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## 2 **Estimation of Natural Hazard Damages by Fusion of** 3 **Change Maps Obtained from Optical and Radar** 4 **Earth Observations**

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14 **Abstract:** The Earth's land-covers are exposed to several types of environmental changes, issued by  
15 either human activities or natural disasters. On 11 March 2011, an earthquake occurred at about 130  
16 km of the east coast of Sendai City in Japan. This earthquake has been followed by a huge tsunami,  
17 which caused devastating damages over the wide areas in the eastern coastlines of Japan. Due to  
18 the occurrence of natural disasters across the world, there is a strong need to develop an automated  
19 algorithm for fast and accurate extraction of changed landscapes within the affected areas. Such  
20 techniques can accelerate the process of strategic planning and primary services for people to move  
21 into shelters, damage assessment, as well as risk management during a crisis. Therefore, a variety  
22 of change detection (CD) techniques has been previously developed, based on various requirements  
23 and conditions. However, the selection of the most suitable method for change detection is not easy  
24 in practice. To our best of knowledge, there is no existing CD approach that is both optimal and  
25 applicable in the cases of using a variety of optics and radar remote sensing images. In order to  
26 resolve these problems, an automated CD method based on Support Vector Data Description  
27 (SVDD) classifier is proposed. This method used the information contents of radar and optical data  
28 simultaneously by decision level fusing of obtained change maps from these data. In order to  
29 evaluate the efficiency of the proposed method and extract the damaged areas, the Sendai 2011's  
30 tsunami was considered. Various optical and radar remote sensing images from before and after of  
31 Sendai 2011's tsunami acquired by IKONOS and Radarsat-2 were used. The results confirmed the  
32 fundamental role and potential of using both optical and radar data for natural hazard damage  
33 detection applications.

34 **Keywords:** Natural hazard; Change detection; SVM; SVDD; Decision level fusion; radar and optical  
35 imageries  
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### 37 **1. Introduction**

38 Due to the occurrence of natural disasters across the world, there is a strong need to develop an  
39 automated algorithm for fast and accurate extraction of changed landscapes within the affected areas.  
40 Such techniques can accelerate the process of strategic planning services for people to move into  
41 shelters, damage assessment, as well as risk management during a crisis [1,2]. Therefore, several

42 methods have been developed for this purpose and efforts were put in considering low and medium  
43 resolution imagery [3]. Changes detection in multi-temporal remote sensing images of high spatial  
44 resolution is challenging. In the case of low resolution images, change detection techniques are mostly  
45 based on analysis of spectral and statistical information [4]. Such methods may be efficient for broad-  
46 scale images or large-scale changes for reason that noise caused by registration errors and radiometric  
47 variation can be restricted to low level compared to real changes by preprocessing or other means.  
48 But for high resolution images, there are many new problems to be concerned in design of change  
49 detection algorithms. First, accurate registration (e.g., half or quarter pixel accuracy) of different  
50 images is not easily achieved. Second, variations of lighting and environmental conditions are rather  
51 locally and diversified between different images, such as shadow of buildings [4]. Besides these, there  
52 are more imaging noises in high spatial resolution images. Finally, in many applications, users desire  
53 to detect small size changes including lines, buildings, bridges and other man-made targets.  
54 However, the performances of current change detection methods are not satisfying for high spatial  
55 resolution remote sensing images in both effect, efficiency and false alarm rates are relatively high  
56 [4].

57 Recently, Support Vector Machines (SVM) and Support Vector Data Description (SVDD)  
58 classifiers have demonstrated their effectiveness in several remote sensing applications. The success  
59 of such approaches is related to the intrinsic properties of this classifiers: can handle ill-posed  
60 problems and to the curse of dimensionality, provides robust sparse solutions and delineates  
61 nonlinear decision boundaries between the classes [3]. In order to take advantage of the large amount  
62 of information present in the multispectral difference image, we formulate the change detection  
63 problem in the higher dimensional feature space [5]. As all kernel methods, SVMs and SVDD show  
64 some interesting advantages over other techniques, like intrinsic regularization and robustness to  
65 noise and high dimensionality [5], [6], [7], [8], [9], [10]. On the other hand, specify the threshold  
66 requires prior knowledge of the nature of the data, the study area, skilled user and often is associated  
67 with a large error.

