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# LANDSLIDE DETECTION IN 3D POINT CLOUDS WITH DEEP SIAMESE CONVOLUTIONAL NETWORK

*Iris de Gélis<sup>1,2\*</sup>, Thomas Bernard<sup>3</sup>, Dimitri Lague<sup>3</sup>, Thomas Corpetti<sup>4</sup>, Sébastien Lefèvre<sup>2</sup>*

<sup>1</sup> Magellium, F-31000 Toulouse, France

<sup>2</sup> Université Bretagne Sud, IRISA UMR 6074, F-56000 Vannes, France

<sup>3</sup> Univ Rennes, CNRS, Géosciences Rennes, UMR 6118, F-35000 Rennes, France

<sup>4</sup> CNRS, LETG UMR 6554, F-35000 Rennes, France

## ABSTRACT

Generally caused by extreme events, landslides cause severe landscape modifications and may endanger local population. It is important to be able to map them in order to better understand landscape evolution. 3D LiDAR point clouds (PCs) are a relevant choice compared to 2D imagery to directly sense ground shape modification under vegetated areas. Most of the studies propose to rely on rasterization of PCs, or multi-step semi-automatic process with tedious manual results refinement in the 3D PCs. In this study, we aim at experimenting a deep learning method to directly extract landslide sources and deposits from raw 3D PCs. To this end, we train an Encoder Fusion SiamKPConv network, designed for 3D PCs change detection, for the specific task of landslides identification in PCs acquired before and after Kaikōura earthquake (New-Zealand). The experimental results (93.87% of accuracy) show the relevance of this model.

**Index Terms**— Landslide detection, 3D point clouds, deep learning

## 1. INTRODUCTION

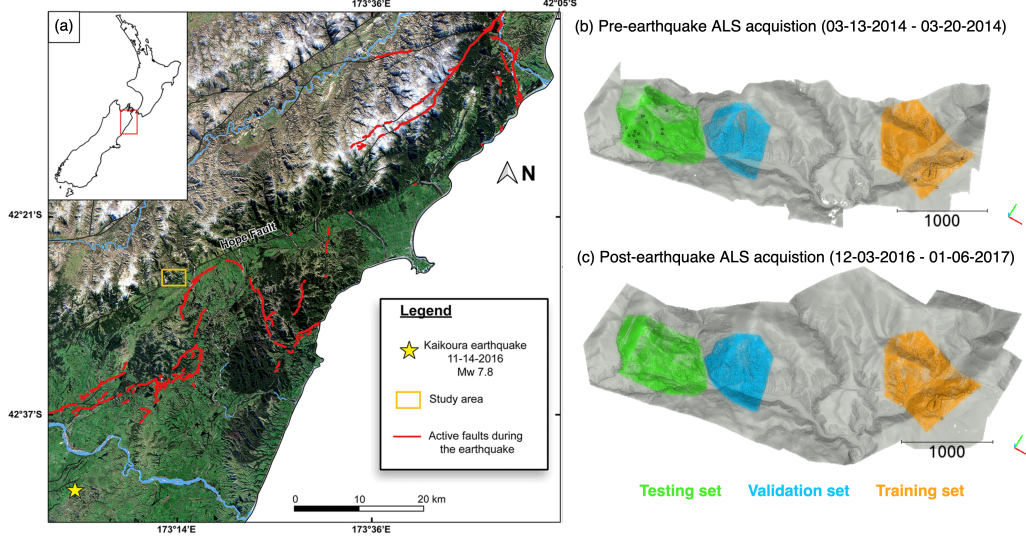
Extreme events such as earthquakes and storms often cause thousands of landslides leading to hazards for local populations [1], and cause severe hillslope and landscape erosion [2]. Landslide analysis is essential to better understand the mechanics of landslides, hillslope erosion [3], and to predict hydro-sedimentary hazards such as alteration of river dynamics due to landslide sediment deposit [4]. To this end, the creation of efficient and exhaustive landslide maps is essential. In mountainous areas, topographic changes are difficult to localize because of the access difficulty and the large size of studied areas. Thereby, landslide mapping is performed through 2D satellite or aerial images [3, 5] or 3D Point Clouds (PCs) acquired via Aerial Laser Scanning (ALS)

