Exploiting SAR and VHR Optical Images to Quantify Damage Caused by the 2003 Bam Earthquake

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Abstract—Using satellite sensors to detect urban damage and other surface changes due to earthquakes is gaining increasing interest. Optical images at different resolutions and radar images represent useful tools for this application, particularly when more frequent revisit times will be available with the implementation of new missions and future possible constellations of satellites. Very high resolution (VHR) images (on the order of 1 m or less) may provide information at the scale of a single building, whereas images at resolutions on the order of tens of meters may give indications of damage levels at a district scale. Both types of information may be extremely important if provided with sufficient timeliness to rescue teams. The earthquake that hit the city of Bam, Iran, has been taken as a test case, where QuickBird VHR optical images and advanced synthetic aperture radar data were available both before and after the event. Methods to process these data in order to detect damage and to extract features used to estimate damage levels are investigated in this paper, pointing out the significant potential of these satellite data and their possible synergy.

Index Terms—Damage detection, earthquake, synthetic aperture radar (SAR), very high resolution (VHR) optical image.

I. INTRODUCTION

ON DECEMBER 26, 2003, the southeastern region of Iran was hit by a 6.5 moment magnitude ($M_w$) earthquake whose epicenter was located very close to the city of Bam. The event had a tremendous impact all over the world, due to a heavy loss of life, injuries, and destruction; the earthquake caused the death of more than 26,000 residents and injured another 30,000. Additionally, the city of Bam was a UNESCO World Heritage site and as such plays an important historical role. The Bam earthquake was the worst seismic event in recent Iranian history. The damage was concentrated in a relatively small area around Bam [1]. Ninety percent of the structures in the city of Bam were left more or less heavily damaged or totally collapsed. In particular, the main historical and traditional adobe buildings collapsed. Contemporary houses demonstrated better resistance to earthquake shake, even though many collapsed due to poor construction practices and the presence of weak storeys in the buildings.

In the event of such destructive disasters, a prompt overview of the damage of the human settlements is very important to be able to manage the rescue efforts and, subsequently, to organize restoration activities [2]. This is particularly true in the case of remote regions or heavily damaged communication infrastructures. Damage to settlements is not necessarily correlated with seismic magnitude, but it is obviously correlated with human injuries. Here, satellite-based Earth Observation techniques may provide a unique tool for evaluating damage and its impact on societal activities. Remote sensing of urban damage due to earthquakes is gaining interest in the research community. Different types of sensors can be exploited from satellite platforms, including optical radiometers with different ground resolutions (from tens of meters to submeter resolution), as well as radar sensors with comparable resolutions.

Changes in synthetic aperture radar (SAR) backscattering and phase have been used in the literature for earthquake damage mapping purposes. An index to estimate damage level from SAR data by combining image intensity changes and the related correlation coefficient has been applied to some case studies: the Hyogoken-Nanbu earthquake [3], [4] and the Izmit and Gujarat seismic events [5], [6]. Yonezawa and Takeuchi [7] compared changes in the SAR backscatter intensity and phase with damage observed in Kobe. Ito et al. [8] assessed different SAR change indicators, derived from L- and C-band sensors, and evaluated the frequency-dependent effects of spatial and temporal decorrelations. Chini et al. [9] detected wide uplift and subsiding areas, as well as large modifications of the coastline associated to the Indonesian earthquake of 2004, using only pre- and postearthquake SAR backscattering.

The presence of shadows, variations in solar illumination, and geometric distortions may prevent the use of automatic damage detection procedures in optical images. Because of these problems, visual image inspection is still the most widely used method to produce a realistic and reliable inventory of damage [10], [11]. Sakamoto et al. [12] compared an automatic technique with the visual interpretation results using QuickBird (QB) data. Matsuoka et al. [13] proposed to detect damage by analyzing edges in high-resolution images. More in general, automatic change-detection algorithms using either QB [14], [15] or SAR images [16] are also present in the literature.

The utility of remote sensing for earthquake damage assessment strongly depends on the number of available images, their type (SAR, optical, or both), and quality and timeliness of the data sets (i.e., time delay of the postseismic images with respect to the destructive event). Although many different
experiments and methods have been investigated, a systematic assessment of the potential contribution of remote sensing in this field is lacking in the literature. Moreover, the mutual contribution of different sensor types and procedures for their possible integration has not been extensively investigated.

