Learning representations to predict landslide occurrences and detect illegal mining across multiple domains

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Abstract

Modelling landslide occurrences is challenging due to lack of valuable prior information on the trigger. Satellites can provide crucial insights for identifying landslide activity and characterizing patterns spatially and temporally. We propose to analyze remote sensing data from affected regions using deep learning methods, find correlation in the changes over time, and predict future landslide occurrences and their potential causes. The learned networks can then be applied to generate task-specific imagery, including but not limited to, illegal mining detection and disaster relief modelling.

1. Introduction

Landslides occur throughout the world and are caused by a range of factors, including *natural:* earthquakes, volcanic eruptions, heavy rainfalls, *man-made:* deforestation, dam constructions, and illegal mining (we refer the reader to (Gariano & Guzzetti, 2016; Lewkowicz & Way, 2019) for relevant literature). Fig. 1 shows one such location in the village of Malin, located in Pune (Maharashtra, India). This landslide was classified as *occurred due to heavy rainfall*, although there are other possible factors that may have led to the eventual slide: (1) deforestation, (2) agriculture, (3) mining, and (4) the construction of a dam in the area. These factors tend to have a long term effect of on soil formation and properties. For example, deforestation is a major contributor to climate change due to the removal of natural carbon sink, but it is equally responsible for loss of root structures that firmly hold the soil. We propose to leverage the data available from affected landslide(s) locations to study the underlying changes and predict potential future events based on similarity in patterns. Furthermore, by knowing the probable causes and effect, we propose to use conditional generative adversarial networks (cGANs) to model what an area would look like under certain conditions. For example, if there is suspicion of illegal mining in a region, a network that has been trained to look for variations due to natural and human activities can infer what the composition would look like post mining. This information can be used to more easily detect and halt the activity. Similarly, we can infer the best possible locations to plant trees and mitigate soil erosion through reforestation efforts. At this stage, we consider gathering data from six main causes of landslide occurrences—volcanic eruptions, earthquakes, deforestation, heavy rainfall, mining, and construction—and one positive sample—thriving forest ecosystem.

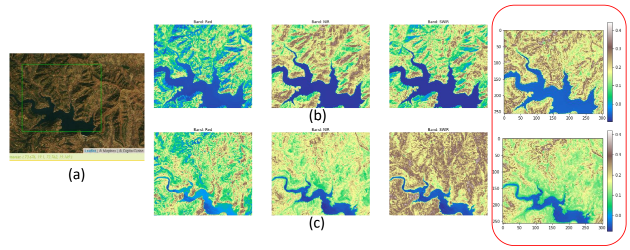

Figure 1. The overlooking scene of *2014 Malin landslide area* in India from the Landsat 8 satellite. (a) denotes the area marked for capture by a green box, (b) is the capture in Red, Near Infrared (NIR) and Short Wave Infrared (SWIR) on 12/14/2013, (c) same three spectral resolutions on 6/8/2014; few days before the landslide. The images in the red box are the corresponding normalized difference vegetation index (NDVI), which measure the vegetation in a given scene. As observed, (b) has significantly less vegetation as compared to (a), which may have resulted in the soil underneath to lose its formation and ultimately lead to a landslide under heavy rainfall conditions. Our idea aims at using these sort of cues to predict potential landslide occurrences in the future.

2. Related Works

For the scope of this paper, we briefly review previous landslide detection approaches and relevant deep learning architectures.

Literature review. Landslide modelling and detection has been a topic of interest, primarily concerned with mapping regional landslide susceptibility (Dou et al., 2019a; Kang et al., 2019; Dou et al., 2019b; Meena et al., 2019; Ghorbanzadeh et al., 2019; Xiao et al., 2018; Shirzadi et al., 2018; Uemoto et al., 2019). All of the existing work uses different machine learning approaches on highly regionlocalized data and specific imaging platforms. For example, Uemoto *et al.*processed synthetic aperture radar (SAR) data from the 2016 Kumamoto earthquake (Japan) for generating amplitude and height difference maps which they later fused for performing landslide detection. Ghorbanzadeh *et al.*compared different machine learning approaches (e.g. random forests) for landslide detection by combining optical data from the Rapid Eye satellite and topographic information at Rasuwa district (Nepal). To the best of our knowledge, no one has yet combined data from various locations and created a common model that is location-agnostic and can be used to predict future occurrences. Inspired by ExtremeWeather (Racah et al., 2017), one piece of this idea is to gather a global dataset spanning multiple domains of satellite imagery to facilitate large-scale learning.

