Abstract: Rapid urbanization and increasing population in cities with a large portion of them settled in deprived neighborhoods, mostly defined as slum areas, have escalated inequality and vulnerability to natural disasters. As a result, monitoring such areas is essential to provide information and support decision-makers and urban planners, especially in case of disaster recovery. Here, we developed an approach to monitor the urban deprived areas over a four-year period after super Typhoon Haiyan, which struck Tacloban city, in the Philippines, in 2013, using high-resolution satellite images and machine learning methods. A Support Vector Machine classification method supported by a local binary patterns feature extraction model was initially performed to detect slum areas in the pre-disaster, just after/event, and post-disaster images. Afterward, a dense conditional random fields model was employed to produce the final slum areas maps. The developed method detected slum areas with accuracies over 83%. We produced the damage and recovery maps based on change analysis over the detected slum areas. The results revealed that most of the slum areas were reconstructed 4 years after Typhoon Haiyan, and thus, the city returned to the pre-existing vulnerability level.

Keywords: deprived areas; slums; disaster; recovery; damage; remote sensing; machine learning; SVM; SDG; Sendai Framework
build back better concept in the recovery and reconstruction process [7]. Consequently, providing information regarding the recovery process, including damage assessment after a disaster as well as reconstruction of deprived/slum areas, is critical to support decision-makers and recovery planners to effectively make decisions toward implementation of the build back better goal. Given that the urban deprived areas are one of the most vulnerable areas to disasters, decreasing of their size during the post-disaster recovery process is an indicator of successful build back better concept implementation.

Remote sensing (RS) data have become one of the main geospatial information sources to support the assessment of different components of disaster risk management [8] such as damage [9–11] and vulnerability [12,13] assessments. In addition, different data processing and machine learning methods were developed to extract information from RS data to support disaster risk management [10,14–16]. Only recently, a few studies addressed recovery assessment using RS, mostly focusing on the physical recovery assessment. For instance, Burton et al. [17] employed repeated photography to evaluate the post-Katrina reconstruction process in Mississippi. Brown et al. [18] used RS and survey data to assess the damage and early recovery after an earthquake. They showed that RS data could provide rapid support in terms of physical damage assessment. However, they extracted most of the information, e.g., building damages, manually. Hoshi et al. [19] used binary classification of RS data in addition to ground survey information to monitor post-disaster urban recovery. Contreras et al. [20] integrated high-resolution RS imagery and ground data to monitor the recovery process after the 2009 L’Aquila earthquake, in Italy. de Alwis Pitts and So [21] proposed a semi-automated object-based change detection method using pre-disaster map data and very high-resolution optical images to monitor buildings after the Kashmir earthquake, Pakistan. In addition, Derakhshan et al. [22] used remote sensing-based indices to monitor land cover changes in urban areas for post-earthquake recovery time. They showed the usefulness of such indices for general recovery assessment. All these studies demonstrated the importance of using RS in reducing the required ground data for post-disaster recovery assessment. Machine learning methods have been recently employed for post-disaster recovery monitoring. Sheykhmousa et al. [6] used Support Vector Machine (SVM) as the main classifier to assess the post-disaster recovery. They also conceptualized the recovery assessment using RS data and provided the information to translate the RS-derived land cover and land use changes to positive and negative recoveries. Random Forest classification executed in a cloud computing platform, i.e., Google Earth Engine [23] and Extreme Gradient Boosting (XGBoost) methods were also used to monitor the recovery [24]. Moreover, advanced deep learning methods, i.e., Convolutional Neural Network (CNN)-based approaches, were developed to extract information from very high-resolution satellite images [25] and update the building database [26]. These studies mostly focused on providing general information in recovery without investigating the build back better concept focusing on specific groups living in an urban area, i.e., slum dwellers.

There is no unique term or definition for deprived areas. “Informal settlement”, “slum”, and “inadequate housing” are examples of used terms [4]. In the current study, we consider the widely accepted term and definition provided by UN-Habitat that defines a slum household as a household or group of individuals with a lack of durable housing, adequate living space, safe water, sufficient sanitation, or security of tenure [27]. In addition, the physical appearance of the human settlements is one of the indicators of socio-economic status of dwellers, and thus, it can be employed to locate deprivation and discriminate it from other areas (e.g., formal settlements/buildings) in particular in urban areas [28,29]. Hence, remote sensing data due to providing spatial information and different physical features of the urban areas can be used for this purpose [30–32]. Remote sensing images have also been used to extract land cover and land use maps [33–36] as well as other urban objects [37–39]. Slum detection and extraction from remote sensing images was also the focus of several studies [40]. While early studies in this topic used traditional image processing methods [32,41–43], recent ones used more advanced machine learning
methods [44] such as SVM [45,46], Random Forest [47], and CNN-based approaches [48,49]. For example, Kuffer et al. [50] used gray-level co-occurrence matrix (GLCM) features to extract slum areas from very high-resolution images. They showed that such techniques could improve the accuracy of slum areas extraction. Ajami et al. [48] developed a deep learning-based method to identify the degree of deprivation from Very-High-Resolution (VHR) images. In addition, Wang et al. [30] developed a CNN-based method to identify the deprived pockets from VHR satellite images. However, their method requires extensive training samples to produce reliable accuracies. In another study, Wurm et al. [51] used a Random Forest classifier to map slum areas from Synthetic Aperture Radar (SAR) data. They showed that their developed machine learning method produces a high accuracy rate in extracting slum areas when combined with spatial features. However, the temporal changes of slum/deprived areas have not yet been studied in case of disaster recovery.

