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Brief Biography (100 words): I am Naresh. N, currently working as Assistant Technical Specialist (Model development) in RMS India Pvt. Ltd. I had done my M. Tech in Geological Remote Sensing and Geoinformatic from Bharathidasan University and M.Sc & B.Sc in Geology from Presidency College. I was also working as a project trainee at "Space Application Centre (SAC)", ISRO for 8 months prior to my current employer. Since my inception to corporate sector, I have been engaged in several geospatial projects for natural and manmade catastrophe risk modelling.

Damage loss estimation of the 2011 Japan tsunami: A case study

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Abstract
In the recent 2011 tsunami, Japan faced huge losses in terms of human lives, built-up urban areas, agricultural fields, and forested areas. For accurately estimating the building losses for such a huge catastrophic event, tsunami footprints and building inventory are required. Multi-temporal remote sensing images are very useful to extract the tsunami-inundated regions through change detection algorithms. In this case study, pre-event and post-event MODIS images are used to delineate the inundated area. To accurately estimate losses from this event, the building footprints are collected from various open sources within the tsunami footprint. For the development of the building inventory data, the prerequisite information of building height and lines of business (residential, commercial, or industrial) are assigned for all the buildings based on the road block level. Final results indicate the total losses using the cumulative cost of the impacted buildings, which is calculated through the total building volume cost.

1. Introduction

Devastating catastrophic events such as earthquake, typhoon, floods, and tsunamis result into huge impact to the lives of millions around the world. Japan is one such nation in East Asia which experiences numerous catastrophic events. The frequent nature of these events batters the economy of the country due to loss of human lives, structures etc. It is important to estimate the losses on a regional scale soon after the occurrence of such an event for easy initial assessment of the impact which would help various organizations to take quick actions. The 8.9 magnitude earthquake struck off the north coast of Japan (epicentre was approximately 43 miles east of the Oshika Peninsula of Tohoku and depth of 24.4.kilometre) on March 11, 2010 which is the world's fifth largest since 1990 and biggest in Japan in 140 yrs. This cataclysmic incident brought tsunami waves up to 20 feet which swept over the cities and farmland in the northern part of the country. So it is a challenging task for the catastrophe modellers to estimate the losses as soon as possible with the available data for disaster management processes.

For identifying the accurate losses actual affected region with the respective exposures of built-up area are required. Nowadays, change detection algorithms based on remote sensing are utilized for extracting the actual affected region in a short time span. Change detection is a process of identifying differences in the state of objects or phenomena by observing them at different times (Singh 1989). It is based on the analysis of the difference in the spectral response of a pixel between two multi-temporal images on the same geographical location (Varshney *et al.* 2012). In the literature, Change detection algorithms have been classified into two clusters of binary change detection and must class change detection. Image differencing, image rationing and change vector analysis (CVA) (Malila *et al.*1980) are the part of binary change detection algorithms. These change detection algorithms generate two change classes: change and no change. On the other hand multi class change detection algorithm extract the change of one land use/ land cover class to the other land use /land cover class. The multi-class change detection algorithms include artificial neural network (ANN) (Gopal and Woodcock 1996, Dai and Khorram 1999), improved change-vector analysis (Chen *et al.* 2003), unsupervised change vector analysis with kernel based

thresholding (Kontoes 2008) and Median change vector analysis (Varshney *et al.* 2012). Although researchers have used different algorithms over the years for various change identification case studies; choosing the best method that caters to the requirements of an application is an enormous task and impacts the final output significantly. In several case studies, researchers have shown the importance of change vector analysis algorithm for identifying the flood/tsunami impacted regions (Varshney *et al.* 2011, Sepehry and Liu 2006).
For Japan, there is enormous spatial data available at building level at Geospatial information Authority of Japan (GSI) (*http://www.fgd.gsi.go.jp/download/)* and Open Street Map (OSM) (*http://www.openstreetmap.org/*). This can be combined together to get high resolution information after refining it. This study is about identifying the impacted region using MODIS satellite images and computing the actual losses at building level for different Line of Business using various open source data like OSM, GSI and others.

2. Case Study Area and Data Used

Japan lies on the cusp of Pacific-Philippine-Eurasian triple plate junction. The westward movement of the Pacific plate results in subduction of the tectonic plates, resulting into high seismic and volcanic activity in the subduction zones. The sheer number of earthquakes experienced by Japan is very high as small tremors can be experienced every other day. In certain cases, the earthquake induces tsunami which is merely dependent on the epicentre and the magnitude of the earthquakes. These tsunamis have the potential to cause damage to the Coastal areas on a large scale.
Due to the geography of Japan, secondary events like tsunami, dam failures, nuclear plant damage and many others are common and every year lot of life and property losses are occurring. As our case study is about the recent 2011 tsunami, it covers major coastal part of north east Japan. Our study area includes the coastal stretch of Ishinomaki to Sendai of Miyagi prefecture. It stretches about 70 kilometre from north to south of east coast of Japan with tsunami inundated region (refer below figure). Sendai is the largest city in the Tohoku region and had a one million population prior to the tsunami in 2010.

