VINEYARD IDENTIFICATION AND CHARACTERIZATION BASED ON TEXTURE ANALYSIS IN THE HELDERBERG BASIN (SOUTH AFRICA)

Antoine Lefebvre [1], Thomas Corpetti [1,2], Valérie Bonnardot[1], Hervé Quénol[1], Laurence Hubert-Moy[1]

[1] COSTEL, UMR CNRS LETG / IFR 90 CAREN
[2] CNRS – LIAMA, RSIU Team

1. INTRODUCTION

Since 1973 and the introduction of the Wine of Origin System, vineyards in South Africa are demarcated, at national scale, into four classes according to geographical and climatic characteristics or administrative borders While wine-producing are identified at a estate, ward, district and region level, no mapping of precise spatial demarcation of vineyards has been performed yet at a higher resolution scale. This step remains a gap in the GIS data base of viticultural "terroirs" studies. In this paper, a methodology for the spatial identification of vineyards using texture analysis is proposed to meet the need of ongoing and further viticultural "terroirs" studies.

As part of the wine industry terroir research programme, meso-scale and sea breeze air circulations studies were undertaken over the Stellenbosch district [1] due to the relevant climatic implications on grapevine performance and wine characteristics. Some numerical simulations have already been performed using the Regional Atmospheric Modelling System (RAMS), in which parametrizations have been designed for mesoscale or higher resolution scale grids (http://www.atmet.com). It included four nested grids, each grid covering a different domain size with different horizontal resolutions (25 km, 5 km, 1 km and 200 m), using a two-way interactive exchange of information between grids. RAMS takes large scale atmospheric data (in our case meteorological fields from the European Center for Medium-Range Weather Forecasts) as well as surface data into account. Among the required surface data taken into account by RAMS are sea surface temperature, topography, soil (texture and humidity) and land cover. RAMS uses 30 land cover classes mostly characterized by vegetation type or whether the surface was covered with water, bare ground or urban. As for vineyard analysis, their precise delineation at a high resolution can improve the RAMS simulations output. This is the scope of this paper.

A quick and inexpensive means of producing spatial data is the processing of remote sensing data. With the development of Very High Spatial Resolution sensors, it is now possible to identify textures inside an 'entity' (like an agricultural parcel for instance). These entities, resulting from combination of items, could be characterized by their spatial arrangement. In case of vine-plot, alignment of rows constitutes a periodic pattern composed of parallel lines entirely related to an anisotropic texture. Thus it is noteworthy that texture analysis is one of the best ways to identify and characterize vine-plots. Many methods have been used to detect vine-plots. In [2], the authors have highlighted the performance of frequency methods in relation to co-occurence ones. Frequency techniques based on Fourier transform are most often used [2, 3], while [4] have used Gabor filters. Finally, [5] used a wavelet transform to discriminate vine-plots to other land uses, but did not estimate row-orientation. In this paper, a wavelet-based method is proposed to identify vineyards as well as estimate row orientation of each plot. The key idea is to find the rotation angle that best concentrates energy in a given direction of a wavelet decomposition of the wavelet image.

2. METHOD

In order to find the direction angle of a textured patch, we propose to iteratively rotate the original image and to keep out the angle that concentrates the maximum of detail information in a single band (vertical in practice). Therefore, if one represents an image I_θ (corresponding to the original I rotated by θ as $\{A_\theta^1, H_\theta^1, V_\theta^1, D_\theta^1, \dots A_\theta^J, H_\theta^J, V_\theta^J, D_\theta^J\}$, where A_θ^J (resp $H_\theta^J, V_\theta^J, D_\theta^J$) represents the approximation (resp. horizontal, vertical and diagonal) band along j^{th} level of a wavelet decomposition, we search the angle $\hat{\theta}$ such that:

$$\hat{\theta} = \max_{\theta}\left(\mathcal{E}(\boldsymbol{\mathcal{D}}, \{I_\theta\})\right) = \left\{\theta | \mathcal{E}(\boldsymbol{\mathcal{D}}, \{I_\theta\}) = \mathcal{E}_{max}\right\}, \text{ where } \mathcal{E}(\boldsymbol{\mathcal{D}}, \{I_\theta\}) = \sum_{j=0}^{J}\left(\boldsymbol{\mathcal{D}}(V_\theta^j, H_\theta^j) + \boldsymbol{\mathcal{D}}(V_\theta^j, D_\theta^j)\right).$$

Here, $D(\cdot_1, \cdot_2)$ is the symmetric Kullback-Leibler distance between coefficient $\cdot_1$ and $\cdot_2$. The ε criteria will reach its maximum ε_{max} when differences between vertical bands and the other ones will be at maximum. This corresponds to a major orientation of the pattern along the vertical axis. Therefore, the value of $\hat{\theta}$ corresponds to the angle between the vertical axis and the oriented pattern.

