AN OPERATIONAL APPROACH TO MONITOR VEGETATION USING REMOTE SENSING

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ABSTRACT

This paper addresses vegetation monitoring in European agricultural areas using Earth Observation satellites. Due to the small size of typical European fields, two complementary sensors are used, SPOT and NOAA-AVHRR, bringing the spatial and the temporal information respectively. A sub-pixel analysis of NOAA data using one SPOT image is performed to characterize fields with high spatial and temporal resolutions.

To be used in an operational context, the method must have realistic data requirements. We define an operational scenario making use of only one SPOT image per site and a one year NOAA sequence, covering a large part of Europe. We first proceed to an unsupervised segmentation of the SPOT image; the NOAA data analysis on test sites provides the temporal evolution of vegetation; then, identification of fields is performed by minimizing a cost function measuring the similarity between the global reflectance observed on NOAA pixels and the reflectance computed from corresponding regions at SPOT resolution.

1. INTRODUCTION

Thanks to their ability of providing precise, dense and regular ground measures, Earth Observation satellites represent powerful tools in environmental decision making processes. Hence in the specific case of agricultural policy, satellites are expected to monitor the vegetation cycle of some cultivations (cereals, maize, etc.) at the parcels level and at high frequency, in order to estimate crops yields and detect anomalies such as hydric stress.

In this paper we address these objectives, in the specific context of European agricultural areas. Due to the relatively small size of European fields, one has to use two satellites (SPOT, with high spatial resolution and NOAA-AVHRR, with a lower one but with daily acquisitions) to (i) discriminate at high spatial resolution (20m) the different cultivated species and to (ii) estimate up to daily frequency, agronomic parameters, such as the *Normalized Differential Vegetation Index* (NDVI), related to each farming.

The fusion of two different data sources, as well as the specificity of European agricultural landscapes, raise specific image analysis problems. Firstly, one has to handle vector data since satellites provide multispectral measures; secondly, the difference in spatial resolution between the two data sources is significant, and one has to lead sub-pixel studies; lastly, the developed methods must take into account the landscape characteristics and handle the presence of non-agricultural areas, such as towns, forests, water, etc.

The general approach is detailed in section 2. This presentation is focused on a specific applicative scenario, that makes use of solely one high resolution image for operational purposes. In section 3 we detail how this image is segmented into fields, and how non agricultural areas are managed. This spatial segmentation, combined with the information provided by daily low resolution images, allow the recognition of vegetal species on the basis of the temporal evolution of their reflectances, as described in section 4. Results and analysis are discussed in section 5.

2. MONITORING VEGETATION BY SATELLITE

Data. Studying vegetation requires measures in the red and near infra-red channels, which are provided by several satellites, to estimate the vegetation index (NDVI). The spatial resolution must be sufficient to analyze fields (10 or 20 meters resolution is required for Europe). Data must be acquired frequently to be used in agronomic models. As these data requirements are conflicting, one has to use two complementary sensors: here we are using SPOT-XS data (20 meters ground resolution, 26 days orbital cycle) and NOAA-AVHRR data (1.1 km resolution and daily cycle). The study is led on a selected test site, located around the city of Chartres (France), with provided ground truth at SPOT resolution.

Overview of the study. After geometric registration, each NOAA pixel is associated with a set of 55×55 SPOT pixels.

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NOAA data is then subject to subpixel analysis, up to SPOT resolution: if the land use at SPOT resolution is known, NOAA data can be used to estimate reflectances and NDVI of major vegetation species (see [2, 3]). These temporal profiles can be used to estimate crops yields or, by comparison with standard temporal evolution, to detect anomalies. They also can be used in conjunction with SPOT data, to achieve one objective of the study, *i.e.* the characterization of vegetation with SPOT spatial resolution and NOAA frequency. As a result, one can fulfill this objective if the NOAA sequence and ground truth at SPOT resolution are available. However one cannot expect getting ground truth at European scale. It can alternatively be computed using a SPOT sequence (see [2]), but purchasing SPOT sequences every year covering Europe is not a realistic data requirement.

