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Research paper

Landslide detection based on contour-based deep learning framework in case of national scale of Nepal in 2015

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ABSTRACT

The deadly threat that landslide has brought about is drawing more and more attention to analyze the mechanisms of landslides and the relationship between landslides and climate change. Due to the limited record of historical landslides in developing countries, relevant research is mostly conducted in developed countries. Owing to the publicly available global long time-series Landsat images, such unbalance can be avoided by proposing a practical landslide detection model, especially in terms of national scale. This paper takes the advantage of google earth engine platform to synthesize the annual Landsat images covering the national scale of Nepal into one image and builds an end-to-end contour-based landslide detection deep learning framework. The framework consists of two parts, one is potential landslide detection using vegetation index and degradation of DEM, the other is exact landslide detection using semantic segmentation deep learning model based on the contour regions extracted from the detected potential landslide. The proposed method is applied to detect landslides of Nepal in the year of 2015 and achieves a satisfactory performance with 65% recall and 55.35% precision. The performance is 44% higher accurate than similarly published works, validating its promising applicability in practical landslide detection for national cases.

1. Introduction

Landslides, known as one of the top natural hazards in triggering human deaths globally (Tien Bui et al., 2018), are driving calls to better understand mechanisms of geomorphological hazards and exploring their risk relationships with other hazard chains, such as earthquake (Keefer, 2002) and rainstorm (Gariano et al., 2015). Apart from that, there is research claiming that climate change is influencing the frequency of landslides with its variations of precipitation and temperature (Crozier, 2010; Dhakal and Sidle, 2004; Sidle and Ochiai, 2006). Landslides can occur in the global continents (Gariano and Guzzetti, 2016), but the research in exploring the mechanisms of landslides and the role that landslides play in the hazard chains is mostly conducted in developed countries that have detailed records of historical landslides with location, magnitude and type (Gariano and Guzzetti, 2016; Guzzetti et al., 1999). The lack of landslide records in Asia, South America and Africa triggers the imbalanced quantity of research, and forms a gap in the geographical understanding about landslides compared with developed countries. Such gap hinders further analysis of landslides in large scale. There is great need to propose a practical method to detect massive landslides from large-scale area for multiple years, not only to fill up the gaps, but also to monitor and understand landslides deeply.

Landslide records are mostly collected by field investigation (Crovelli, 2000). It is believed to be the most reliable method, but highly limited by the locations and geological scale of the study area. The advent of remote sensed technology makes it possible to visualize earth continuously at different spatial resolutions. Visual interpretation from the remote sensed images is dominating in preparing landslide inventory maps (Xu, 2015), but it is time-consuming and manpower wasting, especially for the large-scale area. By incorporating advanced image processing technologies in computer vision and machine learning, the methods in landslide mapping can generally be grouped into two

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groups, one is object-based, and the other is pixel-based.

Object-based landslide mapping groups pixels with similar spectral or textural features into one object and sets thresholds to classify each object to be landslide or not. It assigns semantic meaning for each object but requires many user-determined thresholds. Pixel-based landslide mapping examines each pixel in the image and determines whether it is landslide or not. It mostly adopts change detection strategy by quantifying vegetation change over time through surface reflectance (Hervas et al., 2003) and band ratio (Cheng et al., 2004). Some researchers also apply image processing techniques, such as image enhancement (Nichol and Wong, 2005) and image correlation (Lucieer et al., 2014). However, change detection requires much image pre-procession of radiation correction and geometric correction. There is numerous research about landslide mapping based on post-event image, which aims to build automatic detection models using machine learning framework, such as support vector machine (SVM) (Cheng et al., 2013) and maximum likelihood (Parker et al., 2011). The published studies are mostly conducted in local area using high spatial resolution images, which cover limited landslide events (a few hundred) with relative pure background objects, such as vegetation only (Li et al., 2016). Moreover, the study cases are simpler than practical applications, especially for large scale implementation (Cheng et al., 2013; Li et al., 2016). There is another thing to point out that the published models require a balanced distribution of training data for each category (Cheng et al., 2013; Parker et al., 2011). That is very difficult to meet in large-scale study area with complicated background objects, such as national scale, because landslide is a kind of natural hazard, the quantity of landslide pixels is scarce compared with other background objects, such as vegetation, urban area and water. The extremely imbalanced data distribution hinders the novelty of pixel-based model for large-scale study.

Contour-based method provides a practical way to deal with the imbalanced data distribution issue (Chen et al., 2018). Through image enhancement and slope calculation, most background objects are removed, and multiple regions with potential landslides (mixed with bare soil & rocks) are obtained. Based on the regions, connective-contours are generated and the corresponding spectral and textural features are calculated to build the exact landslide detection model. However, the features used for building landslide detection model are all manually designed, which heavily rely on the research experience and consume much work in feature engineering. That can be avoided with the help of deep learning framework (LeCun et al., 2015) by learning features automatically through convolution operations.

