Multisensor and multitemporal image fusion methods to improve remote sensing image classification

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Abstract : remote sensing data contains more and more information with the evolution of acquisition techniques. For a good comprehension of the fundamental interest of data fusion, let us list the diversity of remote sensing data: optical and radar images, low, high and very high-resolution, multitemporal hyperspectral images, derived images, physical or ancillary data (database, D.E.M, G.I.S.). Data fusion is the joint use of heterogeneous images for decision-making. It is essential to group the available information from various sensor images, temporal data, expert information…. In this paper, fusion is used for improving classification on two levels within classification: pixel by pixel or after independent "sub classification". This fusion is particularly interesting in the case of imperfect data to obtain more reliable information. Thus, it takes advantage of the best of each data type and it overcomes individual limitations of each type. For example, optical and radar sensors are not sensitive to the same kind of information. We exploited the complementarities in these data to extract more complete information and to make a better distinction between various classes. We present some applications such as fusion between radar and optical images for detection of agricultural practices on bare soil (TerraSar-X and Formosat2) which improves by 12 % the overall accuracy for supervised classification. Radar images bring more precision to bare soil classes and optical image more accuracy to active vegetation classes. We also show temporal complementarities with different dates of the same source (Formosat2).

METHODS

Definition : Fusion is the combination of heterogeneous images to aid in decision making [Bloch &Maitre].

Why : The various sources provide generally imperfect information i.e. uncertain, imprecise, incomplete, contradictory or inaccurate. Fusion will use benefits of each data type to overcome individual limitations of each one. So we can exploit the complementarity of these data to extract more information, and allow a clearer distinction between different classes.

Historical background : The main approaches to data fusion are Bayesian probabilistic methods (the oldest), fuzzy sets and possibility theory introduced by Zadeh [Zadeh] and belief (or evidence) theory of Dempster-Schafer (first Dempster (1960) and renormalized by Shafer (1976)), widely used in image processing.

Methods presented fusion is used in the sense of classification combination, which requires the quantification of information relevance from different data. The applications will use multisensory and multitemporal classification from remote sensing data in a context of land use.

Fusion and supervised classification

Confusion matrix : For supervised classification, confusion matrix, based on proportion of pixels correctly classified, objectively quantify the quality of classification with mathematical and statistical criteria. Two main coefficients calculated from these matrices: MPCC (Average of PCC, Pixels Correctly Classed or Overall Accuracy) and Kappa determine the global quality of the classification and quality for each class.

Automatic extraction and systematic measurements of image combinations: it is impossible to analyze manually each matrix for a long time series. An algorithm is developed to give an automatic and exhaustive way to compute confusion matrices for all possible date combinations with MPCC & PCC. We can extract the best combinations by classes, to choose the best combinations to discriminate classes (for 7 dates, 127 possibilities).

Automatic fusion algorithm: several classifications ("sub classifications") are made on ***n*** image batches; every batch contains ***m*** spectral and/or temporal images chosen according to the confusions of certain classes. An image batch (giving the first "sub classification"), is taken as reference generally the best classification (best MPCC and kappa). Certain classes are better discriminated with other combinations, which shows the relevance to merge these classified images. This principle can be applied in the classification or later in a post-treatment.

The diagonal elements $m_k ii$ of M_{Sk} (S_k image batch classification) and $m_l ii$ of M_{Sl} (S_l 2nd image batch classification), represent the pixel percentage well assigned to class ***i*** (confidence degree of assignment allocation to this class). The non-diagonal elements $m_k ij$ and $m_l ij$ is the percentage of pixels in class ***i*** assigned to class ***j***. Example of certain rules:

If $i \cap j = \varnothing \Leftrightarrow m_k\, i\, j = 0$ and $m_k\, j\, i = 0$, necessary and sufficient condition, confusion between classes ***i*** and ***j***, the confidence degree is maximum on ***i*** for the source S_k.
Else $x \in i \cup j$, pixel $x \in S_k$
    If $m_k\, i\, j \neq 0$ **then** there is confusion between ***i*** and ***j***, some pixels of class ***i*** are assigned to class ***j***.
    If $m_k\, j\, i \neq 0$ **then** there is confusion between ***i*** and ***j***, but the pixels of class ***j*** are assigned to class ***i***.

If there is confusion between ***i*** and ***j*** in the source S_k ($i \cap j \neq \varnothing$ with a high score for $m_k ij$), the source S_l can remove this ambiguity if $i \cap j = \varnothing$ in S_l or if the score is low for $m_l ij$.

