SPATIO-TEMPORAL WAVELET STATISTICS OF SAR BACKSCATTER FOR THE CHARACTERIZATION OF FOREST DEGRADATION IN CAMEROON

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ABSTRACT

Spatio-temporal analysis of ENVISAT SAR backscatter statistics was undertaken to characterise different landcover types including grassland, forest/agriculture mosaic, degraded forest and intact forest in Eastern Cameroon, Central Africa. The spatial statistics analysis was based on texture measures including wavelet variance and spectra. While, temporal analysis called into play multi-temporal features (swing and linear regression parameters) of pixel trajectories along image acquisitions for tracking landcover changes between 2003 and 2009.

Index Terms— ENVISAT ASAR, spatio-temporal statistics, wavelet variance, multi-temporal features, degraded forest.

1. INTRODUCTION

Forests play a fundamental role in the exchange processes between the atmosphere and biosphere especially in connection with carbon sequestration. In particular, degraded forests in tropical ecosystems do affect the carbon balance but are yet not considered in emission estimates. Recognition of the role of forest degradation by the UN General Assembly has stressed the need for mapping the extent of degraded forests. For the purpose, orbital SAR is an ideal observation instrument in tropical areas, where optical imagery is hampered by persistent cloud cover. SAR spatial statistics can in principle provide measures of the forest horizontal structure, and therefore be a fingerprint of forest degradation. While, temporal statistics can give insight into the evolution of changes in a time framework.

The present work seeks experimental evidence for this assumption, by using wavelet spatio-temporal statistics for the purpose.

2. STUDY SITE

The study site encompasses the Deng Deng National Park and its surroundings located in Lom et Djerem, Eastern Cameroon (13˚4’31.45” E, 5˚28’39.24”N). The area has undergone extensive disturbance with the main areas being those located closer to villages (e.g. Belabo, Mbombia and Sakudi) and cities (e.g. Bertoua). The main drivers of forest degradation are logging and small scale farming, especially where access is facilitated by the construction of road networks. A logging concession (UFA 10 065) is also present in the study site.

3. DATASETS

Nine ENVISAT ASAR scenes (supplied through an ESA grant 1 proposal) were acquired from 2003 to 2010 at VV polarization and mode IS2 (23˚). The datasets were processed (multi-looked, co-registered, and geocoded to UTM projection (zone 33 N) at 15 m pixel spacing), using SARScape 5.0 [1].

4. METHODOLOGY

Measures of the SAR backscatter spatial statistics (texture) were provided by a wavelet frame representation of SAR backscatter in two-dimensional estimation windows selected by visual inspection within thematic classes of interest. The analysis is therefore supervised, while the texture classification problem is not addressed here.

Signals associated with these windows can be considered as random processes, these including fluctuations of the radar cross section (RCS) and residual system and speckle noise. Statistical properties of these random processes depend on many parameters, among which the sensor’s viewing geometry and impulse response function, and vertical and horizontal distribution of the vegetation scattering elements. Scope of the analysis was to identify sensitivity of the measures to differences in vegetation structure, which could be associated to ecological characteristics (e.g. forest closeness, homogeneity, degradation). On the other hand, the measures do not provide a one-to-one correspondence with geometrical parameters of vegetation, such as tree crown, width or density.

In more detail, the texture measures were computed by the following steps: 1) Speckle reduction by a multi-temporal wavelet based filter; 2) Supervised extraction of 65 x 65 pixels windows for each class; 3) Discrete wavelet frame transform of each window; 4) Wavelet coefficients statistics as a function of scale and space.

A 4-voice scheme was adopted for the discrete wavelet frame transform (DWT). In this way, sampling of the

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coefficients' trajectories with scale was improved. The following statistics of the wavelet coefficients $Wg(x, s)$ were computed (with s being the scale, and x the space coordinate and g the signal):

a) Wavelet variance: $\langle Wg(x,s)^2\rangle_x = f(s)$
b) Wavelet spectra: $Wg(x,s)^2 \otimes h_\sigma(x) = f(x,s)$
c) Wavelet normalized covariance:

$$\frac{\langle Wg_1(x,s).Wg_2(x,s)\rangle_x}{\sqrt{\langle Wg_1(x,s)^2\rangle\langle Wg_2(x,s)^2\rangle}} = f(s)$$

The wavelet spectrum provides local (in space) estimates of the wavelet variance by convolution of the wavelet coefficients with a smoothing kernel of support σ.

