A methodology for the detection of land cover changes: application to the Toulouse southwest region

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Abstract

➢ A methodology to highlight changes in the landscape based on satellite image classification has been developed involving unsupervised and supervised approaches. With past acquisitions, ground truth data are in general not known, therefore the **classification can only be unsupervised (step 1)**.

➢ After radiometric correction, the images are not free from defects; this is why a **normalization method** has been developed **(step 2**).

➢ These classifications provide labels but not surface types. The main difficulty lies in the interpretation of these classes. An **automatic interpretation (step 3)** method has been developed to allocate semantics to classes thanks to a radiometric value catalogue. However, it requires radiometrically comparable images.

➢ We propose a specific methodology to evaluate changes consisting in **regrouping** classes of the same theme, **smoothing** and **eroding** contours without taking "mixels" into account and comparing the classified images to provide statistics and image changes (**step 4**). The different steps of the process are essential to avoid false changes and to quantify land cover change with a high degree of accuracy.

➢ Various statistical results are given: **changes** or no changes **(step 5)**, types of changes, and **crop rotations (step 6)**over several years.

➢ Land use /cover change **(LUCC)** can provide an estimate of carbon capture and storage **(step 7)**.

Reforestation, changing land use and best practices can increase carbon sequestration in biomass and soils for a period of several decades, which may constitute a significant contribution to the fight against the greenhouse effect. Deforestation, conversely, can lead to significant levels of CO2 emission.

By application to the South-West region of Toulouse, we observe significant land cover changes over 11 years (1991- 2002). The crop rotations are given for 4 years (year per year 2002-2005).

Unsupervised Classification and automatic interpretation

Step 1 : **Unsupervised classification** because ground truth are not always known

- Contextual algorithm of classification : Iterative Conditional Mode (ICM) based on Markovian model → robust

- Improve by exogenic data : segmentation, GIS , …

Step 2 : **Normalization**

MNBD (Multitemporal Normalized Band Difference) is calculated to enhance robustness and automaticity by using objective spectral difference measure and statistical thresholds.

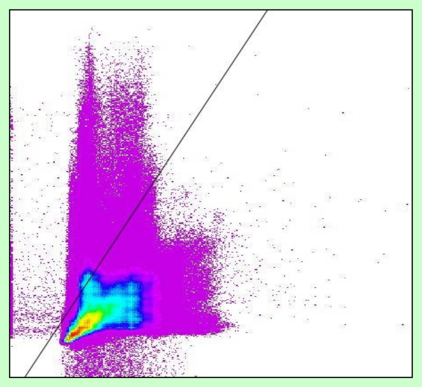


Figure 1

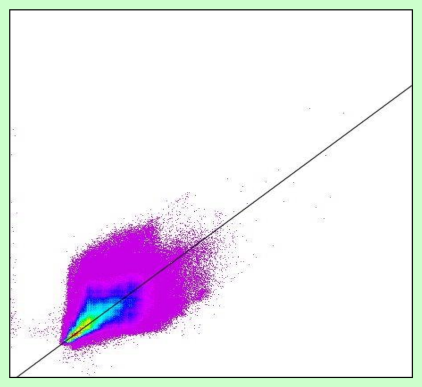


Figure 2

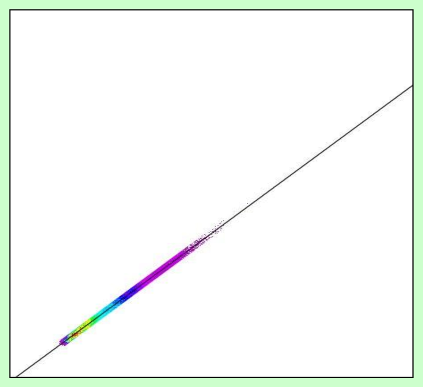


Figure 3

Figures 1, 2 and 3: Multitemporal scattergrams showing cloud and shadow effects on the first principal component and principal component masking on the reflectance values of band 3 (red wavelength) with two dates.

