A MACHINE LEARNING SOLUTION FOR OPERATIONAL REMOTE SENSING OF ACTIVE WILDFIRES

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ABSTRACT

Quantitative wildfire behavior data is invaluable for model development and real-time situational awareness during a fire emergency. However, there exists at present no scalable solution to acquire consistent information about active forest fires that is both spatially and temporally explicit. Spaceborne sensors must meet exigent tradeoffs between spatial and temporal resolution, and there is no single platform that allows detailed measurement of fire behaviour from space. To overcome this limitation, we developed a machine learning solution designed to leverage the complementary features of various remote sensing platforms. Our system relies on a machine learning algorithm to statistically downscale Geostationary (GEO) satellite imagery and continuously monitor active fire location with the spatial resolution typical of Low Earth Orbit (LEO) sensors. In order to achieve this, the model trains on LEO imagery, land use information, vegetation properties, and terrain data. This paper describes the system architecture and demonstrates its performance in two case studies. Results presented here prove the viability of the proposed strategy and encourage further development.

***Index Terms*—** Wildland fire, remote sensing, fire management, decision support, machine learning, fire spread

1. INTRODUCTION

The number of stakeholders, from on-the-ground firefighters to emergency managers and city mayors, involved in determining and executing an evacuation order during a wildfire requires shared intelligence on fire behavior and its impact, especially for events that occur in regions with vulnerable populations [1, 2]. Critical decisions during a wildfire need to be made based on data about fire front location, fire spread characteristics, and demographics of the population that may be impacted, all of which have variable degrees of uncertainty. Improving decision making capabilities requires reduction of these uncertainties, which makes the collection of data from wildfires critical not only for individual events but also to better characterize wildland fire spread and improve models for future events [3, 4].

Remote sensing provides valuable opportunities to gather fire behavior intelligence, mostly in the form of active fire location, rate of spread and radiated energy. Among remote sensing platforms suitable for wildfire monitoring, airborne systems usually provide enough resolution to achieve detailed fire progression mapping. However, they must be deployed during an emergency, which may not always be possible due to safety and financial constraints. In addition, they do not offer temporal consistency in data collection [5] and the significant variety of available sensors hinder standardized data processing [6]. On the contrary, Earth Observation (EO) satellites are highly reliable and provide a consistent stream of data. EO sensors have been thoroughly validated and their behavior can be predicted. The main limitation of spaceborne wildfire monitoring is the lack of spatial and/or temporal resolution.

The most widely used spaceborne EO platforms work on either Geosynchronous Equatorial Orbits (GEO) or Low Earth Orbits (LEO). On the one hand, GEO sensors allow observing the Earth at high temporal resolution but they have significant restrictions on spatial resolution. Moreover, wildfire monitoring sensors usually operate in mid-wave and long-wave infrared ranges, which further limits image resolution. On the other hand, LEO satellites fly closer to the Earth but they typically provide 2-4 snapshots of the same area per day [7]. Both GEO and LEO platforms have been used operationally for fire monitoring, but their use requires a compromise between pixel size and temporal resolution [8, 9, 10, 11, 12, 13, 14].

Nonetheless, GEO and LEO data are complementary and existing Artificial Intelligence (AI) algorithms provide suitable strategies to fuse them and achieve detailed wildfire monitoring at high spatial and temporal resolution. In this paper, we demonstrate the applicability of AI techniques to the detailed monitoring of active forest fires from space. The proposed system architecture is described and its accuracy is demonstrated in two case studies.

2. SYSTEM ARCHITECTURE

The proposed system is based on a statistical downscaling algorithm used to increase the spatial resolution when locating active fire pixels within a GEO satellite image. In order to achieve this, a U-Net Convolutional Neural Network [15] was designed to be trained on LEO active fire products and auxiliary terrain, vegetation and land use data. The use of remote sensing products for labelling instead of manual annotation allowed automating the training process, which enabled continuous system improvement and seamless integration of newly available data. Figure 1 outlines all system components and their connections.

Terrain, vegetation, and land use information were manually downloaded from the LANDFIRE program repository[1]. Since this information is not expected to vary frequently, our system treats these layers as static. Nonetheless, these static layers can be easily updated whenever new versions become available.

