k-\bar{x})^2)(\sum_{k=0}^{N-1}(y_k-\bar{y})^2)}} \quad \text{or} \quad L\geq 0 \qquad (3)$$

where, $\bar{x}$ and $\bar{y}$ are the means of the sample populations $x=(x_0,x_1,x_2,...,x_{N-1})$ and $y=(y_0,y_1,y_2,...,y_{N-1})$ respectively, *L* is the lag and *k* is a constant.

3.3. Assessment of Vegetation Resilience

The resilience of vegetation to the ENSO perturbations was measured by estimating the time length of the interannual periodicities in the signal extracted NDVI series. This was measured by applying an autocorrelation model that provides information about the structure of a signal or its behaviour in the temporal domain and is particularly useful for identifying hidden periodicities (Ifeachor & Jervis, 1993; Grau & Vblen, 2000). Autocorrelations were calculated for lags 1, 2,…, to 116 (i.e., generated on interannual time scales), where the ‘lag’ is a transformation that brings the past values of a series into the current case. Mathematically, the function computes the autocorrelation $P_x(L)$ of a sample population x as a function of the lag L :

$$P_x(L)=P_x(-L)=\frac{\sum_{k=0}^{N-L-1}(x_k-\bar{x})(x_{k+L}-\bar{x})}{\sum_{k=0}^{N-1}(x_k-\bar{x})^2} \qquad (4)$$

where, $\bar{x}$ is the mean of the sample population $x=(x_0,x_1,x_2,...,x_{N-1})$ and *k* is a constant. The lag is an *n*-element integer vector in the interval $[-(n-2),(n-2)]$, specifying the signed distances between indexed elements of *x*. Similarly; the same model was used to estimate the seasonalities of the vegetation after re-parameterisation to the annual scale.

3.4. Assessment of Temporal Vegetation Processes

To test the outputs of the time series analysis in respect to vegetation response, simulations were generated using an Auto Regressive Integrated Moving Average (ARIMA) model. This part of the investigation was based on the assumption that the South American terrestrial (vegetation) ecosystem responds to perturbations based on some order, which leads to a generic predictability of its behaviour and provides a better understanding of the system of concern. ARIMA models are an established (forecasting) technique in econometrics (Box et al., 1994) and are used as a complement to the ‘trend regression approach’. The model assumes that a one-dimensional data series evolves through time as the outcome of a statistical process (Clifford & McClatchey, 1996), capturing more elements of the behaviour of potentially inhomogeneous series (Janacek & Swift, 1993). In the environmental sciences, ARIMA modelling is used to represent a complex and possibly poorly specified system that operates in the presence of one or many noise sources, which is attractive when considering the nature of both terrestrial systems and the AVHRR NDVI record. The moving average (MA) component of the model incorporates past random fluctuations or ‘shocks’ to represent the time series (Z_t):

$$Z_t=a_t-f_1a_{t-1}-f_2a_{t-2}-...f_qa_{t-q} \qquad (5)$$

where f_1 and f_2 are the MA coefficients and a is the random shock term. The auto regressive (AR) component estimates values of the dependent variable as a regression function of previous values and is expressed as:

$$Z_t=f_1Z_{t-1}+f_2Z_{t-2}+...f_qZ_{t-q}+a_t \qquad (6)$$

Mixing these models produces the ARIMA model, which generically takes the form:

$$(p,d,q)(P,D,Q)S \qquad (7)$$

where the lower- and upper- case symbols represent the non-seasonal and seasonal components respectively, p is the order of differencing of the AR model, d is the order of series differencing, q is the order of differencing of the MA model and S is the seasonality (= 12 for an annual trend in monthly data). This model provides two key advantages in relation to other forecasting techniques. First, they can be used to examine complex series, as they provide more *parsimonious* model fits (i.e., fewer model parameters have to be estimated) than pure AR or MA models alone (Vandale, 1983). Second, the mixed structure can provide additional flexibility when an output series may result from more than one interacting process (Salas et al., 1980).

