Detection of 2011 Tohoku Tsunami Inundated Areas in Ishinomaki City Using Generalized Improved Fuzzy Kohonen Clustering Network

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Abstract
In this paper, a framework for identifying tsunami inundated areas using an innovative Generalized Improved Fuzzy Kohonen Clustering Network (GIFKCN) is proposed. GIFKCN hybridizes the Kohonen clustering network with Generalized Improved Fuzzy Partitions FCM (GIFP-FCM) algorithm to build a more efficient and effective neuro fuzzy classifier. GIFKCN classifier combines the advantages of both a neural network and fuzzy systems. A number of spectral indices are computed and the mean values of these indices are used to train the GIFKCN classifier. The novel classifier was applied to identify March 2011 Tohoku tsunami inundated areas in Ishinomaki city. The performance of the classifier is satisfactory with high overall accuracy and Kappa coefficient.

Keywords: Tsunami, KCN, Spectral Indices, Confusion Matrix.

Introduction
Earthquake is an unpreventable natural disaster caused by the release of energy stored along geologic faults. This causes sudden shaking of the earth crust resulting in destruction of millions of properties and lives. Earthquakes of high magnitude that occur under the sea, generate another natural disaster known as tsunami. Tsunami may be formally defined as long period sea waves caused by rapid vertical seafloor movements due to fault rupture during earthquake [Kramer, 1996].

Traditionally, field surveys or ground inspections were used to assess damage caused by disasters. A major limitation with field survey methods is that at the time of disasters, it becomes difficult and dangerous to reach at the actual site. Also, the damage may extend a vast area, thus surveying the entire area may take a long time. In case of natural disasters, getting the right information at the right time may save a lot of human lives as well as natural resources. With the advent of satellite technology and easy availability of satellite
images, remote sensing techniques are being widely used for damage assessment [Brunner et al., 2010]. The use of satellite images overcomes the limitations associated with the traditional methods. Satellite images not only speed up the damage assessment process but also provide accurate and timely estimation of the damage [Vu et al., 2006; Voigt et al., 2007].

In the recent years, a number of methods for damage assessment and change detection have been developed by various researchers. Change detection methods broadly fall under two categories: supervised and unsupervised. Supervised methods require training for identifying changes for instance support vector machine (SVM) [Bovolo and Bruzzone, 2007b; Volpi et al., 2011], post classification comparison [Alphan et al., 2009; Yang et al., 2011], artificial neural network (ANN) based methods [Atkinson et al., 1997; Liu and Lathrop, 2002; Mehrotra and Singh, 2014]. Unsupervised methods do not require any training rather these methods analyze the image to identify changes. Some commonly used unsupervised methods are image differencing [Radke et al., 2005], principal component analysis (PCA) [Celik, 2009], and change vector analysis (CVA) [Bovolo and Bruzzone, 2007a].

A number of researchers have worked on satellite images for detecting different land cover changes and have proposed different methods for the same [Singh et al., 2014a]. Tangjiaoshan Barrier Lake, induced by the Wenchuan earthquake was detected by applying a method based on post classification and background subtraction on remote sensing images. The drawback of this method is that its efficiency is highly dependent on the image classifier chosen to obtain the change information [Xu et al., 2010]. Aerial images along with Landsat images of area of Avellino (Southern Italy) are used to analyze the changes that occurred over a fifty year period using remote sensing embedded with GIS. The limitation with this method is that it is very complex to use due to a number of factors. Firstly, the method requires a large amount of data, i.e., aerial photographs, digital aerial photographs, satellite images. Secondly, it uses supervised classification method and thus training the classifier and selecting the training samples from satellite images is a tedious job and makes the method impractical to be used [Fichera et al., 2012]. An object oriented classification method along with an edge-based segmentation and SVM classifier was used to find the channel change that occurred on the Chaping River upstream as a consequence of the Wenchuan earthquake. The method requires three images pre disaster, post disaster and during the disaster. Pre disaster and post disaster images are available in most cases but image during the disaster is rarely available thus using this method is not possible in those cases where the image during the disaster is not available [Gong et al., 2012]. In order to overcome these limitations, this paper presents a novel Generalized Improved Fuzzy Kohonen Clustering Network (GIFKCN) classifier which is hybridized neuro fuzzy classifier. The proposed classifier is applied on Landsat TM images of Ishinomaki city to identify the inundated areas due to the March 2011 Tohoku earthquake and Tsunami.