The objectives of this paper are threefold. It aims to analyze the sensitivity of different parameters extracted from different types of remotely sensed images to the level of damage in urban areas relative to ground survey information. We will see that the parameters to be extracted and the preprocessing scheme are strictly related to the type of exploited data (i.e., their resolution and spectral channels). Additionally, this paper aims to demonstrate how very high resolution (VHR) images can detect damage at the pixel scale (≤ 1 m) with semiautomatic techniques. Problems associated to this task when dealing with submeter resolution images are pointed out, and ways to overcome them are proposed. Finally, the possible synergy of data from different sensors is also investigated.

We note that this paper is based on images of opportunity and cannot address the timeliness issue that would be so important for mapping future seismic events. It is assumed that interested agencies would order QB or similar high-resolution optical images to be collected as soon after the earthquake as possible.

The satellite data set available for this catastrophic event was composed of three ENVISAT advanced SAR (ASAR) images from descending orbits, which have a geometric ground resolution of 20 m, and two images collected by the optical panchromatic sensor onboard the QB satellite, with a geometric spatial resolution of 60 cm. Two ASAR images were collected before the event, about six months earlier and one month earlier, respectively; the third one was collected 12 days after the earthquake. QB captured a clear image of Bam on January 3, 2004, eight days after the event. The city was also observed by QB on September 30, 2003, about three months before the event.

In order to validate the information obtained using remote-sensing data, a detailed ground-based damage map (i.e., the ground truth) has been used. It is a map of the collapse ratio (percentage of completely collapsed buildings with respect to the total number of buildings within a city block), which has been provided by the Geological Survey of Iran [17].

For this paper, the data set is sufficiently complete, pre- and postseismic data being available from both radar and optical sensors. This has allowed us to show also the advantages of the combination of both types of sensors, which have different resolutions and extremely different spectral channels.

II. EXPLOITING VHR OPTICAL IMAGES

The new-generation VHR images (≤ 1 m) enable the detection of very small changes on the surface, but they introduce some new problems, which were not encountered with the previous satellite missions which had optical sensors with a resolution of tens of meters. For this reason, change-detection techniques applied to previous generations of data with lower resolution do not provide satisfactory results when applied to submeter resolution images. VHR sensors are particularly affected by varying shadows, since different sun illumination during different seasonal acquisitions produces different projections of the building’s shadow on the ground. Error may also originate from different sensor observation angles (i.e., the off-nadir angle between the sensor viewing direction and the vertical to the Earth surface), which changes the parallax and, thus, the shape of the objects as a function of their height. In fact, these satellites can change the image acquisition angle in order to increase their revisit cycle. This is very common in case we want to monitor an area hit by an earthquake or other catastrophic event, where a matter of primary importance is to collect data as soon as possible. Indeed, for this paper, we have a huge difference between acquisition angles, i.e., 9.7° off-nadir angle on September 30, 2003, and 23.8° off-nadir angle on January 03, 2004, respectively. Few works addressing this problem are present in the literature, trying to better coregister the house roofs between two acquisitions [18], [19]. In [20], only the rotational effects between images were taken into account.

Fig. 1 shows the ground truth map superimposed to the panchromatic QB image taken before the catastrophic event. It identifies different ranges of collapse ratio with different colors.

As already exploited by Stramondo et al. [6], for the Izmit, Turkey, earthquake in 1999, the normalized difference (the so-called change image) between one preseismic and one postseismic panchromatic radiance image (i.e., the difference between radiances divided by their sum) was sensitive to the damage level, and there was a good agreement between the collapse ratio (the percentage of collapsed buildings with respect to the total number of buildings within a region) and this parameter extracted from optical images within homogeneous areas.

That study used IRS panchromatic images, with a spatial resolution of 5 m, which suffer less from the problems aforementioned. In this paper, we tried to use the same procedure to investigate the sensitivity of VHR optical sensor data to damage level obtained by the ground survey. Before computing the normalized image difference, coregistration and histogram matching algorithms were applied sequentially to the images. As for the coregistration, we have adopted a polynomial warping based on visually selected control points (image to image). The area is quite flat so that the use of a DTM was not required. The histogram matching procedure has been used in order to diminish the effect of different sun illumination angles [21]. It consists of modifying the gray level of the image by a nonlinear function in such a way as to make the histogram of the new
image more similar to a reference image. In our case, we make the histogram of the second image match that of the preseismic image. To achieve this aim, it is important to select only those portions of the reference image characterized by urban cover and where no changes between pre- and postseismic data have occurred. The histograms of these areas have been used to construct the transfer function to be applied to the second image. Despite the previous precautions and preprocessing steps, the correlation between the change image and the damage level provided by the ground survey was not very high. Namely, the undamaged area exhibits a normalized difference value comparable with that of the slightly damaged area (20%–50% of collapse ratio) and greater than that of the highly damaged areas (50%–80% and 80%–100% of collapse ratio), which is the opposite of what was expected from the Izmît experience based on 5-m resolution images [6]. This result indicated the need to account for some effects, such as the presence of shadow, vegetation, and temporary objects in the image (i.e., cars) that were not apparent to the same extent in medium resolution data. Indeed, the main outcome of this paper is the identification of possible strategies to correct these effects.

