Semiautomatic Object-Oriented Landslide Recognition Scheme From Multisensor Optical Imagery and DEM

Jiann-Yeou Rau, Jun-Jyao Chen, and Ruey-Juin Rau

Abstract—Rainfall-induced landslides are a major threat in Taiwan, particularly during the typhoon season. A precise survey of landslides after a super event is a critical task for disaster, watershed, and forestry land management. In this paper, we utilize high spatial resolution multispectral optical imagery and a digital elevation model (DEM) with an object-oriented analysis technique to develop a scheme for the recognition of landslides using multilevel segmentation and a hierarchical semantic network. Four case studies are presented to evaluate the feasibility of the proposed scheme. Three kinds of remote sensing imagery, namely pan-sharpened FORMOSAT-2 satellite images, aerial digital images from Z/I digital mapping camera, and images acquired by a digital single lens reflex camera mounted on a fixed-wing unmanned aerial vehicle are used. An accuracy assessment is accomplished by evaluating three test sites containing hundreds of landslides associated with the Typhoon Morakot. The input data include ortho-rectified image and DEM. Four spectral and one topographic object features are derived for semiautomatic landslide recognition. The threshold values are determined semiautomatically by statistical estimation from a few training samples. The experimental results show that the proposed approach can counteract the commission/omission errors and achieve missing/branching factors at less than 0.12 with a quality percentage of 81.7%. The results demonstrate the feasibility and accuracy of the proposed landslide recognition scheme even when different optical sensors are utilized.

Index Terms—Digital evaluation model (DEM), landslide recognition, object-oriented analysis (OOA), ortho-image.

I. INTRODUCTION

O N AVERAGE, three to four typhoons strike the island of Taiwan each year. Generally, each typhoon drops more than 800 mm of cumulative rainfall. On August 7–9, 2009, Typhoon Morakot battered Taiwan for three days bringing a maximum rainfall accumulation of 3060 mm [1]. This triggered more than 10,000 landslides in the mountainous areas and caused serious flooding on the plains. According to the official report from the National Disaster Prevention and Protection Commission, Taiwan, this catastrophic typhoon led to 769 deaths, especially in Shiao Lin village where more than 500 people were buried under a deep-seated landslide [2].

According to landslide surveys reported from several agencies, the total area of landslides induced by Typhoon Morakot ranged from 274 km² [3] to 349 km² [4] and up to 369 km² [1] in size. All of these reports were based upon FORMOSAT-2 satellite images and a pixel-based change detection technique for landslide detection but came up with quite different results. The major reasons for these uncertainties are: 1) the data acquisition dates might have been different and thus cloud cover and weather conditions might have varied; 2) the thresholds for change detection were different; and 3) the operators who were in charge of editing and quality control were different. Although rapid landslide survey results can be achieved by means of satellite imagery, the difference in estimated area, i.e., 95 km², is high. For some applications, such as landslide susceptibility, hazard analysis, and forestry and water resource management, knowledge of the precise landslide extent and location is mandatory, for which a more accurate and reliable landslide detection scheme is essential.

Different types of remotely sensed data are available for the study of landslides including both terrestrial-based and aerial-based photography, terrestrial-based and aerial-based laser scanning, and satellite-based optical and synthetic aperture radar imagery [5]–[7]. Although airborne laser scanning (ALS) has attracted much interest for use in landslide studies in recent years [8]–[10], digital stereoscopic aerial photography is still often used to derive diagnostic features (e.g., disruptions in vegetation and the protrusion of scarps) and qualitative characteristics (e.g., number, distribution, and type) [11], [12].

Image analysis techniques are commonly used for landslide study in the fields of geoscience and remote sensing. Comparisons between pixel-based and object-based image analysis (OBIA) methods have been made in several studies [13]. Most agree that more reasonable and accurate results can be achieved with the object-oriented approach [14]. Object-oriented analysis (OOA), also called OBIA or geospatial object-based image analysis [14]–[16], partitions land-cover parcels into objects and classifies them on the basis of expert rules or a hierarchical semantic network. These are knowledge-driven methods, whereby the spectral, morphometric, and contextual diagnostic features of an object are integrated on the basis of expert knowledge [17]. This allows the user to incorporate both spectral information (tone, color) and spatial features (size, shape, texture, pattern, and relationship to its...
neighboring objects) that are similar to human visual interpretation of images [18]. This strategy is particularly useful for high-spatial-resolution images that contain homogeneous areas [19]. On the other hand, the pixel-based method [1]–[4], [20]–[22] generally creates a pepper-and-salt effect, making onsite identification difficult and the generally observed poor transferability [23].

Landslides are classified as terrigenous mass movements, a geological hazard commonly occurring around the world [24]. Generally, rainfall-induced or earthquake-induced landslides occur on sloped terrain and result in a lack of vegetation on their upper surface. A landslide generally includes a source, transport (debris or runout), and deposition areas. In recent years, OOA has been widely applied for landslide mapping [22], [25], identification [26], inventory [12], [27], recognition [22], detection [28], etc. Although the terminology used is different, their goals are mainly the delineation of the extent of the landslides. On the other hand, some studies refer to the landslide type classification [27], such as fall, topple, slide, spread, flow, etc. When OOA is used, the major issues discussed include the selection of the training sample, determination of threshold values, selection of scale parameters, and the development of a rule-based hierarchical semantic network classification strategy and method for accuracy assessment. A brief description and comparison of these approaches is discussed in the following paragraphs.

Martha et al. [29] proposed a three-step procedure for landslide classification, including identification of landslide candidates, elimination of false positives, and landslide types classification. At the false-positive elimination stage, small vegetation patches within a larger landslide are eliminated by the inclusion of one more chessboard segmentation step and the detected landslide objects are merged for further landslide type classification. For the purpose of optimal segmentation, multiscale parameters are further determined through a plateau objective function from among 50 different scales based upon brightness mean and variance [30]. Generally, three to four scale parameters are used to eliminate false positives on different scales. Meanwhile, the threshold values for landslide classification are determined automatically and objectively by K-means clustering.

