Rapid Response to the 2014 King Fire: Final Report

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Executive Summary

In September 2014, the California King megafire burned 97,717 acres (~39,545 ha) in the mixed conifer forests in the Sierra Nevada Mountains. This fire was a classic case of an emerging class of megafires changing the landscape of the Western US. Because of the pre-HyspIRI airborne campaign covering ~40% of California 3-4 times per year from 2013-2015, images of before, during, and after the King Fire were obtained using visible to shortwave infrared imaging spectroscopy (AVIRIS) and multi-band thermal infrared (MASTER). Additionally in 2012 part of the area burned by the King Fire was surveyed using Light Detection And Ranging (LiDAR). To complement these observations, we proposed to acquisition the fire area with a 2 km buffer immediately post-fire using LiDAR to capture observations of changes in forest structure and topography. In order to obtain a high spatial resolution topographic map and create a baseline for fire science and ecology, LiDAR had to be flown before snowfall in the area. These data were then used in immediate post-fire mitigation activities with the US Department of Agriculture (USDA) Forest Service.

Introduction

In recent years there has been an increase in the occurrence of wildfires of extreme size, economic cost, and likely long-term ecological and hydrological impacts (i.e., megafires). Many of these fires cost millions in fire suppression alone (http://inciweb.nwgc.gov) as well as consuming natural resources and structures, and damaging water resources (e.g., from erosion an additional stress in already drought-impacted regions). Thus, there is a need to improve understanding of these how these fires behave. However, because megafires exhibit behavior different from other fires [1–3], they are poorly understood. For example, extreme weather in the weeks leading up to and post-ignition[2] distinguish large fires across the western United States from other fire, and the effects from other controls (e.g. forest management practices[4]) can be neutralized[5,6]. Furthermore, large fires create their own meteorology[3], which is not captured in traditional fire behavior models that are used in active fire management. Also contributing to our lack of understanding of drivers of megafires are the historically rare nature of these events[7]. Nevertheless, with increasing extreme events like drought and heat waves[8,9], and projected increases of megafire occurrence[10,11], there is urgency to understanding what drives such fires.

Fortuitously, Sept. 13 through Oct. 9, 2014, the California King Megafire (38.782°N,120.604°W) burned areas recently flown using remote sensing technologies capable of high spatial resolution mapping of vegetation type, condition, amount, and structure. These technologies include visible to shortwave infrared imaging spectrometer (AVIRIS), the high-spatial resolution multi-band thermal infrared imager (MASTER) and Light Detection and Ranging (LiDAR). By January 2015, after the fire had extinguished the full fire perimeter with a 2 km buffer had been survey again using all three technologies. This rare opportunity of unprecedented remote sensing data before, during, and after a megafire, provides the necessary data to analyze megafire behavior and influencing agents.

Proposed Objectives

This project provides data critical to address two key objectives for both science and land resource management:

1. **understanding the behavior and post-fire ecological recovery for these new megafires** by advancing basic science needed to forecast and respond to megafires. This includes improving models of fire behavior to better predict megafires by capturing wildfire-driven meteorology from the King Fire and characterizing key influencing agents across space and time.
2. **informing immediate post-fire and long term management response to the fire by numerous stakeholder agencies and organizations**; specifically by providing necessary data products to partner agencies including post-fire forest structure and condition. Immediate post-fire management requires mapping the environmental change since fire (e.g., fire severity and structural changes) within the first few months post-fire so that recovery and restoration mitigation can begin before the next growing season. Longer-term, improved understanding of megafire behavior can inform management decisions such as fuel treatments and harvesting plans.

These objectives address NASA Applied Sciences goals of:

- using NASA's capabilities and higher-level derived data products to improve natural disaster forecasting, mitigation and response, and
- aiding to understand the natural processes that produce wildfire hazard, and developing appropriate hazard mitigation approaches.

While these objectives have practical applications, they also address related NASA Terrestrial Ecology goals to improve understanding of the wildfire as a factor in the structure and function, and its interactions with the atmosphere and water cycle. Specifically, this project provides data to study not only megafire behavior, but also the modeling of megafire impacts related to carbon emissions and water resources.

Summary of Activities

Activities for this work included:

1. fire severity ground-truth *in situ* field campaign
2. an airborne campaign with the Airborne Snow Observatory (ASO)
3. processing LiDAR, AVIRIS, and MASTER data into level 2 and 3 data products
4. archiving the data on the Oak Ridge National Laboratory (ORNL) Distributed Active Archive Center (DAAC) (http://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1288), and
5. analyzing the King Fire, fire behavior and drivers.