Example SPOT/ERS : for two "sub classifications" with combinations of different dates, two classes can be in conflict, caused by their attribution to the same pixel. The ambiguity is removed by comparison of confusion matrices of both images which reveal the conflicts between classes.

SPOT	Corn	Sunflower
Corn	61.23	30.5
Sunflower	20.6	71.02

M_{Sk} (1)

ERS	Corn	Sunflower
corn	90.5	10.1
Sunflower	2.8	50.3

M_{SL} (2)

ERS	Corn	Sunflower
Corn	90.5	1.1
Sunflower	42.1	50.3

M_{SL} (3)

1st classification (1) Corn is confused with Sunflower; the confusion is removed thanks to the fusion with the 2nd classification (2) without ambiguity with the fusion rules . (3) Corn seems well classified (90.5%), but it is over-represented and often replaces Sunflower (42.1%), fusion between 1st and 3rd classifications would be incorrect. The algorithm avoids this type of confusion.

Probabilistic models : method implemented

- Fusion is carried out thanks to the Bayes rule, which requires the estimation of the probability which is compute by training (supervised or random).
- For every image batch can be associated a weight which gives more or less of importance (credibility) to every batch.
- Given the inaccuracy of these data, why do we keep a single class? The difference between the ***n*** first best measures is unimportant. The class which has the best score is generally very close to the next classes. Thus, there is no more reason to choose the 1st than the 2nd and so on. Several classes are thus acceptable for a pixel. For a given pixel, the measures of the ***n*** classes is ordered in descending order, we could have for example [0.3865, 0.3864, 0.3862, 0.3861, 3858, 0.29…]. In that case, first five classes of this image batch have very close measures, we select them.
- For every image batch, the ***n*** best classes are chosen, their associated measure is kept, and the global decision is carried out for these ***n*** classes.
- The intersection of acceptable class sets for every image batch is made, to determine the most representative class.

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APPLICATIONS

1- **Temporal series automatic fusion : Southwest project of the CESBIO, Formosat-2 8m*8m (2008) images**

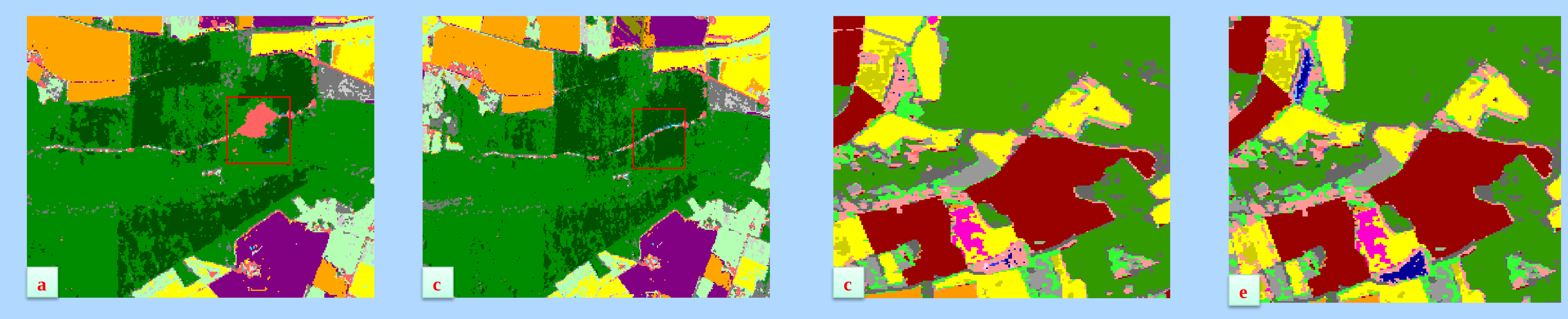
a - Classification, 9 dates: 2008/02/11, 2008/06/19, 2008/07/10, 2008/07/31, 2008/08/21, 2008/09/25, 2008/10/06, 2008/10/10, 2008/10/26., 4 spectral bands: B (0.45 - 0.52 µm); G (0.52 - 0.60 µm); R (0.63 - 0.69 µm), PIR (0.76 - 0.90 µm)

b - Classification without February which contains some clouds. Classes under clouds are classified in Built classes