or photogrammetry [6, 7]. In particular, elevation data ease landslide volume computation and change detection [8] while 2D images may lead to omitted topographic changes due to limited spectral variations or change below forested areas [7]. For this reason, 3D data appear again to be an interesting solution. Yet, the majority of studies rely on 2.5D rasterization of 3D data into Digital Elevation Models (DEMs) of each epoch [8], and then subsequently using a Difference of DEM (DoD) [7, 8]. However, on top of information loss due to the rasterization process (cell size and interpolation), DoD leads to strong errors in very steep surfaces [7]. To overcome these issues, it is important to deal directly with 3D PCs.

In this study, we propose to apply a deep learning method processing the raw PCs to detect landslide sources and deposits. 3D PCs change detection has been tackled by deep learning only recently, with a model called Siamese KPConv [9]. Inspired by both deep learning methods for 2D change detection as well as recent progress in the definition of convolutions dedicated to 3D PCs, Siamese KPConv performs multi-change segmentation directly from raw 3D PCs. Even more recently, Encoder Fusion SiamKPConv outperformed Siamese KPConv thanks to an encoder that fuses both monodate and change information [10]. While both networks have been first developed in urban environments, Siamese KPConv has been successfully applied to erosion detection in steep cliffs [11]. However, landslide detection differs from cliff erosion for several reasons. First, when forested areas are present, incorrect ground classification in the first LiDAR epoch can lead to false positive detections. Second, high variability in slopes steepness and orientation makes the change detection process more complex. Thereby, we propose to experiment and retrieve landslides sources and deposits using Encoder Fusion SiamKPConv deep network on two PC acquisitions made pre- and post-earthquake.

In Section 2, the study area and data are presented. Then, a description of the method is given in Section 3. Finally, results are described and discussed in Section 4.

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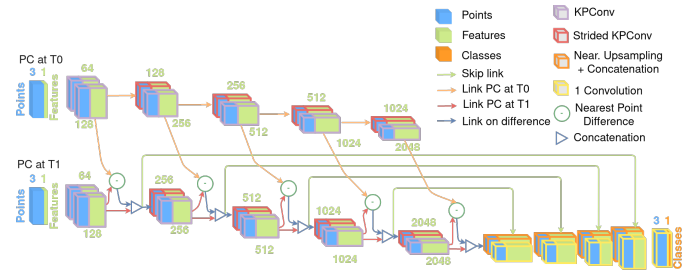
**Fig. 1. Kaikōura study area:** (a) regional map of the regional context and location of the study area near Kaikōura (Figure from [7]); (b-c) pre- and post-earthquake ALS acquisitions colored as function of the split for our deep learning experiments.

## 2. DATA AND STUDY AREA

We focus on the Kaikōura region in New-Zealand where severe topographic modifications have been sensed following the magnitude  $M_w$  7.8 earthquake of 14 November 2016 (see Figure 1a). Following this extreme event, around 30,000 landslides over a 10,000 km<sup>2</sup> were detected [12]. Two aerial LiDAR acquisitions were realized with 2 years and 8 months difference before and after the earthquake. Acquisitions have an average ground point density of  $3.8 \pm 2.1$  and  $11.5 \pm 6.8$  points/m<sup>2</sup> respectively.

A semi-automatic workflow called 3D point cloud differencing (3D-PcD) for the detection of landslide sources and deposits from multi-temporal airborne LiDAR data has been introduced in [7]. This method is based on the Multi-Scale Model-to-Model Cloud Comparison (M3C2) algorithm [13] and on a two-step approach to filter out false detections that can emerge due to vegetation classification errors and geometrical inaccuracies: i) using significant topographic changes (provided by M3C2 algorithm) and ii) exploiting a patch-based metric to detect remaining false detections. Thereby, the ground truth has been obtained by a combination of 3D-PcD [7], vegetation filtering (to prevent from the detection of inaccurate changes), and manual visual analysis for label refinement. This labellisation is used as ground truth to train the network in the following experiments.