Proposed scenario. This is why we define the following operational scenario. Several representative test sites are studied using all possible data (NOAA and SPOT sequences), to obtain ground truth and NOAA temporal reflectances. These reflectances are assumed to be still usable in the vicinity of the test site. Our method uses these reflectances and only one SPOT multispectral image as input, and outputs vegetation reflectances at SPOT spatial scale and NOAA frequency. There are two processing steps: firstly, an unsupervised SPOT spatial segmentation is performed, taking into account the specificity of agricultural landscapes (see section 3). Land covers identification is then performed using NOAA temporal reflectances (section 4).

3. MULTISPECTRAL SPOT IMAGE SEGMENTATION

Automatic segmentation is a necessary step in our study. It is performed in order to divide the SPOT image into regions representing agricultural fields and non-agricultural zones as towns. Problems that have to be studied in this case are related to the characteristics of SPOT images as well as those of the landscape which they represent. So two points are taken into account in the image processing: firstly, we deal with multispectral data, and we have to exploit information held in the spectral SPOT channels; we are then interested in the agricultural parcels and fields which have generally, a polygonal shape; but there are some textured zones as wood and urban areas which are difficult to detect because of their important heterogeneity. This is in fact one of the major problems encountered for the segmentation of land cover scenes acquired by satellite.

To achieve SPOT image segmentation several approaches can be used: edge detection [2], Markov Random Field modeling [4], region growing [5]. Some authors [4] pay a particular attention to detect urban areas in order to improve segmentation results. The segmentation algorithm tested in our case makes use of the method introduced in [8], where textures are described through the local gray level histogram. The Euclidean norm of a local histogram (which is considered as a N_g vector, N_g is the maximal gray level in the histogram) measures the region's homogeneity. The maximal values of this norm represent homogeneous regions and the minima correspond to noisy areas or boundary between two regions.

Let H_{V_P} be an histogram computed in the neighborhood V_P of the point P, the Euclidean norm of this histogram is obtained by the equation 1

$$\|H_{V_P}\| = \sqrt{\sum_{i=0}^{N_g} {H_{V_P}}^2(g_i)} \qquad (1)$$

Owing to this norm properties a region growing segmentation method is developed, where the chosen regions seeds correspond to maximal norm's values. Then the growing criterion is based on the correlation coefficient, which represents a similarity measure between two histograms as shown in the equation 2

$$r(H_1, H_2) = \frac{H_1.H_2}{\|H_1\|.\|H_2\|} \qquad (2)$$

$r(H_1, H_2)$ has values from 0 to 1, the more its value is close to 1 the greater is the similarity between textures characterized by H_1 and H_2.

On a SPOT image, information about vegetation behavior is represented especially by XS2 and XS3 SPOT bands (90% of information [6]). Moreover, the Normalized Differential Vegetation Index derived from these two channels (NDVI) by the formula 3, has the advantage to reduce external effects like solar illumination, and soil optical properties, which can affect satellite measures.

$$NDVI = \frac{XS3 - XS2}{XS3 + XS2} \qquad (3)$$

The segmentation algorithm is therefore applied on the Euclidian norm computed from NDVI image and it is described as following:

- **step 1** : Selection, in the non-segmented part of the image, of an access point corresponding to maximal norm value.
- **step 2** : Computation of an histogram of reference H_{ref} in the neighborhood of the found access point, let L_k be its label ($k = 1$ initially).
- **step 3** : Computation of a correlation image between the local and the reference histograms.
- **step 4** : Points with correlation coefficient greater than a given threshold are labeled L_k.