It is worth noting that the postseismic QB image was acquired in January, when the sun’s low elevation produces more shadow. Because of the false alarms produced by building shadows, the changes in the undamaged area have been largely overestimated. Additionally, there are a lot of vegetation patches within the regions where the normalized difference has been computed, which, of course, were not taken into account by the team performing the ground survey. It is very interesting to notice that the mostly vegetated class was that with a collapse ratio value of 20%–50%; thus, it is evident that the overestimations of changes (false alarms) due to different shadow projection and different tree foliation are both caused by different seasons in which the images have been taken. This evidence prompted us to preliminarily classify the preseismic image in order to identify the built-up areas and to compute change detection only for those pixels covered by man-made structures. In this way, we were able to remove all change-detection false alarms due largely to shadows, cars, and highly variable vegetated areas.

The extraction of buildings from just one single panchromatic image is not an easy task, since there are many targets that could be confused, as they may have similar radiance values (e.g., cars and some buildings, shadow and some asphalt roads, and soil and some kinds of roofs) [22], [23]. This results in the need for additional attributes to characterize and distinguish some objects from others. Without having spectral channels other than the panchromatic one, morphological operators can be useful for extracting object attributes related to their dimensions and geometry [24]. For example, cars have similar values of radiance as some houses, but they are smaller with respect to the latter. Some roofs may have also the same reflectance as soil, which however generally covers larger areas. Therefore, in this paper, the task of extracting buildings from a single panchromatic image is composed of two steps. First, the morphological composition of opening and closing operations with different sizes of structural element is used to build a morphological feature vector, based on the original QB panchromatic image, accounting for the geometric characteristics of objects. In the second step, we use the morphological feature vector, plus the panchromatic image, as input to an unsupervised Isodata classifier [21] to obtain the mask of the built-up area (the building mask).

In mathematical morphology, there are two important operators: “erosion” and “dilation” [25]. Normally, they are applied to images with structuring elements (SEs) of known shape, corresponding to specific geometrical elements, which demonstrates how structures in the image match those specific elements on the ground (e.g., the SE). Generally, these two operators, namely, erosion and dilation, are dual but noninvertible. These operators are the basis of mathematical morphology, since all other morphological operators can be represented as a combination of erosion and dilation. Two morphological operators obtained from them are the “opening” and “closing” operators. The function of opening is to dilate an eroded image in order to recover as much as possible the original image. On the contrary, the function of closing is to erode a dilated image in order to recover the initial shapes of image structures that have been dilated. The main property of the filtering process provided by the opening and closing operators is that not all structures within the original image are recovered when these operators are subsequently applied.

Normally, we use the opening and closing filters to isolate bright (opening) and dark (closing) structures in the image. For bright and dark, we mean brighter and darker with respect to other neighboring structures. It may be used in a multiscale approach based on a range of different SE sizes, so as to investigate a range of different spatial domains and to use the best response of the structures in the image corresponding to specific objectives of our classification process [26]. Our morphological feature basis is composed of the panchromatic image plus the panchromatic image filtered by open and close operators with different window sizes. Then, although the original data set contains only one channel, the use of the morphological operations provides us with additional features for classification purposes. The window size spans from 3 × 3 up to 125 × 125 pixels. In the new feature vector composed of 37 elements (the original panchromatic radiance, plus 18 new ones derived from the closing operators and 18 from the opening operator), different objects have different morphological profiles, as shown in Fig. 2.

