Abstract—In this work we investigate the effects of pan-sharpening on multitemporal multispectral (MS) and panchromatic (PAN) images for applications of change detection (CD). The rationale of the analysis consists in understanding in what conditions and to which extent the merging process can improve the results of a standard unsupervised method of change detection. In order to properly analyze and study this problem, different multiresolution fusion algorithms are tested to compare the CD results obtained from original MS and PAN data and from spatially enhanced MS data. Several experiments are carried out by applying some fusion techniques to coregistered Quickbird images acquired at different times. From these experiments some interesting conclusions are derived on the effectiveness and the appropriateness of the different investigated multiresolution fusion techniques with respect to the change detection application.

I. INTRODUCTION

The ever increasing availability of multitemporal very high geometrical resolution (VHR) remote sensing images results in new potentially relevant applications related to environmental and land monitoring and management. The most of these applications are associated with the analysis of dynamic phenomena (both anthropic and non anthropic) that occur at different spatial and temporal scales, and result in changes on the Earth surface. The effects of these phenomena can be detected when developing change-detection techniques capable to automatically identify changes occurred between two VHR images acquired at different times on the same geographical area. The last generation of VHR multispectral sensors (e.g., the ones mounted on board of Quickbird, Ikonos, SPOT-5 satellites) can acquire a panchromatic (PAN) image characterized by very high geometrical resolution (i.e., 0.7-2.8m) and low spectral resolution; and a set of multispectral (MS) images with lower spatial resolution (i.e., 2.8-11.2 m), but higher spectral resolution. In order to take advantage of both high geometrical and spectral resolutions in the change detection process, proper pre-processing is required, that merges the properties of PAN and MS data according to multiresolution fusion (pan-sharpening) techniques, resulting in a set of MS images with both a high spectral resolution and an enhanced geometrical resolution. The aim of the present work is to analyze the impact of pan-sharpening process on the accuracy of change-detection maps investigating whether the multiresolution fusion represents a useful pre-processing step for an accurate change detection, or if the introduced artifacts significantly affect the quality of the change-detection maps.

II. PAN-SHARPENING TECHNIQUES

Data-fusion techniques exploit the complementary spatial/spectral resolution characteristics of PAN and MS images for producing spatially-enhanced, or pan-sharpened MS observations. Two main methodological approaches are considered: methods based on detail injection driven by local filtering operations, classified as multiresolution analysis (MRA) fusion methods, and methods that perform fusion on a pixel basis, classified as vector analysis (CVA) technique [6],[7].

The paper is organized in six sections. Sections II and III present a detailed description of the adopted pan-sharpening and change detection techniques, respectively. The unsupervised approaches based on similarity for ranking pan-sharpening techniques are described in section IV. Section V illustrates the data set used for the experiments and reports the experimental results. Finally, section VI draws the conclusion of this work.

• Generalized Intensity Hue Saturation (GIHS) fusion

Most literatures recognized IHS as a three order method because it employs a matrix as its transformation kernel in the RGB-IHS conversion model. More recently, the Generalized IHS algorithm has been proposed [1], which is capable to extend traditional three order transformations to an arbitrary order. The generalized intensity (GI) image obtained by a weighted linear combination of all MS bands is subtracted from the PAN image. Such difference image is added to each MS image. Image fusion techniques with an arbitrary order are advantageous because they can easily handle hyperspectral or multispectral images with more than three bands. However its main critical point, due to GI generation, is that the fusion products may exhibit significant spectral distortion.
• **Gram-Schmidt (GS) spectral sharpening**
  The GS method [2] enhances the spatial resolution of the MS image by merging the high resolution PAN image with the low spatial resolution MS bands. The main steps of the method are the following: 1) a lower spatial resolution PAN image is simulated; 2) the Gram-Schmidt transformation is applied to the simulated lower spatial resolution PAN image and the lower spatial resolution spectral band images. The simulated lower spatial resolution PAN image is employed as the first band in the Gram-Schmidt transformation; 3) the first transform band is substituted by the higher spatial resolution PAN image after histogram matching; 4) the inverse Gram-Schmidt transformation is applied to the new set of transform bands to produce the enhanced spatial resolution MS images.

