

Identification of Damaged Building Regions From High-Resolution Images Using Superpixel-Based Gradient and Autocorrelation Analysis

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Abstract—An efficient and accurate identification of damaged buildings after earthquakes is critical for ensuring a quick response and efficient rescue operations. Considering the time pressure during disaster emergency response and the convenience of practical application, a new approach for identifying areas with damaged buildings is proposed in this study. The approach is validated on high-resolution images from areas impacted by the Haiti earthquake. The approach consists of the following steps. (i), the simple linear iterative clustering method is improved to segment the images into high-quality superpixels by combining both color and texture information; (ii) the characteristics of the damage in the area within the cluster and the difference between pre- and post-earthquake images are obtained at superpixel level using the Sobel gradient; and (iii) local indicators from the spatial association analysis are used to extract the result of the gradient clustering using the synthetic-damage index calculated by an improved relief algorithm; and (iv) vegetation and shadows are masked out to identify the damaged buildings. This framework achieved an overall accuracy of $\sim 90\%$ in terms of visual interpretation, with precision and recall of $\sim 85\%$ and $\sim 90\%$, respectively. Inaccuracies mainly occur around the boundaries of the damaged building regions. It is evaluated that the proposed framework is more convenient compared to other supervised and unsupervised methods. The successful application in different scenes demonstrates that the proposed framework has the ability to rapidly and accurately identify regions with damaged buildings, which is beneficial for post-disaster emergency assessment.

Index Terms—Earthquake, building damage, simple linear iterative clustering, synthetic damage index, improved-relief, local indicators of spatial association analysis.

I. INTRODUCTION

ASSESSING building damage is crucial in the coordination of fast responses after earthquakes. A rapid and accurate assessment of damage provides a reliable reference not only for rescue and emergency responses, but also for the subsequent reconstruction. Remote sensing (RS) technologies, which

have rapidly developed and nowadays permit multi-platform, multi-sensor, multi-scale, multi-angle, all-weather, and all-day Earth observations, provide efficient tools for obtaining timely building damage information [1], [2].

In the past decades, studies on building damage extraction have mainly focused on localizing and quantifying the damaged buildings, evaluating the proportion of collapsed buildings, and assessing the type of damage suffered by each building [3]–[5]. The detailed assessment of building damage using multi-sensor data has recently become a popular research topic. With the development of very high resolution (VHR) and multi-source RS technologies, VHR optical, synthetic aperture radar (SAR), and light detection and ranging (LiDAR) data – which provide more detailed damage characteristics compared with RS images – have been used to discriminate specific damage types [6], [7]. Moreover, spaceborne, airborne, and ground-based data acquisition platforms have significantly contributed to the extensive use of VHR imagery in precise damage extraction [8], [9]. However, considering the possible limitations in terms of data availability and computing resources, a general method for accurate and rapid building damage assessment over a large area is still required. This method would contribute to obtaining first-time disaster information, thereby facilitating post-disaster emergency operations. In summary, the approaches for building damage extraction can be categorized into three groups: (1) mono-temporal methods, (2) change detection methods, and (3) multi-data fusion methods [10]–[13].

1) *Mono-temporal methods*: By extracting various damage-related features, such as spectral features, texture features, and structural features, damaged regions can be identified in post-disaster images, which are commonly used for disaster emergency applications [14]. Concluded from recent research, supervised classification methods have gradually become the most important technique in damage detection [15]. Based on user-defined or automatically defined features, appropriate classification models are used to train and predict the areas possibly suffering damages on the basis of VHR images. However, the adoption of such methods in practice remains challenging, mainly owing to the poor generalization capability of the features. In addition, these methods rely on a priori feature selections, and therefore depend on expert knowledge and on the specificity of the available imagery. Apparently, a general feature representation technique needs to be developed.

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- 2) *Change detection methods*: Visual interpretation is commonly used to detect changes between pairs of images. By identifying significant changes between pre- and post-disaster VHR images, the damaged regions can be determined. These changes are identified according to typical features that depend on the image source (coherence features in SAR images, height features in Lidar data, and spectral/texture changes in optical images) [16], [17]. This method, however, requires strong expertise in damage discrimination. Image enhancement is another widely used method for damage detection. Images acquired before and after an earthquake are co-registered and subtracted to highlight differences. However, the stringent requirements in terms of data type, image resolution, and quality reduce the applicability of this method. Moreover, changes do not necessarily imply damages: a time-consuming post-processing remains necessary. Another strategy entails the comparison between the classification results of pre- and post-event data. The main advantage of this strategy is that it minimizes the effect of the radiometric difference between the two data sets. However, the accuracy is completely dependent on the initial classification results. In contrast, combining this change-detection method with other methods can alleviate this drawback.
- 3) *Multi-data fusion methods*: By combining data from diverse sources, such as SAR, LiDAR, optical cameras, and geographical information system (GIS) data, some complex and detailed information on building damage can be accurately extracted [18]. Although these fusion methods have brought some improvements to the extraction of building damage information, several issues need to be resolved. Data acquisition, registration, and fusion accuracy limit the applicability to actual disaster responses. For some regions, special pre-event data or building vector boundaries cannot be obtained, thereby reducing the possibility of damage detection. Considering the processing and time complexity, these methods remain mostly suitable only for fine and accurate post-event damage assessments.

With the development of artificial intelligence and computer vision, deep learning (one of the state-of-the-art techniques in machine learning and visual recognition) has become a popular method for extracting discriminative and representative high-level features. An advantage of deep learning is that it learns high-level features directly from the original data, showing greater flexibility and capability compared to traditional classification methods. Recently, convolutional neural networks (CNNs) have been widely used for identifying damaged buildings, demonstrating their effectiveness in damage extraction [19], [20]. However, deep learning requires a large training set and a long training time owing to its complex structure. The recently developed weakly supervised learning (WSL) technique can provide binary labels for each training image and reduce the cost in terms of human labor. This technique can improve the efficiency of data processing and accelerate the damage detection to some extent [21]–[23]. However, typical damage characteristics may vary across regions and depending on the

spatial resolution of the input images. In this respect, the poor generalization ability of a trained CNN model still limits its further application.

Existing studies mainly focused on specific features in the feature selection process (such as post-disaster image features or image change features), while they rarely combined multiple features together. In addition, most studies performed image extraction at the pixel level. This remained true even in routing applications of CNN methods in recent research. Pixel-based methods suffer from poor boundary identification and object localization, as well as from the so-called “salt-and-pepper” effect. Furthermore, recent studies focused on the target recognition accuracy, while they ignored the roles of convenience and efficiency, which directly affect the practical application in emergency responses. It is thus apparent that a more general method for building damage extraction – conveniently applicable to different damaged areas and image resolutions while ensuring accuracy and efficiency – needs to be developed.

To address this research gap, this study proposes a SGDL (superpixel segmentation – gradient extraction – damage index calculation – local Moran’s index analysis) approach for rapid damage extraction based on VHR images. An improved simple linear iterative clustering (SLIC) segmentation was used to restrict the boundary of the feature and reconstruct the analysis objects. The Sobel operator was used to detect the gradient characteristics. Based on gradient features and superpixel-level results, the building damage characteristics – Including the gradient cluster index (GCI) and gradient difference index (GDI) – were obtained at the object level. The synthetic damage index (SDI) based on an improved relief algorithm was also employed to complement the extracted information. Then, the local indicators of spatial association (LISA) approach was utilized for the cluster analysis based on the SDI. Finally, the areas with high SDI values were identified as containing damaged buildings after masking out shadows and vegetation. The accuracy of the proposed method was evaluated through an error matrix using visual comparison. To generate a damage classification product, it is important to rely on a damage scale that is recognized as a standard. Here, the EMS-98 scale was used to discriminate between heavy/moderately damaged buildings (damage grade ≥ 3 in the EMS-98 scale) and less damaged/undamaged buildings (damage grade < 3 in the EMS-98 scale) [24]. Considering the actual image resolution and the available roof damage characteristics, the former was termed “damaged regions,” and the latter “undamaged regions”.

The proposed approach provides the following novel contributions. 1) The SLIC algorithm was improved by combining color and texture features, which can well reflect the boundary of the image area or the outline of the damaged object. In addition, the proposed distance measure can dynamically balance the relative importance between color/feature proximity and spatial proximity in each iteration to generate good-quality superpixels. 2) Different from traditional single-image features at the pixel level, the combined use of gradient clustering features and gradient difference features at the superpixel level from pre- and post-disaster VHR images contributes to improving the final accuracy, both in terms of object classification accuracy and spatial

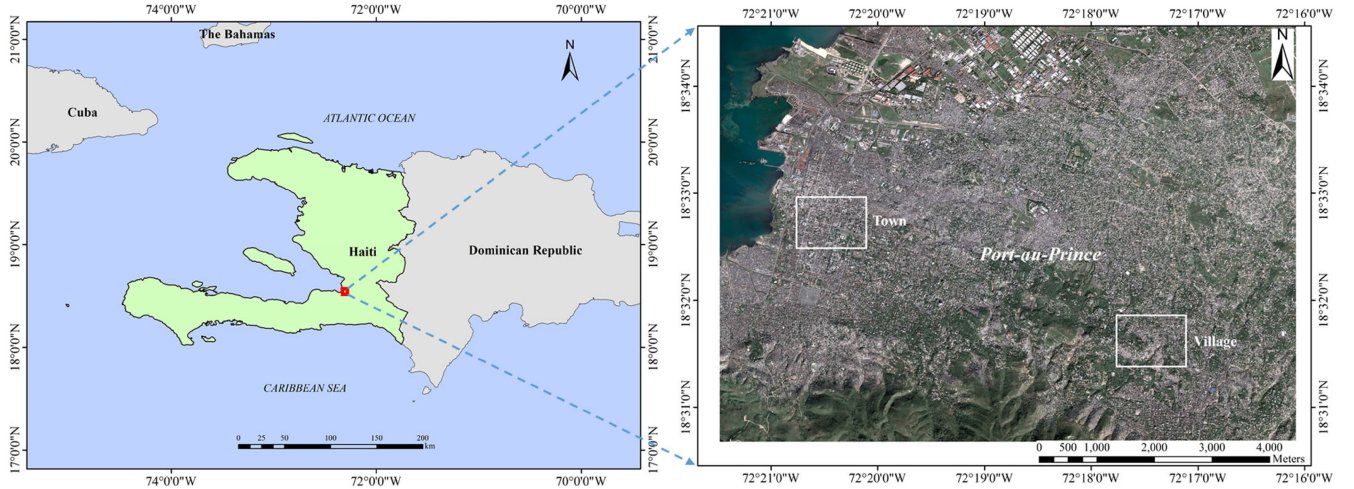


Fig. 1. Location map of the study area.

location accuracy. 3) The autocorrelation analysis (commonly used in spatial statistical research), was used for building damage extraction for the first time. Based on the resulting damage index and potential spatial relations, the damaged regions can be extracted while ensuring both accuracy and efficiency.