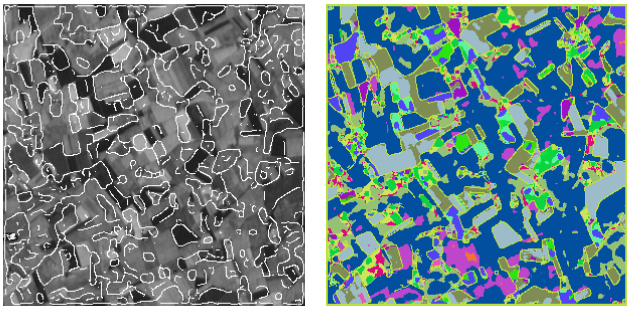

Figure 1: In the left an image of NDVI superposed to the contours of the found regions, at the right the result of segmentation.

- **step 5** : $k = k + 1$, go to **step 1**.

This algorithm tends to merge together regions having similar texture. In addition, it allows the localization of urban areas: because of their heterogeneity, they represent zones composed of very small regions that can be easily detected by applying a threshold on regions size. An example of segmentation result is presented in figure 1. We are currently working on improving it by introducing information brought by the image's contours.

4. LAND COVER IDENTIFICATION

In this section we propose to use temporal information, extracted from NOAA data, in the purpose of refining spatial segmentation obtained on the SPOT image. Thus, fields recognition is the result of combining the segmentation and the reflectances profiles describing the temporal behavior of land covers, as it is depicted in the figure 2.

The identification process is applied separately on each NOAA pixel i. This pixel is segmented into K_i regions of areas s_k ($k = 1, \ \ldots, K_i$). $R_i(t)$ are temporal global reflectances observed on NOAA data. The objective is the estimation of the values $P(k/n)$, probability of a region k to be the land cover n, which is described by its temporal reflectance $\mathcal{R}_n(t)$. $\mathcal{R}_n(t)$ are learned on test sites.

The problem is addressed as a minimization of the function f_i represented by the equation 4:

$$f_i = \sum_t [\sum_{k=1}^{K} s_k [\sum_{n=1}^{N} P(k/n)\mathcal{R}_n(t)] - R_i(t)]^2 \qquad (4)$$

The principle of the minimization process is described in [1, 7]. After performing this minimization on all the NOAA pixels, each region is finally assigned the vegetation type which has maximal probability $P(k/n)$ if it is ≥ 0.5. If all $P(k/n)$ are less than 0.5 decision is considered ambiguous and the region is described in terms of probabilities.

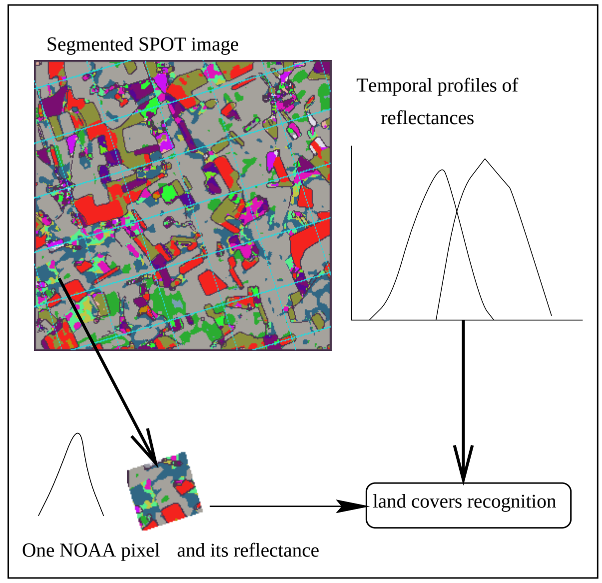

Figure 2: Coupled SPOT-NOAA segmentation.

5. EXPERIMENTAL RESULTS AND DISCUSSIONS

The proposed method is experimented on real data concerning the region of Chartres. Results quality and validity are then discussed. The identification of regions as vegetal species is performed at each NOAA pixel. After the application of this process on the whole image of Chartres, a number of observations are brought out: the NOAA Chartres image contains some "pure" pixels (containing only one land cover type). They are nearly always well identified (see figure 3), except in the case of urban areas. Small regions may be misclassified for three reasons: the first one is related to the pixel composition: if one cultivation occupies a significant part of the pixel (cereals occupy 49.33% of the total surface of Chartres), the smaller regions may be confused with the dominant land cover (see figure 4); the second one concerns the reflectances $\mathcal{R}_n(t)$ used to describe land covers behavior: their estimation is actually inaccurate for marginal cultivations; at last, the precision of the SPOT-NOAA registration is insufficient to study small areas.

