UNITECH 2023 GABROVO

INTERNATIONAL SCIENTIFIC CONFERENCE
17-18 November 2023, GABROVO

TYPES OF REMOTE SENSING ANALYSIS IN DISASTER MANAGEMENT AND LANDSLIDE IDENTIFICATION

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Abstract
The objective in this investigation is to compare different approaches to landslide identification. The purpose if this paper is to find common approach and introduce new ideas to landslide identification. The scope of this paper is present the potential in using satellite imagery such as Airbus Pleiades Neo for landslide identification after disasters.

Keywords: change detection, remote sensing, satellite images, SAR, NDVI

INTRODUCTION

The advancements of remote sensing field in the last decade is leading to new studies in management of landslides. The broad approaches in management of landslides after natural disasters is relatively new and is based around usage of multispectral imagery and Synthetic Aperture Radar (SAR). There is relatively large pool of approaches regarding the issue of management of landslides.

The main approaches reviewed in this study are the following:

(1) correlating multispectral imagery with DGPS data to analyze landslides over long period of time;
(2) using DInSAR and SAR for identification of newly formed landslides;
(3) usage of NDVI extracted from various multispectral imagery to correlate the landslides using object detection based on dataset of local area;
(4) utilizing machine learning algorithms on Enhanced Natural Terrain Landslide Inventory (ENTLI).

Those methods have potential in combining some approaches to create better-optimized process for detecting landslides.

USAGE OF MULTISPECTRAL IMAGERY

Usage of multispectral imagery in case of SPOT5 is used to correlate date with combination of DGPS in order to find common unmodified point to monitor shift in earth surface. The correlation used Image Control Points (ICP) and SIFT method (Scale Invariant Feature Transform). The resolution of SPOT5 2.5m on 1 pixel is not reliable source of provable displacement. For the displacement to be reliable, it needs to be at least 10m (4 pixels). The displacements need to be larger than shift value to be estimated and the value needs to be corrected before it is threated as displacement value. The ICP outside of the landslide area considered for correlation of the area so it could be interpreted in the terms of landslides.

This approach is relevant for a monitoring of slow- and fast-moving landslides that are active. Using this approach, it may be possible to perform detection of landslide event in cases of natural disasters for example earthquake.

The use if ICP is useful for detecting landslides in areas where those ICP could be determined for example cities or villages.

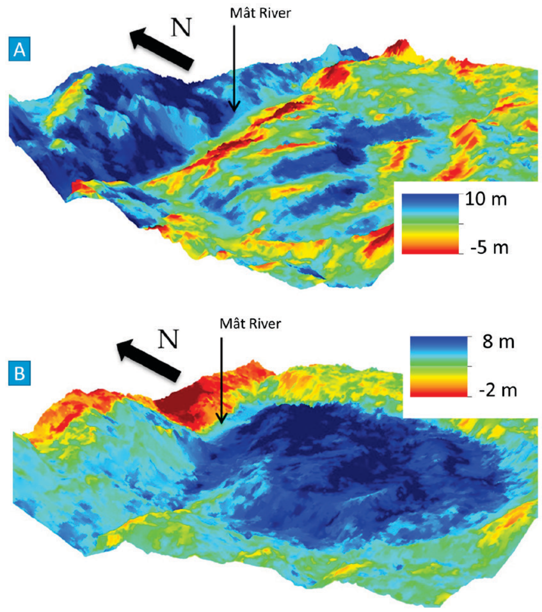

Figure 1 (A) East-west shift measured by MicMac and draped on the topography of the study area. Positive values toward the east. A strong correlation appears between the slope aspect and the shift for the 2006–2008 period; (B) South-north shift measured by MicMac.

USAGE OF SPATIAL AUTOCORRELATION WITH SAR

The usage of SAR is based on capturing pre and post images from sentinel-1 and performing change detection. The change detection algorithm uses LR index (Log-Ratio) this captures the changes in both images. Based on the previous date of LR index is performed Spatial Autocorrelation Estimation. The Moran's index is used to locate homogeneity across neighboring pixels to detect strong and week spatial autocorrelation 1 and -1 respectively. If the autocorrelation is showing increase in the then there is high probability of landslide event. This then is with ancillary data around the landslides to identify if the event is there and perform segmentation based on the area.

This method could be used to track future landslide event. Automating the capturing of data and performing LR index with Moran's index to identify probable landslide events to be monitored remotely before capturing ancillary data. If used correctly this method could be advanced with introduction of machine learning segmentation to perform human speculation about the event. In this case landslides located in remote locations could be localized and analyzed more efficiently.

