# LAND-COVER MAPS FROM PARTIALLY CLOUDY MULTI-TEMPORAL IMAGE SERIES: OPTIMAL TEMPORAL SAMPLING AND CLOUD REMOVAL

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## 1. PROBLEM POSITION

In the coming years, several optical space-borne systems with high temporal frequency revisit will be launched: Venus, Sentinel-2. Formosat-2 is already providing this kind of data. The availability of these data opens the opportunity for the development of new applications which need to closely follow the temporal trajectory of the characteristics of land surfaces. In our case, we are interested in deriving land cover and change information for agricultural areas. We aim at providing near real-time classifications of crop types, soil and crop states as well as agricultural practices. One of the main difficulties for obtaining a dense time sampling with optical remote sensing data is the presence of clouds. Clouds and their shadows hide or distort the measure by the sensor, thus making it impossible to properly estimate the crop parameters of interest.

In order to overcome this difficulty, one can acquire the maximum number of images allowed by the satellite revisit in order to maximize the chances of getting cloud-free images during key phenological periods. On the other hand, the satellite tasking and data acquisition have a high cost and therefore the number of acquisition attempts should be reduced. Also, a lower number of images implies a reduced computing burden.

In this paper we will study how temporal sampling can be optimized in order to fulfill the above-mentioned goals. We will also analyze the impact of cloudy data in terms of crop classification accuracy. Finally we will assess the use of cloud removal techniques as a pre-processing step for the land cover map production.

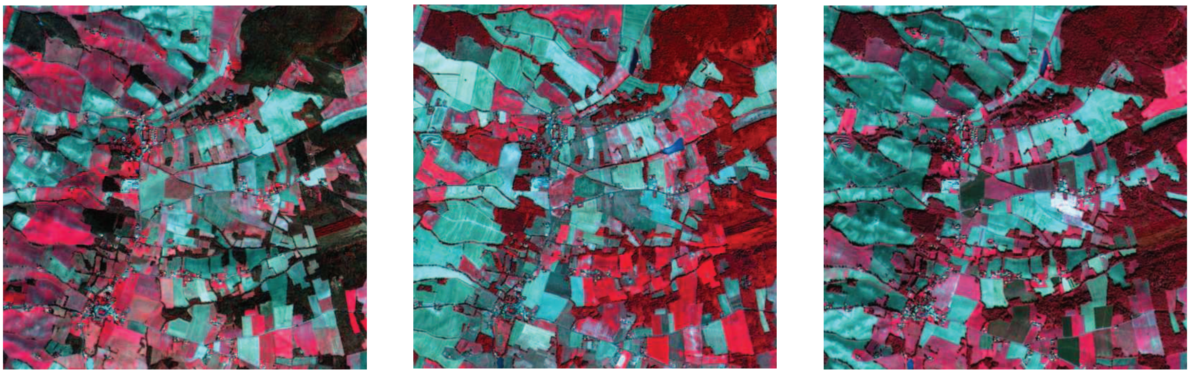
## 2. TEST SITE

A very rich data set is used for the assessment and validation tasks carried out in this work. The test site is located in the South-West of France, near Toulouse and covers an area of 500 km2 presenting 24 thematic classes described below.

A series of 49 Formosat-2 images during the period going from February to November 2006 are available. The images have a size of 4000× 4500 pixels and have been ortho-rectified with a 8 m. ground sampling distance. They have 4 spectral bands (blue, green, red and near infra-red). Three images of the series are presented in figure 1.

