PNNL-36676

Improving North American Wildfire Prediction by Integrating a Machine-Learning Fire Model in a Land Surface Model

September 2024

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U.S. DEPARTMENT OF ENERGY

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Abstract

Wildfires have shown increasing trends in both frequency and severity across the Contiguous United States (CONUS). However, process-based fire models have difficulties in accurately simulating the burned area over the CONUS due to a simplification of the physical process and cannot capture the interplay among fire, ignition, climate, and human activities. The deficiency of burned area simulation deteriorates the description of fire impact on energy balance, water budget, and carbon fluxes in the Earth System Models (ESMs). Alternatively, machine learning (ML) based fire models, which capture statistical relationships between the burned area and environmental factors, have shown promising burned area predictions and corresponding fire impact simulation. We develop a hybrid framework (ML4Fire-XGB) that integrates a pretrained eXtreme Gradient Boosting (XGBoost) wildfire model with the Energy Exascale Earth System Model (E3SM) land model (ELM) version 2.1. A Fortran-C-Python deep learning bridge is adapted to support online communication between ELM and the ML fire model. Specifically, the burned area predicted by the ML-based wildfire model is directly passed to ELM to adjust the carbon pool and vegetation dynamics after disturbance, which are then used as predictors in the ML-based fire model in the next time step. Evaluated against the historical burned area from Global Fire Emissions Database 5 from 2001-2020, the ML4Fire-XGB model outperforms process-based fire models in terms of spatial distribution and seasonal variations. Sensitivity analysis confirms that the ML4Fire-XGB well captures the responses of the burned area to rising temperatures. The ML4Fire-XGB model has proved to be a new tool for studying vegetation-fire interactions, and more importantly, enables seamless exploration of climate-fire feedback, working as an active component in E3SM.

Summary

This project focuses on improve the predictability of wildfires over the Contiguous United States (CONUS), by developing a hybrid framework that integrates a machine learning (ML) fire model with an Earth system model. Due to the complex human activities in both igniting and suppressing wildfires, and the impact of climate change altering vegetation growth and fuel flammability, wildfire prediction over the CONUS is an ongoing challenge. ML models based on statistical relationships bypassing the insufficient physical understanding have been proven overperformed process-based fire models. Despite the improved fire predictions, fire impacts on the ecosystem, climate, and human community cannot be evaluated without integrating the wildfire process into the Earth system. In addition, climate change impacts on the burned area, either directly through fire weather conditions, or indirectly through ecosystem productivity, vegetation type, fuel loads, and fuel moisture – cannot be fully understood without explicitly representing the complex interplays between climate, ecosystems, and fire. Viewing wildfire as an active and interactive component in the Earth system is important. In this project, we have developed an integrated climate-vegetation-wildfire framework that leverages the Energy Exascale Earth System Model (E3SM) land model (ELM) to simulate the response of vegetation to climate change and other disturbance, and a pretrained eXtreme Gradient Boosting (XGBoost) wildfire model to predict burned area. ELM provides fuel amount and moisture to ML fire model for burned area prediction, the burned area, is in turn, passed back to ELM to update the vegetation properties and calculate fire emissions. This hybrid framework (ML4Fire) significantly improves burned area prediction in terms of both spatial distribution and temporal evolution. Two papers and a dataset are under review that describe the ML4Fire framework and evaluate the process fire model. The team also presented six presentations on this work.

Acknowledgments

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Acronyms and Abbreviations

CONUS	Contiguous United States
E3SM	Energy Exascale System Model
ELM	E3SM Land Model
ML	Machine Learning
ML4Fire	Machine Learning for Fire
XGBoost	eXtreme Gradient Boosting

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1.0 Project Overview

Recent wildfire outbreaks worldwide have raised alarms due to wildfires burning longer and more intensely in many regions, posing significant threats to human livelihoods and biodiversity. The continental United States (CONUS) has emerged as a hotspot for wildfires, where both climate change and human activities have fueled a 42% increase in the burned area (Jones et al., 2022). Such expansive burned areas release an average of 162 million tons of CO_2 and 0.9 million tons of $PM_{2.5}$ annually into the atmosphere, resulting in over $200 billion health costs due to exposure to wildfire smoke (Samborska et al., 2024; JEC, 2023). Accurate prediction of wildfire risks has become an urgent need.