Deep learning has gained the state-of-the-art performances in computer vision, such as semantic segmentation (Noh et al., 2015), object detection (Ren et al., 2015) and image classification (Chan et al., 2015). Semantic segmentation is effective to segment multiple objects simultaneously by assigning each pixel in the image a label and has achieved remarkable performance with the continuously developed architecture, such as fully connected network (FCN) and the pyramid scene parsing network (PSPNet).

In this paper, we are aiming to propose a practical end-to-end framework to detect landslides of Nepal and evaluate the model in year of 2015. The framework is a contour-based semantic segmentation deep learning model, modified from PSPNet, as done in (Yu et al., 2018). PSPNet is widely used in applications where samples are mostly balanced distributed, but landslides in our case are extremely unbalanced distributed, because landslide is a natural hazard, and the number of landslide samples is severely lower than that of other ground objects. Therefore, we propose a contour-based version of PSPNet to deal with the sample imbalanced issue. It mainly comprises of two parts, potential landslide detection and contour-based deep learning landslide detection model built up. The contour-based detection model is also different from the published works (Chen et al., 2018) in that our model is an end-to-end deep learning workflow, which overcomes the shortage of feature engineering as done in (Chen et al., 2018).

The introductions of our study area and data preparation are in Section 2, and the detailed description of landslide detection model is demonstrated in Section 3. Section 4 shows the detection results and discussions. Final conclusions are drawn in Section 5. The main contributions of our manuscript are as follows:

1) Resist the imbalanced distribution of landslides using contour-based method
2) Avoid feature engineering by applying deep learning framework
3) Enlarge the practical applicability by evaluation in Nepal.

2. Study area and data preparation

2.1. Study area

With the help of ArcMap 10.1 (Kneissl et al., 2011), our study area is demonstrated in Fig. 1. It covers Nepal and mainly locates in Himalayas towards the collision boundary between Indian Plate and the Eurasian Plate (Amos, 2015). Such collision makes Nepal vulnerable to earthquakes. Frequent earthquakes, deforestation and heavy monsoon rains are raising more and more landslides. The ground objects inNepal are very complicated, comprising vegetation, rocks, bare soil, urban area and river. The complexity and national-scale area can be used to evaluate the robustness of the proposed landslide detection model reliably. Since Gorkha earthquake in year of 2015 has raised thousands of landslides and lead to tremendous fortune loss (Chen et al., 2018), we take national scale of Nepal in 2015 as study area to assess the efficiency of our model.

2.2. Data preparation

In order to conduct landslide detection from national scale, we generated the annual Landsat image to explore the detailed spectral and textural characteristics of various ground objects and collected the corresponding DEM to supplement detection by providing the spatial patterns of our study area.

2.2.1. Annual Landsat image of study area

Landsat images (NASA, 2018) are playing a dominant role in supporting research in natural resources management (MacAlister and Mahaxay, 2009), such as forest cover change (Hansen et al., 2013) and land cover change (Hansen and Loveland, 2012) at continental or global scale by providing the longest record of earth from 1972 to present. The Landsat program has launched eight satellites, and seven satellites succeeded to acquire images. The program collects mid-resolution global optical images with multiple spectral bands at a temporal resolution of 16 days, and the amount of total images covering the national scale of Nepal throughout a year reaches 274 scenes. To construct a continuous annual landslide detection model, we applied google earth engine (Gorelick et al., 2017) platform to synthesize all the annual scenes covering Nepal into one image. Google earth engine is a planetary-scale geospatial processing platform, comprising publicly available remote sensed datasets, powerful computing resources, APIs in JavaScript and Python for setting commands to the Earth Engine servers. It provides an online Integrated Development Environment for editing code and visualizing the complicated spatial analysis.

Google earth engine is integrated with multiple image pre-processing functions, including image mosaic, image composition and cloud removement. The cloud mask is built by Fmask (Zhu et al., 2015), which works robustly well. In terms of image composition of the same location throughout the annual images, we calculated NDVI (normalized difference vegetation index) and ranked the NDVI value for each pixel. The intensity of each pixel is determined to be the value of pixel whose NDVI ranks the top 80% of all the values in the pixel location throughout the year. We selected pixel with top 80% NDVI to resist band noise and maintain vegetation information, since landslides mostly occur in the background of vegetations. Such strategy can also overcome the