Stumpf and Kerle [31] adopted the random forests method for feature selection and reduction among 96 and 62 object metrics for satellite and aerial imagery, respectively. They applied multiresolution image segmentation on 15 different scales (ranging from 10 to 100). In their method, the RF-based variable importance measures are evaluated to determine the most suitable scale parameters and the most useful object metrics. Eventually, 20% of the training data with three scales (10, 30, and 70) are suggested and evaluated during the accuracy assessment. The proposed scheme is able to balance the user and producer accuracy. However, for real cases, it may not be possible to collect up to 20% training data, and the optimal features may differ among different areas, which will limit its transferability for fast landslide surveying after disasters.

Lu et al. [32] utilized an object-oriented change detection technique for rapid landslide mapping. They performed multiscale image segmentation by iteratively comparing the spectral characteristics of image objects generated from 11 scale parameters. Although, they encountered no over or under-segmentation issues in the segmentation results, topographic variation within image objects is not considered in the procedure. The proposed scheme can determine the threshold values automatically but, when applied to another study site or utilized with different image sources, the estimate thresholds need to be adjusted accordingly.

Lahousse et al. [25] first collected reference data from aerial photographs for a study site, and then performed multiresolution image segmentation using seven scales, i.e., 10, 30, 50, 70, 100, 200, and 500, which were determined according to landslide size distribution. In addition to the original color and elevation data, eight more feature metrics were derived with their approach. During classification, threshold values were obtained interactively by comparing feature values from landslide and non-landslide regions of four subwatershed training areas. Later, these thresholds were applied to four other subwatersheds for landslide mapping through a coarse-to-fine divide-and-conquer classification rule set. Similar to Martha et al. [30], landslide detection is carried out first, and false positives are eliminated later. Finally, the modified success rate, which is the average number and extent of successful detections, is adopted and independent samples are also validated for those four subwatersheds. Although the thresholds are determined on the basis of statistical analysis, the proposed approach is specific to the study site and the landslide type within the training area. This is not efficient for fast landslide surveying after disasters because a large training sample is required, particularly when different image data sources or disaster areas are treated.

Höllbling et al. [28] adopted a semiautomated OBIA approach for landslide detection which utilized two scales (36 and 82) for multiresolution image segmentation. In this method, the scale parameters are determined by a statistical tool called the estimation of scale parameter (ESP) [33], which calculates the local variance of an object’s heterogeneity within a scene. Later, about 10 object features are used in a rule-based class modeling procedure to classify the landslides into flow-like landslides and other landslide types.

In this paper, we propose a multilevel segmentation and hierarchical semantic network scheme [34], [35] for semiautomatic landslide recognition. The idea of the root scale proposed by Vu et al. [36] is used for empirical determination by visual verification, while the other two scales are adjusted automatically using two constant values. In order to avoid over and under-segmentation, multiresolution image segmentation has been proposed in several studies. Vu et al. [36] suggested a three-scale scheme with the root scale applied to link the extracted objects with its superobjects and subobjects. They are then derived from a smaller and larger scale during segmentation. However, in this paper, the feature relationship between the superobjects and subobjects is not considered during rule-based classification; instead, we pay more attention to refine the user and producer accuracy. In the meantime, the elevation data and derived slope gradient are adopted in order to separate a large landslide with high topographic variation into several sublandslide objects. Based on statistical
estimation, a small training sample is selected manually from which to calculate the required threshold values for all landslide classification stages. Except for the original multispectral information and elevation data, only five feature derivatives are required. The proposed four-stage landslide classification scheme starts from preliminary land cover classification, landslide seed detection, landslide region growth, and false-positive elimination. The feasibility and transferability of the proposed scheme will be verified using data from different optical sensors and platforms.

II. METHODOLOGY

To meet the requirements for an accurate and reliable landslide inventory after the occurrence of a disaster, the goal of this paper is to adopt an OOA approach for semiautomatic recognition of the extent of landslides from high-spatial-resolution aerial and spaceborne optical images. First, we detect the landslide seeds, and then later focus on those seeds with region growth and false-positive elimination. This means that we do not apply the detection or classification methodology to the whole scene, in order to avoid too many omission/commission errors. The whole concept and procedure are realized through the process of eCognition [37].

A. Image Segmentation and Scale Determination

Image segmentation is the first step in OOA and is crucial to the detection extent and classification accuracy. Multiresolution image segmentation is the most popular method used, as noted in the above discussion. It is an optimization procedure that locally minimizes the average heterogeneity of image objects for a given resolution and maximizes their respective homogeneity [38]. Thus, the segmentation is controlled by the internal heterogeneity, which is defined by the color and shape of the object. The shape is composed of compactness and smoothness. The scale parameter is highly correlated to the spatial resolution of the image, but might not be directly linked to a certain object size. This makes it very difficult to find an appropriate value of scale parameter without some trial and error [33]. Although there have been some algorithms published for scale parameter estimation [30], [31], [33], it is still necessary to perform exhaustive testing and visual verification in order to find an appropriate value. Generally, a larger scale parameter will result in larger image objects. On the other hand, choosing a smaller scale will lead to over segmentation and smaller image objects [18]. Wu and Loucks [39] suggested the hierarchical patch dynamics paradigm where a complex ecological system can be broken down through a hierarchical scaling strategy. This means that the landslide can be treated as spatially nested patch hierarchies, as a larger landslide made up of smaller ones [34]. Since landslides may vary in size from 100 m\(^2\) to 90,000 m\(^2\) [25], in this paper we focus on sublandslide object detection and further perform merging to obtain complete landslides.