Taking the 5 km<sup>2</sup> area where landslide sources and deposits were retrieved in [7], we selected three non-overlapping areas to constitute our training, validation and testing sets. These three splits are depicted in Figure 1(b,c). Unlike [7], our network is fed with raw 3D PCs without any filtering of vegetation. It is trained to highlight sources and deposit areas in a single prediction step.



**Fig. 2. Encoder Fusion SiamKPCConv network** [10].

## 3. METHODOLOGY

### Encoder Fusion SiamKPCConv

In this study, we propose to use the latest deep learning methods in order to detect landslides. In particular, we rely on *Encoder Fusion SiamKPCConv* deep network [10]. As visible in Figure 2, the network is composed of two encoders to extract features from both input PCs. However, the encoder of the second PC (at the bottom of Figure 2) also fuses change information (given by the nearest point feature difference  $\ominus$ ) at each different layer of the encoder. This concatenation operation allows the network to focus more on change-related features extraction. In the decoder part, some skip links are used from the output of the concatenation and the corresponding decoding layer. As for Siamese KPCConv network, to deal with 3D PCs without any rasterization, these networks rely on 3D Kernel Point Convolution (KPCConv) [14]. Thus, in this work, we reuse the model described above, which we train from scratch on our ground truth made of landslides sources, deposits and unchanged areas.

## Experimental settings

In the following experiments, only the 3D coordinates of points are given as input to the network. In this context, interesting changes are more of vertical nature, thus as for urban change detection, and unlike steep cliff application, we use vertical cylinders to segment the dataset. In particular, cylinders of a radius of 30 m are used with a first sampling rate  $dl_0$  at 0.8 m. Concerning other hyper-parameters, we use similar values as those considered for urban settings. In particular, 3,000 samples are used at each training epoch, selected using the same random drawing according to the class representativity as in urban context. We use data augmentation process by adding cylinder rotation and Gaussian noise.