Traditional fire models, predominantly process-based models, simulate the behavior of individual wildfires using theoretical equations for ignitions and fire spread (Hantson et al., 2016). While process-based wildfire models have proven effective in simulating global burned area distribution (Hantson et al., 2020), they often fall short of accurately predicting the extent and temporal changes of wildfires over the CONUS (Forkel et al., 2019; Teckentrup et al., 2019). Recent advances have explored the application of machine learning (ML) techniques in wildfire prediction (Zhu et al., 2022). Despite the improved fire predictions, fire impacts on the ecosystem, climate, and human community cannot be evaluated without integrating the wildfire process into the Earth system. In addition, climate change impacts on the burned area, either directly through fire weather conditions, or indirectly through ecosystem productivity, vegetation type, fuel loads, and fuel moisture – cannot be fully understood without explicitly representing the complex interplays between climate, ecosystems, and fire.

The goal of this project is to develop a novel hybrid framework to integrate a pretrained ML wildfire model with the E3SM land model (ELM) to study the full atmosphere-vegetation-wildfire feedbacks. This integration facilitates a dynamic feedback loop where outputs from the ML model (i.e., predicted burned areas) inform the land surface processes in ELM, which in turn update the inputs for the ML model for subsequent predictions. This approach leverages the detailed physical understanding of surface biogeophysical and biogeochemical processes provided by ELM and the predictive power of ML-based wildfire models to create a more accurate and robust framework for wildfire prediction and impact assessment.

2.0 Introducing of the Hybrid Framework

2.1 Default Wildfire Model in ELM

The ELM is part of the E3SM project which started with a version of the Community Earth System Model (CESM1). The ELM default wildfire module originated from the Community Land Model (CLM4.5) (Li et al., 2012). This wildfire model calculates burned areas by multiplying the number of wildfires and burned area per fire on a grid-cell level. The number of wildfires (fire count) is derived using anthropogenic and natural ignition sources, fuel load and combustibility, surface meteorology, and anthropogenic suppression. The natural ignition source is derived from the number of cloud-to-ground lightning flashes multiplied by a constant ignition efficiency (Prentice and Mackerras, 1977). Anthropogenic ignitions are simply parametrized using a fixed number of potential anthropogenic ignitions by a person and population density (Venevsky et al., 2002). Humans also suppress wildfires. The capability of fire suppression is assumed to be a function of gross domestic product. The ignition efficiency is also altered by fuel conditions, including the fuel load (aboveground biomass) and fuel combustibility (approximated using relative humidity, temperature, and top or root zone soil moisture). The spread of each fire is approximated using an ellipse shape with its length-to-breadth ratio determined by wind speed and fuel moisture (Rothermel, 1972). This simple concept well captures the major constraints for predicting the global wildfire distribution and seasonal variations (Rabin et al., 2017; Li et al., 2014; Huang et al., 2020).

Like many other process-based wildfire models, the default fire model in ELM benefits from the full ecosystem interactions from its hosting land model, as well as the potential to be coupled with atmospheric models. With the BGC processes being turned on, ELM-BGC reallocates carbon and nitrogen in leaf, wood, root, litter, and soil pools after fire based on plant functional type (PFT)-dependent carbon combustion and mortality rate. The biogeochemical changes subsequently influence biogeophysical properties such as leaf area index (LAI), vegetation canopy height, and albedo, disturbing the land-atmosphere exchanges of energy and water fluxes. The post-fire vegetation recovery depends on the plant photosynthesis processes and PFT competition strategy. The interactions between wildfire and vegetation under historical climate have been thoroughly assessed in CLM long-term simulations (Li and Lawrence, 2017; Seo and Kim, 2023). The model framework is illustrated in Figure 1. Hereafter the ELM coupled with the process-based fire model is referred to as ELM-BGC.

Besides ELM-BGC, we also obtained burned area from four state-of-the-art process-based wildfire models participating the Fire Model Intercomparison Project (FireMIP) (Rabin et al., 2017), including the Canadian Land Surface Scheme Including Biogeochemical Cycles (CLASSIC) (Melton et al., 2020), the Simplified Simple Biosphere model coupled with the Top-down Representation of Interactive Foliage and Flora Including Dynamics model (SSiB4-TRIFFID) (Huang et al., 2020, 2021), the SPread and InTensity of FIRE (SPITFIRE) coupled with the Organizing Carbon and Hydrology In Dynamic Ecosystems (ORCHIDEE) (Yue et al., 2014), and the Vegetation Integrative Simulator for Trace gases (VISIT) (Ito, 2019). The burned area simulation from the process-based fire model over the CONUS will be used to benchmark that from the hybrid framework.

