# NOAA ROSES Semi-Annual Report

**Reporting Period: September 2021 – February 2022 (3rd report)**

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**Project Title**: Development of a Next-Generation Science-Quality Geostationary Satellite Active Fire Product

## Executive Summary

Our focus during this reporting period was on 1) delivering multi-layer perceptron (MLP) pixel-based fire detection software for testing in the NOAA/NESDIS near-real time processing environment, and 2) recommending targeted FDC algorithm refinements and code improvements for inclusion into the research-grade FDC software.

## Progress toward FY21 Milestones and Relevant Findings

*Software and Algorithm Refinement*

During this period we completed a software wrapper that will permit us to run and test portions of the research-grade FDC algorithm software outside the full Geocart environment. Following our FDC software review and testing, we provided the first block of a planned series of algorithm refinements and code recommendations, which include an improved cloud mask to help mitigate commission errors (i.e., false fires) in the proximity of cloud edges and along coastline (Figure 1).

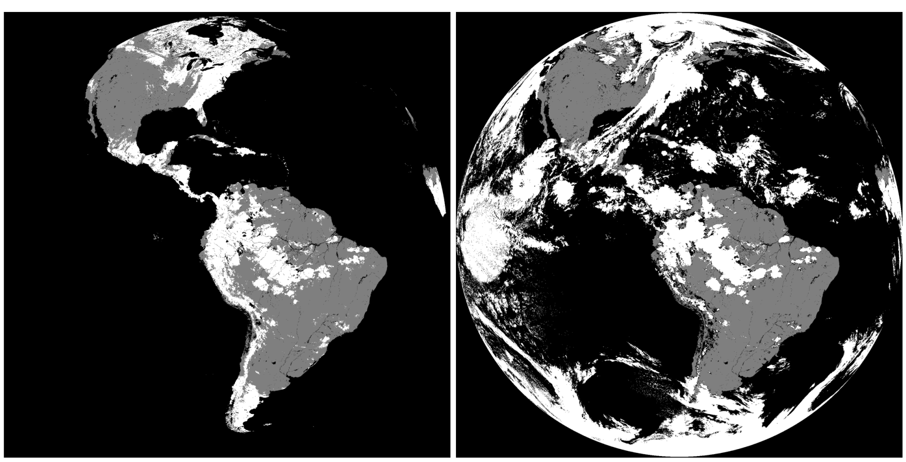

Figure 1: Example of existing FDC internal cloud mask (left) and proposed cloud mask (right) for GOES-16 ABI full-disk scan acquired on 30 Sep. 2020 at 00:00 UTC (white = cloud pixels, grey = clear land pixels). Unlike the existing FDC cloud mask, the proposed replacement functions over water.

*Machine Learning Analysis*

In early 2022 we delivered to NOAA/NESDIS our MLP pixel-based fire detection software for testing in their near-real time processing environment. Our initial accuracy assessment using additional training data (Figure 2) showed improvement over the current FDC product. We are now developing a Convolutional Neural Network (CNN) patch-based model to improve upon our MLP pixel-based results. Drawing on lessons learned from our MLP-based approach, the CNN model is designed to include additional features related to sun angle, latitude/longitude (as a proxy for pixel size), and the land-water state. Current efforts are focused on determining the optimum training/testing window and patch sizes to ensure there is sufficient fire-relevant contextual information within the smaller patches for the CNN model to exploit without being overwhelmed by background information. Additional testing with regard to feature scaling is underway to ensure standardization across the input variables.

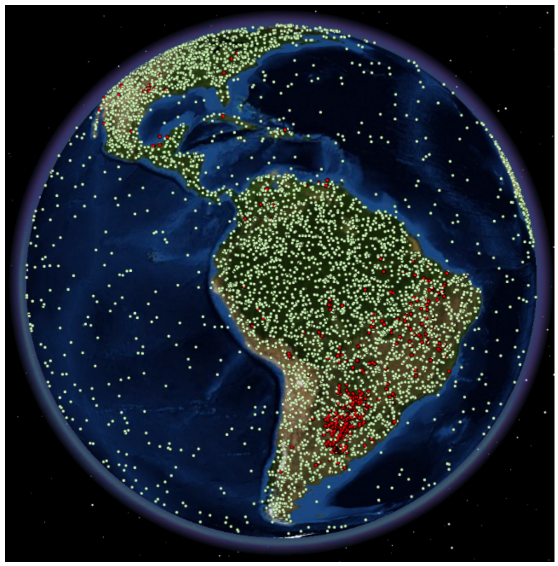

Figure 2: Distribution of training samples from the GOES-16 ABI full-disk frame acquired on 14 July 2020. Red dots represent fires, while green dots represent non-fire samples. While more than 760,000 training pixels were sampled throughout the full day, only samples from the 10-minute period from 19:20 to 19:30 UTC are shown to reduce clutter.

## Plans for Next Reporting Period

1. Make additional targeted additions to our training data set to support the machine-learning component of the project.
2. Complete development of a CNN patch-based machine-learning model to improve upon our MLP pixel-based results.
3. Recommend additional algorithm refinements and code improvements for incorporation into the research-grade FDC software.
4. Coordinate our product-level FDC recommendations with existing NOAA/NESDIS efforts toward this goal.
5. Commence GOFC regional coordination as part of the first post-covid GOFC Fire Implementation Team meeting (now deferred to 21–23 June 2022).
6. Collaborator C. Schmidt will provide updated FDC outputs to facilitate validation of this forthcoming version of the FDC product with our pool of Landsat-based reference imagery.