CROP-ROTATION STRUCTURED CLASSIFICATION USING MULTI-SOURCE SENTINEL IMAGES AND LPIS FOR CROP TYPE MAPPING

S. Bailly[1], *S. Giordano*[1], *L. Landrieu*[1], *N. Chehata*[1,2]

1. Univ. Paris-Est, LASTIG MATIS, IGN, ENSG, F-94160 Saint-Mande, France
2 : EA G&E Bordeaux INP / Université Bordeaux Montaigne, France

ABSTRACT

Automatic analysis of Sentinel image time series is recommended for monitoring agricultural land use in Europe. To improve classification capacities, we propose a temporal structured classification combining Sentinel images and former vintages of the Land-Parcel Identification System. Inter-annual crop rotations are learned and combined with the satellite images using a Conditional Random Field. The proposed methodology is tested on a 233 km^2 study area located in France and with a 25 categories national nomenclature. The classification results are globally improved.

***Index Terms*—** Classification, Temporal regularization, Conditional Random Fields, Agriculture, Monitoring, Sentinel.

1. INTRODUCTION

Sentinel image time series exhibit unprecedented characteristics that are perfectly tailored with agriculture monitoring. Spatial resolution of both optical and radar images are very consistent with a parcel-level approach. More remarkably, the high temporal frequency of acquisition (5-6 days) and the fact that this program is at least maintained until 2030 pave the way to chronicle short and long-term evolutions. In Europe, several use-cases for agricultural monitoring with Sentinel images have been proposed [1] such as for example crop monitoring, controlling Common Agricultural Policy (CAP) payments with remote sensing, updating and quality control of the Land Parcel Identification System (LPIS) or precision farming at the farm-level. In the LPIS, the information on the agricultural parcels (cover types and areas) are usually derived from annual declaration by the farmers followed by manual controls by national paying agencies.

In this context, recent studies have assessed the classification accuracy that can be obtained with Sentinel images on agricultural land covers [2, 3, 4, 5]. However, in all of them the nomenclature is restricted to few and most frequent annual crops. Classes known to be challenging to determine with remote sensing such as permanent grassland or permanent crops are not taken into account. Furthermore when a parcel-based approach is used, small parcels are usually ignored ($<$ 250 ha in [4]).

To overcome this issue, we believe that modelling the spatio-temporal structures concerning agricultural parcels in combination with the Sentinel image time series, can lead to significant gains in accuracy with more exhaustive nomenclatures. These structures are of different types and can concern for example (i) the choice of a crop type on a given parcel (annual or multi-annual crop rotations), (ii) local similarities in events (ploughing, seeding or harvesting dates) or (iii) management practices for the parcels belonging to a same farmer. In this paper, we investigate the modelling and the integration in the classification of inter-annual crop rotation information.

Two different approaches can be used to model rotations. The first one consists in using *a priori* agronomist expert knowledge. Several models have been proposed and assessed [6]. However, the models are strongly dependent on the study area and have no adaptation capacity to environmental or agricultural management changes. The second approach is learning rotations as way of overcoming the limitations driven by the expert knowledge *a priori* approaches. The data that can be used for learning are the former versions of LPIS. This method has recently been studied by [7]. Nevertheless, only very few studies have focused on the integration of crop rotation information into classification pipelines. A prediction model based on the Markov logic is proposed by [7]. However, there is no combination with remote sensing observations.

The objective of this paper is then to propose a method to integrate the crop rotation temporal structure into a Sentinel-based classification process and to assess the capacity of the method to improve classification results. The methodology is explained in Section 2, the experimental set-up (study area and datasets) along with result analysis are proposed in Section 3. Conclusions are drawn in Section 4.

2. METHODOLOGY

The classification method proposed is made up with a data term (Section 2.1) combined with a Conditional Random Fields (CRF) for temporal structured prediction (Section 2.2).