The trial-and-error method is adopted to find an approximate and reasonable root scale [36] parameter in advance because optical sensors with different spatial resolution are utilized in this paper. The scale parameters for the second and third step segmentation are 1.5 and 0.75 times the root scale, respectively. After exhaustive testing and visual comparisons, a rule of thumb is found to determine the root scale that may approximately describe the boundary of a sublandslide object that has similar spectral and topographic properties. The rule is that the root scale multiplied by the ground sampling distance (GSD) of the optical image is approximately a constant number of 50. This means, for a 2-m GSD image, the root scale is about 25, i.e., 50 divided by 2. Thus, for a 0.2-m GSD image the root scale is 250, i.e., 50 divided by 0.2. This heuristic formula might not be perfect for all images. In fact, a perfect scale is not required, since our strategy is to first expand or grow the landslides from landslide seeds and then eliminate small false positives later. Meanwhile, for the purpose of time reduction, we could start from the suggested root scale in the first trial and adjust it through visual verification.

B. Object Features

Compared with other landslide studies described in the literature review, we economically utilize only five object features from the DEM and color information, namely the slope gradient, vegetation index (VI), i.e., green-red vegetation index (GRVI)/normalizes difference vegetation index (NDVI), contrast, brightness, and density. Their properties and reasons for the landslide classification are explained below.

A landslide is basically a mass movement due to a sloped terrain without vegetation on top of its surface [25], [30]. The slope gradient and the VI have been widely used in past studies related to landslide and landform classification. The slope gradient describes the steepness of the terrain and is particularly important for landform classification [23]. The VI is adopted to discriminate between regions of vegetation and other nonvegetated ground objects. Depending on whether the ortho-image used has the near-infrared channel or not, the GRVI or the NDVI will be considered as the vegetation index. The equation for GRVI is similar to NDVI except that the green and red spectral bands are used. Their values range from \(-1\) to \(+1\) and they make it useful to identify green vegetation (VI \(> 0\)), soils (VI \(< 0\)), and water/snow (VI close to 0). Since the images used in this paper are not radiometrically calibrated, we consider the estimated VI a relative index rather than an absolute one, thus a proper threshold has to be determined by training samples.

Brightness is the weighted average of the image intensity for each image object [37]. The image used may be radiometrically enhanced or color-balanced during the process of image mosaicking for the purpose of improving the visual effect. Thus, the landslide area has a higher intensity than the other image objects, especially vegetation. The brightness feature is sometime more significant than the VI to filter out vegetation or bare soil.

Contrast is used only to differentiate cloud and shadow from the background. If there are no clouds and shadow within the test site, this feature can be ignored. The gray-level co-occurrence matrix contrast is used to estimate the contrast
feature. This is in contrast to homogeneity which is used to measure the amount of local variance in the object.

The density describes the distribution in space of the pixels of an image object. Based on the covariance matrix, the density is calculated by the number of pixels forming the image object divided by its approximated radius [37]. The most dense shape is a square. The more an object is shaped like a filament, the lower its density. Since roads are filament-shaped and without observed vegetation, they appear as false positives as landslide areas and it is important to eliminate the road features from the bare ground objects.

C. Classification

The second important step in OOA or OBIA is to categorize the ground objects into the corresponding classes by rule set classification or hierarchical semantic network, which is defined according to expert knowledge. For example, in the above studies, the spectral, relief, shape, and textural features are widely used to recognize landslides and to discriminate false positives. In this paper, four classification stages are proposed to perform preliminary land cover classification, to detect landslide seeds and intermediate landslides, and to eliminate landslide false positives. Among the defined classification rule sets, two kinds of classification methods are adopted: fuzzy and binary classification.

With binary classification, the members of a given set of objects are classified into two groups through a step function, i.e., using one specific threshold to discriminate between two groups of objects. For example, “vegetation: \( (VI > 0.2) \)” means any image object that has a VI exactly larger than 0.2 will be classified as vegetation.

In contrast, based on fuzzy logic theory, fuzzy classification utilizes two parameters to define the left border and right border of the membership function used. A membership value ranging from 0 to 1 is used to define the fraction of truth. This means a membership value of 0 is completely false, and any value between 0 and 1 is partially false or partially true. The expression of the membership functions “fuzzy smaller than \((<\gamma)\)” and “fuzzy larger than \((>\gamma)\)” used in this paper are specified with left-border and right-border threshold values. For example, “Class Name: \((VI < a \sim b)\) and \((Brightness > c \sim d)\)” means any object that has VI fuzzy smaller than \((a \sim b)\) and brightness fuzzy larger than \((c \sim d)\) will be categorized as Class Name. Here, the values \(a\) and \(b\) are the left border and right border of the VI feature, which correspond to the membership values of \((1 \sim 0)\). On the other hand, the values \(c\) and \(d\) are the left-border and right-border limits of the brightness feature in the fuzzy membership function corresponding to the membership values of \((0 \sim 1)\). Details about the fuzzy membership functions for clarification can be found in the eCognition manual [37].

D. Proposed Approach

A flowchart of the proposed landslide recognition scheme is shown in Fig. 1. In the beginning, the DEM and ortho-image are adopted within the multiresolution image segmentation. Later, the slope gradient is derived from the DEM for all objects, while the VI, brightness, contrast, and density are calculated from the ortho-image. After this, two more steps of multiresolution image segmentation and a hierarchical semantic network created for classification are performed for landslide recognition. Fig. 2 depicts the flowchart of the hierarchical network. Detailed descriptions of all the steps will be discussed below.

1) Multiresolution Image Segmentation Using Root Scale: During the first step of multiresolution image segmentation, segmentation is applied on the pixel level using the suggested root scale. A bottom-up pairwise region merging algorithm is used for segmentation, which starts with a single image object (i.e., one pixel) and consecutively merges neighboring pixels or image objects together [38]. The image segmentation is performed at the pixel level using red, green, blue, and DEM with equal weights. The shape and color criteria are set as 0.1 and 0.9, respectively, while the compactness and smoothness criteria are 0.9 and 0.1, respectively. These shape and color criteria settings emphasize the importance of the spectral and topographic information for extracting detailed boundaries during segmentation. These four criteria remain the same for the other two multiresolution image segmentation steps in the proposed scheme.