The aim of this study was to investigate the implementation of the build back better concept after a disaster, given that the presence of urban deprived areas is a proxy for vulnerability assessment [8], through the development of a robust machine learning approach to monitor temporal changes of deprived/slum areas in the recovery process. We developed a machine learning-based approach using SVM and Conditional Random Field (CRF) methods to extract slum areas from high-resolution satellite images for the pre, event, and post-disaster times. The slum areas were detected using the SVM method supported with Local Binary Patterns (LBP) features, and then, the DenseCRF [52] model was executed to refine the results and extract final slum areas for the selected time-lapse. In addition, the changes in slum areas were extracted to monitor their damage and recovery process. Tacloban city, located in the Leyte island, the Philippines, was selected to test the developed method. Accordingly, the damage and recovery of slums from super Typhoon Haiyan, which hit the area on 8 November 2013, were assessed, and implementation of the build back better concept was investigated in this area.

2. Materials and Methods

2.1. Case Study and Remote Sensing Data

Tacloban city is the largest city and the capital of Leyte province in the Philippines (Figure 1). Super Typhoon Haiyan (locally known as Yolanda) hit the area (the eye of the typhoon passed close to the south of Tacloban) causing massive damages. It was one of the strongest tropical typhoons ever landed worldwide [53]. It was also followed by a storm surge up to 5 m, which led to an increase in the number of fatalities mostly in the coastal neighborhoods [54].

Slum areas were detected from three high-resolution WorldView2 satellite images, which were acquired 8 months before (T0), 3 days after (T1), and 4 years after (T2) Haiyan, using our developed machine learning method (Table 1).

| ID | Satellite  | Acquisition Date   | Spatial Resolution |
|----|------------|--------------------|--------------------|
| T0 | WorldView2 | 17 March 2013      | 2 m                |
| T1 | WorldView2 | 11 November 2013   |                    |
| T2 | WorldView2 | 18 March 2017      |                    |

2.2. Methods

Figure 2 illustrates the developed methodological framework to monitor slum areas and assess them in terms of the build back better concept. The developed approach consists of two main steps: (i) slum area extraction from high-resolution satellite images using the developed LBP-based SVM and fully/dense CRF (DenseCRF) methods, and (ii) generate damage and recovery maps and evaluate the build back better concept based on change detection.
Figure 1. The overview of Tacloban, the Philippines, and the satellite images for the urban area acquired before (T0), 3 days after/event (T1), and 4 years after (T2) typhoon Haiyan. Red circles denote the slum areas in the northern part of Tacloban city, which were devastated by the typhoon.

Figure 2. The proposed framework for slum area extraction and build back better concept evaluation from multi-temporal satellite images in case of disaster recovery.
2.2.1. Mapping Deprived Areas with SVM and DenseCRF

We used the Support Vector Machine (SVM) method as the main classifier to extract the deprived/slum areas from the high-resolution satellite images. SVM is a kernel-based non-parametric supervised machine learning algorithm, which is widely used for image classification tasks and produces reliable results [55–57]. SVM splits and groups the data by identifying a single linear boundary in its basic form. Thus, in such a case, the main goal of SVM is to determine an optimal line to separate the data into predefined classes using the training samples. SVM is popular due to its performance when only a small amount of training samples are available, contrary to deep learning methods that require big data for training [58–60]. SVM is well suited for urban area classification and object detection; in comparison to other machine learning algorithms, it produces competitive accuracy [6,61–63]. To execute the SVM classifier, we collected areas for both slum and non-slum areas from the images for each image separately. The selection of these areas was based on our field knowledge (field verification), and using different platforms including Google Earth Pro historical images, panchromatic very high-resolution satellite images and OpenStreetMap data to ensure the quality of the collected areas (Figure 3). Then, 70% of the areas were randomly selected to train the SVM method, and the rest were used for testing and accuracy assessment purposes.

