WAVELET BASED PATTERN ANALYSIS TO DETECT CHANGES IN VEGETATION GROWTH

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Abstract: This study aims at identifying patterns to detect changes in vegetation growth. Soil and topographic relationships with the greenness index were applied to analyze the growth of Guatemala grass. Wavelets such as Haar, Daubechies and Symlets were extensively used to extract information at different scales and compared with different levels of decomposition. Informative patterns at each stage of growth were selected using spatial correlation while superior information could be obtained from levels 3 and 4. It was observed that compound topographic index (CTI), slope and flow accumulation were weakly correlated with the extracted patterns. Daubechies-4 (db4) and Symlet-8 (sym8) gave better results compared to Haar with db4 having the ability to extract fine features while sym8 could extract smooth features. It also shows that flat and elevated patterns and the topographic parameters remain weak. From this study it was concluded that wavelets can be used as a useful tool to extract relevant patterns and interpret spatial variations observed at different stages of vegetation growth.

INTRODUCTION

Remote sensing is often used for detecting seasonal vegetation changes. Various methods using daily Normalized Difference Vegetation Index (NDVI) data have been developed for monitoring crops and natural vegetation (Akiyama et al., 2002; Saito et al., 2002; Xiao et al., 2002). Several frequency analysis studies have used the Fourier transform for separating the high-frequency components of noise and the low-frequency components of seasonal changes of vegetation index (Azzali and Menenti, 2000; Roerink et al., 2000; Viovy et al., 1992). Lark (1999) illustrated the application of multi-resolution analysis of discrete wavelet transform (DWT) on fairly small sets of soil sampled data and found the technique to be very efficient in revealing those local feature variations that had been lost in the traditional methods of analysis, and express them quantitatively both in scale and magnitude. Lark et al. (2007) extended their work and concluded that Discrete Wavelet Packet Transform (DWPT) is an advance wavelet technique compared to DWT as it works well for both stationary and non-stationary data sets. Verhagen et al. (2000) used wavelets to compare the interpolated yield, of 10years for a 2.5 hectare field with their respective rainfall distribution of growing season and quantified the reoccurring pattern which can guide the irrigation in dry and wet years. Epinat et al. (2001) used wavelets for extracting patterns in phenological study of crop on high resolution Dutch airborne scanner images. Geerken et al. (2005) used Fourier filter cycle similarity (FFSC) method for classifying rangeland vegetation and described its superiority over traditional unsupervised classification. The method gives a synoptic visualization of vegetation coverage variation and is independent of background reflectance and scene statistics. Evans et al. (2006) extending the work of Geerken described the Discrete Fourier Transform (DFT) as a computationally inexpensive and rapid method for rangeland vegetation classification with all FFCS capabilities. Quantifying patterns of crops and soil conditions during the growing seasons increasingly helps in proper management and decision-making. Therefore, patterns extracted from remotesensing images may be useful to support such quantification by applying wavelets. Patterns are the non-random distribution and arrangement of low and high values (Epinat et al., 2001). Wavelets have been applied in pattern analysis for various crops. Schmidt and Skidmore (2003) used wavelets and confirmed that increased spectral resolution of hyperspectral sensors can improve the mapping of floristics, whereas Cosh and Brutsaert (2003) examined the spatial structure of vegetation density at the land surface. Later, Choua et al. (2007) found wavelet analysis to be a good tool for identifying and describing crop features.

The objective of this paper is to monitor spatial patterns of vegetation's and to better understand the causes of the patterns. A pattern analysis based on wavelets was applied to multi-temporal satellite data at different resolutions. The results of the three wavelets – Haar, Daubechies (db4) and Symlet (sym8) were then compared and the patterns were extracted. Standard wavelet functions such as db4, sym8 and Haar were applied in this study.



Here wavelets were applied to the Guatemala grass which is considered to be the soil rehabilitation grass and used by the tea plantation sectors.

METHODS AND EQUATION

A wavelet is a small, localized wave in time or space and here satisfies the orthogonal condition. Since a wavelet has compact support, which means that its value becomes 0 outside a certain interval of time, the time components of time-series data can be maintained during wavelet transformation.

