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Cloud-based Deep Learning system for on-demand Near Real Time flood modeling using SAR data

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1. INTRODUCTION

Floods are one of the most common yet most destructive natural hazards around the world. Floods can also be devastating in economic terms: in 2018 alone, the worldwide economic loss due to floods reached up to 82 billion US dollars [1].

This research is focused on the design and deployment of scalable cloud-based Deep Learning systems for on-demand Near Real Time modeling and prediction of flooding. Our system employs Convolutional Long-Short Term Memory (ConvLSTM) models to predict the next image in a time series, which can then be compared to the real world observation to detect inundated areas. Results from study cases in Australia, Mozambique and Brazil show high accuracy, as measured by Cohen's Kappa: 0.92, 0.78 and 0.68, respectively.

2. OBJECTIVES

To construct a Cloud Deep Learning-based framework for modeling of patterns in Synthetic Aperture Radar (SAR) intensity time series useful for flood detection and mapping.

3. METHODS

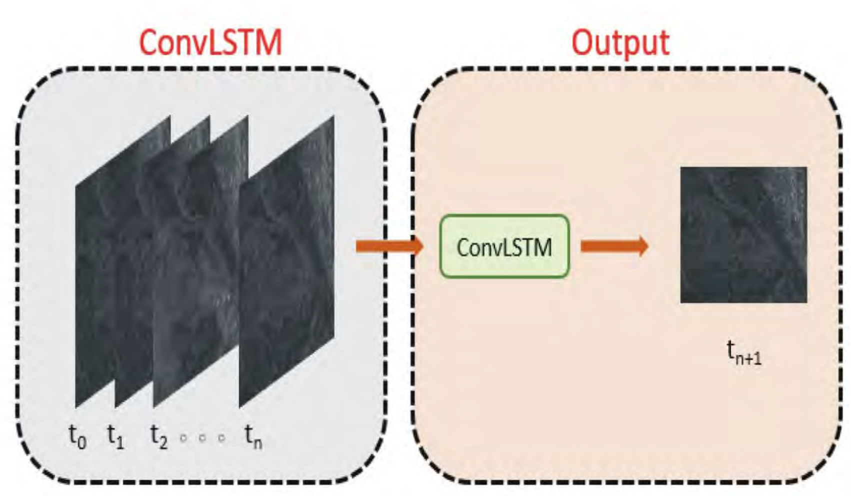

Figure 1. Representation of input and output of ConvLSTM model

ConvLSTM input and output elements, are 3-D tensors that preserve the spatial structure of the data [3,4]. We believe that by levering the strong representational power of a model with stacked ConvLSTM layers, we can generate a prediction backscattering image given a sequence of previously observed scenes, even over areas with complex dynamics.

The model architecture utilized in this study is as follows: 3 ConvLSTM layers with 20 cells in each layer, with convolutional filter size of 3, and with one 3D convolutional layer at the top that generates the final prediction.

4. RESULTS

In the Australia case, ConvLSTM models produced flood maps with the highest classification accuracy compared to baseline models. The Cohen's Kappa coefficient were 0.93 and 0.92, for co- and cross-polarization, respectively. Similarly, ConvLSTM outperformed the rest of the models in our Mozambique dataset in both polarizations, achieving Kappa values of 0.75 (VV) and 0.78 (VH).

In the Brazil site, ConvLSTM was still able to generate moderately good results (Kappa of 0.66) when the cross-polarized dataset was used, showing the applicability of our proposed method in areas where traditional SAR-based change detection methods struggle, such as mountainous and vegetated areas.