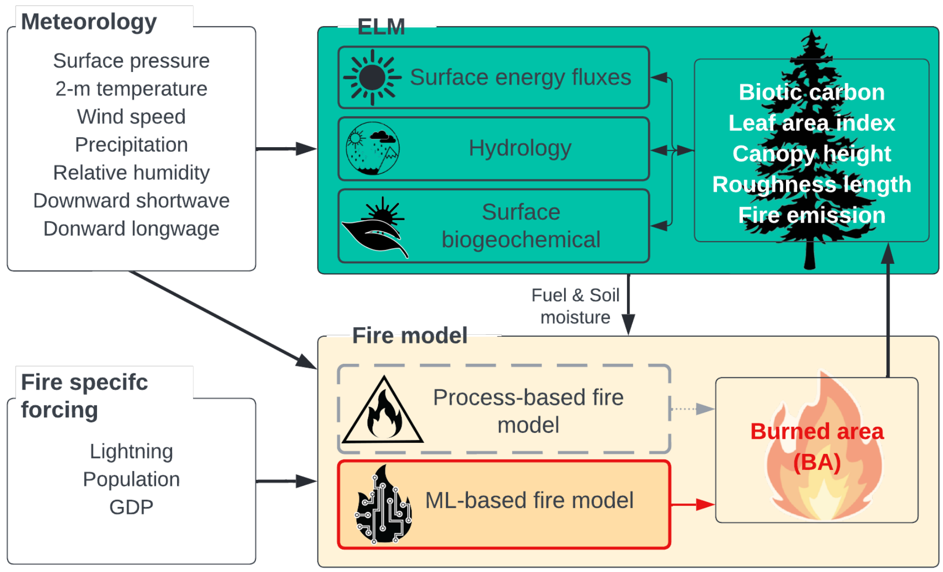

Figure 1. Schematic diagram of the hybrid model framework

2.2 Machine Learning Wildfire Model

In this study, we tailored a pretrained XGBoost wildfire model to use variables directly provided by ELM at each grid cell. XGBoost is a highly efficient and scalable implementation of gradient boosting, designed for performance and speed (Chen and Guestrin, 2016). It builds sequential decision trees to correct errors from previous models, using techniques like regularization to prevent overfitting and parallel processing for faster computation.

To reduce overfitting, we build a separate ML model for each year from 2001 to 2020 using the remaining 19 years' data. Model performance was evaluated based on its accuracy in predicting the spatial distribution and temporal variation of burned areas. Validation metrics included root mean square error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2). This pretrained XGBoost model is referred to as offline-XGB in the following analysis.

2.3 Hybrid Modeling Framework

The pretrained ML wildfire model is integrated with the ELM using the ML4ESM coupling framework. The ML4ESM framework offers a robust and flexible solution for integrating ML parameterizations into ESMs through a Fortran-Python interface (Zhang et al., 2024). The interface leverages C language as an intermediary for efficient data transfer by accessing the same memory reference, instead of the extra data copy or through files, minimizing memory overhead and computational inefficiencies. In our application, all surface meteorology, lightning, and socioeconomic data, alongside the ELM simulated fuel conditions are passed to the pretrained ML-based wildfire model to predict the burned area. The burned area is returned to ELM to calculate fire impacts and update surface properties.

2.4 Model Configuration and ML4Fire-XGB Training Processes

In ELM-BGC, vegetation properties, including canopy height and LAI, vary with carbon allocation and distribution, driven by climate variability and disturbances such as wildfires. To bring the model's carbon and nitrogen pools into equilibrium, we first conduct long-term spin-up simulations as suggested by Lawrence et al. (2011). We adopt a two-step approach consisting of a 400-year accelerated decomposition (AD) spin-up followed by a 400-year regular spin-up, driven by cycling NLDAS-2 meteorological forcing from 1981 through 2000. In the AD spin-up, acceleration factors will be applied to accelerate decomposition in soil organic matter pools, and for plant dead stem and coarse root mortality. The terrestrial carbon pools and vegetation distribution after spin-up simulations reach quasi-equilibrium states after the 800-year simulations.