Haar Wavelets.

The Haar wavelet is a sequence of rescaled square-shaped functions which together form a wavelet family or basis. The Haar sequence is the first known wavelet basis and has been extensively used in the theory of wavelets.

The Haar scaling function (Burrus et al., 1998) is defined as

$$\phi(x) = \begin{cases} 1, \ for \ 0 < x < 1 \\ 0, \ elsewhere. \end{cases}$$
[1]

The Haar mother wavelet is therefore given by

$$\psi(t) = \begin{cases} 1, for 0 < t < 1/2 \\ -1, for 1/2 < t < 1 \\ 0, otherwise \end{cases}$$
[2]

Haar scaling function generates the subspaces V_j consisting of the space of piecewise constant functions of finite support whose discontinuities are contained in the set of integer multiples of 2^{-j} . This verifies that $\{V_j, j \ge 0\}$ together with Haar scaling function ϕ satisfies the definition of multiresolution analysis. So Haar wavelet is the function of

$$\psi(x) = \phi(2x) - \phi(2x-1)$$
 [3]

Daubechies Wavelets.

Daubechies wavelets (1988) form a family of orthogonal wavelets characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function which generates an orthogonal multiresolution analysis. The scaling function equals (Boggess and Narcowich, 2001):

$$\phi(x) = \sum_{k} p_k \phi(2x - k)$$
 where p_k are the coefficients. [4]

Once the p_k have been identified and ϕ has been constructed then the associated wavelet is given by:

$$\psi(x) = \sum_{k \in \mathbb{Z}} (-1)^k p_{1-k} \phi(2x - k)$$
[5]

The Daubechies scaling and wavelet functions are continuous but not differentiable. Daubechies also showed that for every N there will be 2N non-zero, real scaling coefficients $p_0, ..., p_{2N-1}$, resulting in a scaling function and wavelet that are supported on the interval $0 \le t \le 2N-1$. The corresponding degree 2N-1 polynomial

$$P_N(z) = \frac{1}{2} \sum_{k=0}^{2N-1} p_k z^k$$
 has the factorization:

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[6]

$$P_N(z) = (z+1)^N P_N(z)$$

where P_N is N-1 and $P_N(-1) \neq 0$. Therefore, the associated wavelets have precisely N vanishing moments. The scaling function ϕ_N and wavelet Ψ_N generated by P_N have Fourier transforms as the coefficients of P_N are real, $P_N(-z) = P_N(-\overline{z})$, leading to the equations:

$$\overline{\phi_N}(\xi) = \frac{1}{\sqrt{2}} \prod_{j=1}^{\infty} P_N\left(e^{-i\xi/2^j}\right)$$
^[7]

$$\overline{\psi}_{N}^{(k)}(0) = (-e^{-i\xi/2}P_{N})\overline{\phi}_{N}(\xi/2)$$
[8]

Symlets Wavelets.

Symlet wavelets are proposed by Daubechies in 1992 and are a variation of Daubechies wavelets. An orthogonal, compactly supported wavelet of finite length with linear phase filters is impossible to construct. The purpose of the variation to the Daubechies wavelets was to create a wavelet of the same size and same number of vanishing moments as the Daubechies wavelet, but with near linear phase filters. Because of its near symmetry this wavelet was called the Symlet wavelet.

Perpendicular Vegetation Index (PVI)

The PVI is the perpendicular distance of the measured point from the soil line, defined as:

$$PVI = \frac{NIR - (a \times R - b)}{\sqrt{1 + a^2}}$$
[10]

where NIR = Near Infrared band (band giving highest reflection to vegetation)

- R = Red (band giving lowest reflection to soil)
- a = slope of the soil line

b = gradient of the soil line.

Using the concept of PVI, soil index was derived among the set of spectral bands that shows highest variation between vegetation and soil. The PVI was calculated by drawing a linear regression line between the highest dry and wet vegetation points in the feature space. By calculating the euclidean distance between the points and the perpendicular intercept to the regression line, all the other points were shifted towards this regression slope line.

