Estimation and monitoring of bare soil/vegetation ratio with SPOT Vegetation and HRVIR

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***Abstract*— Leaving fields with a vegetation cover during the winter is one of the main ways to reduce water pollution, in restricting pollutant fluxes towards rivers. The bare soils/vegetation ratio monitoring can be carried out daily at a coarse spatial resolution with SPOT VEGETATION (1 km), and also at a higher spatial resolution with SPOT HRVIR (20 m), but with less repetitive and spatially more restricted data. Land-cover changes detected at a regional scale with this ratio can be explained by winter vegetation covering changes as well as by influence of climatic events. Therefore, observed changes have to be validated from a local scale analysis. The aim of this study is to develop a method that allows to assess high or low variations detected at a regional scale from SPOT VEGETATION images with data registered at a higher scale, SPOT HRVIR images in our case. In this study, the link between the images of the two sensors is set up from the design of an Artificial Neural Network method based on a Kohonen Self-Organizing Features Map. The originality of this method lies in the use of temporal dimension to solve such a change of scales.**

I. INTRODUCTION

Monitoring of winter land cover is one of the most important stakes for water pollution reduction in intensive agricultural areas. In fact, vegetation covering fields during winters reduces pollution transfers through waterways. Thus, bare soil/vegetation ratio becomes a good farming practices indicator, but this ratio may represents winter land cover variations as well as climatic factor influences when it is expected from large scale remotely sensed data. A local analysis is necessary to validate the large scale estimation of the ratio. Then even if large scale pollution occurs in regions such as Brittany (in west of France), local analysis have to be engaged. Also, local and large scale are the scales of intervention of some institutions (for agriculture or water resources). Decisions of changing land use concern areas from the field to the watershed.

Remote sensors induce the actual precision of winter land use monitoring. SPOT VEGETATION can offer a daily estimation of the ratio bare soil/vegetation at large scale – resolution is 1km a pixel. SPOT HRVIR can also offer an estimation of the ratio, but at a finer scale – 20m a pixel – for smaller regions – 60km a scene – and only once or twice a winter. Then conjonction of fine and coarse resolution has several advantages: to precise at finer scale an observation acquired at a coarse scale and then to understand changes observed at larger scale; to guaranty regular observation and prevent from missing data at key-periods. In this last case, it is necessary to simulate a higher resolution observation from the coarse acquisition, taking into consideration older data to integrate temporal behavior of land cover changes.

The goal of the study is to make an estimation of the finer scale observation that would have to be acquired, giving a large scale acquisition. This local estimation is necessary to explain local abrupt or trend variations of winter land cover, while knowing the only SPOT VEGETATION observation.

II. OVERVIEW OF CHANGE SCALE ANALYSIS

Several algorithms have been proposed in the litterature for processing images acquired by sensors of different scale. Fusion and unmixing methods proved to have limitations when applied to SPOT HRVIR and SPOT VEGETATION images.

Fusion methods are based on the spectral and spatial information to improve characterization of objects. One of those is based on a radometric combination (panchromatic and multispectral). Cliche's, IHS, Brovey's methods or the spotimage P+Xs are of the most famous. Nevertheless, it is considered that those approaches are relevant for visual interpretation since spatial characterization is integrated into the spectral point of view and radiometric distorsion may be significant. Some other methods, such as *ARSIS*, are based on the integration of the structural representation of high resolution image to the low resolution image while radiometric and structural information have been separated with a wavelet transform. Even if this approach may be powerfull, resulting images may not suit a spectral analysis [1]. Also, it does not match the inter-scale ratio (*i.e. 50*) we are facing from SPOT VEGETATION at 1km to SPOT HRVIR at 20m.

Unmixing methods may be though of as desintegration where a coarse pixel has to be characterized with finer elementary components. Images of fine resolution can be use to find spectral signature of those end-members while pixels of the image of coarse resolution have to be decomposed into composition or membership value to the end-members [2]. Those methods (through spectral unmixing or fuzzy C-means) may fit the inter-scale ratio of SPOT VEGETATION and HRVIR. Nevertheless, it is not possible to add the localization of the end-members and then to analyse at finer scale a change detected at coarse scale.

Neuronal methods are of interest in this topic. One of the advantage is the integration of temporal knowledge into a spatially oriented fusion problem. Then, ART nets have been used with success for change detection. Also, ARTMAP appears to be a better alternative than classical unmixing methods [3].

Localization of end-members has been achieved through a Hopfield net by Tatem [4]. This approach does not fit, as is, the inter-scale ratio of SPOT VEGETATION and SPOT HRVIR.

It is proposed in this study to achieve spectral unmixing with localization of end-members by integrating temporal knowledge within a Kohonen self organizing map.

III. The Kohonen map

A. Network design

The Kohonen's self-organizing map consists of a two-dimensional network of neurons arranged on a square grid [5]. Each neuron is connected to its eight nearest neighbours on the grid. The neurons store a set of weights (a weight vector) each of which corresponds to a spectral signature. The overall map corresponds to a pixel of VEGETATION observation while each neuron corresponds to a pixel of HRVIR simulation at a resolution of $20m$. Then, the map is of 50×50 neurons to fit the link between SPOT VEGETATION and SPOT HRVIR resolutions.