Model architectures. We derive our inspiration for this project from cGANs (Isola et al., 2017), variational autoencoders (VAE) (Kingma & Welling, 2013), Augmented CycleGAN (Almahairi et al., 2018), and MUNIT (Huang et al., 2018), which all learn mappings between either the same domain or different domains for generating new imagery.

3. Idea

We propose to develop a framework to identify temporal patterns that can lead to robust predictions over a heterogeneous set of locations around the world. Formally, we seek to answer the question: *Given a model that has seen variations across America and China, can it generalize to an unseen formation in India? What are the limitations and how can we overcome them?*

Within this framework, we seek to collectively train an ensemble of networks on different image domains. To start, we propose the use of Landsat 8 and SAR-equipped satellite (e.g. Sentinel 1) data, combined with position metadata. Each of these data sources has its own set of advantages and limitations. For example, Landsat 8 cannot see through clouds, but Sentinel 1 is easily able to see through clouds, haze, and darkness. Position metadata is required for the network to get an idea of the location and weather conditions for the images it is processing. Christie et al. (2018) found that appending an LSTM-converted (Hochreiter & Schmidhuber, 1997) metadata feature vector to the image vector helped in classifying aerial images at varying locations. We propose to adapt a similar approach for generating relevant embeddings.

In this paper, we propose to model three sets of networks (Fig. 2):

- **VAE:** As an initial proof of concept to observe if latent encoding can capture variety in distribution as a function of parameters like location and weather conditions. This helps to understand how difficult it is will be to create an overall network modelled across images from all over the globe.

- **Predictor:** A spatio-temporal network with attention to observe past t-frames and predict landslide occurrence along with a confidence score. The attention module is required for the network to learn to ignore imagery that has high cloud density in Landsat 8 domain as it does not contain valuable information. The network also outputs a distribution over probable landslide causes for pre-disaster management.

- **cGAN:** To generate future possible outcomes for a given scenario that includes a variety of tasks (e.g. model movement to assess damage quantity in a given region and begin relocation). This is currently based on a single image but can be extended to include a series of images, or even trained in a multitask fashion alongside landslide prediction. The task itself is encoded into the network using a latent-space distribution which can be later varied to generate multiple outcomes.

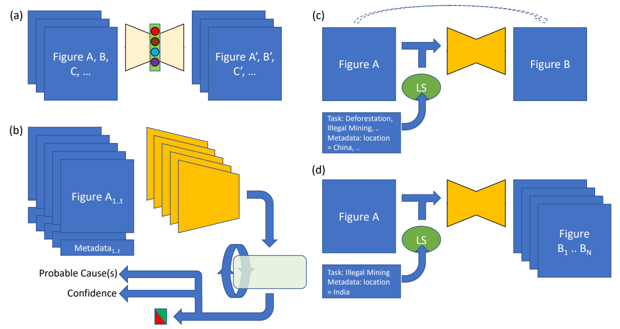

Figure 2. The proposed frameworks in brief; (a) VAE to capture image variations in a latent space encoding without metadata support, (b) Spatio-temporal network that takes in past t-frames and metadata information to predict the probability of landslide occurrence, (c) and (d) training and testing cGANs that generate future frames to assess damage by varying appropriate parameters.

4. Conclusion

In this paper, we propose to build a novel large scale dataset of landslide affected areas for purpose of observing correlations between different regions across the globe. The main goal is to develop a location-agnostic network for predicting the likelihood of a landslide occurring and its probably cause. We will also investigate whether it is possible to detect illegal mining by having the network sample a suite of possible post-mining scenarios and comparing them with the imagery at hand. Lastly, we will also explore the potential application of the same trained network to predict disaster relief by modelling the extent of damage caused by a landslide event.

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