68 As mentioned, in high spatial resolution images the underlying class distributions are often  
69 strongly overlapped, resulting in hardly classifiable pixels even using robust methods as SVM. The  
70 high within-class variances as well as the low between-class distance, due to the low spectral  
71 information, increase the need for approaches that enhance separability between the different classes.  
72 On the other hand, in most of the above studies, the benefits of combining optical and radar images  
73 have not been used. While radar images with different polarizations contribute greatly to the  
74 separation of complex land cover classes. Radar images are sensitive to scattering processes and are  
75 affected by the shape, direction, and dielectric properties of scatterers.

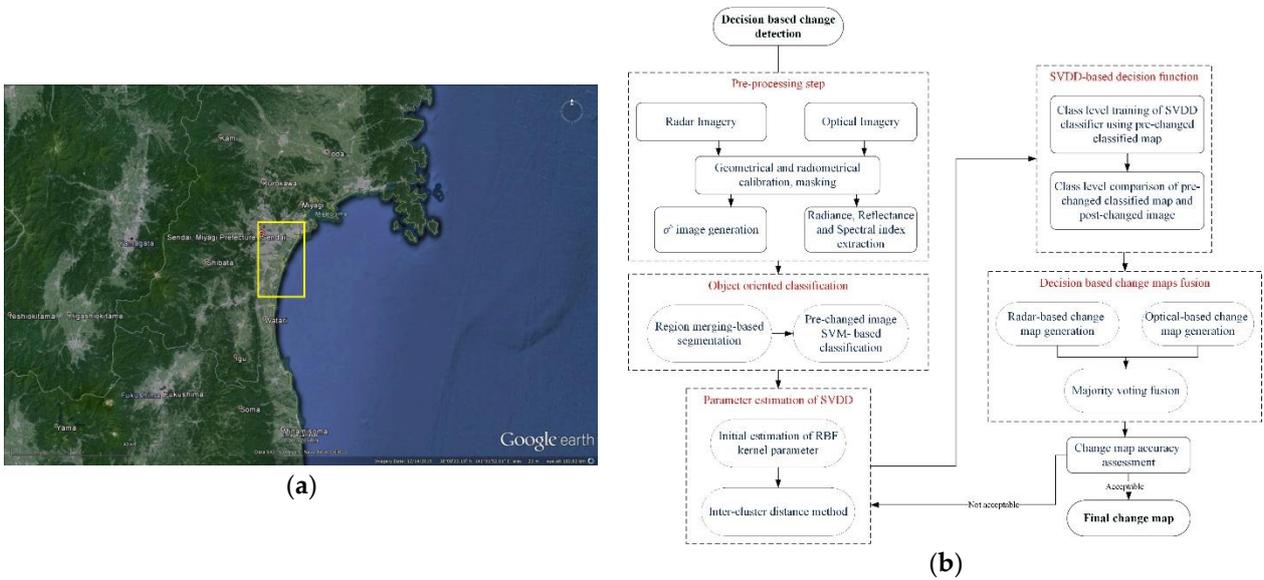
76 In order to solve these problems, in this paper, an object-level and kernel-based change detection  
77 method based on the integration of object-based image analysis (OBIA) and support vector data  
78 description (SVDD) method was proposed. This framework is indeed an automatic CD framework  
79 for either optical or radar remote sensing data, where users need easy and rapid access to real-time  
80 geospatial information to support disaster management. This proposed kernel-based method leads  
81 to a strong decrease in the false alarm rate (classifying a background pixel as a change class), and a  
82 slight accuracy improvement in the generated change map. This method used the information  
83 contents of radar and optical data simultaneously by using the decision level fusing of obtained  
84 change maps from these data.

## 85 **2. Experiments**

### 86 *2.1. Case Study and Remote Sensing Data*

87 In order to assess the effectiveness of the proposed approach, the Sendai 2011's tsunami was  
88 considered as the case study, where multi-temporal optical and radar images were collected by a  
89 variety of satellite remote sensing sensors. These data sets have been acquired before and after this  
90 natural disaster. In Japan, on March 11, 2011, at 05:46:23 UTC, an earthquake occurred near the

91 subduction plate boundary between the Pacific and North American plates. The epicenter has been  
92 located at about 130 km east of Sendai City at a depth of about 32 km. This earthquake has been  
93 followed by a tsunami caused devastating damages over wide areas of the East Japan, particularly  
94 along with the coastline of the Pacific Ocean [11]. In order to extract the destroyed areas, we  
95 considered two different data sets acquired by both optical and radar sensors, i.e. IKONOS and  
96 Radarsat-2. The geographical location and the extent of the study area over Sendai, Japan is shown  
97 in Figure 1 (a).