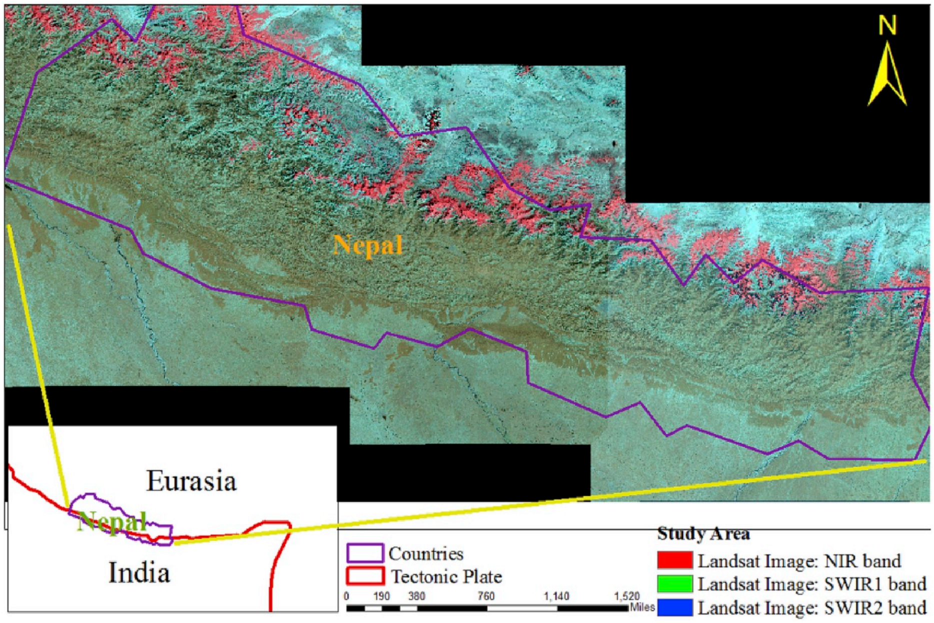

Fig. 1. Demonstration of study area.

seasonability of vegetation, since it is a synthesis of the annual pixels.

There is another point that the spectral band sequence in Landsat 8 is different from that in Landsat1-5 and Landsat 7. As shown in Table 1, Band 2–7 of Landsat 8 correspond to Band 1–5 and 7 of Landsat 1–5 and 7 respectively. Therefore, the synthesized annual Landsat image is composited using the corresponding bands among them. According to the image composition rule, the annual Landsat image covering Nepal in year of 2015 were produced.

2.2.2. *Elevation gradient of study area*

Elevation gradient is essential in supplementing landslide detection by providing landscape pattern, because most landslides are likely to occur in slope areas. We calculated the elevation gradient from 1 arc-second global DEM (Digital elevation model) product of SRTM (shuttle radar topography mission) using the Sobel filter (Aqrawi and Boe, 2011). It is designed to achieve the first-order gradient of an image in both horizontal and vertical directions. The calculated elevation gradient of our study area was resized to the same size as the synthesized annual Landsat product by bilinear interpretation (Arif and Akbar, 2005).

3. Landslide detection framework

A general demonstration of our landslide detection framework is shown in Fig. 2. It mainly consists of two components, one is to detect potential landslide and the other is to detect landslides based on deep learning framework. Detailed descriptions of each component are given below.

Table 1
Corresponding band between Landsat 8 and Landsat 1–5,7 in image composition.

Landsat 1–5,7	Landsat 8
Band 1	Band 2
Band 2	Band 3
Band 3	Band 4
Band 4	Band 5
Band 5	Band 6
Band 7	Band 7

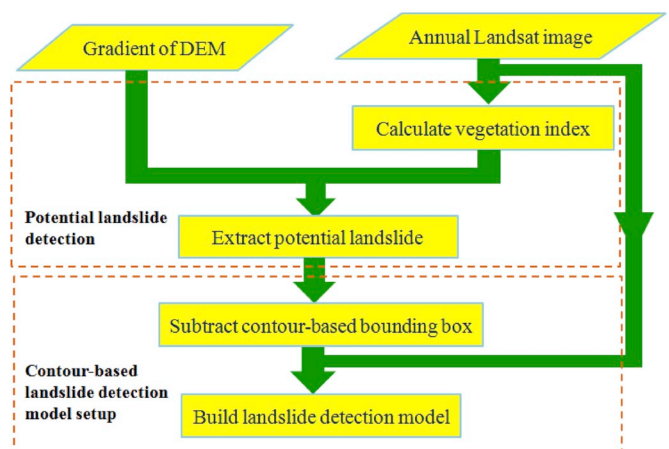

Fig. 2. Landslide detection framework.

3.1. *Potential landslide detection*

Potential landslide detection is specifically significant in building landslide detection model, because landslide is a sort of nature hazard that the number of its sample pixels are quite limited and recognized as scarce compared with other background objects, such as vegetation and bare soil. The landslides we aim to detect in this study mainly occur in mountainous area with a size of larger than 450 m^2 (5 pixels in the Landsat image with 30 m resolution) in the background of vegetation. They are commonly mixed with bare soil or rocks. It is difficult to detect exact landslides directly. Threfore, detecting potential landslide (landslide pixels mixed with bare soil & rocks) is an efficient method to reduce the amount of background object samples (including roads, rivers, constructions, vegetation and so on) to a large extent and balance the sample distributions from different object categories.