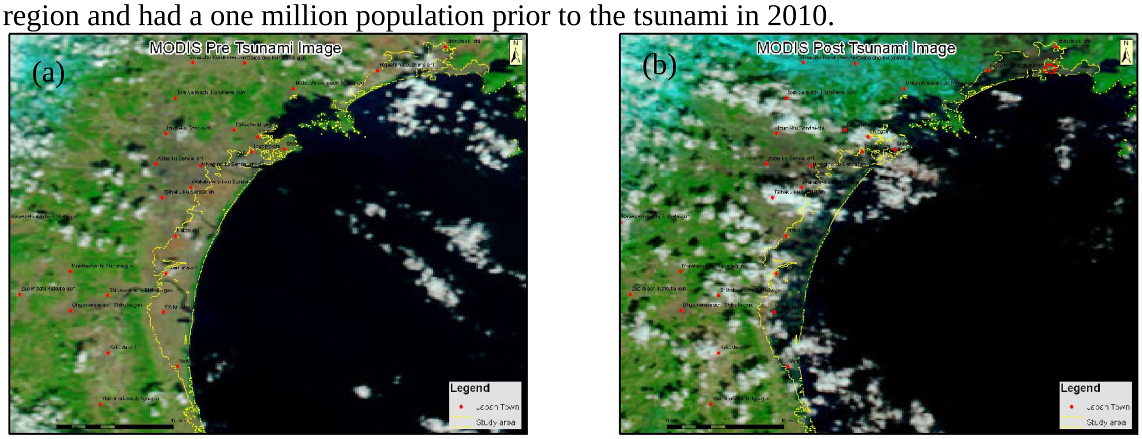

Figure 1. MODIS pre and post event images of study area: (*a*) Pre event image; (*b*) Post event image.
In this case study two different type of data sets are used: Remote sensing Images and open source building footprints,

a) For delineating the tsunami inundated region multi-temporal MODIS images are used in this study (Figure 1).
b) Developing the building level inventory using various open source,

i. Building footprint downloaded from GSI (Geospatial Information Authority of Japan) for major city extent
ii. Open street map (OSM)
iii. Google Earth utilities are used as references for estimating the quality of the available building footprints.

3. Methodology

3.1 Delineating the Tsunami Area

The change detection algorithm can be applied on remote sensing multi-temporal data after the following pre-processing steps:

i. Image to image registration
ii. Radiometric Normalization

The accuracy of change detection deteriorates if the pixels are not aligned and normalized properly. The root mean square error (RMSE) was less than 0.25 of a pixel after the image to image registration of the MODIS images. Histogram matching (Leonardo *et al.* 2006) algorithm is applied in this study to normalize the radiometric affects. After the data is geo-referenced and radiometrically normalized, the CVA method is executed to extract the tsunami impacted region. This is described below:

3.1.1 *Change Vector Analysis* (*CVA*)

Using the Magnitude and direction of the changes, CVA (Malila *et al.* 1980) algorithm is used to identify the impacted region. For two time point images, with two bands only, pixel of time1 image and time2 images can be denoted

For multi-temporal images with two bands only, the pixel of date1 and date2 can be denoted by (a_1, b_1) and (a_2, b_2) respectively. The magnitude of the change vector $\vec{M}$ is defined below:

$$\left|\vec{M}\right| = \sqrt{(a_1 - a_2)^2 + (b_1 - b_2)^2} \tag{1}$$

and the direction of change θ can be derived as,

$$\cos\alpha = \frac{(a_1 - a_2)}{\left|\vec{M}\right|} \tag{2}$$

where, α is angle of change and a_i and b_i are the spectral response of pixels in band i (here i =1, 2).

To separate the change and no-change region, kernel based thresholding (Kontoes 2008) algorithm is used after computing the magnitude of the change vector. After this process, cleaning and gap filling methods are applied to extract the flood extents.