• **The Minimum Mean Square Error pan-sharpening method (MMSE)** [3] applies a Generalized Intensity-Hue-Saturation (GIHS) transformation to the MS bands properly modified. The weights of the linear combination which provides the intensity image and the gains that regulate the injection of the difference image are calculated in a minimum mean squared error sense. The solution that minimizes the squared error between the original MS image and the fusion result obtained by spatially enhancing a degraded version of the MS image through a degraded version, by the same factor, of the PAN image is used to fuse data at full scale. The fusion result is also optimal at the highest spatial resolution under the assumption of invariance of the fusion parameters across spatial scales.

• **The High pass filtering (HPF) method** [4] consists of an addition of spatial details, taken from a high resolution PAN band, into a bicubically resampled version of the low-resolution MS image. Such details are obtained by taking the difference between the PAN image and its lowpass version achieved through a simple local pixel averaging, i.e., a box filtering. The HPF method is very easy to implement, but it may produce poor fusion results, especially in specific MS bands (B band, in the blue wavelengths, for Quickbird and Ikonos data).

• **The Proportional additive wavelet to the L component (AWLP) pan-sharpening method (AWLP)** [5] combines a high-resolution PAN image and a low-resolution MS image by adding some wavelet planes of the panchromatic image to the intensity component of the low-resolution image. It is an extension of the AWL method which can be applied only on three images. The intensity component obtained by the decomposition of the original RGB image into the LHS color space is not substituted by the panchromatic image, but the highest resolution features present in the multispectral image are introduced into the merged image by adding the first wavelet planes of the panchromatic image to the intensity component. The "à-trous" wavelet coefficients of the n-MS bands are emphasized by the details of the high resolution image proportional to the original radiance value of the low resolution MS image.

The first three fusion techniques which are based on the transformation of the low resolution MS images without any filtering operation of the PAN image can be classified as CS algorithms. The last two are based on MRA, i.e. the spatial details extracted from the PAN image are injected in the MS images.

### III. CHANGE DETECTION TECHNIQUE

In order to perform the change-detection process, we considered the Change Vector Analysis (CVA) technique, which is a simple and widely-used unsupervised change-detection technique. CVA has been demonstrated its effectiveness in detecting and characterizing different radiometric changes in multitemporal multispectral data sets in several application domains [8], [9], [10]. The simplicity of CVA allows us to properly evaluate pan-sharpening effects without bias related to the change detection technique. CVA is usually applied to multispectral images acquired by passive sensors and involves multidimensional spectral vectors in order to exploit the most possible available information on the investigated change. Finally it reduces the multidimensional problem to a one-dimensional problem where change \( \omega_c \) and no change \( \omega_n \) classes can be easily separated according to a thresholding procedure.

Let us consider two radiometrically corrected and co-registered multispectral images, \( X_1 \) and \( X_2 \), of size \( P \times Q \), acquired over the same geographical area at different times, \( t_1 \) and \( t_2 \). Let \( \Omega = \{ \omega_c, \omega_n \} \) be the set of classes of unchanged and changed pixels to be identified. Let \( B \) be the number of spectral channels of \( X_1 \) and \( X_2 \). The CVA technique emphasizes the change information by computing a multispectral difference image \( X_D \) subtracting spectral feature vectors in corresponding spatial position of the two considered images \( X_1 \) and \( X_2 \) as follows

\[
X_D = X_2 - X_1
\]

In order to transform the \( B \)-dimensional problem in a one-dimensional problem the magnitude of \( X_D \) is computed as:

\[
X_D^M = \sqrt{\sum_{i=1}^{B} X_D^2_i}
\]

where \( X_{Di} \) is the \( i \)-th component of the multispectral difference image.

According to eqs.(1),(2), it is possible to demonstrate that unchanged pixels present small magnitude values, whereas changed pixels show large values [6], [7]. Let us denote with \( x_{M}^{D}(p,q) \) a generic pixel in spatial position \( (p,q) \) in the magnitude image \( X_D^M \). Then the final change detection map \( Y \) can be computed according to the following decision rule:

\[
y(p,q) \in \begin{cases} \omega_c & \text{if } x_{M}^{D}(p,q) \geq T \\ \omega_n & \text{if } x_{M}^{D}(p,q) < T \end{cases}
\]

where \( y(p,q) \) is the label associated to the pixel at spatial position \( (p,q) \) in the change-detection map, and \( T \) is the decision threshold. The threshold \( T \) can be defined either manually or automatically; we refer the reader to [6] for more details on automatic threshold selection techniques.
IV. UNSUPERVISED TECHNIQUE FOR THE ESTIMATION OF THE IMPACT OF PAN-SHARPENING ON CHANGE DETECTION

In order to properly understand the impact of different pan-sharpening techniques on the change-detection process, we propose to perform an analysis at different resolution levels: i) the one of the panchromatic image (high resolution level); and ii) the one of the multispectral image (medium resolution level). In the first case the original multispectral images were fused with the panchromatic one, while in the latter case the original PAN and MS images were spatially degraded down to a lower resolution before applying pan-sharpening. The latter option makes it possible a comparison between fused products at MS resolution with the original MS set.