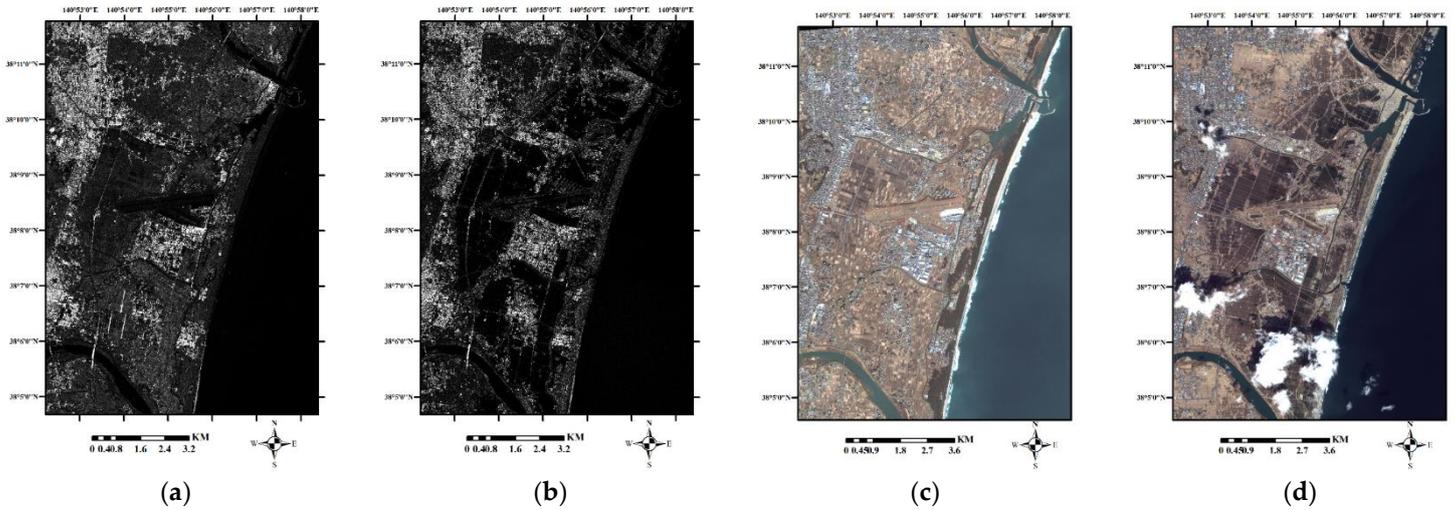
98 **Figure 1.** (a)The geographical location and the extent of the study area over Sendai, Japan and (b) the  
99 overview of proposed decision fusion based change detection method.

100 The acquisition dates, spectral and spatial resolutions of these image data sets from Sendai,  
101 Japan are presented in Table 1.  
102

103 **Table 1.** The acquisition dates, spectral and spatial resolutions of imageries from Sendai, Japan.

Dataset		Pre-change acquisition	Post-event acquisition	Bands Specifications	Spatial Resolution (m)
Sendai, Japan	IKONOS	Dec 11, 2010	Mar 28, 2011	R,G,B, NIR	3.2
	Radarsat-2	Mar 17, 2010	Mar 12, 2011	C-Band (HH)	6.25

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105 Optical and radar remote sensing images from before and after of Sendai 2011's tsunami  
106 acquired by Radarsat-2 and IKONOS are illustrated in Figure 2.



107 **Figure 2.** The sigma0 and true color images provided by Radarsat-2 and IKONOS imageries from (a,c)  
108 before and (b,d) after of Sendai 2011's tsunami, respectively.

