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Next Generation Science and Wildfire Risk Forecast Models for Enhanced Electricity Grid Resiliency (Pyregence)

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CLIMATE CHANGE
ASSESSMENT

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Contribution to California's Fifth Climate Change Assessment

This Final Report describes original, energy-related research that contributes to California's Fifth Climate Change Assessment (Fifth Assessment). The Fifth Assessment comprises a broad portfolio of research and synthesis reports that addresses California-specific research needs and knowledge gaps relating to climate change. To ensure scientific rigor, Fifth Assessment research was peer reviewed. This research effort was peer reviewed through external journal publications (listed in Chapter 4: Knowledge Transfer).

PREFACE

The California Energy Commission's (CEC) Energy Research and Development Division supports energy research and development programs to spur innovation in energy efficiency; renewable energy and advanced clean generation; energy-related environmental protection; transportation; and energy transmission and distribution.

In 2011, the Electric Program Investment Charge (EPIC) was established by the California Public Utilities Commission to fund public investments in research to create and advance new energy solutions, foster regional innovation, and bring ideas from the lab to the marketplace. The EPIC Program is funded by California utility customers under the auspices of the California Public Utilities Commission. The CEC and the state's three largest investor-owned electric utilities — Pacific Gas and Electric Company, San Diego Gas & Electric Company, and Southern California Edison Company — were selected to administer the EPIC funds and advance novel technologies, tools, and strategies that provide benefits to their electric ratepayers.

The CEC is committed to ensuring public participation in its research and development programs to promote greater reliability, affordability, and safety for California electric ratepayers. EPIC investments advance these values by:

- Providing societal benefits.
- Reducing greenhouse gas emissions in the electricity sector at the lowest possible cost.
- Supporting California's loading order to meet energy needs, first with energy efficiency and demand response, next with renewable energy (distributed generation and utility-scale projects), and finally with a clean electricity supply.
- Supporting low-emission vehicles and transportation.
- Providing economic development.
- Using ratepayer funds efficiently.

Next Generation Science and Wildfire Risk Forecast Models for Enhanced Electricity Grid Resiliency (Pyregence) is the final report for EPC-18-026 conducted by Spatial Information Group, LLC. The information from this project contributes to the CEC Energy Research and Development Division's EPIC Program.

For more information about the Energy Research and Development Division, please visit the [CEC's research website](http://www.energy.ca.gov/research/) (www.energy.ca.gov/research/) or [contact](mailto:ERDD@energy.ca.gov) the Energy Research and Development Division at ERDD@energy.ca.gov.

ABSTRACT

California is facing growing wildfire risks that threaten communities, natural resources, and the reliability of the state's electricity system. Hotter temperatures, longer dry seasons, and expanding development in fire-prone areas have collectively increased the likelihood of extreme wildfires, which can damage electric power infrastructure, disrupt service, and raise costs for utility customers. California's climate and energy policies call for reducing greenhouse gas emissions, protecting public safety, and strengthening the resilience of critical infrastructure, which in turn are increasing demands on utilities and regulators to better understand and manage wildfire risks.

This research project was designed to address these challenges by improving the science and tools used to anticipate wildfire behavior and its impacts on the state's electricity grid. This work responds to regulatory needs identified in California Public Utilities Commission proceedings, which emphasize proactive wildfire mitigation, informed planning, and cost-effective investment in grid safety. The project brought together researchers, utilities, and public agencies to develop more accurate and timely ways to assess wildfire risk over both short- and long-term timeframes.

Key project outcomes include improved methods to identify dangerous fire weather, better understanding of how dead and dry vegetation affects fire behavior, and the development of a publicly accessible forecasting platform that provides near-term wildfire risk and spreads information. The project also produced long-range projections showing how wildfire patterns may change under future climate and land-management conditions, supporting long-term grid planning and climate resilience.

Together, these results provide utilities, regulators, and policymakers with actionable information to reduce wildfire impacts, support safer grid operations, and help meet California's energy, conservation, and climate goals while protecting ratepayers and communities.

Keywords: wildfire, climate change, extreme weather, weather station optimization, tree mortality, wildfire behavior models, PyreCast, public safety power shutoff (PSPS), laboratory fire behavior experiments, machine learning models, long-term wildfire projections, decision support tools, California's Fifth Climate Change Assessment.

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EXECUTIVE SUMMARY

Background

California's escalating wildfire risks are driven by climate change, legacy forest-management practices, and continued expansion of development into fire-prone landscapes. These factors have increased the frequency and severity of extreme wildfires, which increasingly strain communities, ecosystems, and the electric grid. Existing wildfire modeling and monitoring systems, many of which were developed decades ago, are increasingly insufficient to capture modern fire behavior characterized by extreme weather, large fuel loads, and complex fire-atmosphere interactions. In turn, for electric utilities, these challenges translate into higher costs, reduced reliability, increased safety risks, and heightened regulatory scrutiny, which together underscore the need for improved science, models, and decision support tools.

Project Purpose and Approach

The purpose of this project was to advance wildfire science and develop next-generation models and decision-support tools that enhance the resiliency, safety, and cost-effectiveness of California's electric grid. The project addressed wildfire hazards (defined here as the potential physical characteristics of a wildfire at a given location, such as the likelihood of ignition, expected flame length, fire intensity, rate of spread, and burn severity) across multiple spatial and temporal scales, from near-term operational forecasting to long-term climate adaptation planning. An interdisciplinary team was organized into four coordinated workgroups focused on extreme fire weather and monitoring, fuels and fire physics, and both near-term wildfire forecasting and long-term wildfire projections. Together, these efforts integrated field observations, remote sensing imagery, laboratory experiments, advanced fire behavior modeling, and climate-driven landscape simulations. An additional core principle of this approach was open access; all models, data, and software developed through the project are transparent, reproducible, and transferable to utilities, agencies, researchers, and other stakeholders.

Key Results and Conclusions

This project demonstrated that modern wildfire hazards are strongly shaped by a combination of extreme weather, evolving fuel conditions, and large-scale climate dynamics that are not adequately represented in legacy fire-behavior models.

Results from various weather analyses show that California's current weather monitoring network does not fully capture fire-relevant conditions in high-risk and complex terrain. Upper-air wind observations can provide added value for anticipating extreme wind events critical to both wildfire behavior and public safety power shutoff decisions. Fire weather analyses also revealed that a small number of large-scale atmospheric patterns (fire weather types) account for most extreme fire growth days, and that climate change is likely to shift fire hazards toward more intense summer conditions driven by thermal low-pressure systems.

Laboratory and field research on fuels and fire physics demonstrated that large woody fuels and deep organic layers, now widespread in some regions due to drought-driven tree mortality, fundamentally alter fire behavior, producing longer-duration, higher-intensity fires that exceed the assumptions of conventional fire models. New fuel measurement systems and tree mortality mapping products developed as part of this project showed promise for providing more realistic inputs for both near-term and long-term modeling.

Near-term forecasting efforts culminated in the development and deployment of PyreCast, an open-source, web-based wildfire situational awareness platform with demonstrated forecast skills comparable with peer operational systems and measurable potential for utility cost savings.

Long-term fire forecasting was developed through an integrated, multi-model framework to project long-term wildfire activity, vegetation change, and carbon outcomes across California under a range of future climate, urban land-use, and vegetation management scenarios. This modeling advances a user's ability to evaluate interacting fire-climate-fuel-carbon dynamics across multiple spatial and temporal scales. Projections incorporated the latest dynamically downscaled and hybrid-statistical climate datasets, providing consistency with California's Fifth Climate Change Assessment and capturing a broad range of possible future climate conditions. The project produced publicly accessible, reproducible datasets between the years 1985 and 2100 for a dynamical forest landscape model and between 2020 and 2065 for coupled statistical wildfire and dynamical vegetation models. These scenario-based outputs provide the foundation for long-range utility planning, climate adaptation, and infrastructure resilience efforts.

Machine learning models can effectively characterize key components of California's wildfire regimes. Models developed for this project delivered their strongest performance for ignition and burn probability, with more limited skill for rare outcomes such as large fire size and burn severity, underscoring the importance of explicitly representing uncertainty. Results highlighted weather as the dominant driver of wildfire patterns, with development, vegetation, and topography exerting regionally variable influences that illustrated the need for tailored mitigation strategies. Machine learning models have the added benefit of being computationally efficient to run when compared with physically based models, so that many more simulations can be performed to better characterize uncertainties.

Knowledge Transfer Activities and Next Steps

A central outcome of this project was the transfer of knowledge, tools, and data to utilities, agencies, and the broader wildfire community. This included stakeholder workshops, technical advisory committee engagement, public webinars, peer-reviewed publications, and the establishment of open data and code repositories. These efforts position the project's outputs for continued use, refinement, and integration into operational and planning contexts. Future work could continue to refine fire behavior and climate models, expand monitoring of fire-relevant weather and fuels, and further develop decision-support capabilities that translate advanced science into actionable insights for practitioners.

Benefits to California Ratepayers

The project delivers benefits to California ratepayers by improving the ability of utilities and agencies to anticipate, manage, and reduce wildfire hazards. Enhanced forecasting and monitoring support more targeted and cost-effective mitigation actions and reduce unnecessary outages, infrastructure damage, and long-term recovery costs. Tools such as PyreCast demonstrated the potential to lower operational costs through improved situational awareness and faster decision cycles, while long-term projections informed strategic investments in grid hardening and resilience. Collectively, these outcomes support a safer, more reliable, and more affordable electricity system, while advancing regulatory compliance, environmental protection, and public safety objectives for the state of California.

CHAPTER 1:

Introduction

California's clean energy transition is unfolding alongside escalating climate-driven hazards to the electricity grid, most notably from wildfires and extreme weather. The overlap of rising temperatures, prolonged drought, and more frequent high-wind events has intensified wildfires, in turn straining both electricity transmission and distribution infrastructure. These conditions have increased both the risk of wildfires associated with grid operations and the likelihood of service disruptions, including public safety power shutoff (PSPS) events (Do et al. 2025). As the state advances ambitious decarbonization goals (for example, expanding renewable resource generation, electrifying end uses, and modernizing the grid), ensuring system reliability, affordability, and public safety under increasingly unpredictable environmental conditions has become a critical challenge.

The purpose of this project was to improve the scientific and technical foundations for understanding, forecasting, and managing wildfire hazard¹ as it relates to California's electricity system. Specifically, the project addresses the need for more accurate, geographically specific, and climate-informed information on fire weather, wildfire behavior, and long-term wildfire hazard trends that support utility operations, infrastructure planning, and regulatory decision-making. By advancing new data, modeling approaches, and analytical tools, the project sought to improve accuracy and reduce uncertainty in wildfire risk assessments and strengthen California's capacity to plan for and adapt to a changing climate.

This work supports California's clean energy and climate objectives by helping safeguard the reliability of an increasingly renewable-dependent electricity system. State policies and regulatory proceedings, including climate adaptation planning, utility wildfire mitigation plans, and resilience investments overseen by the California Public Utilities Commission, depend upon credible assessments of present and future wildfire risks. At the same time, recent wildfire seasons have revealed limitations in existing tools used to inform operational decisions such as PSPS activations, asset hardening priorities, and long-term infrastructure investments. Improving weather observations, fire behavior modeling, and climate-informed risk projections are therefore essential for maintaining public safety while enabling continued progress toward emissions reduction goals.

Prior to this project, wildfire hazard forecasting models (fire behavior and weather) and tools, while increasingly sophisticated, still faced technical and integration challenges. Operational fire weather forecasting provided to Geographic Area Coordination centers, including advanced products from the California and Nevada Smoke and Air Committee smoke and air quality forecasting system and targeted Weather Research and Forecasting (WRF)-SFIRE wildfire

¹ Wildfire hazard refers to the potential physical characteristics of a wildfire at a given location, such as the likelihood of ignition, expected flame length, fire intensity, rate of spread, burn severity, and ember production, based on fuels, weather, and topography. In other words, hazard describes how a fire is likely to behave if it occurs. Wildfire risk refers to the potential consequences of wildfire to people, property, infrastructure, ecosystems, or other valued resources. Risk combines wildfire hazard with exposure (what is in harm's way) and vulnerability (how susceptible those assets are to damage). In simple terms, hazard describes the fire's behavior; risk describes the damage that fire could cause.

simulations under high-danger conditions, offered valuable full-profile atmospheric analysis. However, gaps remained in routinely capturing and operationalizing fine-scale wind dynamics within the lower atmosphere, particularly in the boundary layer and terrain-influenced flows between the surface and several thousand feet aloft, which often drive extreme wind events and rapid-fire growth.

While efforts such as California's Air Resources Board's Scoping Plan modeling have begun integrating climate and emissions-related drivers, long-term wildfire hazard projections generally lacked a tightly coupled treatment of climate, land use, vegetation dynamics, and fire behavior within a unified modeling framework.

For decision-makers, these gaps translated into uncertainty about where and when extreme fire conditions are most likely to occur, how wildfire risk may evolve over coming decades, and how effectively policy choices might mitigate wildfire risk.

This project addressed information gaps by deepening understanding of the weather patterns and atmospheric processes that drive extreme fire behavior. It assessed how improved weather observations, fuels characterization, and operational near-term wildfire forecast tools can be beneficial, and created integrated modeling systems to predict wildfire hazards, changes in land use, and shifts in vegetation under future climate conditions. In addition, the project team employed machine learning and other data-driven techniques (alongside traditional models) to develop practical insights into ignition risks, fire spread, and burn severity throughout California's challenging terrain.

Several technical concepts are central to understanding the analyses presented in the following chapters. Fire weather refers to the combination of atmospheric conditions (such as wind, temperature, and humidity) that influence fire ignition and spread. Fire behavior models simulate how fires move across the landscape in response to fire weather, fuels, and terrain. Long-term wildfire risk projections extend beyond individual events to examine how climate change, vegetation succession, land management, and development patterns may shape future fire mitigation practices. These concepts together form the foundation for assessing both near-term operational risks and long-term planning challenges.

The project's goals were to: (1) improve characterization of extreme fire weather and its role in wildfire risk; (2) demonstrate the value of enhanced observational and modeling approaches for operational decision-making; (3) develop integrated, climate-informed projections of wildfire hazards, vegetation change, and carbon outcomes; and (4) make resulting data, models, and analyses accessible to stakeholders. Success was measured through metrics including model performance relative to historical observations, the ability to reproduce observed fire patterns and extremes, the generation of actionable spatial products, and the adoption or use of project outputs by utilities, researchers, and planners.

The primary audience for this research includes electric utilities, state and local agencies, regulators, researchers, and other stakeholders engaged in wildfire mitigation, grid resilience, and climate adaptation. Factors supporting the use of these results include the transparency of methods, public availability of data and codes, compatibility with existing planning and regulatory processes, and relevance to real-world operational and investment decisions. By

strengthening the scientific basis for wildfire risk assessment, this project supports safer, more resilient, and climate-aligned energy systems in California.

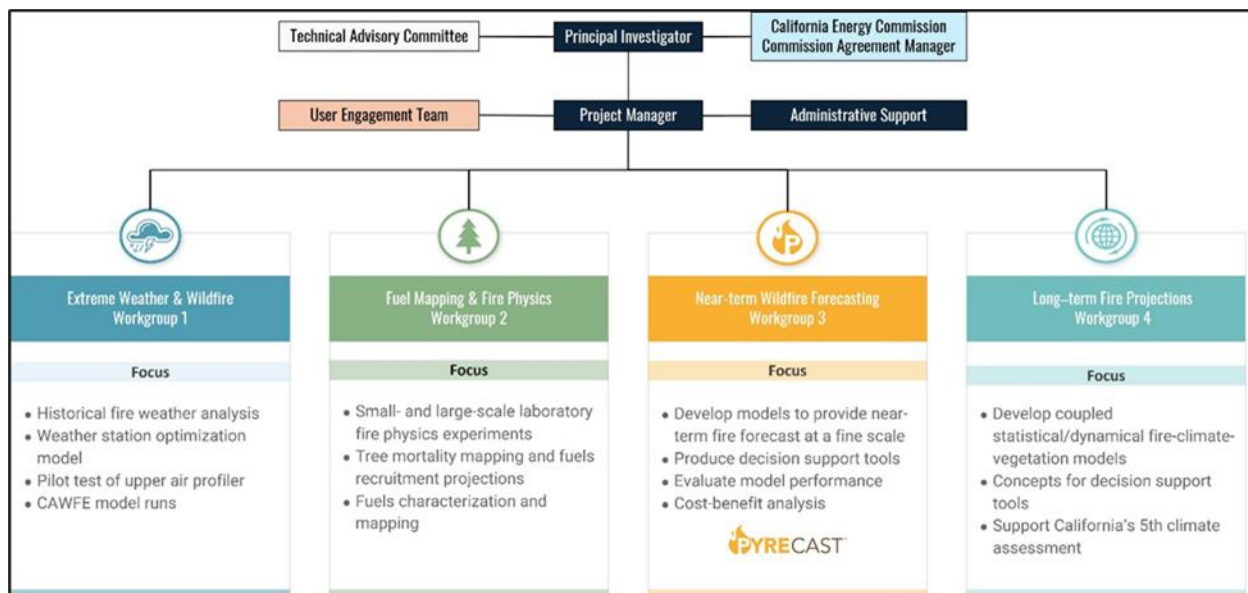
CHAPTER 2:

Project Approach

Overview

The multidisciplinary project team was organized into four technical workgroups focused on different areas of wildfire science and modeling (Figure 1). Workgroup 1 and Workgroup 2 focused on foundational wildfire science, extreme fire weather, fuels, and associated fire behavior, while Workgroup 3 and Workgroup 4 focused on applied modeling systems including near-term wildfire forecasting (PyreCast), a machine learning modeling approach, and long-term wildfire risk projection dataset products. The team also engaged with a technical advisory committee to ensure scientific rigor and stakeholder alignment. Central to the team's approach was making all research outputs, models, code, data, and tools open-source and publicly accessible to encourage widespread use and additional contributions from the wildfire science community. Through this approach, the project team focused on products and outputs to advance scientific understanding, striving for their practical applications. Through a series of tasks carried out by the workgroups, the project provided investor-owned utilities (IOUs) and other stakeholders with the tools and knowledge that could be integrated into operational practices.

Figure 1: Organizational Structure and Focus Areas of the Project



The figure highlights coordination across four technical workgroups: extreme weather analysis (Workgroup 1), fuel mapping and fire physics (Workgroup 2), near-term wildfire forecasting (Workgroup 3), and long-term fire projections (Workgroup 4). Workgroup were supported by a project management team, user engagement, and oversight from the technical advisory committee and the California Energy Commission.

Source: Shane Romsos, Pyregence Consortium (Spatial Informatics Group)

Extreme Weather and Wildfire (Workgroup 1)

Workgroup 1's research helped fill knowledge gaps related to 1) identifying appropriate locations to invest in additional weather monitoring stations across California, weather regions, and within IOU service territories; 2) increasing understanding of the relationship between wildfire and extreme weather and the use of an advanced coupled atmospheric-wildfire behavior model application; and 3) demonstrating the value of upper-air sensor measurements that supplement surface wind observations in fire-weather forecasting.

Weather Station Optimization Modeling

The goal of the weather station optimization modeling component of the project was to improve wildfire hazard forecasting and grid resilience by identifying where additional weather monitoring stations would most effectively enhance coverage of critical fire-weather conditions across California, both currently and into the future. The study determined locations where existing meteorological networks underrepresented key weather variables, particularly those associated with extreme wind events, low humidity, and other drivers of rapid fire spread that pose risks to electricity infrastructure. By applying a spatial modeling framework, the research optimized weather station placement to better capture terrain-driven wind variability and high-hazard meteorological patterns that were not adequately resolved by the current network. A maximum entropy model (MaxEnt; Phillips et al. 2006, Merow et al. 2013) was used to identify areas where additional monitoring would most effectively improve coverage of high-hazard meteorological conditions.

To assess current day gaps in monitoring stations, the analysis used bioclimatic variables from WorldClim (Fick and Hijmans 2017), which included 19 fire-weather related variables derived from monthly temperature and precipitation data from 1970 to 2000. These variables captured aspects such as annual mean temperature, precipitation seasonality, and extreme conditions like the temperatures of the warmest and coldest periods and precipitation during the wettest and driest months. Future climate conditions were modeled using data from the WRF Model, downscaled from global climate models (GCMs) under the high-end greenhouse gas emissions scenario (RCP 8.5) for the late 21st century (Liu et al. 2017). This dataset included temperature, humidity, precipitation, wind speed and direction, soil moisture and canopy moisture, with a spatial resolution of approximately 4 km² across California. Notably, Workgroup 1 used different climate projections than Workgroup 4 for long-term fire projections because newer climate projections for wildfire projections were not yet available at the time of this analysis.

The MaxEnt model was trained using the locations of existing weather stations as "presence points," and 1,000 randomly selected background points within the region of interest as "absences." The model also incorporated various environmental predictor variables that were primarily related to fire weather. MaxEnt uses machine learning techniques to fit a series of features (mathematical transformations, both linear and non-linear) to the environmental variables, thereby distinguishing presence points (weather stations) from background points. This fitting is done by maximizing a gain function, which allowed the model to identify areas where new weather stations could be placed to more completely cover the range of climate conditions: that is, sites that were most dissimilar to those of existing stations.

The output of the MaxEnt model was a relative occurrence rate, referred to in this analysis as a "similarity score." These similarity scores indicated how similar the climate conditions at any given location are to those where weather stations already exist. High similarity scores suggested that an area has climate conditions well-represented by existing weather stations, while low scores indicate areas where the climate conditions differ significantly from those already monitored.

The project team evaluated the model's performance (k-fold cross-validation), reserving 11 percent of the weather station data for testing in each model fit. The performance of the model was measured using area under the curve (AUC) scores, which ranged from 0 to 1. A score of 0.5 indicated that the model was no better than random chance at distinguishing weather stations from background points, while scores closer to 1 indicated better model performance.

The MaxEnt model created continuous surface maps of similarity scores for the entire state of California and for individual electric utility service territories to identify specific locations within an area of interest that are underrepresented in terms of weather station coverage, particularly those with unique or extreme climate conditions relevant to wildfire hazard. For example, under present-day conditions, much of Modoc and Del Norte counties (within PacifiCorp's service territory) showed gaps in weather monitoring stations.

Regional Fire Weather Types Across California

California has experienced an escalation in wildfire impacts over recent decades, with a small number of extreme fire events accounting for a disproportionately large share of total burned areas, economic losses, and infrastructure damage. While prior research established strong (but regionally varying) links between wildfire activity and rising temperatures, drying fuels, and expanding human development, much less is understood about how changes in large-scale atmospheric dynamics influence the most extreme fire-growth days. Existing fire weather indices and climate models often struggle to capture these synoptic (large)-scale drivers accurately, limiting confidence in their projections of future wildfire risk.

