Sentinel-2 Agriculture

Design Definition File

Algorithm Theoretical Basis Document for L4 dynamic crop mask product

Milestone	Milestone 2
Version	1.1
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Table of recorded changes

Issue record sheet

Issue/Rev.	Date	Reason
1.0	19/04/2015	1st version for ESA
1.1	13/01/2016	Modifications applied in the gap filling and smoothing step of the crop mask without in situ data imply an adjustment of the ATBD.

Detailed record sheet

From version 1.0 to 1.1

RID	Section	Problem description	Change
/	1.		Modification of the Flowchart (Figure 1-1.) and his text description. Both crop mask (with and without in situ data) have now a different gap filling step.
	2.1		In the previous release, the gap filling was a common step. Previous section 2. is now incorporated in the former section 3. as section 2.1.
	3.1.		The smoothing of the data is now joined to the gap filling step using the Whitaker filter. Processing details added.

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1 Logical model

The classification process transform the L2A_R imagery into a 1/0 mask, 1 indicating the presence of cropland and 0 the presence of non-cropland.

The processing chain is run by tiles.

The processing chain can run in two different modes, depending if the user counts with field data for training the classifier or not:

- If the user has field data to train the algorithm, an extensive number of features related to the NDVI, the NDWI profiles and the brightness will be extracted from the imagery time series for feeding a supervised algorithm based on a Random Forest (RF) classifier;
- If there is no field data, training samples will be selected from an existing reference map (local/regional/global land cover map, crop mask, etc.) through an iterative trimming. These samples will be used to feed the same supervised algorithm than in the first case (i.e. based on a RF classifier) but this classifier will here be fed by reflectance values coming from determinate moments of the growing cycle.

The principal steps of the classification process are schematized in Figure 1-1.

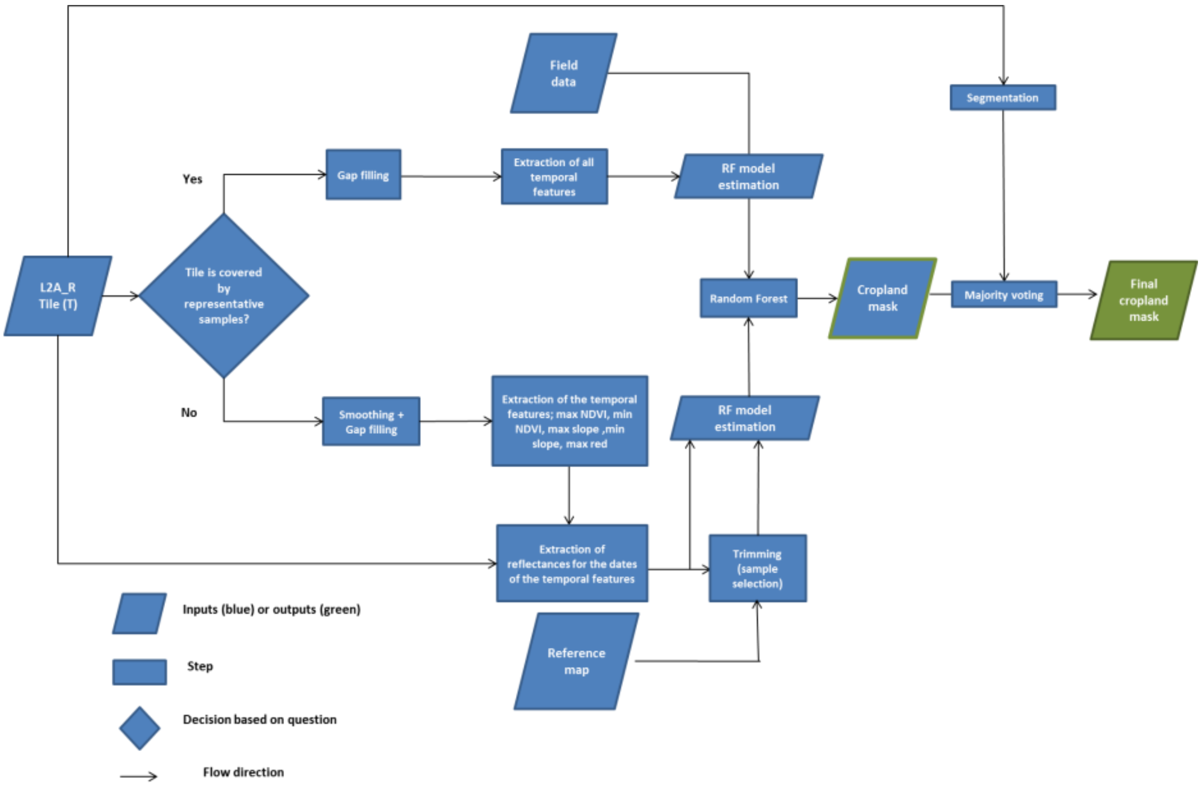

Figure 1-1. Flowchart of the processing chain developed to generate the cropland mask

Two steps are common for the 2 modes:

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- the supervised algorithm based on the RF classifier;
- the a posteriori filtering of the cropland mask.

The next sections of the document present in detail all the steps of the processing chain, distinguishing between the 2 modes and highlighting the common ones.

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2 Mode based on in-situ data

The processing chain to run when field data exist is illustrated in Figure 2-1, which must be interpreted from left to right. This flowchart can be easily divided in three main tasks: the feature extraction, the classification and the post-filtering step. The post-filtering step is common with the "no field data module" and will thus be detailed later, in section 4. All other steps are detailed in this section.

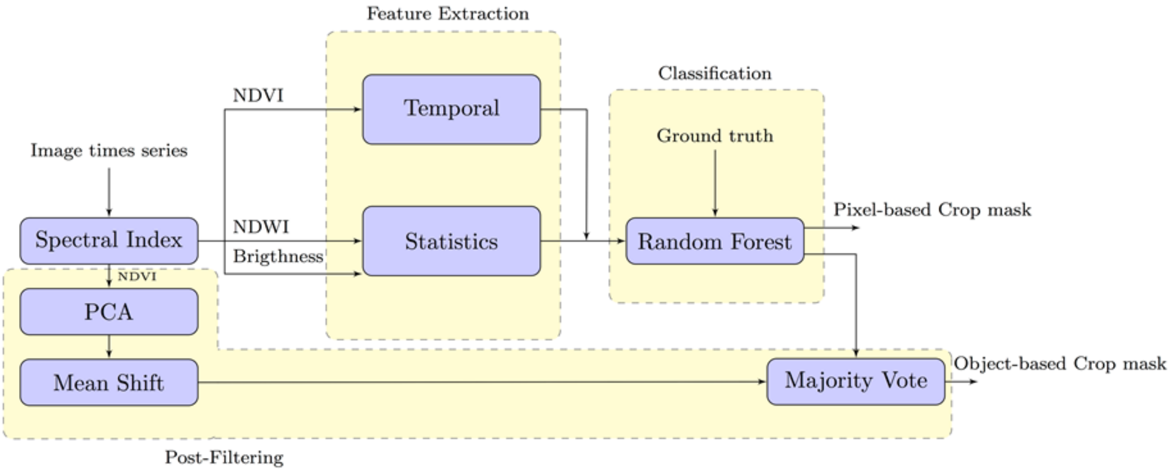

Figure 2-1. Flowchart describing the processing chain when field data exists

<u>Input Data</u>

The reflectance image times series that don't contain gaps (i.e. the output of the preliminary step detailed in section 2.1.).

As shown in Figure 2-1, the input data will be used in the first purple block whose name is *Spectral Index*. This task corresponds to the computation of three spectral indices: the NDVI, the NDWI and the Brightness index.

<u>Output Data</u>

The pixel-based crop mask product will be the output of the processing chain.

2.1 Preliminary step : gap filling

The goal of the gap filling is to produce a reflectance image time series which is gap-filled with respect to missing data (identified thanks to the "validity masks" which contain clouds, cloud shadows and saturated pixels). The workflow of the gap filling is illustrated in Figure 2-2.

Figure 2-2. Gap filling workflow

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The gaps are filled by using the same linear interpolation method presented in Section 2.3.2 of the ATBD crop type document and is therefore no more recalled here. For this method, the cloud mask image times series needs to be used.

Input data: the original image times series

Output data: the gap filled image time series.

2.2 Pre-processing: spectral indices computation

The pre-processing workflow is illustrated in Figure 2-3, resulting in the three spectral indices: NDVI, NDWI and Brightness. This step is based on the algorithm presented in detail in Section 2.3.3 of the ATBD crop type document and is therefore no more recalled here.

Figure 2-3. Pre-processing workflow, computing NDVI, NDWI and Brightness indices

2.3 Feature extraction step

Three different indices have been generated: the NDVI, the NDWI and the Brigthness. These indices are used in order to compute different features: temporal features (see sub-section 2.3.1) and statistic features (see sub-section 2.3.2).

17 temporal features are derived from the NDVI. Concerning the other two spectral indices, 5 statistics features are computed for each of them. In total, 27 features are computed, which are concatenated as a vector image (see sub-section 2.3.3) to be used in the subsequent classification step (that will be detailed in section 2.4).

2.3.1 Temporal features

The workflow developed to generate temporal features is illustrated in Figure 2-4.

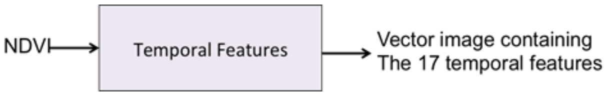

Figure 2-4. Temporal features generation workflow

Input data: the full gap filled NDVI times series

Output data: a vector image made of 17 channels, one for each temporal feature

Available code: a C++ code compatible with OTB has been developed.

The different features are described below.

- **Global features**

These features characterize the global trends on NDVI times series. The three features detailed Table 2-1 are computed.

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Notation	Description	Equation
$\mathbf{x_{max}}$	Maximum NDVI value	$\max_i x(t_i) = \{ x(t_i) \mid \forall j : x(t_j) \leq x(t_i)\}$
$\mathbf{x_{mean}}$	Mean NDVI value	$\frac{1}{T}\sum_{j=1}^{T} x(t_j)$
$\mathbf{x_{std}}$	Standard deviation NDVI value	$\sqrt{\frac{1}{T}\sum_{j=1}^{T} (x(t_j) - x_{mean})^2}$

Table 2-1. Global features description

Parameters:

- x(ti) corresponds to the NDVI value at instant ti.
- T is the length of the NDVI times series
- mean is the mean NDVI value computed by using the T values

- **Features detecting largest local NDVI transitions**

These features describe the difference between consecutive windowed NDVI values. They are presented in Table 2-2. The goal is to detect the largest transitions corresponding to the greenness and the senescence onset periods.