## 109 2.2. Methodology

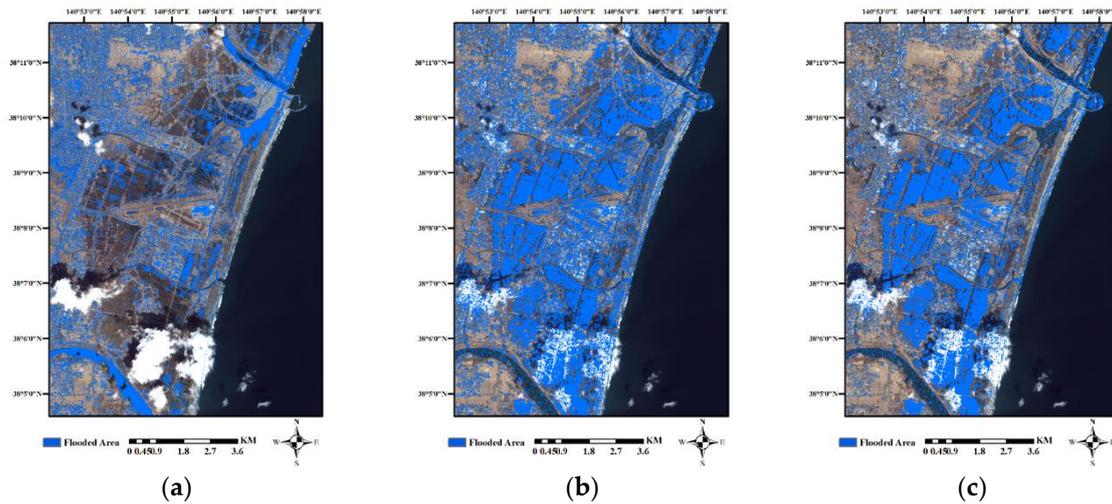
110 Proposed decision fusion based CD framework consists of several steps, including: (a) Pre-  
111 processing step, (b) Object-based classification, (c) kernel parameter estimation, (d) one class classifier  
112 and (e) change maps fusion. In the first step of proposed CD method, the geometric and the  
113 radiometric pre-processing performed on the multi-temporal images. In each case study, optical  
114 multi-temporal images were co-registered manually to each other, while radar images were co-  
115 registered automatically using an angular histogram based co-registration method [12]. Clouds in  
116 optical images were symmetrically masked. Figure 1 (b) presents the flowchart of this automatic  
117 decision-based change detection method. The mathematical details for each of the steps in the  
118 proposed CD framework are presented in [14,15].

119 In the second step, the pre-change image was classified using an object-based support vector  
120 machines (SVM) classifier. For each class of interest in this image, SVDD classifier was then trained  
121 using randomly selected samples. At this stage, the SVDD separation function, in the form of a hyper-  
122 sphere in high dimensional space, covers the pixels of this class of interest. All corresponding pixels  
123 in the post-event image enter then into the SVDD classifier as unknown pixels. If the unknown pixel  
124 in the post-event image does not belong to the no-change (target) class, it will be placed outside of  
125 the hyper-sphere and considered as a changed pixel or outlier. On the other hand, if a pixel is placed  
126 inside this hyper-sphere, it will be a no-changed class. This process is repeated for all classes in both  
127 optical and radar images until all pixels in post-event image are classified and final change map is  
128 produced [13].

129 In the final step, the produced change map from optical and radar images were fused together  
130 using decision based fusion method such as voting strategies. These strategies can be applied to a  
131 multiple classifier system assuming that each classifier gives a single class label as an output. There  
132 are a number of approaches to combination of such uncertain information units in order to obtain the  
133 best final decision. However, they all lead to the generalised voting definition. In this paper enhanced  
134 majority voting method was used for fusing the change maps obtained from optical and radar  
135 imageries. In simple majority voting method the final change and no-chnage classes are chosen when  
136 all SVDD classifiers produce the same output. But in our proposed enhanced majority voting method,  
137 in the areas that SVDD classifiers produce the different output, the spectral similarity measure  
138 between multitempoarl radar and optical imageries were calculated. If this criteria for each pixel was  
139 lower than predefined threshold, the corresponding pixels assign to change class and vise versa.

## 140 3. Results and Discussion

141 In order to analyze the accuracy of the proposed decision fusion based CD method, the test data  
 142 have been extracted from the optical images and google earth high resolution images by visually  
 143 comparing the multi-temporal images. These samples are selected so that they spread over the entire  
 144 area that the effects of sun angle and topography should be carefully considered in the analysis. Two  
 145 criteria, i.e. kappa coefficient of agreement and Overall Accuracy (O.A.) extracted from the confusion  
 146 matrix, were used for quantitative accuracy analysis of the results. Figure 3 show the change maps  
 147 obtained from proposed object-based CD method for IKONOS and Radarsat-2 imageries from  
 148 Sendai, Japan. The blue color indicates the change class.



149 **Figure 3.** Change maps obtained from proposed CD method for (a) IKONOS imagery, (b) Radarsat-2  
 150 imagery (c) decision fusion of change maps obtained from IKONOS and Radarsat-2 imageries over  
 151 Sendai, Japan. IKONOS and Radarsat-2 Satellite images, courtesy of the Digital Globe Foundation  
 152 and MacDonald, Dettwiler and Associates Ltd. Geospatial Service respectively.