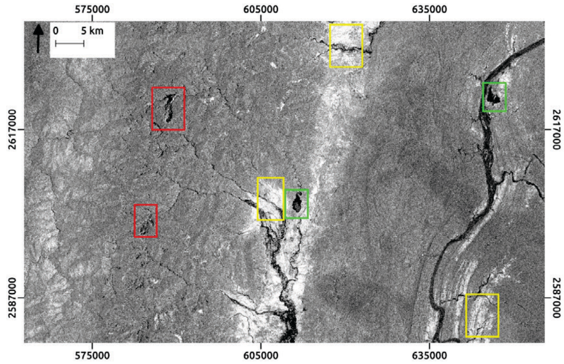

Figure 2Log-Ratio (LR)-between layer in part of the Sentinel-1 swath. The yellow squares show areas with signs probably left by recent floods, the green current flooded areas, and in red event landslides. Squares here do not coincide with moving windows.

USAGE OF OBJECT DETECTION BASED ON NDVI

This approach uses multiple multispectral satellite imagery to extract NDVI image. With combination of object detection and Digital Elevation Model (DEM) for additional variables to enhance the machine learning algorithm.

The base idea is the use of DEM for high point and slope degrees. With the extracted data and polygons of landslide masses over 30 years of data. The data is trained to perform object detection. The process includes extracting the DEM, calculate the flow direction then vectorize the data that streams to the DEM to extract watersheds. With the extracted watersheds the data is intersected and vectorized where the resulting polygons are eliminated based on area threshold to determine slope units and remove small polygons that are more likely data error.

This approach is focused on working alongside experts in speculating future landslides based on previous data from over 30 years. Results based on this method show accuracy of roughly 81% in the best-case scenarios. This approach is useful in speculation of future landslides of broad area with sufficient data of previous landslide data. That being said the approach lacks the process of detecting new landslides where there is no previous data for example natural disasters.

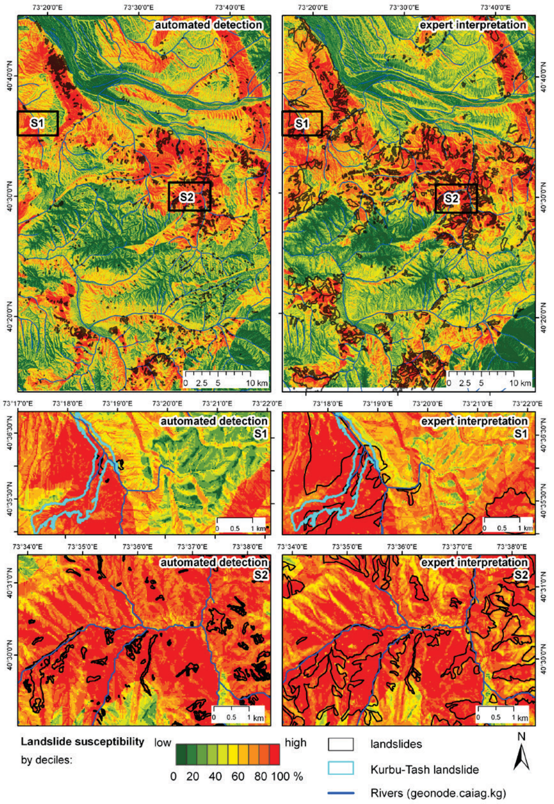

Figure 3 Results of susceptibility assessment produced using automatically detected landslide masses (1986–2016) and landslides obtained by expert interpretation: study area and two subsets.

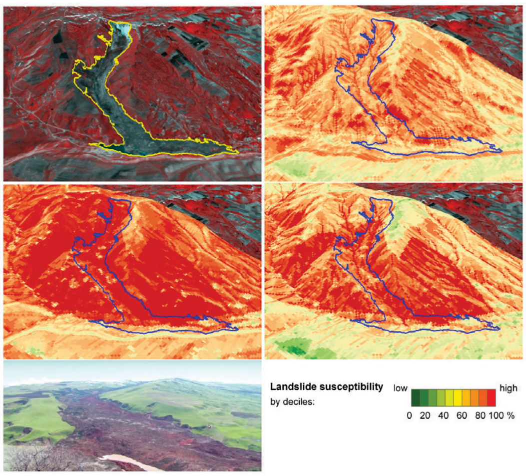

Figure 4 The 4.3-km-long Kurbu-Tash landslide that occurred in April 2017 (extent determined by automated detection) overlaid over a false-color near-infrared RapidEye image acquired on 2 May 2017 (top left). Overlay with the susceptibility map based on the highest points of automatically detected landslides (top right), masses of automatically detected landslides (middle right) and expert interpretation (middle left). (Bottom left): a video frame by AKIpress acquired in the first half of May 2017 showing the landslide mass.

USAGE OF MACHINE LEARNING

The approach of using machine learning algorithms for use in landslide identification includes collection of raw data. The contents of the data could be categorized in two fundamental groups:

(1) DEM
(2) Landslide inventory

This approach excludes the use of optical imagery because of possible dense layer of vegetation that could obscure the earth surface.