On March 11, 2011, at 14:46:23 Japan Standard Time (5:46:23 UTC), the east coast of Honshu, Japan was hit by a great earthquake ($M_w = 9.0$). The earthquake occurred due to the subduction zone interface plate boundary between the North American and Pacific plates with reverse fault. The rupture area was about $450 \, \text{km} \times 200 \, \text{km}$. The earthquake triggered a highly destructive tsunami 130 km off the coast of Miyagi Prefecture, northeast Japan.
with wave height of up to 10 m. The tsunami affected large coastal areas of Japan and a
number of areas around the Pacific Ocean including Indonesia and California [Mori et al.,
2011]. Ishinomaki city was majorly affected by the 2011 Tohoku tsunami. Tsunami waves
of about 10m height had hit the city up to 5 km from the coast. Almost 80% of the houses in
the coastal region were completely damaged. Ground surveys reported that about 46% of
the city was inundated due to tsunami.

This paper presents a novel Generalized Improved Fuzzy Kohonen Clustering Network
(GIFKCN) classifier that uses spectral indices for identifying different land cover types.
Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index
(SAVI) are analyzed for vegetation identification, Normalized Difference Water Index
(NDWI) and Modified normalized difference water index (MNDWI) for water, Normalized
Difference Built-up Index (NDBI) for built-up areas. The GIFKCN is a neuro fuzzy
classifier that hybridizes Generalized Improved fuzzy partitions FCM (GIFP-FCM) with
Kohonen Clustering Network (KCN). The proposed method is applied on Landsat TM
images of Ishinomaki city for identifying the inundated areas that have occurred in the due
to the March 2011 tsunami is presented. The pre and post disaster images are classified
using GIFKCN and the classified images are further used to identify the inundated areas
using post classification comparison technique.

Site Description and Satellite Data used
The study area taken in this paper is Ishinomaki, situated in Miyagi, Tohoku, Japan, its
geographical coordinates are 38° 25’ 0” North, 141° 18’ 0” East. Ishinomaki is the 2nd-
largest city in Miyagi Prefecture having a total area of 555.35 km² with about 12 km of
coastline, which includes warehouses, fishing port, commercial port as well as densely
populated urban area. Figure 1 shows the geographic location of the study area. Satellite
images were collected from LANDSAT 5 Thematic Mapper (TM) sensor. Landsat 5 was
launched on March 1, 1984. USGS center for Earth Resources Observation and Science
manages, collects and distributes the Landsat 5 data. The TM sensor has six reflectance
bands with a resolution of 30 m and one thermal band with resolution of 120 m. The
specifications of Landsat 5 TM are shown in Table 1.

| Band   | Wavelength Interval | Resolution |
|--------|---------------------|------------|
| Band 1 | 0.45-0.52 µm        | 30 m       |
| Band 2 | 0.52-0.60 µm        | 30 m       |
| Band 3 | 0.63-0.69 µm        | 30 m       |
| Band 4 | 0.76-0.90 µm        | 30 m       |
| Band 5 | 1.55-1.75 µm        | 30 m       |
| Band 6 | 10.40-12.50 µm      | 120 m      |
| Band 7 | 2.08-2.35 µm        | 30 m       |

The pre tsunami image acquired on 4th June 2004 and the post tsunami image taken on 20th
March 2011 are shown in Figure 2 (a) and 2 (b) respectively [http://glovis.usgs.gov].
Figure 1 - Geographical location of Ishinomaki situated in Miyagi prefecture of Japan.

Figure 2 - False color composite (R: NIR, G: Red, B: Green) of (a) Pre Tsunami satellite image of Ishinomaki area acquired on 4 June 2004 (b) Post Tsunami satellite image of Ishinomaki area acquired on 20 March 2011.
Figure 2 (a) and (b) show the false color composite (R: NIR, G: Red, B: Green) of the pre and post tsunami images of the study area. The study area mainly consists of four types of land cover; these are vegetation, water, barren land and urban area.