Post-Fire Data Collection

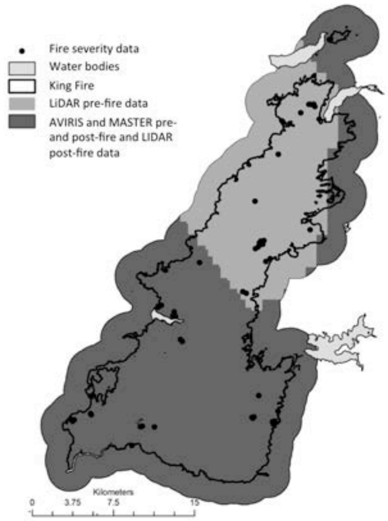

Figure 1. Data coverage pre- and post-King Fire with a 2 km buffer.

Ground truth fire severity data was collected at 52 plots across topographic and vegetation gradients across the King Fire extent from October 2014-January 2015. Fire severity *in situ* data employed a the change since fire metric, Geo Composite Burn Index[12] (GeoCBI)[13]. The GeoCBI is a weighted average of classifications of change since fire across fraction cover of five different strata from substrates to big trees taller than 20 m described by factors such as soil and rock cover/color change and char height. GeoCBI provides a fire severity score between 0 ("no effect") and 3 ("high severity").

As part of the pre-HyspIRI airborne campaign, flights with AVIRIS and MASTER were already scheduled for November 17, 2014. While it would have been ideal to have ASO flown as close to this acquisition date as possible, due to winter storms and aircraft availability, the soonest flight acquisition post-King Fire with the ASO was January 15, 2015. Although multiple rainstorms had occurred resulting in snow at very high elevations and erosion of ash, it was clear skies and no snow accumulation at the time of this acquisition. Data collection information is shown in Table 1 and coverage demonstrated in Figure 1.

Table 1. King Fire sensor and aircraft information.

	Instrument	Sensor	Data Acquisition	Swath width (km)	Pixel size (m)	Data	Platform
King Fire	AVIRIS		19-Sep-13	11	14.6	L2 & L3	ER-2 approximately 20 km above sea level, at about 730 km/hr
			17-Nov-14				
	MASTER		19-Sep-13	35	35		
			19-Sep-14				
			17-Nov-14				
	LiDAR	Optech Gemini	1-7-Nov-12	0.3-0.4	1 to 30	L2	Cessna 337 skymaster approximately 0.6-0.8 km above ground level at about 216 km/hr
		Riegl Q1560	13 & 14-Jan-15	23.28 (ave.)			King Air A90 approximately 2.1 km above ground level at about 333 km/hr

Data Processing

After data collection, all data was processed to Level 2 and Level 3 data products (Table 2). We paraphrase the processing steps here, but details are described both on the DAAC website and in Stavros et al. (in review). For AVIRIS, data was downloaded from the AVIRIS website (http://aviris.jpl.nasa.gov/) as Level 2 orthorectified surface reflectance. Geolocation was then manually adjusted and a bi-direction reflectance function applied. MASTER Level 1b geolocated calibrated radiance for visible to shortwave infrared and Level 2 land surface temperature and emissivity were downloaded from the MASTER website (http://masterweb.jpl.nasa.gov/). The Level 1b was then processed to surface reflectance using MODTRAN (v5.2) radiative transfer model and then topographically corrected using a modified c-correction method[14]. LiDAR data was provided by each vendor as Level 1 point cloud data, which was processed through USFS FUSION/LDV software package[15], version 3, to produce Level 2 mosaicked data files of forest structural metrics. These data products were then quality checked and archived at the ORNL DAAC.

Table 2. Description of data products produced and distributed from this project.

Instrument and Product Level	**Description of data product (*products developed by this project)**
AVIRIS and MASTER	
Level 1	Calibrated, geo-located radiance by flightline
Level 2*	Orthorectified, atmospherically- and topographically-corrected surface reflectance mosaicked flightlines over the fire extent with a 2 km buffer
Level 3*	Operationally useful metrics (e.g., Normalized Difference Vegetation Index – NDVI) from Level 2 over the fire extent with 2 km buffer
LiDAR	
Level 1*	Point cloud
Level 2*	Topography and forest canopy metrics over the fire extent with 2 km buffer

Data Archiving

Data has been archived with the Oak Ridge National Laboratory (ORNL) Distributed Active Archive Center (DAAC), with the following citation:

Stavros, E.N., Z. Tane, V. Kane, S. Veraverbeke, R. McGaughey, J.A. Lutz, C. Ramirez, and D.S. Schimel. 2015. Remote Sensing Data before and after California Rim and King Forest Fires, 2010-2015. ORNL DAAC, Oak Ridge, Tennessee, USA. http://dx.doi.org/10.3334/ORNLDAAC/1288