It is worth noting in this figure that, if we had taken into account just a panchromatic image, it would not be possible to recognize differences between some classes (i.e., gray roofs with respect to soil, white roofs with respect to cars, and roads and house’s shadows) due to their similarity in terms of radiance. By taking white roofs and cars as an example, it can be noticed that they have similar radiances but different morphological profiles. The open operator does not modify their radiance (the values of radiance in the entire open profile do not diverge from the original) because they are usually surrounded by objects with lower radiances (roads, shadow, vegetation, etc.). On the contrary, the close profile differs a lot. For cars, the decrease of radiance starts with small windows because of the small dimensions of the car relative to the filtering window (SE). The 3 × 3 size closing operator is enough to modify the
Fig. 2. Morphological profiles of six different classes selected by visual interpretation (supervised). The vertical gray line in the middle indicates the panchromatic original image. Close to this line are small windows of morphological filters. The left part shows the output of the open operator, while the right part shows the close operator.

Fig. 3. (a) Detail of panchromatic image taken on September 30, 2003. (b) Classification map showing the buildings in white.

Radiance of the car. In order to modify the radiance of a house, we need a window around 15 $\times$ 15 pixels (9 $\times$ 9 m, a reasonable house dimension).

The result of the classification process for the extraction of the man-made features is shown in Fig. 3, where, for the sake of clarity, only a neighborhood of Bam City is presented.

There is good agreement between the building map obtained by this classification and what can be inferred from the visual inspection of the original panchromatic image. It is worthwhile to notice that in the Bam area, the buildings have two main different types of reflectance. The morphological parameters have worked quite well in both cases, since they add new features which are related to the geometric size of the objects more than to its reflectance. We have also two different kinds of urbanization, i.e., country side with houses surrounded by vegetation and urban scenario, which is composed of roads, sparse trees, cars, and houses with different architectures.

When computing the average normalized difference between pre- and postseismic radiances within the ground-surveyed regions, the consideration of just pixels falling in the built-up area slightly improves the comparison between this quantity and the collapse ratio. Now, the sensitivity of normalized difference to collapse ratio is always positive as expected. However, it is still quite low (from 0.05 to 0.11) and saturates in the two mostly damaged classes, mainly because of the disturbing effect of the vegetation covering part of the QB images.

The sensitivity of normalized radiance differences to the collapse ratio is quite low if compared with a previous case study based on 5-m resolution IRS images [6]. Therefore, we have developed a different approach to better exploit the VHR QB data and generate a damage map at a resolution of 60 cm (which is one of the goals of this paper). From the analysis of the images, we found that both positive and negative radiance differences should be considered related to damage, without any particular information brought by direction of the change (i.e., the sign of the difference). This may be partially associated to the high resolution (60 cm) that retains a high level of scene details (e.g., objects above the building roof) having different signatures, which does not allow one to characterize univocally the single object by its radiance values. For the detection of destroyed buildings, a threshold has been defined based on the absolute value of the difference between the two panchromatic images, applied just to those pixels containing buildings. The amplitude of the threshold has been selected by a supervised approach guided by a photo interpreter. In Fig. 4, we show the entire damage map of Bam City obtained by this procedure, where the pixels representative of damaged objects within the scene are highlighted in red. A detail of damage occurred and recognized...
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CHINI et al.: EXPLOITING SAR AND VHR OPTICAL IMAGES TO QUANTIFY DAMAGE

Fig. 5. (a) Detail of panchromatic image taken on September 30, 2003. (b) Detail of panchromatic image taken on January 3, 2004. (c) Damaged pixels, singled out in red, superimposed to the difference between pre- and postseismic radiances.

Fig. 6. Block diagram for producing the damage map at pixel scale using only one preearthquake and one postearthquake panchromatic QB image.

by the automatic procedure is shown in Fig. 5 as well. The entire procedure for producing the damage map at pixel scale (60 cm) is summarized in the block diagram shown in Fig. 6.

To analyze the damage at a district level, the percentage of pixels classified as “damaged” relative to the pixels classified as “built” in the first image [Rate of Damaged Pixels (RoDP)] has been computed within areas identified by the ground survey (see colored areas in Fig. 1). This percentage has been shown in Fig. 7 as a function of the collapse ratio provided by the ground survey. In the same figure, we also show the percentage of pixels classified as “damaged” with respect to the total pixels within each ground truth area (i.e., without considering the building mask). It is possible to notice that the RoDP corresponds well to the collapse ratio, with a fairly good correlation, particularly when damage pixels are calculated using the building mask. Computing RoDP without using the mask markedly overestimates the damage in the “not damaged” class and underestimates it in the “damaged” classes. The cause is still related to the differences in the shadow caused by buildings and vegetation, as well as changes in tree foliation.