Notation	Description	Equation
$\mathbf{x_{Dif-max}}$	Maximum NDVI difference found in a slicing temporal neighborhood having a size w (default value w=2).	$\max_i \frac{1}{w}\sum_{j=i}^{i+w-1} x(t_j) - \frac{1}{w}\sum_{j=i+w}^{i+2w-1} x(t_j)$
$\mathbf{x_{Dif-min}}$	Minimum NDVI difference found in a slicing temporal neighborhood having a size w (default value w=2).	$\min_i \frac{1}{w}\sum_{j=i}^{i+w-1} x(t_j) - \frac{1}{w}\sum_{j=i+w}^{i+2w-1} x(t_j)$
$\mathbf{x_{Dif-Dif}}$	Difference between $\mathbf{x_{Dif-max}}$ and $\mathbf{x_{Dif-min}}$ value estimating the transition jump	$\mathbf{x_{Dif-max}} - \mathbf{x_{Dif-min}}$

Table 2-2. Description of features detecting largest local NDVI transitions

Parameters:

- x(ti) and x(tj) correspond to the NDVI values at instants ti and tj.
- w is the size of the slicing temporal window used to compute the differences

- **mbiFeatures associated to the maximum NDVI value:**

These features are associated to the area containing the maximum NDVI value, as identified in Figure 2-5. The features are described in Table 2-3.

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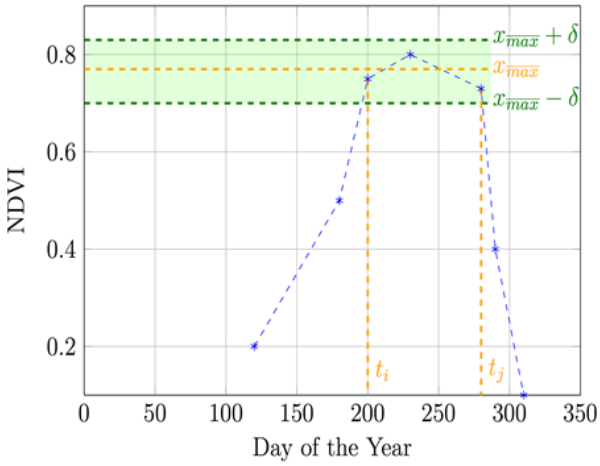

Figure 2-5. Maximum NDVI values identification from a full NDVI time series

Notation	Description	Equation
$\mathbf{x_{\overline{max}}}$	Maximum mean NDVI value found in a slicing temporal neighborhood having a size w (default value w=2).	$\max_i \frac{1}{w} \sum_{j=i}^{i+w-1} x(t_j)$
$\mathbf{x_{\overline{max}-Lg}}$	It estimates the length of the flat zone containing the peak area associated to $x_{\overline{max}}$ value.	$\max_{j,i} t_j - t_i =$ $\{\forall k \in [i,j] \mid x_{\overline{max}} - \delta \geq x(t_k) \leq x_{\overline{max}} + \delta\}$
$\mathbf{x_{\overline{max}-Sur}}$	It estimates the surface of the flat zone area containing the peak value associated to $x_{\overline{max}}$	$x_{\overline{max}-Lg}\ x_{\overline{max}}$

Table 2-3. Maximum NDVI features description

Parameters:

- x(ti) and x(tj) correspond to the NDVI values at instants ti and tj.
- w is the size of the slicing temporal window used to compute the differences
- delta δ parameter is a user threshold, whose default value is equal to 0.05. In order to estimate the surface, a rectangular shape has been considered.

- **Features associated to the greenness onset**

These features are associated to the largest increasing period of the NDVI function. As it can be seen in Figure 2-6, the greenness onset period is highlighted in orange. These temporal features are subject to the next constraint :

$$\{\forall k \in [i,j] \mid x'(t_k) \geq 0\}$$

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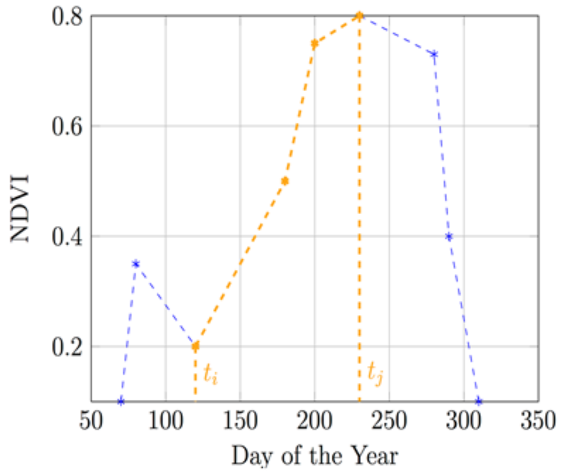

Figure 2-6. Identification of the largest increasing period in a full NDVI time series

Table 2-4 describes the features associated to the greenness period. In order to estimate the surface, a triangular shape has been considered.

Notation	Description	Equation
$\mathbf{x_{Pos-Sur}}$	It estimates the maximum surface of the first positive derivative period	$\max_{j,i} \frac{(x(t_j)-x(t_i))(t_j-t_i)}{2}$
$\mathbf{x_{Pos-Lg}}$	It estimates the length of the first positive derivative period associated to $\mathbf{x_{Pos-Sur}}$ value.	$t_j - t_i$ subject to $\operatorname{argmax}_{t_i,t_j} \frac{(x(t_j)-x(t_i))(t_j-t_i)}{2}$
$\mathbf{x_{Pos-Rt}}$	It estimates the rate of the first positive derivative period associated to $\mathbf{x_{Pos-Sur}}$	$\frac{x(t_j)-x(t_i)}{t_j-t_i}$ subject to $\operatorname{argmax}_{t_i,t_j} \frac{(x(t_j)-x(t_i))(t_j-t_i)}{2}$

Table 2-4. Greenness period features description

<u>Parameters:</u>

– x(ti) and x(tj) correspond to the NDVI values at instants ti and tj.

- **Features associated to the senescence onset:**

These features are associated to the largest decreasing period of the NDVI function. They are presented in Table 2-5

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Notation	Description	Equation
$\mathbf{x}_{\mathbf{Neg-Sur}}$	It estimates the maximum surface of the first negative derivative period	$\max_{j,i} \frac{(x(t_i)-x(t_j))(t_j-t_i)}{2}$
$\mathbf{x}_{\mathbf{Neg-Lg}}$	It estimates the length of the first negative derivative period associated to $\mathbf{x}_{\mathbf{Neg-Sur}}$ value.	$t_j - t_i$ subject to $\operatorname{argmax}_{t_i,t_j} \frac{(x(t_i)-x(t_j))(t_j-t_i)}{2}$
$\mathbf{x}_{\mathbf{Neg-Rt}}$	It estimates the rate of senescence of the first negative derivative period associated to $\mathbf{x}_{\mathbf{Neg-Sur}}$	$\frac{x(t_i)-x(t_j)}{t_j-t_i}$ subject to $\operatorname{argmax}_{t_i,t_j} \frac{(x(t_i)-x(t_j))(t_j-t_i)}{2}$

Table 2-5. Senescence onset features description

<u>Parameters:</u>

– x(ti) and x(tj) correspond to the NDVI values at instants ti and tj.

- **Features characterizing bare soil transitions**

These features detect if there is a transition between the bare soil before the greenness onset or after the senescence onset. Bare soil transition is illustrated in Figure 2-7 and corresponding features are given in Table 2-6. The resulting value is 0 or 1.

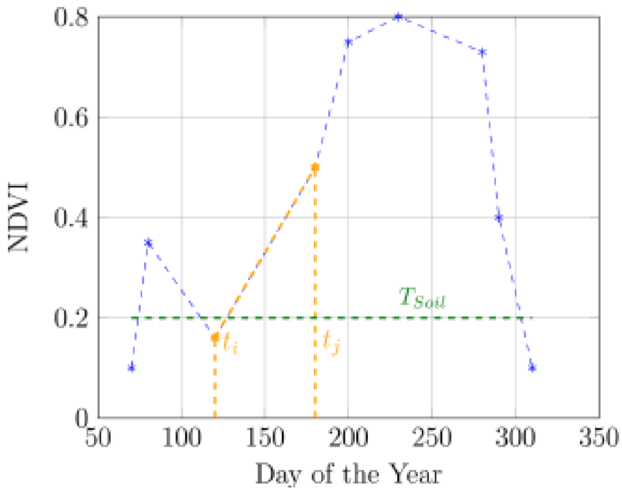

Figure 2-7. Identification of bare soil transitions in a full NDVI time series

Notation	Equation
$\mathbf{x}_{\mathbf{Pos-Tr}}$	$\begin{cases} 1 & \text{if } x(t_i) \leq T_{soil} \text{ and } x(t_{i+1}) \geq T_{soil} \\ 0 & \text{otherwise} \end{cases}$
$\mathbf{x}_{\mathbf{Neg-Tr}}$	$\begin{cases} 1 & \text{if } x(t_i) \geq T_{soil} \text{ and } x(t_{i+1}) \leq T_{soil} \\ 0 & \text{otherwise} \end{cases}$

Table 2-6. Bare soil transition features description

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Parameters:

- x(ti) corresponds to the NDVI values at instant ti
- T_soil is a threshold defining non cultivated areas

2.3.2 Statistic features

The workflow developed to generate statistic features is illustrated in Figure 2-8.

Figure 2-8. Statistic features generation workflow

Input data: the complete Brightness and NDWI image times series

Output data : a vector image made of 10 channels. These 10 channels correspond to 5 statistic features computed on Brightness and 5 statistic features computed on NDWI

Available code : A C++ code compatible with OTB has been developed.

As explained before, the statistic features correspond to a set of 5 global features. These 5 features are presented in Table 2-7. They are computed for Brightness and NDWI indices.

Notation	Description
x_{max}	Maximum value of the complet index times series
x_{min}	Minimum value of the complet index times series
x_{mean}	Mean value of the complet index times series
x_{median}	Median value of the complet index times series
x_{std}	Standard deviation value of the complet index times series

Table 2-7. Statistic features description

2.3.3 Feature image concatenation

The complete set of temporal and statistic features are then concatenated as shown in Figure 2-9. The resulting feature vector image is the output of the "feature extraction" step and will be used as a input for the next step : the classification.

Figure 2-9. Workflow of the temporal and statistic features concatenation

Concatenation can be done using the next OTB application:

```
otbcli_ConcatenateImages -il Temporal_Features.tif Statistic_Features.tif
-out Feature_Concatenate_Images.tif
```


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2.4 Classification step

The classification step can be divided in two subtasks:

1. The construction of the classification model
2. The use of the classification model in the complete image times series and its evaluation

2.4.1 Constructing the classification model

The workflow underlying the construction of the classification model is illustrated in Figure 2-10. It is made of 3 main tasks: splitting polygons for training and testing, randomly selecting training pixel samples and random forest training. They are detailed in the above sub-sections.

