VEGETATION DYNAMICAL PATTERNS RELATED TO RAINFALL VARIABILITY ANALYSED WITH WAVELET COHERENCY FOR SOUTHERN AFRICA

E. Swinnen[a]

[a] Flemish Institute for Technological Research (VITO) – Centre for Remote Sensing (TAP), Belgium,
else.swinnen@vito.be

Commission VII, WG VII/5

KEY WORDS: Multi-spectral remote sensing, Change detection, Environmental monitoring, Image interpretation, Spatial-temporal Analysis, wavelet transformation

ABSTRACT:

This study contributes to a better understanding of the spatial and temporal patterns of ecosystem dynamics in Southern Africa in response to climatic variability. First, we identified the areas where NDVI is covarying with precipitation, and where rainfall anomalies are correlated with NDVI anomalies. The results suggest that these correlations are related to quasi-periodicities in rainfall patterns. Further, we studies the strength of these relationships over time, and analysed the spatial patterns of these correlations and relate them to physical properties, like soil type, vegetation type and topography. In order to do this, we proposed a new methodology based on wavelet transforms of the time series of NDVI and rainfall.

1. INTRODUCTION

Africa's regional environment is closely linked with its climate, so that climatic constraints have been a major force in the development of vegetation, soils, agriculture and general livelihood. Life in Africa revolves around subsistence farming of rain-fed crops, which renders its society vulnerable to climatic fluctuations (Hulme et al., 1996). Because environmental changes in Africa are most directly related to rainfall, we focus on the relation between rainfall and vegetation dynamics (Richard and Poccard, 1998, Vanacker et al., 2005, Camberlin et al., 2007).

It remains unclear whether and how much climate change is affecting rainfall variability in the Southern African region. Still, seen the large climatic variability in the region, an improved monitoring method and understanding of the relationship between rainfall and vegetation dynamics creates potential for better management its natural resources. Analysis of present links between rainfall and NDVI will identify areas that are potentially sensitive to changes in rainfall patterns, and thus where future changes in rainfall patters will affect vegetation dynamics most.

The objectives of this study are, first to identify the areas where NDVI is co-varying with precipitation, and where rainfall anomalies are correlated with NDVI anomalies. Second, to relate these correlations to the quasi-periodicity in rainfall patterns. The third objective is to study the strength of these relationships over time. In order to do this, we propose a methodology based on wavelet transforms of the time series of NDVI and rainfall. The last objective is to analyse the spatial patterns of these correlations and relate them to physical properties, like soil type, vegetation type and topography.

2. DATA

Data from SPOT-VEGETATION is extended back in time with imagery from the various daytime AVHRR sensors. In order to construct a homogeneous time series, the VEGETATION preprocessing was taken as a baseline and the AVHRR preprocessing was performed with the same methods and standards. After processing the AVHRR archive, the NDVI datasets were integrated taking into account the difference in spectral response of the sensors. The integration of the data sets was investigated using data from an overlapping year. The resulting data set covers the Southern African region below 15°S for the period February 1985 – December 2006 and includes the 10-day composited NDVI. Full details on the processing and evaluation of this long-term archive are given by Swinnen and Veroustraete (2008).

The rainfall data used is from the ECMWF ERA-40 dataset and was obtained from the MARS-FOOD Unit of the JRC (Ispra). It consists of 10-day rainfall totals at 1° resolution.

For both datasets, the actual 10-day values are used, but also the anomaly time series. The standardized anomalies are defined as the actual value subtracted by the mean over time for that compositing period, divided by the standard deviation of the NDVI over time for that compositing period.

3. METHOD

3.1 Continuous wavelet transformation

Wavelet analysis of time series provides a particular time-scale representation of that time series. It is a tool to examine localized variations of power in a time series, as it breaks down a signal into frequency components that occur during a certain time period (Antoine, 2004).