RESULTS

LISS III image was fused with CARTOSAT II stereo data to generate an input image of 2.5m resolution. Wavelets such as Haar, Daubechies (db4) and Symlets (sym8) were applied to the input image and at level 3, information were obtained at 20m resolution. This enabled the patterns to be extracted from the young Guatemala grass. The information extracted at level 3 by sym8 was then correlated with slope and compound topographic index (CTI). It was observed that vegetation has better correlation with slope as seen from the cross correlation (Figure 1). However, this relation was absent in the correlation map (Figure 2). The northern and the eastern part of the young Guatemala plot also shows least flow accumulation and the inverse correspondence can be seen between the vegetation and the flow accumulation (Figure 2). The sedimentation index was calculated based on slope percentage. Possibility of greater variability in Guatemala grass can be seen in the western part of the plot due to clear correspondence between the slope gradient and higher sedimentation. With a slope of 45%, topographical relations seem better. For flow accumulation, 12% correlation was observed giving a range longer than 40 pixels and indicating 100m resolution on the ground. An 80-100m ground resolution was also observed for slope, wetness, sedimentation and elevation although the correlation was found to be weak about less than 10% and following a symmetric trend. This enabled the relationship to be better modelled and can be considered stable.

The perpendicular vegetation index (PVI) for the young Guatemala plot calculated from the input image shows a mean and a standard deviation of 7.34 and 1.8, respectively. Red region in Figure 3 indicates vegetation,



reflecting healthy soil, while the blue region shows low vegetation, reflecting stressed soil conditions. The PVI image decimated using the Haar, db4 and sym8 wavelets up to level 6 shows that loss of information increases beyond level 4 and therefore only levels 2 and 3 can be considered for the study. Loss of information was observed from level 3 onwards, having less than 90% correlation with the PVI while at level 4, information further gets reduced to 40 m ground resolution. So only levels 2 and 3 were considered and compared. Although the db4 and sym8 wavelets provided a similar approximation, sym8 shows a larger range and higher correlation with the input PVI image, ranging between 0.90 and 0.95. Sym8 wavelet at level 3 best represents the young Guatemala with a mean and a standard deviation of 7.3 and 1.6, respectively, indicating the absence of fine features. The image could be generalized at 20 m ground information.



Figure 1: Level3 approximation by sym8 wavelet cross correlated with (a) Flow Accumulation (b) Elevation (c) Slope map (d) Sedimentation map and (e) Compound Topographic Index (CTI) Map for young Guatemala grass.



Figure 2: Patterns extracted from sym8 wavelets and correlated with different maps

However, the PVI image of mature Guatemala grass shows a mean and standard deviation of 0.79 and 0.844, respectively, thus indicating less variation in the mature Guatemala. The PVI was calculated at 2.5 m resolution (Figure 4) and was decimated and correlated with the input image. Level 3 gave better results at a pixel size of 2.5 m corresponding to 40 m ground resolution. Using the Haar, db4 and sym8 wavelets, three-dimensional mesh plots were drawn for level 3 (Figure 4). The db4 and sym8 wavelets gave similar correlations with the PVI image. The plot reveals that db4 is more similar to the input PVI image than the other wavelets.

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Figure 3: Approximation by Haar, db4 and sym8 wavelets for Young Guatemala grass

The mature Guatemala section has an elevation of 345-356 m and a slope of 44%. The slope and the sedimentation of the section were 10-12% correlated with Guatemala variations (Figure 5). The northeastern part of the plot shows low vegetation. Changes in the pattern could be observed between the mature Guatemala plots. Topographic parameters and drainage networks contribute significantly to pattern extraction. The two main drain lines show an inverse relation to vegetation, whereas the other field drains are positively related to vegetation. The Guatemala section has better vegetation cover with more flow accumulation. The northeastern part of the section showed stress, which may be due to soil condition.



Figure 4: PVI image and three-dimensional mesh plots for mature Guatemala plot.