Several kinds of reference data will be used in this work. First of all, cloud masks are available for each image in the series allowing us to select or reject some dates depending on cloud cover. We will also use these data as classification feature. There is also available a ground truth over 1764 agricultural plots, which adds up to about 80 km2. These ground truth is available for most dates of the temporal series and gives the phenological state and the thematic class for each region. Only the thematic class will be used for this work. There is a total of 24 classes, which are then grouped into 14 and 5 classes later on, so different levels of thematic detail can be studied and assessed. See table the following table for the detailed nomenclature.

| 24 classes | 14 classes | 5 classes |
|---|---|---|
| broad-leaf forest | forest 1 | forest |
| poplar | forest 1 | |
| needle-leaf forest | forest 2 | |
| eucalyptus | | |
| wheat | wheat | agricultural |
| rape | rape | |
| barley | barley | |
| corn | corn | |
| corn 2 | corn | |
| sunflower | sunflower | |
| sorghum | sorghum | |
| soybean | soybean | |
| peas | peas | |
| fallow | low vegetation | |
| wild-land | low vegetation | |
| temporary pasture | low vegetation | |
| permanent pasture | low vegetation | |
| river | water | water |
| lake | | |
| tune | | |
| dense built-up | built up | built up |
| industrial area | | |
| fuzzy built-up | | |
| mineral surface | | |



(a) March 14, 2006 (b) July 7, 2006 (c) November 2, 2006

**Fig. 1**. Example of image data.

## 3. WHAT CAN BE DONE

This work is a part of a more complete study about the choice of features for classification, the optimization of the land cover map production, the comparison of pixel-level versus object level classification approaches. In this paper we will concentrate on the temporal sampling, the cloud removal and the use of cloudy data in the classification process.

### 3.1. Optimal temporal sampling

As stated above, the goal of the temporal sampling analysis is two-fold:

1. Concentrate the image acquisitions in the optimal periods for crop class discrimination.

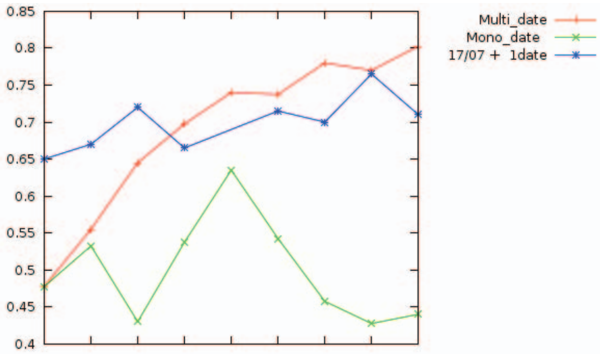
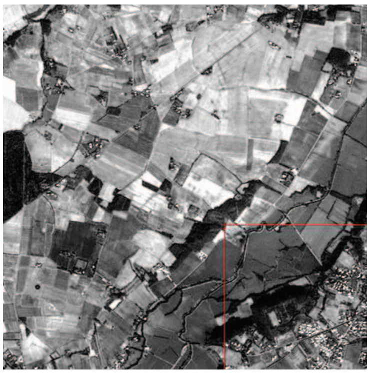
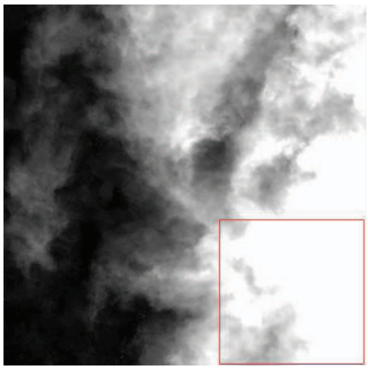


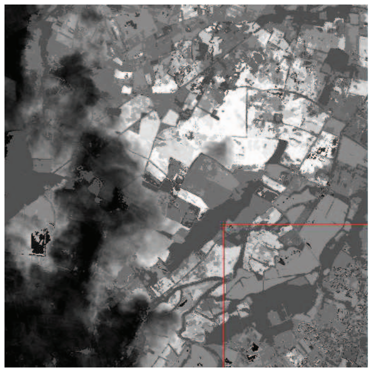

**Fig. 2**. Classification accuracy and temporal sampling.



(a) Cloud free



(b) Cloudy



(c) Cloud removal

**Fig. 3**. Example of cloud removal.

2. Reduce the number of data in order to optimize cost and processing burden.

In order to assess the quality of the several sampling strategies analyzed in this work, we will use the kappa coefficient – definition – as a quality metric. Details on the classifier setup will be given in the final paper.