Potential landslide is detected by calculating inverse of EVI (enhanced vegetation index) to enhance the spectral characteristics of non-vegetation ground objects, including landslides. The calculation of inverse of EVI is conducted according to equation (2) and the definition of EVI is proposed in (Zheng et al., 2016).

$$EVI = 2.5 \times \frac{B5 - B4}{B5 + 2.4 \times B4 + 1} \tag{1}$$

$$\overline{EVI_n} = \frac{EVI_{\max} - EVI}{EVI_{\max} - EVI_{\min}} \tag{2}$$

Before rescaling the intensity values of image $\overline{EVI_n}$ to 0–255, we remove the pixels with intensity value of smaller than 80 in DEM gradient image, which are recognized as flat areas, by assigning their intensity as 0 in the image $\overline{EVI_n}$. After rescaling $\overline{EVI_n}$, the pixels whose intensity values are greater than 180 are extracted as potential landslides. The threshold 180 is determined by trial and error. It can easily distinguish between background vegetation and bare soil, rocks and landslides in the reversed vegetation index image. However, bare soil, rocks and landslides are mixed together in the detected potential landslides due to similar spectral characteristics in $\overline{EVI_n}$ (as shown in Fig. 3). A build stronger model is required to detect landslides exactly.

3.2. Contour-based landslide detection deep learning model set-up

Based on the potential landslide detection image, we calculated connective contour according to the algorithm proposed in (Korfiatis et al., 2017). It starts from a foreground pixel and keeps tracking the foreground pixels until the contour is fully closed. Based on each connective contour, we calculated a bounding box and extended the bounding box to cover more landslides and background objects relying on its area size. If the area of a bounding box is smaller than 300 × 300, the bounding box is extended to 300 × 300, as demonstrated in the yellow dotted box in Fig. 4. In this way, each small bounding box is extended to cover more ground objects, which are highly possible to be landslides. Since the quantity of landslide samples is limited compared with other background objects, the bounding box extension can enlarge the variability of training dataset. Such strategy is different from the one proposed in (Yu et al., 2018), whose bounding box region subtracted was directly used for classification model set-up, without any spatial extension. The classification model in (Yu et al., 2018) is aimed to classify each connected contour in the bounding box to comprise landslide or not, while the proposed model in our paper is trying to segment landslides from the subtracted bounding box region at pixel-level. The proposed model in this paper is more accurate at pixel-level, because the connective contour classified in (Yu et al., 2018) may comprise many other false alarm pixels, including bare soil and rocks, which are mixed with landslide pixels in the process of contour generation.

On top of the subtracted bounding box region in our proposed method, the corresponding region from prepared annual 6-channel Landsat image is extracted, which is used as input image to build the semantic segmentation landslide detection model. The general framework of the deep learning model is shown in Fig. 5. It mainly stems from the structure proposed in (Zhao et al., 2017) and consists of two components, one is ResNet-101, the other is pyramid pooling module. ResNet-101 (He et al., 2016) is a typical convolutional neural network with residual structure of 101 layers. It is aimed to extract features and encodes input image into feature map (shown in Fig. 4). By importing shortcut connection to skip one or more neural network layers, the residual structure is introduced to solve accuracy saturation issue, which is raised by continuously increasing network layers but the accuracy degrades. Importing shortcut connection enables the optimization of weights of network layers to approximate shortcut connection, thus simplifying model training. We applied RestNet-101-v2 (Szegedy et al., 2017) in our proposed framework, because it is cheaper in computation (Szegedy et al., 2017), easy to implement and achieves promising recognition accuracy in the ImageNet dataset (Deng et al., 2009).

Pyramid pooling module in the landslide detection framework is applied to extract local features at multiple scales and concatenate with the input feature map \ for final segmentation result calculation. The pyramid pooling module consists of four components, pyramid pooling in multiple scales, convolution to reduce the channel of feature maps, upsample the convoluted features to be the same size with input feature map and concatenate the multi-scale features with the input feature map. The pyramid pooling kernel sizes are *M_size*, *M_size*/2, *M_size*/3 and *M_size*/6, wherein *M_size* indicates the size of input feature map. The pooling strategy is average pooling, following the works in (Zhao et al., 2017). Moreover, two auxiliary losses are added to the 3rd and 29th residual network blocks to supplement and accelerate the whole model to optimize.