153 The results show that, when using optical or radar imageries separately, leads to increase the  
 154 false alarm rate in the change maps. In this case, flooded areas have not been fully identified, due to  
 155 the inability of optical data to separate flooded areas from other areas. Using only radar data to detect  
 156 flooded areas, due to the complexity of the region and the proximity of the change classes and the  
 157 limitation of input information to the proposed CD algorithm, leads to the inability to detect all  
 158 flooded areas as well as the misdiagnosis of flooded areas in some agricultural areas and bare land.

159 As can be seen in Figure 3 (c), the noise level in the change maps is very low and the proposed  
 160 fusion based CD algorithm is completely succeeded to separate flooded areas from other areas. It is  
 161 clear that by fusing the change maps obtained from optical and radar imageries, changed areas are  
 162 well extracted. The results got limited isolated pixels and they were less noisy in essence and better  
 163 results have been achieved. As well as the areas devastated by the earthquake and flood-affected  
 164 areas have been extracted with high accuracy. The exploitation of optical images together with radar  
 165 data allows to obtain a sharp boundary between change and no-change area, which is the basis of the  
 166 statistical approach to estimate the changes. Indeed, an accurate knowledge of the homogeneous  
 167 regions given by the joint segmentation allows a better exploitation of the entire available information  
 168 in pattern changes detection phase. The accuracy analysis of proposed decision fusion based CD  
 169 method for Sendai are presented in Table 2.

170 **Table 2.** The accuracy analysis of proposed CD method on Sendai case study.

Acc. Criteria	Tsunami, Sendai, Japan		
	IKONOS	Radarsat-2	Fused change maps
Kappa	0.85	0.82	<b>0.91</b>

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For optical dataset, the accuracy analysis of proposed CD method showed that, the best results were obtained by using the RBF kernel function. For C-band HH intensity image of Radarsat-2 imagery, the best results were obtained by using the sigmoid kernel function. The fusion of change maps obtained from optical and radar imageries always provides better results than without completing the fusion phase.

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Several conclusions can be deduced from the accuracy assessment of proposed CD method. Preliminary results show that objects may be well suited to quantify changes when only one class of the landscape features is the research emphasis. Therefore, in order to mapping the flooded areas, using radar imageries are more appropriate choice. As high resolution optical imageries are a more appropriate choice for extracting the earthquake-affected and flooded-affected in builtup and crop lands areas. Therefore, it is suggested that in order to explore the environmental changes caused by natural disasters, integration of optical and radar imageries to be used.

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There are several reasons that account for the superiority of the object and fusion based CD approach. First, in this classification step, the proposed algorithm is able to extract the boundaries of changed (damage or flooded) areas from the adjacent no-changed areas. This allows the changed areas to be processed as homogeneous objects, instead of individual pixels. Second, by fusion of optical and radar data, the objects then have spectral, textural, spatial, contextual patterns and backscatter information that can be used to aid in the CD process. By integrating the change maps obtained from optical and radar imageries, a CD approach can detect the various land cover change on the ground.

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#### 4. Conclusions

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In this paper, a decision fusion based CD method at object-level is presented for change detection from both optical and radar remotely sensed data over the 2011's Sendai, Japan. This proposed method shows great flexibility for the problem of change detection by finding nonlinear solutions to the problem. This method aims at exploiting both the high information content available with the radar imageries and the high level of spectral information available even in a multiband optical image. The proposed method is largely automated and was small influenced by some of the errors issued by the classification process. In addition, all the change detection analyses are in object-level and therefore the obtained change maps have lower level of noise and the boundary between the change and no-change classes have high contrast.

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Experimental results showed that, the proposed CD approach leads to an acceptable level of accuracy for both optical and radar imageries. The results confirmed the fundamental role and potential of using both optical and radar data for natural hazard damage detection applications. The microwave signals have high sensitivity to water content of wetland and flooded areas which increase the intensity of the backscatter signal. Consequently, radar sensors have high potential in detecting environmental changes during natural disasters with adverse weather conditions. In future research, efforts will be on the integration of various remote sensing sensor types using information level and feature level methods for multiple change detection. Thus more accurate change map and complementary information is achievable from this kind of high level fusion framework in natural hazard damage detection application.

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**Author Contributions:** Reza Shah-Hoseini, Abdolreza Safari and Saeid Homayouni conceived and designed the experiments and wrote the paper; Reza Shah-Hoseini performed the experiments and analyzed the data.

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**Conflicts of Interest:** The authors declare no conflict of interest.

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