In order to set the ground for further comparisons, we will proceed as follows:

1. We will select a cloud-free image per month, that is, 9 images
2. We will perform the classification on each image alone. This will give us 2 types of information:
   (a) Which is the reference performance of the classification (lower bound)
   (b) Which are the periods which are more informative with respect to the classes of interest
3. We will perform an online classification: for each date, all previous dates are also used for the classification
   (a) This allows to integrate the crop temporal trajectory as additional information for the classification
   (b) Classification accuracy will increase with time
   (c) This gives an upper bound of the accuracy which can be obtained by sub-sampling the temporal series

Given these 2 bounds (lower and upper) for the classification accuracy of a multi-temporal series, we will try to find temporal sampling strategies that maximize the accuracy and simultaneously minimize the number of images used. As an example, figure 2 shows the results obtained by using the most informative image in the single-date case (reference classification result) together with another image of the time series. The results show that, if carefully chosen, 2 images can yield the same accuracy that that obtained using the full temporal series. Other strategies will be presented in the final paper.

### 3.2. Cloud removal

As stated above, the presence of clouds in the images hides the observation of the ground. In order for the classification algorithms to perform correctly, one can assume that the hidden information can be reconstructed by trying to impose temporal regularity constraints on the missing data. One simple way of doing that is to apply temporal interpolation assigning values to the cloudy pixels. Yet simple to implement, this approach lacks physical soundness and might even yield strange behaviors when a given pixel is cloudy in adjacent dates. In our work we have used the approach proposed by [1] which has been successfully applied to MODIS data. This cloud-removal procedure is based on neural learning and allows to take into account, not only the time series for the cloudy pixel, but also the temporal series of pixels which have a similar behavior to it. Figure 3 presents an example of cloud removal using this approach. The final paper will also present the parameter setting optimization needed in order to adapt the original work on MODIS data to higher resolution images.

### 3.3. Using cloudy data

One can argue that using temporal interpolation, even with sophisticated approaches, generates information which is not present in the original data. Therefore we have also investigated several strategies for using images which are not cloud-free in the learning and classification steps. Three main strategies have been compared in the case where :

1. Reject the cloudy pixels
2. Use the cloudy pixels and add the cloud mask as attribute
3. Use all pixels without distinction

The first strategy is the most straightforward, but implies loosing even the cloud-free dates for a pixel which might be cloudy only a few times in the temporal series.

The second strategy uses all the available information, but adds the cloud mask information for each date, therefore flagging the cloudy pixels as not reliable for the cloudy dates.

The third strategy does not need any external information, as for instance the cloud masks, and it might suffer from outliers introduced in the learning by the cloudy pixels.

The following table summarizes the results of one of the experiments. 3 scenes with a different amount of cloudy pixels have been used. For each one of these scenes, the 3 strategies have been applied and the kappa coefficient result is reported in the table.

| Cloud-free pixels | 70% | 58% | 15% |
|---|---|---|---|
| Reject masked | 0.90 | NA | NA |
| Mask as attribute | 0.91 | 0.91 | 0.80 |
| Use all pixels | 0.90 | 0.89 | 0.83 |

First of all, one can conclude that the 3 strategies are very similar when the amount of cloudy pixels is low.

As one can see, rejecting the cloudy pixels in the learning step may induce the loss of some of the regions of the image, and therefore the impossibility to perform learning since some classes are lost.

The use of the mask as a classification attribute yields the best classification results, except for the most cloudy scene, where the estimation of the cloud mask might be less reliable.

Finally, it is very interesting to note that using all pixels without distinction, yields results which are very close to the best ones having the advantage of not needing to have the cloud masks. It is well known that SVM (which is the classifier used here) is robust to the presence of outliers in the training data. That seems to be verified here.

## 4. EVALUATION METHODOLOGY

The final paper will present the detailed evaluation methodology, the experimental setup and the main results of this study.

## 5. REFERENCES


[1] B. Abdel Latif, R. Lecerf, G. Mercier, and L. Hubert-Moy, ," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 46, no. 7, pp. 2083–2096, July 2008.