By using the building mask, the dynamic range of RoDP in percentage terms reaches 35%, which is much larger than the case where the vegetated pixels are not filtered, producing a dynamic range of only 7%. The relationship between RoDP and collapse ratio is however still not one to one. A false detection of about 13% has been observed in the “not damaged” class. The false alarms could be related to different phenomena, such as parallax error between two acquisitions, inaccuracy of the building classification, threshold limitations, and other tailoring of the automatic classification chain. Concerning the apparent underestimation in the heavily damaged areas (collapse ratio in the range of 80%–100%), it must be pointed out that the ground survey labels the building as totally collapsed even if they are partially destroyed, regardless of damage and building extensions. Instead, RoDP accounts for fractional building damage with respect to the total built area, so that a lower percentage is to be expected. In addition, the concertina effect, when floors collapse on top of one another, could be another source of underestimation. This type of building collapse is actually hardly detectable by optical images. A possible approach could be based on the change in the shadow, but at the moment, our procedure simply masks the shadows; thus, it is not capable of detecting its change.

III. EXPLOITING SAR DATA

Radar data are attractive for this application, mainly because they ensure data availability in any weather condition. The ENVISAT ASAR images have been coregistered by automatically searching for control points in the single-look complex images. Image intensity has been computed, and in order to
partially reduce the speckle noise [27], a spatial multilook operation has been performed by averaging 5 × 1 pixels, leading to a SAR intensity image with 20 m × 20 m pixel spacing.

When a pair of SAR images is available, additional parameters, namely, InSAR complex coherence and intensity correlation, can be computed. Both parameters can be derived by combining the preseismic pair, the postseismic, and the coseismic (i.e., one preseismic and one postseismic image) ones. The complex coherence of two images is defined as follows:

$$\rho = \frac{E(s_1 s_2^*)}{\sqrt{E(s_1 s_1^*) E(s_2 s_2^*)}}$$

where $s_1$ and $s_2$ are the corresponding complex pixel values and $E(\ldots)$ indicates the expected value.

The intensity correlation of the two images is defined as

$$\rho_1 = \frac{|E[(I_1 - E(I_1))(I_2 - E(I_2))]|}{\sqrt{E((I_1 - E(I_1))^2 E((I_2 - E(I_2))^2)}}$$

where $I_1$ and $I_2$ are the corresponding values of the pixel intensity $I = |s|$.

Note that these two features contain slightly different information concerning changes in the scene. The complex coherence is primarily influenced by the phase difference between radar returns, which is a distinctive parameter measured by a coherent sensor. It is particularly related to the spatial arrangement of the scatterers within the pixel and, thus, to their possible displacements. Conversely, the intensity correlation is more related to changes in the magnitude of the radar return. Unfortunately, ASAR interferometric image pairs have very high values of the perpendicular baseline, around 500 m for both pairs, and the resulting high spatial decorrelation prevented us from detecting damage levels through the InSAR phase coherence, which has almost the same values both in damaged and undamaged areas when the baseline is too large.

The expected value in (2) is estimated by an averaging procedure. The size of the averaging window can affect the sensitivity of the derived parameters to the changes in the scene [7]. Thus, a preliminary analysis has been performed to determine the best window size providing the best compromise between spatial resolution and discrimination performances. As a result, an averaging window size of 7 × 7 pixels has been applied in this paper, leading to a 140 × 140 m spatial resolution. One preseismic intensity correlation map has been obtained from two preseismic ASAR images (June 11, 2003 and December 3, 2003); one coseismic intensity correlation map has been obtained from one preseismic and one postseismic ASAR image (December 3, 2003 and January 7, 2004).