II. STUDY AREA AND DATA SET

The study area (Fig. 1) is located in Port-au-Prince, the capital city of Haiti. An earthquake with a 7.0 M_w magnitude occurred on January 12th, 2010 about 25 km west of the city. As Port-au-Prince features highly complex and heterogeneous residential areas, the earthquake caused extensive damage to buildings, facilities, and more than 200 thousand victims. Many buildings were destroyed, including government offices, public buildings, and hospitals.

To illustrate the effectiveness of the proposed approach, two representative regions (one town subarea and one village subarea) were investigated (Fig. 2). For the urban region, pre- and post-earthquake multispectral images (4060×3022 pixels) with blue, green, red, and near-infrared bands acquired by the Geo-Eye satellite on October 1st, 2009 and January 13th, 2010 were used. After the fusing the multispectral and panchromatic images, the spatial resolution reached 0.5 m. For the rural region, pre- and post-earthquake images (4060×3022 pixels, 0.3 m resolution) with blue, green, and red bands were obtained from Google Earth, and were acquired on August 26th, 2009 and January 24th, 2010. The pre- and post-earthquake images were co-registered using conjugate tie points. Twenty tie points were manually extracted with a sub-pixel root mean square error of less than 0.5 pixels. Each image was geometrically corrected and rectified to the WGS_1984 (UTM Zone 50N) coordinate system using ArcGIS software.

III. METHODOLOGY

The methodology (Fig. 3) comprises the following steps: (1) image processing, including image registration and gradient calculation; (2) image segmentation using an improved SLIC algorithm; (3) calculation of the damage feature index at the

superpixel level, including the evaluation of GCI, GDI, and SDI; (4) rapid extraction of damaged regions, including LISA clustering and post-processing; and (5) accuracy evaluation and validation.

A. Improved SLIC Superpixel Segmentation

The segmentation quality determines the target recognition accuracy. The SLIC algorithm, which can output good quality superpixels that are compact and roughly equally sized, is widely used to conduct the superpixel segmentation [25]. However, this algorithm only uses the CIELAB color space to measure the color similarity between seed points and pixels within clusters. Although this algorithm can account for spatio-temporal complexity, the resulting segmented boundary does not accurately reflect the actual one, especially for damaged building regions with significant color features and abundant texture features. Consequently, the CIELAB color space measurement cannot be used for the segmentation of post-earthquake VHR images featuring complex objects. This work proposes an improved SLIC (ISLIC) algorithm, which enhances the similarity measurement by analyzing the color and texture features comprehensively. This combined feature measurement cluster replaces the color feature of the original algorithm. As a result, the ISLIC can generate higher quality superpixels from the VHR images. The specific steps of this algorithm are as follows.

1) *Seed Point Initialization*: To obtain evenly-distributed seed points over an image with n pixels and t superpixel seed points, the area of each superpixel should be $A = (n/t)$, and the distance between adjacent seed points should be $DS = \sqrt{(n/t)}$. To avoid the identification of a seed point as a noise pixel, as well as to avoid the occurrence of seed points on the edge of the image, problematic seed points were moved to the location having the smallest gradient in a 3×3 window, and were then given independent labels.

2) *Color and Texture Feature Selection*: Damaged building regions usually exhibit bright colors with low intensity and high saturation. The color space transformation to the hue, saturation, intensity (HSI) color model was performed, and incorporated in

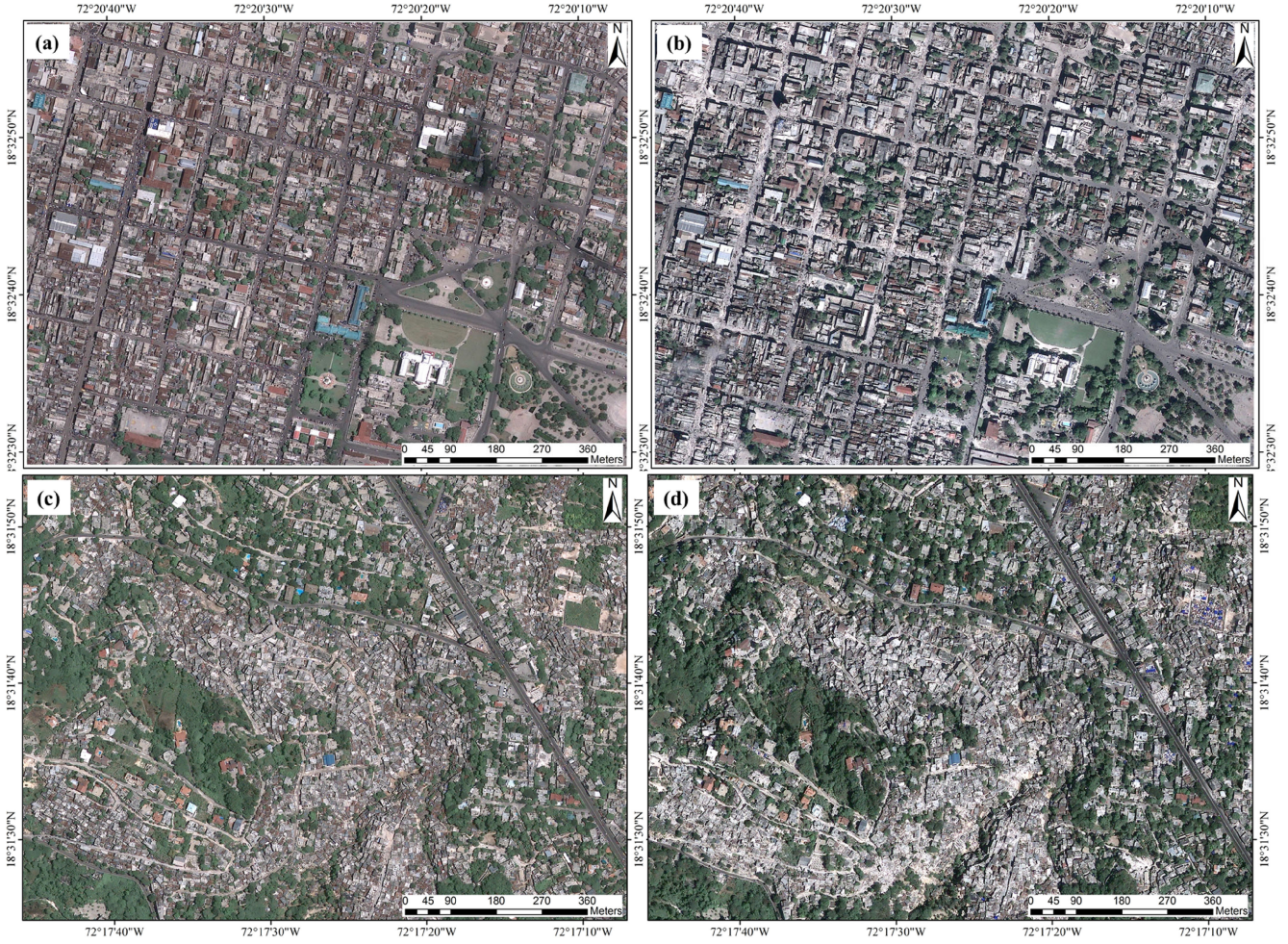


Fig. 2. Pre- (a) (c) and post-event (b) (d) maps of the study area in Port-au-Prince, Haiti.

the improved superpixel delineation method. On the contrary, the texture of intact building regions is uniform and rather homogeneous compared with the broken and disordered texture of damaged building regions. Considering the requirements of high retrieval efficiency and real-time performance, the texture features in the image were measured by a histogram. The local binary pattern (LBP) operator – a rotation- and gray-invariant operator - was used to extract the texture information. The result was then transformed into a histogram and regarded as the image feature.