Figure 2. Location of the three study sites. Brumadinho, Brazil (A), Queensland, Australia (B), and Mozambique (C)

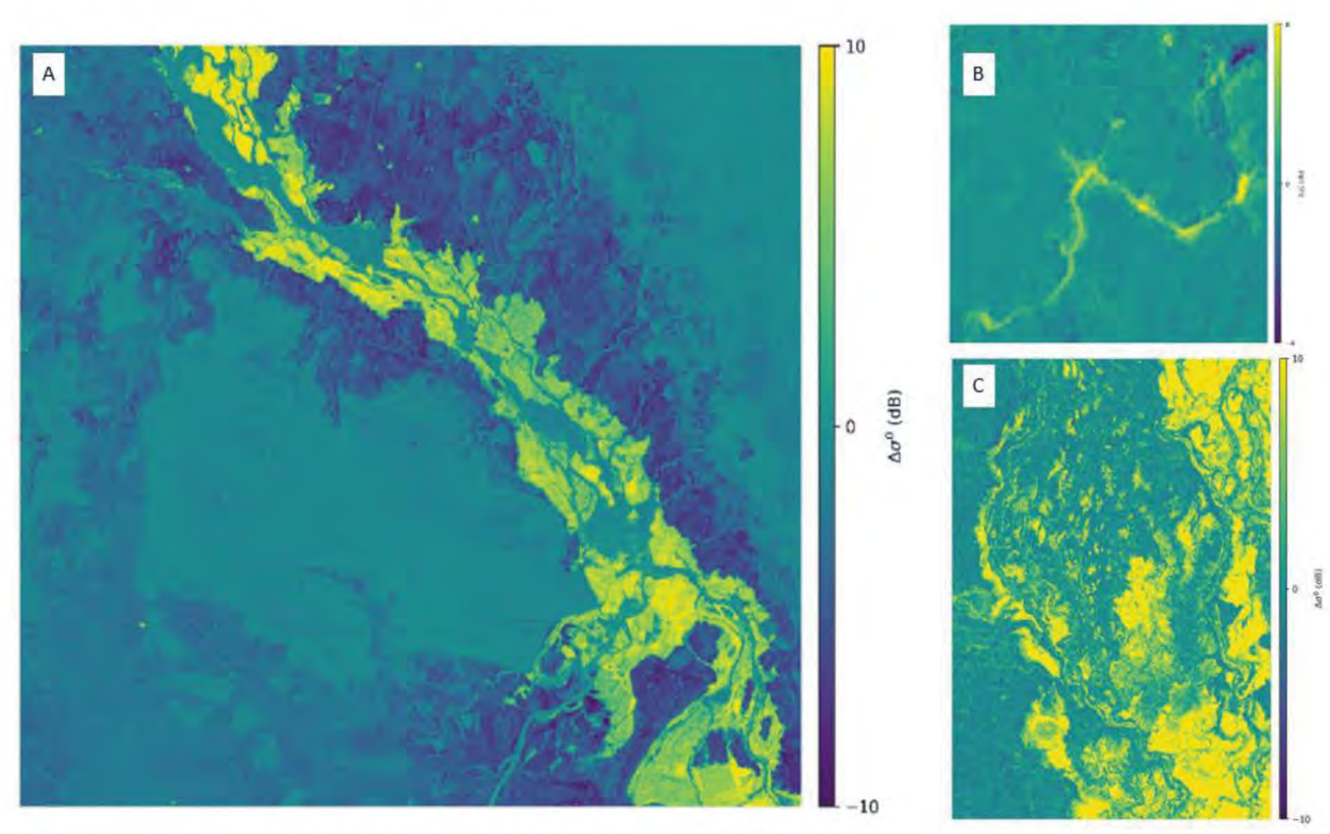

Figure 3. Results for Australia (A), Brazil (B) and Mozambique (C) study sites. The images represent the difference between predicted and detected images at the time of the event. Flooded areas are show large intensity delta (e.g. areas with yellow cast)