In terms of training the whole landslide detection framework, the widely used ReLU (rectified linear unit) (Nair and Hinton, 2010) active function is applied to our case and poly learning strategy (Chen et al., 2016) is adopted to learn the weights and bias in the network layers. The learning rate is set according to equation (3), wherein lr_base is the initialized learning rate, determined to be 0.001. ti is the ith time of iteration and $tmax$ is the maximum times of iteration, set as 200k. P is the power exponent, as 0.9. The experiments are implemented on the platform of Caffe[2] (Jia et al., 2014) with 2 GPUs. They are both graphics cards of NVIDIA TITAN X with a memory of 12 GB each. The detailed code can be referred to from website.[3]

$$lr_{ti} = lr\_base \times \left(1 - \frac{ti}{t\max}\right)^{p} \tag{3}$$

4. Detection results and discussions

To evaluate the efficiency and robustness of the proposed landslide detection model, we applied it to detect landslides of national scale of Nepal in year 2015. In terms of training the deep learning framework, we collected the ground truth landslide pixels of Nepal in year of 2014. To balance the sample distribution between landslide and non-landslide ground objects, we cropped bounding box regions from potential landslide image produced in Section 3.1. The corresponding Landsat image patches in year of 2014 are used for training the deep learning semantic segmentation model for landslide detection. The annual Landsat image in year of 2015 is used for model evaluation. Moreover, the ground truth landslide samples of year 2014 and 2015 are achieved by visual interpretation with the help of google earth and the publicly released lines by international cooperation among five organizations (University, 2015). In our visual interpretation, two experienced individuals conducted double check for each other to guarantee the accuracy. We calculate recall, precision and F1-score to analyze the performance objectively, in both terms of regional case and national case. Precision, recall and F1-score are widely used measurements in evaluating the performance of object detection (Sujatha and Selvathi, 2015). Precision indicates the percentage of pixels that are correctly detected as category A of all the pixels detected as A. Recall stands for the percentage of pixels that are correctly detected as category A of all the ground truth pixels belonging to A.. F1-score is a synthesized measurement of recall and precision to evaluate detection performance generally.

We performed landslide detection for Nepal on the same GPUs used for model training and consumed 160 min to finish the entire detection on the image with a size of 31913 × 17111 pixels. The corresponding visual detection performances are shown in Fig. 6. Generally, most ground truth landslide clusters have been detected, especially the major clusters in blue box. The shapes of the clusters have been well maintained, and substantial background objects have been removed. There are 2761 landslide event polygons in our ground truth image and 1965 landslide event polygons in our detection result. It indicates that our detection framework is performing reasonably well in general. We also calculated the precision, recall and F1-score to evaluate the pixel-level

[2] Available: http://caffe.berkeleyvision.org.

[3] https://github.com/yubozuzu123/Landslide-detection-model_pspnet/tree/master.

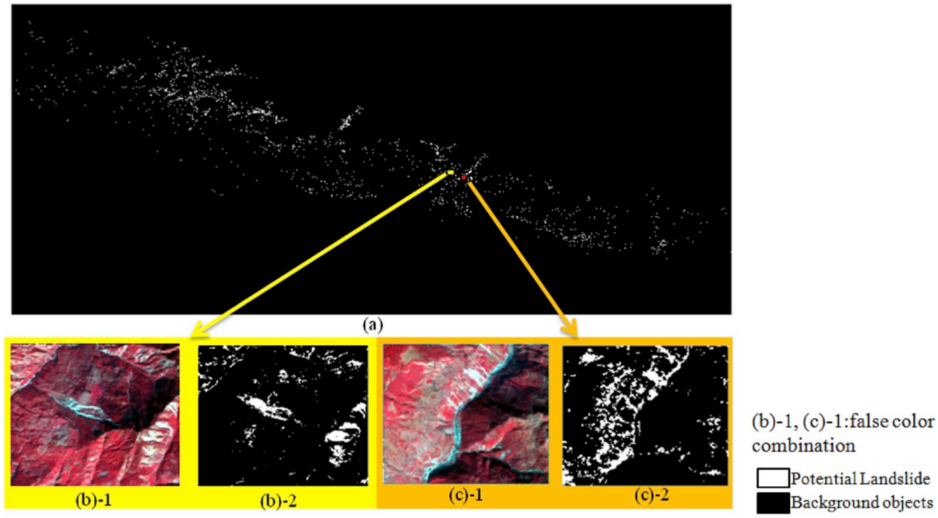

Fig. 3. Potential landslide detection result of Nepal in year of 2015 based on vegetation index: (a) potential landslides detected; (b) and (c): sample sub areas indicating the great number of bare soil, rock pixels mixed with landslide pixels.