As no a priori information about the investigated scene is available, in this work we propose an unsupervised strategy for evaluating the impact of fusion techniques on the change detection process. Considering different pairs of pan-sharpened multitemporal images, we compute a similarity measure among pairs of change detection maps. This strategy is based on the rationale that different pan-sharpening techniques result in different artifacts in the change detection map. Therefore the lower the impact of a given pan-sharpening technique on the change detection process the higher the similarity between the obtained change detection map with all the others obtained after different pan-sharpening.

The proposed strategy considers $N$ change-detection maps obtained by CVA on different pan-sharpened multitemporal pairs. Let us represent the labels $\omega_i$ and $\omega_j$, assigned according to eq.(3) with $+1$ and $-1$, respectively. For each pair of change-detection maps $Y_i$ and $Y_j$ ($i, j = 1, ..., N$) we compute a measure of similarity $H_{ij}$ of the change-detection results on the $P \times Q$ pixels of the images as:

$$H_{ij} = \frac{1}{PQ} \sum_{p=1}^{P} \sum_{q=1}^{Q} y_{i}(p, q) \cdot y_{j}(p, q) \quad \forall i, j = 1, ..., N, i \neq j$$

(4)

where $y_{i}(p, q)$ and $y_{j}(p, q)$ are the labels of the pixel in position $(p, q)$ in the change-detection maps $Y_i$ and $Y_j$, respectively. As $y_{i}(p, q)$ and $y_{j}(p, q)$ can assume values in $\{-1, +1\}$, their product is equal to $1$ if $y_{i}(p, q) = y_{j}(p, q)$ and to $-1$ otherwise. Accordingly, the value of the similarity measure $H_{ij}$ is equal to $1$ if $Y_i$ and $Y_j$ are identical, and is lower than $1$ otherwise. In general $H_{ij}$ belongs to the interval $[-1, +1]$. On the basis of this measure, an absolute measure of similarity of each map $Y_i$ to all the others can be defined by computing the average value of $H_{ij}$, i.e.

$$H_i = \frac{1}{N-1} \sum_{j=1}^{N} H_{ij} \quad H_i \in [-1, +1]$$

(5)

Finally, according to the value of the average measure of similarity $H_i$ the $N$ considered pan-sharpening techniques can be ranked from the one that less affects the change detection process (high average similarity) to the one that most affects it (low average similarity). This strategy can be applied either to the high resolution pan-sharpened images as well as to the medium resolution pan-sharpened images.

Instead of considering relative references as change detection maps obtained by applying CVA to different pan-sharpened multitemporal pairs, an absolute reference $Y_{ref}$ can be selected which is common to all $N$ change-detection maps $Y_i$ ($i = 1, ..., N$). As an example $Y_{ref}$ can be a map built according to available a priori information about changes occurred on the ground, or, in the case of the spatially degraded data set, it can be the change detection map computed applying CVA to the original multitemporal MS images. Another possible choice is to compute $Y_{ref}$ by applying a majority voting rule to the set of $N$ change-detection maps $Y_i$ ($i = 1, ..., N$) as:

$$y_{ref}(p, q) \in \left\{ \begin{array}{ll}
\omega_c & \text{if } \sum_{i=1}^{N} y_i(p, q) > 0 \\
\omega_n & \text{if } \sum_{i=1}^{N} y_i(p, q) \leq 0
\end{array} \right.$$

(6)

The similarity can be computed by applying (4) with $Y_j = Y_{ref}$.

