## Machine learning and artificial intelligence for wildfire prediction

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**Focal Area:** Wildfire ignition, intensity, and spread rates are tightly linked with water cycle extremes. The science of wildfire prediction has traditionally encompassed the use of physical and empirical models to quantify the direction and speed of fire spread, plume injection and fire-aerosol impacts on atmospheric composition, predictions of fire season severity on subseasonal-to-seasonal (S2S) time scales, and assessment of the spatial and temporal patterns of fire risk across landscapes. Together with expanding observation networks, machine learning and artificial intelligence (AI) have the potential to revolutionize the application of such models for fire science, saving lives, protecting critical infrastructure, and providing more accurate estimates of wildfire-climate feedbacks.

**Rationale:** Over the past three years wildfires in the western US have had devastating impacts, including the death of over 100 civilians and firefighters, many tens of billions of dollars of damages to infrastructure, and widespread health and safety concerns from poor air quality. Multiple lines of evidence suggest that the legacy of past land management decisions and climate change together have contributed to increasing trends in burned area over the past several decades. These drivers will continue to spur new extremes in wildfire activity in the foreseeable future. In this context, improved wildfire predictions are needed to improve management outcomes, limit fire damages, and prevent, in many biomes, runaway changes in fire regimes from causing negative impacts to terrestrial ecosystem function, water quality, and biodiversity.

The use of machine learning to improve different classes of fire models has the potential to be transformative. While there has been some initial work using different machine learning approaches for different challenges in fire prediction, the field is nascent. New advances in machine learning can leverage major investments by the U.S. Dept. of Energy in high resolution physics-based fire models that simulate interactions between energy released during combustion, fire behavior, and fire impacts on local and regional atmospheric circulation, as well as the Energy Exascale Earth System Model (E3SM) that simulates regional variations in climate and surface hydrology, which in turn, influence the composition, amount, and moisture status of dead and live fuels.

At the same time, new sensor capabilities, including dual copies of the Visible and Infrared Imaging Radiometer Suite (VIIRS) on NASA Suomi-NPP and NOAA 20 satellites, remote camera networks, drone observations, and expanding surface weather networks provide a data-rich environment needed to train more complex models.

New machine learning approaches are needed to fully exploit the capabilities of new high-resolution physically-based models and fire observations. Key goals, in this context, are: 1) to link fire behavior with water cycle dynamics, 2) to make more accurate predictions of surface winds and fire spread in regions with complex topography, 3) to mimic the performance of dynamical models used to predict the evolution of fire plumes, 4) to provide more accurate maps of fire risk on S2S timescales, and 5) to improve capacity for early fire detection.



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**Narrative:** Here we outline examples of several fire prediction challenges where DOE investments in machine learning and artificial intelligence have the potential to be transformative.

***Fire spread:*** Multiple classes of fire spread models are currently used by research and fire operations communities. Many of these models start with an ignition point (or existing fire front) as an initial condition, and predict how the fire perimeter will evolve over a period of hours to several days using weather forecasts and land surface properties as driver variables. In today's operational fire predictions, local fire spread rates are predicted using empirical functions of fuel type, load, and moisture content, and other environmental variables including wind speed and direction, slope, and aspect. More sophisticated fire models combine fire-process models with atmospheric models, allowing for self-determining capture of the feedbacks from between the fire and surrounding atmosphere including the influences of dynamic winds and heterogeneity in vegetation structure and moisture content. This latter class of models can allow for simulation of fire plumes and pyro-cumulus cloud formation based on burning patterns and rates as well as vegetation conditions, but also requires considerably more computing resources. Key uncertainties with existing physical models are introduced from incomplete or inaccurate information on surface winds, and fuel status (amount, structure, moisture content). When widely used empirical models are used in a stand-alone mode for fire prediction (i.e., not coupled to atmospheric models), one of the biggest shortcomings is their current lack of explicit representation of the multi-scale interaction with the surrounding atmosphere. In this context, we note that several widely used empirical models rely on fire behavior parameterizations and fuel classes that were developed decades ago from experimental burns, before the availability of moderate resolution satellite thermal imagery that can now systematically track the growth of large wildfires from the middle of the day (1:30 PM local overpass time) through the middle of the night (1:30 AM).