2.1. Parcel-based multi-source and multi-temporal classification

The data term is obtained with common state-of-the art methods. Sentinel images were automatically downloaded from the French national mirror *Peps* [8] (Sentinel-1) in the Ground Range Detected (GRD) format and from the national downstream service *Theia* [9] (Sentinel-2) in ground geometry and calibrated in Top of Canopy (TOC) reflectance. Dual polarisation GRD Sentinel-1 images were first calibrated to σ_0 radar backscattering coefficient. Orthorectification is performed using the SRTM digital terrain model and the georeferencing information supplied with the GRD files. The speckle is slightly removed using a simple 5×5 Lee filter [10]. An extra radar feature ($\frac{\sigma_{0_{VH}}}{\sigma_{0_{VV}}}$) is computed. This ratio is known as being more independent to the slope and moisture content effects of each agricultural parcel [11]. For optical images, the missing data (clouds) are filled in using provided cloud masks with a multi-temporal spline interpolation. Average and standard deviation of these 3 radar channels and the 10 optical reflectance bands are then computed for each date of the satellite time series for each agricultural parcel geometry of the LPIS. At the parcel-based level, a Random Forest classifier is used. Decision tree votes are gathered to model the data term probabilities $p(y_n|x_n)$ of Equation 2, y_n being the agricultural classes considered and x_n the parcel-based multi-source and multi-temporal time serie features.

2.2. Temporal-structured classification of parcels

In order to model the temporal structure of the crop rotations, we used the graphical model given in Figure 1. This first order Markov chain can be generalized to greater orders. However, because of the specifications of LPIS data, only the first order has been applied and assessed in this paper. Indeed, the LPIS are known at the parcel-block level (i.e. a group of contiguous parcels with the same operator but possibly different land covers) before 2015. The agricultural parcel class of a given n year is modeled by a random variable Y_n. We consider this variable only influenced by the previous year variable Y_{n-1}. The satellite observations of each n year X_n are taken into account with a Conditional Random Field (CRF).

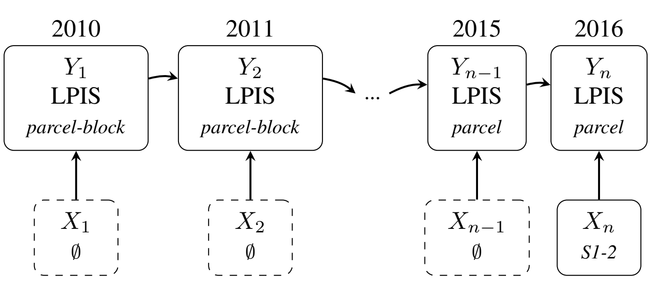

Fig. 1. Conditional Random Field.

With such a modelling and under the hypothesis of the independance between transitions Y_n and observations X_n, the factorisation of the graphical model given in Figure 1 can be written with Equation 2.

$$p_\theta(\mathbf{y}|\mathbf{x}) \propto p(y_1) \times p(y_1|x_1) \times \prod_{i=2}^{n} \left(p(y_i|y_{i-1}) \ \times \ p(y_i|x_i)\right) \tag{1}$$

Nevertheless, the use of $X = \{X_1, X_2, ..., X_{n-1}\}$ in dashed line in Figure 1 is not necessary. The former LPIS versions give a robust knowledge of the realization of the random variables $Y = \{Y_1, Y_2, ..., Y_{n-1}\}$. Indeed, errors concerning crop types in the initial declaration by farmers are in minority and furthermore this information is thereafter controlled by National Paying Agencies. Therefore, we propose a simpler form given in Equation 2. The data term is estimated with the Random Forest method (Section 2.1) and a temporal structure term $p(y_n|y_{n-1})$ is necessary.

$$p_\theta(y_n|x_n, y_1, \ldots, y_{n-1}) \propto \underbrace{p(y_n|y_{n-1})}_{\text{temporal structure}} \ \times \ \underbrace{p(y_n|x_n)}_{\text{data term}} \tag{2}$$