**Methodology**

This paper aims at finding the changes that have occurred in the Ishinomaki city occurred due to the March 2011 tsunami using pre and post disaster satellite images. Some preprocessing operations like image registration and geometric correction were done on both the images. A number of spectral indices were calculated to be used as training data for the proposed GIFKCN classifier. The GIFKCN classifier was used to classify both the images (pre and post tsunami images). Finally, to identify the inundated areas, post classification comparison of the water areas using background subtraction was done. The flow chart of the proposed method is shown in Figure 3.

**Image Preprocessing**

The pre and post tsunami images were first geometrically corrected according to the Universal Transverse Mercator (UTM) projection at 30 × 30 m resolution using second-order polynomial and bilinear interpolation. Forty five ground control points (GCP) with root mean square error less than one pixel were used for image registration. The GCPs were selected using ERDAS software. For effective image comparison, the registration of these
images with each other is important since the images acquired at different moments are taken from different viewing angles.

Spectral indices
Remote sensing researchers use a number of spectral indices to predict or identify a particular type of land cover. These indices are widely used for monitoring vegetation, water, soil etc. A number of spectral indices like Normalized Difference Vegetation Index (NDVI) [Rouse et al., 1973], Soil Adjusted Vegetation Index (SAVI) [Huete, 1988], Normalized Difference Water Index (NDWI), Modified normalized difference water index (MNDWI) [Xu, 2006], Normalized difference building Index (NDBI) [Zha, 2003] are used to increase the accuracy of classification. Use of spectral indices has many advantages:

- highlights a particular type of land cover (e.g. vegetation, water etc.);
- compensate background effects;
- normalize the effects of atmospheric distortion caused due to sun angle, viewing angle etc.

Table 2 - Various spectral indices.

| S.No. | Index                                      | Mathematical Expression |
|-------|--------------------------------------------|-------------------------|
| 1.    | Normalized Difference Vegetation Index (NDVI) | \( \frac{\rho_{\text{air}} - \rho_{\text{red}}}{\rho_{\text{air}} + \rho_{\text{red}}} \) |
| 2.    | Normalized Difference Water Index (NDWI)    | \( \frac{\rho_{\text{green}} - \rho_{\text{air}}}{\rho_{\text{green}} + \rho_{\text{air}}} \) |
| 3.    | Soil Adjusted Vegetation Index (SAVI)       | \( \frac{(\rho_{\text{air}} - \rho_{\text{red}}) \times (1 + L)}{(\rho_{\text{air}} + \rho_{\text{red}} + L)} \) |
| 4.    | Normalized Difference Building Index (NDBI) | \( \frac{\rho_{\text{mir}} - \rho_{\text{air}}}{\rho_{\text{mir}} + \rho_{\text{air}}} \) |
| 5.    | Modified Normalized Difference Water Index (MNDWI) | \( \frac{\rho_{\text{green}} - \rho_{\text{mir}}}{\rho_{\text{green}} + \rho_{\text{mir}}} \) |

Note: \( \rho_{\text{air}}, \rho_{\text{mir}}, \rho_{\text{red}}, \rho_{\text{green}} \) denote the near infrared, mid infrared, red, green bands respectively and L is the soil brightness correction factor.

Different spectral indices are calculated using Model Maker of ERDAS™ software. The mean values of the various spectral indices are used as the training data to the proposed GIFKCN classifier. The results of applying the various spectral indices listed in Table 2 are shown in Figure 4. The value of L used for computation of SAVI is 0.5. The features highlighted by each index appears brighter as compared to other features.
Figure 4 - Response of various spectral indices applied on (a) pre tsunami image (b) post tsunami image.
The spectral indices images are normalized into (0, 255) for determining the optimal threshold value, using the following equation:

$$I = \frac{(SI - SI_{\text{min}})}{(SI_{\text{max}} - SI_{\text{min}})} \times 255 [1]$$

where $I$ is the normalized image, $SI$ is the input image, $SI_{\text{max}}$ and $SI_{\text{min}}$ represent the maximum and minimum pixel value of the input image. The vegetation appears bright in NDVI and SAVI as compared to other features and the value of pixels belonging to vegetation reaches to 255 as indicated by the greyscale in Figure 4. Similarly, water is highlighted in NDWI and MNDWI, urban area in NDBI.

