FOREST MONITORING IN GUATEMALA USING SATELLITE IMAGERY AND DEEP LEARNING

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ABSTRACT

Forests cover 34% of Guatemala. The Guatemalan government have taken proficient actions in past decades to reduce deforestation and are looking toward new space technologies to improve forestry monitoring. This paper demonstrates the ability to automatically detect pixel-level changes in satellite images of forested areas that can be used to assist Guatemalan agencies, using satellite imagery from the Copernicus program and specially-developed deep learning algorithms for image segmentation.

Index terms – deforestation, change detection, machine learning, remote sensing, Guatemala, convolutional neural network

1. INTRODUCTION

There has been significant deforestation in Guatemala over the last few decades primarily due to illegal exploitation that has caused environmental and socio-economic impacts [4]. Toward the Belize border, tree cover has decreased from 40,883.7 ha (83.15%) to 17,880.9 ha (31.52%) since 1991 [1]. Tackling illegal extraction and land crime fast enough through the Guatemalan government and associated partners is challenging because of the large 6.7 million hectares of forest [4].

Several studies have monitored and estimated long-term deforestation using optical and radar satellite imagery [1, 5] however at the time of this paper, this is limited to time-series analysis and does not use deep learning to track near real-time changes.

Deimos has been working on deep learning algorithms for pixel segmentation in satellite imagery since 2016. Initial work was based on the Visual Geometry Group (VGG) algorithm [2] and further work has included successful detection of palm trees, roads and cars, all using deep neural networks [3].

In collaboration with Astrosat and Telespazio, and under the UK Space Agency International Partnership Programme, this study aims to support Guatemalan agencies by providing remote sensing data and derived information for three applications: illegal logging, forest fire scars and plantation monitoring.

The objective is to create a Forestry Management And Protection (FMAP) tool to monitor forestry changes in near real-time and ultimately deliver early warnings using the latest available satellite imagery. This could then be utilised by all stakeholders to protect and prevent any illegal activity.

2. STUDY SITE & DATASET

The study focuses on three priority areas in Guatemala: Laguna Del Tigre and Sierra Del Lancadon Natural Parks located in the north of Guatemala and Alta Verapaz located in central Guatemala (figure 1).

The dataset for all three applications consisted of Sentinel-2 optical imagery (13 bands, 10 metre resolution) over Guatemala obtained from the European Space Agency (ESA) Copernicus service, as well as very high-resolution imagery from Digital Globe and Planet platforms that were used as validation sources for the changes.

Figure 1. Study areas in Guatemala (Bing Aerial as the background map).

To supplement fire location detection, an archive of daily fire data known as Fire Information for Resource Management System (FIRMS), provided by NASA's Moderate Resolution Imaging Spectroradiometer (MODIS, at 1 km resolution) and Visible Infrared Imaging Radiometer Suite (VIIRS, at 375 m resolution) was also used.

Finally, ground truth in the form of GPS coordinates were provided by the Guatemalan government in locations of recent, legal logging activities.

3. ALGORITHMS

Ideally, an abundance of labelled training data is required for deep learning, however in this absence, Deimos experimented with shallow convolutional neural networks (see figure 2). The network consisted of layers such as Convolution2D, Dropout and MaxPooling2D and was trained to detect a change between images. Two input images were used and the output was a labelled map of pixel changes.

Training was adapted for each application by varying parameters such as sample size, filter size and number of layers to produce the most optimum model. Training data were augmented using geometric (e.g. rotation, flipping, scaling, shearing) and radiometric (e.g. brightness) transformations. The training dataset included satellite image pairs over the years 2017 and 2018, with or without clouds.