Note that DEM is adopted during image segmentation with equal weight to the spectral information. We observe that the DEM is very important in separating a large landslide into several sublandslide objects, particularly when a steep sublandslide near a river bed where the slope gradient is low but the spectral characteristics are similar. Meanwhile, when a landslide crosses a road which has been restored after the event, it should be separated into three parts, i.e., two steep sublandslides and one flat road area. Two types of DEMs are adopted in this paper. It should be noted that the 1-m ALS DEM can better segment the roads out of neighboring steep terrain. Experimental comparison will be given in Section IV.

2) Collection of Landslide References: To meet the requirements for accuracy assessment, landslide references are collected after the initial segmentation. The purpose of this is to avoid the effort of manual digitization. It is assumed that a proper scale parameter has been chosen so that the sublandslide boundary should be accurate enough. It is observed that large landslides appear separated into several subobjects according to the multispectral information adopted and variation in terrain elevation. The extracted image objects along with the ortho-image are further rendered on the corresponding DEM in a 3-D visualized environment and selected manually through a 3-D editing tool developed by Rau et al. [20]. Thus, we can collect the landslide references through visual interpretation intuitively and accurately. This procedure is done by a landslide expert or a well-trained operator in order to avoid bias and to provide typical landslide samples.

3) Determination of Classification Threshold Values: Since the spectral response is generally affected by the adopted sensors, weather condition, seasons, etc., the threshold values need to be adjusted case by case. A few training samples for landslide, vegetation, cloud, and shadow objects are manually selected using the eCognition software [37]. Then, for each image object, we can calculate its mean \((\mu)\) and standard
deviation ($\sigma$) of VI, slope gradient, brightness, and contrast. To minimize human intervention, the threshold values used in the following classification rule set are based on the concept of statistical estimation via the confidence intervals for a mean. This describes the range of values the true mean could fall into, based on the training samples and given confidence level. For example, 1 standard deviation has a confidence interval of 68.3%, 2 standard deviations 95.5%, and 3 standard deviations 99.7%. Confidence intervals are more informative than the simple results of hypothesis tests since they provide a range of plausible values for the unknown parameter [40]. We believe this is a suitable way to determine the classification threshold values semiautomatically, and this will be verified in the experiments. In the following three classification stages, all threshold values are determined in terms of $\mu$ and $\sigma$ during this step. For example, ($\mu - 2\sigma$) and ($\mu + 2\sigma$) mean the threshold value chosen has a left-tailed or right-tailed normal distribution to the mean with a total 95.5% confidence interval. The remaining percentages after the left tail and right tail are both 2.25%.

4) First Stage—Preliminary Land Cover Classification: We perform fuzzy classification of nonlandslide classes using the following criteria at this stage.

1) Vegetation: ($VI > \mu - 2\sigma$).
2) Low slope: (slope $< 15–20$).
3) Road: (density $< 1–1.2$) and (slope $< 20–25$).
4) Cloud: (contrast $< \mu$ to $\mu + 2\sigma$) and (brightness $> \mu - 2\sigma$ to $\mu$).
5) Shadow: (brightness $< \mu$ to $\mu + 2\sigma$) and (contrast $< \mu$ to $\mu + 2\sigma$).

Similar to other studies discussed above, the surface of the detected landslide is normally assumed to be bare, without vegetation, and so eliminated through the VI. Here we utilize
binary classification for the VI with a low threshold in order to reduce the omission error. The threshold values used in low-slope and road classes are based on heuristic testing and general concepts about these objects. For example a road will be filament-shaped and flat, which is different from the low-slope class used to separate dry river beds (debris flow or run out area) from suspected landslide areas. Generally, a cloud appears on the image having high brightness with low contrast, but in cases where the image contains no clouds, the rule for classifying cloud is not necessary. On the other hand, a shadow looks dark and certainly has low brightness and contrast. Other image objects are classified into the others class for further landslide seed classification.

5) **Second Stage—Landslide Seed Classification:** Following on the “others” class after the previous classification step, we further detect the landslide seeds using another fuzzy classification rule set with the following criteria:

1) landslide seeds: (VI < \(\mu + 2\sigma\)) \((\text{Brightness} > \mu - 2\sigma \text{ to } \mu) \& (\text{Slope} > \mu - 2\sigma \text{ to } \mu)\).

The purpose for landslide seed detection is to detect as many landslide regions as possible, then perform region growth to expand their extent later. If any landslide seed is omitted during this stage, there is no chance to recover them in the following procedures; thus this step is critical to the final detection accuracy and the threshold values should be reasonably lower. We use fuzzy classification for all three object features, including the VI. We consider that landslide seeds may: 1) contain a low degree of vegetation on top of their surface; 2) appear to have a high level of brightness; and 3) have a slope gradient larger than 2.25% for all possible landslides. Be aware that the density feature is no longer used after the first image segmentation, because most of the filament-like objects have already been rejected.

6) **Multiresolution Image Segmentation Region Growth From the Landslide Seed Objects:** In eCognition, multiresolution image segmentation can be applied to a chosen object (class) for region growth. Here, in the second step, multiresolution image segmentation is applied to the landslide seed objects by merging neighborhoods with similar characteristics. The nonlandslide class objects detected during the first stage of classification are excluded during this step of image segmentation to avoid commission errors. The object features used are VI, red, blue, and slope gradient (with weights of 1, 1, 1, and 2, respectively). Notice that, in this case, the green channel is skipped to avoid incorrect classification of vegetation as landslides. Meanwhile, the slope gradient is emphasized in order to expand its extent to tolerate higher elevation variation. In order to expand the landslide regions as much and as reasonable as possible, a larger scale parameter is chosen, i.e., 1.5 times the root scale. The segmentation results are named expanded landslide seed objects.