## 4. RESULTS AND DISCUSSION

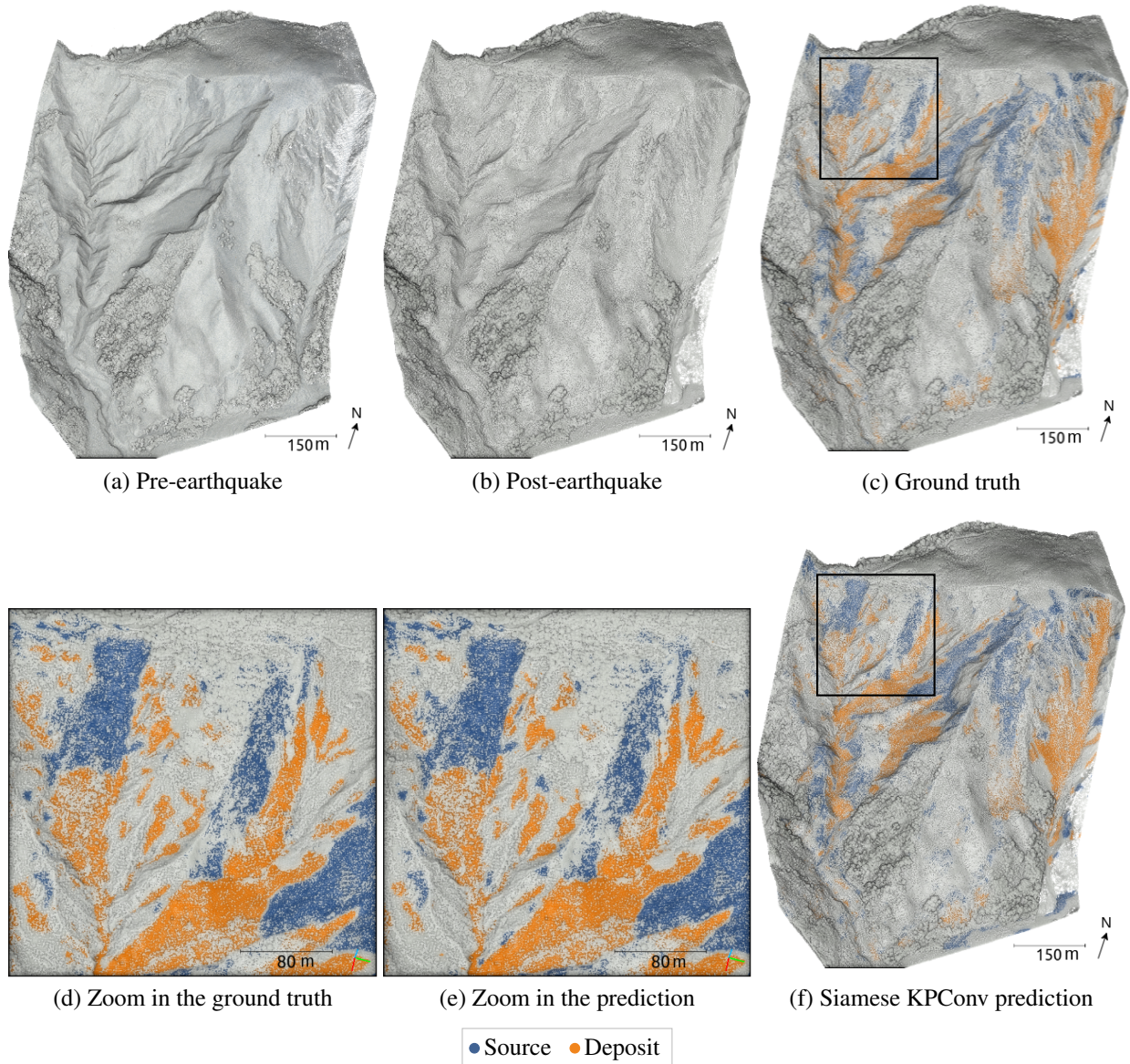
Quantitative and qualitative results are presented in Table 1 and Figure 3. *Encoder Fusion SiamKPConv* seems to perform well on this application. In particular, the main landslide sources and deposits have been correctly retrieved even under the vegetation cover. Principal differences between the ground truth and the prediction appear in smaller changed areas. Some overdetection of sources are visible, as for example in the river bed at the bottom of Figure 3f. This is not so surprising since there are indeed some modifications in the river bed, despite these modifications being not interesting for landslide source and deposit identification task. River bed in the training and validation set represents only a small proportion of the data, surely explaining why the network has not learned that changes in river bed are out-of-interest, as it does for changes related to vegetation. This highlights the added value of deep learning methods over distance-based methods that cannot be used as is to identify landslides and other ground changes in vegetated areas. Indeed, a first step of vegetation removal is required, as done for the ground truth annotation of Kaikōura dataset. However, errors in the vegetation identification impact the change detection step as outlined in [7]. Conversely, we show here *Encoder Fusion SiamKPConv* is able to directly use raw 3D PCs.

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**Table 1.** Results on Kaikōura landslide detection dataset given in %. mAcc is the mean Accuracy, IoU is the Intersection over Union and mIoU is the mean IoU.

Method	mAcc (%)	mIoU (%)	Per class IoU (%)		
			Unchanged	Source	Deposit
Encoder Fusion SiamKPCConv	93.87	83.84	93.58	74.38	83.57



**Fig. 3.** Qualitative results of Encoder Fusion SiamKPCConv deep network prediction of landslides sources and deposits in the testing area. Pre- (a) and post-earthquake (b) input PCs are shown along with the ground truth in (c). The resulting sources and deposits prediction is visible in (f). Zooms in the PCs of the ground truth (d) and the prediction (e) are also presented.