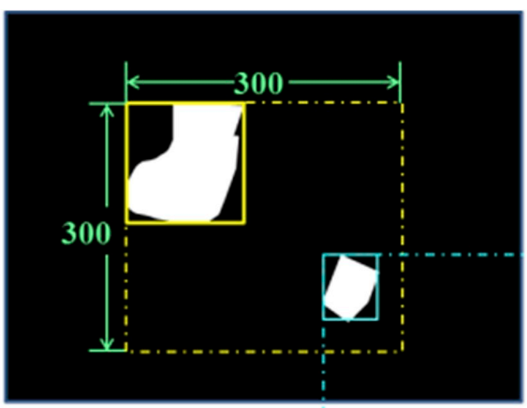

Fig. 4. Demonstration of bounding box extension.

landslide detection performance objectively, as listed in Table 2. Compared with the work in (Chen et al., 2018), which detects landslides in terms of national scale of Nepal using contour-based random forest model, our detection framework improves the detection accuracy by 44% in recall and 15% in precision. That indicates that the proposed deep learning framework is able to correctly locate far more ground truth landslides than the typical machine learning method. The number of more detected ground truth landslides reaches almost half of the all the ground truth landslides of national scale of Nepal. Such improvement stems from the automatic multi scale feature learning in the proposed deep learning framework without the reliability of feature engineering in machine learning method. Moreover, the pixels recognized as landslides are 55.35% accurate, 15% higher than the random forest method, which further validate the strong applicability of the proposed landslide detection framework in distinguishing bare soil, rock and landslide.

However, due to the limit of page size, it is difficult to visualize the landslide detection performance in terms of national scale in details in Fig. 6. We sampled four sub-regions with landslides and performed statistical evaluation. The detection performances are visually demonstrated in Fig. 7 and the corresponding evaluation statistics of precision, recall and F1-score are listed Table 3. From Fig. 7, we can clearly recognize that most landslides have been neatly and completely extracted. The bare soil, which takes similar spectral and textural characteristics, is mostly removed, as shown in the yellow circles in Fig. 7(a), (b) and (c). The statistics in Table 3 further validate the strong practical applicability of our proposed deep learning framework in detecting landslides for national scale area. F1-score is a synthesized measurement of detection performance, and it reaches higher than 0.7 of all the four sub regions. For cases of Fig. 7(a) and (b), whose landslides are densely distributed among massive bare soil as background objects, the precision gets higher than 64% in both cases and recall higher than 75%. Such performance can be recognized as satisfactory reliable. In terms of Fig. 7(d), whose landslides are solely distributed in the main background of vegetation, which can be recognized as an easy case, our proposed method provides a promising performance with its precision reaching 94.04%.

The evaluation statistics of sub regions (listed in Table 3) are all higher than the statistics in national scale of Nepal (listed in Table 2), because the background objects in the sub images are comparatively simple. The sub images are subtracted with regions covering landslides and limited bare soil, while national scale Nepal covers many areas with disturbing bare soil but without landslides. However, there is still some bare soil mis-classified as landslides in the sub images. It indicates that

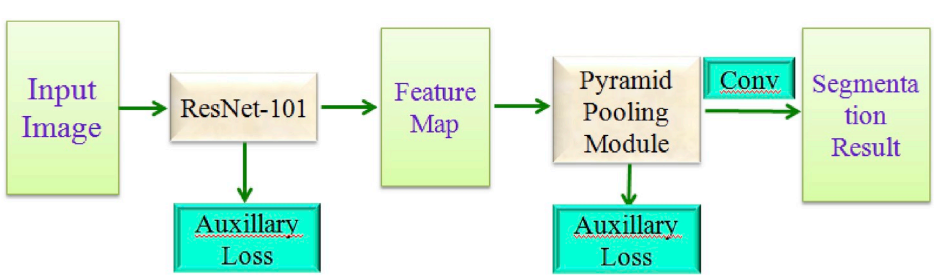

Fig. 5. Deep learning framework of landslide detection.