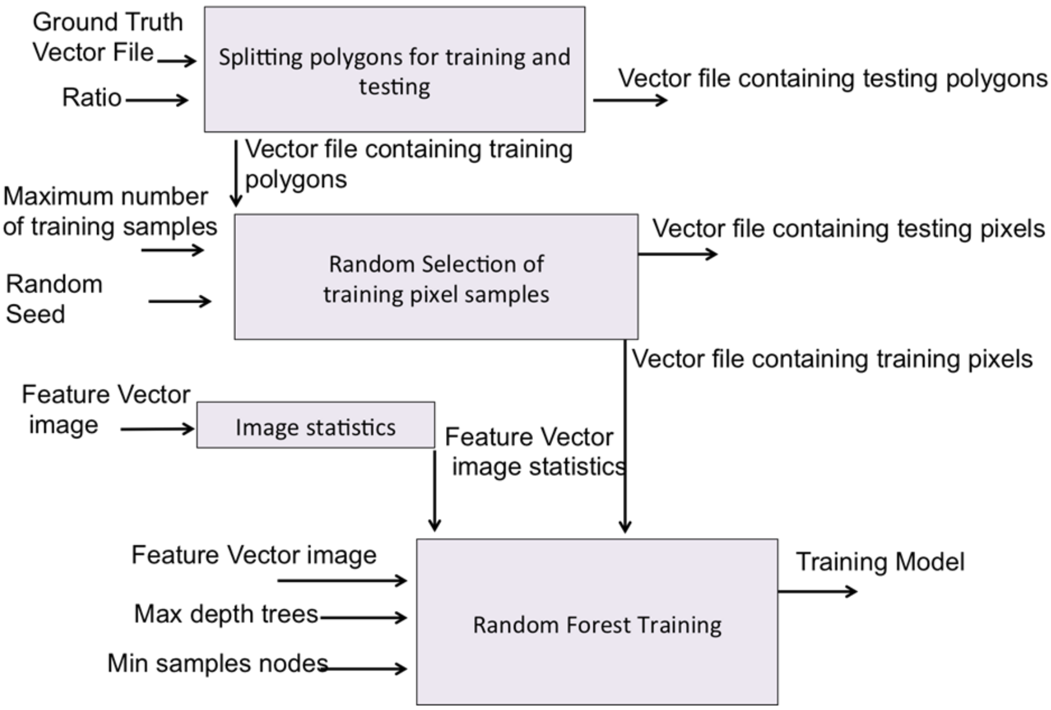

Figure 2-10. Workflow of the classification model construction

2.4.1.1 Splitting polygons for training and testing

This first task consists in splitting the in-situ dataset into 2 disjoint subsets: the training set and the validation set (Figure 2-11).

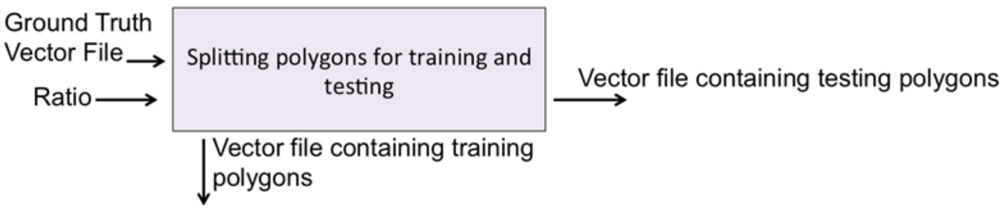

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Figure 2-11. Workflow of the in-situ dataset splitting sub-task

Input data:

Ground Truth Vector File – vector file containing in-situ data

Ratio – parameter expressing the ratio between the number of training and validation polygons per class (corn, soybean, rice, no-crop, etc.)

Output data

Vector file containing training polygons – a vector file containing in-situ data for training.

Vector file containing testing polygons – a vector file containing in-situ data for validation.

The output sets are made of polygons and not individual pixels. The algorithm performing this task is explained in Section 2.2.1 of the ATBD crop type document and is therefore no more recalled here. An illustration is provided in Figure 2-12, with a ratio of 0.5 between the 2 subsets.

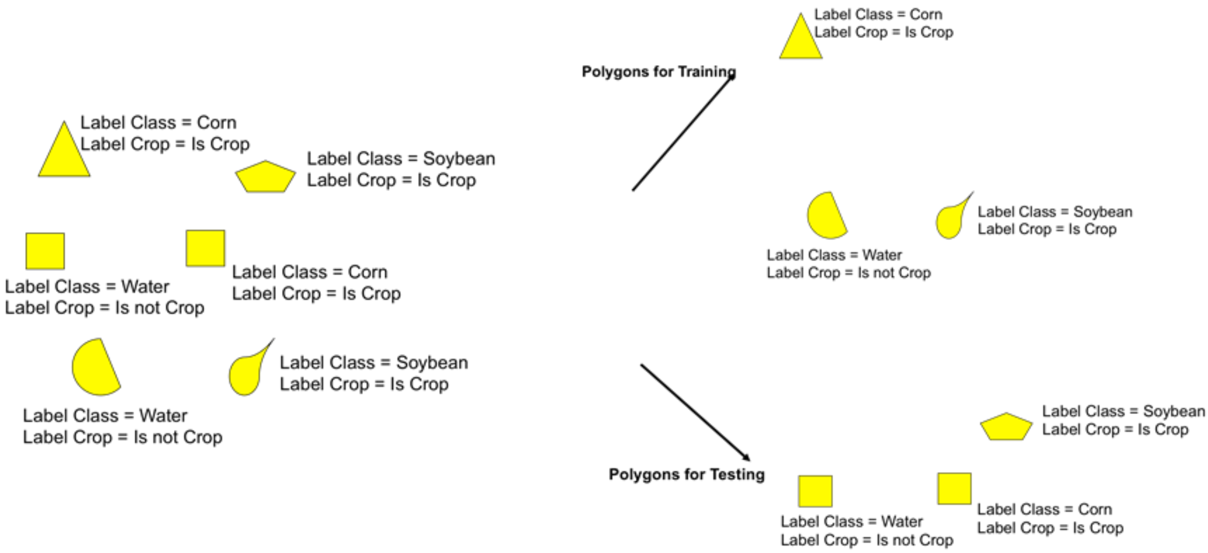

Figure 2-12. Illustration of the in-situ dataset split into two subsets for training and validation using a ration equal to 0.5

2.4.1.2 Random selection of training pixel samples : Crops and Not Crops

This step consists in randomly selecting a number of samples (i.e. pixels) for each class : “crop” and “no-crop”. The workflow is illustrated in Figure 2-13. The output selection will be class consistent, meaning that if 33% of crops belong to soybean class, 33% of the crop class training samples will also belong to the soybean class.

This reduction of the training sample size is needed to reduce the time complexity of the RF classifier. If it is possible from the operational point of view, this step could be removed and the set of the training pixels samples will correspond to the set of the training polygon samples.

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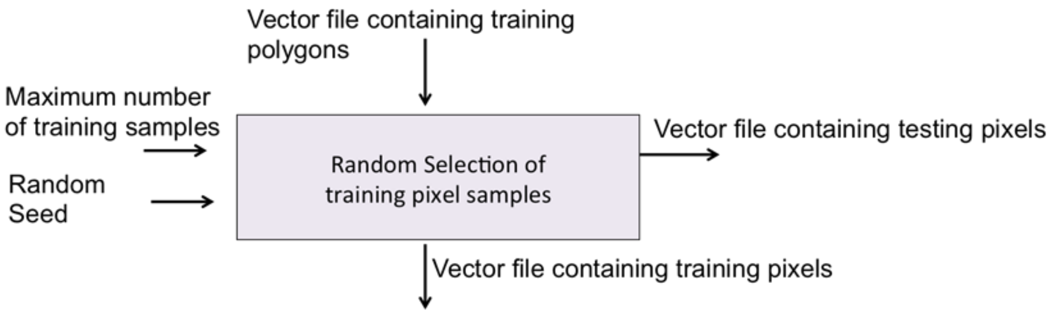

Figure 2-13. Workflow for reducing the size of the training sample

Input data

Vector file containing training polygons – vector file containing in-situ data for training obtained by the previous splitting algorithm (section 2.4.1.1). It must be remarked that the polygons of this vector file as associated with two kinds of label: class label and crop label. For instance, a polygon will be composed by the class label “corn” and the crop label “Is a crop”.

Maximum number of training samples – the second input data corresponds to the limited number of training samples that will be used for training. For instance, if this number is equal to 1000, it means that the output data will be made of 1000 crop and 1000 no crop samples.

Random seed – the third parameter is the random seed that will be used to do the random selection of the pixels. If the third parameter is not specified, a random seed will be generated automatically.

Output data

Vector file containing testing pixels – vector file containing the limited in-situ data for training. Polygons will be associated with one label: crop (with value 1) or no-crop (with value 0)

Vector file containing training pixels – vector file containing the data from Reference_polygons which are not included in the training_vector_file. Polygons will be associated with one label: crop (with value 1) or no-crop (with value 0)

Available code

A C++ code compatible with OTB has been developed. This code is inspired from the OTB class “*otbListSampleGenerator*”.

Algorithm

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Algorithm 1: Random Crop Samples Selection

```
Data: reference_polygons, Nb_tr_samples, random_seed
Result: training_vector_file, testing_vector_file
begin
    for poly ∈ reference_polygons do
        Nb_samples(Label_class_of(poly)) ← Nb_samples(Label_class_of(poly)) + area_polygon(poly);
        if Label_crop_of(poly) = crop then
            total_nb_crop_samples ← total_nb_crop_samples + area_polygon(poly);
        else
            total_nb_no_crop_samples ← total_nb_no_crop_samples + area_polygon(poly);
        end
    end
    Nb_tr_samples ← minimum(Nb_tr_samples, total_nb_crop_samples, total_nb_no_crop_samples)
    for cl ∈ Nb_samples do
        if cl = crop then
            Nb_tr_samples_to_be_selected(cl) ← Nb_samples(cl) ∗ Nb_tr_samples/total_nb_crop_samples
        else
            Nb_tr_samples_to_be_selected(cl) ← Nb_samples(cl) ∗ Nb_tr_samples/total_nb_no_crop_samples
        end
        training_vector_file ← Select randomly Nb_tr_samples_to_be_selected(cl) samples according to
        random_seed
        testing_vector_file ← Include all the samples that are not included in training_vector_file file
    end
end
```

2.4.1.3 Random Forest Training step

The training of the classifier step is illustrated in Figure 2-14.