3) *Distance Measure Design*: A weighted distance measure combining color, texture, and spatial proximity was used to perform the superpixel segmentation. Each pixel in the image was compared with the closest neighboring seed points to evaluate feature and spatial similarities, and the label of the most similar seed point was assigned to the pixel. The color similarity measure between the i_{th} pixel and the j_{th} seed point is defined in (1), where D_C denotes the similarity measure for color, and H , S , and I represent the hue, saturation, and intensity values, respectively.

$$D_C = \sqrt{(H_i - H_j)^2 + (S_i - S_j)^2 + (I_i - I_j)^2} \quad (1)$$

The texture similarity measure between the i_{th} pixel and the j_{th} seed point is defined in (2), where D_T is the texture similarity measurement, k is the texture value for each pixel, $h_j(k)$ is the texture histogram of the seed pixel, and $h_i(k)$ is the texture histogram of adjacent pixels between the window and the seed point. A small $\chi^2(h_i, h_j)$ indicates a high similarity between pixels and seed points.

$$D_T = \chi^2(h_i, h_j) = \frac{1}{2} \sum_k \frac{[h_i(k) - h_j(k)]^2}{h_i(k) + h_j(k)} \quad (2)$$

The spatial proximity between the i_{th} pixel and the j_{th} seed point is defined in (3), where D_S is the similarity measure for spatial distance, x_j and y_j are the abscissa and ordinate components of the seed point, respectively, and x_i and y_i are the horizontal and vertical components of the pixel points adjacent to the seed points, respectively.

$$D_S = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (3)$$

Finally, the total similarity measure between seed points and pixels is defined in (4):

$$D_S = D_C + D_T + \frac{m}{D} D_S \quad (4)$$

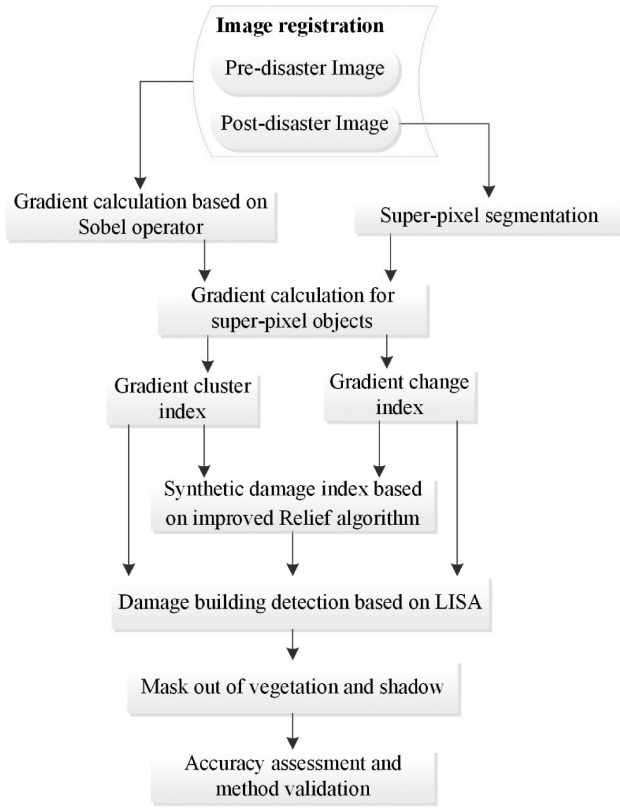


Fig. 3. Flowchart of the rapid damage extraction.

where m is a constant parameter and D is the distance between adjacent seed points. The parameter m , usually ranging between 1 and 20, is used to control the relative importance between feature similarity and spatial proximity. Generally, a higher value of m indicates that the spatial distance is more important than the feature proximity, and the last generated superpixels are more compact. After repeated trials, α was set to 16. As for the parameter D , in the *SLIC algorithm* it usually has a constant value. For the *ISLIC* in this study, D is changed with iterative clustering and used for adjusting the impact of the spatial distance D_S on pixel clustering when searching for the nearest distance center. When the compared cluster center belongs to a large cluster region, D can weaken the influence of D_S , which can ensure that the pixel far from its cluster center is segmented into the correct cluster and avoids small superpixels in large homogeneous regions (over-segmentation). Conversely, when the cluster center belongs to a small cluster region, the influence of D_S is enhanced, thus reducing the probability of large superpixels occurring in complex texture regions (under-segmentation).

4) *Clustering of Global Regions*: Pixels with the same seed point labels are clustered into one superpixel. However, to ensure sufficient computational speed, the entire image cannot be taken as the search window. Instead, a $2S \times 2S$ window (S is the area of the superpixel) centered on the seed point is chosen to search pixels with similar clustering.

B. Damage Feature Extraction at the Superpixel Level

In VHR images, various spectral characteristics can be extracted, and more local details can be found. The Sobel operator

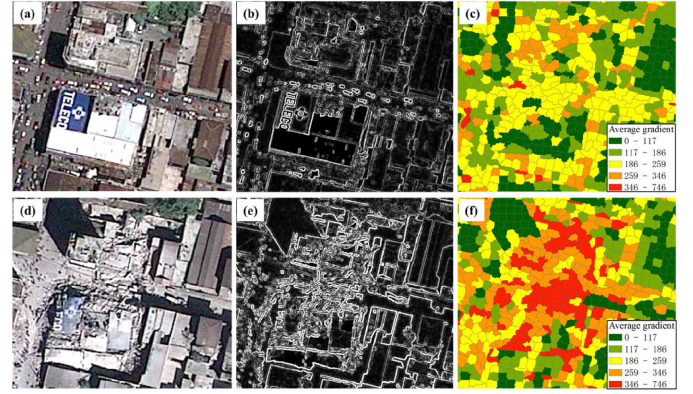


Fig. 4. Damaged buildings in the pre- and post- images and corresponding gradient feature using Sobel operator. (Images (a) and (c) are the same building, which was acquired before and after the disaster respectively. Images (b) and (e) are the corresponding gradient images at pixel level. Images (c) and (f) are the corresponding gradient images at superpixel level.)

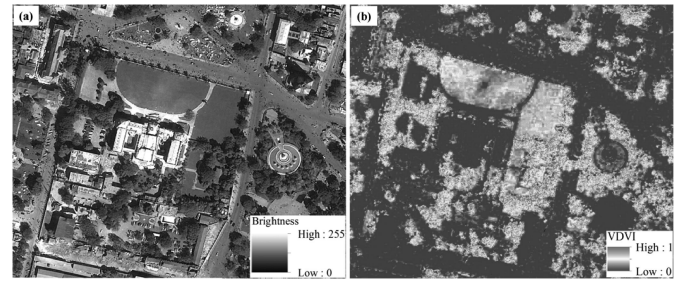


Fig. 5. Example of generated brightness map and VDMI map.

is widely used to obtain first-order image gradient information and detect edges. Although many algorithms have been used for edge detection (such as algorithms focusing on morphological characteristics), the Sobel operator was used in this study as it offers the best compromise among convenience, efficiency, and flexibility [25]. In Fig. 4, the gradients derived from the pre- and post-disaster images are illustrated. In both cases, structural features were successfully extracted based on grey-level intensity. Regions in which high-value grey levels distribute randomly tend to contain damaged buildings. Based on the boundaries of the superpixel segments, the mean gradient within each superpixel was calculated, and was used as the basic unit to detect the damaged buildings.

1) *GCI of the Post-Disaster Image*: As seen in Fig. 4, the patterns of the gradient clustering feature of damaged and undamaged regions are obviously different. At the pixel level, the gradient distribution within intact buildings is homogeneous, while it is not homogeneous within damaged buildings. At the object level, the spatial correlation in damaged regions is high notwithstanding the random distribution at the pixel level. Regions with high correlation values tend to exhibit a cluster distribution pattern. In this study, a gradient cluster index (GCI; 5) was proposed to calculate the correlation of adjacent objects and represent the cluster characteristics [27]. This index contributes to the detection of potential damage hotspots. Generally, the higher the GCI is, the greater will be the probability of the

region being damaged.

$$GCI = \frac{\sum_{j=1}^n w_{ij}(d)x_j}{\sum_{j=1}^n x_j} \quad (5)$$

where d is the lag, w_{ij} is the spatial weight (1 or 0) representing the impact between superpixels i and j , x_j is the gradient value of superpixel j , and n is the total number of superpixels. d was set to 1 and the adjacent superpixels in the up, down, left, and right directions were used to calculate the spatial weight.

2) *GDI Between Pre- and Post-Disaster Images*: The variation of the gradient between pre- and post-disaster images is also a significant feature that can be used for damage extraction [28]. The GDI contributed to finding all gradient changes and detecting all the probably damaged regions. However, it should be noted that not all regions with gradient changes were damaged. Although some large gradient variations are found around the building boundaries because of registration errors, this phenomenon can be reduced or even eliminated by averaging over the superpixel segments. Considering the influence of different bands on the Sobel calculation, three bands were taken into account. The final formula was defined as follows (6):

$$GDI = \sqrt{\sum_{i=1}^n (s_i^a - s_i^b)^2} \quad (6)$$

where $n = 3$ is the number of bands, and s^a and s^b represent the Sobel gradient values of the super-pixel segments.

3) *SDI Based on the Improved-Relief Algorithm*: The GCI and GDI proposed in this study were sufficiently representative to perform the damage extraction. However, they only provided the approximate location of damaged building regions based on a single image feature, for which the extraction ability was relatively low. To address this issue, a novel approach based on an improved relief algorithm was proposed to evaluate the feature weights.

The relief algorithm aims to achieve a binary classification. It evaluates the features according to its ability to distinguish between near samples, and assigns higher weights to features with good classification ability [29]. Final weight approach in the traditional relief algorithm is affected by the number of samples. Conversely, the improved relief (IR) algorithm proposed herein considers the same number of samples from each type of target. The basic process is shown in Algorithm 1.