The ARIMA simulation was performed for a hypothetical scenario that the interannual variability of vegetation processes was regulated by the ENSO throughout

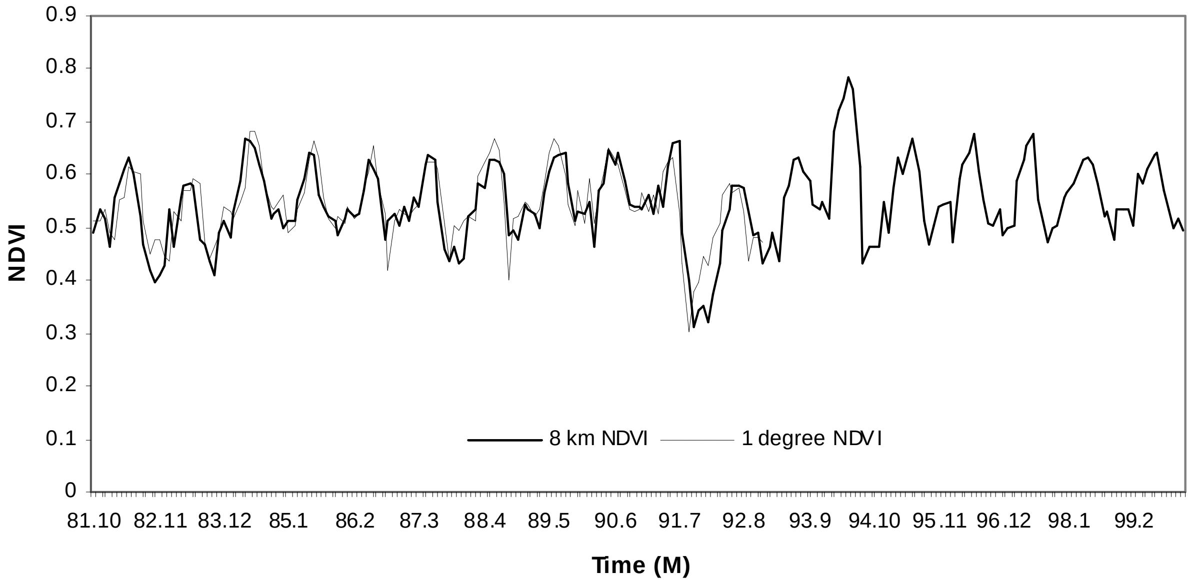

Figure 1. A comparison of the 1 degree × 1 degree and 8 km × 8 km NDVI data sets.

the period of investigation. Spatially smoothed 1 degree x 1 degree NDVI data from October 1981 to December 1990 were used as the primary input. The input data was limited to this period due to the reported anomalies in the AVHRR record in 1990 (Asner et al., 2000). A seasonal ARIMA model that was driven using SOI as the regressor was used in this investigation. The raw (unprocessed) SOI data for the period of concern was used as the regressor (i.e., independent variable) to drive the model on the interannual scales. In other words, the model simulates the seasonal trends of the vegetation based on the cyclicities it infers from the NDVI time series and the interannual patterns based on the fluctuations of the regressor series. The outputs of the simulations were then compared against the trends exhibited in the 8 km x 8 km NDVI series.