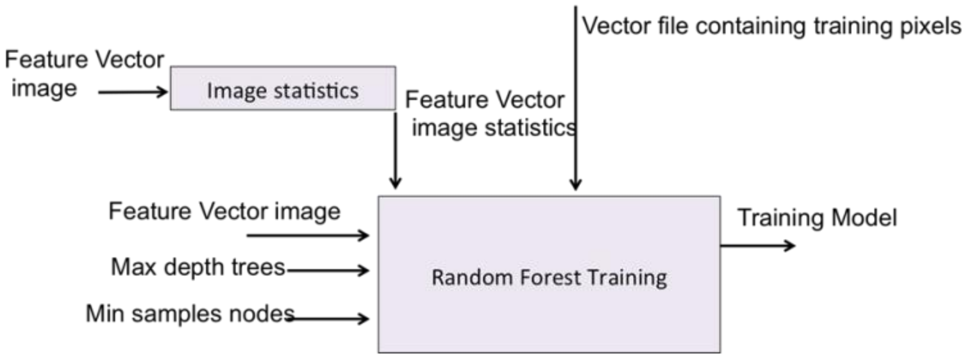

Figure 2-14. Workflow of the classifier training

This task has been developed on C++ and it is based on the "*otbcli_TrainImagesClassifier*" application. The OTB application is composed of two steps:

1. Random selection of training and testing samples;
2. Training of the classifier by using the previous training samples.

In our case, the splitting task is done by using the algorithm presented in the previous section (2.4.1.2). For this reason, the developed code implemented in C++ and compatible with OTB Library focuses on the second step.

Input data

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Feature Vector Image – vector image containing the 27 temporal and statistic features

Feature Vector Image Statistics – the mean and the variance of each feature composing the feature vector image. This result can be obtained by applying the OTB application presented in 2.3.1 of the ATBD crop type document.

Max depth tree – maximum depth of the trees used for Random Forest classifier

Min samples nodes – minimum number of samples in each node used by the classifier.

Vector File containing training pixels – vector file containing the training pixels

Output data

Training model – resulting RF model to be used in the classification step.

2.4.2 Classification of the image times series and classifier evaluation

2.4.2.1 Random Forest classification step

This step consists in the classification of all the pixels of the image times series made of all the statistic and temporal features (see section 2.3). The general workflow is illustrated in Figure 2-15.

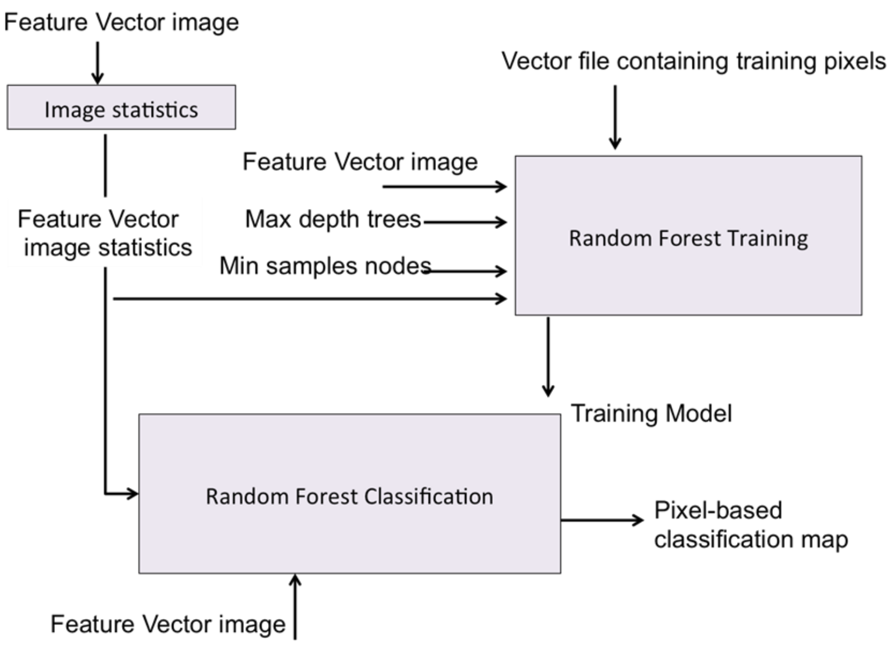

Figure 2-15. Workflow of the RF classification

Input data

Feature Vector Image – vector image containing the 27 temporal and statistic features

Feature Vector Image Statistics – the mean and the variance of each feature composing the feature vector image.

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Training model – resulting Random Forest model obtaining from the training step.

<u>Output data</u>

Pixel-based classification map – resulting crop mask product.

2.4.2.2 Classifier Evaluation: Computing evaluation quality measures

The classification result will be evaluated using all the vector files which contain the testing pixels and polygons which have not been used for the training (Figure 2-16).

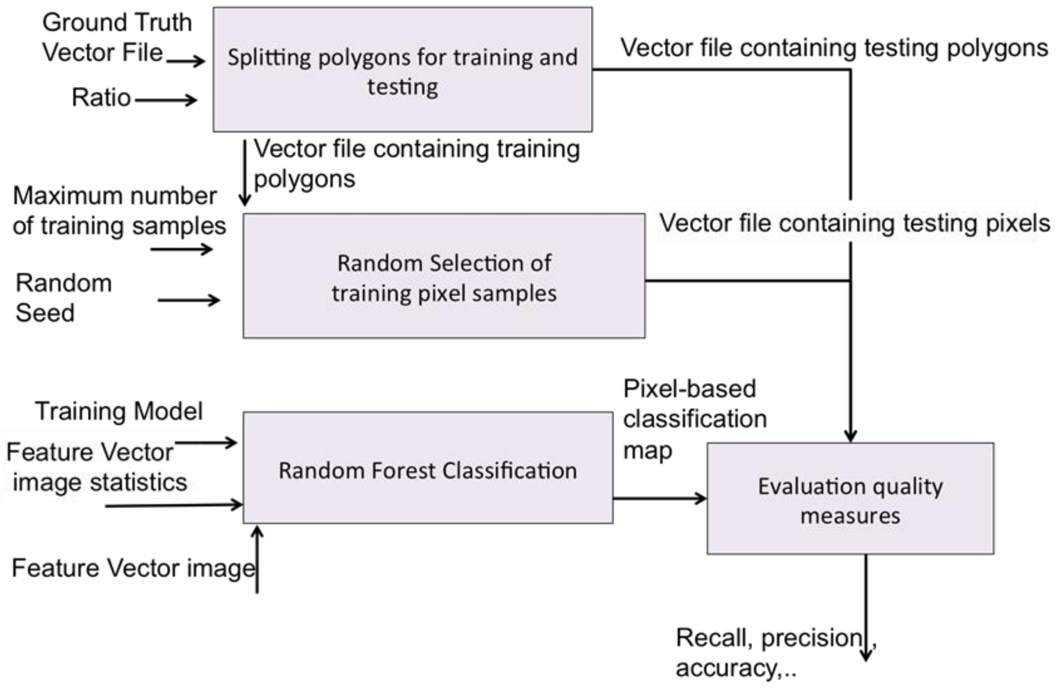

Figure 2-16. Workflow of the classification assessment

The evaluation quality indices (recall, precision, accuracy, etc.) that are computed are detailed in crop mask chapter of the Design Justification File.

All these indices are derived from a confusion matrix result. This confusion matrix can be computed by using the OTB application "*otbcli_ComputeConfusionMatrix*", as it is done for the crop type product (see Section 2.4.2 of the ATBD crop type document).

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2.5 Processing chain working in the iterative operational model

The processing chain detailed in the section 2.4 (i.e. the classification step) will have to run in an operational mode in which the cropland mask will be obtained iteratively. Two different cases must be taking into account regarding the satellite acquisitions: the first year of Sentinel-2 images and the other years. These two situations are analyzed here after.

2.5.1 The first year of Sentinel-2 images

The "in-situ processing chain" works if it exists ground truth data from the current year. Satellite data captured from the 6 first months will be necessary to produce the first cropland mask product. Considering that the first cropland map will be constructed at instant T, Figure 2-17 shows how the cropland product will be computed in an iterative way for the following instants of time.

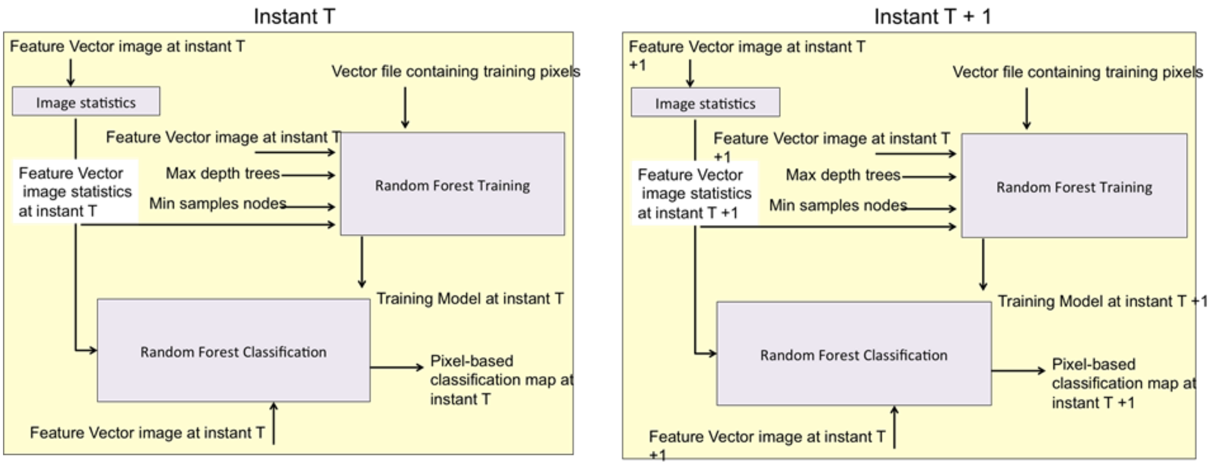

Figure 2-17. "In-situ" classification chain running at instants T and T+1, when we are during the first S2 year

The right figure shows how since the instant T, the feature image will be recomputed at each instant of time. Besides, this image will be used: (i) to compute the image statistics, (ii) to train the classifier and (iii) to classify the complete image.

2.5.2 The rest of the years

For the rest of the years, some considerations have been done:

1. A complete year of data acquisitions exists from the previous year;
2. The ground truth in-situ data exists from the previous year;
3. The satellite data of the current year have been interpolated, in order to have the same acquisition dates than during the previous year.

According to these last assumptions, a classifier model is computed for the previous year. This allows developing the system presented in Figure 2-18 and Figure 2-19. In these figures, Year X-1 corresponds to the previous year, whereas Year X corresponds to the current year.