Based on the feature weight, the SDI was calculated using (7), where w_c represents the feature weight of GCI and w_d represents the feature weight of GDI.

$$SDI = W_c \times GCI + W_d \times GDI \quad (7)$$

C. Rapid Extraction of Damaged Regions Based on LISA

As explained above, the gradient feature of damaged building regions exhibits a certain spatial correlation. In addition, these regions usually present high gradient variation and gradient clustering features. These distinctive characteristics can be analyzed using tools of spatial statistical analysis [30]. In particular, the spatial autocorrelation analysis has been widely used to statistically analyze spatial distribution patterns. The local autocorrelation reflects the degree of correlation of one attribute

Algorithm 1 Improved Relief Algorithm

Input: Labeled samples with class 1 and class 2; building damage features of GCI and GDI

1. Set the initial feature weight.
2. Calculate the center point X_c for samples of same class.
3. Calculate the Euclidean distance between the selected sample and the center sample.
for class = 1 **to** class = T **do**
for sample = 1 **to** sample = M **do**
 $Dist(X, X_c) = \sqrt{\sum_{i=1}^n (s_i - s_{c_i})^2}$
end for
end for
4. Select the middle samples. Based on X_c , samples of each class are divided into f groups. Then, the interval Euclidean distance Δd for each group is calculated using the formula below. Finally, the middle sample can be used in the following calculation.
 $\Delta d = (\max(Dist) - \min(Dist)) / f$
5. Conduct the relief analysis using the selected middle samples from each class.

For different samples **do**

Select the nearest neighboring samples of same class for each sample

For different classes **do**

Select the nearest neighboring samples of different class for each sample

Calculate the weight for each feature.

Output: Final weight of GCI and GDI.

with adjacent areas in a small region. In this study, the local Moran's index was used to visualize and analyze the local cluster characteristics of the gradient index, as shown in (8). Compared with the proposed GCI for gradient clustering analysis, the local Moran's index is more sensitive to slight differences, and can identify statistically significant spatial outliers.

$$Local\ Moran's\ I = \left(\frac{x_i - \bar{x}}{m} \right) \sum_{i=1}^n W_{ij}(x_j - \bar{x}) \quad (8)$$

$$m = \left(\sum_{j=1, j \neq i}^n x_j^2 \right) / (n - 1) - \bar{x}^2 \quad (9)$$

where n is the total number of superpixels, x_i and x_j are the gradient values of superpixels i and j , respectively, $\bar{x}$ is the average gradient value for the entire study area, and W_{ij} is the spatial weight matrix, which represents the degree of impact between superpixels i and j . The LISA analysis not only calculates the local Moran's index, but also performs the clustering of the index values. Based on the clustering results, four spatial distribution patterns of SDI can be identified:

- 1) HH type, in which the SDI within the area is high, the SDI around the area is high, and the spatial correlation is also high; this pattern identifies the spatial distribution of building damage features with large areas.

- 2) HL type, in which the SDI within the area is high, but the SDI around the area is low; this pattern identifies the spatial distribution of building damage features with a small area.
- 3) LL type, in which the SDI within the area is low, and the SDI around the area is also low; this pattern identifies the spatial distribution of relatively undamaged and large homogeneous regions.
- 4) LH type, in which the SDI within the area is low, but the SDI around the area is high; this pattern identifies the spatial distribution of undamaged regions with small areas.

In summary, the HH- and HL-type regions are consistent with the distribution of typical damage features. Therefore, they were used to represent the damaged regions in this study.

D. Post-Processing And Accuracy Assessment

1) *Masking Out Vegetation and Shadows:* Vegetation and shadows need to be removed from the final extraction results as they may interfere with the damage assessment. Vegetation and shadows were first extracted at the pixel level, and an image superpixel was then identified as a specific class using majority rules for image objects. To enhance the applicability of the proposed method to different types of images, the Visible-band Difference Vegetation Index (VDVI) was used, which was calculated by (10) [30]. In the formula, R/G/B represents the red/green/blue channel information of the VHR image. A pixel with a VDVI value higher than the selected VDVI threshold was classified as vegetation; otherwise, it was classified as non-vegetation.

$$VDVI = (2G - R - B) / (2G + R + B) \quad (10)$$

The brightness, that is the average of pixel values in the red, green, and blue bands, can effectively be used to discriminate between shadows and non-shadows. Because of the significant difference between shadow and non-shadow brightness values, a thresholding method was adopted for shadow extraction, and the optimum threshold was easily identified.

In this study, to conduct the threshold segmentation of the gray images of VDVI and brightness, the OTSU method was used, which is based on an adaptive threshold selection and maximization of interclass variance. By performing a statistical analysis of the histogram features of the entire image, the optimal global threshold can be easily determined. After the masking process based on the selected threshold, two land cover types were extracted at the pixel level. Then, a majority rule was used to produce extraction results at the object level. Specifically, if the majority of pixels within the object belonged to a specific class, the entire image segment was identified as belonging to that class. Finally, the extracted shadows and vegetation were masked out from the final cluster result to optimize the extraction result.

2) *Accuracy Assessment:* To evaluate the accuracy in terms of image classification and damage extraction, the results were compared to manually-labeled reference data based on visual interpretation. Precision (Pre.), Recall (Rec.), Overall Accuracy (OA), and F1-score were used to evaluate the segmentation and

extraction performance, as shown in (11)–(14). Although the OA can be used to evaluate the overall accuracy of the classification results, it can easily fail if the positive and negative samples are uneven. Thus, Pre. was used to evaluate the false detection ratio, Rec. was used to evaluate the missed detection ratio, and the F1-score was computed to evaluate Pre. and Rec. comprehensively. In the equations, TP computes the true positives, i.e., the positive samples correctly classified as positive, FP computes the false positives, i.e., the negative samples incorrectly classified as positive, FN computes the false negatives, i.e., the positive samples incorrectly classified as negative, and TN computes the true negatives, i.e., the negative samples correctly classified as negative.

$$Pre. = TP / (TP + FP) \quad (11)$$

$$Rec. = TP / (TP + FN) \quad (12)$$

$$OA = (TP + TN) / (TP + FN + FP + FN) \quad (13)$$

$$F_1 - score = (2 \times Pre. \times Rec.) / (Pre. + Rec.) \quad (14)$$

IV. RESULTS AND DISCUSSION

The proposed framework was implemented in Microsoft Visual C++ (embedding PCL1.8.1) and PyCharm 2019. All the experiments were carried out on a PC with a 40 GB memory and an Intel Xeon E5 CPU working at 2.7 GHz.

A. Effectiveness of the Improved Superpixel Method

The segments are the basic units in the building damage extraction process. To evaluate the effectiveness of the ISLIC algorithm, its performance was compared with that of some segmentation algorithms, namely the Fractal Net Evolution Approach (FNEA), graph-based segmentation (GS), mean-shift segmentation (MSS), and traditional SLIC algorithms.

1) *Qualitative Evaluation:* As shown in Fig. 6, the FNEA, GS, and MSS methods consider different object scales, thus the resulting segments are very sensitive to the boundaries. Specifically, the FNEA method seems to be more focused on the local boundary information, which leads to some pedestrians and cars also being segmented. With the GS and SLIC methods, some large segments were identified in regions with complex textures, and some segments were found in boundary regions. Compared with traditional segmentation methods, the ISLIC method can obtain more compact and regular superpixels, which match with the boundaries of the damaged buildings very well. The proposed distance measure can dynamically adjust the relative importance between color/texture proximity and spatial proximity in each iteration, and thus optimize the search of the nearest cluster center within the entire image. As such, it can avoid small superpixels in large homogenous regions (over-segmentation), and reduce the probability of large superpixels in complex texture regions (under-segmentation). The final result demonstrates that the proposed method is visually superior to the traditional method and yields satisfactory segmentation results.

2) *Quantitative Evaluation:* To assess the object shape and computational time to obtain the final segmentation results, five statistical indices were utilized, namely the average area (AA),

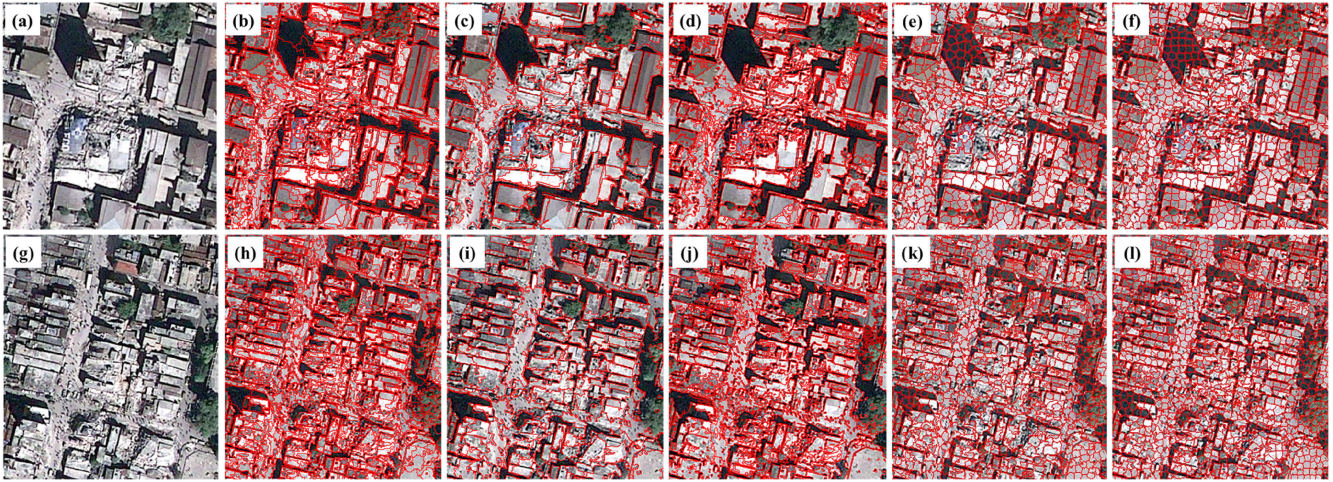


Fig. 6. Examples of image segmentation using FNEA (b) (h), GS (c) (i), MSS (d) (j), SLIC (e) (k) and ISLIC (f) (l).