4. Results

Figure 1 is comparison of the mean 1 degree × 1 degree (or 110 km × 110 km) and 8 km × 8 km time series NDVI data with series highly correlated (r = 0.81, s = 0.01, p = 0.001). The minor differences in NDVI values can be attributed to the spatial scale used to derive the data. Both series show pronounced seasonal oscillations, which correspond to the vegetation phenological cycles where maximum NDVI values are observed between May and August and with annual variations in the NDVI values ranging from 0.2 to 0.3 units[*]. Statistically modelled outputs of the 1 degree x 1 degree and 8km × 8km NDVI and SOI series are compared in Figure 2. Interannual variation of the NDVI range from 0.04 to 0.05 units. The ENSO event of the early 1990s differs from the well-defined events that occurred in the 1980s (Li & Kafatos, 2000). In both series, the anomalous decrease in NDVI values in the post 1991/92 El Niño period can be explained by the volcanic eruption of Mt. Pinatubo, which injected sulphate aerosols into the stratosphere (Vermote et al., 1997). However, the anomalous increase in the NDVI values during the 1994/95 period remains unexplained. A clearly marked phase difference with SOI is observed for both of the NDVI series with values decreasing after an El Niño period. However, this trend can only be observed over the period from 1981 to 1992/93. Despite the perturbation by the severe El Niño of 1997/98, the vegetation response appears to be static and almost stable with NDVI values that are relatively higher than in previous years. From the modelled SOI curve it can be seen that whilst less severe than those that occurred in 1982/83 and 1997/98, the El Niño of 1991/92 persisted for a longer period (nearly 46 months) and took approximately 30 months to develop (from October 1989). The slow development and the long persistence of this particular perturbation could also be an additional cause of the anomalously low values exhibited by modelled NDVI series for that period. However, post 1993 the NDVI values increase to a slightly higher level and remain relatively static despite the severe El Niño perturbation of 1997/98. This leads to the hypothesis that the terrestrial vegetation could have become more resilient to the ENSO fluxes.

The cross-correlation model estimates the ‘lag’ between ENSO perturbations and vegetation response to be generally in the range of 4 – 6 months. It should be noted that the ‘lags’ differ for each El Niño event depending on their phase and amplitude. The NDVI series were divided into periods

[*] NDVI is a dimensionless unit and for vegetation the values are constrained between 0 and 1.

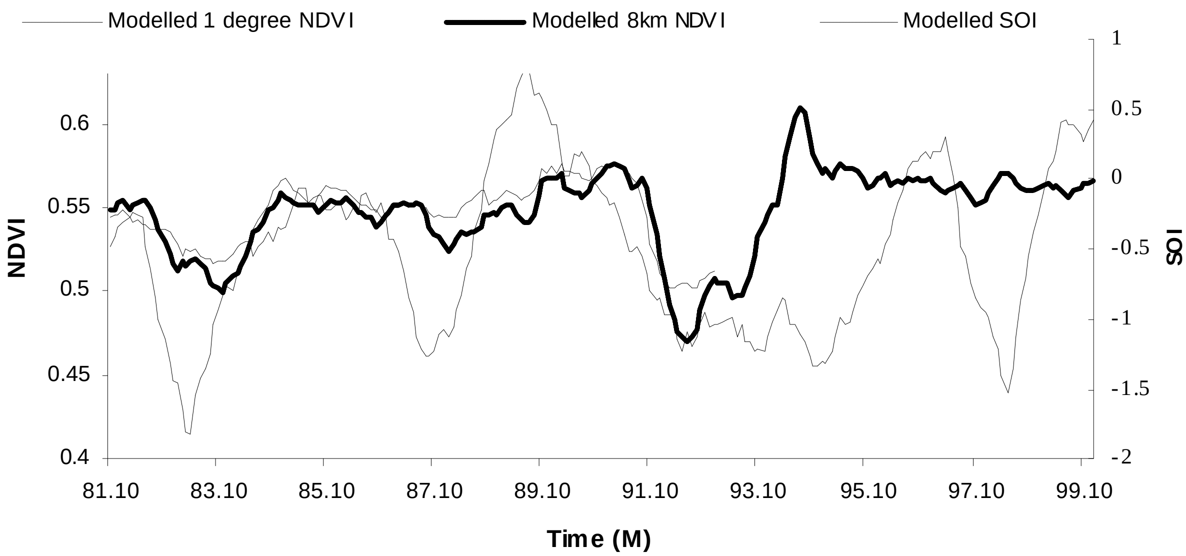

Figure 2. Comparison of the modeled NDVI and SOI series.