The CWT of a discrete time series xn=x(tn) with a sampling interval of t, and of length N, is defined as the convolution of the time series with a scaled (s) and translated (i) version of the wavelet function :

$$W_i(s) = \sum_{n=0}^{N-1} x_n \Psi\left[\frac{(n-i)\delta t}{s}\right]$$

In this study, the Morlet wavelet was used, because it wavelet is a good choice for data that are varying continuously in time and are periodic or quasi-periodic. Because of its periodicity, it combines positive and negative peaks into a single broad peak, making it suited to capture oscillatory behaviour in a signal. Since the Morlet wavelet is complex, it returns information on the amplitude and the phase. The Morlet wavelet is of the form:

$$\Psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\eta^2/2}$$

3.2 Wavelet coherency

Wavelet transformation is a useful tool for the analysis of single time series, but also to investigate the time-scale representation between two time series. In this study, the NDVI – rainfall relationships for Southern Africa are investigated in wavelet space, using wavelet coherency. The wavelet coherency (WCOH) is a normalized time and scale resolved measure for the relationship between two time series (Maraun and Kurths, 2004). It is defined as the amplitude of the wavelet cross-spectrum normalized to the single wavelet power spectra:

$$WCOH_i(s) = \frac{\left|W_i^{XY}(s)\right|}{\sqrt{\left|W_i^X(s)\right|^2 \left|W_i^Y(s)\right|^2}}$$

With $W_i^{XY}(s) = W_i^X(s) W_i^{Y*}(s)$ the cross-wavelet spectrum (* denotes the complex conjugate), and $\left|W_i^X(s)\right|^2$ the wavelet power spectrum of X (same for Y). It is a quantity between 0 and 1 and is used to identify both frequency bands and time intervals within which two time series are co-varying, thus it expresses the frequency dependence of the linear correlation between the two signals, and how this correlation evolves over time.

To be able to calculate the wavelet coherency, it is necessary to smooth the cross spectrum beforehand, otherwise it will always equal 1 (this is similar to coherency in Fourier analysis) (Maraun and Kurths, 2004; Torrence and Compo, 1998). The reason for this smoothing is that coherency should be calculated on expected values. But in most cases this is impossible, as there is only one realisation of the time series and not a sample from the population. To overcome this problem, one should always simulate ensemble averaging by smoothing the coherency (Torrence and Webster, 1999; Maraun and Kurths, 2004; Gurley et al., 2003).

Because a complex mother wavelet is used, the Morlet wavelet, the phase difference between the rainfall and vegetation is also extracted pixel-wise, which provides information on how this lag varies over time.

3.3 Significance testing

Maraun and Kurths (2004) define a method for significance testing of wavelet coherency. The null hypothesis is formulated as “the two processes are not coherent”. In order to test this hypothesis, the probability distribution of the coherency under H0 is estimated.

An empirical method for the significance testing is applied, because an analytical test is not possible due to the high correlation between vicinal wavelet times and scales. Monte Carlo simulations were performed to estimate the distribution under H0 numerically. The α significance level was determined from a Monte Carlo simulation of 10,000 sets of two white noise time series with the same length as the input time series. If a significant relationship can be detected between the two time series based on the coherency, one can use the cross-wavelet spectrum to estimate the phase (Maraun and Kurths, 2004).

4. RESULTS AND DISCUSSION

4.1 Dominant modes of coherency

To assess the dominant modes of coherency between NDVI and precipitation, the frequency of occurrence of significant global wavelet coherency (gWCOH) was analysed. The gWCOH is the time-averaged wavelet coherency. This was done on the actual data, as well as on the anomaly time series (SDVI: standardised difference vegetation index, SDPI: standardised difference precipitation index).

The NDVI and rainfall time series show in certain part of Southern Africa a strong coherency at the frequency bands centred around 1.5, 2.3, 3.5 and 5 years, besides the seasonal pattern (see Figure 1). These frequencies agree well with some well-known meteorological phenomena, like the Quasi-Biennual Oscillation, Sea Surface temperature fluctuations and ENSO (Nicholson, 1989 and 2001).