TABLE I
STATISTICS FOR SEGMENTATION RESULTS USING DIFFERENT METHODS

	AA	SDA	ALWR	SDLWR	Time (s)
FNEA	101.14	243.01	7.58	10.54	90.36
GS	791.28	1322.64	11.57	18.31	53.25
MSS	251.52	871.35	6.39	13.66	61.54
SLIC	89.38	102.35	1.86	2.39	97.82
ISLIC	78.26	82.93	1.26	1.19	102.62

standard deviation of area (SDA), average length-width ratio (ALWR), standard deviation of length-width ratio (SDLWR), and cost time (Time), to evaluate the performance of different segmentation methods. As shown in Table I, the SDA and SDLWR of segments computed using the ISLIC method were lower than those obtained using other methods. Thus, it is concluded that the method proposed in this study can produce segments with a more uniform grain size. Despite the increased time required to segment the image (about twice), the improvement in segmentation accuracy is significant.

B. Gradient Feature Analysis of Superpixels

In this study, the average gradient within each segment delineated on post-earthquake image was employed to calculate the GCI and GDI using (5) and (6). Conversely, if segment boundaries from pre-earthquake images were used to obtain the damage feature, one segment would correspond to several damaged and undamaged regions in the post-earthquake images. This would result in the segment not having a typical feature representation for damage extraction. As shown in Fig. 7, the calculated GCI and GDI present different spatial distribution features. The distribution of GDI values is relatively more dispersed, while ‘hot’ regions of GCI are more spatially concentrated. The GCI focuses on the local gradient correlation and consistency, which are effective for the identification of large regions containing damaged buildings. In contrast, for small or discontinuous regions, discriminating between damaged and undamaged regions only on the basis of the GCI can be difficult. The GDI is effective in overcoming the limitations of a GCI-based approach. This gradient feature helps to find all regions

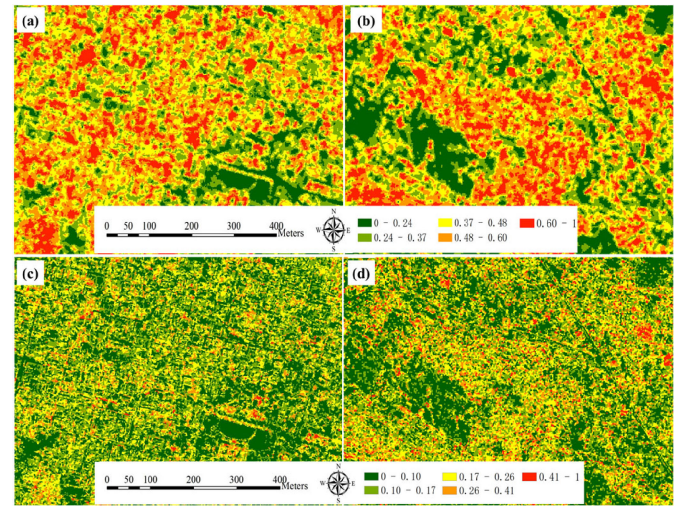


Fig. 7. The calculated GCI (a) (b) and GDI (c) (d) of study area.

with gradient variations, so that all the potential damaged regions can be considered. However, not all regions with gradient variation contain damaged buildings. In conclusion, the combined use of GCI and GDI is meaningful.

To illustrate the boundary effect arising in other methods, the feature representation results of the FNEA and ISLIC methods were compared. As shown in Fig. 8, the size and shape of the objects segmented by the ISLIC algorithm are more regular. In contrast, the FNEA method focuses on the boundary effects of ground objects, making the size and shape of the segmented objects discontinuous and variable. The gradient difference is more obvious in the boundary area, as seen from the blue rectangle in Fig. 8(b) (d). The boundary effects will cause some boundary areas with high GCI and GDI to be misclassified as damaged regions, thus influencing the overall representation of the characteristics of the damaged buildings. Although the superpixel segmentation results for these damaged regions were still discontinuous, clearly high GCI values were computed, and a tendency of clustering for the damaged regions was observed. Moreover, the superpixel segmentation algorithm effectively

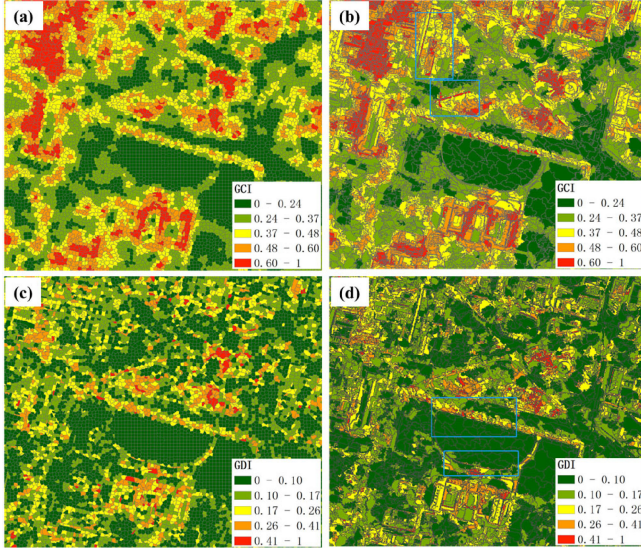


Fig. 8. Example of GCI GDI at object level using ISLIC (a) (c) and FNEA (b) (d) methods.

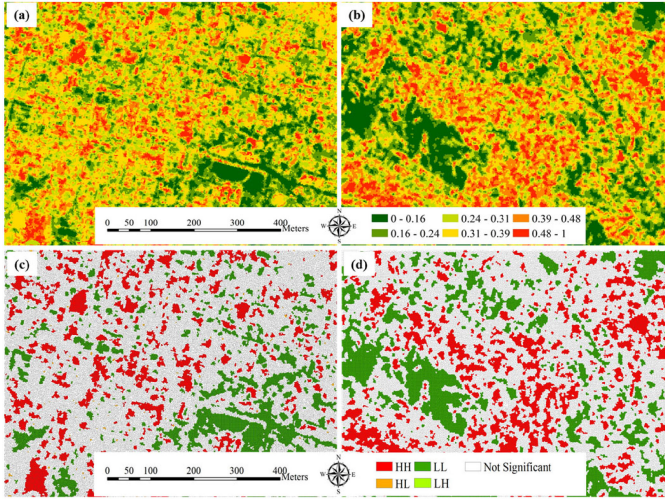


Fig. 9. Calculated SDI (a) (b) and cluster map using LISA (c) (d).

avoided the boundary effect by calculating the average gradient across each superpixel, so that the gradient difference between damaged and undamaged regions was sufficiently large.

C. Damage Extraction and Post-Processing

1) *Damage Extraction Based on SDI Using LISA*: In this study, the weights of GCI and GDI were obtained by an improved relief algorithm. Based on visual inspection, 4000 damaged samples and 4000 undamaged samples, were used to evaluate the feature weights. After weight calculation and normalization, the average weights of GCI and GDI resulted equal to 0.55 and 0.45, respectively. Then, the SDI was calculated using (7). Based on the computed SDI and (8), the damaged buildings were conveniently and rapidly extracted using the LISA method. The SDI and clustering results are shown in Fig. 9.

Compared with the GCI map in Fig. 7 (a) and (b), the spatial distribution feature is no longer spatially consistent across large

TABLE II
CLASSIFICATION ACCURACY OF DIFFERENT LAND OBJECTS

	Pre-earthquake		Post-earthquake	
	Pre.	Rec.	Pre.	Rec.
Vegetation	0.9427	0.9417	0.9583	0.9397
shadow	0.9516	0.9412	0.9485	0.9358
others	0.9609	0.9717	0.9503	0.9714
OA	0.9540		0.9519	

areas. Compared with the GDI map in Fig. 7 (c) and (d), not all regions with gradient variation had a high damage index. It can be concluded that the SDI can effectively balance GCI and GDI and maximize their advantages. Based on the optimized damage index, the regions with damaged buildings can be rapidly extracted using the LISA approach. As shown in Fig. 9 (c) and (d), HH and LL are significantly clustered, while few HL and LH clusters are identified. This indicates a significant hotspot clustering effect, and confirms the effectiveness of the SDI in representing the distribution of damaged buildings. In addition, large HH regions exhibited a high degree of compactness and almost covered the damaged building regions. The small HH regions only cover limited areas. Nonetheless, the LISA approach was able to extract both large and small damaged regions effectively.

2) *Post-Processing and Accuracy Assessment*: Shadow and vegetation changes can influence the identification of damaged regions. Therefore, they must be removed from the final clustering results. Following the histogram analysis using the OSTU method at the pixel level, the optimal segmentation thresholds for vegetation and shadows were set to 0.03 and 60, respectively. Regarding the threshold for the object-level majority rule, an optimal value of 75% was found after several trials, which will be discussed in the following section.

The classification accuracy for three land objects on pre- and post-earthquake VHR images is shown in Table II. The stratified sampling scheme, which guaranteed that the selected points were uniformly distributed and derived from different objects, was used for the selection of the validation points. The table shows that both the precision and recall reached 0.93, and the overall accuracy for all three types was very high (> 0.95), indicating that the extraction results are acceptable.