3. STUDY AREA AND DATA

A trial study area of 25 ha in the Helderberg basin (Figure 1), situated in the Stellenbosch wine district of South Africa, has been selected to establish and test the methodology for spatial demarcation of vineyards. The Helderberg basin is orientated SW-NE and opened to the sea to the southwest. It is surrounded by mountain ranges from northwest (The Dome 1137m) to north (Haelkop 1384 m) and east southeast (Sneeukop, 1590m). The trial surface encompasses different land cover: vineyards plots (with different row orientations), olive-trees and decidious fruit-tree orchards; wind breaks, water surface, estate building, bush and forest.

Color aerial photographs were used for the study. Images were georeferenced with a 50 cm spatial resolution. Before texture analysis, images were converted to grayscale and an anisotropic filtering was processed to reduce image noise while preserving image contours.

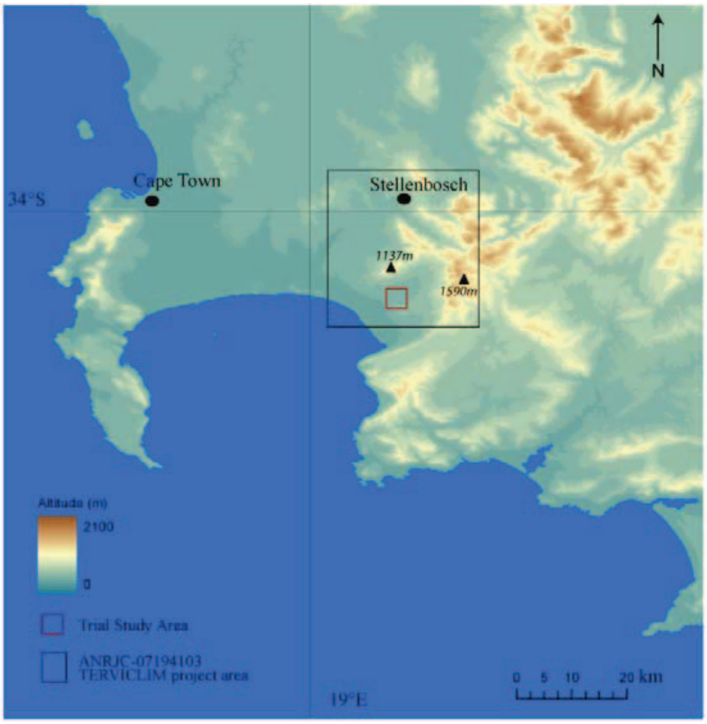

Figure 1-Heldeberg basin: map of location

4. RESULTS

The method provides two types of results: the highest measured energy and each plot main orientation. Figure 2a represents an example with vine-plots, forest, and bare soil. From Figure 2b, it was noted that vine-plots displayed significant higher values than other land-uses. The energy measure classification could then easily discriminate vineyards, olive groves, woods and bare soil. The highest energy measure was selected using a threshold to extract vine-plots. Then each selected vine-plot was assigned a row-orientation angle value (Figure 2c).

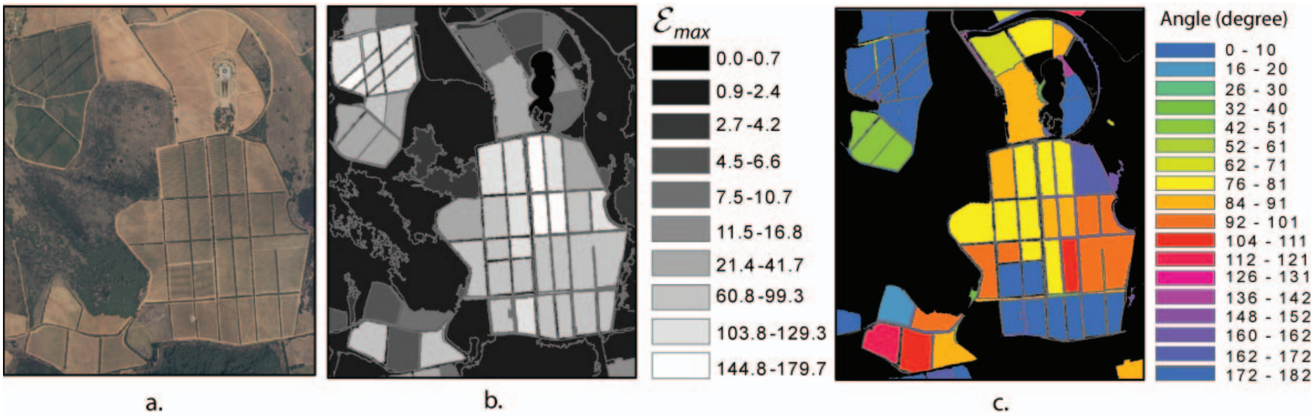

Figure 2- (a) Aerial photograph, (b) Maximum measured energy map, (c) Main row-orientation map

5. CONCLUSION

After validation on the present study test area, this methodology will be extended to a larger surface (100 000 ha) covering the ANR JC-07194103 TERVICLIM project study area (figure 1) and further on to the entire wine producing regions of South Africa in order to produce a map demarcating vineyards accurately at fine scale. The spatial demarcation and characterization of vineyards will be a useful product in a GIS platform and in further environmental studies. The wavelet-based method brings additional and valuable information for micro climatic studies as vine-plots were also parted according to their row-orientation.

6. REFERENCES

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