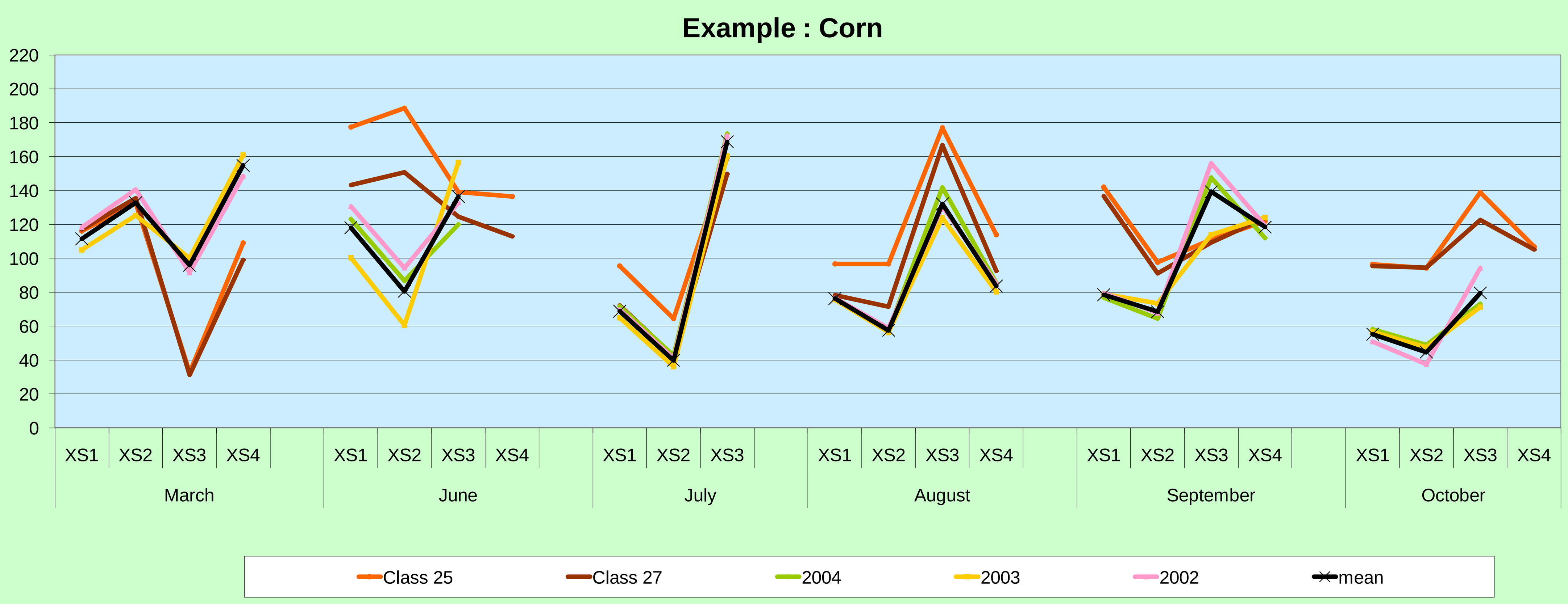
Figure **1** shows uncorrected reflectance values and the calculated first principal component.

Figure **2** shows values after cloud removal and spectral distance filtering, with the corrected first principal component.

Figure **3** shows the first principal component and values after principal component masking. Colours from violet to red indicate increasing frequency of values.

Step 3 : **Interpretation**

- Automatic recognition method : based on statistical radiometric values (spectral catalogue of classes)

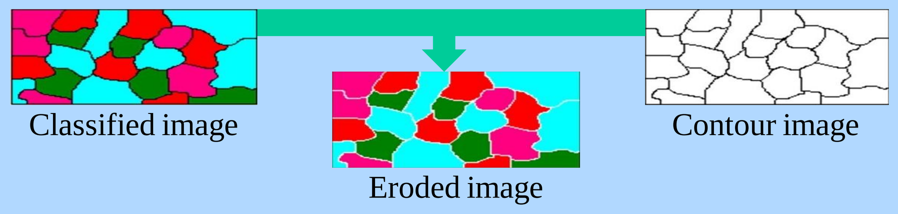


- Calculation of distances and divergences such as Euclidian distance, Bhattacharyya, Manahalobis or Kullbach-Leibler divergences to find the nearest classes.

- Evaluation of the interpretation with confidence index.

Change detection

Step 4 : **Regrouping, smoothing and contour erosion** of the classification image: elimination of mixed pixels or "mixels" (pixels on border of two classes).



Example of eroded image: erosion in white

Step 5 : Comparison of classified images from **change matrices**: pixel-by-pixel comparison, change-classes are created.