So the recognition quality depends on the pixel composition. But because it is difficult to evaluate it in every NOAA pixel we propose to calculate a global recognition rate on all the image of Chartres, keeping in mind that there is a big variation of quality result from one pixel to another. For the major cultivation of the region (cereals), we achieve 62% of correct identification, and a rate of 13.4% representing ambiguous decision (with maximal probability corresponds to the correct land cover but < 0.5). This rate is considered satisfying especially because we are interested

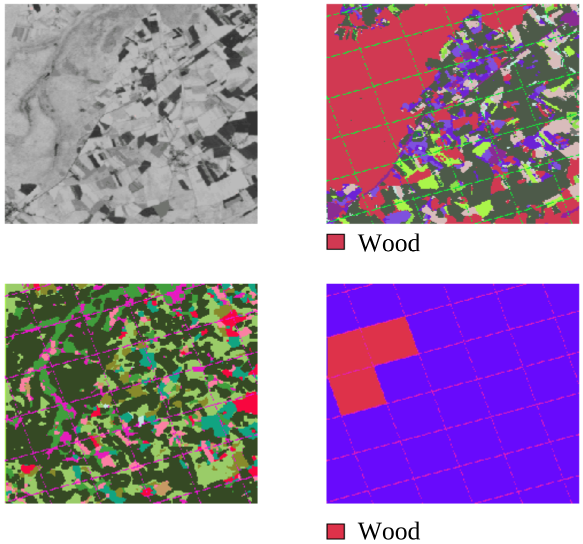

Figure 3: Result obtained on three pure pixels of wood in the region of Chartres ; the first image represents NDVI used for segmentation, the second describes the ground truth, the third image corresponds to SPOT segmentation result and the fourth shows the result of recognition process applied to the three pixels.

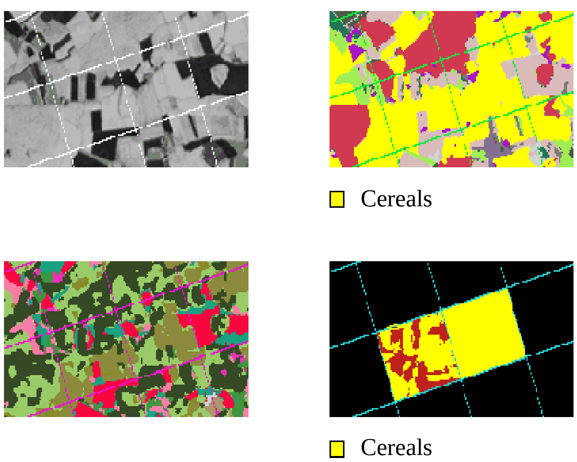

Figure 4: Example of identification result for two heterogeneous pixels containing mainly cereals; the first image represents NDVI used for segmentation, the second describes the ground truth, the third image corresponds to SPOT segmentation result and the fourth shows the result of recognition process applied to the pixels: we observe that all the regions of one of the two pixels (the right one) are identified as cereals though it contains others land covers (according to the land truth)

in studying major cultivations.

6. CONCLUSION

The study described in this paper presents a fusion process which allows the collaboration of temporal and spatial data provided by different sources in order to improve analysis of agricultural regions.

The obtained results by coupling SPOT and NOAA data are promising especially for the major occupation of the studied region. For the less important land covers the recognition rates are still poor. One can however expect results improvements when VEGETATION data are available (expected beginning of 1998). This will improve particularly geometric registration and radiometric calibration.

7. REFERENCES

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