**Generalized Improved Fuzzy Kohonen Clustering Network**

The proposed method hybridizes the Kohonen clustering Network (KCN) [Kohonen, 1989] with Generalized Improved fuzzy partitions FCM (GIFP-FCM) [Zhu et al., 2009]. The KCN is the simplest neural network, without any activation function and hidden layer. The network consists of only two layers, i.e., input layer and output layer. The neuron with minimum Euclidean distance from the input vector is the winner. The weight of the winner and its predefined neighbors are updated using a learning rule [Singh et al., 2014b].

Fuzzy c-means is a fuzzy clustering algorithm that is widely used for data clustering. The fuzzy c-means algorithm partitions a collection of data points into c fuzzy clusters. Each cluster has a cluster center. The cluster centers are such that they minimize the value of the objective function. Fuzzy c-means employs fuzzy partitioning, where a point can belong to several clusters with degrees of membership. A membership matrix is made which has elements in the range (0, 1) representing fuzzy partitioning. A point’s total membership of all clusters, however, must always be equal to unity to maintain the properties of the membership matrix. The limitation of FCM is that its performance depends upon the choice of fuzziness index $m$. An inappropriate value of $m$ leads to unsatisfactory results. Another limitation with FCM is that it does not consider the spatial information between pixels. Therefore, it is very sensitive to noise [Bezdek, 1981]. To improve the FCM, Improved fuzzy partitions FCM (IFP-FCM) was introduced by Höppner and Klawonn [Höppner and Klawonn, 2003]. IFP-FCM improved the fuzzy partitions by assigning crisp membership degrees and hence seems less sensitive to noise and outliers. But the limitation associated with IFP-FCM is that the value of $m$ is limited to two. GIFP-FCM is an advanced and generalized form of the IFP-FCM algorithm. It overcomes the limitation of FCM by proposing a novel membership constraint function so that the algorithm is not limited to the value of $m = 2$.

The proposed Generalized Improved Fuzzy Kohonen Clustering Network (GIFKCN) uses a neuro-fuzzy hybrid approach. The use of neuro-fuzzy method overcomes the limitation of the conventional methods and has advantages of both neural network and fuzzy systems. The proposed GIFKCN further improves the performance by hybridizing the GIFP-FCM with KCN. GIFKCN algorithm assign the pixels $I_k$ ($k = 1, 2, \ldots, n$) into $c$ clusters.
The fuzziness index $m_t$ is updated by

$$m_t = m + \frac{t(m-1)}{t_{\text{max}}} \quad \text{for } 1 < t \leq t_{\text{max}} \text{ and } m > 1 \quad [2]$$

The fuzzy membership matrix $u_{ik}$ is calculated as:

$$u_{ik} = \left( \sum_{l=1}^{c} \left( \frac{\|z_i - I_k\|^2 - \beta_k}{\|z_i - I_k\|^2 - \beta_k} \right)^{\frac{1}{(m-1)}} \right)^{-1} \quad \text{for } 1 \leq i \leq c \text{ and } 1 \leq k \leq n \quad [3]$$

where, $\beta_k = \alpha \min \{\|z_i - I_k\|^2 \mid \tau \in \{1, \ldots, c\}, \ 0 \leq \alpha < 1 \} \quad [4]$

The learning rate $\Upsilon_{ik,t}$ of the $ik_{th}$ neuron for $t_{th}$ iteration is given by [5].

$$\Upsilon_{ik,t} = (u_{ik})^{m_t} \quad [5]$$

The weight of the output neuron is updated by

$$z_{i,t} = z_{i,t-1} + \frac{\sum_{k=1}^{n} \Upsilon_{ik,t} (I_k - z_{i,t-1})}{\sum_{s=1}^{n} \Upsilon_{is,t}} \quad [6]$$