Research on fire weather types was motivated by the need to identify dominant large-scale weather patterns that consistently coincide with extreme wildfire growth across California and to determine how the magnitude or frequency of these fire-conducive weather regimes could change under future climate forcing. By focusing on synoptic (large)-scale weather types (features that are more reliably represented in climate models), the study bridged a critical gap between observed extreme fire behavior and long-term climate projections. Understanding whether past increases in hazardous fire weather were driven by natural variability or anthropogenic forcing, and how future greenhouse gas and aerosol changes may reshape these patterns, is essential for improving wildfire risk assessments, infrastructure resilience planning, and climate adaptation strategies across the state.

For this task, members of Workgroup 1 used a methodology that included a combination of observational data analysis, reanalysis data (datasets that combine historical observations with modern weather models), and climate model simulations to identify and examine fire weather types (WTs) that contributed to large daily burned areas in California (see Prein et al. 2022 for

details). For fire observations, daily burned area estimates were derived from satellite active fire-detection data provided by the Global Wildfire Information System dataset (Artés et al. 2019). This dataset spanned January 2001 to November 2019 and was primarily based on the Moderate Resolution Imaging Spectroradiometer (MODIS) burnt area product.² To identify days associated with large fire growth, the study used daily atmospheric fields from the European Centre for Medium-Range Weather Forecasts fifth-generation global reanalysis (ERA5) data (Hersbach et al. 2020). The study tested 31 different atmospheric variables to determine their suitability in identifying days with large burned areas, focusing on variables relevant to larger-scale (weather phenomena greater than 1,000 km) flow conditions that impacted fire behavior (Amiro et al. 2005, Haines 1989, and Van Wagner 1974). To analyze historical and future changes in WT frequencies across eight Californian fire regions identified by the project team, the study employed:

- ERA20C reanalysis data (Poli et al. 2016), providing data from 1900 to 2010.
- NOAA-CIRES-DOE 20th Century Reanalysis (NCD20C; Slivinski et al. 2019), which allowed statistical analysis with 80 ensemble members, covering 1900 to 2015.
- Community Earth System Model (CESM) Large Ensemble (LENS; Kay et al. 2015), covering 1920 to 2100, with a focus on both natural variability and forced climate change.
- CESM Single Forcing Runs (Deser et al. 2020), to isolate the effects of greenhouse gases and aerosols.

Workgroup 1 members identified WTs by clustering daily atmospheric variables using a combination of hierarchical clustering and K-means clustering (Prein et al. 2022). This approach was optimized by testing all possible combinations of up to three variables out of the 31 tested, with the final WTs selected based on their accuracy in distinguishing between days with large fire growth days and other days. Accuracy was assessed using metrics such as the Area Under the Receiver Operating Characteristic Curve and the average precision-recall score. Changes in WT frequencies were evaluated over time using a 41-year moving average. This analysis was extended to forecast future changes in WT frequencies under different future climate scenarios, focusing on the impact of greenhouse gases and aerosols.

Testing of Coupled Atmospheric Wildfire Model

Workgroup 1 also conducted several modeling case studies of 22 damaging wildfires within and outside of California that occurred between 2002 and 2020, using an advanced atmospheric coupled wildfire behavior model – the Coupled Atmosphere-Wildland Fire Environment (CAWFE) model (Coen 2013). The CAWFE model, previously developed by Workgroup 1 lead Janice Coen, is an advanced modeling environment designed to simulate the interactions between wildland fires and atmospheric conditions. The model was applied to a range of historical fire events to demonstrate its capability to capture complex fire behaviors that are often missed by traditional fire models. Its application to the set of fires examined was also used to highlight both the strengths and limitations of the modeling approach,

² [MODIS Burned Area Product](https://modis.gsfc.nasa.gov/data/dataproduct/mod45.php) (https://modis.gsfc.nasa.gov/data/dataproduct/mod45.php)

offering insights into its overall application for operational situational awareness and risk management.

Upper Air Profiler Pilot Test

Workgroup 1 operated a sonic detection and ranging (SODAR) wind profiler instrument (sensors that measure weather conditions above the earth's surface) in Northern California to collect upper-air data from July through October 2020. The primary objective of the pilot test was to demonstrate how upper-air profiler data can improve short-term forecasts of high-wind events and enhance situational awareness during extreme weather events, both crucial for making informed PSPS decisions and improving fire-weather forecasts. A secondary objective of the pilot study was to explore how upper-air profiler data could be integrated into the operational data management systems used by utilities and next-generation fire models in future improvements in fire-weather forecasting.

The pilot study involved data collection, processing, and analysis. Workgroup 1 team members deployed a SODAR wind profiler instrument (Atmospheric Systems Corporation Model 2000; Figure 2) to gather upper-air wind data in Northern California at Cobb Mountain in Lake County. This instrument was installed following a detailed site selection process based on historical weather data and specific siting criteria, which included factors like land ownership, access, and potential noise interference.

Figure 2: Upper Air Profiler System



Photograph of the ACS Model 2000 Sodar system used at the upper-air monitoring site near Cobb Mountain, California

Source: Tami Lavesso and Brian Penfold, Pyregence Consortium (Sonoma Technologies)

Before deployment, the SODAR instrument underwent extensive testing to ensure that all systems, including power sources, data management, and communications, were functioning correctly. After installation at the field site on July 25, 2020, the SODAR was remotely monitored and maintained throughout the study period to October 26, 2020. Data were

collected continuously and transmitted hourly to a server, where they were processed and stored in a database.

The data collected by the SODAR, including wind speed and direction across various heights (measurements ranged from 80 m to 650 m above ground level, recorded at 20 m height intervals), were periodically reviewed for quality by trained data analysts. Additionally, real-time data were made accessible via a website linked to the Pyregence project website, allowing stakeholders to monitor the wind conditions throughout the pilot study. Challenges such as noise interference from nearby structures, were addressed through several corrective measures, including repositioning the SODAR and making software adjustments.

Following the data collection phase, the research team also evaluated opportunities to integrate upper-air profiler data into fire-weather forecasts.

Tree Mortality, Fuel Measurement, and Fire Physics (Workgroup 2)

Operational wildfire behavior models simulate critical fire characteristics such as direction, burn probability, flame length³, rate of spread, and heat flux. These models can help wildfire managers identify and prioritize risk mitigation interventions. However, most operational wildfire models are empirical (that is, based on observed, experimental, or historical data rather than on fundamental theoretical principles), and cannot be adapted to predict extreme fire behaviors resulting from long residency or prolonged heat releases by large woody fuels and deep duff layers typical of modern California forests. Current fire and fuel models were developed to predict the steady advance of a thin linear flame zone assuming heat release only from flaming combustion of continuous fine fuels for periods of between 10 and 30 seconds (Finney 1998). Fuel model predictions do not account for the post-front combustion and thus miss incorporating the 10 to 100 times greater fuel biomass of large diameter woody material and deep duff layers now common in many landscapes across the state, much of it resulting from massive tree mortality that occurred because of the extreme drought from 2012 to 2016 (Axelson et al. 2019). These fuels burn for hours, leading to large area fires (not thin flame zones) and heat release rates that vary widely depending on fire induced winds of solid phase combustion and smoldering-to-flaming transitions. With millions of drought-killed trees and their eventual fall to the ground, developing an understanding of solid fuel combustion under large fuel wildfire conditions is critical to approximate actual fire behavior and the loads and extent of woody fuels. Stephens et al. (2018) hypothesized that this kind of fuel buildup could lead to unprecedented “mass fires” in California forests, similar to past fire storms in cities that were bombed in World War II.

In response, Workgroup 2 was charged with expanding knowledge about tree mortality and associated fuels across California. Specific goals included to:

- Develop repeatable and controlled fuel materials and mixtures that can be burned at different laboratory scales, and complete experiments that vary the type, size, and configuration of woody materials on a test bed.

³ Flame length is the distance from the base of a fire at the ground surface to the tip of the flame, measured along the flame’s path (not vertically unless the flame is upright).

- Devise and test experimental apparatus in a laboratory setting to estimate predicted heat release rates across a range of fuel structures and environmental conditions found in wildland areas. Complete experiments that measure the amount of heat released by type, size, and configuration of fuel beds, along with varying wind velocities.
- Develop and deploy a new fuel measurement and mapping system to quantify the magnitude of fuel components (live and dead vegetation including trees, needles, leaves, and organic soils) and their spatial distribution across multiple scales.
- Map current and projected future fuel conditions in areas of elevated tree mortality.
- Evaluate how to integrate the products into both near-term risk forecasts and long-term risk projections, emphasizing wildland-urban interfaces when possible.

Laboratory Experiments

Understanding smoldering fire behavior is important because smoldering combustion, unlike flaming fire, is slow, persistent, and often hidden, making it difficult to detect and therefore suppress. Smoldering fires can burn deep into organic soils, duff layers, or woody fuels for days or even weeks, reigniting surface flames under favorable conditions and prolonging fire events. These residual hotspots pose risks to wildfire containment efforts, particularly during mop-up operations or in post-burn landscapes near critical infrastructure. Moreover, smoldering produces disproportionately high levels of smoke and fine particulate emissions, contributing to public health risks and regional air quality degradation. In the context of a changing climate, with increased tree mortality and accumulation of coarse fuels, understanding smoldering behavior is essential for predicting fire persistence, assessing reburn potential, estimating total emissions, and developing effective suppression and mitigation strategies.

Workgroup 2 investigated the smoldering behavior of simulated wildland fuels under varying wind speeds and fuel bed spacing configurations. Researchers conducted a series of small-scale controlled laboratory experiments using wooden cribs to represent wildland fuel beds. These cribs were burned inside a bench-scale wind tunnel, and the smoldering behavior was characterized by measuring both mass loss and emissions throughout the combustion process.

The experiments were designed to simulate the conditions that occur after the passage of a flaming wildfire front, where large woody fuels continue to burn in a smoldering state (Cobian-Iñiguez et al. 2022). That experiment explored how different wind speeds (ranging from 0.5 meters per second [m/s] to 1.25 m/s) and fuel bed porosities (spacing between wood planks used in the experiment) affected the smoldering combustion rate. To analyze the experimental data, theoretical models of mass transfer and heat transfer were applied (Cobian-Iñiguez et al. 2022).

Experiments on burning larger woody fuels were conducted using a controlled laboratory-scale burn facility designed to isolate and quantify the physical processes governing long-duration combustion of coarse woody debris and deep organic fuels. The burn chamber was constructed during the project at the U.S. Forest Service Missoula Fire Science Laboratory (Figure 3).

Figure 3. Large-Scale Burn Chamber



Photos showing the exterior (left) and interior (right) of the Grain Bin-Ventilation Controlled Combustion Facility at the U.S. Forest Service Missoula Fire Science Laboratory

Photo Source: Mark Finney, Pyregence Consortium (U.S. Forest Service Missoula Fire Laboratory)

A series of 35 experimental burns were carried out by the project team using beetle-killed lodgepole pine logs of varying diameters, rails, mulch, compost, and bark shreds, with systematically varied fuel sizes, arrangements, total loadings, moisture contents (typically between 7 percent and 10 percent), and imposed wind speeds ranging from approximately 0.5 to 4.5 m/s (Mark Finney, pers. comm. 2025). Each experiment measured fuel mass loss, oxygen consumption, carbon monoxide and carbon dioxide emissions, heat release rate, and, where feasible, fine particulate matter (PM_{2.5}) over time to characterize the full temporal evolution of flaming, smoldering, and char oxidation. Experimental designs included isolated logs, intersecting fuel configurations, and mechanically fractured logs to examine the effects of fuel interactions, geometry, and structural failures on burning rates and duration. Observations from these experiments were used to develop and test a simplified, physically based, one-dimensional burning model that represents wood-to-char and char-to-ash transitions, which explicitly incorporated wind-driven temperature and heat-flux effects that captured the dominant processes controlling the long-duration combustion of large woody fuels for application in coupled fire-atmosphere modeling and emissions estimations.

Fuel Measurement System

Wildland fuels, the live and dead vegetation that burns during wildfires, are primary drivers of fire behavior, fire effects, and emissions. While fuels are commonly categorized into canopy, surface, and ground components, available fuel load (biomass per unit area) is the single most influential factor governing how fires burn and how much carbon and smoke they release (Burgan and Rothermel 1984). As a result, in forested landscapes, fuel-load reductions are central to wildfire hazard mitigation, carbon accounting, and ecosystem management (Agee and Skinner 2005, Stephens and Moghaddas 2005, Hurteau et al. 2008). However, most

operational fire behavior models and fuel classification systems (for example, Scott and Burgan 2005) assume that fuel loads are uniformly distributed within a map unit, despite evidence that fuels vary dramatically at fine spatial scales and that this heterogeneity strongly influences fire spread, intensity, severity, and ecological outcomes (Foster 2022). Empirical and simulation studies show that small-scale variations in surface and ground fuels can dampen fire intensity, influence tree mortality, and shape post-fire recovery; yet current methods either rely on statistical correlations that lack physical realism, provide only sparse or descriptive representations of fuels, or depend on computationally intensive fire-atmosphere models that are impractical for widespread application and often misrepresent surface fuels (summarized in Foster 2022).

To address these limitations, Workgroup 2 developed and tested novel, spatially explicit methods for measuring and modeling fine-scale fuel heterogeneity, with a particular focus on surface and ground fuels that cannot be reliably mapped using remote sensing, but are nevertheless critical to fire behavior (Foster 2022). The team collected detailed data on various Sierra Nevada mixed conifer (within a 17 km² study area at Sequoia National Park) and wildland fuel components affected by the 2012 to 2016 California drought including duff, litter, fine woody debris, coarse woody debris, understory vegetation, trees, and saplings. This was done using a modified forest inventory protocol that emphasized spatially explicit sampling at a fine scale (sub-meter to tens of meters). The sampling protocol aimed to capture the spatial heterogeneity of these components across plots stratified by differing severities of drought mortality. A total of 21 inventory plots were sampled, representing 7 plots per drought mortality class. Within each plot, multiple fuel components were sampled using the following modified forest inventory protocols:

- Trees: 500 m² fixed-area plot
- Saplings: 116 m² fixed-area plot
- Surface and ground fuels (duff, litter, fine woody debris, coarse woody debris, understory vegetation): sampled along four 30-m transects extending from plot center in cardinal directions

Across all 21 plots, this amounted to thousands of spatially explicit observations per fuel component, including:

- 1,344 duff observations
- 1,344 litter observations
- 672 fine woody debris quadrats
- 2,520 coarse woody debris locations
- 2,520 understory vegetation locations
- 10,500 tree quadrats
- 2,436 sapling quadrats

In addition, individual particle diameters were measured for both fine and coarse woody debris, resulting in tens of thousands of woody fuel measurements.

Hierarchical spatial statistical models were used to evaluate field data, incorporating Gaussian process spatial random effects, to quantify and describe the fine-scale spatial patterns of the collected fuel load data. These models accounted for the spatial autocorrelation within each fuel component and allowed for the generation of realistic simulations of fuel beds that could be used to predict fire behavior under varying conditions. The models were validated against three criteria: ability to make pointwise predictions, reproduce fine-scale observations, and replicate coarse-scale mean fuel loads. The approach provided a framework for integrating observational field data with predictive fuels modeling, offering insights that could improve forest management practices for mitigating fire risks (Foster 2022).

Forecasting Surface Fuel Loads

Workgroup 2 used a combination of field data collection and modeling techniques to assess the progression of snags (standing dead trees) falling to the ground and fuel succession following a significant tree mortality event caused by the 2012 to 2016 drought in California (Northrup 2022, Northrup et al. 2024). The team used data from two key studies: the Drought Mortality Network and the Forest Demography Study (Axelrod et al. 2019), both of which provided extensive, long-term datasets on tree mortality and forest dynamics in the southern Sierra Nevada. These data were unique from the datasets described in the previous section.

Field data collection monitored tree and fuel inventory plots established across the Sierra Nevada to quantify how recently dead trees influenced fuel loads and fire hazards. These plots were strategically placed across different levels of drought mortality severity to capture variations in fuel accumulation and snag fall rates. The team used snag fall models with long-term data from the Forest Demography Study. The data from the Drought Mortality Network allowed documentation of immediate impacts and provided predictions for future fuel accumulation and snag fall rates.

To analyze and predict fuel-load changes over time, Workgroup 2 used hierarchical spatial statistical models, which integrated empirical (field) data with predictions of future snag fall rates (Northrup 2022, Northrup et al, 2024). These models accounted for species-specific and size-dependent variations in snag longevity and decay rates, providing insights into how fuel loads could evolve in coming decades. The study's findings were used to refine vegetation simulation models

such as the Forest Vegetation Simulator⁴, particularly in its snag fall algorithms, to improve predictions of fuel load dynamics in response to tree mortality events.

Contemporary Tree Mortality Mapping

The objective of the contemporary tree mortality mapping effort was to provide detailed, high-resolution maps of tree mortality that could be integrated into wildfire behavior models that assess and mitigate the risks posed by elevated tree mortality. The primary method involved training a deep learning model using multi-temporal satellite data from multi-spectral and

⁴ [USFS Forest Vegetation Simulator](https://www.fs.usda.gov/managing-land/forest-management/fvs) (<https://www.fs.usda.gov/managing-land/forest-management/fvs>)

radar sensors. Researchers from Workgroup 2 first created a response variable from 1-meter resolution maps of red-phase conifer mortality (dead conifers with reddish-brown needles still attached), which was then averaged to a 10-meter resolution to match the satellite covariates. These covariates included 10-band multi-spectral data from Sentinel-2 and 2-band radar backscatter data from Sentinel-1. The model incorporated 24 bands of data from different seasons and sensors to capture the necessary biophysical changes associated with tree mortality.

The deep learning model used was a U-net model, a type of 2D Convolutional Neural Network architecture, which is particularly effective in ecological contexts due to its ability to quantify spatial orientations of nearby objects and include contextual information about the surrounding environment. The model was trained on over 91,000 samples, validated on approximately 16,000 samples, and tested on nearly 19,000 samples, including measures to adjust for sample imbalance to minimize underpredictions.

Model validation was conducted by comparing the satellite-based mortality predictions with field data collected by the United States Geological Survey (USGS) Western Ecological Research Center and high-resolution training data. The results showed that the model provided conservative estimates of tree mortality, with fewer prediction biases in areas of extreme mortality.

This work provided high-resolution, spatially continuous estimates of dead-tree cover across California, at higher spatial resolutions than polygon-based summaries from the United States Forest Service Aerial Detection Survey (ADS). Unlike ADS's generalized trees-per-acre maps, the satellite product measured fractional dead canopy cover at 30-meter resolution, accurately reflecting fine-scale patterns vital for fire modeling. Using multi-temporal satellite data and deep learning, the approach tracked annual mortality trends and distinguished true die-off from seasonal changes. By combining Sentinel-2 multispectral data, Sentinel-1 radar, and a U-Net model, it better separated dead trees from bare ground and leaf litter, overcoming key ADS limitations. Validation showed that the satellite estimates were conservative yet consistent with ADS, reliably capturing regional mortality patterns without overestimating severity.

Near-Term Wildfire Forecasting Models (Workgroup 3)

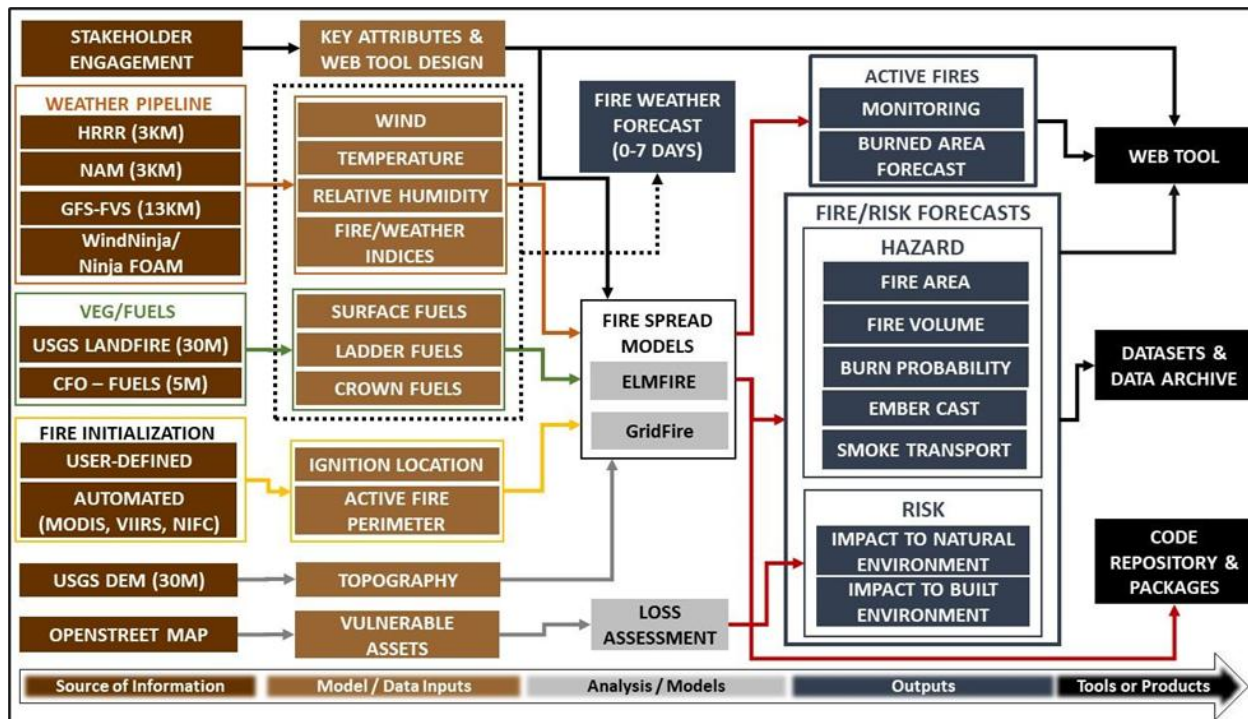
The objective of Workgroup 3 was to develop computationally efficient models to provide near-term risk forecasts over a 0- to 7-day period at a fine (30 m) spatial scale to simulate the spread of extant fire ignitions. Additionally, Workgroup 3 was tasked to work with electric utilities to integrate models into their respective wildfire situational awareness programs. The overarching approach that the team used to accomplish these objectives was to refine, test, and evaluate the performance of near-term fire forecasting models previously developed by Workgroup 3 members.

Following guidance provided through stakeholder engagement early in the project, the team developed and deployed an easy-to-use, open-source, near-term fire forecasting platform called PyreCast. The team evaluated its potential benefits to electric utilities using a case study of the value of more timely forecasts for pretreating power poles.