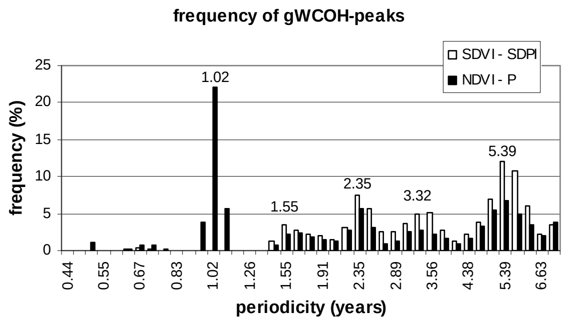

Figure 1. Frequency histogram of the global wavelet coherency peaks calculated on the time series (black) and the anomaly time series (white).

4.2 Analysis of the spatial patterns of these dominant modes

To assess the spatial patterns of these dominant modes, the time length of significant coherency within a frequency band centered around the dominant frequencies was calculated. In addition, the strength of this relationship over time was analysed using the standard deviation of the wavelet coherency over time.

The WCOH applied on the S10 NDVI and rainfall time series, reflects co-varying processes. To determine the conditions for which rainfall exerts an effective forcing on NDVI, it is necessary to distinguish the interannual variations of both parameters from their seasonal cycle (Richard and Poccard, 1998). Therefore, the WCOH of the standardised anomalies of NDVI and rainfall was also calculated for the lower frequencies. In the remainder of the text, the analysis on the yearly cycle was performed on the original dataset, whereas for the lower frequencies the standardized anomaly datasets were used. The results for the time length of significant WCOH for the periodicities of 1, 2.3 and 3.5 years are presented in Figure 2, and the standard deviation of the WCOH over time in Figure 3.

At the seasonal cycle (periodicity = 1 year), vegetation dynamics are significantly co-varying with rainfall over the full time series for 62.28% of the region. When considering all pixels having this significant relationship for at least a duration of 90% of the 20-years time period, then 80% of the land pixels are selected. NDVI and rainfall are strongly co-varying at the seasonal cycle and this relationship is stable over time, as suggested by the small standard deviation of WCOH at 1 year (Figure 3, upper).

For the southeastern part of the study area, except the area around Cape Town, the two time series are not co-varying when looking at WCOH at 1 year (Figure 2, upper). This is also the case, for some distinct areas, like the Etosha Pan, the Makgadikgadi Pans, which have no or little vegetation cover, and the Okavango Delta, which receives water from the Okavango upstream. The WCOH length at 1 year periodicity is considerably shorter for the mountainous areas of the Drakensbergen in South Africa and Mashonaland in Zimbabwe, and also for the deep arenosols of the Kalahari in South-West Botswana and South-Namibia. Here, the low vegetation cover might explain this pattern. The areas with a shorter significant WCOH-length are associated with higher standard deviations in the relationship over time.

The anomaly time series show no significant coherency between NDVI and rainfall for the seasonal cycle, suggesting that all remaining variability in NDVI is distributed over other periodicities or is not caused by rainfall variability.

The second frequency component in the coherency between NDVI and rainfall occurs at a frequency band around 1/2.3 years. The gWCOH at this periodicity is significant for 3.54% of the area. Only a few pixels (1.8 %) show a consistent significant WCOH over the time period at 2.3 years periodicity, but for more than 25% of the pixels WCOH(2.3) is significant during half of the time period (Figure 2, middle), of which the majority in one single period. The areas with high WCOH at 2.3 years periodicity are generally associated with low standard deviations (Figure 3, middle). The east of South Africa shows a stable non-relationship between NDVI and rainfall at this frequency.