that correspond to each El Niño event and the lags were measured individually (Table 1). Note that the cross-correlation model measures the phase differences between series and is not affected by the unusual anomalies in the amplitudes (i.e. caused by atmospheric effects) in any of the series. The decreasing lags, from 5-6 months in 1981/82 to 1-2 months in 1991/92, again indicate a more active response and hence again support the hypothesis that the vegetation is becoming more resilient. From an ecological perspective the overall length of the time series (i.e., 20 years) is a relatively short period within which a system becomes resilient, however, it is argued that the signal-processed components in the data provides evidence of resilience to a perturbation that has become more pronounced and frequent. That is, a system, in this case South American terrestrial vegetation, is considered to be stable if it is capable of absorbing perturbations and adjusting to its 'norm' within the shortest time possible.

Using an autocorrelation model calibrated on interannual time scales, vegetation resilience to the ENSO fluctuations was estimated to be 54 month units (Figure 3). That is, the characteristic return time to the'norm' by the terrestrial vegetation after an ENSO perturbation is on an interannual scale of 54 months (4 years and six months). Correlogram outputs for the raw 1 degree x 1degree and 8km × 8km NDVI series, estimated using the re-parameterized autocorrelation model, indicate that vegetation activity has a well pronounced seasonality of 10 – 12 months (Figure 4). This suggests that the terrestrial vegetation exhibits an annual rhythmic (seasonal) behavior despite interannual disturbances by ENSO.

The ARIMA simulation outputs were compared with

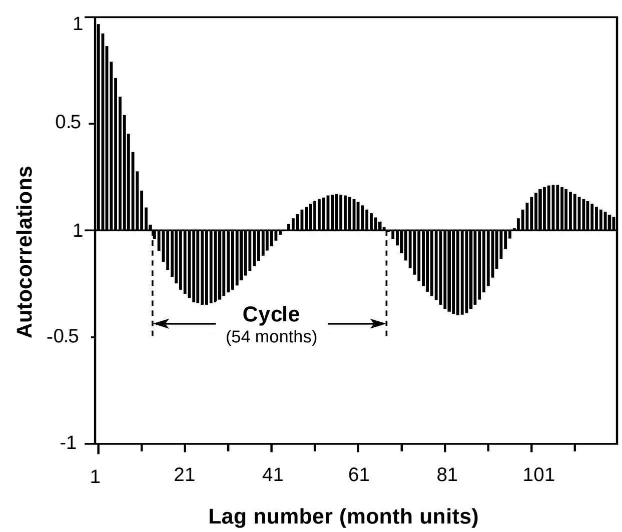

Figure 3. Correlogram output of the extended autocorrelation model.

the raw 8 km × 8 km NDVI data (Figure 5). Considering the spatial scales involved, the reasonably high correlation between both series (r = 0.6204, s = 0.01, p < 0.001) indicates that the model provides accurate outputs. The seasonal trends of the vegetation are clearly displayed in the simulation outputs. A marked difference between the simulation output and the anomalous drop in the NDVI values in the 8 km × 8 km data for the period of 1991/92 can be observed and provides an indication of the magnitude of atmospheric interference in the data. However, as previously stated, the anomalously high NDVI values in the 8 km × 8 km data in