4.1 Multi-temporal Trajectories

A pixel trajectory is defined as a set of values of all backscatter resolution elements at the same row and column position in the stack of images. Backscatter trajectories can be used to track changes in landcover (e.g. change from undisturbed to disturbed forest). Analysis of the trajectories over an area by means of a set of parameters (features) that characterize its time evolution can give insight on the nature and changes of landcover. The following set of trajectory features was computed:

1) Swing (relative change): $\frac{\max(P_j)-\min(P_j)}{(\max(P_j)-\min(P_j))/2}$
2) Trend analysis by linear regression of P_{n_j} resulting in 3 parameters: line intercept, slope and coefficient of determination.

5. SELECTED RESULTS

5.1. Wavelet Space-Scale Signatures

Fig. 1 shows the wavelet variance as a function of scale (5 dyadic scales and 4 voices) for four classes. In the long scale region all classes are well separated, with the mosaic class showing the highest variance (black line), followed by the degraded forest class (red line), the intact forest (blue) and the grassland (green). These trends are in line with the intuitive notion of more heterogeneity in the mosaic and degraded forest spatial distribution, and of more homogeneity in the grassland and intact forest distribution.

Examples of wavelet spectra are presented as density plots in Fig. 2. The spectrum for the grassland window is characterized by smooth distribution (low texture). Fig.2a shows wavelet spectrum for degraded forest. Notice how this class is more heterogeneous compared to the grassland class (see green areas). The spectra confirms these different characteristics in the scale domain, and, importantly also in the space domain. These observations could therefore set the stage for a classification based on wavelet variance trajectories in the combined scale-space domain.

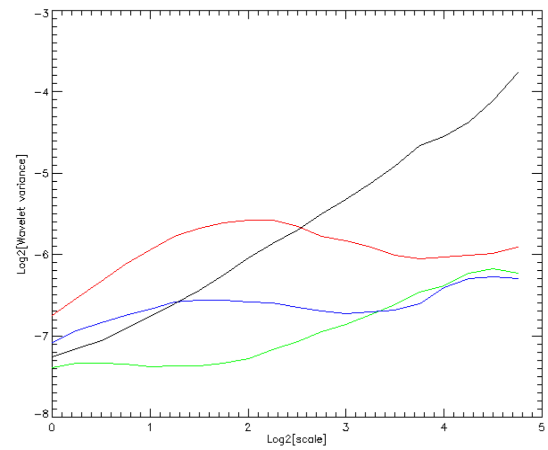

Fig. 1 Wavelet variance scaling signatures for four classes based on single data set of ENVISAT ASAR backscatter (2006). forest-agriculture mosaic (black line), degraded forest (red line), intact forest (blue), grassland (green).

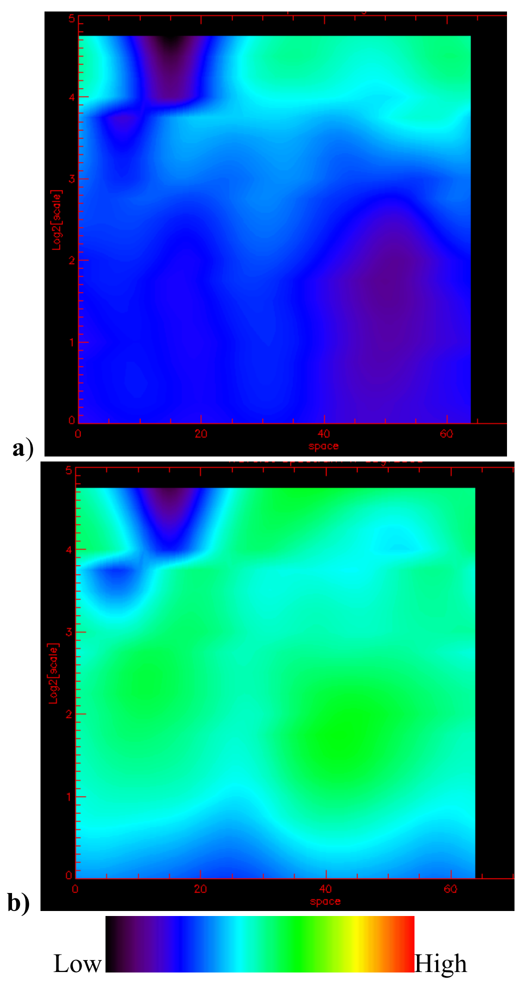

Fig. 2 Wavelet spectrum for a) grassland and b) degraded forest.