7) **Third Stage—Intermediate Landslide Classification:** After the second multiresolution image segmentation region growth, the landslide areas have mostly expanded in extent and their feature metrics updated as well. Thus, we now perform one more fuzzy classification for expanded landslide seed only to obtain intermediate landslide objects using the following criteria:

1) intermediate landslides: (VI < \(\mu + 2.5\sigma\));
2) (brightness > \(\mu - 2.5\sigma \text{ to } \mu\)) \((\text{Slope} > \mu - 2.5\sigma \text{ to } \mu)\) \((\text{area} > 400 \text{ m}^2)\).

The adopted object features are the same as for the second stage of classification. However, due to the increase in size of the expanded landslide seed, the thresholds are modified from 2\(\sigma\) to 2.5\(\sigma\). The threshold values are purposely raised in order to increase the producer accuracy after classification.

It should be noted that the minimum area for a landslide object is limited to 400 \(\text{ m}^2\) at this stage. This threshold is chosen according to the surveyor’s ability to recognize landslides from aerial stereophotographs and considered to be the minimum size to give the required probability and least reliability [12], [41]. Meanwhile, binary classification is applied to reject any suspicious landslide object with too low reliability. Although smaller area landslides can be found by means of the proposed scheme using smaller scale parameter, we consider reliability more important than the ability to detect the smallest landslide. On the other hand, one may argue that this filtering criterion should be applied at the end of the whole procedure after merging all connected sublandslide objects. Indeed, the results will be very close, because any small sublandslide object will be merged with its neighborhood. The remaining small landslide objects will be those isolated objects without connection to other landslides. This means that the final results due to rejection of small suspicious landslides at this stage or in the end will be similar.

8) **Multiresolution Image Segmentation at the Object Level:** The purpose of this step is inspired by Martha et al. [29], [30] to improve the precision of landslide coverage, in particular to remove small vegetation objects embraced by a larger landslide. Instead of the chessboard segmentation method used by Martha et al. [19], [20], we propose again using multiresolution image segmentation at the object level (i.e., at the intermediate landslide object level) by utilizing a smaller scale parameter, i.e., 0.75 times the root scale. The object features used are red, green, blue, and DEM (with equal weights). Be aware that the green channel is reconsidered during segmentation in order to detect the smaller vegetation patches.

9) **Final Stage—Precise Landslide Classification:** In the end, we perform final landslide recognition through binary classification using the following criteria:
Fig. 3. Geographic locations, images used, and pseudo-color DEMs of the three study sites.

1) final landslide: \((VI < \mu + 2.5\sigma)\) and \((\text{Brightness} > \mu - 2.5\sigma)\) and \((\text{Slope} > \mu - 2.5\sigma)\).

The same object features and confidence level are used as for the third stage of classification; however, binary classification is used in order to refine the user accuracy. Small vegetation objects can thus be removed to improve the classification accuracy.

III. MATERIALS

A. Study Areas

The study areas are located in the middle and southern mountainous regions of the island of Taiwan. The geographic location, images used, and corresponding pseudo-color DEMs are illustrated in Fig. 3. The major landcover types within these study areas include forests, rivers, bare soil (including landslides, barren rock, river beds, etc.), farm land, roads, and a few man-made buildings. All such areas were affected by Typhoon Morakot which triggered hundreds of landslides.

B. Data Sources

The major geospatial information used in this paper comprises ortho-images and DEMs, which describe only the terrain surface, without trees, buildings, etc. Their characteristics are summarized in Table I. The selected optical sensors are those typically and widely used for landcover classification, monitoring, and topographic mapping. They include FORMOSAT-2 satellite images and images from an aerial digital mapping camera (ZI/DMC), and a Cannon EOS 450D DSLR camera mounted on a fixed-wing unmanned aerial vehicle (UAV). The FORMOSAT-2 image is pan-sharpened and fused from an 8-m GSD multispectral image containing the red, green, blue, and near-IR spectral bands and a 2-m GSD panchromatic image [26]. The 5-m DEM is created by stereo-image matching with manual editing, whereas the 1-m ALS DEM is produced by ALS after human interpretation and manual editing. It should be noted that the DEM for case #3 was acquired before Typhoon Morakot, whereas the images were collected after the event; thus inconsistencies in the topography do exist. Their effect on landslide recognition will be evaluated in this paper.

IV. RESULTS AND DISCUSSION

Some statistics of landslide recognition result are summarized in Table II. The term training area ratio denotes the percentage of selected training area compared to all landslide reference areas. The slope gradient for all detected landslides ranges from 18 to 67 degrees. Figs. 4–7 demonstrate the landslide recognition results for cases 1–4, respectively. Related issues will be discussed in the paragraphs below.
TABLE I
SUMMARY OF TEST DATASET

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<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
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<td>II</td>
<td>III</td>
<td>III</td>
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<td>TengZhi</td>
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<td>63.56</td>
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<td>FORMOSAT-2</td>
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<td>UAV</td>
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<td>Post-event</td>
<td>Post-event</td>
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</tr>
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<td>158</td>
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<td><strong>GSD (m)</strong></td>
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<td>0–61</td>
<td>0–73</td>
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</table>

In this paper, the reference data are created from visual inspection and selected manually from the first segmentation results, including shadowed landslides. Although cloud cover will cause deterioration in the image quality and affect the gray level distribution, the landslides beneath clouds are considered in the reference data if they are visible. On the other hand, rocky outcrops that appear similar to the landslides are not selected as reference data.