5. SOC Platform

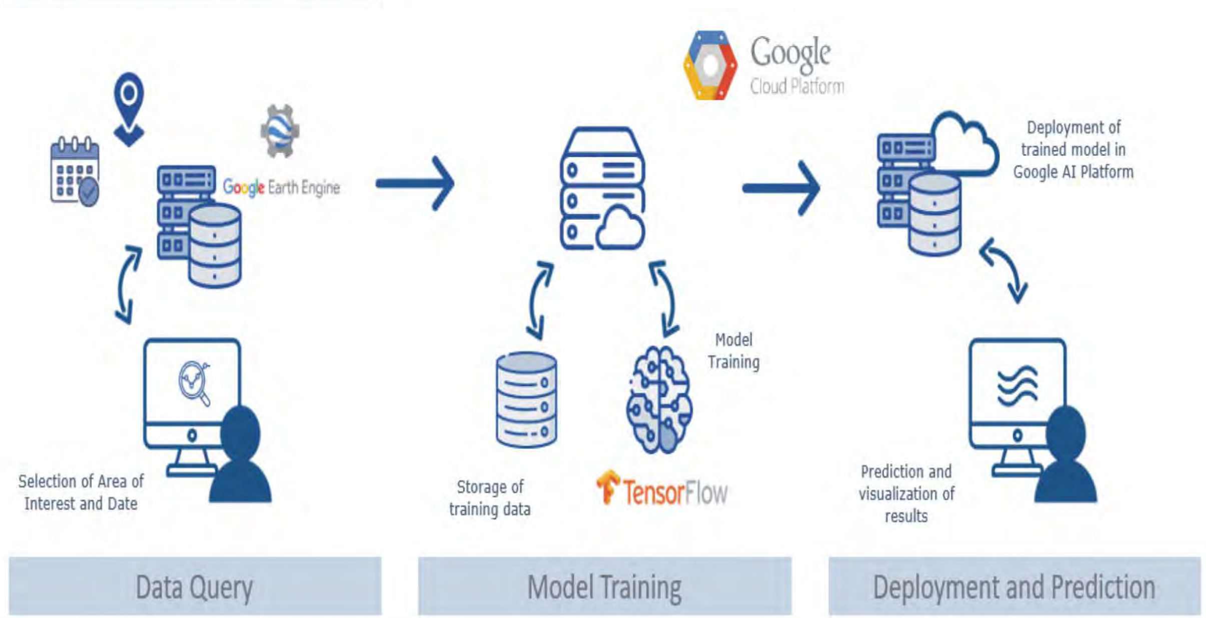

Figure 4. SOC ConvLSTM System Framework

A product that was derived from the work of this dissertation is the SOC ConvLSTM (Scalable, On-demand, Cloud-based) system. This system, currently in development and with Alpha Build provided as a demo only, offers users the option of performing on-demand training of deep learning models (i.e. ConvLSTM) on the Google Platform using data streamed directly from Google Earth Engine for time series prediction and flood detection.

The scalable component refers to this system's ability to allocate the necessary computational resources in accordance to the amount of data to be analyzed: regional or continental analysis demand much higher resources than local ones. A representation of the system's framework can be seen in Figure 4.

The application of the SOC ConvLSTM is limited to flood detection and mapping. The system is built so that, with minor modifications to the source code, many different real world problems such as deforestation, draughts, landslides, etcetera, that can be analyzed.

6. Publications

Chiang, S.-H., & Ulloa, N.I.. Mapping and Tracking Forest Burnt Areas in the Indio Maiz Biological Reserve Using Sentinel-3 SLSTR and VIIRS-DNB Imagery. Sensors, 19(24), 5423. (2019) SCI Journal (Engineering, Electrical & Electronic)

Ulloa, N.I., Chiang, S.-H., & Yun, S.-H. Flood Proxy Mapping with Normalized Difference Sigma-Naught Index and Shannon's Entropy. Remote Sensing, 12(9), 1384. (2020) SCI Journal (Remote Sensing)

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4. A. Kumar, T. Islam, Y. Sekimoto, C. Mattmann, and B. Wilson, "Convcast: An embedded convolutional LSTM based architecture for precipitation nowcasting using satellite data," PLOS ONE, vol. 15, no. 3, p. e0230114, 2020.