To estimate the regularization term $p(y_n|y_{n-1})$, we learn a transition matrix $\widehat{M}$ built up with a series of parcel-block LPIS. An hypothesis of spatio-temporal homogeneity of the parcels is considered. Only geometrically stable and pure in terms of land cover parcel-blocks are used. Equation 3 shows how to estimate the $p(y_n|y_{n-1})$ with past agricultural land cover transitions.

$$\begin{gathered}\widehat{M_{k,l}} = \frac{n_{k,l}}{n_k} \\ \text{with } n_{k,l} \text{ the number of transitions } k \rightarrow l \text{ (for all parcels of all} \\ \text{years considered) and } n_k \text{ the number of occurences of the} \\ \text{agricultural class } k \text{ (for all the parcels of the n-1 first years)}\end{gathered} \tag{3}$$

3. RESULTS

3.1. Experimental Set-up

The method has been tested on a 233 km^2 study area located 60 km at the East of Paris. A national 25 classes land cover classification was used to estimate the transition matrix of Equation 3 on a French department administrative area (5 915 km^2). 36 891 geometrically stable and pure in terms of land covers parcel blocks contribute to the estimation of the $\widehat{M}$ matrix.

As for the data term, only the land cover classes present on the study area were learned. This agricultural classes and the number parcels considered are *Corn* (350 parcels), *Barley* (158), *Other Cereals* (889), *Rape seed* (85), *Protein (peas)* (76), *Fiber plants* (76), *Forage crops* (46), *Permanent grassland* (725), *Fruit trees* (30), *Vegetables (131)*. These classes are categories and can possibly gather a large number of agricultural land covers (16 different classes for *Other Cereals*) on the department area. The average area of the parcels on the study area is 4.5 ha with high standard deviation ($\sigma = 6.5$ ha). The 2016 parcel-based LPIS has been used for training and validation of the data term.

Table 1 gives the number of features used for the estimation of the data term. Sentinel-2 acquisition technical problems on the particular orbit covering the study area had limited the amount of optical images available.

	Sentinel-1 (radar)	Sentinel-2 (optical)
Number of dates	85	12
Features per date	6	20
Total	509	240

Table 1. Features used for the estimation of the data term.

Table 2. Global classification metrics after 10 iterations.

Configuration	Overall Accuracy *OA*	Unweighted F-score *F-score*	Weighted F-score *F-score-w*
Unstructured			
Radar	0.892	0.734	0.878
Optical	0.824	0.624	0.809
Radar+Optical	0.890	0.744	0.885
Structured			
Radar	0.919	0.776	0.911
Optical	0.870	0.675	0.853
Radar+Optical	0.916	0.762	0.906

In the following a configuration named **unstructured** corresponds to the results of the parcel-based classification. The Random Forest was trained with 100 decision trees using all aggregated attributes from Table 1 and a maximum depth of the trees of 15. Then a second configuration called **structured** in the rest of the paper corresponds the product of the two probabilities defined in Equation 2 for classification. The 2015 parcel-based LPIS was needed to determine the necessary previous land cover observed on a parcel. 5 years (2010-2014) of the parcel-block LPIS were used for the estimation of the transition matrix. For the unstructured and temporal structured classification, 50% of the parcels were used for training and 50% for validation, and the results proposed are the average of 10 iterations.

The classification was assessed with global metrics (overall accuracy (OA), weighted (*F-score-w*) and unweighted *F-score* by the number of samples of each classes) and per-class metrics (F-score, recall and precision).

3.2. Result analysis

The transition matrix estimated contains very relevant information. For instance, strong inter-annual crop rotation are observed. The probability to grow *Other Cerals* (common wheat) after *Rape seed* is 97.09% or *Protein (peas)* to *Other Cereals* (94.85%). The permanent grassland remains stable (94.45%), such as permanent crops like *Fruit trees* (83.65%).