3.2 Developing Building Footprint in the Impacted Region

For Japan, GSI provides building level information which is available for public use. This information was used in this study for estimating the accurate losses. Downloaded building footprints were over laid on Google Earth for accuracy assessment. It is found that GSI building footprints are developed using the 2003 vintage images and match perfectly with the Google Earth 2003 images. There are a few building footprints that are missed in the impacted region due to the vintage of the developed data and also because data is available only for the main city area. So there were a few gaps in between Sendai and Ishinomaki region. OSM building footprints data is used to fill those gaps (figure 2).

Using the extracted tsunami inundated extent from the MODIS images, building footprints are selected for analyzing damages on the affected buildings. After selecting the impacted building footprints, noise corrections are done in the available building footprints to enhance the accuracy of the losses. The building footprints are classified manually into residential, commercial and industrial using Google Earth and Emporis website (*http://www.emporis.com/country/japan*) and also height of the buildings are assigned based on block level (road blocks).

Due to the large amount of building footprints in the impacted region, entire affected region is split into 10 ×10 kilometre grid (figure 3) for assigning the building inventory (like height and lines of business). After this each grid level is divided into road block level (figure 4) to assign the building inventory in a quick manner. Apart from this, commercial and industrial buildings are analyzed carefully because the exposure values for these types of buildings are very high when compared to residential buildings. Also the exposure value varies from building to building due to region and height. Tall rise buildings, using the Google Earth and Emporis website have also been used for assigning the inventory.

Using the final building footprints (i.e., after combining both GSI and OSM building footprints and removing the other noises like two building footprints for same location), area for each footprint is computed using ARCGIS function. Using the number of floors and respective building footprint area, total building area is computed by using the formula as given below,

$$\textit{Total Area} = \textit{Area of building} \times \textit{Number of floors} \tag{3}$$

Total cost of the building can be calculated by multiplying the cost per square meter to the total area:

$$\textit{Building Cost} = \textit{Total area} \times \textit{Cost per square meter} \tag{4}$$

The aggregated approximated loss is calculated by taking the summation of the cost of buildings falling inside the tsunami extent.

$$\textit{Aggregated Loss} = \sum \textit{Building Cost} \tag{5}$$

4. Validation and Results

Tsunami inundated regions are indentified using equations 1 and 2 through MODIS multi-temporal images after pre-processing of the data sets. Yellow line indicates the changes identified through CVA in figure 1. Tsunami inundated region and building footprints are validated by over laying spatial layers over Google Earth utility. Building footprints are converted into a KML file and opened over the available images on Google Earth and verified if they are exactly matching with the actual buildings (blue oval shape in figure 4). All the building footprints are almost matching with the images. Building footprints were checked for any duplicate footprints for the same location and removed in case of any overlay of building. After cleaning the building footprints, aggregated loss of the building footprints are computed by using equations 3 to 5. From the study, impacted loss is calculated to be in-between \$60 billion to \$75 billion due to this event.

5. Conclusions

In this case study, losses occurred due to the 2011 Japan tsunami are computed by using MODIS multi-temporal images through remote sensing based change detection algorithms and available digital building footprints. The current study shows potential to compute the first cut losses/damage to take action on disaster management within a short time frame after the occurrence of a catastrophic event. Also the historical event footprints and overall losses help catastrophe modellers to generate the accurate risk associated with a building. This study also indicates the use of the digital building inventory to calculate the accurate losses for a catastrophic event. If accurate building footprints will be available for a region, one can compute damage/impact cost for an event on that region quickly.