Near-Term Fire Forecasting Models and Tools

Stakeholder input indicated the need for both an improved wildfire behavior model and a platform that could display a range of wildfire hazard and risk related model outputs. Accordingly, Workgroup 3 developed a framework that was used to guide development of a near-term fire forecasting platform (Figure 4). The framework identified datasets required for wildfire model inputs, underlying modeling and analysis methods, and data outputs and final products. The framework was deliberately structured for modularity and accessibility so that data and models within the framework could be easily updated to reflect the latest available science, users could customize back-end or front-end functionality as desired through additional software enhancements, and the geographic scope of forecasts could be scaled.

Figure 4. Near-Term Fire Forecasting Modeling Framework



The framework used to guide the development of the PyreCast near-term fire forecasting platform

Source: Chris Lautenberger and Maria Theodori, Pyregence Consortium (Reax Engineering)

Wildfire Behavior Models Used in PyreCast

The wildfire behavior models shown in Figure 4, currently used for the PyreCast “risk” and “active fire” spread forecast tools were ELMFIRE (Eulerian Level set Model for FIRE spread; Lautenberger 2013, Lautenberger 2017) and “GridFire” developed by Gary Johnson from Spatial Informatics Group (Johnson et al. 2022). These models were selected because they were high performance, open-source fire behavior models that could be scripted easily and flexibly to run in automated, cloud-based computational pipelines and wrapped in microservices. ELMFIRE was additionally subjected to prior peer-review scrutiny (Lautenberger 2013, Lautenberger 2017). Models used could be extended when new functionality was needed for the Pyrecast platform. In contrast, the United States Forest Service Fire Lab (Fire Lab) models were effectively closed source and could not be extended by the project team.

Fire Lab models could not be scripted easily to run on the compute pipelines designed for this project because they are mostly Windows (only desktop programs). Additionally, Fire Lab models run more slowly than GridFire and ELMFIRE, which limited the number of forecasts that could be computed and issued on PyreCast each day.

ELMFIRE

ELMFIRE is the primary wildfire behavior model used in PyreCast. The ELMFIRE (Eulerian Level Set Model of FIRE spread) wildfire behavior model (Lautenberger 2013, Lautenberger 2017), previously developed by Chris Lautenberger of Workgroup 3, uses advanced mathematical and computational techniques to simulate the spread of wildfires in both real-time and historical contexts. The model is built on the principles of level set methods, which allow it to accurately track the progression of complex fire fronts across various terrains. Using level set methods, the model tracks the hot edge of a fire and then spreads the fire from those hot edges. As fire behavior responds to wind, fuels, slope, and atmospheric forcing, the fire edge moves smoothly across the landscape, naturally capturing changes in fire shape, direction, and rate of spread. ELMFIRE predicts fire behavior, employing the Rothermel (1972) model to calculate the spread rate in the direction of maximum spread (head fire). ELMFIRE includes features for estimating annual burn probability, fire severity, and quantifying landscape-scale fire behavior potential.

GridFire

During the project, GridFire was a secondary wildfire behavior model used in the PyreCast platform. Although GridFire is functional in PyreCast, ELMFIRE was used as the primary wildfire modeling engine to simplify user interface and management of the system, and to conserve compute resources. The GridFire wildfire behavior model was developed by members of Workgroup 3 prior to the project and refined during the project with a focus on leveraging the latest fire science literature and computational methods to create an accurate and computationally efficient tool for simulating wildfire spread. The model was implemented using efficient programming and integrated seamlessly with spatial databases. GridFire employs a series of well-established fire behavior formulas, including those for surface fire spread (Rothermel 1972), crown fire initiation (Van Wagner 1977), and flame length and fire-line intensity (Byram 1959). The model was designed to handle complex environmental inputs such as fuel models, weather data, and topography, translating them into detailed fire-spread simulations. One of its key features is the use of a raster grid system, which allows the user to define time steps in fire progression forecasts and fractional distances in fire-spread calculations. The development approach of GridFire also included dynamic fuel loading adjustments, wind adjustment factors, and sophisticated algorithms for translating 1-dimensional (spatial) fire spread equations into 2-dimensional (space and time) spatial simulations.

For both GridFire and ELMFIRE active-fire forecasts, model runs were based on reported initial ignition locations from various sources (for example, CALFIRE, Fire Guard, others), then rerun about every 12 hours, based on hotspot data retrieved from open-source satellite hotspot data.

Evaluation of PyreCast Fire Model Performance

To assess how well the ELMFIRE wildfire behavior model performed, both qualitative and quantitative methods were used. The overall evaluation process follows.

Data Collection and Model Initialization: The performance evaluation process began with gathering extensive data from previous fires that occurred in different regions within the contiguous United States, including satellite-based hotspot data, infrared perimeters from aircraft, and other fire polygons, to initialize the models. This data served as the foundation for forecasting fire spread and behavior in the PyreCast system. Notably, actual fire perimeter data representing a timestep and associated satellite hotspot data were used to inform ignition locations for model runs in the performance evaluation.

Retrospective Analysis: The evaluation involved retrospective assessments of model performance by comparing forecasted fire spread and behavior with actual observed fire perimeters. This included running hindcasts of historical fires (such as the 2018 County Fire) and comparing the modeled fire perimeters against observed data for a given time period. It should be noted that the fire spread model used did not account for fire suppression actions, which could account for differences between the modeled and observed fire footprints.

Ensemble Simulations: To address uncertainties in modeled fire spread predictions, the ELMFIRE model, for example, runs in ensemble mode, where multiple simulations with slightly varied inputs (such as wind speed and fuel moisture) were conducted allowing model outputs to vary and be binned into 10th, 30th, 50th, 70th, and 90th percentile active-fire forecasts. The results from these ensemble runs were then analyzed to determine the overall fitness and accuracy of the model predictions to determine which forecast best represented the observed fire perimeter for a given fire.

Correlation and Fitness Metrics: The evaluation process included calculating correlation metrics between modeled and observed fire perimeters, which helped quantify how well the model predictions aligned with actual fire behavior. This process was critical for identifying areas where the model performed well and where improvements were needed.

Challenges and Improvements: The evaluation process also qualitatively identified challenges such as spurious heat detections, fuel moisture data, and the influence of weather conditions like smoke inversions, which can impact model accuracy.

Recommendations: Based on the results of the different evaluations performed, the team generated a list of recommendations to improve model performance.

Cost/Benefit Assessment of PyreCast

The approach to evaluating the possible benefits of the PyreCast system focused on a case study of utility pole pretreatments during the 2020 Glass Fire. Treating poles (for example, with applications of fire retardant, pole wraps, vegetation clearing) before a fire can prevent their loss; utilities can use fire spread forecasts to decide which poles to treat and how far in advance they need that information to make the most effective decisions. Outdated forecasts can lead either to poles not being protected or to poles being protected unnecessarily, both causing wasted expense. The evaluation emphasized the value of reduced data latency (or

delay) in providing fire forecasts, which allowed more frequent and accurate updates to wildfire risk simulations, ultimately improving decision-making in real-time mitigation efforts. The evaluation compared the traditional "status quo" approach of once-daily forecasts to utility pole pretreatments with an enhanced approach with multiple updates per day (2+ per day) enabled by PyreCast, leading to more responsive and timely actions guided by rapidly changing weather forecasts. By modeling the impact of the frequency of forecasts during the 2020 Glass Fire, the evaluation quantified the number of utility poles that could be saved from damage. The benefits were monetized by calculating the avoided costs of pole replacements and of unnecessary pole treatments, considering factors like the probability of pole damage, the cost of pole replacements, and the depreciation of pole values over time. The evaluation scaled the findings from the Glass Fire case study to estimate the potential statewide benefits in reducing the economic impacts of wildfires on utility infrastructure.

Long-Term Wildfire Projections (Workgroup 4)

The goal for Workgroup 4 was to use the best available data and science to build the next generation of coupled statistical/dynamical fire-climate-vegetation models to run long-term (such as to the end-of-century) wildfire risk projections. Workgroup 4 developed two coupled modeling approaches (combining the Land Use and Carbon Scenario Simulator [LUCAS] with the U.C. Merced Fire Risk Simulation Model [FRSM], and the second-generation Landscape Disturbance and Succession Model [LANDIS-II] model). In addition, the workgroup explored the application of machine learning models to predict future wildfire activity.

Overview of Coupled Wildfire/Climate/Vegetation Model Framework

The modeling framework developed by Workgroup 4 to support California's Fifth Climate Change Assessment was a multi-model, multi-scale system that integrated (coupled) statistical fire simulation, land-use and carbon accounting, and dynamic vegetation modeling under different climate, urban growth, and vegetation management scenarios. This structure enabled exploration of how California's future wildfire regimes may evolve under changing environmental and societal conditions and provided a foundation for evaluating fire mitigation strategies for communities, ecosystem resilience, and long-term carbon outcomes.

The modeling framework was designed to meet three core objectives to:

1. Project future wildfire disturbances under a range of future climate, land-use, and vegetation management scenarios consistent with a selection of Coupled Model Intercomparison Project climate projections from the Intergovernmental Panel on Climate Change 6th Assessment Report (CMIP6).
2. Capture coupled feedbacks between wildfire, vegetation, and land-use change that influence future fuels, carbon storage, and emissions.
3. Provide decision-relevant outputs at spatial and temporal scales suitable for both statewide climate policy and local planning, including applications for utilities, land managers, and carbon accounting.

The framework was designed to be both computationally fast and realistic by using different models built for specific tasks and scales, then connecting them through shared data, feedback loops, and flexible scenario planning.

As part of this work to project long-term scenarios of wildfire risk, FRSM and LUCAS were coupled within a single modeling workflow to generate projected annual outcomes for vegetation, biomass, carbon, and fire disturbances. The LANDIS-II modeling system has an internal wildfire disturbance extension that was used in place of the FRSM to generate a range of similar outputs for that modeling approach.

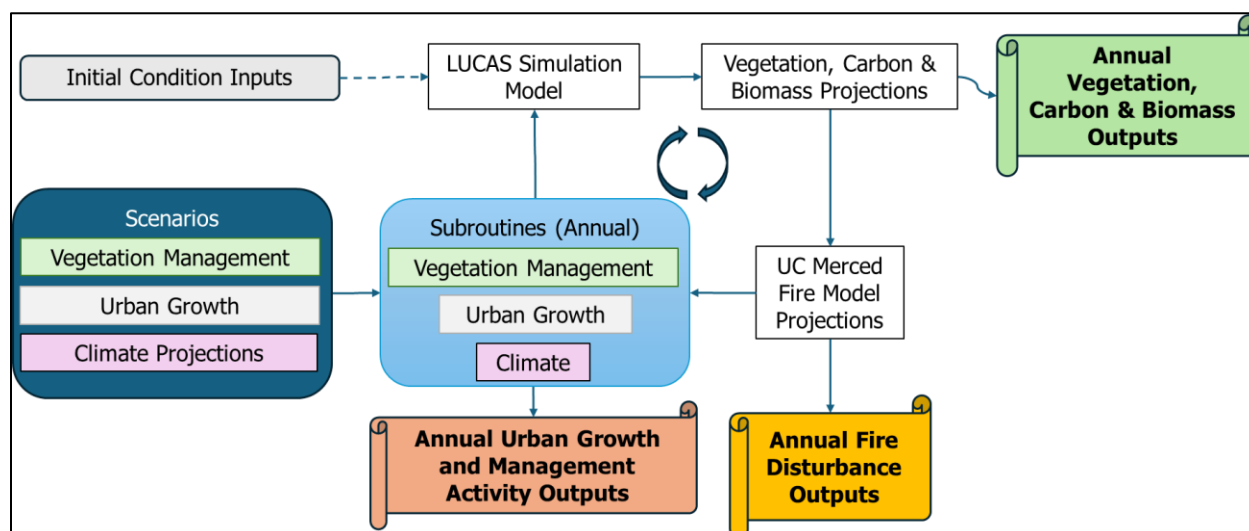
Coupling between model components (whether between LUCAS and FRSM or internally within LANDIS-II) occurred through a bi-directional data exchange at compatible spatial and temporal scales. This process involves several key linkages.

- *Climate Forcing:* Downscaled CMIP6 climate projections (using localized construct analogs-hybrid (LOCA2) hybrid statistical methods) provided consistent temperature, precipitation, humidity⁵, and wind inputs across all model components.
- *Fire-to-Vegetation Feedback:* FRSM outputs, projected fire occurrences, burned areas, and severity fractions were projected onto 1-km grids and used to update vegetation and carbon states within LUCAS. A similar fire-to-vegetation feedback occurred within LANDIS-II, but at a finer 150-m spatial resolution.
- *Vegetation-to-Fire Feedback:* Updated biomass, fuels, and vegetation structure from LUCAS informed subsequent FRSM simulations, modifying ignition probabilities and fire spread potential. LANDIS II similarly provided vegetation-to-fire feedback.
- *Land-use and Urban Development Feedback:* LUCAS simulates changes in land cover and urban area based on vegetation management and urban growth scenarios, influencing ignition sources and exposure metrics in FRSM. LANDIS-II simulates changes in land cover based on vegetation management only, given that it was only parameterized over forested areas of the state where urban growth will not be as significant. The team purposefully constrained the footprint of LANDIS II model runs to forested landscapes due to known deficiencies in modeling herbaceous vegetation.

The described feedback was implemented as iterative model runs; FRSM simulates fire for a given time step (for example, annually), LUCAS updates land cover and biomass/fuels accordingly, and revised fuel and vegetation data were passed back to FRSM for the next simulation period (Figure 5). The LANDIS-II approach similarly cycles feedback, but excludes urban growth scenarios and California forested landscapes, using a different fire simulation model (Figure 6). This design allowed the system to account for cumulative and nonlinear interactions among climate, vegetation, and human activity into the future.

⁵ Relative humidity was simulated statistically using temperature and precipitation from CMIP6 climate projections (See Appendix B).

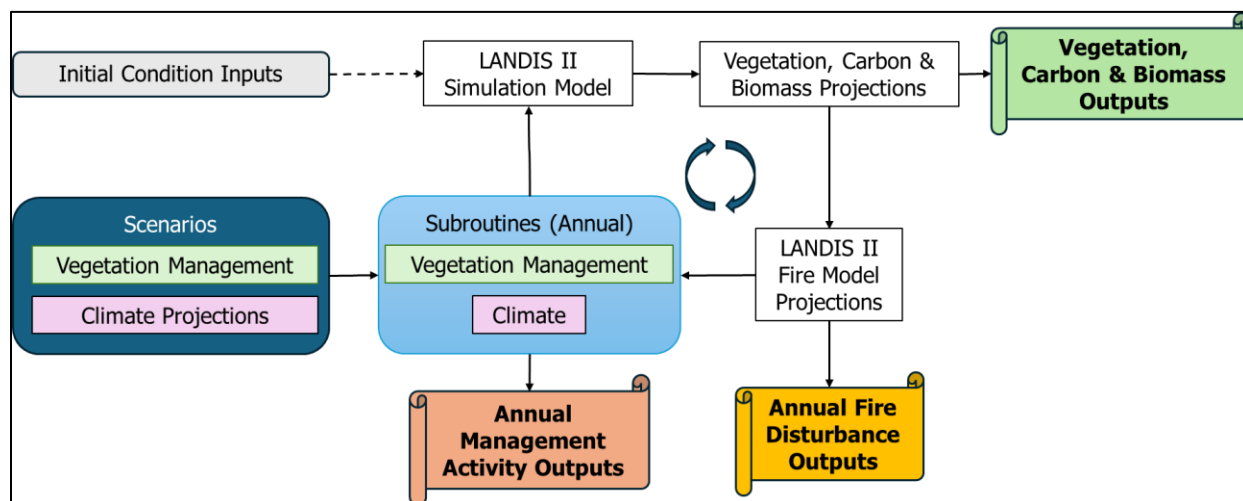
Figure 5. Generalized Representation of the Coupled LUCAS - FRSM Modeling Approach



Bi-directional coupling between the LUCAS simulation model and U.C. Merced FRSM. Climate projections drive both models; LUCAS supplies landscape state (land use and land change, dead organic matter stocks, biomass, shrubland fraction) to FRSM, which returns simulated burn area, severity fractions, and ignition probabilities. The feedback loop captures fire-vegetation interactions at annual timesteps across 10 Monte Carlo iterations.

Source: Shane Romsos, Pyregence Consortium (Spatial Informatics Group)

Figure 6. Generalized Representation of the Coupled LANDIS-II Modeling Approach



Source: Shane Romsos, Pyregence Consortium (Spatial Informatics Group)

The framework operates across nested spatial resolutions to capture processes relevant at multiple decision levels (Table 1).

Table 1. Spatial and Temporal Resolution and Geographic Scope of Each Model Used as Part of the Project

Model	Spatial Resolution	Temporal Resolution	Geographic Scope
Uncoupled FRSM	3 km	Semi-Monthly, Monthly to Annual	Statewide CA
Uncoupled LUCAS	1 km	Annual	Statewide CA
Coupled FRSM-LUCAS	1 km	Annual	Statewide CA
LANDIS-II	150 m	Annual	Forested Landscapes CA

Source: LeRoy Westerling, Ben Sleeter, Charles Maxwell, and Shane Romsos, Pyregence Consortium (UC Merced, USGS, Spatial Informatics Group)

Projections were run for historical scenarios: 1984-2020, (all models), mid-century (2020-2065, coupled FRSM-LUCAS model framework), end of century (2020–2100, LANDIS II), uncoupled FRSM, and uncoupled LUCAS periods aligned with CMIP6 forcing intervals (2015 to 2100)⁶. These nested scales ensured that coarse (3 km), long-term climatic trends inform regional ecological dynamics, while finer-scale vegetation and management feedback refine statewide wildfire projections.

The modeling framework supported scenario-based analysis that combines climate forcing from CMIP6 (for example, SSP2-4.5, SSP3-7.0, SSP5-8.5), land-use trajectories from LUCAS (concentrated versus sprawled urban growth) and vegetation management regimes (for example, low- versus high-effort vegetation management).

The climate scenarios evaluated were selected to span the full range of plausible future climate conditions relevant to wildfire risk in California rather than relying upon a single emissions pathway or model outcome.

For climate scenarios, the project team prioritized a subset of CMIP6 GCM projections to represent the breadth of projected temperature and precipitation changes across Northern California and Southern California at both mid-century and end-of-century. These scenarios include combinations of warmer-drier, warmer-wetter, and extreme drought-prone futures to ensure that wildfire-relevant climate uncertainty was explicitly captured. Together, the selected set of 11 climate scenarios captured uncertainty in future warming, precipitation variability, and drought intensity, providing a foundation for evaluating how wildfire hazards, vegetation dynamics, and carbon outcomes may evolve across California under different but plausible climate futures.

To provide regionally realistic climate inputs, the selected CMIP6 scenarios were bias-corrected and downscaled using two complementary approaches: 1) dynamical downscaling with the WRF model, producing physically based regional climate simulations, and 2) LOCA2 hybrid-statistical downscaling, which bias-corrects GCM outputs for consistency with observed station

⁶ CMIP6 forcing interval refers to the specified time steps or periods for applying and updating external climate drivers (such as greenhouse gas concentrations, aerosols, solar variability, and land-use changes).

data (Pierce et al. 2023a, Pierce et al. 2023b, Rahimi 2023). In addition, ERA5–WRF reanalysis and a synthetic relative humidity dataset (derived by the project team) ensured historical fidelity and preserved observed drying trends critical for wildfire modeling.

Vegetation management scenarios were defined to bracket plausible future treatment pathways (such as prescribed and cultural fire and thinning) based on historical treatment rates and policy-driven management targets. Two scenarios were identified with TAC input⁷ and implemented.

- *High Ambition Vegetation Management Scenario:* This scenario models forest treatments that meet the goal of 1-million acres treated per year, a goal identified in a 2018 Executive Order [B-52-18] and emphasized in the 2021 California Wildfire and Forest Resilience Action Plan⁸. The plan prioritizes reducing fuels (through vegetation management) in areas classified with “high” or “very high” wildfire hazard potential (Vogler et al. 2022).
- *Business-as-Usual (BAU) Vegetation Management Scenario:* This scenario represents an attempt to sustain the vegetation management effort from the previous decade (2010–2019). The total average annual treatment rate across the state was estimated at approximately 140,000 acres per year, or 86-percent less activity than the high ambition scenario, so is referred to as the low-effort scenario.

Vegetation treatments in the LUCAS and LANDIS-II models were assigned using spatial allocation rules and assumptions based on factors like land management zones, surface characteristics, and underlying wildfire hazard levels. Eligible vegetation types for treatment were prioritized (constrained areas excluded), and annual treatment targets assigned randomly across eligible pixels (see APPENDIX B for details). Treated pixels were updated annually in the modeling framework to reflect changes in vegetation structure, biomass, and carbon pools, and these updated fuel conditions were then passed from LUCAS to the FRSM fire model either in the coupled model framework or internally within LANDIS-II to its fire module, allowing treatment effects to influence subsequent wildfire disturbance and severity through dynamic fire-fuels feedback.

Two urban development footprint scenarios were identified for use in wildfire model simulations, including:

- *Sprawl:* a scenario based on historical urban growth patterns that represents a “business as usual urban sprawl” development pattern. Under this scenario, development would be allowed throughout areas designated as wildland-urban interfaces (Kearns et al. 2022 per WUI definition provided in Federal Register 66 FR 751, #01-52).

⁷ Note that modeling for the California Air Resources Board 2022 Scoping Plan showed that 2.3 million acres treated per year would be needed to realize the carbon stock target called for in this [Scoping Plan](https://ww2.arb.ca.gov/sites/default/files/2023-04/2022-sp.pdf) by 2045. <https://ww2.arb.ca.gov/sites/default/files/2023-04/2022-sp.pdf>. This target was set after the recommendation by the project TAC had already been adopted

⁸ [2021 California Wildfire and Forest Resilience Action Plan](https://wildfiretaskforce.org/wp-content/uploads/2022/04/californiawildfireandforestresilienceactionplan.pdf) - <https://wildfiretaskforce.org/wp-content/uploads/2022/04/californiawildfireandforestresilienceactionplan.pdf>

- *Concentrated/Infill*: this scenario represents a concentrated/infill development pattern that limits development to within or directly adjacent to existing development.

Urban growth scenarios were based on the anticipated amount of new development (“transition targets”), the adjacency of new urban development relative to existing developed areas (“spatial adjacency”), and the concentration of growth relative to land use type (“spatial multiplier”). Transition targets for scenarios were based on historical rates of development specified for each county based on California Farmland Mapping & Monitoring Program (FMMP) data.⁹ Future projections would draw development area targets randomly from the full range or a subset of past years to allow future variations of high or low growth in each time step.

