The Use of LSTM-Based RNN and SVM Models to Detect Ludian Coseismic Landslides in Time Series Images

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Abstract. With the increase of temporal frequency of satellite images, time series analysis based on Artificial Neural Network has become a tendency to detect land cover changes in images. We briefly introduces a case study that uses Long-Short Term Memory (LSTM), a specific Recurrent Neural Network (RNN) for time series modelling and forecasting, and Support Vector Machine (SVM) to detect landslides triggered by Ms.6.5 earthquake in Ludian, China in 2014. The study uses 72 available images with 16/30m spatial resolution from Landsat-7/8, Gaofen-1 and HJ-1A/1B satellites. Firstly, per-pixel LSTM models are trained by Normalized Difference Vegetation Index (NDVI) images before the earthquake. Secondly, the trained LSTM models are used to predict NDVI images after the earthquake. Then, anomalies or changes are detected by comparing predicted and observed NDVI images. Finally, anomalies related to landslides are separated from other changes with a SVM model which was trained by multi-spectral images in the study area. Experiment demonstrates that the recall rate and precision rate of landslides detection are 82.09% and 76.21%, respectively. The study shows a potential that the combination of LSTM and SVM models can be used to detect landslides in Landsat-like time series images with 30m resolution.

1. Introduction

As one of the major natural disasters, landslides, especially triggered by earthquake, often cause injuries and deaths as well as destructions of buildings and infrastructure. It is of practical significance to timely and accurately detect and interpret landslides to support post-earthquake relief as well as to reduce the losses after landslides.

The approaches for landslide detection in satellite images can be categorized with respect to the temporal of the images used. (1) Single-temporal image classification. Spectral, texture and/or colour features from selected samples of landslides and others are used to train some rules or models for classification [1, 2]. It requires image with high spatial resolution, e.g., 0.5 to 5 meters, which is usually unavailable in the coming days after the earthquake. (2) Bi-/multi-temporal images change detection. Pixel or object based change detection followed by features analysis are used to recognize new landslides in the newer image [3, 4]. It generally requires images captured in the same season to avoid effects of phenological changes among different seasons. Therefore, change detection in the images with different acquisition seasons would lead to some false alarms [5, 6]. (3) Time series images anomaly or change detection. With the increase in the temporal frequency of images, it makes great progress of time series analysis method for anomaly detection [7, 8]. Analysis of temporal patterns of land cover has been used to identify historical landslides in the images [9-13].
In view of the tendency in research on time series images analysis for anomaly detection [14, 15], and the fast development of machine learning techniques, this study uses Long-Short Term Memory (LSTM) and Support Vector Machine (SVM) models to detect landslides caused by earthquake. Time series of Normalized Difference Vegetation Index (NDVI) from images with 30-meter medium spatial resolution are used for LSTM modelling and anomaly detection. Spectral and topographical features are used for SVM training and landslide detection. Experiment shows good results with high producer, user and overall accuracies.

2. Study Area and Data
On August 3, 2014, a Ms.6.5 earthquake in Ludian county of Yunnan province of China triggered far more than 1,000 landslides [16]. Time series images from Landsat7/8 ETM+ OLI (30-meter), HJ-1A/1B CCD (30-meter) and GF-1 WFV (16-meter) from the year 2012 to 2014 were used for analysis and landslide detection. There are 72 images in total with the average temporal resolution of 15 days. Figure 1 shows the location of the study area with a true colour image from Landsat after the earthquake.

3. Method
The method mainly includes pre-processing of time series images, training of LSTM models for images prediction, anomaly detection in new observed images, and landslide detection in anomalies using SVM. The flowchart of the method is shown in figure 2.

![Figure 1. Study area and Landsat image.](image1)

![Figure 2. Flow chart of the landslide detection method.](image2)
3.1. Pre-processing of Time Series Images
In order to minimize the heterogeneous deviation among multi-source satellites images, the images need a series pre-processing as the following procedure.

- Radiation correction: in order to reduce the influence of inconsistent radiance, all the DN values of multi-spectral images were converted to the top of atmosphere (TOA) reflectance.
- Orth rectification and resample: all the multi-spectral images were orth-rectified using 30-meter DEM data. The spatial resolution of the GF-1 WFV images were resampled from 16 to 30 meters, i.e., the same with those of Landsat-7/8 and HJ-1A/1B images.
- Image registration: Using a Landsat-8 image as reference, all the HJ-1A/1B and GF-1 images were registered, with a sub-pixel overall accuracy of image registration.
- NDVI images generation: Calculated NDVI time series images from corresponding multi-spectral time series images.

3.2. Training of LSTM Models and Prediction of NDVI Images Time Series
Land covers have intrinsic seasonal changing patterns, showing some regular variations in the NDVI time series data. Time series NDVI data has obvious periodicity and temporal correlation. The patterns in time series NDVI data can be exploited by a LSTM model. Modelling the pattern of time series NDVI data is getting the seasonal phenological changes of land cover. As landslide can cause abnormal changes of land cover, it is necessary to exclude the anomalies in the historical time series NDVI data. A method based on recovery rate and SVM was used to detect historical landslides in the time series images before the earthquake [12, 13]. After eliminate those landslides, the per-pixel time series NDVI data for non-landslide areas before the earthquake were trained by LSTM model.