Initialized with the quasi-equilibrium state from the spinup simulation, we conduct transient simulations with the process-based fire model in the ELM-BGC utilizing NLDAS-2 meteorological forcings for the period of 2001-2020. The surface soil moisture, LAI, fraction of each PFT output from ELM-BGC transient run are then used to train the offline-XGB prior to the coupled run within ELM. Furthermore, we run the coupled ML4Fire-XGB in which the pre-trained XGB model provides monthly burned area to ELM to update the land surface properties (LAI, PFT fraction, and soil moisture), which are then used as predictors in the ML-based fire model in the next time step. The differences in land surface properties input in offline-XGB and ML4Fire-XGB produce different burned area simulation, and the divergence accumulates over the 20-year simulation period.

In addition to the default transient simulations with ELM-BGC and ML4Fire-XGB which represent historical burned area, we conduct additionally sensitivity simulations with ELM-BGC and ML4Fire-XBG, utilizing the same NLDAS-2 meteorological forcings except for detrended temperatures to evaluate the responses of the modeled burned area to raising temperatures, which are considered as the primary driver of the increasing burned area over the WUS (Parks and Abatzoglou, 2020; Zhuang et al., 2021).

2.5 Model Evaluation over Ecoregions

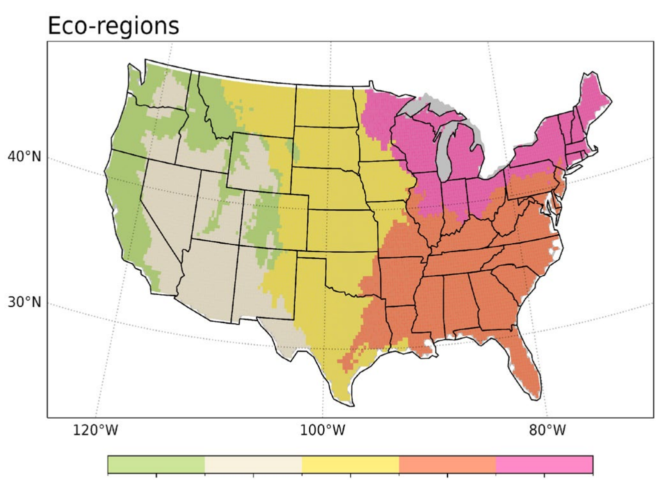

Figure 2. Ecoregions used in fire model evaluation. 1 – Western Forested Mountains, 2 – NA Desert, 3 – Great Plains, 4 – SE Temperate Forests, and 5 – NE Temperate Forests.

We evaluate the model simulation of the burned area for each ecoregion adopted from the U.S. Environmental Protection Agency (EPA). Ecoregions are areas where ecosystems (and the type, quality, and quantity of environmental resources) are generally similar and generally, wildfire properties in each ecoregion are similar. A combination of level I and level II ecoregions is used and some types have been combined to focus on the broad vegetation distribution (Fig. 2). Five Ecoregions including Western Forested Mountains, North American Desert, Great Plains, SE Temperate Forests, and Northeast Temperate Forests are defined.

3.0 Model Evaluation

3.1 Evaluation of the Burned Area Spatial Distribution

Figure 3 show the spatial distribution of observed and simulated burned area over 2001-2020. The offline-XGB model reproduces the burned area distribution over the CONUS well, with a spatial correlation coefficient (R_p) of 0.96 (p<0.01) and a small bias (-0.4 Mha yr^{-1}). While integrated with ELM, the performance holds (R_p=0.70, p<0.01, bias=1.0 Mha yr^{-1}). This degradation is likely due to the vegetation-wildfire feedback. The aboveground biomass and fuel moisture from ELM-BGC have been used to train the ML4Fire-XGB prior to the coupled run within ELM. In the coupled simulation, ML4Fire-XGB updates the biotic carbon and fuel moisture based on the burned area simulated in the previous timestep. Consequently, differences in the simulated burned area compared to the process-based models are reflected in the biotic carbon and fuel moisture, accumulating over the 20-year simulation period and influencing the burned area simulation in subsequent timesteps.