The models produce a variety of spatial and tabular outputs, including probability maps of large fire occurrences, projected fire severities, and vegetation and carbon stocks.

By varying these inputs systematically, the framework generates a matrix of simulations exploring the combined influence of climate, urban development, and vegetation management on long-term wildfire risk, vegetation dynamics, and carbon emissions.

Primary outputs from each time step from the modeling framework include:

- Probability and spatial extent of large fires.
- Burn severity distributions (low, moderate, high) as fractions of the projected burned area. Refined based on research by Xu et al. (2022a), Xu et al. (2022b), and Sam et al. (2022).
- Carbon fluxes and net ecosystem carbon balance.
- Vegetation composition, biomass, and fuels characteristics.
- Urban growth dynamics
- Vegetation management dynamics

Most outputs were stored as gridded raster surfaces (for example, GeoTIFF) with metadata that describe the associated climate model, scenario, and management configuration. Derived spatial layers are intended for integration into other platforms such as Cal-Adapt Analytics Engine, but at this point they have not been optimized for cloud computing. APPENDIX B provides additional details of modeling approaches used for the LUCAS/FRSM modeling framework, LANDIS II, uncoupled LUCAS and uncoupled FRSM.

Application of Machine Learning Models

Machine learning has enabled advances in modeling complex processes. In a separate modeling effort, the project team explored the potential of machine learning to improve wildfire modeling as an alternative to other approaches described here. The approach for predictive machine learning models integrated a variety of data sources, predictive models, and statistical analyses to provide insights into historical wildfire risk in different ecoregions across California (Hawbaker et al. forthcoming). The study used an array of data sources,

⁹ [Farmland Mapping and Monitoring Program](https://www.conservation.ca.gov/dlrp/fmmp) <https://www.conservation.ca.gov/dlrp/fmmp>

including weather data from GridMET¹⁰, land cover data from the USGS Land Change Monitoring, Assessment and Projection Program¹¹, and various topographical and human influence factors. These datasets were processed and resampled to a standardized 1-km resolution to ensure consistency across the analyses.

For predictive modeling, machine learning models (specifically, random forest), were used to predict ignition probabilities, potential fire sizes, burn probabilities, and burn severities. The models use a wide range of predictor variables including historical weather conditions, vegetation types, previous fire history, and human influences such as proximity to powerlines and roads. The research used statistical analysis to evaluate model performance. Metrics such as the AUC, mean error, and root mean squared error were calculated to assess the accuracy of the predictions across different time steps (monthly, annual, and decadal) and ecoregions. The models were validated using cross-validation techniques to demonstrate their reliability.

The research focused on capturing the spatial variability of wildfire risks across California's ecoregions. By downscaling model outputs to a 1-km resolution, the research provided maps of predicted fire metrics, which was helpful for localized fire management and mitigation strategies. Recognizing the role of human activities in wildfires, the research included variables such as housing density, distance from development, and infrastructure proximity. These factors were integrated into predictive models to better understand how human presence influences fire behavior. Although the model was trained on historical weather and wildfire data, it could run simulations of future conditions if provided appropriate climate projections.

¹⁰ [Climatology Lab](https://www.climatologylab.org/gridmet.html) <https://www.climatologylab.org/gridmet.html>.

¹¹ [LCMAP Data Access](https://www.usgs.gov/special-topics/lcmap/lcmap-data-access) <https://www.usgs.gov/special-topics/lcmap/lcmap-data-access>

CHAPTER 3:

Results

The following provides a summary of results from the various project products by workgroup. Detailed results and discussion can be found in referenced documents or from project deliverables linked in the “Project Products and Deliverables” section of this report.

Extreme Weather and Fire (Workgroup 1)

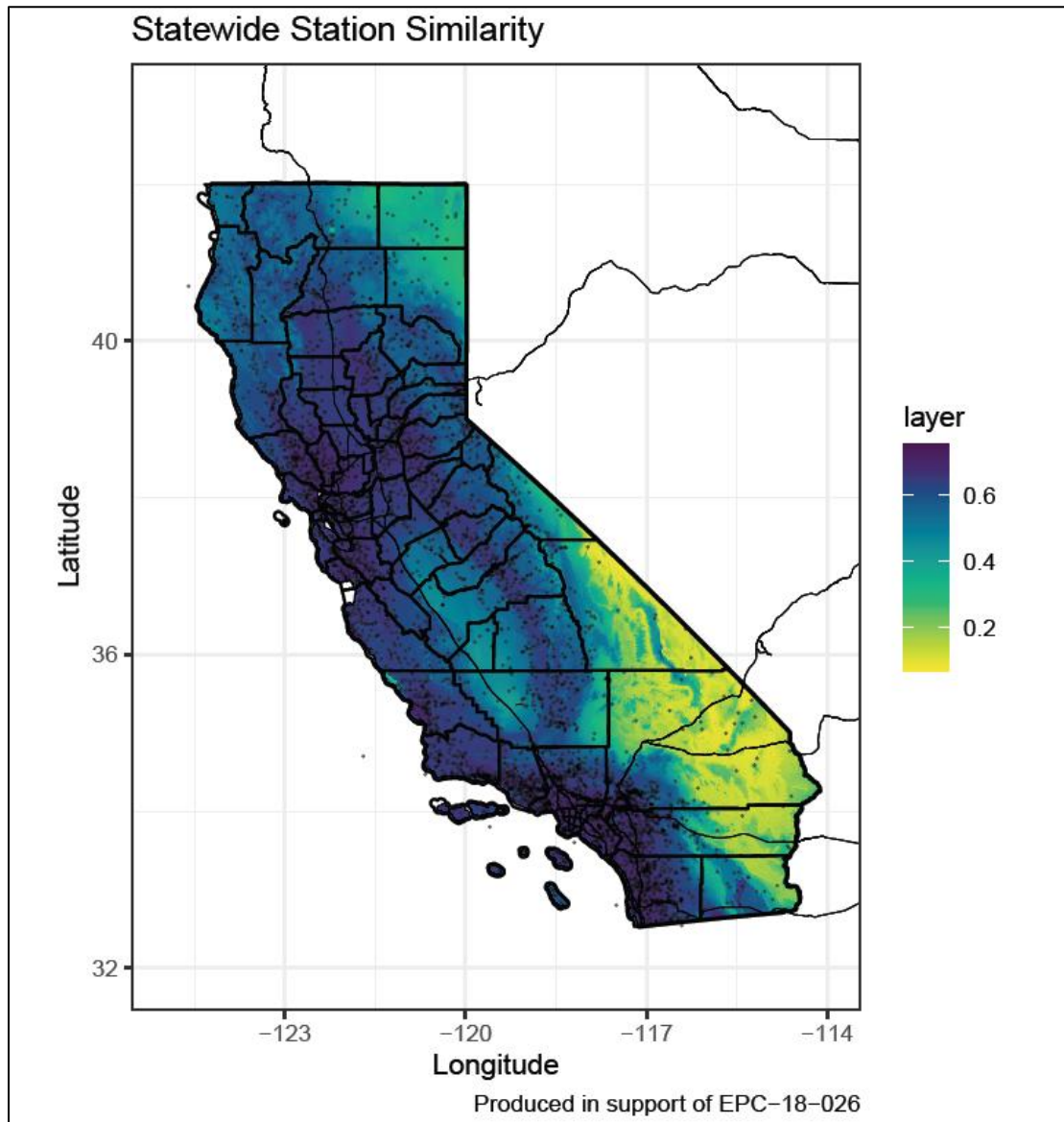
Weather Station Optimization Modeling

This study assessed whether weather station monitoring is sufficient across California for current and future climate conditions. Under current-day conditions, urban regions such as the Bay Area, Los Angeles Basin, and San Diego are well-covered by existing weather stations ($n = 7,647$), representing a range of weather station operators and levels of data quality across California (as of 2021; Figure 7).¹² These areas showed high similarity scores¹³, indicating that the current network of stations captures local climate conditions to a high degree. However, rural regions like the northeastern Modoc, Basin and Range regions, the Mojave Desert, and the highest elevations of the Sierra Nevada exhibit lower similarity scores, signaling that these areas are not as well represented by the existing network.

¹² Weather station information sourced from “*Optimal Location of Weather Stations in California Report*” Appendix Table A.1 (Doherty et al. 2022). A [complete set of model outputs](https://data.pyregence.org/wg1/wx_station_optimization/pred_rasters/) from this analysis can be found at - https://data.pyregence.org/wg1/wx_station_optimization/pred_rasters/;

¹³ A similarity score measures the likelihood of presence of a weather station based on the aggregate climate conditions where weather stations are placed. Based on the locations of weather stations and a random selection of background points, sites on the landscape where there is not a weather station, MaxEnt builds a predictive model based on input climate data to distinguish sites with and without weather stations (Phillips et al. 2006) and produces as an output a relative occurrence rate, which is the relative probability a cell is contained in a collection of presence samples. The relative occurrence rate – here called a similarity score – can be interpreted as how similar the underlying climate conditions are at a given location to sites with weather stations given the climate variables used to build the MaxEnt models, where high values are areas of more similar climate and low values are areas of increased dissimilarity.

Figure 7. Statewide Similarity Scores Under Present Climate Conditions



Similarity scores are shown using color ramp, where higher values (blue) indicate more similar climate conditions to areas with weather stations. Weather stations are shown on map as black dots, including all stations from the three highest quality levels: federally operated, IOU/state operated, and university operated (n = 7,647).

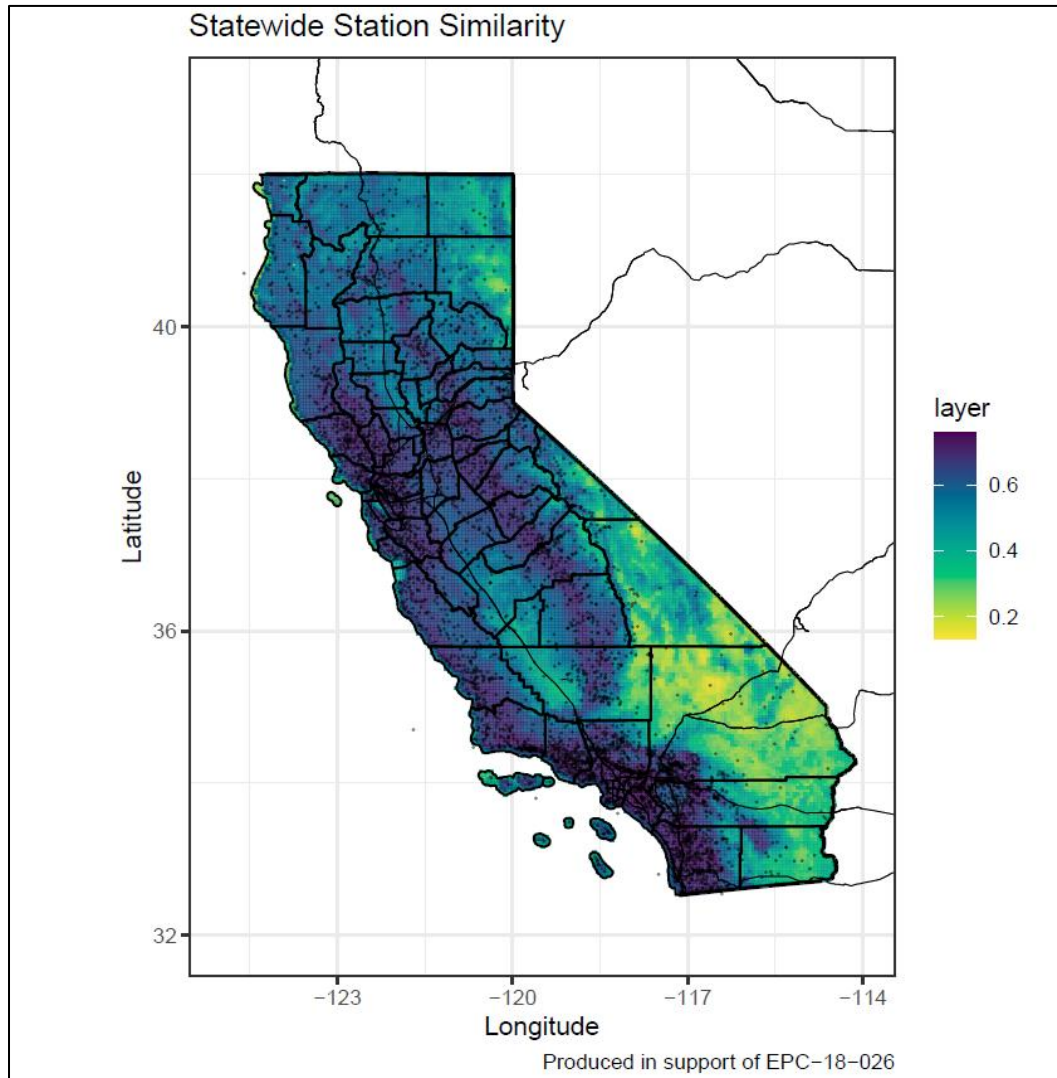
Source: Owen Doherty, Pyregence Consortium (Eagle Rock Analytics)

Looking toward future climate conditions¹⁴, the patterns of insufficient coverage largely persist. Areas that are projected to experience significant climatic changes, such as the Modoc region, the San Joaquin Valley, and the Sierra Nevada continue to show high dissimilarity from conditions captured by current weather stations. Notably, the study found that coastal areas, which may see more variability in future climate conditions, also demonstrate increased

¹⁴ The downscaled WRF runs were driven by a multi-model ensemble mean climate change forcing from the representative concentration pathway (RCP) 8.5 pathway for the end of the 21st century (2071-2100) (Liu et al. 2017)

dissimilarity in the future scenario, suggesting that additional stations would be necessary along the immediate coastline to maintain the current level of representation (Figure 8). Notably, the process measures network similarity without dictating actions for individual IOUs with different cost/benefit tolerances. A possible next step is to extend the tool, so it incrementally adds stations until a target similarity score is reached, recalculating values as each station is added.

Figure 8. Statewide Similarity Scores Under Predicted Future Climate Conditions



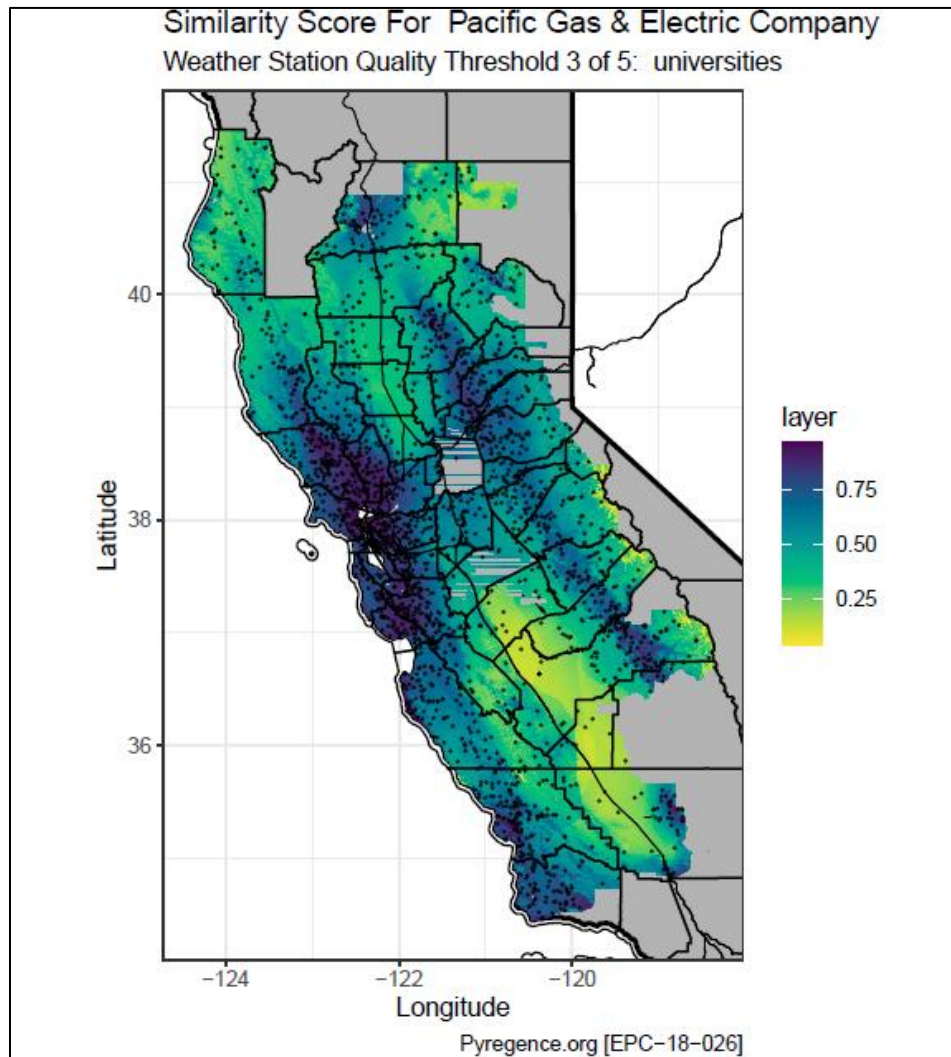
Similarity scores are shown in color ramps, where higher values indicate more similar climate conditions to areas with weather stations. Weather stations are shown on map as black dots.

Source: Owen Doherty, Pyregence Consortium (Eagle Rock Analytics)

This study also provided an analysis of the coverage within different utility service areas (IOU domains) and fire weather regions. It was found that regions managed by utilities such as Pacific Gas and Electric Company (PG&E) and Southern California Edison (SCE) have areas of dissimilarity, particularly in more remote or complex terrains like the Mojave Desert and the Sierra Nevada (PG&E for example, Figure 9). Similarly, within various fire weather regions,

those areas that are not well-represented in the current network of weather stations, particularly in higher elevation zones and those close to wildland-urban interfaces. Notably, other criteria should be considered in actual decisions about siting new weather stations, such as access.

Figure 9. Similarity Scores for Pacific Gas and Electric Company's Service Territory Under Present Climate Conditions



Similarity scores are shown using a color ramp, where higher values (blue) indicate more similar climate conditions to areas with weather stations. Weather stations are shown on map as black dots, including all stations from the three highest quality levels: federally operated, IOU/state operated, and university operated.

Source: Owen Doherty, Pyregence Consortium (Eagle Rock Analytics)

The results emphasize the opportunity for a more coordinated approach to weather station deployment across California, particularly in underrepresented areas that are likely to be affected by both current and future climate variability. This approach should consider not only the density of stations but also the specific climatic and topographic challenges that may influence weather patterns and wildfire risk in these regions.

Extreme Weather Types Analysis

Results were generated from an analysis of synoptic large-scale atmospheric conditions, referred to as weather types (WT), that are most strongly associated with large daily burned areas during California wildfires. The study identified several distinct WTs across eight regions in California (Figure 10); each WT has a significant impact on fire behavior (Prein et al. 2022). These WTs include Santa Ana and Diablo wind events, which are characterized by strong, dry downslope winds primarily occurring in the fall. Reanalysis data indicated that these events have shown an increase in frequency during the 20th century, particularly in Southern California regions and the Bay Area (Prein et al. 2022). However, under continued climate change (late 21st century, high-emissions scenarios), the Prein et al. (2022) study finds a systematic decrease in the frequency of Santa Ana and Diablo weather types across most regions (with exceptions in parts of the Bay Area). Even if these WTs decrease in frequency, the overlap of different weather events with other extreme conditions (for example, higher temperatures and drought) still present elevated future fire concern.

Figure 10. Map Showing Weather Regions and Weather Types in California



Map of California and subregions illustrating major fire weather patterns and atmospheric flow regimes across the state. Subregions, including Northern California, Central Valley, Sierra Nevada,

Bay Area, Los Angeles (LA), San Diego, Central Coast, Modoc, Sierra East and the Desert Southeast. Colored arrows represent different types of wind patterns and atmospheric conditions associated with wildfire risk occurring in different subregions: Red arrows (Santa Ana winds) originate inland and flow toward the southern California coast, particularly impacting the Los Angeles and San Diego regions, Orange arrows (Diablo winds) occur in Bay Area and Central Coast subregions, flowing from inland areas toward the coast, Blue wavy arrows (weak pressure gradients) are shown Central Coast subregion, indicating lighter, less organized wind flow. Yellow arrows (thermal low patterns) form looping patterns over the Central Valley and parts of Sierra Nevada, Sierra East, Bay Area, Central Coast, and Southern California (San Diego and LA subregions), indicating heat-driven circulation. Green arrows (troughing patterns) show directional flow from the Pacific Ocean into California, particularly in Northern, Sierra Nevada and Sierra East subregions. Light blue arrows (anticyclonic/high-pressure patterns) indicate clockwise circulation patterns affecting inland and northern areas, Sierra Nevada and Sierra East subregions. The numbers in the arrows indicate the number of weather types per subregion, for example, in the San Diego subregion there are two predominant weather patterns.

Source: Janice Coen and Andreas Prein, Pyregence Consortium (NCAR)

Additionally, the study found significant future increases in WTs associated with thermal low-pressure systems (occurring when high temperatures cause air to rise, which lowers pressure near the surface), particularly along the California coast and in the Sierra West region (yellow arrows, Figure 10). These increases are largely attributed to the effects of greenhouse gas forcing, which enhances the ocean-land temperature gradient and aerosol-forcing changes, which reduce relative humidity over land and strengthen low-pressure anomalies along the coast. These changes suggest that future weather patterns will likely create conditions more conducive to large fire growth during the summer months, while reducing fire risk in the fall.

The study's results also highlight the variability in WT frequency across different regions and the influence of natural climate variability versus anthropogenic climate change. For instance, the Modoc and Sierra East regions are expected to experience significant increases in WT frequency due to increased greenhouse gases, while the frequency of traditional WTs like Santa Ana and Diablo winds may decrease. This shift could have important implications for wildfire management and risk assessment in California as climate change continues to alter the atmospheric dynamics that drive extreme fire weather.

Overall, this study underscored the need for ongoing monitoring and adaptation strategies to address the changing nature of wildfire risk in California, driven by both natural variability and anthropogenic factors. The analysis of WTs and their projected changes provided in Prein et al. (2022) provides insights into improving fire weather forecasting and enhancing the resilience of communities in fire-prone areas.