Concerning the use of the backscattering correlation as an indicator of surface changes, the approach is founded on the idea that the correlation coefficient is high when two images are similar, while it becomes low when changes have occurred in the surface target. Thus, in the latter case, a decrease of correlation of coseismic images is expected to be relative to preseismic ones, and this phenomenon is expected to increase with the increase of damaged buildings on the ground. We have plotted the difference between the pre- and coseismic intensity correlations [Intensity Correlation Difference (ICD)] averaged within areas of homogeneous damage levels (those shown in Fig. 1) as a function of the damage level from the ground survey used also in the previous section (Fig. 8). The entire procedure is summarized in the block diagram shown in Fig. 9. We have also added to the plot a class of “not damaged” areas recognized by visual inspection of the two QB optical images. In the graph, we can see how the ICD increases with the increase in damage level, and the trend is approximately linear. The optical building mask has also been applied to check whether the optical data could improve the SAR damage detection performances. Radar data and building mask have been coregistered using visual selection of control points (image to image). The SAR ICD has been resampled to 60-cm pixel spacing, so that the mask from VHR has been directly superimposed to it. The resampling procedure aims to superimpose the results obtained from SAR and from VHR optical images, without affecting, of course, the resolution of the SAR data. In this way, any SAR data sample (each 20 m × 20 m) would be associated to several VHR samples, partially covered by building (for example, fraction x) and partially covered by other classes (for example, fraction 1 − x). The choice to resample SAR ICD to the

![Graph showing ICD vs damage level](image)
building mask resolution ($0.6 \times 0.6$ m) makes the SAR samples weighted by a factor $x$ in the final estimation of the damage level from SAR. Using just a medium resolution optical image (e.g., 30 m as Landsat images) would not allow one to identify small objects, and thus, the same SAR sample would probably not be identified as affected by possible errors and would be included in the final estimation of the damage level as such without any weighting factor.

As shown in Fig. 8, restricting the analysis just to the built area derived from QB produces an improvement in terms of sensitivity to damage. Indeed, it is possible to observe an increase of the dynamic range in percentage terms of 25% using the building mask. In this test case, there are a lot of vegetated areas in the scene, which affect the value of the correlation. The same phenomenon is still present in the “not damaged” class, but it is not as evident, since this zone is not so heavily vegetated. Additionally, the availability of a VHR image allows one to detect and filter out areas with small temporary objects, such as cars in parking lots, which are another source of decorrelation in SAR image pairs.

The trend of the graph in Fig. 8 is similar to the one obtained in the case of optical data in Fig. 7. Therefore, even though these two data sets give different levels of detail, they show to be both sensitive to variations in the damage level.

As a final remark, it is worth pointing out that, in contrast to optical sensors, SAR sensors are not affected by the solar illumination angle and, thus, by the associated shadow. Moreover, even better correlation between ICD and damage level may be expected when using image pairs with smaller spatial baselines. Concerning the concertina effect discussed in the previous section, we expect that the change of building height could contribute to decorrelation effects and cause a decrease in image intensity because of the lack of the double-bounce return. Both effects could be detected as changes in intensity correlation or phase coherence (for smaller baselines).

### IV. Conclusion

VHR satellite panchromatic imagery is useful to reveal and highlight land-cover changes due to seismic events. They provide a damage map at a pixel scale of 0.6 m that is able to detect the complete or partial collapse of individual buildings. This represents a powerful tool for providing useful information to rescue teams and for managing crisis issues. Mathematical morphology has proven to be a powerful tool to automatically analyze the panchromatic images. In addition to the single building scale, another useful product can be represented by a draft map of damage level relative to certain areas (district scale) of the affected territory. The comparison between collapse ratio provided by the ground survey and the damaged pixel rate obtained from optical data shows a clear relation, demonstrating the feasibility of estimating the collapse ratio from the satellite data alone. In addition, the satellite radar data revealed itself to be a good instrument for detecting damage, even if, with respect to the higher resolution QB images, only at the district scale, due to its lower spatial resolution. There is a good agreement between the decrease of correlation between the pre- and coseismic SAR image pairs and the different damage classes. It has clearly been pointed out that using a building mask produced by automatic classification of a VHR optical image improves the results obtained with the SAR data. Moreover, the empirical relationship of SAR and optical features with damage level is different, which gives a perspective of improvement for future work, if new generation of satellite platforms were equipped with both types of sensors.

The results of this paper can be limited by the access time of Earth observation satellites to a given geographical site. This kind of requirement can be fulfilled only by commanding a satellite to observe the scene of interest. In the near future, satellite constellations will provide rapid access to a seismic site in line with the requirements from civil protection point of view. A delay on the order of 24 h, or 48 h for very isolated settlements, could represent a significant step ahead with respect to the timeliness of traditional ground surveys.

Further improvements could involve the segmentation of the image to single out individual buildings and better compare the remotely sensed product with the ground survey outcomes and the attempt to detect the concertina effect and to fuse VHR data with recently launched SAR satellites with 1-m resolution.

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### REFERENCES


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