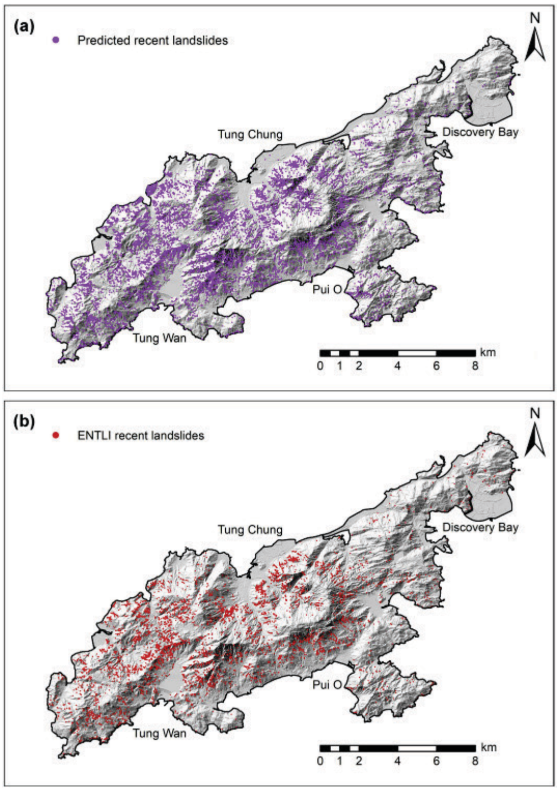

Figure 5 RecLD based machine learning results: (a) predicted recent landslides using DCNN-11 and (b) recent landslides in ENTLI.

The raw data is processed into several datasets that consists of recent, relict and joint landslides. This split into three datasets is used to give weight to the algorithm to prefer and favor recent data into account but also considering relic landslides that took place in the area. After the establishment into the datasets the machine learning model is trained on various models. The relative best model is DCNN-11, that is based on comparison of other models like Logistic regression (LR), Support vector machine (SVM), Random Forest (RF), Boosting, Convolutional neural network (CNN). The CNN-6 contains 6 layers (two convolutional layers, two max-pooling layers and two fully connected layers). The CNN-6 performed slightly worse than DCNN-11 (four convolutional layers, four max-pooling layers and three fully connected layers) where D means deep. Where the DCNN-11 identification accuracy is as high as 92.5%.

This approach is promising in the showing a DCNN model could be potentially useful in detecting new landslides based on broad datasets of a region with extensive DEM data.

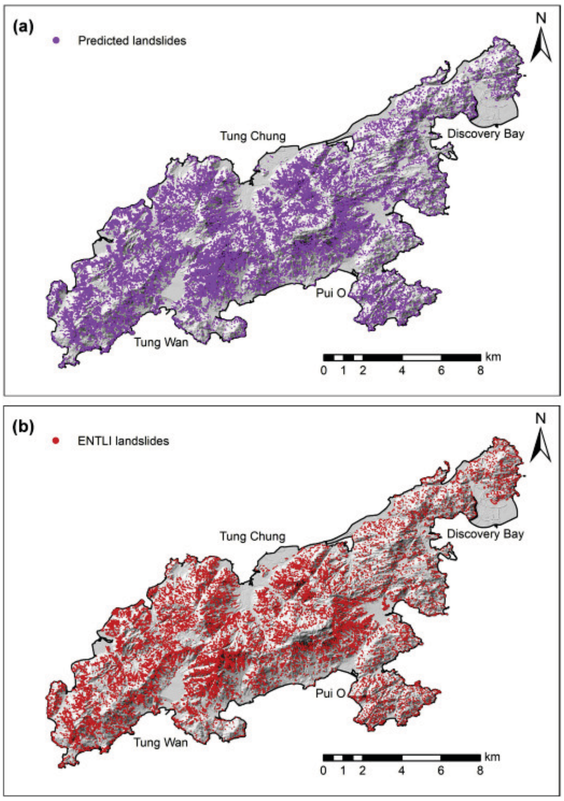

Figure 6 RelLD based machine learning results: (a) predicted relict landslides using DCNN-11 and (b) relict landslides in ENTLI.

CONCLUSION

The common approach in the field of landslide detection and management in the use of DEM and machine learning algorithms. The usage of optical imagery is underutilized because of limitations in detecting landmass in case of heavy vegetation. This is mitigated in some cases with the use of SAR data to limit the vegetation noise and extract landmass data. Some methods that rely on extensive datasets of collected data of previous landslides could be potential limitation in detecting landslides in event of natural disasters.

To mitigate the problem of unavailability of previous data in events of landslides the approach could combine several data streams of raw data for example sentinel-1 SAR and available DEM information of the region. With combination of change detection algorithm to detect new landslides. With combination of multispectral imagery to monitor NDVI the several data streams could be used in DCNN to perform detection of newly formed landslides in various regions after disaster for example earthquake. In the specific extreme cases of landslides this proposed approach may not be viable in monitoring slow landslide events but to detect extreme and fast landslidest.

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