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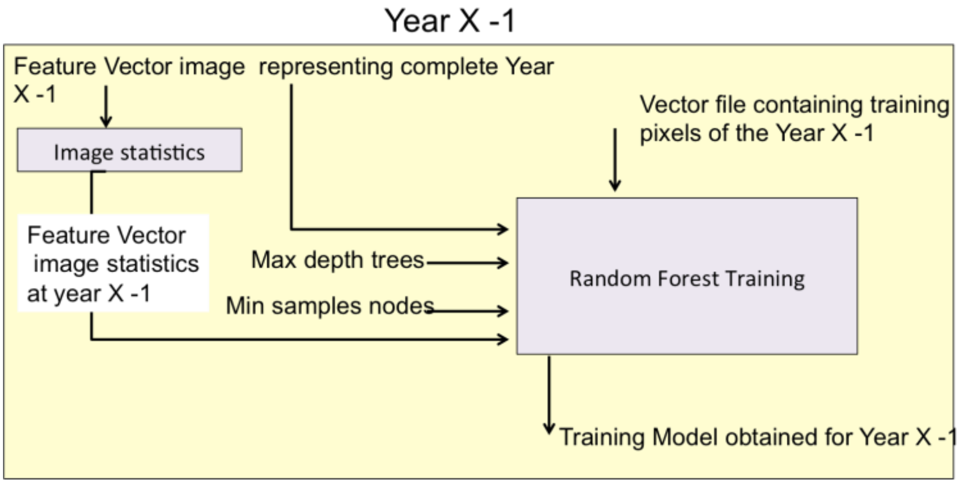

Figure 2-18. “In-situ” classification chain running in Year X-1, when we are not during the first S2 year

By using the classifier model obtained for the previous year (i.e. built on the in-situ data and the images from the previous years), the classification of the current year will be done, after each new acquisition captured at instant T, as illustrated in Figure 2-19.

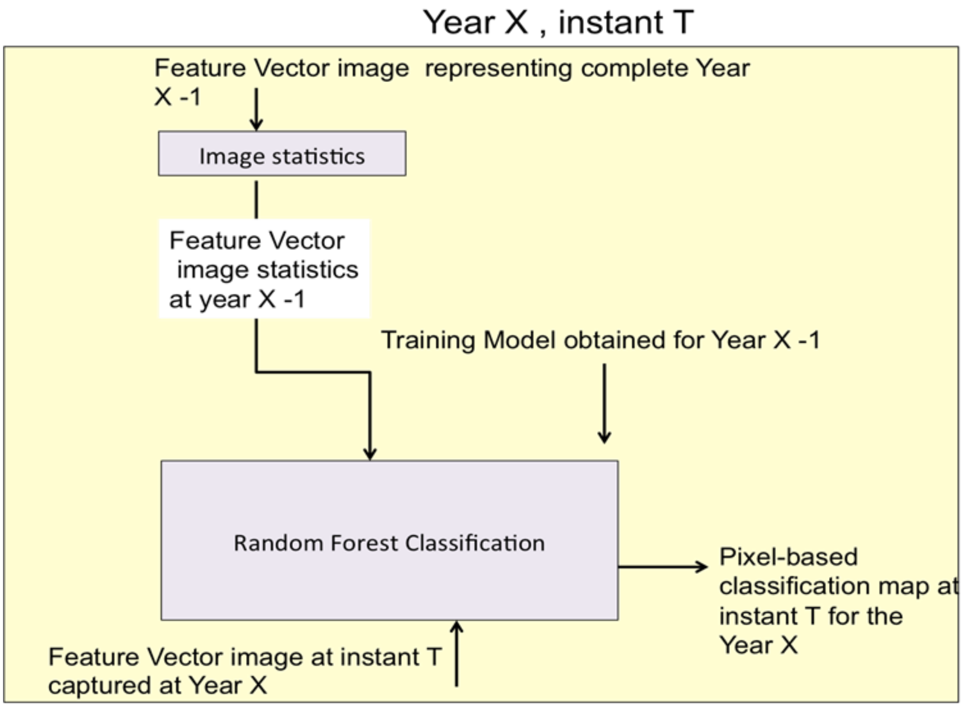

Figure 2-19. “In-situ” classification chain running in Year X, when we are not during the first S2 year

2.6 Processing chain model working for a large area covering several satellite footprints

When working large areas, as shown in Figure 2-20, the construction of the crop mask will need an additional input variable, which has been namely *Reference map*. This map

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corresponds to an image covering the satellite footprint. In it, the values of the pixels correspond to the classifier model that must be used to classify the satellite footprint.

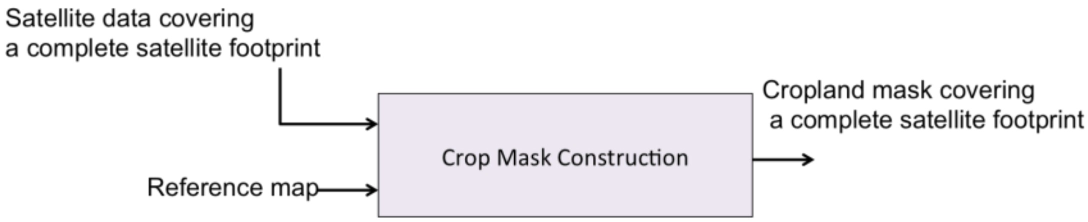

Figure 2-20. Crop mask production logical workflow when working over large areas

For instance, if all pixels of the reference map have a value equal to 1, it means that the classifier model number 1 will be used in order to classify the complete footprint. The classifier model number 1 can be for example a classifier model obtained from a neighborhood footprint. When the reference map has pixels associated with different values, it means that different models will be used for classifying the footprint.

It can be noted that this approach can also contribute to solve the problem where in-situ data is only available in one satellite footprint.

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3 Mode without in-situ data

3.1 Preliminary step: data smoothing and gap filling

A Whitaker filter is applied to the time series, both on the reflectance bands and on the NDVI (Figure 3-1). The filter is applied using the R function "*Whit1*". Whit1 is a function from the "ptw" R package, which is a weighted Whittaker smoothing with a first order finite difference penalty. Additional info can be found at http://cran.r-project.org/web/packages/ptw/ptw.pdf.

The goal of this Whitaker filter is on one hand to smooth the reflectance time series and on the other hand to produce a reflectance time series which is gap-filled with respect to missing data (identified thanks to the validity masks which distinguish the valid pixel from the cloud, the cloud shadows and the saturated pixel). The gap-filling is processed in feeding the filter by a vector of weight matrices. Each weight matrix corresponds to the validity masks of each reflectance image. Into the weight matrices, 1 is set for the valid pixels in the corresponding reflectance image and 0 for the invalid pixels.

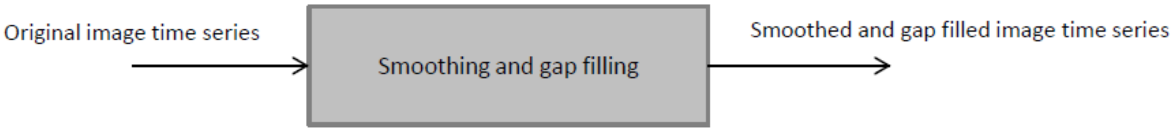

Figure 3-1. Workflow of the smoothing and gap filling preliminary step

Input

They are the original time series :

band<n> – original time series (reflectance values)

NDVI – original NDVI time series

weights – vector of validity masks in the form of weight matrices. Weight of 1 for the valid pixel and weight of 0 for the invalid pixel in the corresponding reflectance image.

Output

band<n>_smoothed – raster files including the smoothed and gap filled reflectance values for all the dates

NDVI_smoothed – raster file including the smoothed and gap-filled NDVI values for all the dates.

Each raster file will have a number of bands equal to the number of image acquisition dates.

Algorithm parameters

The parameters of the Whit1 function are given in Table 3-1.

Table 3-1. Parameters of the Whit1 function.

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Parameters	Description	Value
Lambda	Smoothing parameter (larger values lead to more smoothing)	2
weight	Weights : the “validity masks” related to each acquisition. The validity mask has to be preprocessed to have a value of 1 when the pixel is marked as valid, and a value of 0 in all other cases.	E.g. (SPOT4 _20130206_ EUkraine_ ValidityMask, SPOT4 _20130226_ EUkraine_ ValidityMask, etc.)

Pseudo-code representation[1]

Algorithm “smoothing” **is**

Temporary output:

n raster files, *n* corresponding to the different spectral bands

band_<n>

Creating separated files per spectral band

For each of the *n* spectral bands:

select the layers in the original image time series corresponding to the spectral band *n*

store and save these layers in *band<n>*

Creating the smoothed temporal series of the different spectral bands####

For each of the n files corresponding to the *n* spectral bands:

Create the smooth reflectance values, “out_band”, by applying the R **whit1** function with the following parameter:

whit1(*band<n>*, 2,*weight*)

Save the output “out_band” in *band<n>_smoothed*

Creating a smoothed temporal series of NDVI

Create the smoothed NDVI values, “outW_ndvi”, by applying the R **whit1** function with the following parameter:

whit1(*NDVI*, 2, *weight*)

Save the output “outW_ndvi” in *NDVI_smoothed*

Algorithm 3-1. Time series smoothing

3.2 Features extraction

This step is organized in two consecutive sub-tasks: the definition of temporal features and the spectral features extraction (Figure 3-2). They are detailed in the two sub-sections 3.2.1 and 3.2.2.