V. EXPERIMENTAL RESULTS

A multitemporal data set made of two MS and PAN Quickbird images acquired on Trentino area (Italy) in October 2005 and July 2006 was considered to evaluate the impact of the different investigated multiresolution fusion techniques on the change detection process. In the pre-processing phase the two images were: i) radiometrically corrected by a simple subtraction of the mean value for each spectral channel; and ii) co-registered by means of 12 ground control points. Between the two acquisition dates some changes related to urban and rural areas occurred on the ground (see yellow circles in Fig.1). The five pan-sharpening methods presented in sec.II and simple interpolation by a factor 4 were applied to the considered data set and to a degraded version of it in order to obtain two sets of pan-sharpened/expanded multitemporal multispectral images, one at the geometrical resolution of the PAN image (i.e., 0.7m) and one at the geometrical resolution of the MS image (i.e., 2.8m). The expanded images showed a very poor geometrical content and were therefore not included in further analyses.

In order to apply the proposed unsupervised technique for the estimation of the impact of pan-sharpening on change detection, we applied the CVA technique to all the multitemporal pairs of fused images and to the multitemporal pair of original MS images by considering only the green, red and near infrared spectral channels of each pair. The adopted threshold value $T$ is the same for each magnitude image. This choice is quite reasonable as we expect that differences due to the different pan-sharpening techniques do not significantly change the statistics of the magnitude image; moreover it leads to change detection maps as comparable as possible and avoids possible bias due to the use of automatic thresholding techniques.

Two experiments were carried out. The first one aims at demonstrating that:

- change detection performances with or without reference original bands are in accordance with quality indexes, used for assessment of pan-sharpened images, that require...
Fig. 1. True color composition of the Trentino area (Italy) acquired by the Quickbird VHR multispectral sensor in: (a) October 2005; and (b) July 2006 (changes occurred between the two acquisition dates appear in yellow circles).

reference original bands, such as ERGAS [11], Q4 [12] and Spectral Angle Mapper (SAM) [13];
- approaches which do not require reference original bands (described in Section IV) are in accordance with others that require references.

To this purpose, the data sets have been spatially degraded by four, according to the protocol proposed in [14], and numerical values have been calculated between fused and original data, with the exception of approaches based on majority voting and on average of similarity measures obtained by each pair of different fusion algorithms. From the numerical values reported in Tables I, II and III, it appears that approaches calculated without reference originals, are in trend with the other change detection performances, which require reference originals.

For all change detection maps and for all quality indexes based on pan-sharpening, the MMSE fusion method attains the best global scores, closely followed by AWLP. HPF provides the poorest results, as expected.

The second experiment aims at comparing the numerical values of change detection maps obtained by fused images at the full scale, i.e., 0.7m for Quickbird data with those obtained from degraded originals, at 2.8m. Fusion performed at 0.7m provides the spatially-enhanced images that will be used in

CD practical applications. Although change detection values are scale dependent, when table IV is compared with table III, fusion performances are very similar for the two scales with the exception of AWLP algorithm which is based, as well as HPF, on MRA.

MRA-based methods perform a highpass detail injection that may produce spatial distortions, typically ringing or aliasing effects, originating shifts or blur of contours and textures, and as a consequence can influence the performance of a
change detection algorithm. These drawbacks are emphasized by misregistration between MS and PAN data, especially (but not exclusively) if the MRA underlying detail injection is not shift-invariant. Table IV suggests that extreme care must be taken of the choice of the fusion algorithm for a change detection application, with a particular reference to MRA pansharpening techniques. Figures 2, 3 and 4 are in accordance with the results obtained in Table IV. Best visual results in Fig.2 are provided by the MMSE and AWLP methods. However, the fused image obtained by AWLP clearly shows overenhancement in the vegetated regions which affects the change detection process. The same consideration may be done when observing Fig.3: the best methods for spectral preservation are MMSE and AWLP, with more accurate texture injection by the MMSE method, especially in the green wavelengths.

VI. CONCLUSIONS

A comprehensive study on the effects of pansharpening methods on change detection is presented in this paper. The proposed assessment of the change-detection maps obtained from the pansharpened images, both at full and degraded scales, is in accordance with the objective evaluation of the considered pansharpening algorithms. Even if the results of the different fusion methods can depend on the spatial scale, the performance ranking of the fusion algorithms clearly indicates that both MMSE and, to a lesser extent, AWLP methods provides spatially-enhanced images which can be profitably used for change detection applications.

REFERENCES

Fig. 3. True color (3-2-1 MS bands as R-G-B display channels) composite of 256 × 256 details of 0.7m Quickbird data acquired in July 2006.

Fig. 4. Change detection maps of 256 × 256 details obtained by the two Quickbird data sets