Due to the complexity of urban slum areas in terms of spectral and semantic definition, we used Local Binary Patterns (LBP) to support the SVM-based classification by providing feature layers. LBPs have been successfully used for different remote sensing image classification tasks. Researchers reported an increase in classification accuracies when used LBP features, in particular in areas with complex textural characteristics (e.g., slum areas) [24]. LBP is a powerful tool to discriminate and highlight textural features in the images using two parameters; lag distances (R) and windows sizes (P). We implemented LBP for each band of the satellite images with R = 4 and P = 8. Accordingly, we produced and added 8 textural layers to the original bands to be used for classification.

Yet after implementation of the SVM-LBP method, we verified inaccuracies mostly in the edge of the slum areas. Conditional Random Field (CRF) methods were used to refine and optimize the deep learning-based image classification results in edges, where abrupt changes happen in terms of textural characteristics and spectral values, and they demonstrated effective results [26]. Therefore, we used a fully/dense CRF model (DenseCRF) developed by [52] to alleviate the problem.

CRF iteratively evolves and computes labels and predictions to optimize the results using an energy function. The unary and pairwise potentials are the main components of the DenseCRF energy function. In this method, labels and their relations are considered as random variables and the edges in a graph-based theory, respectively, and they establish the conditional random fields.

**Figure 3.** Examples of used data for training area selection. (a) Original satellite image used for slum detection, (b) panchromatic image, (c) Google Earth image, and (d) OpenStreetMap for before Haiyan time (i.e., 2013).
Let \( l \) be the labels, extracted using SVM, for the input image. Then, the unary potential \( \rho_x(l_x) \) is the probability of each pixel \( x \), and the pairwise potential \( \sigma_{xy}(l_x,l_y) \) is the cost between labels at \( x, y \) pixels. Accordingly, the energy function can be computed as follows:

\[
E(l) = \sum_x \rho_x(l_x) + \sum_{xy} \sigma_{xy}(l_x,l_y).
\]

(1)

The pairwise potential consists of two Gaussian expressions. The first one uses both the location and color of the pixels in a kernel-based process of the similarity between adjacent pixels using the \( \phi_\alpha \) and \( \phi_\beta \) parameters. The second one only uses the position of the pixels for smoothness based on the \( \phi_\gamma \) parameter. Accordingly, the pairwise potential can be computed using the equation below:

\[
\sigma_{xy}(l_x,l_y) = \mu(l_x,l_y) \left[ \omega_1 \exp \left( -\frac{|p_x - p_y|^2}{2\phi_\alpha^2} - \frac{|C_x - C_y|^2}{2\phi_\beta^2} \right) + \omega_2 \exp \left( -\frac{|p_x - p_y|^2}{2\phi_\gamma^2} \right) \right]
\]

(2)

where \( p_x \) and \( C_x \) are the position and color vector for pixel \( x \). \( \mu(l_x,l_y) \) is defined based on the Potts model [64] and is equal to one if \( l_x \neq l_y \); otherwise, it is equal to zero.

2.2.2. Accuracy Assessment

We evaluated the produced slum areas maps for each time step using overall, user’s, and producer’s accuracy measurements. Overall accuracy is computed by comparing all of the reference samples and their corresponding classified results to provide what proportion was classified correctly (usually expressed in percent). However, user’s and producer’s accuracies demonstrate the commission and omission errors, respectively. For accuracy assessment purpose, we selected a proportion of 30% of the collected areas at the start of the classification for slum and non-slum classes employing stratified random sampling and used them to calculate the accuracies [6,23,65].

2.2.3. Change Analysis

We generated the damage map by comparing the slum detection results for T0 and T1 times, and we provided the damaged and not-damaged classes. In addition, the recovery map was created by analyzing the changes in three time steps (T0–T2) and classifying them to four classes: (i) Not-damaged: refers to the areas that were slums in T0 and not damaged during the disaster; (ii) Recovered as slum: refers to the areas that were slums in T0 and have been recovered as slums in T2; (iii) Not-recovered or changed land use: refers to slum areas in T0 that were damaged during the disaster and have not been recovered as slum or changed their land use to other types (e.g., formal buildings) in T2; (iv) Newly built: refers to slum areas that were built after the disaster (in T2) while they were not slums before the disaster (T0). Moreover, we used the recovery and damage maps to evaluate the build back better concept, given that the slums are vulnerable areas to disasters and the reduction of such settlements contributes to the overall risk mitigation of the city, and thus, it can be considered as a positive sign of recovery and building back better.