1) Accuracy Assessment: Accuracy assessments are performed using the extent of the landslides through an area-based confusion matrix [42] that contains only two classes, i.e., landslide and nonlandslide. The success rate is not evaluated based on the number of detected landslides [29] or modified success rate [25], because a landslide could be divided into several sublandslide objects, or several landslides could be connected together. For example, the deep-seated landslide that occurred in Shiaolin village, as shown in Fig. 4(b) is fragmented into several pieces.

![Fig. 4. (a) Landslide recognition results for case #1 (Shiaolin) overlapping the training samples. (b) This enlarged picture depicts the huge landslide deposition area with its flat terrain that causes large omission error. (c) This inset shows the true positive, false positive, and false negative for the same area of (b) to indicate the misclassification area.](image)

Based on true positive (TP), true negative (TN), false positive (FP), and false negative (FN), seven kinds of accuracy indices are evaluated, namely user accuracy (UA) [42],...
are stated in the following equations (DP) [44], and branching factor (BF) [44]. Their definitions are:

\[ \text{UA} = \frac{TP}{TP + FP} = 1 - \text{commission error} \quad (1) \]
\[ \text{PA} = \frac{TP}{TP + FN} = 1 - \text{omission error} \quad (2) \]
\[ \text{BF} = \frac{FP}{TP} = \frac{1 - \text{UA}}{\text{UA}} = \frac{\text{commission error}}{\text{noncommission error}} \quad (3) \]
\[ \text{MF} = \frac{FN}{TP} = \frac{1 - \text{PA}}{\text{PA}} = \frac{\text{omission error}}{\text{nonomission error}} \quad (4) \]
\[ \text{QP} = \frac{TP + FP + FN}{A \times C + B \times D} \quad \text{where } A = TP + FP, \ B = FN + TN, \ C = TP + FN, \ D = FP + TN \]
\[ \text{PC} = \frac{E}{A + C + B + D} \quad \text{where } E \text{ is total area} \quad (6) \]
\[ \text{PO} = \frac{E}{TP + TN} \]
\[ \text{Kappa} = \frac{PO - PC}{1 - PC} \quad (8) \]

User accuracy presents the rate of noncommission error, while the producer accuracy (same as detection percentage) illustrates the rate of nonomission error. A higher user accuracy or producer accuracy indicates a lower rate of commission or omission errors. Those two indices are effective when the classification results contain more than two classes. Martha et al. [27] thus suggested that the branching factor, miss factor, and quality percentage are more effective when the goal is to detect only one class. As indicated in (3), the branching factor indicates the ratio of incorrectly categorized landslide pixels (i.e., commission error) to the noncommission error. On the other hand, the miss factor illustrates the ratio of missed landslide pixels (i.e., omission error) to the nonomission error. This means that a lower branching factor and miss factor represent a better algorithm for landslide detection. Since the denominator of the quality percentage is the summation of all correctly and incorrectly detected landslide pixels, this index describes the likelihood of landslide detection by the proposed approach. In the end, in order to evaluate the consistency between the producer and user accuracy, the kappa index is calculated form the observed agreement (PO) and chance agreement (PC) [43]. Table II illustrates the above-mentioned accuracy indices and their change for all three stages of classification results.

We notice that the kappa index has increased from #1 to #3. The producer accuracy (detection percentage) has improved from #1 to #2 and the user accuracy is mostly improved from #2 to #3. These effects demonstrate that the proposed multilevel segmentation and hierarchical semantic network classification scheme can optimize the landslide recognition accuracy and balance the produce and user accuracy. The miss factors and branching factors are all less than 0.44 and the quality percentages are all greater than 58%. In the case of Lu San, it is even up to 81.7%. These statistics demonstrate that the feasibility and potential of this method for regular landslide surveying are high, even using images acquired by different optical sensors.

The reason a low kappa index was obtained for case #1 is that the major landslide that occurred at Shiaolin village is a deep-seated landslide with a volume of $25 \times 10^6$ m³ [45] being triggered by the typhoon. Most of this mass accumulated on top of the village to a depth of 40–60 m, causing the low slope gradient. A deposition area with a low slope gradient is not detectable through the proposed scheme, which caused the larger omission error, as shown at Fig. 4(b). Due to its large area, the resulting producer accuracy and kappa index were both reduced.

2) Elimination of False Positives: The high intensity and brightness values of clouds allow them to be easily rejected.
but the density around their edges gets thinner, so they cannot be eliminated totally. One may refer to Fig. 4(a) for an example.

Built-up areas generally have flat terrain and can thus be rejected from being landslide seeds. Roads have similar spectral features to the bare ground and landslide but have a filament shape. They can be eliminated by the density feature metric during the first stage of preliminary land cover classification.

Farm land lying fallow during its restoration period also has no vegetation, so when located on sloping terrain, it has similar spectral and topographic characteristics to landslide areas, making it difficult to eliminate. Since the adopted VI is a relative value and dependent on the input image quality, it cannot perfectly identify vegetation areas. In the experiment, it is found that, when using the DSLR digital images, the brightness feature is sometimes more effective at distinguishing landslide from farm land and forested areas. Still, farm land cannot be totally identified and removed in the proposed approach. As for terraces lying fallow without vegetation, their shape, slope gradient, and spectral characters are all similar to those of roads, and thus can be eliminated in the preliminary land cover classification. Fig. 5(b) illustrates several examples of the above mentioned findings.

Rocky outcrops can create false positives as well. However, due to high relief variation and different materials, most of them appear darker in color compared to landslides. Generally, the rocky outcrops can be eliminated by using the brightness feature. Two typical examples are indicated in Fig. 5(c) by the yellow polygons.

Debris flow or run-out areas are mostly in gently sloped terrain and so different from steep landslides. In the designed classification rule set, they are mostly eliminated based on the criteria of slope gradient. That is a low-slope class is designed to constrain the possibility of being landslide seeds. However, during the region growth stage, some of them could still be detected depending on the selection of training samples for threshold determination. Fig. 7(b) illustrates an example of some detected debris flows, but some are omitted, as shown by the green circles. A well-trained operator may be required in a routine operation.