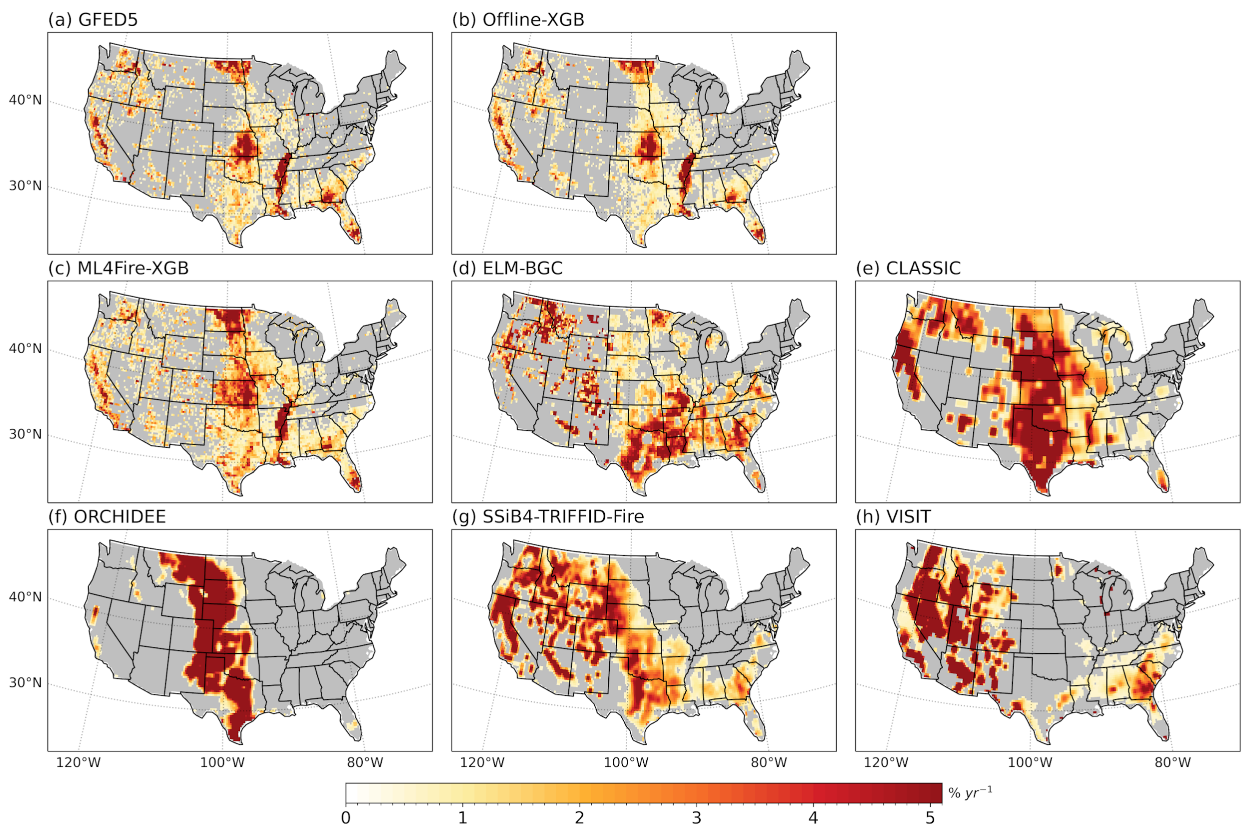

Figure 3. Observed and simulated burned area fraction (% yr-1) averaged over 2001-2020. The dataset names are listed on the top of each panel

In various eco-regions, the offline-XGB model demonstrates minimal biases, and the ML4Fire-XGB model consistently outperforms all process-based fire models in predicting annual mean burned area. The accurate simulation of burned area over the Western Forest Mountains indicates that the ML4Fire-XGB framework generally captures the complex interplays between climate, vegetation, and human activities, with both climate forcings and predicted vegetation status from ELM-BGC. Meanwhile, the ML4Fire-XGB shows superior performance over the Great

Plains, indicating that the ML model effectively describes crop fire thereby utilizing data on crop fraction and LAI.

3.2 Evaluation of the Burned Area Temporal Variability

We evaluate the model performance in simulating the monthly burned area and depicting fire seasons. Fire season is defined as a monthly burned area greater than 1/12 of the annual total burned area. Figure 4 shows the monthly burned area over the CONUS and eco-regions. The COUNS has two fire seasons, i.e., March-April-May and August-September-October, affected by both climate and human activities. The western U.S. fire season spans from early summer to late fall, primarily determined by the dry conditions and high temperature during these months. Specifically, over the Western Forest Mountains, the fire season includes July to November.