[1] In the pseudo-code of section 3, the following color convention is used: green for input data, red for output data and brown for temporary files

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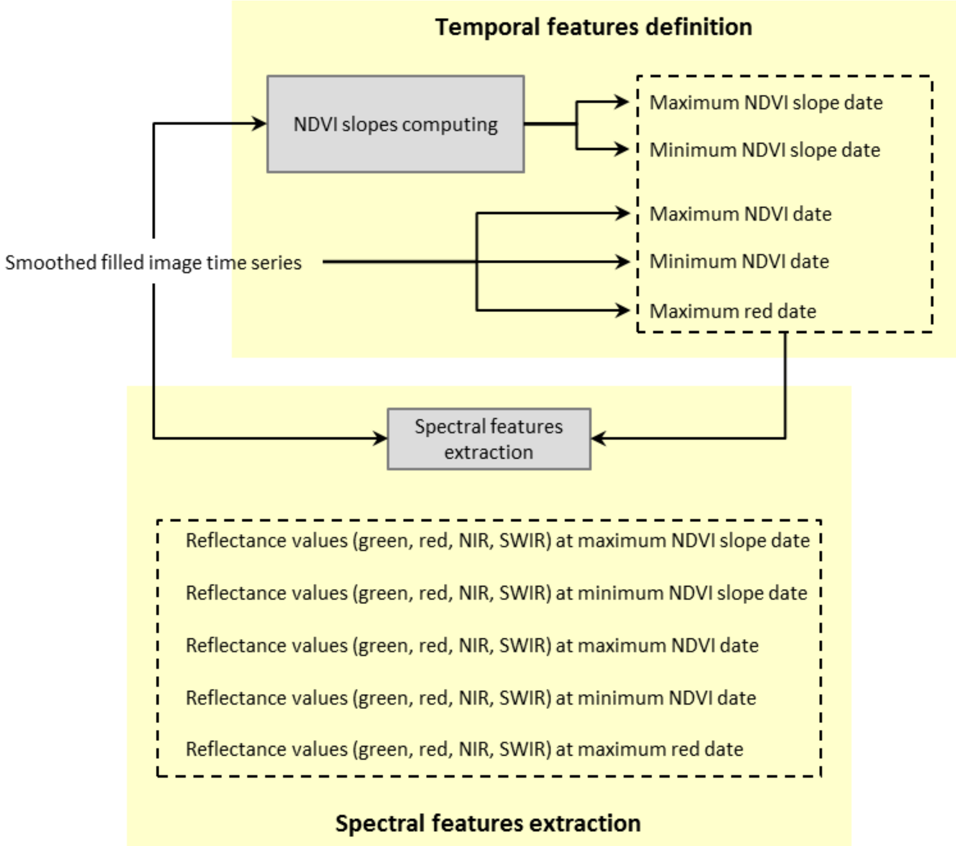

Figure 3-2. Workflow of the temporal and spectral features extraction process

3.2.1 Temporal features definition

This step identifies key dates during the growing cycle, based on the reflectance values and NDVI time series.

First, it computes the slopes of the “NDVI *vs* time” curve using the OTB function “*otbcli_BandMath*” (https://www.orfeo-toolbox.org/CookBook/CookBooksu132.html).

Then, it identifies on a per-pixel basis the date when the maximum and minimum slopes are achieved and the maximum and minimum NDVI are achieved. The algorithm also identifies when the maximum value of the red band is achieved. These processes are based on the R functions “*which.max*”, “*which.min*”, “*fwhmax*” and “*fwhmin*”.

The dates are stored in 5 separate raster (one by date).

The algorithm runs by tile.

<u>Input</u>

band<n>_smoothed – raster files including the smoothed reflectance values for all the dates (output of Algorithm 3-1)

NDVI_smoothed – raster files including the smoothed NDVI values for all the dates (output of Algorithm 3-1)

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Image_dates – a text file giving the acquisition dates of each image within the time series

Output

date_max_slope – raster file which stores, for each pixel, the date corresponding to the maximum slope of the "NDVI *vs* time" curve

date_min_slope – raster file which stores, for each pixel, the date corresponding to the minimum slope of the "NDVI *vs* time" curve

date_max_NDVI – raster file which stores, for each pixel, the date corresponding to the maximum NDVI value

date_min_NDVI – raster file which stores, for each pixel, the date corresponding to the minimum NDVI value

date_max_red – raster file which stores, for each pixel, the date corresponding to the maximum red value

Equations

The slope of the NDVI vs time curve is calculated according to the Equation 4-1.

$$Slope_t = \frac{\left(NDVI_{t+1} + NDVI_{t\_1}\right)}{\left(t_{t+1} - t_{t-1}\right)} \qquad \text{(Eq. 4-1)}$$

Algorithm parameters

The parameters of the OTB function "*otbcli_BandMath*" are given in Table 3-2.

Table 3-2. Parameters of the otbcli_BandMath function.

Parameters	Description	Value
Exp	Mathematical expression	E.g. (im1b3-im1b1)/difft

The R functions "*which.max*", "*which.min*", "*fwhmax*" and "*fwhmin"* don't have parameters.

Pseudo-code representation

Algorithm "temporal features identification" **is**

Temporary output:
d raster (Tif) files, *d* corresponding to the different dates of acquisition corresponding to the slope of the curve "NDVI *vs* time".

NDVI_slope_<d>

Computing the slopes of NDVI####
Read the image dates in the *Image_dates* text file

For *d* in 3:(length(dates)) *(//The loop starts with the 3rd date, because the equation needs three followed dates to be computed)*
Compute "diffdate" as : dates[d] - dates[d-2]
Run the **otbcli_BandMath** function:

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system(**otbcli_BandMath** -il *NDVI_smoothed* -out *NDVI_slope_<d>* -exp '(im1b[d-2]-im1b[d])/diffdate')
End of For

Identification of the temporal features

Look for maximum and minimum NDVI slope####

List the files which contain dates of slopes (output of previous steps):

inFileList <-list of files including all *NDVI_slope_<d>*

In the list, identify the maximum and minimum slopes using the **which.max** and **which.min** R functions:

whmax = **which.max**(inFileList)
whmin = **which.min**(inFileList)

save "whmax" as a raster in *date_max_slope*
save "whmin" as a raster in *date_min_slope*

Look for max/min ndvi value####

Identify the maximum and minimum NDVI values using the **fwhmax** and **fwhmin** R functions:

whMm = **fwhmax**(*NDVI_smoothed*)
whmm = **fwhmin**(*NDVI_smoothed*)

save "whMm" as a raster in *date_max_NDVI*
save "whmm" as a raster in *date_min_NDVI*

Look for max red value####

Identify the maximum Red value using the **fwhmax** R function:

whmax = **fwhmax** (*band2_smoothed*)

save "whmax" as a raster in *date_max_red*

Correction of dates to correspond with smoothed data (since we cannot compute the slope for the first & last dates) => offset=+1

Run the **otbcli_BandMath** function:

system(**otbcli_BandMath** -il *date_max_slope* -out *date_max_slope* -exp 'im1b1+1')
system(**otbcli_BandMath** -il *date_min_slope* -out *date_min_slope* -exp 'im1b1+1')

Algorithm 3-2. Identification of temporal features

3.2.2 Spectral features extraction

This step consists in associated the key dates to their spectral values: for each pixel, the spectral information corresponding to the dates identified for the 5 key dates of the growing cycle (see Algorithm 3-2) are identified and stored in a new raster.

This is achieved thanks to a C++ program, named "*selectInList*".

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Input

band<n>_smoothed – raster files including the smoothed reflectance values for all the dates (output of Algorithm 3-1)

date_max_slope – raster file which stores, for each pixel, the date corresponding to the maximum slope of the “NDVI *vs* time” curve

date_min_slope – raster file which stores, for each pixel, the date corresponding to the minimum slope of the “NDVI *vs* time” curve

date_max_NDVI – raster file which stores, for each pixel, the date corresponding to the maximum NDVI value

date_min_NDVI – raster file which stores, for each pixel, the date corresponding to the minimum NDVI value

date_max_red – raster file which stores, for each pixel, the date corresponding to the maximum red value

Output

ref_max_slope – raster file which stores, for each pixel, the reflectance values corresponding to the maximum slope date

ref_min_slope – raster file which stores, for each pixel, the reflectance values corresponding to the minimum slope date

ref_max_NDVI – raster file which stores, for each pixel, the reflectance values corresponding to the maximum NDVI date

ref_min_NDVI – raster file which stores, for each pixel, the reflectance values corresponding to the minimum NDVI date

ref_max_red – raster file which stores, for each pixel, the reflectance values corresponding to the maximum red date

Each raster file contains n layers (n being the number of spectral band).

Algorithm parameters

The parameters of the “*selectInList*” program are given in Table 3-3.

Table 3-3. Parameters of the SelectInList program

Parameters	Description	Value
inbands	Vector of the different raster files corresponding to each of the smoothed spectral bands	E.g. (‘band1_smo.tif', ‘band2_smo.tif', 'band3_smo.tif, 'band4_smo.tif')

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Pseudo-code representation

Algorithm "spectral features extraction" **is**

Extraction of reflectance values in each spectral band for the 2 dates corresponding to the maximum and minimum slope

define the parameters:
    infile<- *date_max_slope*
    inbands<-(*band1_smoothed*, *band2_smoothed*, *band3_smoothed*, *band4_smoothed*)
    outfile<- *ref_max_slope*

run the **selectInList** function:
    system (**selectInList** outfile infile inbands)

define the parameters:
    infile<- *date_min_slope*
    inbands<-(*band1_smoothed*, *band2_smoothed*, *band3_smoothed*, *band4_smoothed*)
    outfile<- *ref_min_slope*
run the **selectInList** function:
    system (**selectInList** outfile infile inbands)

Extraction of reflectance values in each spectral band for the 2 dates corresponding to the maximum and minimum NDVI
define the parameters:
    infile<- *date_max_NDVI*
    inbands<-(*band1_smoothed*, *band2_smoothed*, *band3_smoothed*, *band4_smoothed*)
    outfile<- *ref_max_NDVI*
run the **selectInList** function:
    system(**selectInList** outfile infile inbands)

define the parameters:
    infile<- *date_min_NDVI*
    inbands<-(*band1_smoothed*, *band2_smoothed*, *band3_smoothed*, *band4_smoothed*)
    outfile<- *ref_min_NDVI*
run the **selectInList** function:
    system (**selectInList** outfile infile inbands)

Extraction reflectance values in each spectral band for the date corresponding to the maximum Red
define the parameters:
    infile<- *date_max_red*
    inbands<-(*band1_smoothed*, *band2_smoothed*, *band3_smoothed*, *band4_smoothed*)
    outfile<- *ref_max_red*
run the **selectInList** function:
    system(**selectInList** outfile infile inbands)

Algorithm 3-3. Extraction of spectral features.

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Program SelectInList **is**:

for each pixel : (// loop over all the pixels)

id = dateID (// dateID is the file containing the key date to select (*date_max_slope, date_min_slope, date_max_NDVI, date_min_NDVI, date_max_red*)

for each input file i:

output(i) = pixelMB(i)(id) (// pixelMB is a list of multiband files (*band<n>_smoothed*) with the first index for list item and the second for band)

Algorithm 3-4. SelectInList program

3.3 Reference map preparation

The reference is the map that will be used to define the training samples that will feed the coming classification algorithm. This is the key dataset that allows generating a cropland mask in the absence of field data.

This step consists in removing, from the reference map, the pixels that are at the border of the different classes (or said differently, that are between two classes) as they have a higher probability to be wrongly classified (Figure 3-3).

Figure 3-3. Workflow of the reference map preparation

The process is based on a function named **classErosion**, written in python during the benchmarking and that relies on the python **erosion** function from the "*skimage.morphology*" module.

<u>Input</u>

Reference – raster file containing the original reference map, with the same extent and projection than the image time series.