Dynamic fire classification features are derived from geostationary multispectral imagery provided by the Advanced Baseline Imager (ABI) sensor installed aboard the National Oceanic and Atmospheric Administration's (NOAA) GOES-16 spaceborne platform. Our fire monitoring system automatically ingests ABI imagery of the Contiguous US every 5 minutes. GOES imagery is made available through the NOAA Big Data Project [16] at a spatial resolution between $0.5km$ and $2km$. Six different multispectral bands are used, ranging from visible red ($0.64\mu m$) to long-wave infrared ($12.3\mu m$).

Finally, LEO labelling data necessary for training is obtained from the Visible Infrared Imaging Radiometer Suite (VIIRS) active fire product (VNP14IMGTDL_NRT). The VIIRS sensor flies aboard the joint NASA/NOAA Suomi National Polar-orbiting Partnership (Suomi-NPP) satellite. Suomi-NPP is a Low-Earth Orbit satellite that observes the Earth's surface twice every 24 hours. The active fire product belongs to a group of Near-Real Time (NRT) data products which become available shortly after their acquisition. Additionally, NRT data is further processed and archived in the form of higher level products.

3. CASE STUDY RESULTS

The proposed monitoring framework was demonstrated in two case studies as proof of concept. System deployment was simulated *a posteriori* in two of the most destructive wildfires recently occurred in California: the 2017 Tubbs and the 2018 Camp fires. In both cases, a U-Net model was used after being trained on a set of over 200 wildfire events occurred in California between July 2017 and August 2018. Neither of the validation events was included in the training dataset.

Our monitoring system was used to resolve active fire pixels at 30-minute intervals with 375-m spatial resolution. This information was processed to reconstruct fire progression, which was validated against the fire evolution archives reported by the Geospatial Multi-Agency Coordination (GeoMAC). The GeoMAC database, maintained by the United States Geological Survey (USGS), compiles fire spread information received from incident intelligence sources, GPS data, infrared imagery from fixed wing aircraft and satellite imagery[2]. Fire perimeter data in GeoMAC is updated daily leveraging data provided by other public agencies such as the National Interagency Fire Center (NIFC), the US Forest Service (USFS), the National Aeronautics and Space Administration (NASA), the Bureau of Land Management (BLM) and the National Oceanic and Atmospheric Administration (NOAA). Therefore, GeoMAC perimeters represent the most reliable ground truth data about wildfire evolution available in the US.

Figure 2 shows a qualitative comparison of the reconstructed fire evolution with the final burned perimeter reported by GeoMAC. In addition, quantitative accuracy metrics are presented in Table 1. Quantitative metrics were computed at the time of the GeoMAC perimeter in each case.

4. CONCLUDING REMARKS

This article presents the design and initial validation results of a machine learning platform for detailed monitoring of active forest fires using remote sensing data. Through the combination of GOES and VIIRS imagery, terrain, vegetation and land-use information, a U-Net was able to track fire perimeter evolution at 5-min time intervals with 375-m spatial resolution. The novelty of our approach resides in the introduction of state-of-the art artificial intelligence techniques and the meaningful combination of available data sources to provide a new solution to an existing limitation.

This work presents the system architecture and its validation in two case studies. Obtained results are encouraging and demonstrate that operational wildfire monitoring is possible with existing remote sensing data. Future work includes the optimization of model parameters as well as a additional validation using an extensive fire database.