Usually, the result of the training is that a pattern of organization emerges in the map. Different units learn to respond to different vectors in the input set, and units closer together will tend to respond to input vectors that are similar to each other. In this application, the organization that will issue from the training will be the expectation of the spectral unmixing joint with the localization of the end-members to link SPOT VEGETATION and SPOT HRVIR resolutions. A cost function E (that may be thought of the energy function to minimize in a Hopfield net [6]) is to be defined to integrate *a priori* knowledge. During the iterative training, each winning neuron $w_t(i_0, j_0)$ is affected in order to minimise the cost function as follows:

$$w_{t+1}(i,j) = w_t(i,j) - \alpha(t)\beta_t(i_0 - i, j_0 - j)\frac{\partial E}{\partial w(i_0, j_0)},$$

where $\alpha(t)$ affects the weightening of the neurons and ensures convergence over iterations t; $\beta_t(\cdot)$ affects the weightening of the neighbourhood of the winning neuron $w_t(i_0, j_0)$.

B. Cost function to minimize

The function E to minimize is defined in order to ensure several conditions:

1) Respect the mixture. The mean of the overall map (the mean $\widehat{w}$ of the neurons $w(i,j), 1 \leqslant i,j \leqslant 50$) has to be as close as possible as the value of the co-located SPOT VEGETATION observation pixel $\mathcal{V}$. E_1 to be minimized is then defined as:

$$E_1 = \left(\widehat{w} - \mathcal{V}\right)^2.$$

2) Make fields homogeneous. An *a priori* knowledge, "*ground truth*" $\mathcal{C}$, has been acquired by field observations for several years. From a thematic point of view, it is more usable to characterize fields with the dominant spectral signature. That is why the winning neuron of position (i_0, j_0) that belongs to the class $n_0 = \mathcal{C}(i_0, j_0)$, E_2 is modify to be as close as possible to the dominant spectral signature $\widehat{w}|_{n_0}$ of the class:

$$E_2 = \frac{1}{\text{card}(n_0)} \sum_{\substack{i,j \\ \mathcal{C}(i,j)=n_0}} \left(w(i,j) - \widehat{w}|_{n_0}\right)^2.$$

3) Use a "*Change Potential*" δ. In the case where the class $\mathcal{C}$ represents roads or buildings, there is no change to expect in our application. Nevertheless, when $\mathcal{C}$ represents bare soil or vegetation, some changes are to be expected. A precise analysis may be achieved fields by fields in order to give a parameter between 0 and 1 that gives the probability for the field to be covered during the winter. More precisely, this change potential is defined for each field as follows:

$$\delta = \begin{cases} 1 & \text{to force estimation to a vegetation field;} \\ \frac{1}{2} & \text{do not interfer in the estimation;} \\ 0 & \text{to force estimation to a bare soil;} \\ -1 & \text{to stop any change.} \end{cases}$$

This constraint affects spectral signatures $w(i,j)$ to a spectral signature $\mathcal{S}_n$ that comes from a bare soil $\mathcal{S}_{\text{bare soil}}$ or a covered field $\mathcal{S}_{\text{covered}}$. Between those two bounds, a spectral signature $\mathcal{S}_n$ has to be defined with respect to δ:

$$\mathcal{S}_n = \begin{cases} 2\delta\, w(i_0, j_0) + (1 - 2\delta)\,\mathcal{S}_{\text{bare soil}} \\ \hfill \text{if } 0 \leqslant \delta \leqslant \frac{1}{2}, \\ (2\delta - 1)\,\mathcal{S}_{\text{covered}} + 2(1-\delta)\,w(i_0, j_0) \\ \hfill \text{if } \frac{1}{2} \leqslant \delta \leqslant 1. \end{cases}$$

Cost function E_3 is then defined as:

$$E_3 = \frac{1 - f(\delta)}{\text{card}(n_0)} \sum_{\substack{i,j \\ \mathcal{C}(i,j)=n_0}} \left(w(i,j) - \mathcal{S}_n\right)^2$$

where $f(\delta)$ is a weightening function that does nothing when $\delta = \frac{1}{2}$ (*e.g.* $f(\delta) = (\sin(\pi\delta))^8$). E_2 is affected the same way by considering $f(\delta)E_2$.

Spectral signatures $\mathcal{S}_{\text{bare soil}}$ and $\mathcal{S}_{\text{covered}}$ are evaluated with older observations of SPOT HRVIR and a selection of the spectral signatures to be considered through their NDVI values.

The training process produces a map where the patterns are organised in order to minimize $E = E_1 + f(\delta)E_2 + E_3(\delta)$ so that the weight vector of the neurones corresponds to the estimation of the mixture of SPOT VEGETATION pixel at the scale of SPOT HRVIR with their localization.

It is understood that only 3 bands out of the 4 of VEGETATION and HRVIR may be considered, *i.e.* 0.61—0.68, 0.78—0.89 and 1.58—1.75μm.