<u>Output</u>

Eroded_reference – raster file containing the eroded reference map, with the same extent and projection than the image time series. Removed pixels are coded with NaN values.

<u>Algorithm parameters</u>

The parameters of the python **erosion** function are given in Table 3-4

Table 3-4. Parameters of the erosion function

Parameters	Description	Value
Image	Image array corresponding to each class	classinRst
selem	Binary array made of 0 and 1 values	sq(3)

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Pseudo-code representation

Function classErosion **is**

def **classErosion**(*Reference*, *Eroded_reference*, size=3):

Reading the input
Reference is opened and stored in "inRst"

Identifying the different classes included in the reference
The different classes of "inRst" are identified and included in "uniqueClass" *(where the classes are identified from 1 to u)*

Defining the size of the erosion
selem = sq(size) *(where size is "3" according to Table 3-4 => selem is squared matrix of 3x3 'ones')*

Erosion of the different classes
for *u* in "uniqueClass":
    all the areas where "inRst" == u are saved in "classinRst"
    "eroded" = **erosion**(classinRst, selem)
    the resulting eroded areas are saved in "outRst"

Saving the output file
An array is written compiling the "outRst" coming from each class
The array is saved in *Eroded_reference*

Algorithm 3-5. Reference erosion.

3.4 Trimming

Trimming consists in truncating a distribution from its least probable values that behave like outliers. The common purpose of this procedure is to reduce the sensitivity to outliers for many parameter estimates, such as the sample mean and variance.

Trimming, coupled with the previous reference map erosion, are two key steps that give robustness to the classification process. They will allow obtaining, from an inexact pre-existing reference map data that will be "clean" enough to train a classifier. They are therefore the core of the "without in-situ mode".

The spectral distribution corresponding to each class of the eroded reference is iteratively trimmed in order to eliminate the pixels that behave as "outliers" from their Gaussian distribution point of view.

The trimming will not be performed on all spectral channels, but on the ones that are the most characteristic for crops – no crops. The selected channels are the red and NIR reflectance values at the minimum NDVI date as well as the green, red and NIR reflectance values at the maximum NDVI date. This selection could be updated when S2 data will be available to better use the S2 spectral richness.

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The trimming is made using a "*MVG_IT*" function specifically created in R that computes iteratively the outliers of a Gaussian distribution. "*MGV_IT*" uses, in turn, two functions from the base core of R, which are the "*qchisq*" and "*mahalanobis*" ones.

From the trimming output (i.e. the identification of clean pixels in the reference map), a selection of samples is done randomly. This selection will constitute the training dataset for the subsequent RF classifier.

It shall be noted that even if the trimming was done on a selection of spectral channels, the RF classifier will run with all available spectral information: red, NIR and SWIR reflectance values from the dates corresponding to the maximum red, minimum and maximum NDVI and minimum and maximum slope.

The workflow of the trimming process is presented in Figure 3-4.

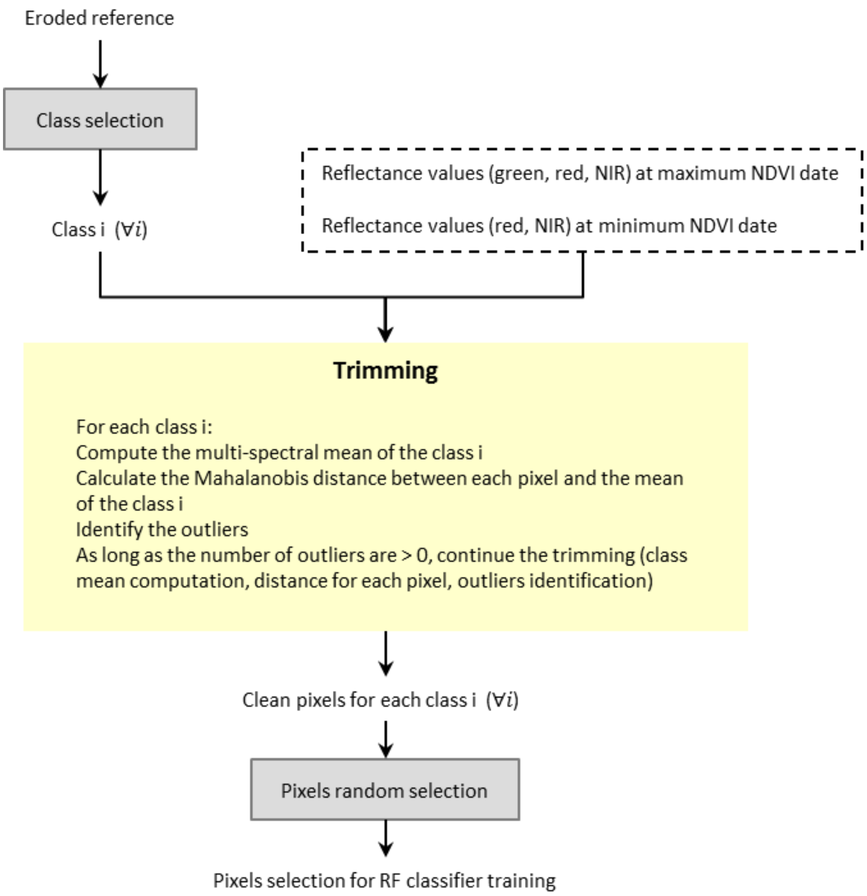

Figure 3-4. Workflow of the trimming process

Input

Eroded_reference – raster file containing the eroded reference map, with the same extent and projection than the image time series. Removed pixels are coded with NaN values.

ref_max_slope – raster file which stores, for each pixel, the reflectance values corresponding to the maximum slope date

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ref_min_slope – raster file which stores, for each pixel, the reflectance values corresponding to the minimum slope date

ref_max_NDVI – raster file which stores, for each pixel, the reflectance values corresponding to the maximum NDVI date

ref_min_NDVI – raster file which stores, for each pixel, the reflectance values corresponding to the minimum NDVI date

ref_max_red – raster file which stores, for each pixel, the reflectance values corresponding to the maximum red date

Output

Training sample – data frame which contains the samples that will be used for the training.

Algorithm parameters

The parameters of the "*MGV_IT*" function are given in Table 3-5. Those of the "*qchisq*" and "*mahalanobis*" functions are described in Table 3-6 and Table 3-7.

Table 3-5. Parameters of the MGV_IT function

Parameters	Description	Value
x	Vector or matrix of a specific class for which the Gaussian model will be fitted	E.g. subset(trimRst,LC_class == class.i)
alpha	Confidence interval used to define what is an "outlier"	0.01
TrimBands	Selection of spectral bands that will be used for the trimming	Red and NIR from the minimum NDVI date // green, red and NIR from the maximum NDVI date

Table 3-6. Parameters of the qchisq function

Parameters	Description	Value
x	Vector of quantile values	(1-alpha), where alpha is 0.01
df	Degrees of freedom	NCOL(x)

Table 3-7. Parameters of the mahalanobis function

Parameters	Description	Value
x	Vector or matrix of data	x.trim
center	mean vector of the distribution	colMeans(x.trim)
cov	covariance matrix of the distribution	cov(x.trim)

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Pseudo-code representation

Algorithm Trimming **is**

Define input working files
Store *Eroded_Reference* in “labelRst”
Store the spectral features (*ref_max_slope, ref_min_slope, ref_max_ndvi, ref_min_ndvi, ref_max_red*) in “featRst”
Define the number of samples needed for the RF training in “ntrain”

Convert input working files in a data frame
Store “featRst” as data frame in “metricRst”
Store “labelRst” as data frame in “LCstack”
Store “metricRst” and “LCstack” as data frame in “Rststack”

Select reflectance values to use in the trimming (i.e. reflectance values whose Gaussian distribution will be cleaned)
Select the bands *TrimBands* (see Table 3-5 for this parameter) from “Rststack”
Select the class information corresponding to “LCstack” (class information) from “Rststack”
Store this information in “trimRst”

Create a list of classes
List all classes ID in a list “classList”

Run the trimming, with the function MVG_IT
Create the list “trimList” that will receive the results of the trimming for the different classes

For each class ‘i ‘ from the “classList”
    class.i <- classList[i]
    X <- selection of trimRst corresponding to class.i
    X.NP_IT <- **MVG_IT**(X)
    trimList[i]<- including the result X.NP_IT for the class ‘i’

From the trimming output trimList, make a random selection for each class of n pixels that will be used to train the RF

For each class ‘i ‘ from the “classList”
    subset.idx<- selects from “trimList[i]” a random sample of “ntrain” pixels
    out.id<-list of ones and zeros with the size of “trimList”, ‘1’ corresponding to the selected pixels (subset.idx)
    trimmed_values.sbs<-subset of “trimList” corresponding to out.id==1
    Training_Sample <- trimmed_values.sbs

Algorithm 3-6. Trimming

Function MVG_IT **is**

MVG_IT <- function(x, alpha = 0.01){
    chi <- **qchisq**((1-alpha), df=NCOL(x))

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(computes the Chi-Squared distribution and selects the threshold corresponding to the alpha p-value of the distribution per class)
x.trim <- x
For every class of the legend
md <- as.matrix(**mahalanobis**(x.trim, colMeans(x.trim), cov(x.trim)))
(Computing the Mahalanobis distance to the mean for each pixel)
x.trim <- x.trim which md is lower or equal to chi
(Selecting the "clean" pixels, i.e. those pixels whose mahalanobis distance to the mean is lower than the threshold)
}
it returns x.trim as output of the function
}

Algorithm 3-7. MVG_IT function

3.5 Random forest classifier

The classification is a supervised method relying on a RF classifier, just like in the "in-situ" mode. The RF classifier is applied to the reflectance values associated with the key dates (maximum and minimum NDVI slopes, maximum and minimum NDVI, maximum red). The RF classifier uses as training data the "clean" pixels selected by the trimming.

This step follows exactly the same logical than the RF classification used for the "in-situ" mode. The presentation is thus rather brief.

3.5.1 RF model estimation

The process follows the same logical than for the "in-situ" mode.

Input

Feature Vector Image – vector image containing the spectral features:

ref_max_slope – raster file which stores, for each pixel, the reflectance values corresponding to the maximum slope date

ref_min_slope – raster file which stores, for each pixel, the reflectance values corresponding to the minimum slope date

ref_max_NDVI – raster file which stores, for each pixel, the reflectance values corresponding to the maximum NDVI date

ref_min_NDVI – raster file which stores, for each pixel, the reflectance values corresponding to the minimum NDVI date

ref_max_red – raster file which stores, for each pixel, the reflectance values corresponding to the maximum red date

Feature Vector Image Statistics – the mean and the variance of each feature composing the feature vector image. This result can be obtained by applying the OTB application presented in 2.3.1 of the ATBD crop type document.

