A wildfire early warning system from meteorology and land surface temperature

Key Terms: wildfire, water stress, land surface temperature

Motivation: The primary wildfire monitoring system in the United States is the **National Fire Danger Rating System (NFDRS)**[1,2]. NFDRS maps are routinely used by land managers and regional governments to allocate fire mitigation resources and track fire risk. Although NFDRS is a standard risk assessment tool, it faces several disadvantages. Calculation of a NFDRS rating requires advance knowledge of site conditions and manual input of user parameters into closed source software. For non-experts, NFDRS is difficult to use. Despite the complexity of NFDRS, its primary fire danger metric is a coarse 5-level categorical scale (from "low" to "extreme") that cannot be forecasted beyond 24 hours. **This project will improve wildfire modeling with empirical techniques that enable proactive wildfire mitigation and long-term forecasting.**

Objectives: Climate change is expected to produce more intense wildfires more frequently in the American West[3]. Wildfires are intensified by high plant biomass (i.e. fuel load) and low fuel moisture. Both of these factors can be remotely sensed over large areas[4,5]. Given that vascular effects of water stress linger in plants weeks to months after a drought[6], drought conditions early in spring may predispose water-stressed forests to wildfire the following summer.

This project will produce remote sensing data streams of plant water stress and vegetation growth as inputs for an open source wildfire predictive model covering forested regions of the western United States at 1 km^2 spatial resolution. **I hypothesize that (1) water stress in early spring increases wildfire intensity the following summer, (2) fuel load can be estimated from a time series of a vegetation growth index and (3) by measuring these variables in early spring (Fig. 1a), wildfire-prone regions can be identified weeks before ignition (Fig. 1b).** In short, water-stressed locations with high plant biomass will be identified as wildfire hotspots before the fire season begins. I will perform computationally-intensive spatial analysis using open source cloud infrastructure to ensure usability by non-experts.

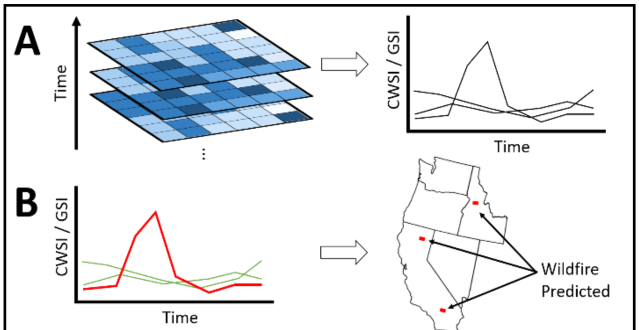

Figure 1. (a) Raster stacks of CWSI and GSI become a time series for each grid cell. (b) Early plant stress may indicate wildfire hotspots.

Aim 1: Calculate and validate water stress index. Water stress can be estimated quantitatively from canopy temperature (i.e. leaf temperature) and vapor pressure deficit using the **crop water stress index (CWSI)**[5]. CWSI is related to evapotranspiration and is applicable to all leaved plants. To calculate CWSI, I will use vapor pressure deficit at daily temporal resolution and 1 km^2 spatial resolution from Daymet, a continuous, gridded meteorological product covering the contiguous United States[7]. To determine canopy temperature, I will use land surface temperature (LST) calibrated with the normalized difference vegetation index (NDVI)[8]. My source of LST and NDVI data will be the Terra MODIS satellite, for which cloud-free, gap-filled LST data have recently been developed[9]. This method of determining canopy temperature requires only occasional NDVI values, so clouds will not prevent canopy temperature measurement[8]. Although MODIS is approaching retirement, its 20-year data archive is desirable. For recent fire years I will also work with the current-generation LST sensor ECOSTRESS. A field campaign will be performed in fire-prone western forests to calibrate CWSI, to validate canopy temperature measurements, and to determine the relationship between CWSI and plant water potential.

<u>Aim 2: Calculate and validate fuel load index.</u> I will employ the **growing season index (GSI)** to estimate fuel load over time. The GSI quantifies how plant growth is limited or unconstrained by humidity, air temperature, or photoperiod[4]. GSI therefore remains measurable under all weather conditions using Daymet data, unlike spectral biomass indices such as the leaf area index. GSI will be validated against *in situ* measurements of fuel load as part of the field campaign in Aim 1.

<u>Aim 3: Model wildfire likelihood.</u> I will use an existing dataset of wildfire occurrence from 2000-2019 to produce annual wildfire presence maps aligned on the same grid as the CWSI and GSI calculations. For each year of data, I will calculate CWSI and GSI for each grid cell at daily temporal resolution from February 1 to May 31 to produce a stack of CWSI and GSI grids through time (Fig. 1a). Possibly, the end of the data collection period will be adjusted later or earlier in the year to optimize model performance and parsimony. Each cell of the raster stack will be inserted into a high-dimensional dataset where each row is a time series of CWSI and GSI values and a single column indicating whether the cell experienced fire that year. I will use the CWSI and GSI time series as predictors in a partial least squares regression (PLSR) model with a logarithm link function. PLSR reprojects the predictor variables in a typical linear regression to a lower-dimensional space that is maximally correlated with the response matrix. PLSR therefore resolves issues with correlated predictor variables and, via weights, identifies which CWSI and GSI measurements contribute most to the model prediction. Wildfire occurrence is a binary response variable, so a logarithm link function will enable calculation of wildfire likelihood for each cell in the modeling area. A variant of PLSR for binary classification tasks, partial least squares discriminant analysis, is also a candidate modeling approach.

I will evaluate the proposed model with standard measures for a binary classifier with an imbalanced response variable. I will also compare the proposed model against NFDRS maps produced on May 31 the same year. **Project success is defined as accurate prediction of 1 km^2 pixels as fire-present or fire-absent, emphasizing a low false negative rate, and a model which land managers prefer over existing NFDRS maps for allocating management resources.**

<u>Intellectual Merit:</u> This study will improve wildfire prediction by employing **empirical methods** and **longer forecasting times.** Improved wildfire modeling will enable proactive wildfire mitigation and clarify factors that drive wildfire occurrence. In particular, this project will produce the most spatially extensive measurement of forest water stress to date and determine how wildfire is influenced by water stress early in the growing season. This study will also demonstrate how remote sensing datasets can be combined to model ecosystem processes.

<u>Broader Impacts:</u> Wildfire intensity and frequency is expected to increase in the American West as climate change continues[3]. Wildland firefighters must effectively allocate tens of billions of dollars to mitigate this annual emergency. Advance warning of fire risk will enable proactive management that utilizes resources effectively. Such warnings also enable the public to avoid injury and property damage. In society at large, less wildfire smoke reduces respiratory illness and avoids air travel disruption. Knowledge of forest response to drought conditions will also improve timber production in the logging industry. All computer code and data products generated by this project will be open source. Model results will be distributed via a non-technical online dashboard. I will demonstrate the analysis workflow at workshops and reach out to potential users who would be interested in using the wildfire model produced by this work.

<u>References:</u> [1] U.S. Forest Service p. INT-GTR-169. [2] W.M. Jolly, National NFDRS 2016 Rollout Workshop (2018). [3] A.P. Williams et al., Earths Future **7**, 892 (2019). [4] W.M. Jolly et al., Glob. Change Biol. **11**, 619 (2005). [5] S.B. Idso et al., Agric. Meteorol. **24**, 45 (1981). [6] C.R. Brodersen et al., Annu. Rev. Plant Biol. **70**, 407 (2019). [7] J.T. Abatzoglou, Int. J. Climatol. **33**, 121 (2013).
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