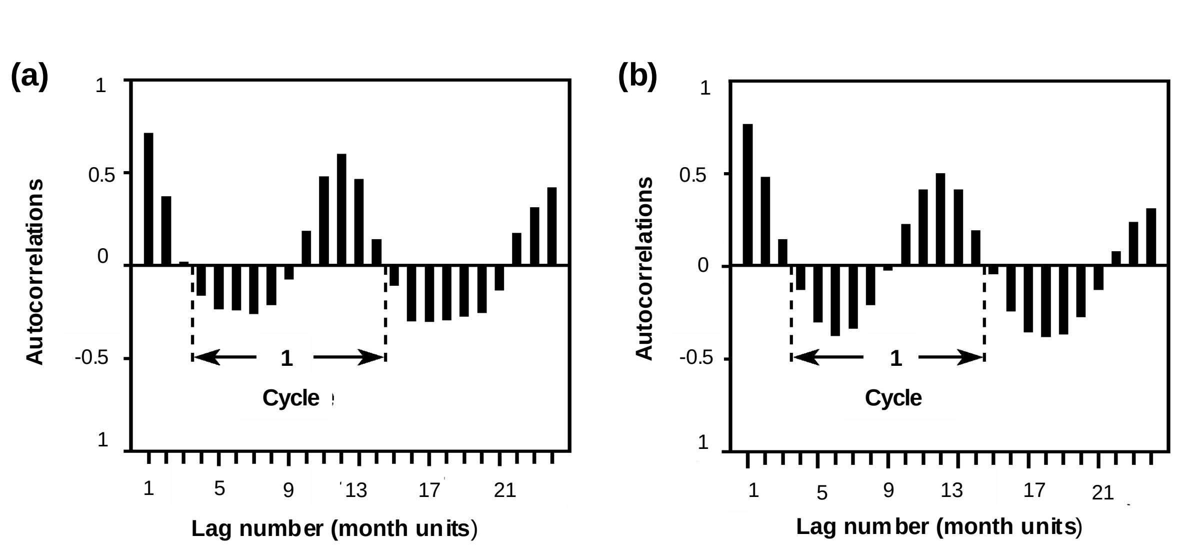

Figure 4. Correlogram outputs for (a) the 1 degree × 1 degree and (b) the 8 km × 8 km data series.

the 1993/94 period are not picked up in the simulation and, therefore, remain unexplained. Interannual components of the ARIMA model simulation output and the 8 km × 8 km NDVI data are compared in Figure 6. Simulated NDVI values are seen to be increasing and decreasing pre- and post-El Niño events.

Table 1. The Estimated Lags for the Processed/Modelled NDVI Series by the Cross Correlation Model

El Niño occurrence	*Time Series length*	*Modeled 1 degree × 1 degree NDVI series*	*Modeled 8 km × 8 km NDVI series*
1981/82	Oct. 81 to Oct. 84	6 months	4 – 5 months
1986/87	Nov. 84 to Oct. 90	5 months	4 – 5 months
1991/92	Nov. 90 to Oct. 96	1 month	2 months
1997/98	Nov. 96 to Dec. 99	Data not available	No pronounced lag/irregular phase difference

To mid-1991 the simulated outputs show identical trends as the processed 8 km x 8 km series. After this period the simulation exhibits behaviors of different magnitudes and does not replicate the anomalous pattern of low and high NDVI values during the ENSO event of 1991/92. Furthermore, whereas the NDVI values are relatively static in the post 1995 period, the simulated NDVI values decrease during the El Nino of 1997/98. A very low correlation ($r = 0.07746$, $s = 0.01$, $p < 0.001$) is obtained between the interannual derivatives of both series. This can be explained by the fact that the simulation was generated based on a null hypothesis that assumed the ENSO effect was responsible for interanual variations in the NDVI throughout the entire period. Table 2 compares the correlation between the simulation and raw 8 km x 8 km NDVI values for both annual and interannual time scales. The series were divided into the three smaller periods, which are referred to as normal, anomalous and less sensitive periods that occur between October 1981 to December 1990, January 1991 to December 1994 and January 1995 to December 1999, respectively. Whilst the seasonal components have high correlative relationships, the interannual derivatives of the simulation and the 8 km x 8 km data have weaker relationships. To further validate this the modelled NDVI values (for both data sets) and the ARIMA simulation output values were correlated against the modelled SOI values on a yearly basis and potted against time (Figure 7). The correlations for the modelled NDVI values show a decreasing trend over the period, as opposed to the increasing correlative trend in the ARIMA scenario. This again indicates that of vegetation activity is becoming less sensitive to the ENSO disturbances.