One of the key parameters in the LSTM structure is the number of input layer nodes. The LSTM model constructed with different number of input layer nodes would result in different prediction accuracies. The testing showed that if the number of input layer nodes gradually increases in a range of 1 to 12, the prediction accuracy will gradually increase. If the input layer node is from 12 to 16, the prediction accuracy does not significantly fluctuate. If the number of input layer nodes exceeds 16, the prediction accuracy will decrease. Therefore, the study selected 12 as the number of input layer nodes. Following the training of LSTM models for all the pixels, they were used to forecast a series of NDVI images in the consecutive timings.

3.3. Anomaly Detection in New Observed NDVI Images
NDVI images after the earthquake were predicted by the trained LSTM models. The predicted NDVI images show normal or tendency of land cover status assuming there is no land cover changes. However, if landslides occur after the earthquake, the truly new observed NDVI images would show significant differences to the predicted NDVI images.

Since there is always an error between the actual observed value and the predicted value, a threshold should be set to differentiate anomalies and non-anomalies. Here we assume that, for the predicted value \( p_1 \) and the actual observed value \( p_2 \), if \( |p_1 - p_2| > k \times \text{RMSE} \), the actual observed value is considered as anomaly. Otherwise, the pixel with \( |p_1 - p_2| \leq k \times \text{RMSE} \) is marked as non-anomaly. With a test on some samples from the study area, anomalies are relatively less and contain more landslide pixels if \( k = 2.4 \).

3.4. Landslide Detection Using SVM model
Landslides can cause abnormal changes of land cover, but the latter may not be caused by the former. Therefore, it is necessary to identify landslides from anomalies with respect to various kinds of changes. Samples of landslides and non-landslides were visually selected from the multi-spectral images. A total of 14 samples features including spectral band values (B, G, R and NIR), NDVI, slope and aspect, as well as their average values of surroundings, were used for training a SVM model. Finally, the trained SVM model was taken as a classifier to distinguish landslides from non-landslides among the anomalies.
4. Experiment and Result
The above method was used to detect landslides triggered by the Ludian earthquake on August 3, 2014. Time series NDVI images from January 15, 2012 to July 15, 2014 were used to predict the NDVI image on August 15, 2014. The predicted NDVI and observed NDVI after the earthquake are shown in Figure 3.

![Figure 3. The predicted NDVI image (left) and the observed NDVI image (right) after the earthquake.](image)

Anomalies were detected according to the differences between the predicted and observed NDVI images. Then landslides were screened out from the anomalies by SVM model. Figure 4 shows the Landsat image captured after the earthquake (a), the landslide interpreted visually by pre- and post-disaster multi-spectral image (b), the anomalies detected based on the observed NDVI and LSTM predicted NDVI images (c), and the landslides detected by applying the SVM model on the anomalies (d). From figures 4b and 4c we can see that landslides as well as flooding areas along the river and clouds were detected as anomalies. Figures 4b-4d illustrate that most landslides were separated from other anomalies.

Table 1 shows the quantitative comparisons between the detections and the interpretation at pixel level. In the first stage, detected anomalies contains 95.33% of true landslide pixels. However, only 22.70% of the anomalies are true landslide pixels. It means that up to 77.30% of anomalies are not landslides. Fortunately, in the second stage, 76.21% of landslide pixels classified by SVM are true landslides, although there is a decrease of recall rate to 82.09%. The missed landslides are too small to be detected in the image with 30-meter spatial resolution. The overall accuracy of landslide detection is as much as 99.37% for the study area, demonstrating the effectiveness of the method for landslide detection.

| Stage                  | Recall   | Precision | Accuracy  |
|------------------------|----------|-----------|-----------|
| Anomaly Detection      | 95.33%   | 22.70%    | 95.20%    |
| Landslide Detection    | 82.09%   | 76.21%    | 99.37%    |
5. Conclusion

Traditional approaches for landslide detection mainly based on image interpretation or classification, bi- or multi-temporal images change detection, which generally requires images with high spatial resolution. This study introduces a case study that used LSTM and SVM models to detect landslides triggered by an earthquake using time series images with 30-meter resolution. The per-pixel LSTM models were trained with pre-disaster time series images and then used to predict post-disaster images. The SVM model were trained by landslides samples and then used to classify landslides and other anomalies. The case study demonstrated the effectiveness of the combination of LSTM and SVM models to detect coseismic landslides with high accuracies. It shows potential to detect post-disaster landslides in areas where lack of images with high spatial resolution. Images from multi-satellites with various resolutions could increase the availability and temporal frequency of time series for rapid response of landslide investigation, but in the meantime, may also lead to miss and false alarms due to the heterogeneity of multi-source images.
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