Figure 5: A section showing the contour lines, slope map, drainage network map and flow accumulation map of the Guatemala grass

DISCUSSION

The study focuses on identifying patterns within young and mature Guatemala grass. Different levels of information were obtained using wavelets. Information at different scales was analyzed using the multi-resolution analysis. The study showed that decimation of level 3 gave more amount of information compared to the other levels. Wavelets were applied on LISS III – CARTOSAT II fused image which could reveal unobservable patterns within the young and mature Guatemala grass. Hence information could be extracted using wavelets.

Remote sensing images and relevant ground truth could contribute to assess, analyze, monitor and model the characteristics of vegetation growth. To achieve timely and accurate information on the status of crops, an up-todate crop monitoring system may provide accurate information. The earlier and more reliable the information, the greater is the value (Hamar et al., 1996, Reynolds et al., 2000). Remote sensing offers an efficient and reliable means of collecting required information, in order to map vegetation type and acreage and also the phenology of vegetation growth. The spectral reflectance always varies with respect to the phenology, stage type and crop health and these could be well monitored and measured using the multispectral sensors.

ACR

Among the three wavelets considered for the study, only db4 and sym8 could extract patterns whereas the Haar wavelet gave less satisfactory results. The sym8 wavelet is found to be almost symmetric with sixteen coefficients and db4 is asymmetric with only eight coefficients. The pattern observed with sym8 is mainly due to its long support size. Db4 wavelet is more suitable for crystals having fine pattern at a lower separation. Regular and smooth patterns were observed with sym8, indicating that sym8 could extract low frequency detailed information. Elevation, slope, flow accumulation, sedimentation index and CTI were chosen to perform the analysis. Correlations were calculated between the parameters but the expected relations between soil wetness, slope and vegetation could not be obtained. Significant spatial dependence could be observed in the mature Guatemala. However, no pixel to pixel correlation could be observed among the vegetation patterns obtained from wavelets decimated images and different topographical and hydrological parameters. The study found that the selected pattern for young and mature Guatemala was weakly correlated with the wetness index, flow accumulation, sedimentation index and 0.2 with elevation. The linear relationship between the extracted pattern and topographic parameters was found to be weak.

Wavelets could delineate site specific management zones to get a better understanding about the soil and vegetation status. The patterns of soil development and its properties varies with topography which gives a relationship allowing prediction of soil attributes from landscape position at larger scale. The wavelets applied shows that patterns could be extracted at different levels and could be monitored.

CONCLUSIONS & RECOMMENDATIONS

From this study it was concluded that wavelets such as Haar, db4 and sym8 could extract patterns from different growth stages of vegetation. Daubechies (db4) and symlet (sym8) could give better results as compared to Haar. The results of Daubechies (db4) and Symlet (sym8) are similar due to their compactness at upper levels, as dilation increases; shape of wavelet comes into play and becomes more prominent at lower levels. Increase in dilation makes the shape of wavelet more prominent at lower levels. The symmetrical sym8 wavelet could reveal smooth details, whereas the db4 wavelet isolated fine details and signal discontinuities. Differences between db4 and sym8 increases when decreasing the level because the wavelet becomes more flattened and its shape become more pronounced.

The study further concluded that the selected patterns of the fields were weakly correlated with slope, flow accumulation and CTI. A strong quantitative linear relationship between the extracted patterns and topographic parameters could not be established. The low vegetation variability was associated with areas that have either a steep slope or a low flow accumulation. It also showed that the influence of the various hydrological processes related to vegetation, accurate DEM, drainage information and soil properties like pH, organic carbon could be properly evaluated using cross correlation.

The recommendation for this study is as follows:

- 1. Wavelet analysis should involve multi-temporal data sets to study different stages of vegetation growth.
- 2. Soil samples with their geospatial information can also help in correlating soil properties with other spatial dataset that shows its effect on vegetation.
- 3. Further studies should include wavelets being applied to different crops and extracting their patterns to understand its growth and development.
- 4. After extraction of pattern it is recommended to carry out field verification to identify the causes of such patterns which may be due to diseases, water logging and other problems.

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