Coupled Atmosphere/Wildland Fire Environment (CAWFE) Model

The CAWFE model played an important role in the project's examination of extreme wildfire behavior in California. As a high-resolution, physics-based simulation platform, CAWFE's primary strength was its ability to dynamically couple fire spread processes with atmospheric feedback, an essential feature for realistically simulating complex behaviors observed in extreme wildfire events. Unlike conventional fire models that treat wind as a static input, CAWFE accounts for two-way interactions between fire and atmosphere, capturing phenomena such as fire-induced vortices, gust surges, and the formation of pyrocumulonimbus clouds.

These features were critical in replicating the escalation dynamics of major fires like the 2020 Creek Fire and the 2018 Carr Fire. The model's spatial resolution (~370 meters) allowed it to resolve microscale wind features such as canyon-channeling effects and pulsing wind maxima, which standard forecast models and weather stations cannot detect.

The CAWFE model was applied to 22 historical fire events across California, including high-profile cases such as the Tubbs (2017), Camp (2018), Carr (2018), and East Troublesome (2020) fires. In these case studies, CAWFE accurately reproduced patterns of rapid-fire growth, dynamic wind shifts, and terrain-influenced spread into urban areas. For example, the Tubbs Fire simulation revealed strong nighttime downslope winds that funneled embers into Santa Rosa, behavior consistent with post-event damage assessments but not captured by conventional mesoscale models. These results confirmed CAWFE's capacity to replicate not only the extent but also the tempo and structure of fire events driven by transient wind conditions. Moreover, the model showed that wind dynamics, not just fuel loads, are often the decisive factor in extreme fire behavior, suggesting that operational fire behavior models and associated situational awareness tools must integrate fine-scale meteorological feedback to remain effective in such cases.

Despite its advanced capabilities, CAWFE has potential limitations that constrain its current use in real-time fire operations. The model is computationally intensive and requires highly detailed input data including terrain, vegetation, ignition timing, and fine-resolution atmospheric profiles. Its predictive accuracy depends heavily on the quality and timeliness of this input data, which can be difficult to obtain during fast-evolving fire conditions. Additionally, the model demands technical expertise to configure, run, and interpret posing barriers to use by field practitioners and emergency managers. While CAWFE excels at simulating extreme, wind-driven events, its application in moderate or prescribed fire scenarios is less explored. Nevertheless, CAWFE provides a vital reference standard for evaluating fire behavior under complex weather and terrain interactions.

Upper Air Profiler Pilot Study

The results from the upper-air profiler pilot study demonstrated that integrating upper-air wind data with existing surface measurements improve the accuracy of short-term and very-short-term forecasts of high wind events that contribute to extreme fire weather conditions.

The SODAR wind profiler successfully collected vertical wind profile data, capturing wind speed and direction at various heights from 80 to 600 meters above ground level. The study analyzed the data collected during two significant wind events: a thunderstorm-induced event on August 15-16, 2020, and a Diablo wind event on September 26-29, 2020. During the August thunderstorm event, the SODAR data showed rapidly changing wind conditions aloft, but these changes did not immediately translate to increased surface winds. This variability highlighted the complexity of predicting wind behavior during thunderstorms and the challenge of using upper-air data to anticipate surface wind speeds under such conditions. In contrast, the September Diablo wind event provided more conclusive results. The SODAR profiler detected stronger winds aloft well before these winds descended to the surface, demonstrating a clear pattern of wind intensification over several hours. This information could allow utilities and fire-weather forecasters to better predict the timing and intensity of surface

winds associated with Diablo wind events, which are notorious for exacerbating wildfire risks. However, questions remain on how many SODARs would be needed, where they should be installed, what is the cost, and how IOUs could integrate the data stream into their respective workflows.

Tree Mortality, Fuels and Fire Physics (Workgroup 2)

Small- and Large-Scale Laboratory Experiments

The small-scale laboratory study on wind effects on the smoldering behavior of wildland fuels conducted a series of bench-scale wind tunnel experiments using wooden cribs to simulate wildland fuel beds (Cobian-Iñiguez et al. 2022). The results demonstrated that the wind speeds tested, which were less than those experienced in natural settings, significantly influenced the smoldering combustion of these fuels. Specifically, the study found that the mean smoldering burning rate generally increased with wind speed across different fuel spacing configurations (porosities), with high porosity (greater spacing between fuels) cribs showing a gradual and substantial increase in burning rates as wind speeds increased. The study also observed that higher wind speeds promoted more efficient smoldering combustion.

The study found that during the smoldering stage, the material burned more slowly as time went on. This gradual slowdown occurred because heat and oxygen were no longer moving through the material as easily, which reduced the intensity of the burn. Theoretical models for both heat and mass transfer were able to reproduce the general trend observed in the experiments, though neither alone could fully explain the smoldering behavior. The study concluded that wind plays a crucial role in enhancing smoldering combustion, particularly in large woody fuel beds, and highlighted the need for further research to incorporate these findings into practical wildfire spread models.

Missoula Fire Sciences Laboratory's experimental work aimed at understanding how large wood fuels, such as logs and coarse woody debris, burn under varying conditions, with the goal of developing a practical model for predicting combustion behavior, energy release, and emissions over time. At the time of this report, the team had completed 35 experimental burns using different fuel loads and wind conditions (Mark Finney, Pers. Comm. 2025). The research focused on capturing real-time data on mass loss, heat release, and smoke emissions (including PM_{2.5}), particularly from smoldering and char (partially burned) combustion, which dominated fuel consumption in these scenarios.

Key results showed that wind speed had a major effect on burn intensity and duration, accelerating char combustion and increasing overall energy release. Logs ignited from the bottom burned more slowly than those ignited from both top and bottom, and the configuration of fuel, such as intersections or partial cuts (fracturing), significantly influenced burn rates. Intersecting logs (that is, logs piled on top of one another) burned more quickly where surfaces touched, and partially cut logs (such as those created by chainsaw cuts) transitioned to sustained flaming more easily, resulting in faster mass loss. These results suggest that fuel geometry, arrangement, and wind exposure are critical factors influencing large wood combustion dynamics. Furthermore, the majority of fuel mass was consumed long after the flame front passed, emphasizing the importance of modeling long-duration

smoldering behavior and its relationship to mass fire events, such as fire behavior recorded during the 2020 Creek Fire (Stephens et al. 2022), or for refining fuel consumption and emission models, such as in the U.S. Forest Service's CONSUME model¹⁵.

Based on these findings, the project team recommended development of a simple, physics-informed, time-dependent model that can be implemented in wildfire behavior and emissions simulations. Such a model would account for key variables including wind speed, moisture content, wood density, and surface configuration, and should be capable of distinguishing between flaming and smoldering phases of combustion. The team demonstrated preliminary success with a one-dimensional burn progression model that approximates char-to-ash conversion rates based on heat flux and wind-enhanced surface temperatures. The project team also called for further experimentation, particularly under varying moisture conditions and with additional fuel types (for example larger log sizes and different tree species) and emphasized the need to measure PM_{2.5} emissions in future trials to better estimate air quality impacts from large wood burning in wildfires and prescribed fire scenarios.

Fuels Measurements System

Workgroup 2 developed hierarchical spatial statistical models to quantify fine-scale spatial patterns of various wildland fuel components in Sierra Nevada mixed conifer forests affected by drought-induced tree mortality following prescribed burn management (Foster 2022). Foster's (2022) research improves the understanding of how forest fuels are arranged on the ground in Sierra Nevada mixed conifer forests and how those arrangements change with management (for example, prescribed burns). The research showed that fuels such as fallen needles, decaying organic material, small sticks, larger logs, and low vegetation are not spread evenly across the forest floor. Instead, they form distinct patterns at small scales, sometimes over just a few feet, which influence how fires ignite, spread, and burn. By combining detailed field measurements with advanced analysis, the study demonstrated that common fuels like litter, duff, and small woody debris tend to cluster in predictable ways, while less common features such as trees, saplings, and large logs are harder to capture at fine scales. Areas that experienced extensive drought-related tree death generally did not show dramatic differences in these small-scale fuel patterns compared with healthier areas, with only modest exceptions related to litter and understory vegetation.

Foster's (2022) results also showed that prescribed fire changes not only how much fuel remains on the ground, but how it is arranged. After prescribed fire, fuels became patchier, with stronger contrasts between areas of higher and lower fuel. Some fuels, like litter and duff, formed smaller, tighter patches, while very small woody fuels tended to form larger patches. Fine-scale variability also increased in some cases. Workgroup 2 findings highlighted how prescribed fire reshapes the forest floor in complex ways that are not captured by simple averages or fuel-reduction totals. Mapping both the amounts of fuel and their spatial patterns

¹⁵ [CONSUME fuel consumption and emissions software](https://research.fs.usda.gov/pnw/projects/consumesoftware#:~:text=Consume%20is%20designed%20for%20re source,grassland%20areas%20in%20North%20America)

<https://research.fs.usda.gov/pnw/projects/consumesoftware#:~:text=Consume%20is%20designed%20for%20re source,grassland%20areas%20in%20North%20America>

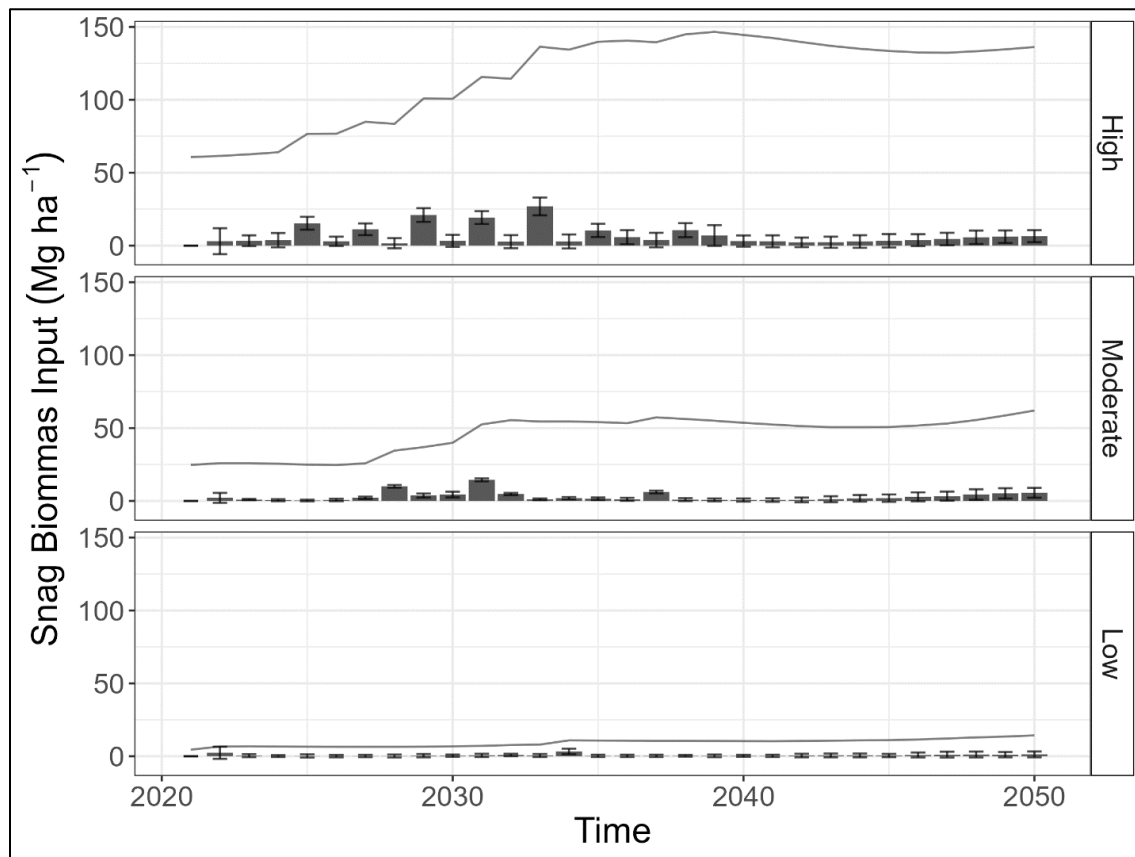
is essential for predicting fire behavior more accurately than by using average values for designing effective, science-based forest management strategies.

Forecasting Surface Fuel Loads

Workgroup 2 research revealed insights into how the 2012–2016 drought-induced tree mortality in the Sierra Nevada will impact future wildfire risks due to changes in surface fuel loads (Northrup et al. 2024). The study found that in the short term (2017–2021), fine woody debris increased by more than 145 percent and litter, as well as duff, increased across the study sites, with total fuel loads increasing by up to 69 percent. Snag (standing dead tree) longevity was observed to vary by species, and larger trees generally remain standing longer. However, yellow pine (for example, ponderosa pine and Jeffrey pine) was an exception, with size playing a minimal role in how soon they fall.

By 2040, the study projected that cumulative biomass inputs from future snag falls will range from 49.4 to 136.1 megagrams per hectare (Figure 11), which exceed current levels and is significantly higher than historical amounts of coarse woody debris in the Sierra Nevada. This increase in surface fuels due to the extensive snag falls is expected to elevate the potential of severe wildfires, particularly in areas with high densities of large yellow pine snags, which are prone to faster fall rates. The study's findings provided empirical data to refine the snag fall rate in vegetation simulation models like the Forest Vegetation Simulator and highlight the potential need for management interventions, such as salvage logging or prescribed burning, to mitigate the increased wildfire risks posed by these fuel accumulations.

Figure 11. Forecasted Biomass Inputs Over Time (to 2050) Based on Standing Snags in 2021 and Model Predictions by Mortality Class (Low, Moderate, High), Based on Median Modeled Fall Rates and Wood Decay



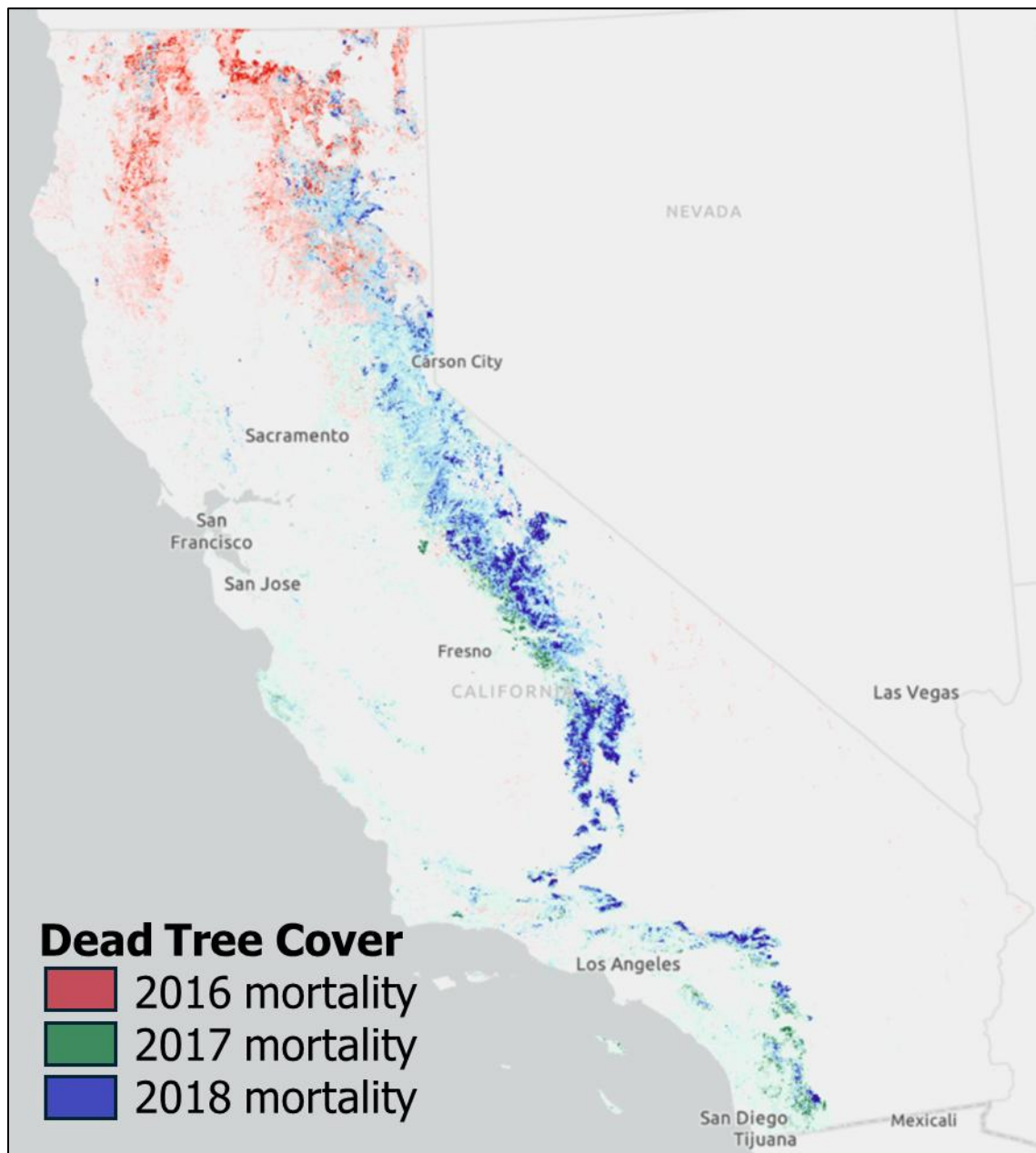
Bars depict forecasted annual biomass input from snag fall, the error bars depict standard error of annual biomass input, and the lines depict total woody fuel load. Mortality classes defined as: High = greater than 18 percent cumulative mortality (dead trees within a plot [0.9 ha to 2.5 ha]); Medium = 7-18 percent cumulative mortality, and Low = less than 7 percent cumulative mortality.

Source: John Battles, Pyregence Consortium (UC Berkeley)

Contemporary Tree Mortality Mapping

Salo Sciences in Workgroup 2 mapped and analyzed the extent of tree mortality in California from 2016 to 2018, using advanced satellite data and machine learning techniques. The study produced high-resolution maps that quantified dead tree cover across the state, particularly in regions heavily impacted by drought and pest infestations. The results indicated that tree mortality was concentrated in the central and southern Sierra Nevada ecoregions, with dead tree cover reaching up to 30 percent in some areas (Figure 12).

Figure 12. Map Showing Progressive Shifts in Tree Mortality Distributions with a Red-Green-Blue Composite (2016 to 2018)



This map shows how dead tree distributions shifted up-slope in the central and southern Sierra Nevada over this period. Red shows tree mortality (percent dead tree cover, darker color tone = greater percent dead tree cover, up to 30 percent) in 2016, green shows new mortality in 2017, and blue shows new mortality in 2018. Mortality was pronounced in the Klamath and Cascades ecoregions of northern California in 2016 (red) and increased in intensity in the Southern California Mountains ecoregion from 2017 (green) and 2018 (blue).

Source: David Marvin and Christopher Anderson, Pyrengence Consortium (Salo Sciences)

The satellite-derived maps produced from this effort aligned well with independent measurements from the U.S. Forest Service Aerial Detection Survey, confirming the mortality patterns captured. The research also demonstrated a link between the spatial distribution of

tree mortality and the occurrence of high-intensity wildfires, such as the 2020 Creek Fire, which burned through areas with severe, progressive tree mortality (Stephens et al. 2022).

Stephens et al. (2022) evaluated the 2020 Creek Fire as part of this project, which demonstrated that extreme wildfire behavior in frequent-fire forests was primarily driven by high levels of dead biomass and dense live trees resulting from drought and bark beetle mortality, which led to extensive high-severity fire and large contiguous burn patches. Despite only moderately extreme weather during peak fire growth, the fire rapidly expanded and exhibited “mass fire” behavior, characterized by intense heat generation within the fire interior and sustained combustion driven by fuel conditions rather than weather alone. The study highlighted that current forest conditions, shaped by climate stress and past management, are highly vulnerable to large, severe fires, and that existing operational fire models fail to capture these dynamics due to limitations in representing post-frontal combustion and fire–atmosphere interactions.

Near-Term Wildfire Forecasting Models (Workgroup 3)

PyreCast Near-Term Fire Forecasting Platform

PyreCast¹⁶ was developed as a web-enabled near-term fire forecasting platform that provides tools for visualizing up to 14-day forecasts for: 1) weather (including curated fire weather indices), 2) wildfire risk and hazards, and 3) active wildfire spread (Figure 13). PyreCast was developed as a suite of tools to address the rising threat of catastrophic wildfires, with specific emphasis on understanding potential near-term impacts to and from the electricity grid. Using these web-based tools, emergency managers can order more timely evacuations, firefighters can position crews to avoid danger and speed fire suppression, electrical utilities can forecast potential wildfire impacts to and from the power grid, and insurance providers can better anticipate impacts to their policies.

¹⁶ [PyreCast website](https://pyrecast.org/) <https://pyrecast.org/>

Figure 13. Display of the PyreCast Near-Term Fire Forecasting Platform User Interface

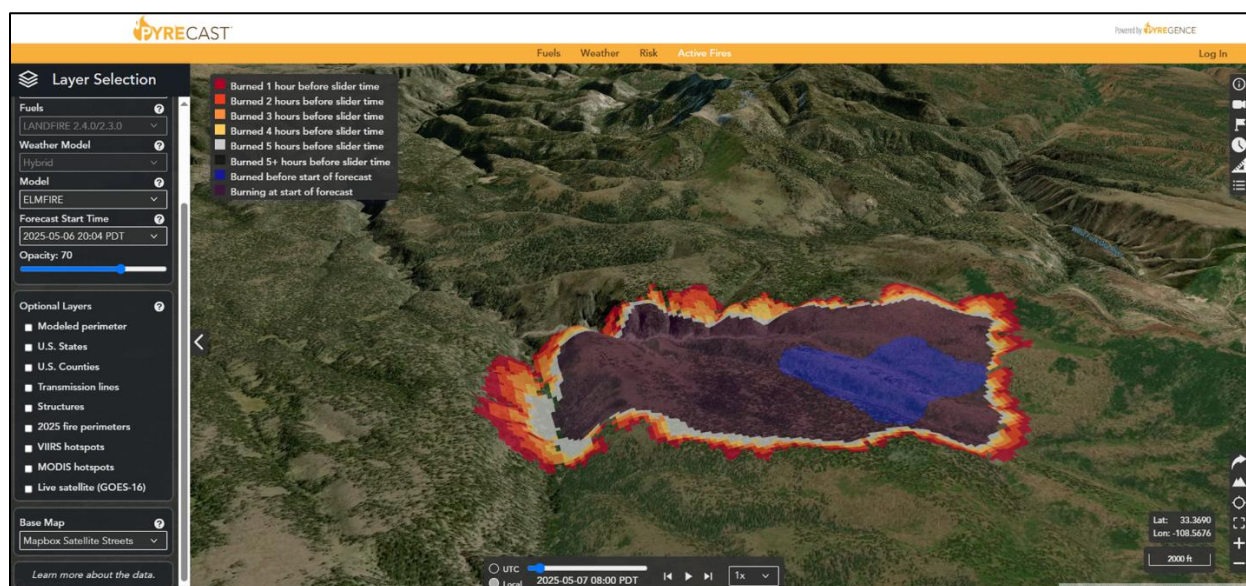


Figure provides an example of the 'Active Fires' tool of a fire modeled and displayed in the PyreCast system. Areas already burned (blue and purple polygons) and forecasted hourly burn perimeters (yellow to orange to red).