Table 2. The Correlation between the ARIMA Output and the 8 km Data Series in the Annual* and Interannual** Time Scales

Time period	*Annual*	*Interannual*
Oct. 1981 to Dec. 1990	r = 0.6481	r = 0.5667
Jan. 1991 to Dec. 1994	r = 0.5258	r = 0.2441
Jan. 1995 to Dec. 1999	r = 0.8064	r = 0.3001

* For raw output and raw series;
** For modeled series;
All correlations were calculated at $s = 0.01$, $p < 0.001$.

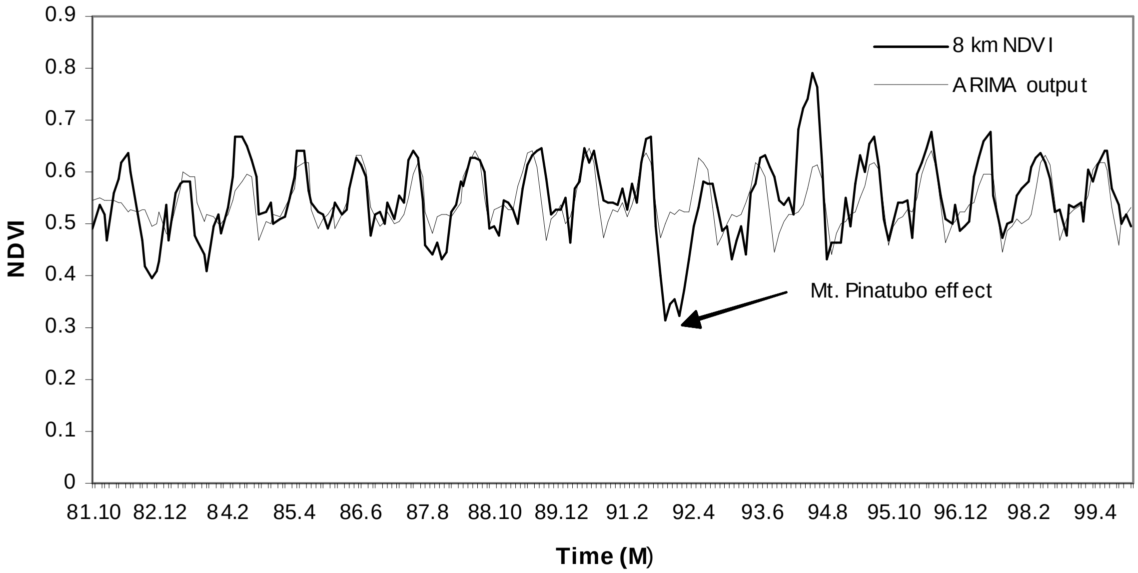

Figure 5. Comparison of the ARIMA simulation output with the 8 km × 8 km raw NDVI data.