WCOH at 3.5 years periodicity is significant during the total time period in 5% of the study area. Only 20% of the area shows a significant WCOH at this periodicity range during at least half of the time series. The majority of these significant periods occur in one single episode. The standard deviation of WCOH at 3.5 years periodicity over time is generally low for areas with a longer significant period.
The spatial distribution of the high coherency at these frequency bands largely coincides with the catchments of rivers, like the Limpopo, Zambezi and their tributaries. The clusters of high coherency in South Africa are located along the Gauteng, and in Angola along the Cunene and the rivers that feed the Okavango Delta. Only the high coherency patches in Botswana are not located along rivers, but these areas are located in depressions in the landscape. These are all areas that receive water from the upstream catchments, suggesting that there is an effect of the additional water availability, which has a periodicity of 2.3 and 3.5 years (Nicholson and Entekabi, 1986), accumulating from the surrounding areas on the NDVI. Absence of significant WCOH is found in mountainous areas (Drakensbergen, Mashonaland, Namibia, Grote Karoo in South Africa), and also in the Namib Desert.

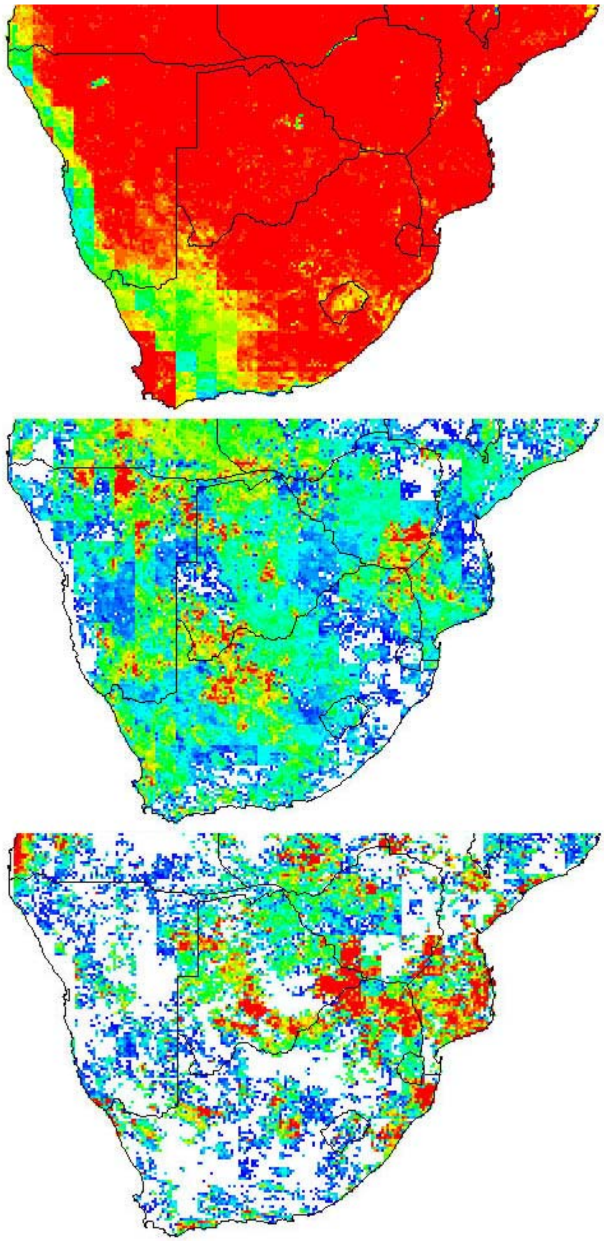

Figure 2. Length of significant wavelet coherency over the time length of the time series for various periodicity ranges: 1 year (upper), 2.3 years (middle), and 3.5 years (lower). Colours range from red (= 100%) over yellow to green (=50%), over cyan to blue (=1%). No significant coherency is represented in white.

Factors affecting the relationship between NDVI and precipitation

In this study, we examined the influence of vegetation type, soil type and topography on the strength of the vegetation response to rainfall. To do so, the patterns of high coherency at the different frequencies were compared to the areas with low coherency, and their correspondence with the areas' physical characteristics was investigated. If a high coherency at a certain frequency predominantly occurred consistently in areas with certain biophysical characteristics (e.g. soil type), it would suggest that these physical factors have an influence on the rainfall – NDVI relationship.