Source: Shane Romsos, Pyrengence Consortium (Spatial Informatics Group)

The PyreCast system provides a comprehensive suite of weather forecasting products and landscape data layers that support wildfire situational awareness and risk assessment. It integrates multiple United States operational weather models with varying spatial resolutions and forecast horizons, ranging from high-resolution short-term models such as the High-Resolution Rapid Refresh (3 km, 48 hours) and the North American Mesoscale 3 km (60 hours), to longer-range global models such as Global Forecast System (up to 16 days), as well as blended products like the National Blend of Models and a custom Hybrid forecast extending to eight days. The platform also incorporates the high-resolution California and Nevada Smoke and Air Committee WRF model (1.33 km, 72 hours, twice daily), and real-time observational analysis through the Real-Time Mesoscale Analysis weather model, updated every 15 minutes. Animated outputs include standard meteorological variables, for example temperature, relative humidity, wind speed and gusts, and precipitation, as well as curated fire weather indices such as the Fosberg Fire Weather Index, Hot Dry Windy Index, vapor pressure deficit, and firebrand ignition probability, enabling users to evaluate both atmospheric conditions and fire potential.

In addition to weather forecasts, the platform integrates landscape datasets used in wildfire behavior modeling, such as LANDFIRE fuel models (30-m resolution) and others. Users can view these fuels and terrain layers directly within the PyreCast interface. The system also provides contextual overlays such as live ALERTWildfire camera feeds, red flag warnings, transmission lines, and structure footprints, supporting comprehensive situational awareness for utilities and emergency managers.

For near-term risk modeling, the "risk" tool quantifies and displays potential fire consequences across California at a 5-day forecast horizon, including both risk from fires to the electric grid

and as risk from the electric grid to other assets at risk. This is accomplished by modeling 500 million randomly ignited hypothetical fire starts each day, ignited at various locations across the landscape (as either overhead transmission line or human cause ignition pattern) and various times in the future under forecasted weather conditions. Two ignition patterns, following, are selectable in the user interface.

1. *All-Caused Fires* (excluding powerline and lightning fires): For this ignition pattern, fires are randomly ignited within areas influenced by human activities – reflecting the spatial and temporal pattern that mimics past human-caused fire occurrence.
2. *Transmission Powerline-Caused Fires*: In this ignition pattern, simulated fires are randomly ignited in a buffer surrounding overhead transmission lines so that potential impacts from the grid to other assets at risk are quantified.¹⁷

Outputs of fire exposure forecasts that are selectable for display in the user interfaces include:

- *Relative Burn Probability*: Relative likelihood that an area will be burned by fires that have not yet ignited within the next six hours of time shown in time slider.
- *Impacted Structures*: Approximate number of structures within fire perimeter for fires starting at specific location and time in the future.
- *Fire Area*: Modeled fire size in acres by ignition location and time of ignition.
- *Fire Volume*: Modeled fire volume (fire area in acres multiplied by flame length in feet) by ignition location and time of ignition.
- *Power Line Ignition Rate*: Estimated power line ignition rate in ignitions per line-mile per hour.

The Active Fire tool in PyreCast calculates and displays hourly forecasted fire perimeters up to 14-days. Initial fire start locations are derived from the U.S. National Guard - FireGuard Program and from other sources (for example, National Interagency Fire Center and CALFIRE). Following the initial fire start location, fire spread models are rerun throughout the life of the fire based on satellite-based heat detection data and refreshed approximately every 12 hours when new Visible Infrared Imaging Radiometer Suite (VIIRS) data become available for download. Fire spread is modeled using an ensemble forecasting method where model inputs are perturbed from their baseline values. Approximately 1,000 simulations are aggregated together so that fire spread forecast outputs can be displayed for a fire event of interest as an animation in the user-interface in terms of burn probability (with selectable hourly outputs for 10th, 30th, 50th, 70th, and 90th percentile fire-spread probabilities).

Between 2020 and 2025, the PyreCast system ran and generated outputs for hundreds of thousands of active-fire-spread model simulations for over 600 unique fire events across California and the lower 48 states of the United States. In addition to active fire spread forecasts model simulations since its launch date in 2020, the PyreCast system produced fire

¹⁷ PyreCast can be modified to include distribution line ignition patterns and display associated near-term forecasts of wildfire behavior, however, due the proprietary nature of these datasets, it was not included in the open-source version of the platform.

risk model outputs up to four times per day, continuously, representing millions of risk model simulations. In terms of platform and data usage from 2022, PyreCast has been used by more than 14,000 unique individuals, representing a wide range of users from electric utilities, fire and emergency professionals, research institutions, and the public. Notably, the PyreCast system is still being maintained by the project team.

Evaluation of PyreCast Model Performance

The evaluation of PyreCast model performance revealed several key challenges and insights. One major issue was the accuracy of satellite data, such as MODIS and VIIRS, which often contained outliers and errors. These inaccuracies, especially during specific conditions like plume dominated wildfires¹⁸, led to skewed model predictions, particularly in complex terrain. Additionally, PyreCast models frequently overestimated fire behavior, especially in areas like wet meadows and during the early stages of the fire, due to faulty underlying data and assumptions, such as incorrect lateral fire spread predictions driven by erroneous MODIS data points.

The models also struggled to account for the effects of smoke inversions, which significantly dampen fire activity. This resulted in over-predictions of fire behavior during periods when the fire was actually suppressed by heavy smoke. Specific challenges during the 2021 Dixie Fire included predicting fire spread in steep terrain, like the Feather River Canyon, where the model failed to account for burning logs rolling downhill causing fire to move faster than predicted and downcanyon winds. Additionally, the models did not accurately integrate the effectiveness of fire suppression efforts, leading to incorrect predictions of fire spread in areas that had already been contained.

To address these issues, several recommendations were made as part of the performance evaluation. Improving data filtering, particularly for discontinued use of MODIS data, was suggested, along with enhancing the model to better handle erroneous initialization data (that is, hotspot information from satellite sensors). Developing better prediction techniques for when fires rekindle after being suppressed by rain, using historical data and machine learning models, would be beneficial. The computational resources for PyreCast were found to be inadequate during peak fire seasons, so implementing a hybrid computational approach that leverages cloud computing resources would improve the timeliness of forecasts.

The performance evaluation of the underlying spread model, ELMFIRE, indicated that while it generally performs well under certain conditions, some challenges remain in accurately modeling fire spread, particularly within highly developed WUI (where fuels data inputs indicate the landscape is unburnable), under rapidly changing weather conditions and during fire suppression efforts. A retrospective assessment of 214 separate 7-day forecasts showed that the model performed better in predicting wind-driven fires than plume-dominated ones, highlighting the need for real-time automated forecast validation to continuously improve accuracy and user confidence. The integration of coupled fire-weather models, such as

¹⁸ A plume-driven wildfire is a type of wildfire where the fire's behavior and spread are significantly influenced by the convection column or "plume" of hot air, smoke, and gases that the fire generates. These plumes can create their own weather patterns, making plume-driven wildfires particularly dangerous and unpredictable.

CAWFE, could also enhance the ability to predict plume-driven fire events if such models can be operationalized.

Cost/Benefit Assessment of PyreCast – Case Study

The PyreCast system was designed to enhance wildfire modeling and prediction, offering significant improvements over existing models based on outdated methodologies. A case study on the 2020 Glass Fire demonstrated the effectiveness of PyreCast in reducing the latency of, or delay in, updating the wildfire risk data, enabling more timely and efficient utility pole pretreatment strategies during actual fire events.

The assessment showed that PyreCast's ability to update wildfire spread simulations up to four times per day, compared to the once-daily updates under the status quo, can significantly reduce the number of utility poles that are damaged or destroyed by wildfires. In the case of the 2020 Glass Fire, PyreCast's more frequent updates could have hypothetically enabled the treatment and protection of more wooden poles, resulting in an estimated net benefit of \$5.9 million per year for California ratepayers, compared with \$0.155 million under the status quo.

Overall, the assessment underscored the importance of advanced wildfire modeling tools like PyreCast in improving the effectiveness of wildfire risk mitigation strategies, leading to potential significant financial savings and enhanced safety for both utility infrastructure and the broader community.

Long-Term Projections (Workgroup 4)

This section summarizes the long-term wildfire projection outputs produced by Workgroup 4, which were prepared to support California's Fifth Climate Change Assessment. The outputs produced include projections of wildfire regimes, vegetation dynamics, and carbon outcomes that may evolve over coming decades under changing climate, land use, and vegetation management conditions. Unlike near-term forecasting efforts that focus on days to weeks, these modeled outputs address multi-decadal time horizons relevant to infrastructure planning, climate adaptation, and policy development, including applications for electric grid resilience. In addition to the coupled process-based and statistical modeling frameworks, this project explored the application of machine learning approaches to support long-term wildfire projections and wildfire hazard characterization.

Coupled Statistical/Dynamic Wildfire-Climate-Vegetation Simulations

The coupled LUCAS/FRSM model simulations produced several outputs across all landscapes in California reflecting the combined influence of climate, vegetation management and urban development (Table 2). In total, outputs for 26 coupled LUCAS/FRSM model scenarios were produced, 20 of which included combinations of the urban growth and vegetation management scenarios (Table 2). A full range of shared socioeconomic pathways (SSP2-4.5 to SSP8.5) were modeled with a selected set of global climate models and ensemble members to cover the essential range of wildfire-relevant climatic conditions. LUCAS/FRSM model simulations covered the historical period of 1984 to 2020, with future projections representing possible conditions between 2021 to 2065.

Table 2. List of Scenarios Modeled Using the Coupled LUCAS/FRSM Framework

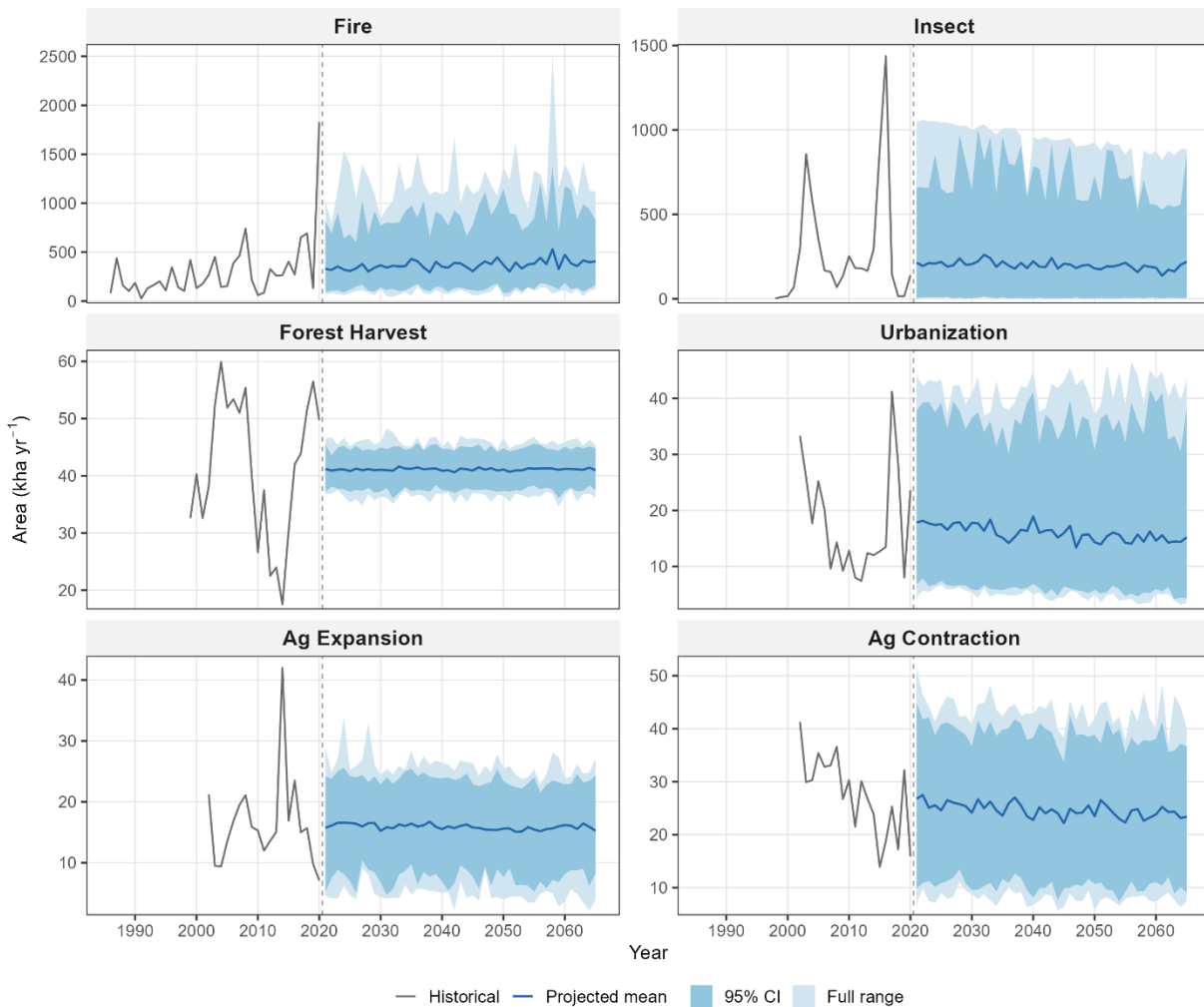
Global Climate Model	SSP	Ensemble Member	Infill Urban Growth	Sprawl Urban Growth	Business as Usual Vegetation Mgmt.	High Ambition Vegetation Mgmt.
ACCESS-CM2	SSP2-4.5	r1i1p1f1	X	X	X	X
EC-Earth3-Veg	SSP2-4.5	r5ip1f1	X	X	X	X
MPI-ESM1-2-HR	SSP2-4.5	r1i1p1f1	X	X	X	X
MRI-ESM2-0	SSP3-7.0	r4i1p1f1	X	X	X	X
HadGEM3-GC31-LL	SSP5-8.5	r3i1p1f3	X	X	X	X
ACCESS-CM2	SSP5-8.5	r1i1p1f1	X	-	-	X
INM-CM5-0	SSP2-4.5	r1i1p1f1	X	-	-	X
HadGEM3-GC31-LL	SSP5-8.5	r1i1p1f3	X	-	-	X
EC-Earth3-Veg	SSP3-7.0	r4i1p1f1	X	-	-	X
CNRM-ESM2-1	SSP5-8.5	r1i1p1f2	X	-	-	X
EC-Earth3-Veg	SSP5-8.5	r1i1p1f2	X	-	-	X

Table provides an overview of the combinations of GCMs, Shared Socioeconomic Pathways (SSPs), and ensemble members (an individual climate simulation that models potential future climate conditions by slightly altering initial conditions, physics, or parameters) used in the LUCAS/FRSM model framework, along with the specific urban growth and vegetation management scenarios that were evaluated for each. An 'X' indicates which urban growth and vegetation management scenarios were simulated by climate scenario. All climate data used were downscaled using the LOCA2 hybrid method.

Source: LeRoy Westerling, Ben Sleeter, and Shane Romsos, Pyregence Consortium (UC Merced, USGS, Spatial Informatics Group)

Figure 14 presents an example of outputs across all full factorial of climate, urbanization, and vegetation management scenarios (that is, ensemble members r1i1p1f1, r5ip1f1, r1i1p1f1, r4i1p1f1, and r3i1p1f3) from the coupled LUCAS/FRSM modeling framework. The figure presents historical (black) and projected (blue line and shaded uncertainty bands) land use and land cover (LULC) transitions measured in thousands of hectares per year (kha/yr) in California for 1984 to 2065 for six processes: wildfire, insect disturbance, forest harvest, urbanization, agricultural expansion and agricultural contraction.

Figure 14. Example Plot of Outputs for Historical and Projected Land Use and Land Cover Transitions (kha/yr) Across California, Shown for Combined Full-Factorial Scenarios Evaluated.



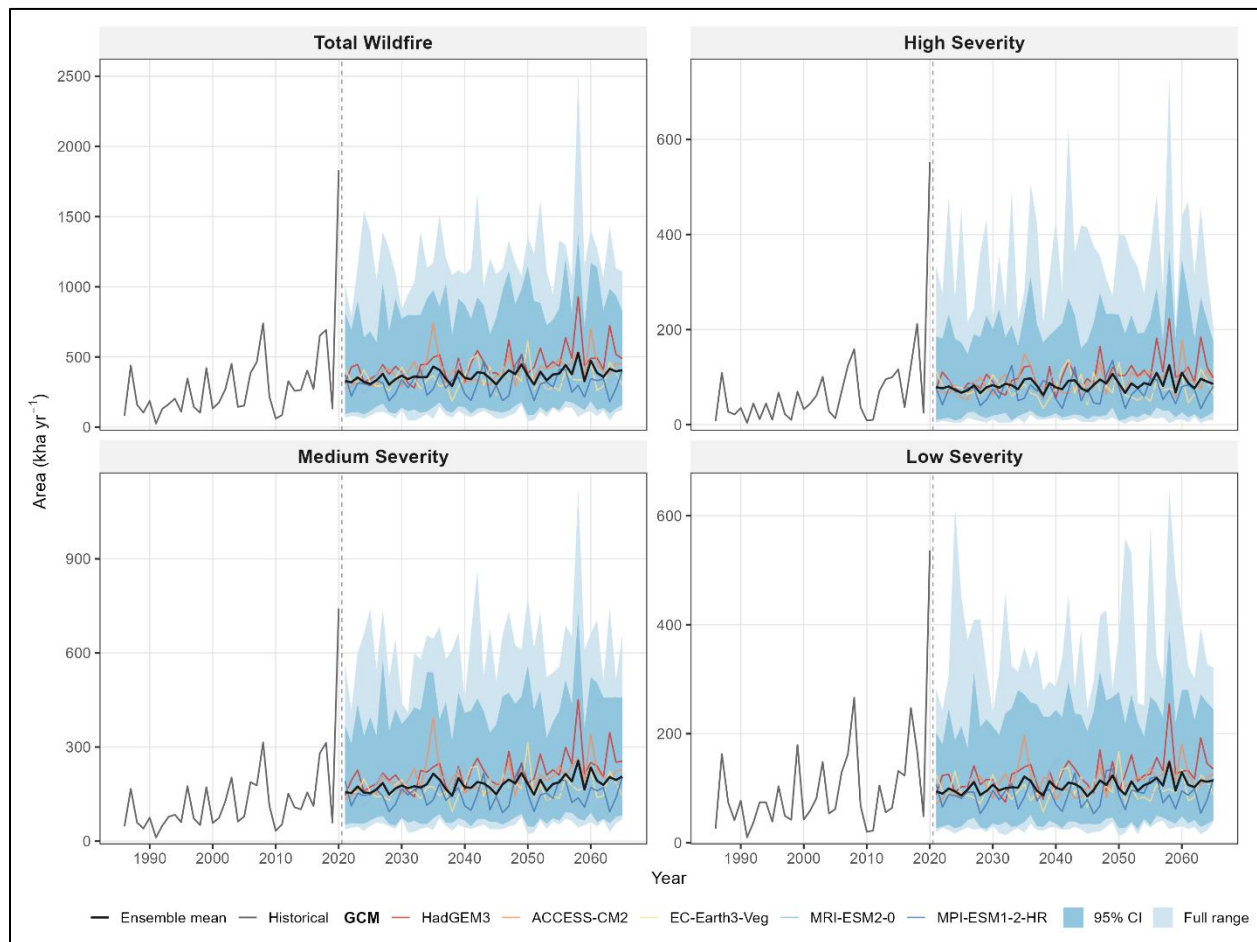
Across the various panels in Figure 14, each plot represents a specific type of LULC transition, such as agricultural (Ag) contraction or expansion, forest harvest, insect disturbance, fire, prescribed fire, intensification, and urbanization, expressed as transition area (thousands of hectares per year) over time. The historical period (black) captures observed variability in land conversions and disturbances through either 1984 to 2020 for fire or around 2000 to 2020 for LULC variables, while the blue projections extend these trends from 2020 through the mid-21st century (2065).

Source: Ben Sleeter, Pyregence Consortium (USGS)

Historical data shows inter-annual variability, particularly for fire and insect disturbances, with notable spikes in certain years. In the projection period, fire activity remains highly variable with an overall tendency toward moderate increases, while insect disturbance stabilizes at lower but persistent levels following earlier peaks. Forest harvest transitions become relatively stable with limited variability compared to historical fluctuations. Urbanization continues at a steady but moderate rate with a wide uncertainty range, indicating variability across scenarios. Agricultural expansion remains relatively low and stable, whereas agricultural contraction shows moderate levels with considerable uncertainty.

Figure 15 presents historical (thin black line) and projected wildfire area across California by severity class - total wildfire, high severity, medium severity, and low severity - measured in kha/yr. A vertical dashed line around 2020 separates historical observations (line black line) from future projections, which include multiple GCM ensemble scenarios (colored lines) and an ensemble mean (dark black line), with uncertainty shown as shaded bands (95-percent confidence interval and full range). Historical wildfire area exhibits high interannual variability, while projections indicate a general increase in total burned area and across all severity classes, with particularly large uncertainty in future outcomes. High severity fire shows a modest increasing trend with episodic spikes, while medium and low severity fire also increase over time, reflecting broader expansion in fire activity under future climate scenarios. Overall, the figure highlights both an upward trend in wildfire extent and substantial variability and uncertainty across models and time.

Figure 15. Example Plot of Historical and Projected Annual Wildfire Area Burned by Severity Class (kha/yr) across California, 1985 to 2065.