The learning rate $\Upsilon_{ik,t}$ is updated. If $\|z_{1,t} - z_{1,t-1}\| > \varepsilon$ then repeat the process by calculating the membership matrix for the updated neurons otherwise the algorithm terminates and the final clustering result is obtained. GIFKCN is said to be generalized since for fixed $m_t > 1$ (i) when $\alpha = 0$, GIFKCN is FCM (ii) when $\alpha$ lies in the range $(0, 1)$, GIFKCN is GIFP-FCM (iii) when $m_t = 2$ and $\alpha$ approaches 1, GIFKCN is IFP-FCM.

| Algorithm of Proposed GIFKCN |
|-----------------------------|
| **Step 1:** Initialize the cluster center $z_i (2 \leq i \leq c)$, the threshold $\varepsilon (\varepsilon > 0)$ and topological neighborhood parameters. Set $t=1$, maximum iteration limit $t_{\text{max}}$ and $m>1$. |
| **Step 2:** Calculate fuzzy membership matrix $u_{ik}$ and learning rate $\Upsilon_{ik,t}$ using [3] and [5]. |
| **Step 3:** The weight of the output neuron is updated using [6]. |
| **Step 4:** Update the learning rate $\Upsilon_{ik,t}$. |
| **Step 5:** $t = t + 1$ for $1 \leq t \leq t_{\text{max}}$ |
| **Step 6:** If $\|z_{1,t} - z_{1,t-1}\| > \varepsilon$ then go to step 2, otherwise go to step 6. |
| **Step 7:** Output the final clustering result. |

Figure 5 - Algorithm of Proposed GIFKCN.
Image classification using GIFKCN

To perform image classification, the spectral indices computed in section 3.2 were used as training data to improve the efficiency and accuracy of GIFKCN. Water has a higher value than others in the NDWI images so the mean value of NDWI was used as training data to the GIFKCN classifier to extract the water area. The pixels with a NDWI value higher than 160 for pre tsunami and 170 for post-tsunami are considered as water. The vegetation tends to appear brighter in NDVI images as compared to other land types; thus, the mean value of NDVI was used as training data to extract vegetation regions. The pixels with NDVI values higher than 180 for pre-earthquake and 105 for post-earthquake were considered as vegetation. The pixels with NDBI values higher than 165 for pre-earthquake and in the range 150-180 for post-earthquake are considered as building. Bare land was identified with NDBI values in the range 118-165 for pre tsunami and higher than 180 for post tsunami. The mean values of the spectral indices for different classes are summarized in Table 3. Mean value of vegetation class, water class, building class and bare land class was used as training data to GIFKCN classifier.

| Indices | Vegetation Class | Water Class | Urban Area Class | Bare Land Class |
|---------|------------------|-------------|------------------|-----------------|
|         | June 4, 2004     | March 20, 2011 | June 4, 2004 | March 20, 2011 | June 4, 2004 | March 20, 2011 |
| NDVI    | 209.0138         | 146.7210     | 43.8993         | 37.8677         | 102.1552     | 78.8331        | 127.6103     | 86.2870        |
| NDWI    | 45.1999          | 93.0607      | 209.6337        | 210.4495        | 120.4716     | 148.9325       | 110.2482     | 139.2434       |
| SAVI    | 208.6688         | 146.4335     | 43.5467         | 37.6918         | 101.6847     | 78.5729        | 127.1084     | 86.0524        |
| NDBI    | 117.2570         | 124.5722     | 136.4027        | 118.6069        | 189.9392     | 166.7422       | 138.3977     | 180.3555       |
| MNDWI   | 54.6391          | 88.7615      | 157.3182        | 180.2479        | 50.6780      | 88.7473        | 87.1737      | 69.0462        |

The pre and post tsunami images were classified using GIFKCN classifier into four classes: vegetation, water, urban area and bare land. The results of the classification are shown in Figure 6.