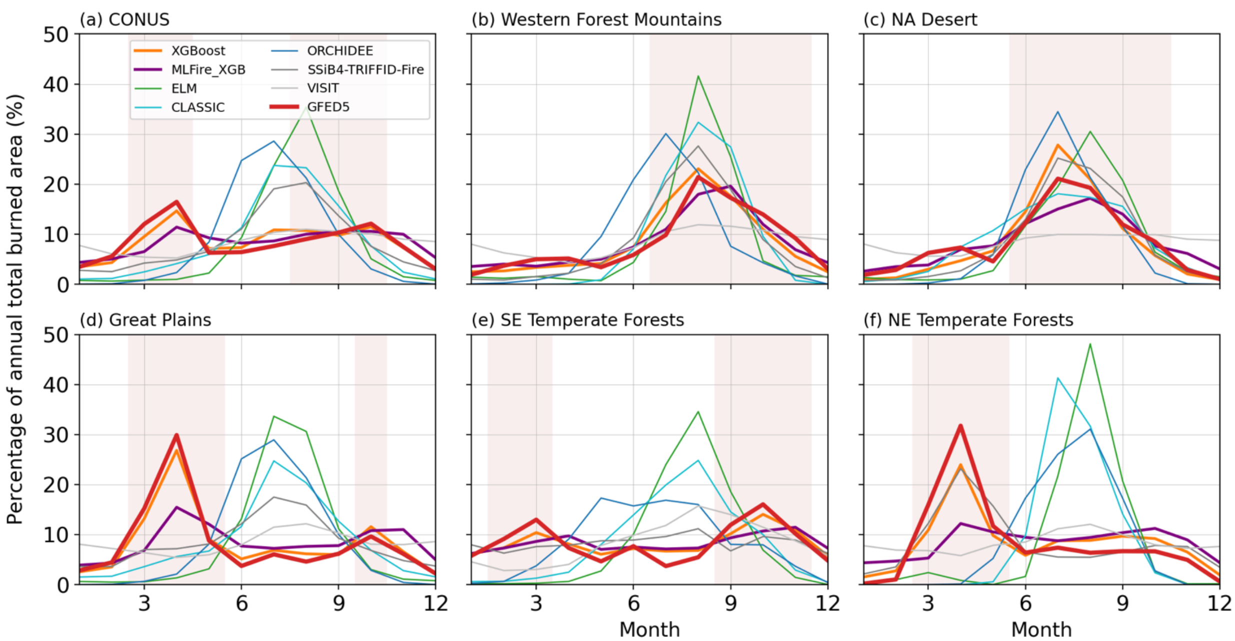

Figure 4. Monthly mean burned area fraction (% yr^{-1}) over each eco-region.

Monthly temporal variability in burned areas demonstrates significant regional differences across the eco-regions. Over the entire simulation period, the ML-based models generally capture the timing of wildfires across the CONUS with a temporal correlation coefficient greater than 0.5 ($p < 0.01$), whereas the process-based models exhibit a correlation of only 0.3 ($p > 0.01$). The ML-based models also effectively capture the temporal variability across the eco-regions, although there is a slight decrease in the ML4Fire-XGB in the Great Plains and eastern U.S. This decrease is likely related to the fire-vegetation feedback, which alters the fuel condition differently from the training set. In contrast, the process-based models show comparable correlations as the ML-based models in the western U.S. but fail to accurately predict burned area temporal variations in the Great Plains and eastern U.S. Process-based models tend to better describe responses of fuel load and combustibility to climate than responses of fire ignition and suppression to human activities.

4.0 Accomplishments

4.1 Conference Proceedings

Liu Y., H. Huang, and D. Xu. 12/10/2024. "Advancing wildfire prediction and ecosystem interaction modeling using an integrated framework." Abstract submitted to AGU Annual Meeting 2024, Washington, District of Columbia. PNNL-SA-202094.

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Liu Y., and H. Huang. 09/27/2023. "Burning Questions: Uncovering the Past, Present, and Future of Wildfires in Washington State." Richland, Washington. PNNL-SA-190709.

4.2 Peer Reviewed Publications

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4.3 Dataset

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