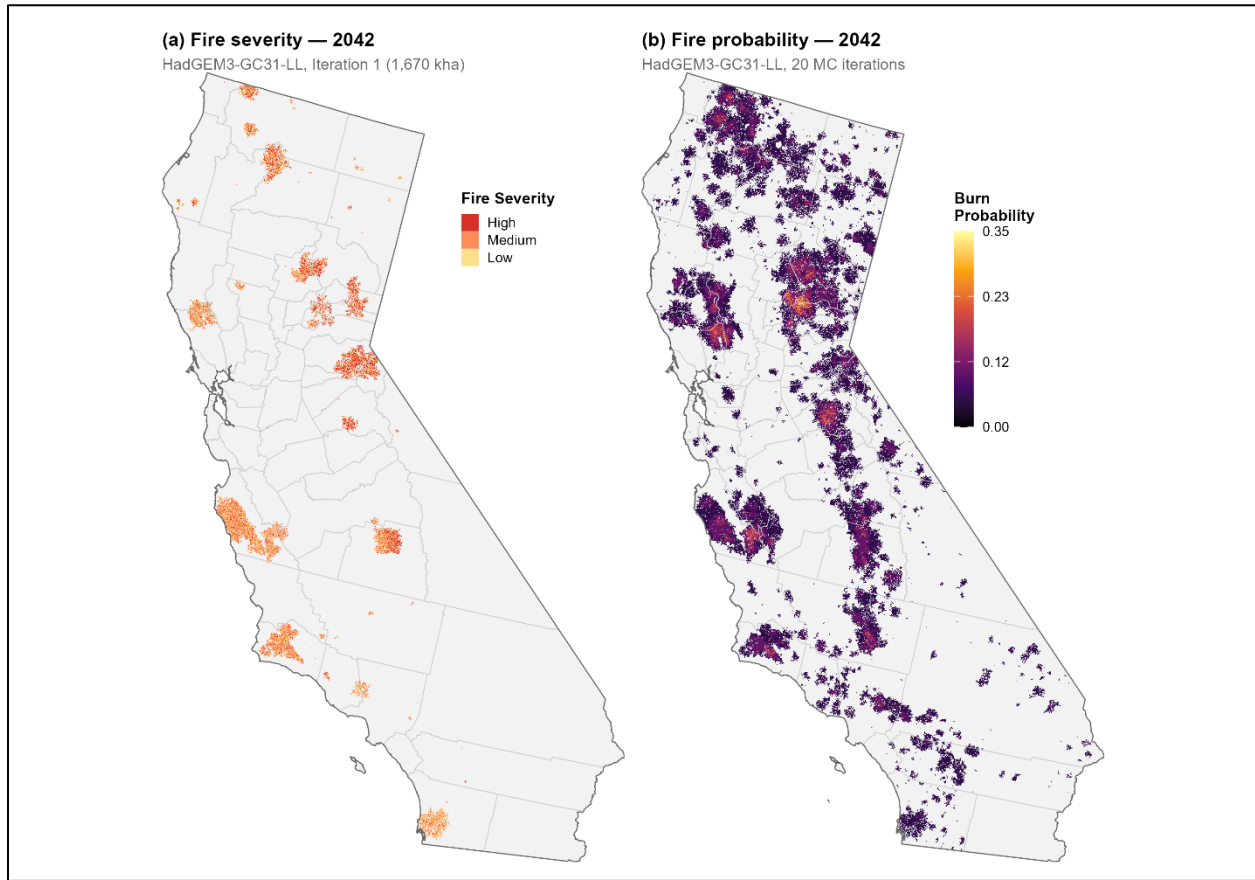
The figure illustrates historical (thin black line, from 1985 to 2020) and projected (multi color lines, 2021 to 2065) burned area in California, separated by total burned area (top left) and fire severity classes - low (bottom right), medium (bottom left), and high severity (top right). Ensemble mean is shown as dark black line, and uncertainty ranges (95% CI and full range) in different shades of light blue. The projections were based on LOCA2 Hybrid downscaled GCMs.

Source: Ben Sleeter, Pyregence Consortium (USGS)

Both low- and high-severity fire areas show overlap in their interannual ranges, suggesting that climate variability, particularly temperature, humidity, and fuel moisture, may continue to drive fluctuations in fire behavior even under similar management conditions. Importantly, although the mean projected burned area does not show an accelerating upward trend, the persistence of large annual spikes implies that climate-forced variability would sustain an elevated baseline of fire activity through mid-century in this example.

Figure 16 provides an example of spatially explicit fire severity and probability outputs and how they are derived for a single year. The figure shows projected wildfire outcomes across California for the year 2042 under the HadGEM3-GC31-LL climate scenario. Panel (a) shows the spatial distribution of fire severity from a single model iteration, with areas classified as low (yellow), medium (orange), and high (red) severity, which highlight projected clusters of more intense fire activity in forested regions such as the Sierra Nevada, Northern California, and parts of Southern California. Panel (b) displays burn probability based on 20 Monte Carlo simulations, with colors ranging from low (dark purple) to high (yellow), indicating the likelihood of fire occurrence across the landscape. Higher burn probabilities are concentrated in similar regions identified in the severity map, reflecting consistent hotspots of wildfire activity. Together, the panels illustrate both the potential intensity and likelihood of wildfire activity, emphasizing areas of elevated future wildfire hazard under projected climate conditions.

Figure 16. Maps of Projected Fire Severity and Fire Probability for the Year 2042 Under the HadGEM3-GC32-LL SSP5-8.5 Climate Model and the Infill Urban Development Scenario and High Ambition Vegetation Management Scenario



Map on the left (a) shows predicted burn severity in 2042 across California for one Monte Carlo simulation. Map on the right (b) shows the average annual fire/burn probability across 20 Monte Carlo iterations for 2042 at 1km resolution (purple showing lower probability, red, orange and yellow color tones show higher probability). Light gray areas in maps were unburned and not predicted to support fire in this time step and suite of Monte Carlo simulations.

Source: Ben Sleeter, Pyregence Consortium (USGS)

LANDIS-II Forest Landscape Model Simulations

LANDIS-II model simulations produced several high-resolution (150 m) outputs related to forested landscapes in California, reflecting the combined influence of climate and vegetation management (Table 3). A subset of climate projections was simulated under two vegetation management scenarios: BAU and High Ambition ($n = 9$). The remainder of the climate model simulations evaluated only the high ambition vegetation management (Table 3, $n = 6$). No urban growth scenarios were applied in these simulations because they were limited to forested landscapes. For LOCA2 Hybrid downscaled climate data, 16 LANDIS-II multi-replicate model simulations were produced, with a subset of multi-replicate model simulations ($n=10$) representing both vegetation management scenarios (Table 3). For dynamically downscaled WRF climate data, a total of eight multi-replicate simulations, representing BAU and High Ambition vegetation management scenarios were produced (Table 3).

Table 3. Summary of LANDIS-II Model Runs Produced by Climate Scenario and Vegetation Management Scenario

Climate Scenario (global climate model_shared socioeconomic pathway_ensemble member)	Business as Usual Vegetation Management	High Ambition Vegetation Management	Downscale Method
ACCESS-CM2_ssp245_r1i1p1f1	X	X	LOCA2
ACCESS-CM2_ssp585_r1i1p1f1	Not Simulated	X	LOCA2
CNRM-ESM2-1_ssp585_r1i1p1f2	Not Simulated	X	LOCA2
EC-Earth3-Veg_ssp245_r5i1p1f1	X	X	LOCA2
EC-Earth3-Veg_ssp370_r4i1p1f1	Not Simulated	X	LOCA2
EC-Earth3-Veg_ssp585_r4i1p1f1	Not Simulated	X	LOCA2
HadGEM3-GC31-LL_ssp585_r1i1p1f3	Not Simulated	X	LOCA2
HadGEM3-GC31-LL_ssp585_r3i1p1f3	X	X	LOCA2
INM-CM5-0_ssp245_r1i1p1f1	Not Simulated	X	LOCA2
MPI-ESM1-2-HR_ssp245_r1i1p1f1	X	X	LOCA2
MRI-ESM2-0_ssp370_r4i1p1f1	X	X	LOCA2
CESM2_ssp370_r11i1p1f1/	X	X	Dynamical
CNRM-ESM2-1_ssp370_r1i1p1f2/	X	X	Dynamical
EC-Earth3-Veg_ssp370_r1i1p1f1/	X	X	Dynamical
FGOALS-g3_ssp370_r1i1p1f1/	X	X	Dynamical

For the High Ambition scenario, two sets of model output data were produced for each climate scenario: 1) for one set of replicates (n=5), High Ambition treatments were implemented annually from 2020 to 2045, and 2) the other set of replicates (n=3 to 5), treatments were implemented annually from 2020 to 2099.

Source: Charles Maxwell, Pyregence Consortium (Spatial Informatics Group)

Model runs were performed on annual timesteps from 2001 to 2100 at 150-m resolution, using both dynamically downscaled WRF data from the University of California, Los Angeles (UCLA) and statistically downscaled LOCA2-Hybrid datasets from Scripps (Table 3). Each modeled climate scenario includes up to five replicate model runs to capture variability. Variables represented in outputs include aboveground net primary productivity, net ecosystem exchange, total carbon, aboveground biomass, biomass removed by management, and categorical maps of forest type, fire severity, and management activity type (Table 4). Model outputs are stored as georeferenced raster files (.tif) and can be accessed on the [Pyregence data repository](https://data.pyregence.org/wg4/CEC-Submitted/) at <https://data.pyregence.org/wg4/CEC-Submitted/>.

Table 4. Description of Output Raster Datasets Produced with LANDIS-II Model Simulations 2001 to 2100

Variable Name	Description
Above-ground Net Primary Productivity	Rate at which plants in a given area accumulate dry biomass above the ground through photosynthesis, after accounting for respiration and tissue loss. It is a key measure of an ecosystem's health and its capacity to capture and convert solar energy. Value represents sum of the flux in grams per square meter for the year at the end-of the calendar year.
Atmospheric Net Ecosystem Exchange	Measures of the total net carbon exchange (CO ₂) between an ecosystem and the atmosphere, and values represent total flux in grams per square meter summed over the course of the calendar year.
Total Carbon	Above and below-ground biomass stocks, all sources, value represent stock in grams per square meter at end-of-calendar year.
Biological Disease Agent	Disease vectors (either insect or disease). Categorical (fir engraver, Jeffrey pine beetle, western pine beetle, white pine blister rust, multi-vector complex)
Biomass Removed	Amount of above-ground biomass removed from the cell from a given management activity in grams per square meter
Total Biomass	Above-ground biomass; value represents stock of biomass on the landscape in grams per square meter at end-of-calendar year.
Forest Type	Species or mix of species that have the most biomass in a cell. Categorical (mixed hardwood conifer, mixed hardwood, mixed riparian, white fir, Doug-fir, red fir, ponderosa, Jeffrey pine, lodgepole pine, giant sequoia, coastal redwood, aspen, juniper, Sierra mixed conifer, high elevation mixed conifer, Klamath mixed conifer, mixed chaparral, incense cedar, sugar pine).
Fire Severity	Categorical classification of fire severity across the landscape that occurred within the year. Categorical (none, low, moderate, high).
Prescribed Management Activities	Categorical classification of broad management activity type that occurred in the year. Categorical (not harvested, transmission line clearance, public/private light/heavy/moderate)

Source: Charles Maxwell, Pyregence Consortium (Spatial Informatics Group)

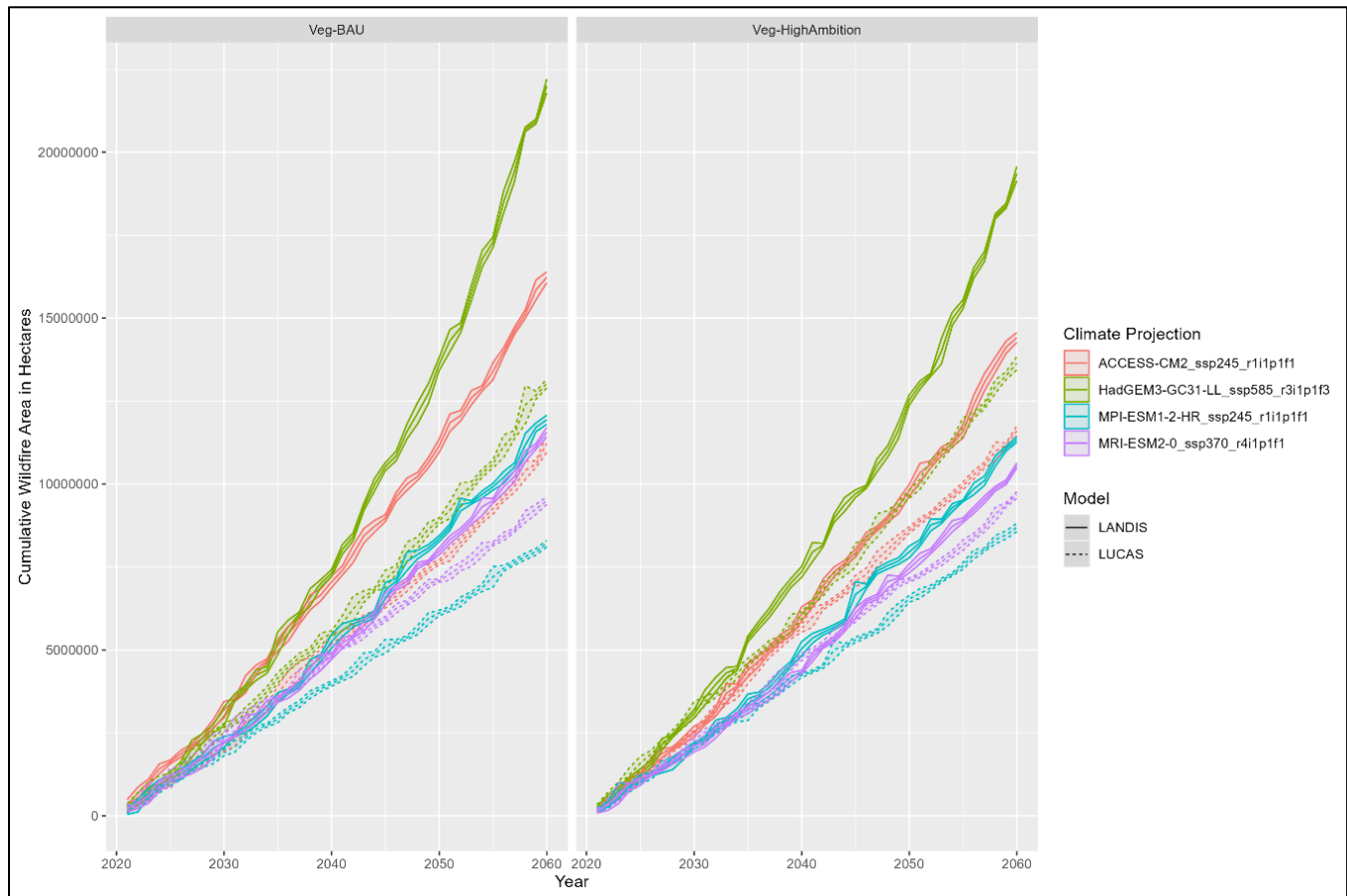
Figure 17 shows an example of projected cumulative wildfire area (hectares) in forested areas across California from 2020 to 2060 under two vegetation management scenarios: business-as-usual on the left and high-ambition on the right. Four climate projections are represented

by different colors, while two modeling approaches are shown with line styles: LANDIS-II (solid lines) and LUCAS/FRSM (dashed lines). Across all scenarios, the greatest cumulative wildfire area is generally associated with the HadGEM3 climate projection and the lowest with MPI-ESM. Comparisons between panels suggest that the high-ambition vegetation scenario modestly reduces cumulative wildfire area relative to business-as-usual. Differences between models are also evident, with LANDIS-II generally projecting higher cumulative burned area than LUCAS/FRSM. Notably, LANDIS-II and FRSM/LUCAS use two different approaches to modeling fire. LANDIS-II responds to individual daily weather conditions, while FRSM (in the coupled FRSM/LUCAS framework) uses semi-monthly averages. As a result, LANDIS-II encounters more frequent instances of extreme fire weather, producing more fire growth events. Approaches that resolve daily climate variability may more accurately represent future fire activity.

Across climate projections and modeling frameworks, the vegetation management scenario appears to exert some influence on cumulative wildfire extent (Figure 17). Relative to the BAU scenario, the high-ambition treatment scenario produces lower cumulative burned area throughout the simulation period (2020–2060), with differences that increase over time. During the early decades (2020–2035), trajectories between scenarios are similar, indicating the limited immediate landscape-scale effects of treatments. However, divergence becomes more evident after approximately 2040, reflecting the potential compounding influence of sustained fuel reduction, altered stand structure, and increased landscape heterogeneity on fire spread dynamics. By the end of the simulation period, especially for ACCESS-CM2 and HadGEM3-GC31-LL, high-ambition reduces cumulative wildfire area by up to 30 percent relative to business-as-usual vegetation management scenario, depending on climate projection and model. Despite this apparent reduction, the relative ranking and overall magnitude of wildfire extent across climate scenarios are preserved, indicating that climate forcing remains the dominant driver of long-term fire activity.

Overall, this example of outputs suggests an influence of climate on wildfire outcomes, with vegetation management providing some but limited mitigation effect depending on climate scenario. Notably, the finer scale of LANDIS-II model simulations likely influences the ability to detect the effect of vegetation management intensity across different vegetation management scenarios compared to the LUCAS/FRSM approach.

Figure 17. Example Model Outputs Showing Projected Cumulative Wildfire Area Burned (hectares) in California’s Forested Landscapes under Business as Usual and High Ambition Vegetation Management Scenarios, Comparing Climate Projections and Model Outputs (LANDIS vs. LUCAS), 2020–2060



This figure consists of two side-by-side panels comparing projected cumulative wildfire area burned (in hectares) across California from 2020 to 2060 under two vegetation management scenarios: Business-as-Usual on the left and High Ambition on the right. The x-axis shows time (years 2020–2060), and the y-axis shows cumulative wildfire area burned, increasing from near zero to over 20 million hectares in some scenarios. Each panel includes multiple colored lines representing different climate projections (ACCESS-CM2, HadGEM3, MPI-ESM, and MRI-ESM), with solid lines indicating results from the LANDIS-II model and dashed lines representing results from the LUCAS/FRSM model.

Source: Charles Maxwell, Pyrengence Consortium (Spatial Informatics Group)

This analysis of the coupled FRSM/LUCAS and LANDIS-II models is merely illustrative and provides only a brief overview of their extensive data. That deeper analysis was beyond the scope of this project. However, the research team is preparing manuscripts to compare these two modeling approaches (Maxwell et al. forthcoming, Sleeter et al. forthcoming).

Application of Machine Learning Models

Workgroup 4 examined the drivers and spatial patterns of wildfire activity across California’s ecoregions (Omernik and Griffith 2014) over a 30-year historical period (1990–2019) using advanced machine learning techniques (Hawbaker et al. forthcoming). The analysis focused on

four key components of wildfire regimes: ignition probability, conditional large wildfire size, burn probability, and conditional burn severity. All components were modeled at a spatial resolution of 1 kilometer and a monthly temporal resolution.

Model performance varied across wildfire regime components. The strongest results were achieved for ignition probability and burn probability, with cross-validation AUC values ranging from 0.70 to 0.90. These models successfully captured both the spatial and temporal patterns of wildfire occurrence, especially in regions where weather strongly influences fire activity. In contrast, the models for conditional large wildfire size and conditional burn severity showed more variable and generally lower predictive skill, with AUC values ranging from 0.36 to 0.78. Predictive accuracy was lowest in ecoregions with relatively infrequent wildfire events, where limited historical samples constrained model learning.

The relative importance of predictors differed substantially among ecoregions (including Cascades, Eastern Cascades Slopes and Foothills, Klamath Mountains, Sierra Nevada, Coast Range, Northern Basin and Range, Central Basin and Range, Mojave Basin and Range, Sonoran Desert, Central California Valley, California Coastal Sage, Chaparral, and Oak Woodlands, and Southern and Baja California Pine-Oak Mountains) and wildfire regime components. Weather-related variables, particularly relative humidity and precipitation, were consistently the most influential drivers of both ignition probability and burn probability statewide. In some regions, however, other factors played a more prominent role. For example, in the Central California Valley, land cover and vegetation were the dominant predictors, reflecting the limited and fragmented distribution of burnable wildland fuels. In contrast, topography emerged as a key influence on large wildfire probability in mountainous regions such as the Sierra Nevada and Klamath Mountains, where terrain strongly shapes fire spread and intensity.

Observed wildfire ignition-counts exhibited high interannual variability, with no clear long-term temporal trends in most ecoregions. Despite this variability, the models reproduced annual wildfire-counts reasonably well, with correlations between modeled and observed values ranging from 0.24 to 0.87. Burn probability predictions were particularly robust, closely matching observed burned area patterns across multiple ecoregions. Model performance was strongest in regions with frequent and extensive fire activity, including the Sierra Nevada and Klamath Mountains, where both spatial distributions and temporal trends in burned area were well represented.

In addition to capturing temporal patterns, the models provided valuable insights into the spatial distribution of wildfire risk. High-probability ignition and burn “hotspots” were identified in several regions, including the Cascades, Eastern Cascades, Sierra Nevada, and California Coastal Sage, Chaparral, and Oak Woodlands.

The study also identified several important limitations. The monthly temporal resolution and 1-kilometer spatial scale limited the models’ ability to represent fine-scale variability in vegetation, land use, wind, and fire behavior. The models were less successful in capturing year-to-year variability in wildfire size and burn severity, particularly in ecoregions with fewer large fire events. These uncertainties highlight challenges in predicting extreme wildfire behavior and suggest caution when interpreting results for rare, high-impact events.

Despite these limitations, the machine learning framework provides a valuable tool for understanding the dominant drivers of wildfire patterns and informing wildfire management and mitigation strategies. The models were designed to integrate with landscape and ecosystem simulation systems, such as LUCAS, enabling exploration of interactions among wildfire activity, land use change, vegetation dynamics, and climate change. Compatibility with downscaled historical and projected climate also allows the framework to be extended to future scenarios. Further refinement of this approach, particularly through tighter coupling with process-based landscape and fire models, could improve predictive skill for large wildfire size and burn severity, strengthening its utility for long-term planning, climate adaptation, and infrastructure resilience assessments. Machine learning models have the further advantage that, once the models are constructed, they can generate many more simulations than the process-based models, allowing greater characterization of uncertainty and variability.

CHAPTER 4:

Knowledge Transfer

Knowledge transfer activities cut across all four workgroups, ensuring that results were communicated effectively and in forms usable by decision-makers and other stakeholders.

Stakeholder Engagement and Technical Advisory Committee: A cornerstone of the project's knowledge transfer strategy was the establishment of a technical advisory committee (TAC) composed of representatives from electric utilities, state and federal agencies, regulators, and the research community. Technical advisory committee members provided guidance on project scope, methods, timelines, and coordination with other state and federal wildfire initiatives. Over the course of the project, nine TAC meetings were held, each tailored to specific phases of the project's research and tool development process.

These meetings served multiple purposes: keeping stakeholders informed of progress, obtaining feedback on modeling approaches and data products, and ensuring alignment with operational and regulatory needs, particularly those of electric utilities developing wildfire mitigation plans and climate adaptation strategies.