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Vector File containing training pixels – vector file containing the training pixels

Output

Training model – resulting RF model to be used in the classification step.

Algorithm parameters

Parameters of the RF classifier are given in Table 3-8.

Table 3-8. Parameter for the RF classifier

Parameters	Description	Value
rf.nbtrees	Number of decision trees	100
rf.min	Minimum number of samples per nodes	5
rf.max	Maximum depth of each tree	25

Pseudo-code representation

The RF algorithm has been presented in detail in Section 2.3.2 of the ATBD crop type document and is therefore no more recalled here.

3.5.2 Classification

The classification process applies the RF model built in the previous step using the training dataset on the image time series in order to generate the cropland mask.

Input data

Feature Vector Image – vector image containing the spectral features:

> *ref_max_slope* – raster file which stores, for each pixel, the reflectance values corresponding to the maximum slope date
>
> *ref_min_slope* – raster file which stores, for each pixel, the reflectance values corresponding to the minimum slope date
>
> *ref_max_NDVI* – raster file which stores, for each pixel, the reflectance values corresponding to the maximum NDVI date
>
> *ref_min_NDVI* – raster file which stores, for each pixel, the reflectance values corresponding to the minimum NDVI date
>
> *ref_max_red* – raster file which stores, for each pixel, the reflectance values corresponding to the maximum red date

Feature Vector Image Statistics – the mean and the variance of each feature composing the feature vector image. This result can be obtained by applying the OTB application presented in 2.3.1 of the ATBD crop type document.

Training model – resulting RF model to be used in the classification step.

Output data

Pixel-based classification map – resulting crop mask product.

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Algorithm

The RF algorithm has been presented in detail in Section 2.4.1 of the ATBD crop type document and is therefore no more recalled here.

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4 Common final step: crop mask post-filtering

As presented in Figure 2-1, the post-filtering task is made of 3 steps: (i) the Principal Component Analysis (PCA), (ii) the mean-shift algorithm and (iii) the majority vote. These steps are detailed in Figure 4-1.

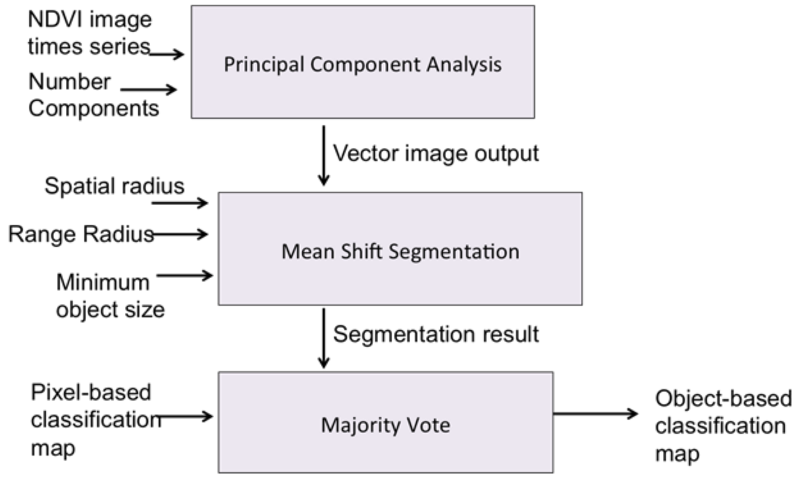

Figure 4-1. Workflow of the post-filtering step

4.1 Principal Component Analysis

Input data

NDVI image times series – vector image containing the complete NDVI image times series.

Number of Components – number of principal components composing the output image.

Output data

Vector image – vector image containing the "*Number of Components"* principal component images.

Available code

A C++ code compatible with OTB has been developed, this code uses the otb filter class "*otb::PCAImageFilter*".

4.2 Mean-Shift segmentation algorithm

Input data

Vector image output – vector image containing the result of the PCA

Spatial radius – spatial radius of the neighborhood

Range radius – range radius defining the radius (expressed in radiometry unit) in the multispectral space

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Minimum object size – Minimum size of a region (in pixel unit) in segmentation. Smaller clusters will be merged to the neighboring cluster with the closest radiometry. If set to 0 no pruning is done.

Output data

Segmentation result – segmentation result image.

Available code

A C++ code compatible with OTB has been developed, this code uses the otb filter class "*otb::MeanShiftVectorImageFilter*"

4.3 Majority vote

Input data

Segmentation result – segmentation image obtained by the mean-shift segmentation algorithm

Pixel-based classification map – pixel-based classification results obtained by the RF classifier (coming from the "in-situ" mode or not).

Output data

Object-based classification map – object-based classification map result

Algorithm

Algorithm 1: Majority Vote Filtering

```
Data: Input_seg_image, ClassificationMap
Result: Result_image
begin
    for region ∈ Input_seg_image do
        RegionClass ← Compute_the_majority_class(ClassificationMap(region));
        for pixelP ∈ region do
            Result_image(pixelP) ← RegionClass;
        end
    end
end
```

4.4 Operational context

It must be remembered that in the operational context, the post-filtering task must also be done following an iterative procedure. This iterative approach will be possible from the first satellite data acquisitions. This can be obtained by following the next flowcharts, Figure 4-2 and Figure 4-3.

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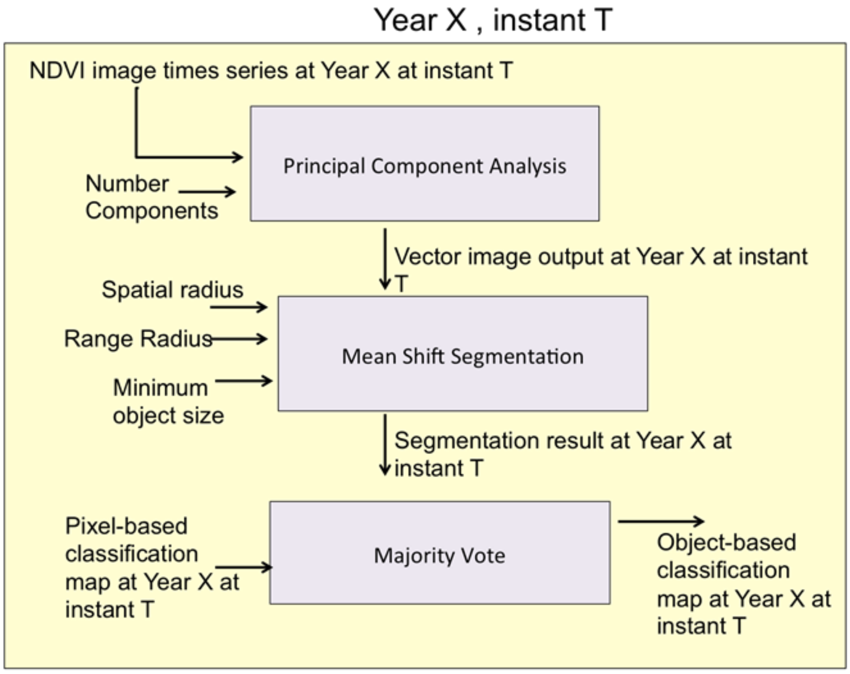

Figure 4-2. Post-filtering workflow, at instant T

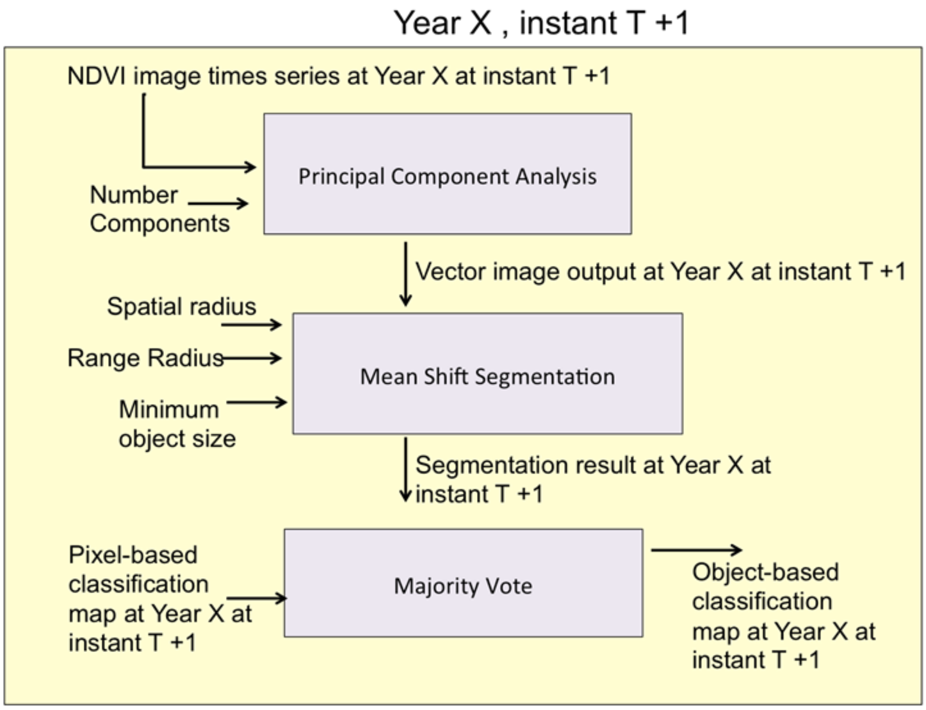

Figure 4-3. Post-filtering workflow, at instant T+1

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5 Appendix - Additional information on the codes of the « in-situ » processing chain

The code, associated with the « in-situ » mode (including the common steps with the "no in-situ" mode) is available on: http://tully.ups-tlse.fr/valeros/s2agri_cropmask

Codes from the OTB project are the following ones:

- **NDVI feature computation task:**

Includes/NdviParameterExtraction.hpp

tests/IndicesComputation/NdviParameterExtractionApplication.cxx

- **Statistics feature computation task:**

includes/IndexParameterExtraction.hpp

tests/IndicesComputation/IndexParameterExtractionApplication.cxx

- **Random selection of training pixel samples task:**

includes/ShpFileSampleGeneratorFast.hpp

src/ShpFileSampleGeneratorFast.cxx

- **Random Forest Training Step task:**

test/sClassification/ ShpFileMRFClassificationFast.cxx

- **Classifiication of the complete image times series task:**

tests/Classification/SVMClassificationMap.cxx

- **Principal Component Analysis task:**

tests/PostFiltering/ACP.cxx

- **Mean Shift Segmentation task:**

tests/PostFiltering/SegmentationACP.cxx

Two algorithms were coded in Python:

- Quality measures (how to evaluate the crop masks - section 2.4.2.2)
- Majority vote (how to apply the majority vote - section 4.3)

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