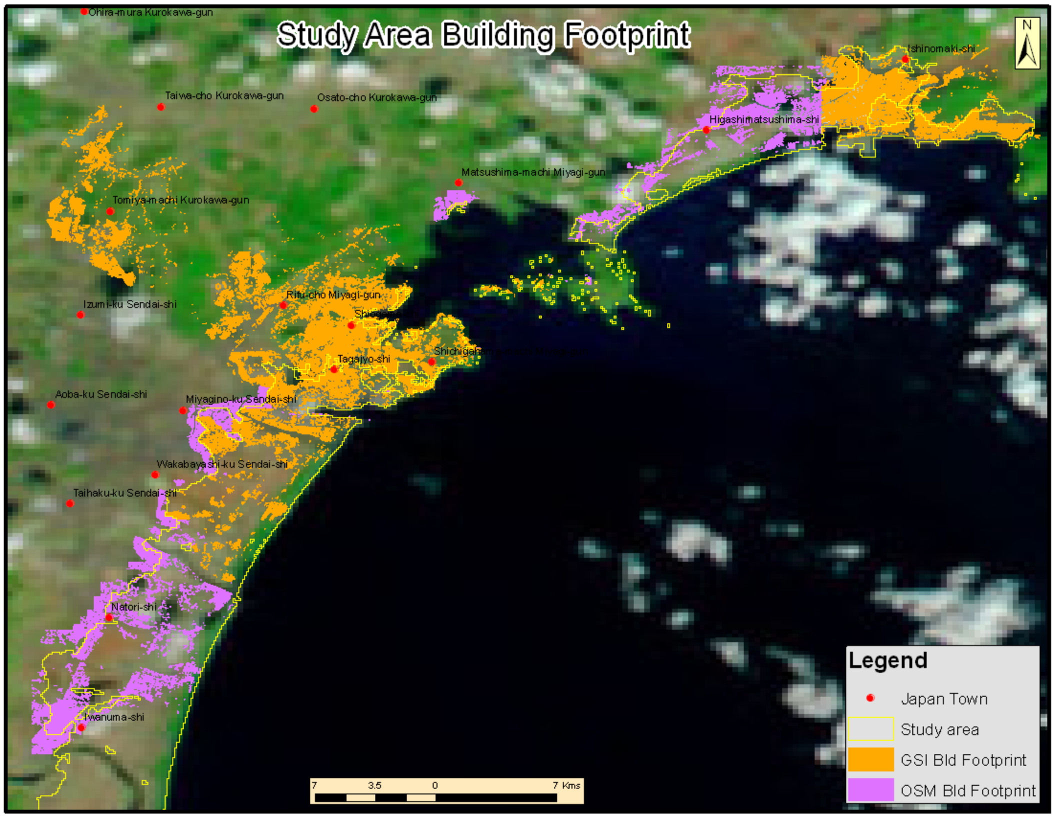

Figure 2. Available building footprints in GSI and OSM

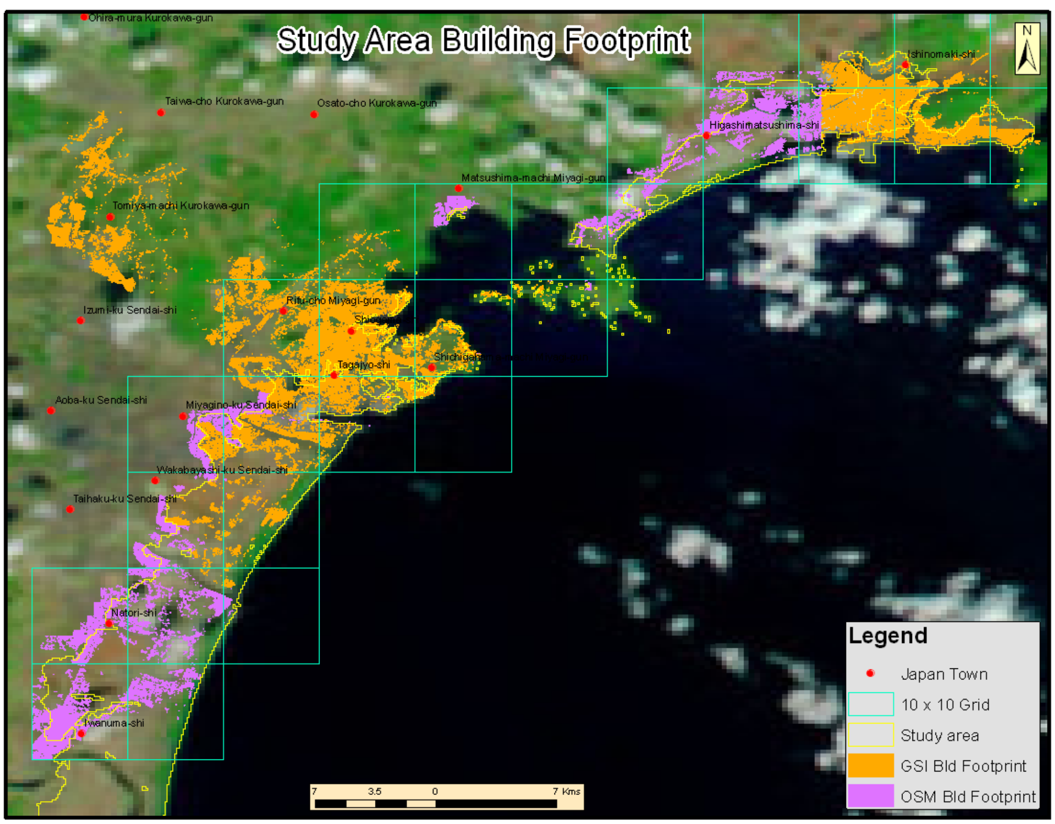

Figure 3. 10×10 kilometre grid for assigning the line of business for the buildings

Figure 4. Road blocks for assigning the line of business for the buildings in a quick manner

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