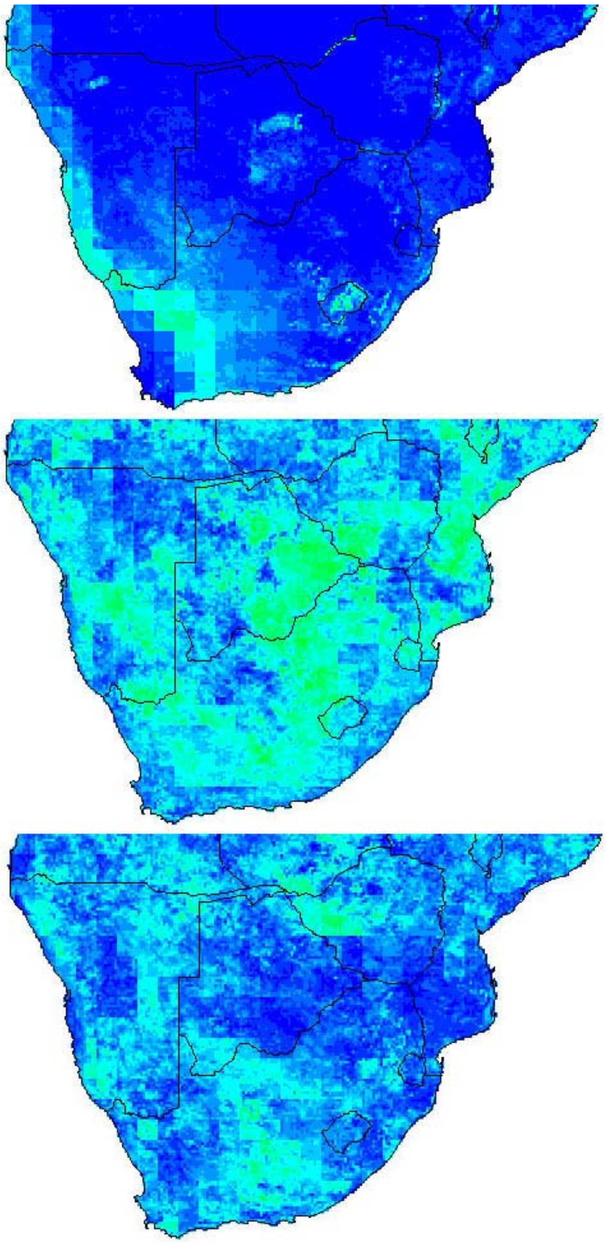

Figure 3. Standard deviation of the wavelet coherency for various periodicity ranges: 1 year (upper), 2.3 years (middle), and 3.5 years (lower). Colours range from green (stdev=0.2) to dark blue (stdev=0.02).

From the observed patterns in the previous section, it was already suggested that some high coherency areas follow the course of large rivers, or are located in depressions (e.g. in Botswana). We investigated whether site-specific characteristics such as topography (altitude and slope), land cover, soil, and mean annual rainfall influence the occurrence of high wavelet coherency and the time lag between NDVI and rainfall.

Vegetation type controls only to a small extent the rainfall – NDVI relationship, but the dependency on soil type for the anomaly time series shows a stronger gradient, suggesting a stronger influence. The importance of topography (altitude and slope) is more pronounced for the anomaly time series. Areas with higher altitude or higher slopes show generally a lower higher coherency, whereas flat, lowland areas show the strongest relationship between rainfall and NDVI. The reason for this is quite obvious. Rainfall will penetrate the soil more in flat areas than in areas with a higher slope, where a part of the rainfall will disappear as run-off to lower areas and will not be available for vegetation growth at the site itself.

For this reason, we believe that the relationship between rainfall and NDVI is not only affected by the site-specific topography, but also by the topography at the landscape scale.

The time lag between the vegetation response to rainfall was also analysed pixel-dependent, whereas for most studies, this is usually taken as a constant. It is found that the response time of vegetation to rainfall can be up to 4 months, with a maximum variability of 1 month over the investigated time period. This variability seems to be larger in depressions in the landscape. Further, we analysed the influence of geographical conditions on the time lag found that mean annual rainfall, soil type, land cover type and topography play a role in the explanation of the time lag variability in the area.