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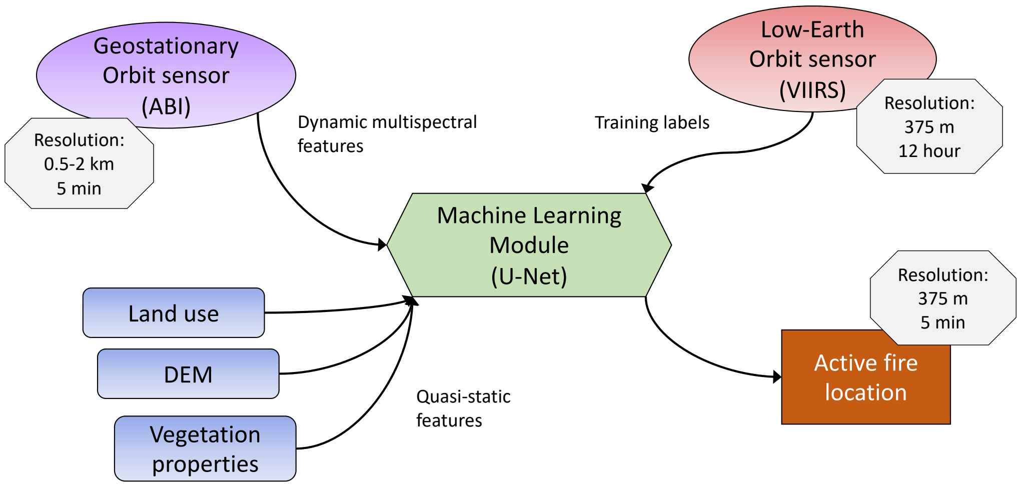
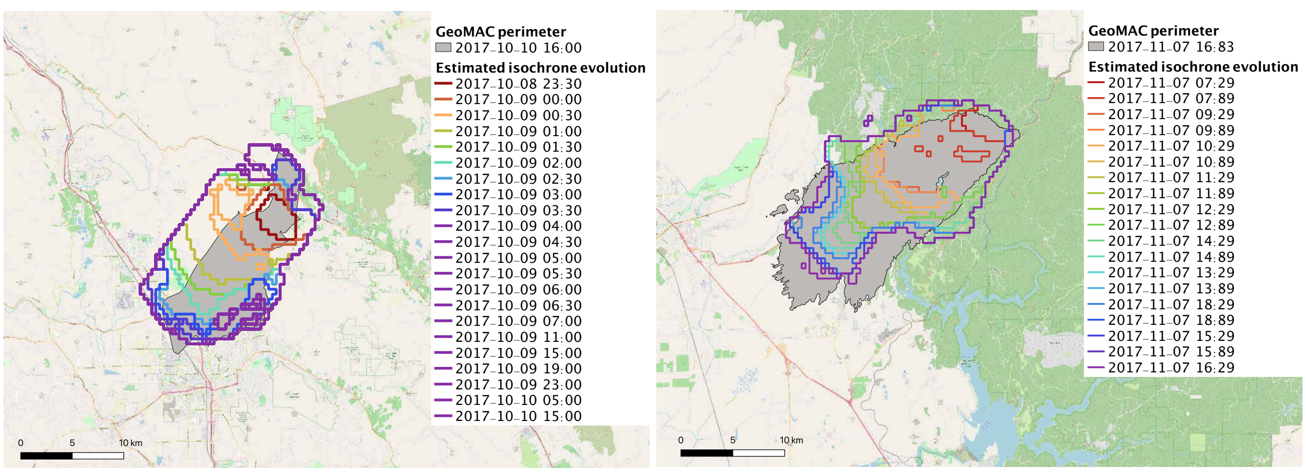


Fig. 1. Block diagram of the proposed framework for high resolution continuous monitoring of active wildland fires.



(a) 2017 Tubbs fire (California, USA)

(b) 2018 Camp fire (California, USA)

Fig. 2. Half-hourly fire progression estimated using the proposed algorithm (color isochrones) in two case studies, compared to official GeoMAC perimeters. All times are local. Map data provided by OpenStreetMap [17].

Table 1. Performance metrics computed for the fire isochrone closest in time to the available GeoMAC perimeters. TP, true positive; FP, false positive; FN, false negative. Precision = TP/(TP+FP); Recall = TP/(TP+FN); F-measure=2*Precision*Recall/(Precision+Recall); CSI, Critical Success Index = TP/(TP+FP+FN).

Fire event	TP rate	FP rate	FN rate	Precision	Recall	F-measure	CSI
2017 Tubbs	0.947	0.853	0.053	0.526	0.947	0.676	0.511
2018 Camp	0.771	0.194	0.229	0.799	0.771	0.785	0.646

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