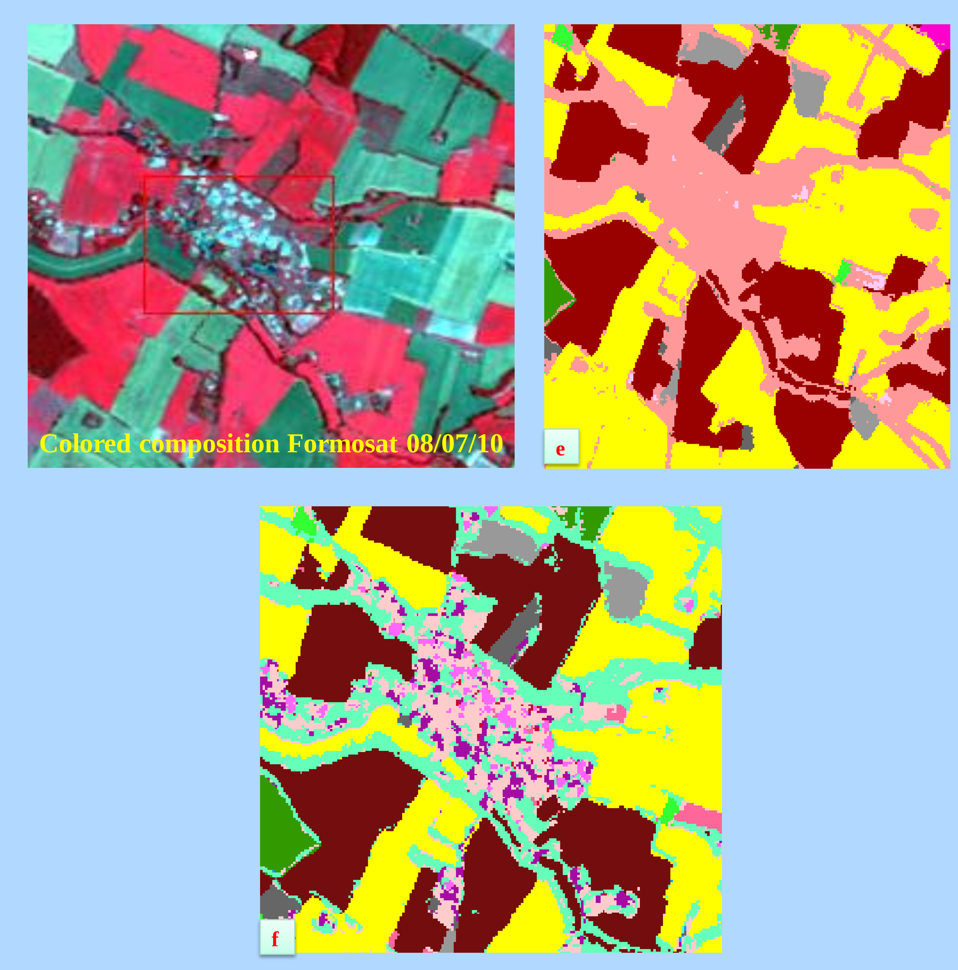
c - February is important to discriminate Rapeseed; fusion between (a) & (b) allowed discriminating Built classes and Rapeseed class

d - Classification with only PIR or NDVIs of every date improves Water, Lake or Gravel pit classes and Wheat class

e - Fusion between (c) & (d) better discriminate these classes (see small lakes appearing in figure e)

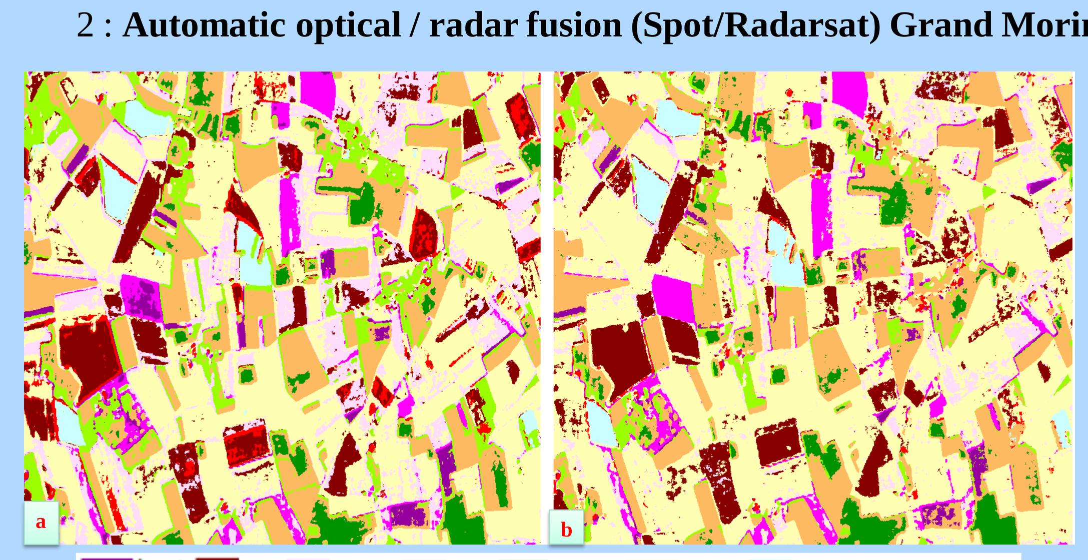


f- fusion between the final result (e) & unsupervised classification which distinguishes different stages of builds and hedges (f) .