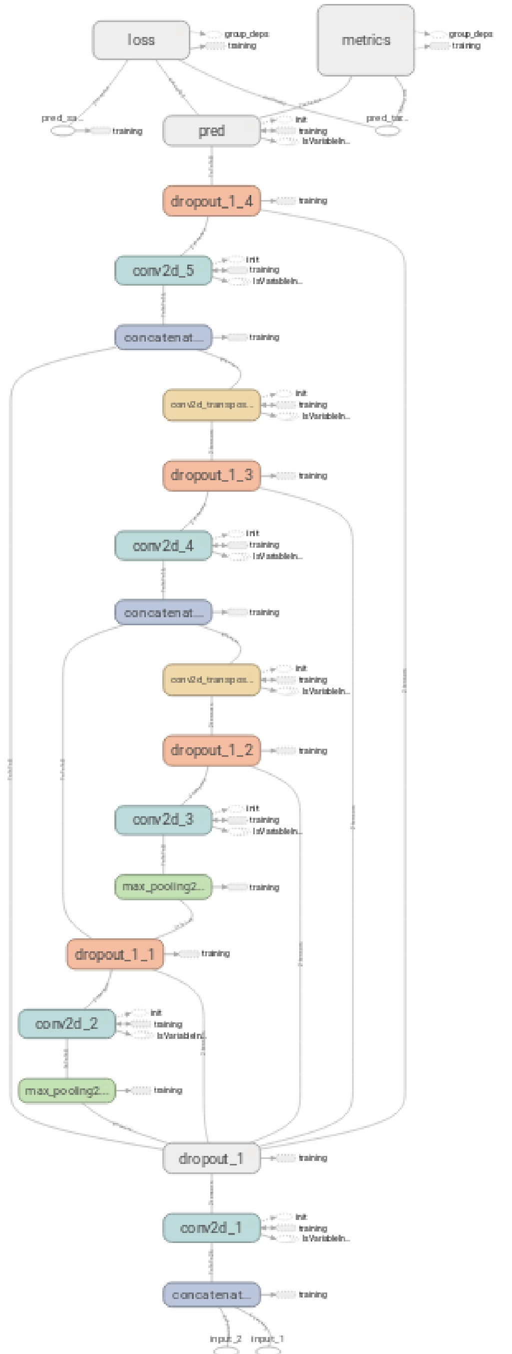

Figure 2. Example of CNN graph used for change detection on Sentinel-2 imagery.

4. APPLICATIONS

A. (ILLEGAL) LOGGING DETECTION

It is important to note that the algorithm is trained to detect logging activities and we cannot confirm at this stage if they are legal or illegal logging. Some of the data used for training and validation are actually legal logging and controlled activities.

Pairs of Sentinel-2 images acting as ‘before’ and ‘after’ known logging events were used to manually create labelled vector data of both single and larger cut tree areas (figure 3). Often, patterns of change were seen between images; single pixel changes to begin, to additional adjacent pixels, indicating repeat activity.

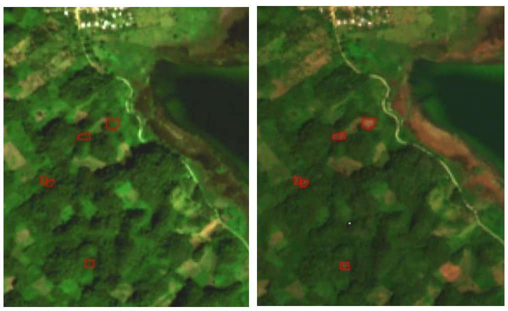

Figure 3. Left to right: Sentinel-2 imagery before and after logging event. Red polygons were manually created over areas of forest change and were used for training data.

High resolution Worldview-02/GeoEye-01 (0.46 m resolution) and Planet (3.0 m resolution) images were used for the same dates to aid manual detection and validate training data created on the Sentinel-2 images.

The preliminary results were encouraging as the majority (> 85%) of visible changes were successfully detected (figure 4).

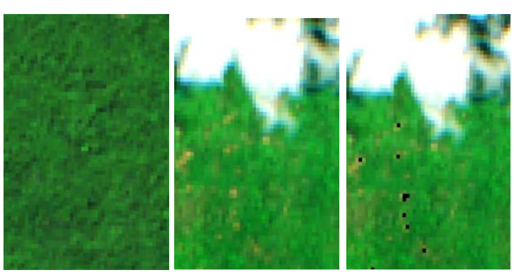

Figure 4. *Example of classification results of cut trees. Left to right: Sentinel-2 image before, image after, and classification map overlaid.*

In the case of very small changes, correct detection is challenging; single cut trees are difficult to detect on 10m resolution Sentinel-2 imagery and depend on canopy size; and in some cases, a shift between ‘before’ and ‘after’ images has been observed where imagery has not been perfectly georeferenced. In addition, training data are highly imbalanced; most pixels represent the ‘no-change’ class and only a few pixels represent the definite ‘change’ class.