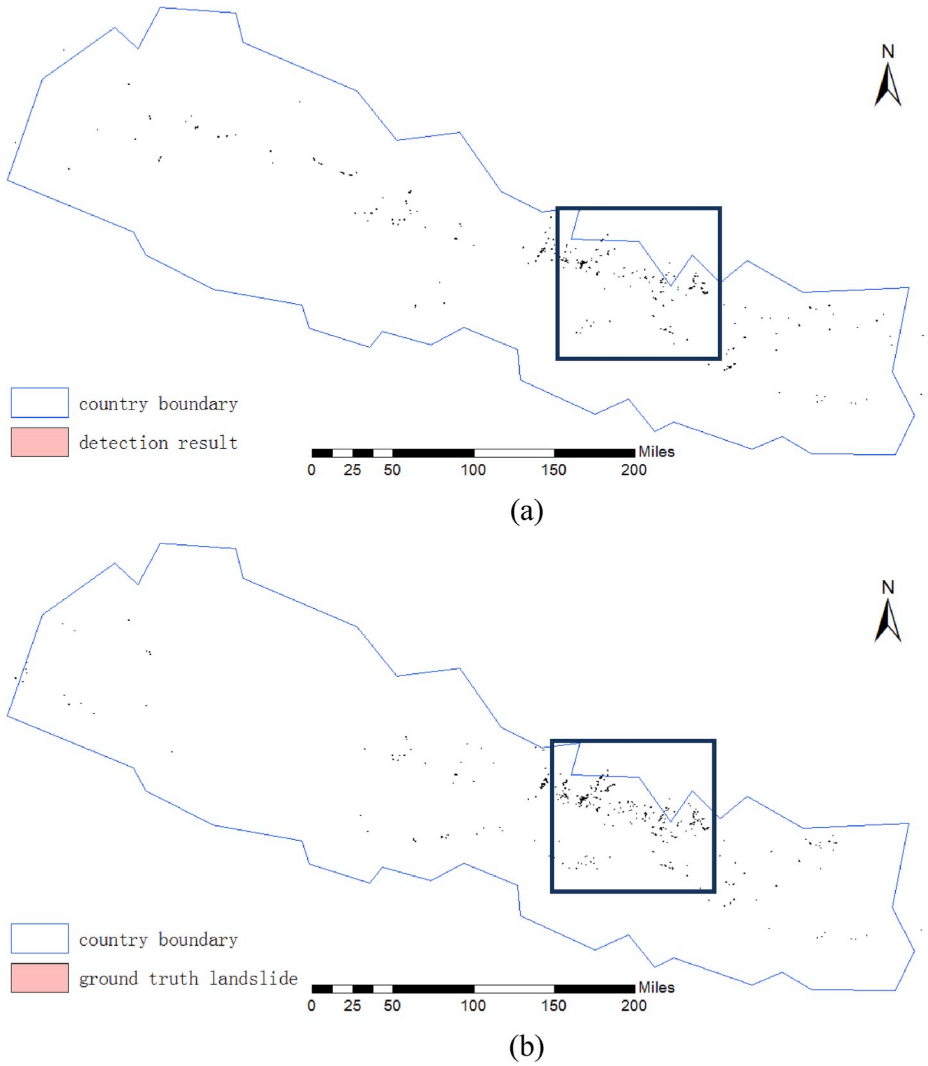

Fig. 6. Landslide detection performance in Nepal by our proposed method: (a) detection result; (b) ground truth landslide.

Table 2
Comparison of evaluation statistics of landslide detection between our proposed framework and the published result (Chen et al., 2018) in terms of national scale of Nepal.

Recall (%)	Precision (%)	F1-score
65.01	55.35	0.60
22.89 (Chen et al., 2018)	29.72 (Chen et al., 2018)	0.26

the capability of our framework in detecting landslide from complicated background needs further enhancement, especially in distinguishing between landslides and bare soil. That may be dealt with by adding more landslide samples and conducting change detection to decrease the impact of bare soil in the future work.

There is another point that our recall and precision, specifically in national scale, are not that high as calculated in other published works (Cheng et al., 2013; Li et al., 2016; Valkaniotis et al., 2018), because the variability of the ground objects in our case is far more complicated with intensive bare soil and rocks in the mountainous regions, and the number of landslide events in our study area (being more than 6000) is much larger than that in other published works (Valkaniotis et al., 2018) (being hundreds or approximate 1000) as well. The difficulties in landslide detection in our case are more challenging, especially for large-scale practical applications. Moreover, through the proposed landslide detecting framework, the performances in our case are twice better than the recently published work in (Chen et al., 2018), which also detects landslides from national scale of Nepal, but bases on random forest classifier. That further validates the novelty and the promising applicability of our framework in detecting landslides from national or even continental area.

5. Conclusions

In this paper, a contour-based landslide detection model is proposed. It consists of two parts, one is potential landslide detection based on vegetation index and degradation of DEM, the other is exact landslide detection based on an end-to-end contour-based semantic segmentation deep learning model. The contour is extracted according to the bounding box of connective contour from the potential landslide image and extended its spatial scale according to its area. Compared with the contour-based landslide detection machine learning model in (Chen et al., 2018), we simplified the process of potential landslide detection by replacing the image saliency calculation with a simple and robust experienced threshold. In terms of box area subtraction, bounding box was not only used in this study, but also extended to cover more landslides to enlarge the training set and variability. Moreover, feature engineering is avoided in our proposed landslide detection framework by applying deep learning framework. Therefore, this study can be recognized as an improved version of the model in (Chen et al., 2018). Our