Change detection

This paper aims at finding the inundation that has occurred due to tsunami, thus finding the change in categories other than water is not needed. Therefore, to find the inundated area, all other classes, i.e., vegetation, urban area and barren land were masked as background and change in the water class by post classification comparison method was done. The result of change in water representing tsunami inundated areas is shown in Figure 7. The result shows that the flooding has occurred along the banks of Kitakami River in both the direction. A parallel river north to the Kitakami River seems to be built up due to flooding. Also, it is seen from Figure 7 that much of the vegetation area along the coastline has merged into the sea, leaving some rocky peaks only. Floating debris is also identified in several inlets.
Accuracy Assessment

The correctness and quality of the classification results were analyzed using accuracy assessment [Congalton and Green, 2008]. Confusion matrix is used widely to compute a number of accuracy elements like overall accuracy, producer’s accuracy, user’s accuracy, and kappa coefficient. For constructing the confusion matrix, some sample pixels are chosen. The results depend largely on the choice of sample pixels, thus the sample pixels should be chosen randomly and must be independent of analyst’s knowledge about the location of classes. Thus, stratified random sampling method is used as it chooses sample pixels randomly spread over all classes [Congalton, 1991]. The accuracy assessment of the classification results in this paper was done by the method combining stratified random sampling. Accuracy assessment of GIFKCN classifier is done using ERDAS™ software.

Confusion matrix was used for a series of descriptive and analytical statistical analysis. The confusion matrices and the various assessment elements for both pre and post tsunami classified images are shown in Table 4 and Table 5 respectively. The overall accuracy is 96.09% and 95.70% for pre and post tsunami image respectively. The value of kappa coefficient is 0.9433 for pre tsunami and 0.9377 for post tsunami image. The high overall accuracy and the value of kappa coefficient show that the results obtained are quite satisfactory. The various assessment elements that are used here are overall accuracy, kappa coefficient, producer’s accuracy and user’s accuracy. A total of 256 reference points were chosen using stratified random sampling.
Figure 7 - Result of change detection applied on water class.

Table 4 - Confusion Matrix of pre tsunami classified image.

| Classified Data | Reference Data | Total | Producer’s Accuracy (%) | User’s Accuracy (%) | Kappa |
|-----------------|----------------|-------|-------------------------|---------------------|-------|
| 1. Vegetation   | 102 1 0 1 104  | 98.08 | 98.08                   | 0.9676              |
| 2. Bare Land    | 1 82 3 0 86   | 95.35 | 95.35                   | 0.9300              |
| 3. Urban Area   | 0 2 29 0 31   | 90.63 | 93.55                   | 0.9263              |
| 4. Water        | 1 1 0 33      | 97.06 | 94.29                   | 0.9341              |
| Total           | 104 86 32 34  |       | Overall Accuracy 96.09% | Overall Kappa 0.9433|

Table 5 - Confusion Matrix of post tsunami classified image.

| Classified Data | Reference Data | Total | Producer’s Accuracy (%) | User’s Accuracy (%) | Kappa |
|-----------------|----------------|-------|-------------------------|---------------------|-------|
| 1. Vegetation   | 110 1 1 1 113  | 96.49 | 97.35                   | 0.9521              |
| 2. Bare Land    | 2 28 1 0 31   | 87.50 | 90.32                   | 0.8894              |
| 3. Urban Area   | 1 2 65 0 68   | 97.01 | 95.59                   | 0.9402              |
| 4. Water        | 1 1 0 42      | 97.67 | 95.45                   | 0.9454              |
| Total           | 114 32 67 43  |       | Overall Accuracy 95.70% | Overall Kappa 0.9377|
Conclusion
This paper presents a novel method for detection of tsunami inundated areas from satellite images. A neuro fuzzy hybrid classifier GIFKCN is proposed here, the classifier uses the mean value of various spectral indices like NDVI, NDBI, SAVI, MNDWI and NDWI as training data to classify the pre and post tsunami images. The classified pre and post tsunami images are compared to obtain the inundated areas. The method is applied on Landsat 5 TM images of Ishinomaki city to identify the inundated areas that occurred due to the 2011 Tohoku tsunami. Landsat 5 images are chosen as these images have seven bands and are well suited for the computation of various spectral indices. The performance of GIFKCN is analyzed by computing the overall accuracy and kappa coefficient of the classifier. The classifier has high overall accuracy and high kappa coefficient which shows that the results are quite satisfactory. The final results show that a large amount of areas of the city were inundated. Most of the inundation occurred along the coastline and the width of Kitakami river has increased at several places.

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