5.2 Wavelet Covariance

The normalized wavelet covariance (correlation) signature (XWASS) provides a measure of how the SAR backscatter within the estimation window (related to a specific landcover class) changes texturally between two dates and as a function of scale. It is therefore a spatio-temporal fingerprint of the SAR statistics. An example is shown in Fig. 3. The signature was computed with the same classes as the WASS in Fig. 1 and refers to changes between acquisitions in 2006 and 2010. It can be observed that the wavelet variance of all classes loses correlation between the two dates, with lower correlation at longer scales. The changes at short scales may be influenced to residual speckle noise, while, as scale increases, variation of the RCS spatial distribution comes into play. Class agricultural mosaic (black line) shows the highest de-correlation (highest temporal change) at all scales. At short scales (up to 2^3), the statistics of class grassland (green line) shows more de-correlation than the ones of class primary and degraded forest. For class intact forest (blue line) there appear to be more textural change in comparison with class degraded forest. This feature must be further investigated to be able to connect it to vegetation changes.

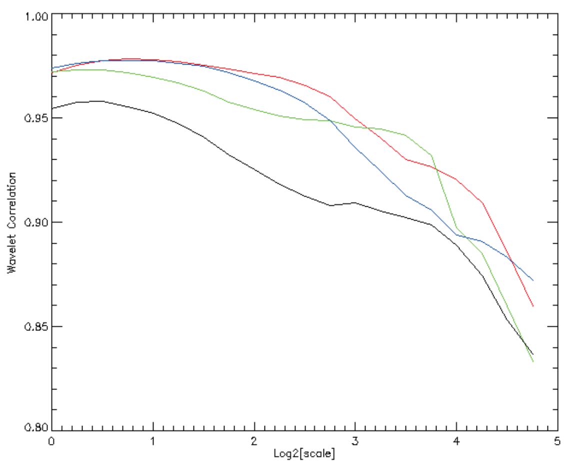

Fig. 3 Wavelet correlation between dates 2006 and 2010 and four classes: degraded forest (red), grassland (green), intact forest (blue) and forest-agriculture mosaic (black).

5.3 Multi-temporal Pixel Trajectories

Multi-temporal pixel trajectories can give insight into landcover changes. Visual interpretation of Fig.4 indicates that the areas which change the most (highest swing) appear red while areas that appear yellow have both a high swing and a high fitting line slope (green). The areas which belong to forest/savannah appear in yellow but also areas which have undergone deforestation and the conversion to agriculture. Areas that appear in red are located both in the forest savannah but also along areas where deforestation and forest degradation has occurred. While, areas that appear in green have a high coefficient of determination which indicates that the trend for these pixels is close to linear compared to other pixels. Areas that appear in purple have high swing (red) and coefficient of determination (blue). The exact causes of the changes visible are yet to be assessed.

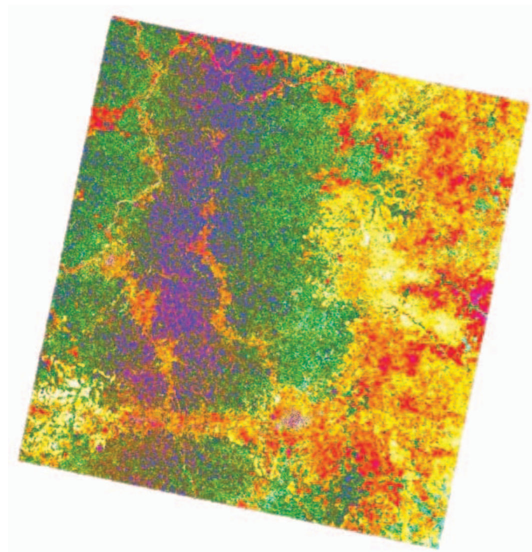

Fig. 4 Multi-temporal pixel trajectories shown as a colour composite of swing (R), slope (G) and coefficient of determination (B).

6. CONCLUSION

The combined use of spatial and temporal statistics of ENVISAT ASAR backscatter was exploited to retrieve information about landcover classes and their changes through time.

Results have shown that wavelet variance, wavelet spectra and multi-temporal features are able to differentiate landcover classes through measures of SAR backscatter statistics, which in turn are fingerprints of the landcover spatial distribution and its changes in time. Future work will include testing of the methodology on additional areas of interest with focus on forest degradation and using other datasets, such as ALOS PALSAR and ESA Sentinel-1.

7. REFERENCES

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