B. FIRE FOREST SCARS DETECTION

The second application looked at detecting forest fire scars. Using a similar approach, the Deimos change detection algorithm was applied on pairs of Sentinel-2 images to detect fire damage in forested areas.

NASA FIRMS fire archive data (used as ground truth) from the same timeframe was overlaid on two Sentinel-2 images and manual training data was produced. Accuracies of FIRMS archive data were up to 1 km. Figure 5 shows a manually-labelled area of change between two Sentinel-2 images.

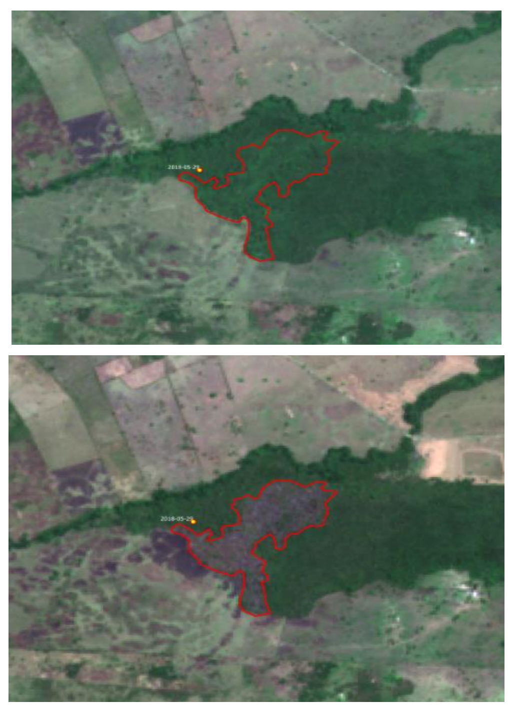

Figure 5. Fire forest scar labelled on a pair of Sentinel-2 images, with NIRS fire point from FIRMS.

Visual inspections were carried out alongside an evaluation algorithm that compared output classification maps with manually labelled changes.

Figure 6 shows an example output map of fire detection results using the custom shallow neural network, with overlaid FIRMS fire data (including non-forest fire). Orange patches represent detected burnt areas whilst red circles represent fire location uncertainties.

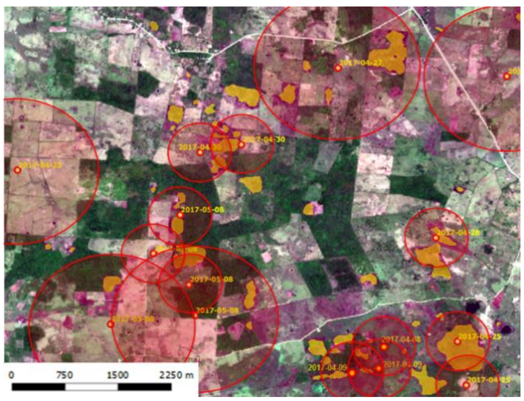

Figure 6. Example of fire burns detection in orange using a custom shallow neural network.

C. MONITORING FOREST PLANTATIONS

The Guatemalan partner institutions include: the National Forestry Institute (INAB), the National Council of Protected Areas (CONAP) and the Ministry of Agriculture (MAGA) amongst others. INAB and CONAP currently run a set of programmes to promote the recovery, restoration, management and production of the Guatemalan forests, and the incentive programme has already successfully registered more than 30,000 new forested areas.

The work of forest plantations monitoring is on-going and the aim is to use machine learning to assess the age of the trees, species and distance between trees using Sentinel-2 imagery, ultimately to help CONAP and INAB address the challenges of sending field workers to check necessary requirements are met for the claimed incentives.

5. CONCLUSIONS

The shallow neural network has been successfully used in two applications related to forestry monitoring and work is in progress to develop tools to monitor plantations. Later in 2019, a demonstration will be delivered to Guatemalan partners for evaluation. The goal is to deliver an automated, operational service, which will use the latest image acquisitions alongside older imagery to detect most recent changes in forest cover.

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