3. Results and Discussion

Figure 4 shows the deprived/slum area detection results for the images acquired before (T0), 3 days after/event (T1), and 4 years after the disaster (T2). The detected slum areas are illustrated and overlaid on the original images by assigning a yellow color. Visual interpretation and qualitative analysis of the results show that the proposed method produced robust results in terms of detecting slum areas in such a challenging case study, which includes slums with different textural and spectral characteristics. The results also revealed that most of the slum areas are located close to the sea (i.e., coastal line), which is declared as the high-risk zone (also known as no-built area) after Typhoon Haiyan for such hazards. This also increases the vulnerability of those areas to typhoon and storm surge hazards due to their high exposure rate. In addition, there are big clusters of slums mostly
located in the northern part of the city, while also others are distributed in smaller clusters all over the city.

![Figure 4. Detected slum areas, denoted in yellow color, for before (T0), 3 days after (T1), and 4 years after (T2) Haiyan.](image)

The overall accuracies for the T0–T2 images were 84.2%, 83.2%, and 86.1% (Table 2). These results demonstrate the efficiency of the developed method in extracting slum areas for different time steps. In addition, producer’s and user’s accuracy were computed for each time step (Table 2). The worst user’s and producer’s accuracies were computed as 74.1% and 71.4%, respectively, for the event time image. Nevertheless, these are also fairly good results, since the presence of debris and rubbles and their similarity in terms of morphology, texture, and spectral characteristics mostly in the areas close to slums in an event time image makes the classification task even more challenging. However, the producer’s accuracy values of the non-slum class in T0 and the slum class in T2 images demonstrate the relatively high omission errors. The presence of slums in between formal buildings and their vicinity, as well as the spectral proximity of the other image objects and features (e.g., roads), were other challenges faced in classifying the images and detecting slums.

Table 2. Accuracy assessment results for slum detection for 8 months before (T0), 3 days after (T1), and 4 years after (T2) after Typhoon Haiyan.

| Time/ID | Pre-Disaster (T0) | Event Time (T1) | Post-Disaster (T2) |
|---------|------------------|----------------|-------------------|
|         | Slum | Non-slum | Slum | Non-slum | Slum | Non-slum |
| Producer’s accuracy (%) | 93.3 | 76.8 | 71.4 | 90.1 | 76.2 | 93.2 |
| User’s accuracy (%) | 76.4 | 93.5 | 74.1 | 88.9 | 88.9 | 84.6 |
| Overall accuracy (%) | **84.2** | **83.2** | **86.1** |

Figure 5 shows the damage and recovery maps based on defined classes in Section 2.2.3 with different colors overlaid on the original post-disaster image. In the damage map, red and green colors illustrate the damaged and not-damaged areas, respectively. In addition, green, red, yellow, and blue colors illustrate not-damaged, not-recovered, or changed land use, recovered as slum, and newly built slum areas after Haiyan, respectively. Most of the slum areas were damaged during the disaster; almost all slums close to the coastal line are devastated and completely washed. In addition, most of the damaged slum areas are recovered/reconstructed as the same land use (slum area), which show no change in the vulnerability rate of the area, and thus, the build back better goal has not been reached.
in Tacloban city after 4 years. For example, the area in the northern part of Tacloban city, denoted as “a” (Figure 5), is recovered as slum area just next to the sea, which was announced as a high-risk/danger zone. However, rarely positive recoveries can be seen in the recovery map, where the previous slum areas are changed to other land use types (e.g., formal buildings) or completely removed/relocated from the danger zone (e.g., the area denoted as “b” in Figure 5).

**Figure 5.** Damage and recovery maps for slum areas after Typhoon Haiyan, and the denoted areas as “a” and “b” show the negative and positive build-back-better goal implementation, respectively.

4. Conclusions

The aim of this study was to monitor the urban deprived areas after Typhoon Haiyan, which hit Tacloban city in the Philippines in November 2013. In addition, we analyze and discuss the results from the build back better perspective defined in the Sendai Framework. For this, we developed a machine learning-based approach based on SVM and DenseCRF models to classify the high-resolution satellite images acquired 8 months before, 3 days after the event, and 4 years after the disaster and detected slum areas, which are accepted as the deprived urban areas. The measured accuracy values for the classification results show the robustness of the proposed method in extracting slum areas in such challenging environment even in an event time image, which contains debris and rubble land covers. Then, we generated the corresponding damage and recovery maps, showing the damaged, recovered, not-recovered, and newly built slums and discussed them from the vulnerability...
assessment and the build back better point of view. The developed methods can be used to monitor and evaluate the urban deprived areas in any other location or in case of any type of disaster. For this, the parameters of the machine learning methods should be fine-tuned for the specific case study and extract slum areas from multi-temporal remote sensing images. However, using additional data types such as survey data can contribute to a more comprehensive social vulnerability assessment [24], and thus, better evaluations in terms of the build back better concept. Moreover, using deep learning, in particular, CNN-based methods can increase the accuracy of the detection work where we have a large amount of data available to train such models.

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