A research program that integrates information from machine learning and physical models of fire spread may enable breakthroughs. A key challenge in this regard is to develop a testbed that allows different types of fire models (machine learning, physic-based, or hybrid) to be simultaneously trained and evaluated using millions of different fire perimeter observations that have become available in the past decade. Important science questions in this domain include:

1. *How are new extremes in drought stress influencing fire behavior, and what are the tradeoffs between machine-learning and physics-based modeling approaches for capturing this new behavior?*
2. *Can machine learning approaches predict surface winds with a higher accuracy and spatial resolution in regions with complex topography than existing simulations with dynamical atmospheric models?*
3. *What are the most effective ways to integrate physical principles into machine learning algorithms for predicting fire spread?*
4. *How can machine learning approaches better represent the three-dimensional structure of fuels and their moisture content in complex landscapes?*

From an artificial intelligence (AI) perspective, we envision a not-too-distant future in which all large wildfires are simultaneously tracked on Earth using satellite observations of fire perimeters, global weather forecasts, and other information on regional hydrologic status. Given existing logic rules built into an AI system, a hierarchy of fire models could then be deployed for each event depending on factors regulating the size of the fire, the complexity of the forecast, risks to local communities and ecosystems, the potential to create a stratospheric plume injection, or other criteria. Uncertainty quantification and the structure of fire prediction errors from such a system would inform the development of a new generation of fire models.

***Fire plume height injection:*** Energy released by wildfires can create turbulent plumes that inject fire aerosols into the middle or upper troposphere, and in even into the lower stratosphere. This process is important because plume height affects long-range transport of fire aerosols, aerosol lifetime, and aerosol impacts on air quality and climate. Extreme events can generate pyro-cumulus convection that inject carbonaceous aerosols into the lower stratosphere. When this occurs, aerosol lifetimes in the atmosphere can be extended by months or even years as a consequence of solar radiation absorption by black carbon contributing to localized atmospheric heating and thus self-lofting of the fire plume. Fire plume models are complex, require detailed information on surface energy release rates from the combustion of surface fuels, and are often embedded within regional or global atmospheric models used for multi-year aerosol and climate simulations. From a machine learning perspective, there are two important and interrelated challenges. First, can the likelihood of a stratospheric injection be predicted from fuel amount, soil and fuel moisture status, and local weather surrounding an individual fire event, potentially saving computational costs associated with deploying a three-dimensional plume model for the million+ wildfires that occur each year? Second, similar to parallel developments with cloud resolving models, can machine learning emulators be trained to mimic the aerosol, water vapor, and trace gas injection profiles of their more complex 3-dimensional physics-based counterparts, with orders of magnitude gains in computational efficiency?

***Subseasonal to seasonal (S2S) fire severity forecasts:*** Fire season severity forecasts are regularly made in the US for different ecoregions, drawing upon S2S seasonal climate predictions from the North American Multi-Model Ensemble (NMME), information on winter snowpack, and expert opinion from fire managers in each region on local drought status. The information from these seasonal outlooks are used to position fire suppression resources (hot shot crews, equipment, and aircraft) prior to the onset of the fire season. At a global scale, recent work suggests S2S fire predictions are possible in many areas in South America, Southeast Asia, Africa, and Australia. Key machine learning challenges in this domain include quantitative evaluation of USFS predictions, and the development of new classes of US and globally-extensive machine learning models that draw upon information from sea surface temperature (SST), terrestrial water storage, and NMME seasonal forecasts. It is currently unclear, for example, whether NMME predictions of fire weather variables over important fire regions yield more accurate predictions than statistical models drawing on implicit teleconnections embedded in SST anomalies from important predictor regions. Participation by E3SM in the NMME needs further exploration, and may allow for improved fire forecasts on this time scale.

***Fire detection, risk and mitigation:*** Early detection and suppression are emerging as important pathways for limiting future fire damages, particularly in the wake of the extreme 2020 wildfire seasons in the western US and Australia. In this context, there is a great potential to bring together non-traditional data streams from lightning detection networks, High Performance Wireless Research and Education Network (HPWREN) cameras, satellite thermal anomalies, social media, and other data streams to reduce detection times in remote wildland environments using probabilistic machine learning approaches. For small initial detections, machine learning models can also be used to evaluate the likelihood of individual events growing large, and thus threatening infrastructure or vulnerable ecosystems. This capability is essential when lightning storms move across an area, synchronizing multiple starts. When this occurs, fire suppression resources may need to be "triaged" among different wildfires, as was the case during the 2020 summer fire season in California. Similar tools may prove effective for planning controlled burns, as climate change and air quality concerns create limited windows for management activity.

**Suggested partners and experts**: A combination of experts from multiple US Dept of Energy National Laboratories, university partners, and other federal agencies would be in a strong position to develop a theme on wildfires in an AI4ESP planning workshop (see authorship list, which also includes several early career scientists from UC Irvine including Coffield, Graff, and Hantson). In addition to a representative from NASA, suggested here as Douglas Morton, we would recommend entraining several other experts from the USFS and private consortia currently working on wildfire prediction (e.g., Pyregence).