Table 2 shows the global results after 10 iterations. The results are proposed only with the radar features or the optical features (Table 1) or with their aggregation. Taking into account the temporal structure improves all the global metrics for all the feature configurations. In *OA*, we observe a gain of $+2.7\%$ for the radar configuration, $+4.6\%$ for the optical and $+2.6\%$ for the combined optical and radar one).

However the improvement of classification accuracy is not homogeneous for the different agricultural classes. Table 3 evaluates the effect of taking into account the temporal structure on each class, with the optical and radar features.

First, we can notice that there is a strong improvement on the stable over time agricultural classes such as *Permanent grasslands* (+8.7% in F_score) and *Fruit trees* (+93% in F_score). Almost all the *Fruit trees* validation samples were classified as *Permanent grasslands* in the unstructured configuration. The temporal structure is also useful to separate classes that have similar data terms. This is for example the cases for *Forage crops* (+70.5% in F_score) and *Permanent grasslands*. These two classes are very similar in the optical and radar features. As a result, *Forage crops* are almost for the most part classified as permanent grasslands. The temporal structure enables to make the distinction.

Then, for annual crops that are used with regular rotation patterns, the class metrics are improved. (*Protein (peas)* (+0.4%), *Rape seed* (+1%), *Other Cereals* (+0.7%). However, when the transitions are less respected by farmers, the temporal structure can cause a loss in the classification accuracy. This is the case for *Corn* (-6.3%) or *Barley* (-8.2%). For the *Barley* class, the decrease (Recall) is partially due to the misclassification of the *Fiber Plants* class. For *Corn* and *Barley* the decrease could be explained by the fact that these crops are used in 3-years rotation, a structure that the 1st-oder Markov chain can not capture completely.

Finally, there is a major drawback with the *Fiber plants* class (-97.4% in F_score). For that particular case, the data term is reliable (97.4% in F-score) and after temporal regularization almost all the *Fiber plants* are classified as *Barley*. The result could be explained by the fact that there is a very small amount of geometrically stable *Fiber plants* on the area. The strong general transition rule learned for the *Fiber plants* could not be useful for those specific parcels.

4. CONCLUSION

In conclusion, we proposed a framework to take into account the crop rotation temporal structure in the classification. The classification is globally improved. The method is based on learning both data term and temporal structure. As a result, it can be easily applied to other areas. Indeed, the LPIS are produced at national scale each year. Results have however to be produced on numerous and diverse areas. Several im-

Table 3. Effect on temporal structure on Class Metrics

Class	F-score	Recall	Precision
	Unstructured		
Corn	0.941	0.929	0.953
Barley	0.898	0.937	0.862
Other cereals	0.947	0.956	0.9378
Rape seed	0.959	0.975	0.944
Protein	0.949	0.932	0.968
Fiber plants	0.974	1	0.950
Forage crops	0	0.1	0
Permanent grasslands	0.868	0.814	0.930
Fruit trees	0.010	0.090	0
Vegetables	0.895	0.914	0.877
Class	**Structured**		
Corn	0.878	0.831	0.935
Barley	0.816	0.785	0.849
Other cereals	0.954	0.941	0.968
Rape seed	0.969	0.985	0.954
Protein	0.953	0.967	0.939
Fiber plants	0 0	0.1	0
Forage crops	0.705	0.778	0.648
Permanent grasslands	0.955	0.943	0.967
Fruit trees	0.940	1	0.892
Vegetables	0.451	0.970	0.297

provement of the method can be proposed. Greater order of the Markov chain could be tested in the future with the upcoming parcel-based versions of the LPIS. Other structures could also be modeled such as spatial relationship between parcels.The exhaustiveness and the few mistakes contained in the LPIS give valuable label information. The approach proposed is this paper will be tested in prototype of operational systems. In this article we only assessed the effet of temporal structure after 1-year of satellite observations. The objective would be to apply the method to partial time series to propose a pre-filled LPIS declaration for the farmers

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