5. CONCLUSION

The analysis showed that wavelets are a suitable tool to analyse both the strength of the relationship and the response time between NDVI and rainfall, and their variability over time.

Using this method, we contributed to a better understanding of the rainfall-NDVI relationships by showing that not only site-specific geographical conditions affect the relationship (both strength and response time), but also the topography of the surrounding landscape. We also showed that the anomalies of NDVI are distributed over a number of periodicities that are also found in the rainfall signal. In addition, we could relate the area where these periodicities occur to the area where these periodicities occur in the rainfall signal. The topography of the watershed level plays an important role in this relationship.

These periodicities in rainfall have been related to well-known meteorological phenomena, which possibly can be affected by global change. This study contributed to the delineation of the areas, which might be sensitive to a change in these meteorological phenomena.

Further, we showed that the variability of the time response of vegetation growth to rainfall varies over time, whereas other studies assumed a constant time lag for the whole time series under investigation, and also for each pixel in the area of interest.

REFERENCES

Camberlin, P., N. Martiny, N. Philippon and Y. Richard, 2007, Determinants of the interannual relationships between remote sensed photosynthetic activity and rainfall in tropical Africa, *Remote Sensing of Environment*, vol. 106, p. 199-216

Gurley, K., T. Kijewski and A. Kareem, 2003, First- and higher order correlation detection using wavelet transforms. Journal of Engineering Mechanics, vol. 129, no. 2, p. 188-201

Hulme, M., J. Arntzen, T. Downing, R. Leemans, J. Malcolm, N. Reynard, S. Ringrose, D. Rogers, E. Chiziya, D. Conway, A. Joyce, P. Jain, C. Magadza, A. Markham, and H. Mulenga, 1996: Climatic Change and Southern Africa: an Exploration of some Potential Impacts and Implications in the SADC Region, *Report to WWF International, Univ. East Anglia, Climate Research Unit and WWF International, Gland Switzerland*, 104 p.

Maraun, D. and J. Kurths, 2004, Cross wavelet analysis: significance testing and pitfalls. *Nonlinear processing in Geophysics*, vol. 11, p. 505-514

Nicholson, S.E. and D. Entekhabi, 1987, Rainfall variability in Equatorial and Southern Africa: Relationships with Sea Surface Temperatures along the Southwestern Coast of Africa. *Journal of Climate and Applied Meteorology*, vol. 26, no. 5, p. 561-578

Nicholson, S.E., 1989, Long-term changes in African rainfall. *Weather,* vol. 44, no. 2, p. 46-56

Nicholson, S.E., 2001, Climatic and environmental change in Africa during the last two centuries. *Climate Research*, vol. 17, p. 123-144

Swinnen, E. and F. Veroustraete, 2008, Extending the SPOT-VEGETATION time series (1998-2005) back in time with NOAA-AVHRR data (1985-1998) for Southern Africa, IEEE Transactions on Geoscience and Remote Sensing, vol. 46, no. 2, p. 558-572

Richard, Y. and I. Poccard, 1998, A statistical study of NDVI sensitivity to seasonal and interannual rainfall variations in Southern Africa. International Journal of Remote Sensing, vol.19, no. 15, p. 2907-2920

Torrence, C and G.P. Compo, 1998, A practical guide to wavelet analysis. *Bulletin of the American Meteorological Society*, vol. 79, no. 1, p. 61-78

Torrence, C. and P.J. Webster, 1999, Interdecadal changes in the ENSO-Monsoon system**.** *Journal of Climate*, Vol. 12, p. 2679-2690

Vanacker, V., M. Linderman, F. Lupo, S. Flasse and E. Lambin, 2005, Impact of short-term rainfall fluctuation on interannual land cover change in sub-Saharan Africa. *Global Ecology and Biogeography*, vol. 14, p. 123-135

ACKNOWLEDGEMENTS

This work was supported in part by the Belgian Science Policy Office under the project GLOVEG (VG/00/01). The author would like to thank the FOOD-SEC group of JRC (Ispra, Italy) to put the precipitation dataset to our disposal.