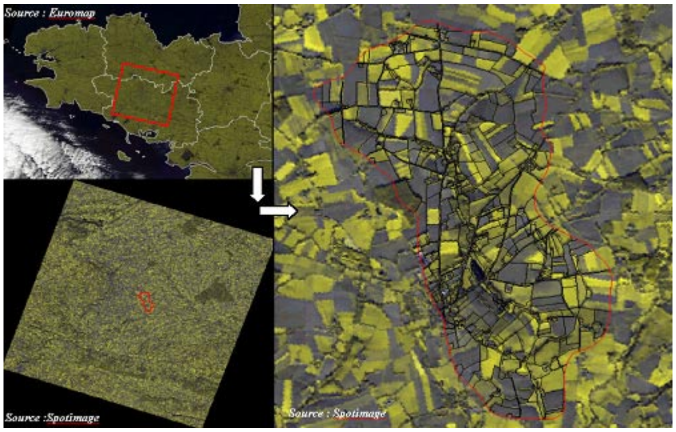
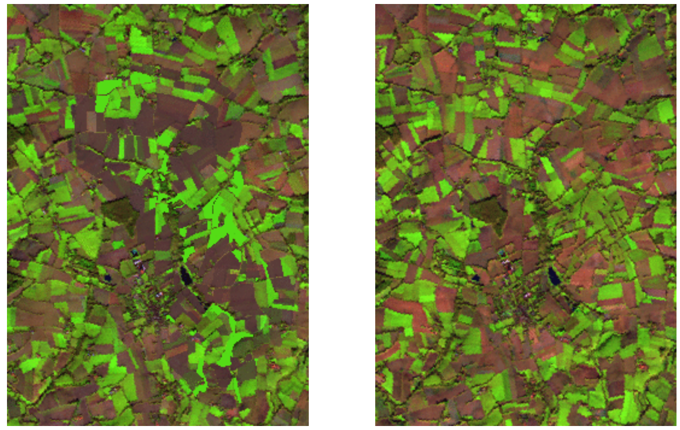


Fig. 1. Localization of the Watershed in Brittany, France.



(a) Estimation of HRVIR for winter 2000–2001

(b) Real SPOT HRVIR observation in winter 2000-2001

Fig. 3. Result of the Mixture estimation and localization by Kohonen's map and comparison with real SPOT HRVIR observation.

IV. Experiments

The analysis has been applied to a watershed (*Coët-Dan*, 1193ha including 1030ha dedicated for farming, located in Brittany, France. Fig. 1) for which land cover and farming activities are studied from several years [7].

For 3 years, data from SPOT VEGETATION and SPOT HRVIR were acquired on winter (from 1999 to 2001). All those data have been spatially corrected and calibrated to reflectance by the mean of 5S.

As shown on Fig. 2, a 5×7 block of the SPOT VEGETATION observation fits the watershed. Each field of the watershed is structurally defined by the ground truth image and associated to a label. This label is used to characterize a change potential for each field. The change potential has been evaluated by considering cultivation during the previous year. In fact, farming activities correspond to given crop rotations.

Mixture estimation and localization results are shown on Fig. 3. This estimation corresponds to the local land cover for winter 2000–2001 at a resolution of 20m, taking into consideration SPOT VEGETATION 1km observation and change potential of each field.

Comparisons with a real SPOT HRVIR observation acquired during winter 2000–2001 proved that the estimation of the mixture by Kohonen and the localization of end-members is relevant. A finer analysis shows that spectral signatures yields by each neuron is similar to the observed data. Then, a local map of NDVI value of each fields may be evaluated with accuracy: by considering SPOT VEGETATION and *a priori* knowledge (*i.e.* cost function $E_1 + E_2$), estimation of bare soil/vegetation at the field scale is accurate at 66%; by considering temporal behavior (cost function $E_1 + f(\delta)E_2 + E_3(\delta)$) the accuracy grows up to 73%.

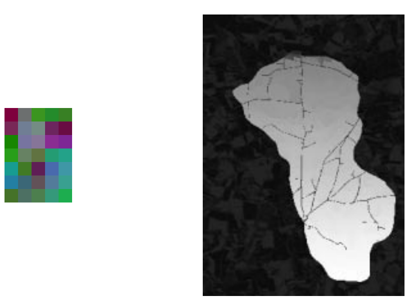


Fig. 2. A priori knowledge: SPOT VEGETATION observation during winter 2000–2001 and ground truth labelling fields of the watershed.

V. Conclusion

The work achieved here is dedicated to explain locally changes of farming land use detected by a coarse scale sensor. The use of the Kohonen map that takes into consideration *a priori* knowledge (that integrates change potential over the time) for training proved to be an interessing alternative for processing images of different resolution. Moreover, an intermediate resolution may help the estimation of bare soil/vegetation ratio during the winter. Several experiments may been achieved with co-located IRS-Wifs observation. Here, Overlapped kohonen maps were used to take into consideration SPOT VETETATION and IRS-Wifs observations.

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