3) Inconsistency Between Ortho-Image and DEM: In case #3, a lower kappa index of 0.70 is obtained due to

<table>
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<th>3</th>
<th>4</th>
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<td>Study sitename</td>
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<td>2.7</td>
<td>2.5</td>
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<tr>
<td>Detected landslide (km²)</td>
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<td>1.08</td>
<td>1.09</td>
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<td>430</td>
<td>284</td>
<td>263</td>
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<tr>
<td>Landslide reference area (km²)</td>
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<td>1.88</td>
<td>1.19</td>
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<td>23.2–57.0</td>
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<td>Root scale</td>
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<td>150</td>
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</table>

| Detection percentage/producer accuracy (%) |
| # 1 | 64.8 | 81.1 | 75.2 | 70.1 |
| # 2 | 72.8 | 92.7 | 79.3 | 77.2 |
| # 3 | 72.5 | 90.3 | 78.2 | 75.6 |

| Miss factor (MF) |
| # 1 | 0.42 | 0.23 | 0.33 | 0.43 |
| # 2 | 0.37 | 0.08 | 0.26 | 0.30 |
| # 3 | 0.38 | 0.11 | 0.28 | 0.32 |

| User accuracy (%) |
| # 1 | 82.3 | 94.2 | 69.2 | 83.3 |
| # 2 | 80.3 | 82.6 | 68.2 | 86.8 |
| # 3 | 80.3 | 89.6 | 69.3 | 88.3 |

| Branching factor (BF) |
| # 1 | 0.22 | 0.19 | 0.45 | 0.20 |
| # 2 | 0.25 | 0.21 | 0.46 | 0.15 |
| # 3 | 0.25 | 0.12 | 0.44 | 0.13 |

| Quality percentage (%) |
| # 1 | 61.0 | 70.3 | 56.3 | 61.4 |
| # 2 | 61.7 | 77.6 | 57.8 | 69.1 |
| # 3 | 61.6 | 81.7 | 58.0 | 68.7 |

| Kappa index |
| # 1 | 0.70 | 0.82 | 0.69 | 0.74 |
| # 2 | 0.74 | 0.86 | 0.70 | 0.80 |
| # 3 | 0.74 | 0.89 | 0.70 | 0.80 |

Fig. 8. Histogram distribution of brightness, GRVI, and slope features collected from training samples for cases #3 and #4.
Fig. 9. (a) Using only spectral information for image segmentation, the extracted road segments are not as expected. (b) Adopting both DEM and spectral information for image segmentation, the detected road segments are more accurate. (c) Preliminary land cover classification results show the omission of one road segment within the violet polygon. (d) Landslide seed region growth results in some commission errors. (e) Intermediate landslide classification results depict the removal of major commission errors. (f) Final landslide classification results. Several small vegetation patches have been eliminated and the omitted road misclassified as landslide due to its high slope gradient. The landslides within the red polygons have been omitted due to shadow effects and a mixture of bare soil and rocky outcrops.

inconsistency of data acquisition dates between the ortho-image and the DEM. That is, the DEM was acquired before the typhoon event whereas the ortho-image was from after the event. This resulted in greater commission error, and thus the user accuracy dropped to 69.3%, particularly along the river bed where the terrain was steep before the typhoon but filled with mass as flat terrain after typhoon. Fig. 6(b) demonstrates the commission errors introduced by this issue. It can be seen that several river beds have been misclassified as landslides. The landslide detection accuracy improved when this inconsistency was corrected, as shown in Fig. 7(c) and (d). Meanwhile, in Table II the kappa index for case #4 is 0.80 and the user accuracy is 88.3%, which are significant improvements over a kappa index of 0.7 and user accuracy of 69.3% from case #3.

4) Training Samples: In Table II, one may observe that the percentage of training samples for all cases ranges between 2% and 7% of the landslide reference area. Although the estimated threshold values are applied to the same study site containing the training samples, its ratio to the whole landslide area is very small. This means their influence to the accuracy assessment will be less than 2%–7%, and thus this can still be treated as an independent checking procedure. From the operational point of view, the suggested training sample selection procedure is more intuitive and efficient, particularly after a super event, since no large area of landslide ground truth or references are required. However, too few or inappropriate training samples will introduce inaccurate threshold determination and cause omission error, such as the debris flow regions depicted in Fig. 7(b) and a lower producer accuracy of 75.6% as observed in Table II. Further studies are necessary in order to address this issue.

Fig. 8 illustrates three histograms for selected training samples obtained from cases #3 and #4 carried out in order to justify the normal distribution assumption for threshold values determination. The training samples include shadowed areas, thus there are two peaks in the histogram for the brightness index. An examination of this figure shows that their distributions are similar to the normal distribution. This indicates that the suggested scheme for threshold values determination is suitable.

Fig. 10. LV-ROC graph is generated by the ESP tool using the same image as in Fig. 9 but the red band only. The results show many sudden peaks and plunges which make it difficult for the user to choose suitable scales for image segmentation.
5) Transferability: As stated by Stumpf and Kerle [18], there are a great variety of types of landslides, as well as environmental conditions, and available imagery, which will reduce the transferability of the developed methods and workflows. In this paper, we try to evaluate the performance of the proposed scheme using different sensors with different spatial resolution images, different illumination conditions, but similar landscapes and landslide types. Except for case #1 where a huge deep-seated landslide occurred and for case #3 where the ortho-image used was acquired after the event and the DEM before, the producer and user accuracies are all above 75.6% (most of them are greater than 85%), while the kappa indices are all greater than 0.80, demonstrating that the transferability is high.