Research and Analysis

Although AVIRIS and MASTER data cover the full extent of the fire before, during, and after the King Fire, LiDAR data only covered ~34% of the extent. We used quadratic regression ($0.53 < R^2 < 0.86$) to extrapolate post-fire LiDAR structural metrics to the full extent of the fire before burning. Using these structural data with dominant vegetation maps generated using weighted multiple endmember spectral mixture analysis (wMEMSA) from AVIRIS (Figure 2), we generated high-resolution fuel model maps (Figure 3). Fuel models are categorical classifications that summarize fuel type, structure, amount and potential fire behavior. These fuel models were used as input to CAWFE™, a high spatial (375 m pixel) and temporal (1 minute) resolution coupled weather-fire simulator[16]. Although other fire models did not represent the King Fire very well, CAWFE did capture the unanticipated surge up the Rubicon Valley and features captured by MASTER resulted from fine-scale mountain airflows and periods of growth apparently driven by fire-induced winds. Results indicate remote sensing tools may be used to optimize data products for fire science and operations.

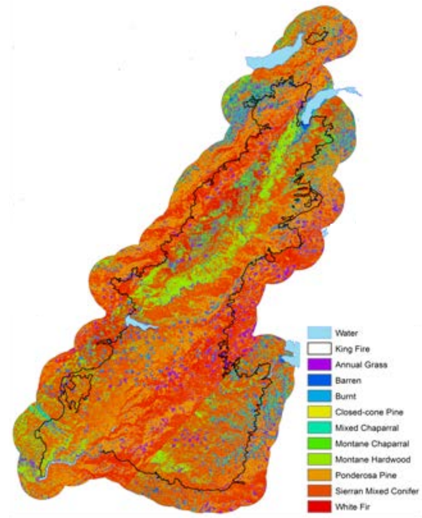

Figure 2. Top of canopy dominant vegetation type derived from weighted multiple endmember spectral mixture analysis.

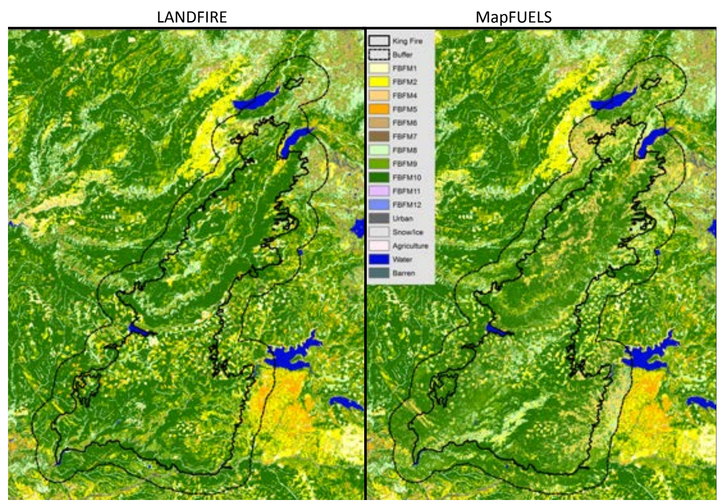

Figure 3. LANDFIRE and MapFUELS fuel model classifications of the 13 Anderson fuel models.

Specifically, we used the data collected over the King Fire to run sensitivity analyses of King Fire behavior simulated by CAWFE to variable, type, structure, amount, and fuel conditions. We tested fire behavior sensitivity to fuel type and structure using two different fuel model maps generated using different techniques (Figure 4). The first was the fire management industry standard, LANDFIRE, which uses Landsat broadband

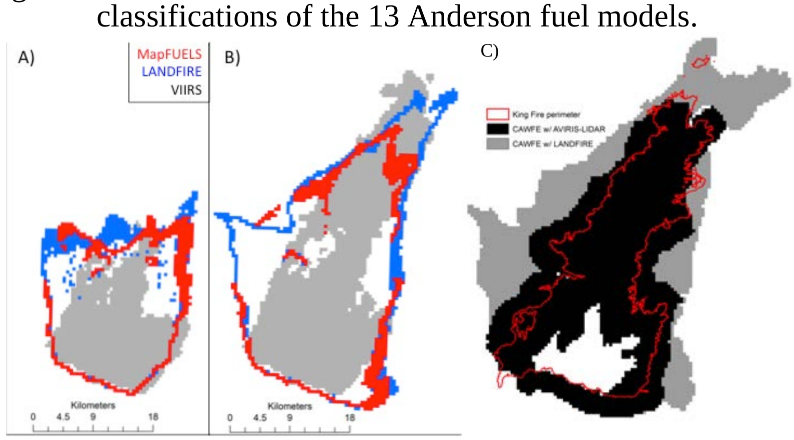

Figure 4. Fire extent on: A) September 17, 2014 1:06 pm, B) September 18, 2014 1:20 am, C) final extent of the fire.