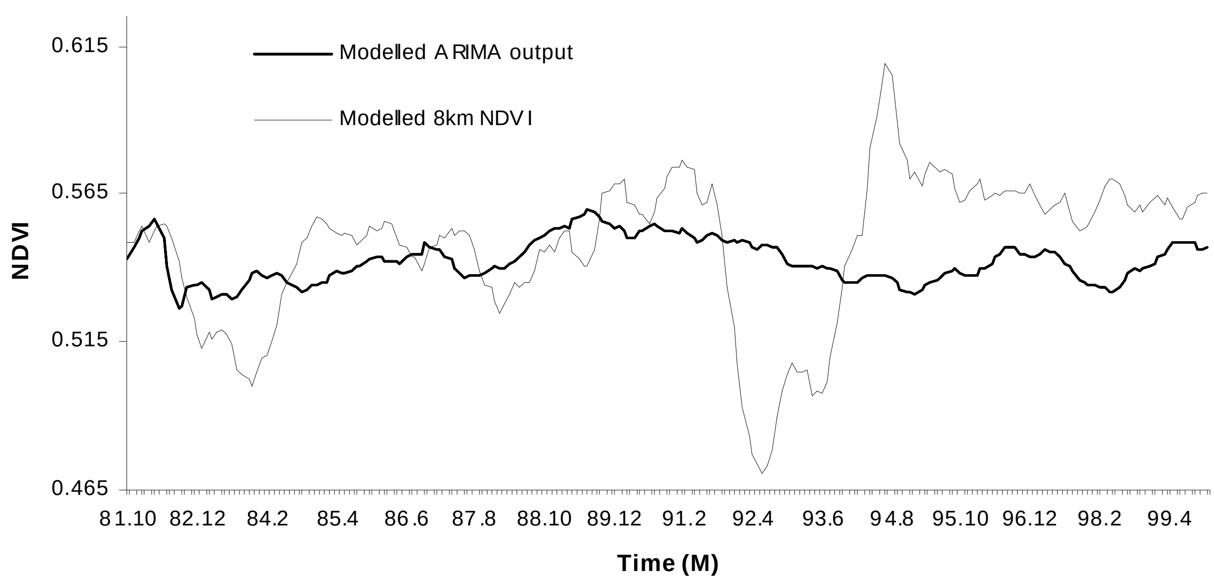

Figure 6. Comparison of the interannual components of the ARIMA output and the 8 km × 8 km NDVI series.

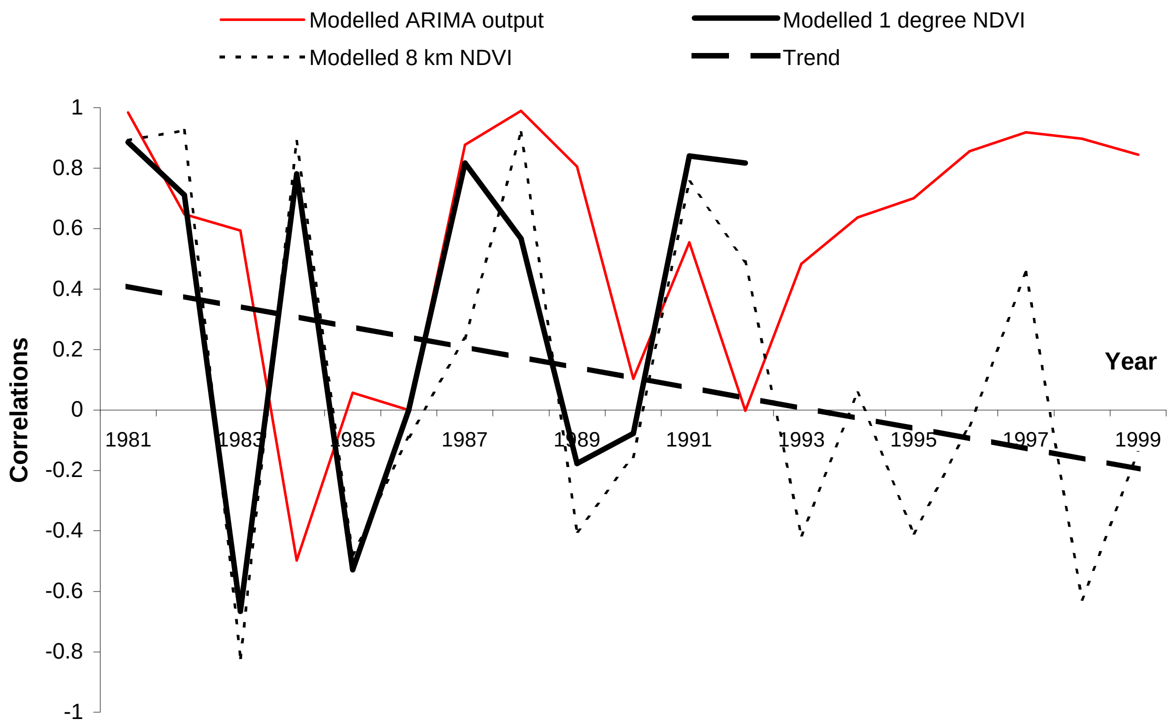

Figure 7. The time line of correlations for the interannual components of the NDVI series and the ARIMA output series against the interannual components of the SOI series.