After masking out the vegetation and shadows the final results are shown in Fig. 10. In terms of spatial distribution, the extracted results covered the severely damaged large regions, as shown in Fig. 10 (a) and (c), as well as the moderately damaged small regions, as shown in Fig. 11 (a) and (c). Moreover, the final extraction result preserved the rich and complete boundary information of the damaged regions. This result is hardly achievable with traditional methods.

The final extraction result contained some false positive and false negatives. For example, some cars and pedestrians located on roads near building debris were misclassified as damaged regions owing to a gradient similarity (Fig. 10 (c)). However, these regions are small and are mainly located around the correctly classified damaged regions. Therefore, it can be concluded that the SDI not only made full use of the advantages offered by the GCI and GDI, but also reduced the adverse effects arising

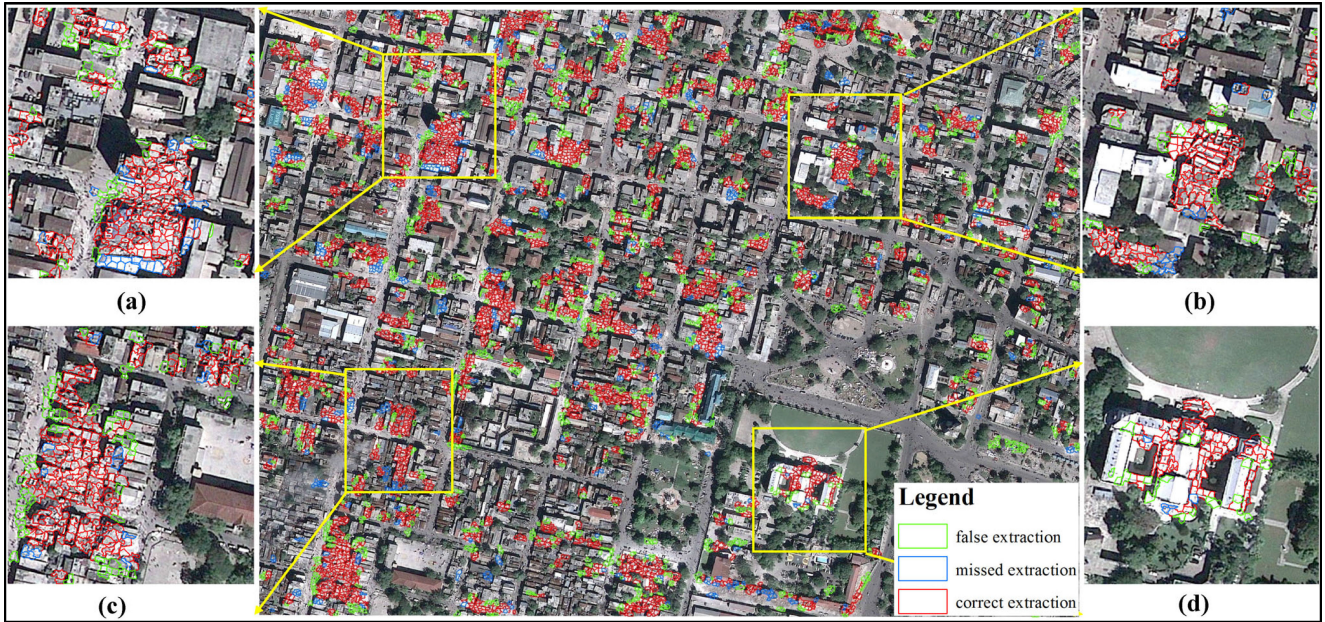


Fig. 10. Extracted damaged building regions after post-processing for urban region.

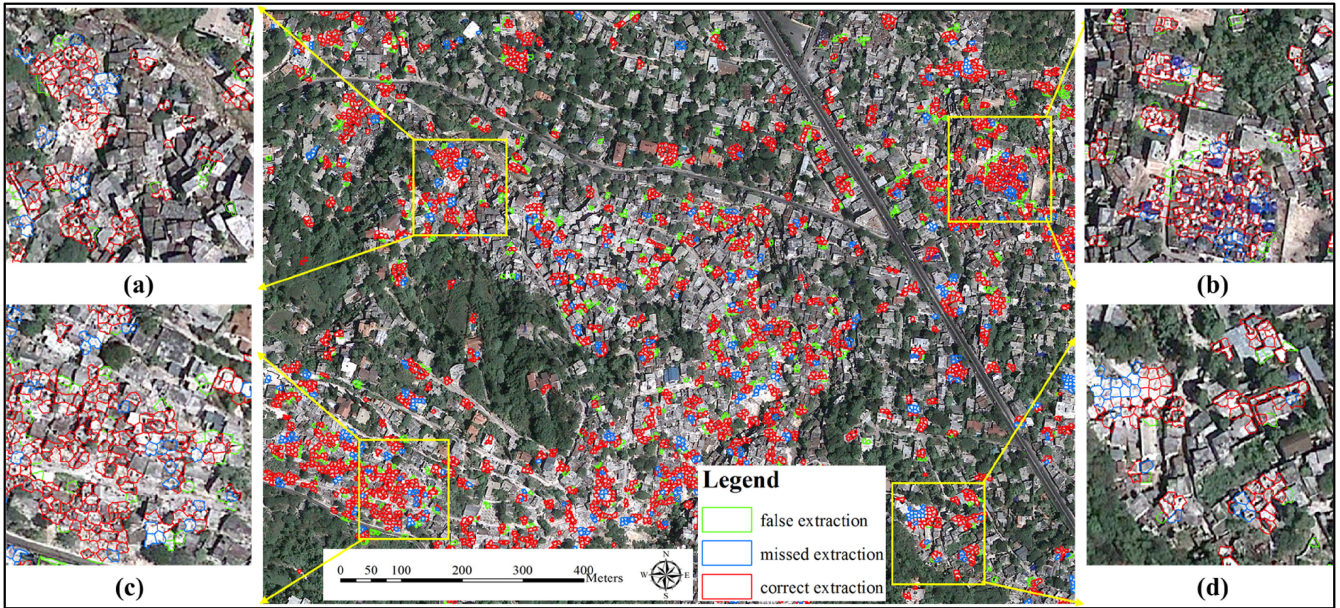


Fig. 11. Extracted damaged building regions after post-processing for rural region.

from their use. In fact, the proposed method can localize and extract damaged regions of different sizes satisfactorily while ensuring the integrity of the extracted damaged regions.

To evaluate the damage extraction accuracy, the extraction results after masking were compared with the results prior to masking. In practice, 6 929 damaged regions and 10 000 undamaged regions were manually classified at the superpixel level for each study region by visual interpretation. As seen in Table III, the comparison showed that the overall accuracy was higher than 0.84 in both cases, but the precision and recall increased by over 5% after masking. This indicates that the masking algorithm is a valuable and important post-processing tool in the

TABLE III
DAMAGE EXTRACTION ACCURACY ON CITY AND TOWN SUBAREAS

	No-mask			Mask		
	Pre.	Rec.	OA	Pre.	Rec.	OA
City	0.7613	0.8530	0.8486	0.8159	0.9082	0.8909
Town	0.7457	0.8506	0.8423	0.8375	0.9168	0.9024
Average	0.7535	0.8518	0.8455	0.8267	0.9125	0.8966

proposed approach. The final precision and recall after masking were over 0.81 and 0.90, respectively, demonstrating that the false negatives were controlled better than the false positives. In addition, similar extraction accuracy in town and city presented

TABLE IV
DAMAGE EXTRACTION ACCURACY BASED ON DIFFERENT SEGMENTS

	Damage		No-damage	
	Pre.	Rec.	Pre.	Rec.
FNEA	0.7203	0.7495	0.8332	0.8113
GS	0.5714	0.5536	0.6807	0.6962
MSS	0.6233	0.6518	0.7693	0.7467
SLIC	0.7926	0.8315	0.8887	0.8608
ISLIC	0.8267	0.9125	0.9451	0.8873

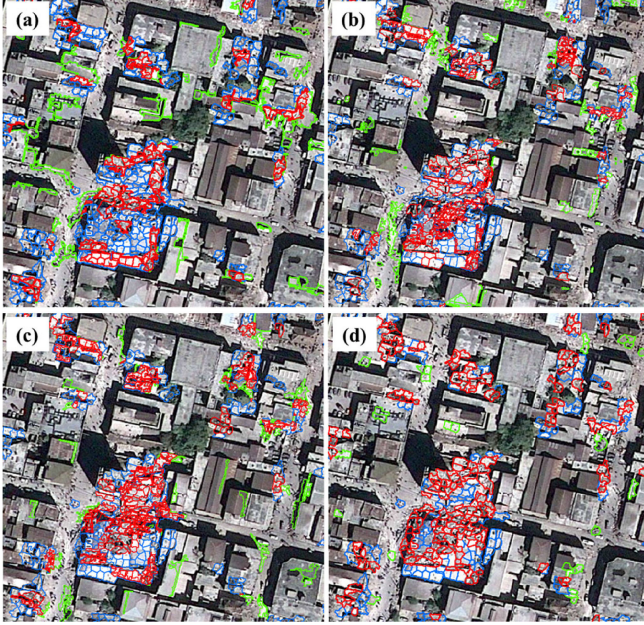


Fig. 12. Extraction results of building damage based on different segmentation results. (a) GS. (b) MSS. (c) FNEA. (d) SLIC.

the good generalization ability in different disaster scenes. In summary, the results demonstrated that the LISA method can be useful and practical for damage extraction based on combined damaged characteristics.