spectral data and dynamic vegetation models to classify fuel models. The second fuel model map, MapFUELS (Mapping Fuels Using Estimates from LiDAR and Spectroscopy), was developed from observations of fuel structure and type derived from LiDAR and AVIRIS respectively. We tested fire behavior sensitivity to fuel amount and fuel conditions by running simulations of CAWFE using fuel model parameterizations spanning the historical range of variability in fuel density and moisture content (Figure 5).

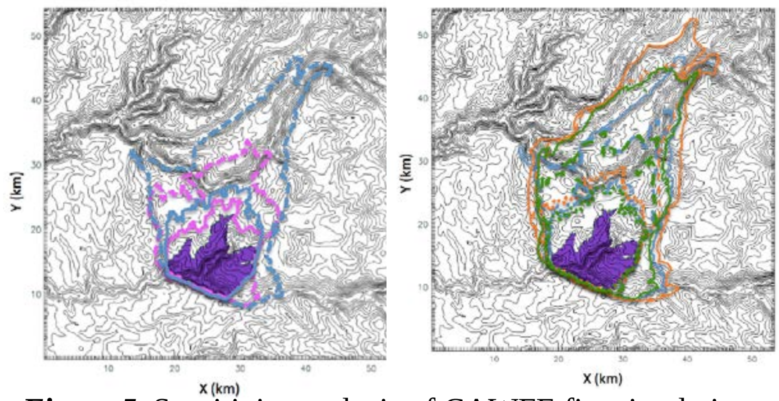

Figure 5. Sensitivity analysis of CAWFE fire simulation of spread rates at different periods during active fire with A) current (blue) and half fuel load and depth (i.e., fuel density) (pink) and B) varied fuel moistures at the historical low (3%; orange), current state (5%; blue), and historical high (8%; green).

There were three major findings from this research. First, fuels matter but they matter differently based on what aspect of fire behavior is considered. Specifically, spread Rate depends on fuel horizontal connectivity and fuel condition, whereas fire Extent depends on fuel type and vertical structure. Second, total heat flux generated by a fire at any given location relates to fire effects, with spread rate having a slightly more influential role in unburned-low severity and fuel type and vertical structure having a slightly more influential role in moderate-high severity. While total heat flux generated by a fire relates to fire effects, it does not entire explain fire effects. Third, contrary to previous thought about extreme fires, neither fuels nor weather are completely responsible for fire behavior and effects. Using the high spatial resolution fuel maps (30 m pixel) and fire simulation (375 m pixel) shows strong coupling in fuels <u>*and*</u> localized fire weather, thus demonstrating the necessity to capture this intrinsic feedback in fire behavior simulation used for active fire detection.

<u>Publications</u>

1. Stavros EN, Tane Z, Kane VR, Veraverbeke S, McGaughey B, Lutz JA, Ramirez C, McGaughey RJ (in review) Unprecedented remote sensing data from before and after California King and Rim Megafires. *Nature Scientific Data.*
2. Stavros EN, Coen J, Signh H, Schimel D (in review) Mapping Fuels Using Estimates from LiDAR-Spectroscopy (MapFUELS) over the 2014 California King Megafire. *Remote Sensing of Environment*.
3. Coen J, Stavros EN, Fites-Kaufman JA, Schimel D (in review) Deconstructing the King Megafire: Impacts of fire-induced winds, drought, fuel buildup, and fuel type. *Proceedings of National Academy of Sciences*.

Application Readiness Level

Although this data was not yet distributed for the Environmental Impact Assessment (typically produced within weeks of a fire), this data is actively providing a baseline for monitoring regeneration post-fire for the USDA Forest Service and other external partners (Carlos Ramirez - Region 5 Remote Sensing Manager, USDA Forest Service, 2016, *personal communication*). Consequently the datasets can be classified as ARL6.

Conclusions

In conclusion, this work has provided data information products that are actively being used by external partner agencies to NASA for post-fire restoration and recovery planning and monitoring. The analyses from this analysis have provided new insights on fire behavior at high spatial and temporal resolutions that can be used to improve both pre-fire fuels management and active fire management decisions by improving understanding of intrinsic fire behavior.

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