6) Effect of DEM on Image Segmentation: Previous discussion regarding the use of DEM in image segmentation is an important factor to separate a large landslide into several sub-objects. Fig. 9(a) and (b) illustrate an example demonstrating the effect of whether a DEM is used or not in multiresolution image segmentation. In these two figures, the yellow polygons are meant to be roads and were manually selected to verify the segmentation results. The results prove that using DEM in segmentation can allow more accurate road boundary detection than when not using it.

7) Intermediate Landslide Detection Results: Fig. 9 also depicts the intermediate landslide detection results for different steps of segmentation and classification. Fig. 9(c) shows the preliminary land cover classification results, in which cyan denotes the detected landslide seeds. Note that the upper-right road segment within the violet polygon is wider and thus not classified as road. Fig. 9(d) shows the expanded landslide seeds and Fig. 9(e) the intermediate landslides where several expand landslide seeds have been rejected. Fig. 9(f) demonstrates the final landslide recognition results where the upper-right road segment has been misclassified as landslide due to the higher slope gradient. In the meantime, the landslides within the red polygons have been omitted, due to shadow effect and a mixture of bare soil and rocky outcrops.

8) Determination of Scale Parameters: ESP [33] is an open source for public access to estimate suitable scale parameters in multiresolution image segmentation. However, it is designed for single-band information which is different from our case that utilizes multispectral bands together with the DEM. For comparison, we utilize the red band of the UAV DSLR image by changing the scales from 20 to 220 in increments of 2. The LV-ROC graph generated by the ESP is shown in Fig. 10. One may see that there are several sudden peaks and plunges, such as 56, 66, 80, 88, 112, 140, 154, and so on, which are the suggested suitable scales from ESP. However, these scales vary a lot and are difficult to choose unless further visual verification is performed, one by one. In this paper, based on visual comparison, we finally select the root scale of 150. The other two scales are determined to be 0.75 and 1.5 times the root scale, i.e., 112 and 225. Fig. 9(c), (d), and (f) also overlap the segmentation results by using the suggested three scales (150, 225, and 112). One may realize that our method for scale determination is particularly appropriate for landslide detection.

V. Conclusion

Based on the demand of operational landslide inventory, the goal of this paper was to develop a reliable and accurate OOA scheme for landslide recognition using existing software and approaches. The input data comprised only multispectral optical ortho-images and the DEM. A semiautomatic procedure was suggested, which requires only a few training samples (less than 7% of the extent of the whole landslide) for threshold determination. The others are fully automated.

Additionally, only five object features were derived for classification, which makes this approach more feasible and transferable. In cases where no huge deep-seated landslide occurs and there is no inconsistency in data acquisition date between the image used and the DEM, the best producer and user accuracies can reach up to 90.3% and 89.6%, respectively, with the best kappa index being 0.89. Meanwhile, the miss factor and branching factor are less than 0.12 with a quality percentage of 81.7%.

The advantages of the proposed scheme can be summarized as follows.

1) The multiscale parameters are defined based on a root scale for each sensor. The root scale is visually verified according to the required target (in this paper, the landslide subobjects). The user needs only a little adjustment to apply the estimated parameters using the same optical sensor to different study sites.

2) The required training samples are about 2%–7% of all landslides, and all threshold values can be determined semiautomatically through statistical estimation using the confidence intervals for a mean. No manual adjustment is required, and the results are promising as long as the training samples cover the typical topographic and spectral characteristics of landslides within the study site.

3) As mentioned in Stumpf and Kerle [31], the selection of significant features is a challenging and time-consuming task. Only five object features are derived and utilized in the proposed rule set landslide classification procedure.

4) The proposed landslide recognition approach is applied to three typical optical images and three study sites with similar landscapes. Its transferability and applicability is high because of using high spatial resolution images for landslide recognition.

5) The experimental results demonstrate that the proposed multilevel segmentation and hierarchical semantic network classification scheme can balance the commission and omission errors, while the classification accuracies are all improved. In the meantime, a low miss factor and branching factor together with high quality percentage can also be achieved. This proves that this method is feasible for real applications for precise landslide mapping purposes.

Several issues remain to be conquered in the future, such as the following limitations and drawbacks of the proposed scheme.

1) The proposed scheme cannot be applied for landslide type classification or to those landslides with vegetation
on their surface, due to the lack of shape and morphometric object features, including curvature. As suggested by Martha et al. [27], [29], [30], characterizing landslide movement and the slope failure mechanism seems a promising approach.

2) It is also difficult to identify landslides in shadow [28] and cloud areas, including those around its edge, using the proposed scheme. Generally, the texture of ground objects under the shadow is still recognizable, but has very low intensity and contrast, and their spectral characters are totally different to those areas without shadow. However, the method suggested by Martha et al. [27], [29], [30], which uses the hillshade raster to correct the image gray values in order to improve landslide detection ability, can also be considered in real applications.

3) The debris and run-out areas are different from the sources of a landslide but are treated as hazard zones. In this paper, they might be rejected according to the estimated slope gradient threshold value from the training samples. Experience is needed for the selection of the training sample in order to include all kinds of typical landslides within the study site and obey the normal distribution rule; otherwise omission errors will be increased. Due to the long run-out area of the debris, the shape features suggested in Martha et al. [27], [29], [30] should be considered. However, as shown in Fig. 6, the debris flows vary in size and shape, and further investigation is needed in order to reduce omission error induced by debris flows.

4) Only five object features are suggested in this paper, which may not be the best choice. Thus a further comparison by using feature space optimization or active learning approach [31] to find an optimal set of features could be considered in future work.

ACKNOWLEDGMENT

The authors are grateful to the Disaster Prevention Research Center (DPRC) of National Cheng Kung University (NCKU), Aerial Surveying Office, Bureau of Forestry, Taiwan, and GeoSat Inc., for providing the FORMOSAT-2, aerial, and UAV DSLR images, respectively.

REFERENCES


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