5. Discussion

A methodology for analyzing the sensitivity of vegetation to interannual climatic disturbances is outlined in this paper. The processed NDVI and SOI time series show significant correlations in the pre 1993 period, suggesting a teleconnective relationship between the ENSO mechanism and terrestrial vegetation processes with a general response delay time of the order of 4 - 6 months. This relatively slow response can be explained by changes in the internal physiology of vegetation components as a result of ENSO forcing and the sensitivity of the NDVI to these changes. If vegetation is stressed, short-term physiological changes will reduce the amount of visible light absorbed by vegetation for photosynthesis to take place. However, the relative change in the amount of visible light absorbed is small and hence no significant change will be recorded in the NDVI. If vegetation is subjected to long-term stress, this leads to a break down of the internal structure of the foliage components, which in turn significantly reduces the amount of near infrared radiation reflected by the canopy, which reduces the recorded NDVI. The trend is reversed in the predominately wet La Niña periods, in which optimal growing conditions lead to an increase in the NDVI values. Whilst the El Niños of 1982/83 and 1997/98 are regarded as the most severe in recent years (Dawson & O' Hare, 2000), results indicate that the terrestrial vegetation becomes more stressed during the El Niño of the 1991/92 period resulting in relatively quick lag periods of 3 months. This may reflect the fact that the El Niño for that period took nearly 3 years (pre 1991) to develop and persisted for almost 5 years. Thus the prolonged stress imposed upon the vegetation lead to a large decrease in NDVI values.

The behavior of the terrestrial system in the post 1993 period contrasts strongly with previous periods. Vegetation processes (as expressed via NDVI values) seem to be relatively static to ENSO perturbations post 1993. A hypothesis that the terrestrial vegetation has become less sensitive to ENSO perturbations is suggested which is supported by the results of the ARIMA simulation. It is observed that the ARIMA simulation is capable of minimization of data artefacts and can be used as means of estimating anomalies in the NDVI time series data arising from non-biological effects. Correlative relationships between vegetation activity (NDVI values) and ENSO show a decreasing trend over the whole of the period of investigation, suggesting that the vegetation is becoming less sensitive to the ENSO perturbations. From a systemic point of view, it can be inferred that the terrestrial system retains its regularity by absorbing the interannual disturbances and readjusting its resistance and resilience in the temporal domain in the shortest time possible. The change in vegetation dynamics could result in a feedback via spatio-temporal succession (Svrizhev & Von

Bloh, 1997) which dampen the effects of the ENSO perturbations where departures from the equilibrium state in the terrestrial system are reversed (Lenton, 1998). It is seen that the seasonal cycles of the vegetation are not affected despite disturbances to the system in the interannual scale. From a terrestrial ecological perspective, vegetation processes exhibit behaviors that are known as periodic (or seasonal) with repetition at regular time intervals (Chapman & Driver, 1996). Behavior that is fluctuating yet periodic is accepted to be an indicator of dynamic equilibrium, an end state in which no further large scale change is anticipated (Coveny & Highfield, 1990). Therefore, it can be argued that the seasonal cycles of the vegetation contribute to the processes of the system as a whole and have actively contributed to the system becoming less sensitive to the interannual climatic variability. In other words, the vegetation responds to perturbations and this state of regulation will continue unless drastic changes (natural or anthropogenic) are made to the system and connected components. However, the possibility of significant spatial changes in vegetation structure and composition should also be taken into consideration. This could lead to a totally different functional approach by the system to the ENSO perturbations. This being the case, future research should concentrate on the integration of remotely sensed data sets with mechanistic models that account for the various components of the Earth System (e.g., ocean-atmosphere coupling) to provide a holistic tool for analyzing the ENSO-vegetation interactions.

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