% corrected classes	fusion final	9 dates	8 dates without february
decideous trees	97.88	96.9	96.4
coniferous	97.05	96.82	96.15
eucalyptus.	74.53	73.84	70.41
wheat	97.48	96.28	92.44
rapeseed	99.33	99.11	98.05
barley	99.06	97.41	95.87
corn	99.6	99.13	98.75
sunflower	99.12	96.91	93.08
sorghum	100	98.17	97.48
soybean	97.36	97.42	97.09
set-aside land	97.75	93.65	93.11
wild land	90.27	91.64	91.19
meadow	95.16	92.61	88.73
river	99.73	97.41	97.28
lake	99.95	99.68	99.68
dense built	96.06	96.06	94.98
industrial built	98.2	98.2	97.48
gravel pit	99.91	99.83	99.78
poplar	98.97	97.87	98.27
diffuse built	95.47	97.46	95.29
bicultural	93.32	95.47	92.15
particular sunflower	100	96.91	96.74
mineral surface	99.82	99.82	99.27
late sunflower	100	100	99.95
MPCC	96.92	96.19	94.98
Kappa	97.23	96.13	94.31

2 : **Automatic optical / radar fusion (Spot/Radarsat) Grand Morin basin in Seine and Marne (France)**



a- classified SPOT image (image multispectral mode XS, 1997/08/13)
b- fusion with the Radar unfiltered images, classified with **contextual Gauss Wishart law** (GW)

Methods and data	Gauss Spot	GW unfiltered Radarsat	Spot + GW unfiltered Radarsat	Spot + Pearson unfiltered Radarsat
forest	98.6	94.87	98.05	98.06
corn	85.46	80.52	99.18	97.54
wheat 1	49.55	59.89	88.87	87.79
wheat 2	86.21	62.3	88.89	90.03
barley	59.62	45.56	59.91	60.35
rapeseed	46.02	40.15	46.02	46.02
pea 1	54.65	60.21	55.43	55.81
pea 2	79.78	70.57	80.66	82.97
beet	97.92	86.32	99.14	94.1
herb	97.09	86.25	97.43	97.44
urban	97.5	93.85	100	91
bare soil	99.56	87.49	100	96.84
MPCC	**79.33**	**72.33**	**84.46**	**83.43**

- improves the results of the SPOT image (Gauss law): Forest, Corn, Beet and Pea classes and the structure of fields
- eliminates pixels from Urban-mineral class spread everywhere in the image
- reduces contour pixels confusion (fields & grass). This improvement is not counted in the percentage of well-classified
- aim: to define an indicator of environment to estimate the natural environment vulnerability (pollutions engendered caused by the human activity)

3. Automatic optical/radar fusion for the detection of the agricultural practices on bare soil (southwest of Toulouse). to take into account the soil work in the modeling of the land parcel carbon inventory

- soils are sinks and sources of CO2. It was shown that a ploughed ground stored 3 to 5 tons of CO2 by hectare and per year; it is less than a slightly worked ground or with direct sowing
- RADAR contribution on optical supervised classification improves the distribution of bare soil classes (12 %) and active vegetation classes is better discriminated with optical images

Fusion 2 Dates	**Formosat2** 4 spectral bands ;**1date** 08/10/10 **TerraSAR-X** 08/10/09 one X band **MPCC** 83.16% **Kappa** : 75.45%									
	RADAR contribution			**Optical contribution**						
Classes	Stubble disking	Deep ploughing	Harrowing	Sowing preparation	Emergence	Inter-crop	*Corn*	*Rape seed*	*Sunflower*	*Rape seed*
PCC	67.43%	91.72%	53.52%	81.28%	93.69%	76.35%	92.54%	93.3%	96.69%	85%
Confused with	Harrowing Sowing preparation	Harrowing	Stubble disking Deep ploughing	Harrowing	Rapeseed Sowing preparation	Stubble disking Corn	Inter crop	Corn	Rapeseed	Emergence Stubble disking

Class definition see [Inglada J.et al]

CONCLUSION

- In complex contexts, with different sensors or long temporal series the objective is to obtain superior scores of classification.
- One most effective solution is to proceed to classification fusions realized with diverse combinations of dates (image batches), chosen according to the class discrimination .
- The various applications presented confirm the advantages of fusion for long temporal series and optical/radar fusion