D. Comparative Analysis

In this section, the different extraction effects are first analyzed based on different segmentation results. Then, the extraction difference are analyzed based on the GCI or GDI. Finally, representative unsupervised and supervised methods for building damage detection are implemented for comparison. To exemplify the differences, two representative damaged regions (Fig. 10 (a) and (c)) are chosen. The final values of accuracy are compared, with reference to 6929 damaged and 10000 undamaged regions. The computation times also are compared, so as to evaluate the computational efficiency.

1) *Damage Extraction Based on Different Segmentation Results:* The spatial and structural characteristics of the segments (the basic units for damage extraction) have a direct influence on the final extraction accuracy. Within the proposed extraction framework, different segmentation methods are explored, as discussed in Section III, and the results in terms of final average extraction accuracy are shown in Table IV. In Fig. 12, the results are compared with reference to a typical damaged area.



Fig. 13. Extraction results of building damage based on GCI in (a) and (b) and GDI in (c) and (d).

TABLE V
EXTRACTION PERFORMANCE BASED ON DIFFERENT FEATURES USING LISA

	GCI		GDI		SDI	
	Pre.	Rec.	Pre.	Rec.	Pre.	Rec.
Damage	0.7637	0.8419	0.7193	0.7938	0.8267	0.9125
No-damage	0.9006	0.8462	0.8705	0.8174	0.9451	0.8873
OA	0.8445		0.8086		0.8966	
Time (s)	90.83		94.71		91.64	

Owing to the boundary effect using the Sobel operator, some undamaged segments around building boundaries identified by the GS, FNEA, and MSS methods were misclassified as damaged regions. This issue is effectively avoided in the SLIC method. In fact, the final model output seems to capture the damaged regions accurately, with relatively few false negatives. However, some issues remain both in terms of false negatives and false positives owing to the over-segmentation and under-segmentation of regions with complex textures. Compared with the aforementioned methods, the ISLIC method is more accurate, as shown in Fig. 11(a) and Table IV.

2) *Damage Extraction Based on GCI and GDI Using LISA:* The GCI and GDI possess certain desirable characteristics for damage detection, yet they also present some limitations in terms of applicability. To illustrate the superior performance of the proposed SDI approach, a LISA analysis is first conducted based on the GCI or GDI alone. Then, the damaged building regions are obtained after masking out the vegetation and shadows, as shown in Fig. 13. The final extraction accuracy for the study area is listed in Table V.

The GCI aims to cluster regions with similar gradients, thus it is sufficiently effective for the identification of badly damaged large regions with similar gradients, i.e., in cases in which a clear spatial clustering exists. However, the boundaries of the extraction results are not sufficiently accurate and suffer

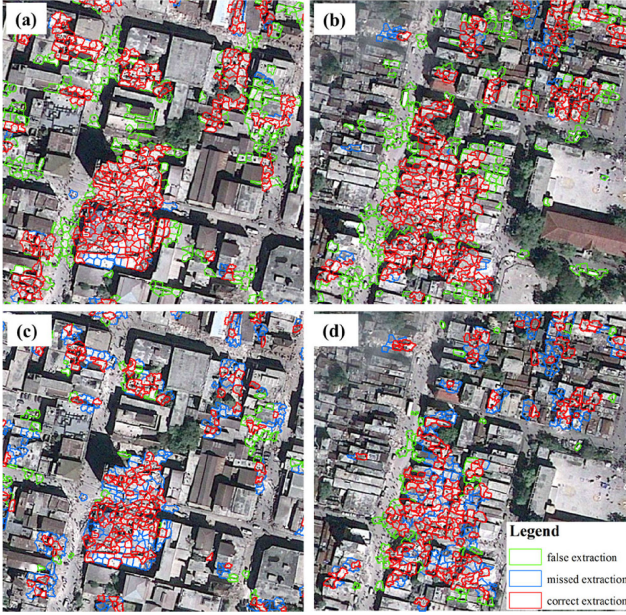


Fig. 14. Extraction results of building damage based on k-means method in (a) (b) and change detection method in (c) (d).

from false positives, as shown in Fig. 13. Conversely, the GDI correctly identifies some regions with large gradient variations, but some undamaged regions are also misclassified as damaged owing to an excessive sensitivity. The spatial integrity of the GCI-based extraction is superior compared to that of the GDI-based extraction owing to the superior clustering ability of the GCI. In terms of computational burden, they perform similarly as they are both based on the LISA approach.

3) *Comparison With Other Unsupervised Extraction Methods:* This study proposed an unsupervised building damage extraction method. To demonstrate its advantages and potential for application, the proposed method was compared with two other unsupervised methods, namely the k-means clustering method for SDI and the change detection method [32], [33]. The k-means method (not LISA), in particular, was chosen to conduct a clustering analysis and demonstrate the superiority of the LISA approach. The change detection method was chosen as it widely used for damage detection, and can be easily implemented. In this article, building objects change is analyzed based on an object-oriented classification [34]. Building change information pre-and post-earthquake is extracted as a basis for damage assessment. For this method, pre-event image time, the classification accuracy for and post-processing directly affected the final damage extraction accuracy.

As shown in Fig. 14 (a) and (b), the final extraction results of the k-means method possess good spatial integrity, which indicates that the generated SDI can identify the damaged regions reasonably well. In contrast, Table VI highlights that the accuracy of this method is relatively lower owing to the larger number of false positives compared with the LISA method. As seen from Fig. 14 (c) and (d), the change detection method also can identify the damaged regions to some extent, but missed extractions are also present, and the final boundary is not sufficiently consistent.

TABLE VI
EXTRACTION PERFORMANCE USING K-MEANS AND CHANGE DETECTION METHODS

	K-means		Change detection		Proposed method	
	Pre.	Rec.	Pre.	Rec.	Pre.	Rec.
Damage	0.7408	0.8127	0.7129	0.7237	0.8267	0.9125
No-damage	0.8817	0.8308	0.8114	0.8031	0.9451	0.8873
OA	0.8240		0.7711		0.8966	
Time (s)	85.92		174.25		91.64	

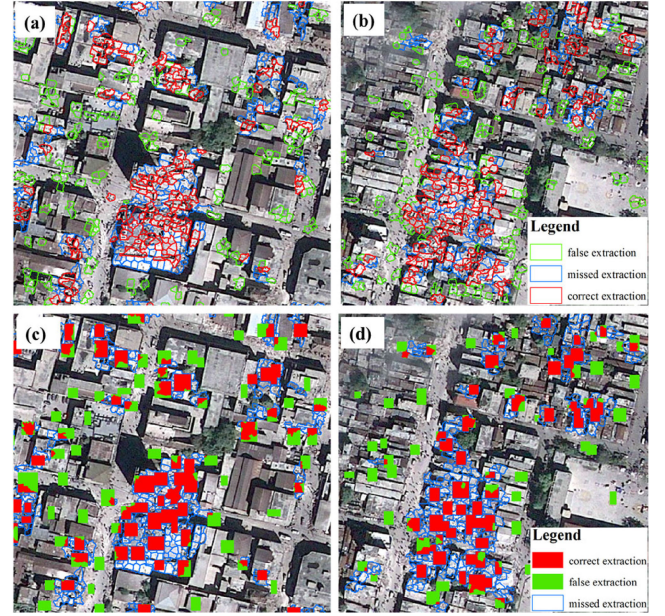


Fig. 15. Extraction results of building damage based on MFF in (a) (b) and CNN in (c) (d).

TABLE VII
EXTRACTION PERFORMANCE USING MFF AND CNN METHODS

	MFF		CNN		Proposed method	
	Pre.	Rec.	Pre.	Rec.	Pre.	Rec.
Damage	0.6685	0.6812	0.6913	0.6902	0.8267	0.9125
No-damage	0.7832	0.7732	0.7849	0.7859	0.9451	0.8873
OA	0.7363		0.7466		0.8966	
Time (s)	157.39		186.53		91.64	

In terms of computational burden, the k-means method is less demanding as it relies on a simpler algorithm, while the change detection method is more time consuming, possibly owing to the time required for the computation of the characteristic for each land cover type.

4) *Comparison With Other Supervised Extraction Methods:* Two supervised methods, namely the multi-feature fusion (MFF) and the CNN methods were implemented, and their results were compared with those of the proposed approach [35], [36]. Half of the samples were chosen as the training set. For the MFF method, the spectral, texture, and geometric shape features extracted from the post-earthquake VHR images were used to identify the damaged regions. For the CNN method, an experiment was conducted with the commonly used AlexNet model, which demonstrated high performance in object detection. The results of the comparison for selected extraction targets and the average model accuracy are shown in Fig. 15 and Table VII.

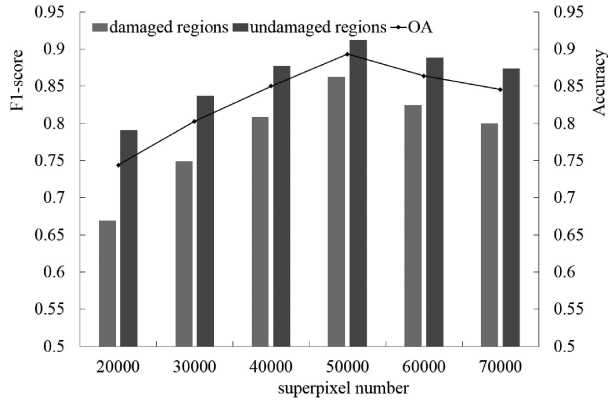


Fig. 16. The effect of superpixel number on the extraction performance.