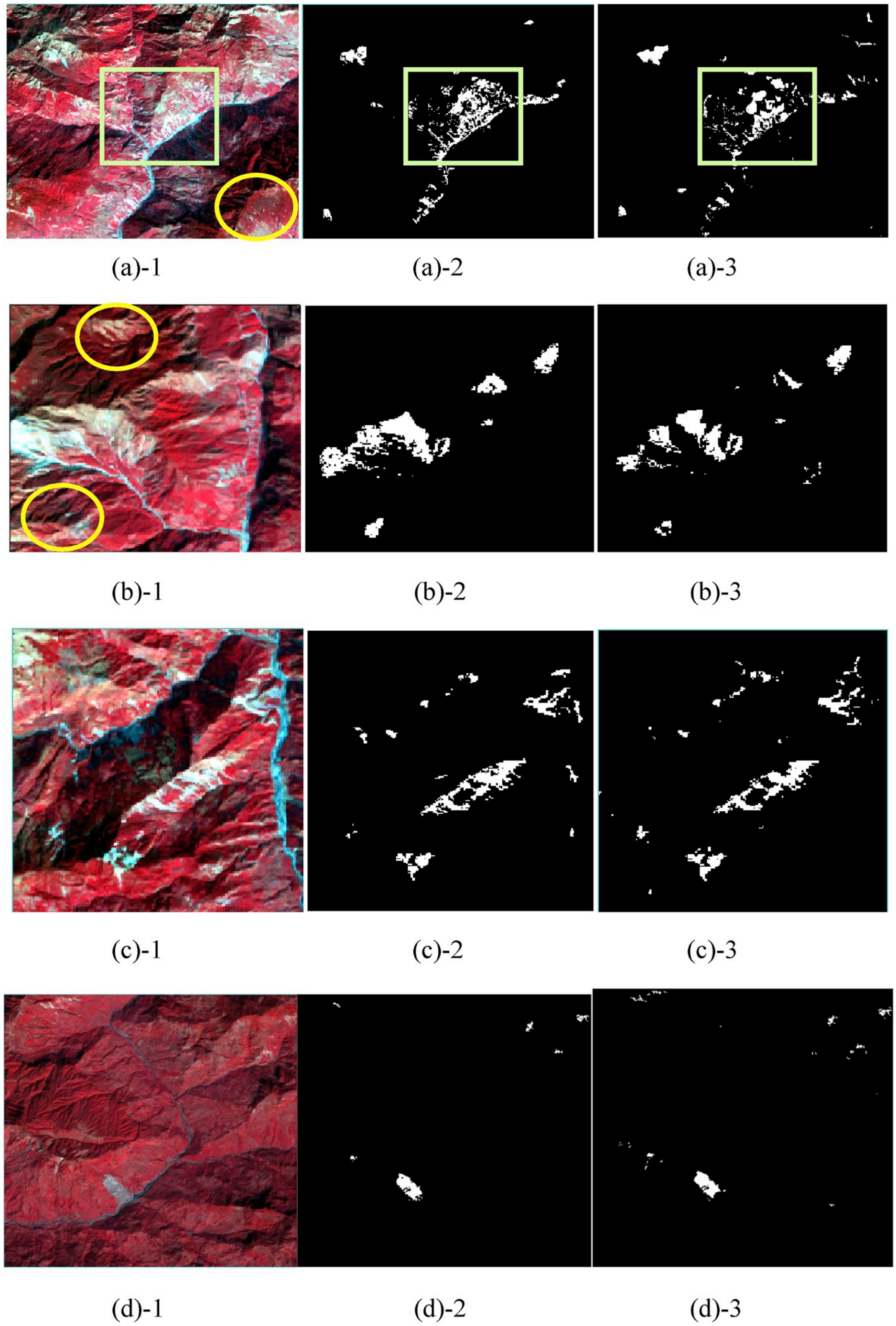

Fig. 7. Landslide detection performance of four sub regions by our proposed method: (a)-1, (b)-1, (c)-1, (d)-1: original image in false color combination; (a)-2, (b)-2, (c)-2, (d)-2: detection results by proposed framework; (a)-3, (b)-3, (c)-3, (d)-3: ground truth landslides of the corresponding sub regions. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Evaluation statistics of landslide detection by our proposed framework in terms of four randomly subtracted images.

Figure	Recall (%)	Precision (%)	F1-score
Fig. 7(a)	75.71	66.66	0.71
Fig. 7(b)	90.83	64.88	0.76
Fig. 7(c)	84.91	81.53	0.83
Fig. 7(d)	83.28	94.04	0.88

method is applied to detect landslides of Nepal in the year of 2015 based on the annual synthesized Landsat image generated from google earth engine platform. The results demonstrate the effectiveness and robustness of the proposed framework and its strong practical applicability in national scale cases with 65% recall and 55.35% precision.

Computer code availability

The implementation source code can be referred to https://github.com/yubozuzu123/Landslide-detection-model_pspnet/tree/master.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cageo.2019.104388.

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