	CLASSIFICATION 2002					
CLASSIFICATION 1991	Wood	Winter crop	Summer crop	Fallow	Meadow Grassland	Mineral Surfaces/built
Wood	**70.89**	2.51	3.01	10.40	10.72	0.09
Winter crop	0.12	**41.99**	42.04	2.32	12.37	0.09
Summer crop	0.47	32.56	**53.79**	2.12	10.03	0.15
Fallow	1.02	12.35	14.37	**6.60**	61.90	0.06
Meadow-Grassland	0.65	13.18	17.84	2.72	**65.18**	0.07
Meadow-Grassland/Fallow	8.00	20.58	25.60	7.19	36.26	0.12
Mineral Surfaces/built	2.64	2.38	4.67	2.78	7.15	**61.17**

Step 6 : **Crop rotation**, comparison of N classifications in N years and obtaining of change matrices with time dimension.

2002 - 2003- 2004 - 2005	Pixel number 2002→ 2003→ 2004→ 2005	area (ha)	Percentage = class pixel number/total pixel number of the eroded image	2002 - 2003- 2004 - 2005	Pixel number 2002→ 2003→ 2004→ 2005	area (ha)	Percentage = class pixel number/total pixel number of the eroded image
monoculture				**Every 3 years:** (main changes)			
Corn-Corn-Corn-Corn	136422	5456.8	**6.339**	Wheat-Wheat-Wheat-Sunflower	84391	3375.64	3.922
Wheat-Wheat-Wheat-Wheat	8891	355.64	0.42	Corn-Corn-Corn-Wheat	22440	897.6	1.043
Soybean-Soybean-Soybean-Soybean	58	2.32	0.003	Corn-Corn-Corn-Sunflower	21931	877.24	1.019
Sunflower-Sunflower-Sunflower-Sunflower	1931	77.24	0.09	Sunflower-Sunflower-Sunflower-Wheat	17116	684.64	0.795
2 crops				Wheat-Wheat-Wheat-Rapeseed	13859	554.36	0.644
Bi-annual (main changes)				Corn-Corn-Corn-Soja	10682	427.28	0.496
Wheat-Sunflower-Wheat-Sunflower	402924	16116	**18.72**	Wheat-Wheat-Wheat-Corn	10483	419.32	0.487
Wheat-Corn-Wheat-Corn	29262	1170	1.36	Wheat-Wheat-Wheat-Corn	10483	419.32	0.487
Every 2 years							
Wheat-Wheat-Sunflower-Sunflower	30826	1233.04	1.43				
Wheat-Wheat-Corn-Corn	8153	326.12	0.38	**Rotation**			
Corn-Corn-Sunflower-Sunflower	3393	135.72	0.16	**Total 2 crops**	***690170***	***27606.8***	***32.07***
Corn-Corn-Soja-Soja	592	23.68	0.03	**Total 3 crops**	***210847***	***8433.88***	***9.8***
Soybean-Wheat-Wheat- Soybean	435	17.4	0.02	**Total 4 crops**	***7937***	***317.48***	***0.37***

Step 7 : LCLU and Carbon Storage/Emission

- The storage or emission of CO2 depends on nature of soil and its evolution over time.

- LCLU used to calculate carbon footprint.

Results

- **monoculture** is mainly **Corn**; it covers **6.34**% of the territory, the others are negligible
- Main rotation: Wheat and Sunflower: biannual rotation (20% of eroded surface with 18.7% Wheat-Sunflower)
- ***32%*** are occupied by crops of 2 types (mainly Sunflower and Wheat) in rotation from 1 to 4 years
- ***9.8%*** of rotation out of 3 crops
- rotation with 4 crops is negligible

Conclusion

➢ Accurate change statistics over several years can be obtained here using the protocol presented. Every step is important: fuzzy contextual classification, automatic interpretation of the unsupervised classification, edge erosion of the classification. Results are facilitated depending on image acquisition conditions. Selection of a sensor series, low cloud cover and matching dates of two image data can restrict uncertainty. It is essential to choose appropriate calendar acquisition dates to obtain correct results. On the other hand, on anniversary dates, phenological discrepancies due to local precipitation and temperature variations can appear as well.

➢ Land cover changes from wood, crop, fields are important to evaluate the emission and storage of CO2, which depend on the nature of the soil and its changes over time. For example: wood stores carbon, while the cutting of a tree will release CO2 into the atmosphere. Absorption does not occur in the same way in wood and in crops.

➢ In post-classification change detection analysis, the minimization of classification errors is fundamental. Thus further work will be requires to improve the fuzzy contextual method presented. In the case of unsupervised classification, the improvements will be in automatic interpretation.

References

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