In terms of spatial distribution, some evident noise was produced by both models in the final extraction results, which may be attributed to the limited number of samples. In addition, the boundaries of some true positives were not correctly defined, substantiating the concerns expressed in Section I. In terms of extraction accuracy, the supervised methods perform worse than the proposed unsupervised method owing to the extraction noise. In terms of computational burden, on the other hand, the AlexNet model approach seems less time-consuming. However, an objective evaluation is difficult owing to possible subjective impacts. The comparison was thus carried out between the trained AlexNet model and the proposed method, including the time required for clustering and post-processing. The results show that, overall, the computational efficiency of the proposed method is higher and a balance between accuracy and efficiency can still be achieved even if damaged samples are lacking.

E. Parameter Sensitivity Analysis

1) *Number of Superpixels*: In the SLIC algorithm, the number of superpixels must be specified prior to performing the image segmentation. This choice has a direct influence on the segment size, which affects the classification accuracy. Therefore, the sensitivity to the number of superpixels need to be investigated. Considering the actual minimum size of the damaged regions, values from 20000 to 80000 (at intervals of 10000) have been investigated. The histogram in Fig. 16 illustrates how the F_1 -score over damaged and undamaged regions changes as the superpixel number increases, while the line graph shows the effect of the number of superpixel on the damage extraction accuracy. By specifying 50000 as the number of superpixels, the extraction performance was maximized. The F_1 -score of the damaged regions ranged from 0.6692 to 0.8624, and the overall accuracy ranged from 0.7440 to 0.8931, indicating that the number of superpixels influenced the damage extraction performance.

2) *Feature Weights of GCI and GDI*: In this study, two optimized weights were assigned to the GCI and GDI using the improved relief algorithm to derive the SDI and extract the damaged building regions. The histogram in Fig. 17 shows how the F_1 -score over damaged and undamaged varies depending on the weights assigned to the GCI and GDI, while the line

TABLE VIII
ACCURACY OF EXTRACTION RESULT USING LISA

	GCI		GDI		SDI	
	Pre.	Rec.	Pre.	Rec.	Pre.	Rec.
Damage	0.7355	0.8150	0.7122	0.8016	0.8006	0.8852
No-damage	0.8445	0.7742	0.8358	0.7572	0.9033	0.8295
OA	0.7919		0.7762		0.8538	

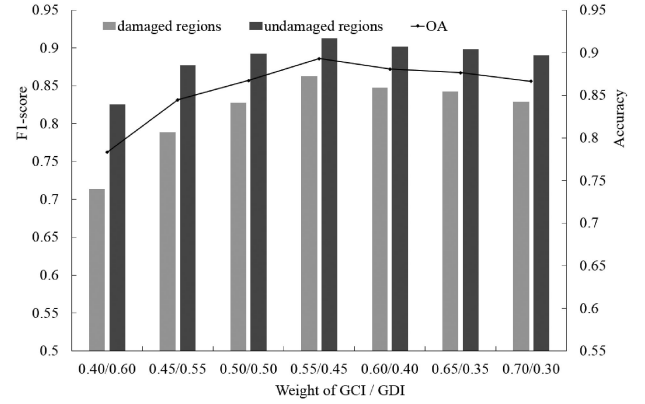


Fig. 17. The effect of weight for GCI and GDI on the extraction accuracy.

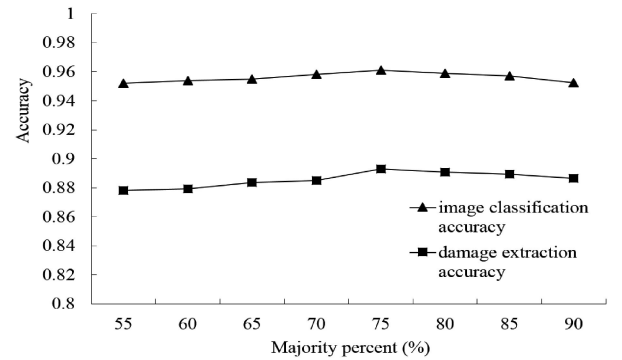


Fig. 18. The effect of majority percent on image classification and damage extraction accuracy.

graph shows how the superpixels control the damage extraction accuracy. It can be seen that the damage extraction based on the customized weights (0.55/0.45) performs well if the improved relief algorithm is used. In addition, the F_1 -score for the damaged regions ranges from 0.7134 to 0.8624, and the overall accuracy ranges from 0.7831 to 0.8931, which indicates that the choice of weights significantly affects the damage extraction performance, and confirms the need to calculate the feature weights using the improved relief algorithm.

3) *Majority Rule at the Superpixel Level For Different Objects*: In the post-processing stage, the initial classification results were optimized based on a majority rule at the superpixel level. To analyze the impact of different majority rules on the post-processing results, different thresholds from 55% to 90% (at intervals of 5%) were explored. As shown in Fig. 18, the variation in terms of damage extraction accuracy was similar to that in terms of image classification accuracy, indicating that the majority rule actually affects the image classification and damage extraction. Nevertheless, the influence is limited

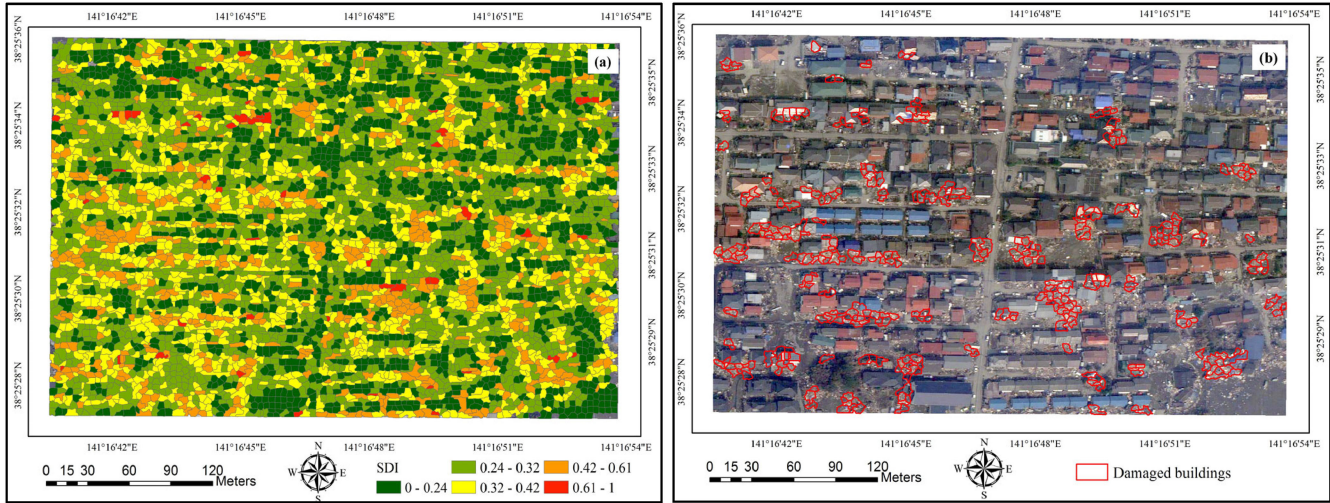


Fig. 19. Some damage extraction results in Ishinomaki, Japan. (a) is the calculated SDI and (b) is last extracted damaged building region.

(within 2%), possibly depending on the fact that the superpixels delineated by the ISLIC algorithm are relatively homogeneous and each superpixel contains only one object class. Referring to Fig. 18 an optimal threshold of 75% was identified.

F. Analysis of Transferability to Other Areas

To validate the proposed approach, a damage extraction was performed based on pre- and post-earthquake VHR images from a major earthquake and tsunami in Japan (occurred on March 11th, 2011). The VHR images comprised blue, green, and red bands and were acquired from Google Earth on June 25th, 2010 and March 19th, 2011. The spatial resolution reached 0.48 m and was sufficient to delineate the object details. The SDI and LISA results are shown in Fig. 19. It can be seen that, overall, the damaged buildings were correctly identified, thereby confirming the transferability of the proposed approach to other study areas. Despite some false positives and false negatives, the general location and extent of the damaged buildings were captured correctly. In addition, the high accuracy achieved (Table VII) confirms the strong potential of the proposed approach for practical application.

V. CONCLUSION

Efficient damage extraction contributes to emergency management and policy-making. Existing approaches have usually focused on improving either the extraction accuracy or the extraction speed, struggling to offer a necessary balance between the two. Here, an SGDL approach using pre- and post-earthquake VHR images has been proposed to identify damaged buildings. To ensure the accurate recognition of building boundaries and accelerate the extraction efficiency, the post-earthquake image was first segmented into superpixels using an improved SLIC method. The improvement was achieved by combining color/texture features and designing a dynamic distance measure, which can delineate accurate cloud boundaries. The post-earthquake image was combined with the bi-temporal

image difference to obtain the damage index. Considering the advantages and disadvantages of using a single GCI or GDI, an improved relief algorithm was used to evaluate the optimal weights in the SDI calculation. The LISA approach, which was used in damage extraction for the first time, performed reasonably well and achieved the desired balance between accuracy and efficiency. By performing a comparison and transferability analysis, it was judged that the proposed approach provides satisfactory and more accurate results than a number of methods available in the literature. In addition, the implementation of the extraction process resulted easier and more convenient, requiring a relatively smaller computational burden and a shorter calculation time. Moreover, the proposed approach provided a good localization of building damage, with accurate extraction of their spatial boundaries. It is concluded that the proposed approach is sufficiently efficient and accurate to be utilized in rapid post-earthquake damage assessments.

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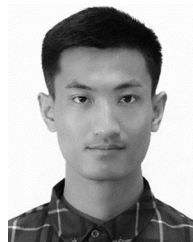
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