Scientific Outputs and Publications: Project researchers documented project findings through peer-reviewed publications, conference abstracts, dissertations, theses, and technical reports. As of the reporting period, the project produced 22 technical reports covering wildfire weather typing, fuel dynamics under drought and tree mortality, fire behavior modeling, emissions estimation, and long-term fire-vegetation climate model development. Several of these publications appeared in peer-reviewed journals such as *Journal of Geophysical Research: Atmospheres*, *Forest Ecology and Management*, *Environmental Research Letters*, and *Proceedings of the Combustion Institute*. A full list of publications (as of June 4, 2026, including anticipated and forthcoming) is provided here.

- Cobian-Iñiguez, J., F. Richter, L. Camignani, C. Liveretou, H. Xiong, S. Stephens, M. Finney, M. Gollner, and C. Fernandez-Pello. "[Wind Effects on Smoldering Behavior of Simulated Wildland Fuels](https://www.fs.usda.gov/rm/pubs_journals/2022/rmrs_2022_cobian_iniguez_j001.pdf)." *Combustion Science and Technology*. https://www.fs.usda.gov/rm/pubs_journals/2022/rmrs_2022_cobian_iniguez_j001.pdf.
- Coen, J. L. 2026. "[Climate Influences Wildfire Activity Through Opportunity: An Event-Scale Perspective](https://doi.org/10.3390/fire9040164)." *Fire*, 9(4), 164. <https://doi.org/10.3390/fire9040164>
- Coen, J.L., Johnson, G.W., Romsos, J.S. and Saah, D., 2024. "A Framework for Conducting and Communicating Probabilistic Wildland Fire Forecasts." *Fire*, 7(7), p.227.
- Foster, D. E. 2022. *Linking pattern and process in the disturbance ecology of Sierra Nevada mixed conifer forests*. PhD Dissertation. UC Berkeley.
- Hawbaker, T. et al. (forthcoming). *Modeling spatial and temporal variability in wildfire patterns for California USA*. US Geological Survey, Geosciences and Environmental Change Science Center, PO Box 25046, DFC, MS 980, Denver, CO, USA.

- Johnson, G. W., D. Saah, M. Moritz, and K. Cheung. 2022. *The GridFire Fire Behavior Model [whitepaper]*.
- Maxwell, C. et al. (forthcoming). Different models, same results: projected loss of forest carbon in California under climate change. Spatial Informatics Group, USGS, UNM, UC Merced.
- Northrop, H. 2022. *Drought Induced Snag Dynamics and Fuel Succession in the Sierra Nevada*. Master's Thesis – U.C. Berkeley.
- Northrop, H., J.N. Axelson, A. J. Das, N. L. Stephenson, E. Vilanova, S. L. Stephens, and J. J. Battles. 2024. "[Snag dynamics and surface fuel loads in the Sierra Nevada: Predicting the impact of the 2012–2016 drought](#)." *Forest Ecology and Management*, 551, p.121521. <https://doi.org/10.1016/j.foreco.2023.121521>
- Prein, A. F., J. Coen, A. Jaye. 2022. "[The character and changing frequency of extreme California fire weather](#)." *JGR Atmospheres*, 127 (9). <https://doi.org/10.1029/2021JD035350>.
- Purnomo, D.M., Y. Qin, M. Theodori, M. Zamaniaelaei, C. Lautenberger, A. Trouvé, and M. Gollner, 2024. Reconstructing modes of destruction in wildland–urban interface fires using a semi-physical level-set model. *Proceedings of the Combustion Institute*, 40(1-4), p.105755.
- Sleeter, B. M., B. Rayfield, L. Frid., C. Daniel, Z. Zhu, and D. Marvin. 2022. "[Operational assessment tool for forest carbon dynamics for the United States: a new spatially explicit approach linking the LUCAS and CBM-CFS3 models](#)." *Carbon Balance and Management*. <http://dx.doi.org/10.1186/s13021-022-00201-1>.
- Stephens, S. L., A. A. Bernal, B. M. Collins, M. A. Finney, C. Lautenberger, D. Saah. 2022. "[Mass fire behavior created by extensive tree mortality and high tree density is not predicted by operational fire behavior models in the southern Sierra Nevada](#)." *Forest Ecology and Management*, 518. <https://doi.org/10.1016/j.foreco.2022.120258>.
- Xu, Q., A. LeRoy Westerling, and W. Jonathan Baldwin. 2022. "[Spatial and temporal pattern of burn severity and biomass burning-induced emissions in California](#)." *Environmental Research Letters*. <https://doi.org/10.1088/1748-9326/ac9704>.
- Xu, Q., Anthony LeRoy Westerling, Andrew Notohamiprodjo, Christine Wiedinmyer, Joshua J Picotte, Sean A. Parks, Matthew D. Hurteau, Miriam E Marlier, Crystal A. Kolden, Jonathan A. Sam, W. Jonathan Baldwin, Christiana Ade. 2022. "[Wildfire Burn Severity and Emissions Inventory: An example implementation over California](#)." *Environmental Research Letters*. <https://iopscience.iop.org/article/10.1088/1748-9326/ac80d0>
- Waeselynck, V., Lautenberger, C. and Saah, D., 2025. PiRPLo: "A single-run method for calibrating wildland fire simulations like statistical models." *Stochastic Environmental Research and Risk Assessment*, pp. 1-38.

- Zamanialaei, M., San Martin, D., Theodori, M., Purnomo, D.M.J., Tohidi, A., Lautenberger, C., Qin, Y., Trouvé, A. and Gollner, M., 2025. "Fire risk to structures in California's Wildland-Urban Interface." *Nature Communications*, 16(1), p. 8041.

This body of work advanced the scientific basis for next-generation wildfire models by addressing known limitations in traditional approaches including inadequate representation of extreme weather, spatial heterogeneity in fuels, and climate-driven changes in vegetation and fire regimes. Importantly, many of these studies were explicitly designed to inform operational modeling tools developed under this project.

Webinars, Workshops, and Professional Conferences: To broaden awareness and build user proficiency, the project team hosted eight project-focused webinars that introduced the project, presented key scientific findings, and demonstrated tools such as PyreCast. These webinars reached audiences ranging from state agencies and utilities to the broader wildfire science management and research communities and were often archived for later viewing.

In parallel, project team members presented project-related work at more than 55 meetings, workshops, and professional conferences. These venues included major wildfire science meetings, utility-focused forums, policy workshops, local forest collaborative meetings, and interdisciplinary climate resilience events. In particular, the project was invited to present at the annual Electric Program Investment Charge (EPIC) Symposium, hosted by the California Energy Commission to highlight key research projects funded by the EPIC program. Presentations emphasized both scientific innovation and practical application, reinforcing the project's role as the bridge between research and operations.

Open-Source Data, Models, and Tools: A key feature of the project was its commitment to open-source development and transparent data sharing. All major data products, model code, and tool outputs were made publicly available through online repositories, consistent with the CEC EPIC program's goals of maximizing public benefit (for example, APPENDIX A and APPENDIX C).

Different modeling systems anchored the project's technical outputs. Workgroup 1 focused on optimizing weather station placement using maximum entropy (MaxEnt) modeling to improve monitoring of fire-relevant weather conditions, particularly in utility service territories. PyreCast provides near-term wildfire-spread forecasts using open-source fire behavior models (ELMFIRE and GridFire), delivered through a web application, APIs, and data servers that support real-time situational awareness. Workgroup 4 addressed long-term wildfire risk projections by modeling the interaction of climate, vegetation, urban development and fire occurrence and providing the resulting datasets to open-access repositories.

These open repositories enable utilities, agencies, and researchers to directly incorporate Pyregeance outputs into their own workflows, modeling efforts, and planning processes.

Media and Public Outreach: The project achieved public visibility through media engagements including newspaper articles, magazine features, online journalism, television segments, and radio interviews. Coverage appeared in outlets such as WIRED, Bloomberg Businessweek, High Country News, Los Angeles Times, Wall Street Journal, NPR affiliates, and regional news

stations. These stories highlighted the project's role in advancing wildfire science, improving forecasting capabilities, and informing policy and infrastructure decisions.

In addition, the project maintained an active presence on social media platforms, using these channels to share updates, publications, and tool demonstrations, which further expanded the project's reach beyond traditional technical audiences. The project team also participated in the [CEC Energize Innovation project reporting](https://www.energizeinnovation.fund/projects) project (<https://www.energizeinnovation.fund/projects>).

Results and Adoption: By the conclusion of the reporting period, project data and tools had already been adopted by a range of target users including electric utilities, state agencies, emergency response organizations, and insurance and property risk analysts. Adoption was facilitated by engagement, open access to resources, and responsiveness to user feedback.

Overall, the project succeeded in advancing wildfire science and modeling capabilities, translating those advances into usable, accessible, and increasingly adopted decision-support resources.

CHAPTER 5:

Conclusions

This project advanced the scientific foundation, modeling capabilities, and decision-making support tools required to address increasing wildfire risks facing California's electricity grid. Through the evaluation of extreme weather, fire physics, fuel and tree mortality, near-term operational forecasting, and long-term climate-driven wildfire projections, the project delivered a range of open-source research, datasets, and tools that support safer, more reliable, and more affordable electricity to California ratepayers. These findings and products are additionally valuable to broader wildfire communities.

Looking to the future, there is a growing need to translate advances in wildfire science and modeling into actionable economic and policy guidance. Future research should explicitly evaluate the costs and benefits of proactive fuel management relative to avoided wildfire damage, including impacts to infrastructure, communities, and ecosystems. Such analyses would support decision-makers in understanding whether near-term investments in mitigation effectively reduce long-term societal and economic losses, particularly under scenarios of increasing wildfire frequency and severity.

Key Implications and Future Opportunities

Extreme Weather and Fire

Research conducted by Workgroup 1 demonstrated that extreme weather, particularly wind-driven and thermally driven atmospheric conditions, is both a dominant driver of California's most damaging wildfires and a critical source of risk to the electric grid. The analyses showed that a relatively small number of large-scale, fire-weather regimes account for a disproportionate share of large fire-growth days, underscoring the importance of short-term atmospheric dynamics over longer-term background conditions alone. While well-known wind patterns such as Santa Ana and Diablo events continue to play an important role, climate projections indicate a shift toward more frequent low-pressure thermal systems, especially in coastal and Sierra regions, suggesting that future wildfire risk may increasingly be driven by hotter, drier summer conditions rather than by fall wind events.

Weather station placement has historically been driven by operational convenience rather than a coordinated, statewide strategy, resulting in gaps in coverage where microclimates and terrain-driven wind patterns strongly influence fire behavior. The project developed a modeling-based optimization approach to more cost-effectively improve situational awareness by siting new stations to fill those gaps.

The upper-air profiler measured winds aloft that provided early indicators of extreme surface wind events, which can improve the short-term forecast performance of atmospheric conditions that elevate the likelihood of wildfire ignition and spread risk when compared with surface observations alone. These findings highlighted the value of vertical atmospheric information for anticipating high-impact fire weather and supporting operational decision-making, including PSPS planning.

Finally, the application of the CAWFE model illustrated both the importance and the challenge of representing fine-scale fire-atmosphere interactions. High-resolution simulations captured terrain-driven wind accelerations, plume dynamics, and localized wind extremes that are not resolved by conventional wildfire forecasting systems, offering insight into the physical mechanisms underlying extreme plume-driven fire behavior. At the same time, the computational and operational demands of such models underscore the need to balance physical realism with practicality for routine use. It would be beneficial to integrate CAWFE or similar models into the PyreCast platform to offer users that option.

Tree Mortality, Fuels, and Fire Physics

Research completed by Workgroup 2 focused on fuel conditions and combustion processes that are not adequately represented in existing fire-behavior models such as the accumulation of large woody material, deep duff layers, and prolonged heat release now common in many forested landscapes with extensive tree mortality.

Laboratory experiments conducted at both small and large scales indicate that wind-driven ventilation (and interactions among winds), fuel size, and arrangement can produce sustained and intense heat fluxes, which contribute more to mass fire behavior than the thin flame fronts assumed in traditional models. More work is needed to integrate these relationships into comprehensive wildfire risk models.

Field-based fuel measurements and spatial modeling revealed that elevated tree mortality increases surface fuel loads, especially coarse woody debris. These changes are spatially heterogeneous and occur at fine scales not currently captured by either conventional fuel classification systems or remote sensing data products alone. More work is needed to develop predictive models of fuel distributions. Projections of snag fall and fuel succession indicate that surface fuel loads in high tree-mortality areas will continue to increase over the coming decades, suggesting higher potential for future severe wildfire behavior even without additional mortality.

High-resolution tree mortality mapping, using multi-temporal satellite imagery and deep learning, provided more accurate and spatially continuous depiction of dead canopy cover than existing polygon-based surveys. These data revealed expanding patterns of tree mortality across large portions of California, offering inputs for both near-term and long-term wildfire modeling projections. The integration of datasets into fire behavior models may improve predictions of fire intensity, severity, and impacts to both infrastructure and communities.

Collectively, the findings from Workgroup 2 underscore the need to modernize wildfire modeling approaches that more accurately represent large-fuel combustion, long-duration heat release, and fine-scale fuel heterogeneity. Incorporating these processes into next-generation fire-behavior models will be critical for accurately understanding extreme fire behavior, informing mitigation strategies near wildland–urban interfaces, and improving the resilience of California’s electric grid given ongoing climate change.

Near-Term Wildfire Forecasting Models

The development and deployment of the PyreCast platform revealed that operationally relevant wildfire forecasts (spanning hours to approximately two weeks) can be delivered at fine spatial resolution and with sufficient update frequency to meaningfully inform utility and emergency management decisions. Evaluation of PyreCast against historical wildfire events confirmed that the system provides forecast skill comparable with peer operational models used by federal agencies, with particularly strong performance during wind-driven fire events that pose the most frequent risk to electricity infrastructure.

Project findings also highlighted critical factors that influence forecast reliability including the quality of fire initialization data, representation of atmospheric stability and plume-dominated fire behavior, and the ability to account for suppression actions and complex terrain effects. While these challenges remain inherent to near-term wildfire modeling, this project demonstrated that targeted improvements such as filtering anomalous satellite heat detections, updating fuels data annually (or more frequently if feasible), and incorporating suppression logic, can enhance both forecast realism and usability. Importantly, the open-source and modular architecture of PyreCast enables continuous refinement as new science, data sources, and operational insights become available. One such enhancement would be to operationalize a coupled atmosphere-wildfire behavior model (such as CAWFE) to offer users a model that successfully forecasts the spread of wind-dominated and plume-driven wildfires.

Additional work is needed to better document and characterize wildfire risk to communities by integrating consequence-based metrics including community vulnerability, infrastructure exposure, and evacuation (ingress/egress) impacts and constraints. Improving the representation of conflagration risk and fire spread dynamics in wildland-urban interfaces (WUI) for near-term fire forecasting will also be critical for understanding impacts to built environments. Incorporating suppression effectiveness into fire modeling frameworks would additionally provide a more complete picture of how management actions influence fire outcomes.

Collectively, these outcomes demonstrate that open-source, near-term wildfire forecasting platforms like PyreCast represent a viable and scalable approach for improving situational awareness, supporting proactive wildfire risk management, and enhancing the resilience, safety, and cost-effectiveness of California's electricity grid. This is further demonstrated by the number of utilities (such as public utilities and co-ops) in other states that have requested customization of PyreCast to support their own operations.

Long-Term Fire Projections

Workgroup 4 developed a multi-model framework for projecting long-term wildfire dynamics, vegetation change, and carbon outcomes across California to determine both the relative strengths and limitations of different model approaches. These were implemented under a range of plausible future climate, management, and development conditions. Both integrated modeling approaches, anchored by the LUCAS, the FRSM, and the LANDIS-II dynamic vegetation model, represent improvement in the state's capacity to evaluate the bi-directional interactions between vegetation and wildfire that drive long-term ecosystem and risk trajectories.

Datasets produced, spanning historical and future periods from 1985 to mid-century (2065), and then to 2100, provide an open, reproducible foundation for decision support and future research. Publicly accessible data included gridded annual vegetation and carbon stocks, land-use transitions, and semi-monthly-to-annual projections of wildfire occurrence, size, and severity, along with model code repositories for LUCAS, FRSM, and LANDIS-II. Together, these resources offer California's scientific and policy communities the additional capacity to evaluate longer-term wildfire risks, carbon resilience, and management trade-offs.

By design, these scenario-based projections are useful for integrating into utility long-range planning processes, including identifying future high-risk wildfire areas where grid hardening, undergrounding, relocation, and decommissioning decisions may be most effective. At the state level, incorporating long-term wildfire hazard datasets into climate adaptation platforms and planning tools would improve consistency across agencies and jurisdictions. Continued development of standardized policy-relevant metrics linking wildfire projections to infrastructure risk, carbon outcomes, and avoided costs, will increase the use of these models (and associated outputs) for regulatory and investment decisions, particularly when uncertainty and scenario dependence are clearly communicated.

In addition to coupled modeling approaches, exploratory machine learning analyses provided complementary perspectives on long-term wildfire risk by leveraging historical datasets to identify empirical relationships among climate, fuels, land use, and human influences. The study demonstrated that statistical and machine learning approaches can provide a useful framework for characterizing historical wildfire regimes across California when underlying processes are complex, partially understood, or computationally expensive to model mechanically.

The machine learning models developed for this project performed best for both ignition probability and burn probability where predictions closely tracked observed spatial and temporal patterns and generally fell within estimated uncertainty parameters. Performance was weaker for large wildfire size and burn severity, reflecting the inherent difficulty of modeling rare and extreme fire outcomes. Nonetheless, even where predictive skill was limited, intervals of uncertainty often captured observed values, reinforcing the importance of explicitly representing uncertainty when using these models for scenario analyses or decision support. The research supports the use of machine learning as a component of integrated wildfire risk assessment and long-term planning under changing climate and land-use conditions.

Overall, for long-term wildfire modeling, future modeling efforts would benefit from exploring a broader range of vegetation treatment scenarios beyond the discrete cases evaluated here. Specifically, analyzing gradients of treatment intensity and spatial extent and appropriate model resolution could help identify thresholds or inflection points where additional treatment yields diminishing returns in wildfire risk reduction and/or other environmental costs that may be at hand (for example, vegetation type conversion, carbon loss). In addition, outputs produced in this project could be further explored to understand the potential future wildfire exposure to communities and electric infrastructure. Such analyses would provide guidance for

optimizing future fuel management strategies and prioritizing investments to maximize resilience benefits.

Benefits to California Ratepayers

Wildfires pose growing threats to many sectors of California's economy and society. Research to better understand these growing risks and to help mitigate them will ultimately benefit California across the board. Although this study focused on the bi-directional risk of wildfire to and from the electricity sector, it inevitably benefits other sectors such as fire emergency management, housing, public safety, and insurance.

Economically, the project demonstrated how improved wildfire intelligence can lower costs by avoiding unnecessary infrastructure damage, reducing emergency response expenditures, limiting prolonged power outages, and ideally reducing liability for damage to property. The PyreCast case study illustrated that even incremental improvements in forecast timeliness can yield millions of dollars in avoided costs during a single fire event, with benefits that scale statewide.

The environmental benefits of this work stem from its potential to reduce the frequency and severity of catastrophic wildfires. Improved forecasting and long-term planning can support more effective vegetation management, reduce extreme fire behavior, and limit wildfire-related emissions of greenhouse gases and particulate matter, with associated benefits for ecosystems, air quality, and public health.

For California utility ratepayers, these environmental and economic benefits can improve affordability. By enabling more targeted wildfire mitigation, better capital planning, and reduced exposure to catastrophic losses and liabilities, the tools and insights developed through this project support a more reliable, resilient, and cost-effective electricity system. Importantly, the open-source nature of the work ensures that ratepayer-funded research delivers durable public value, extending beyond the life of the project and supporting continued innovation across the wildfire science and utility communities.

List of Terms/Glossary

Term	Definition
ADS	Aerial Detection Survey (U.S. Forest Service)
ALERTWildfire	ALERT Wildfire Camera Network
API	application programming interface
AUC	area under the curve
BAU	business as usual vegetation management scenario
ISO	California Independent System Operator
CALFIRE	California Department of Forestry and Fire Protection
CAWFE	coupled atmosphere-wildland fire environment
CBM-CFS3	Carbon Budget Model of the Canadian Forest Sector
CEC	California Energy Commission
CESM	Community Earth System Model
CMIP6	Coupled Model Intercomparison Project (Intergovernmental Panel on Climate Change 6th Assessment Report)
CWD	coarse woody debris
ELMFIRE	Eulerian Level Set Model of FIRE
EO	earth observation
U.S. EPA	United States Environmental Protection Agency
EPIC	Electric Program Investment Charge
ERA5	Fifth generation atmospheric reanalysis of the global climate covering the period from January 1940 to the present by the European Centre for Medium-Range Weather Forecasts
ESMF	Earth System Modeling Framework
FARSITE	fire area simulator
FCCS	Fuel Characteristic Classification System
FIRED	Fire Events Data (global wildfire database)
FMMP	California Farmland Mapping and Monitoring Program
FRAP	Fire and Resource Assessment Program (CALFIRE)
FRSM	Fire Risk Simulation Model (U.C. Merced)
FSim	fire simulation model
GCM	global climate model
GOES	Geostationary Operational Environmental Satellite

Term	Definition
GPL	general public license
GridFire	A raster-based fire behavior model that may be used to simulate the spread of wildfires across a landscape, either individually or in monte carlo simulations over space and time (SIG).
gridMET	Gridded Surface Meteorological Dataset
GSP	generalized state parameter
ha	hectare
HPC	High-performance computing
IOU	investor-owned utility
km	kilometer(s)
LANDFIRE	Landscape Fire and Resource Management planning tools
LANDIS-II	Landscape Disturbance and Succession model
LiDAR	light detection and ranging
LOCA2	localized construct analogs-hybrid
LUCAS	Land Use and Carbon Scenario Simulator
LULC	land use and land cover
m	meter(s)
m/s	meters/second
MaxEnt	maximum entropy
ME	mean error
MODIS	Moderate Resolution Imaging Spectroradiometer
NCAR	National Center for Atmospheric Research
NEP	numerical weather prediction
NOAA	National Oceanic and Atmospheric Administration
NVE	NV Energy
PG&E	Pacific Gas and Electric Company
PMP	product management plan
PSPS	public safety power shutoff
RWPs	radar wind profilers
SCE	Southern California Edison
SDG&E	San Diego Gas & Electric
SIG	Spatial Informatics Group, LLC
SODAR	sonic detection and ranging (upper-air wind profiler)

Term	Definition
SSP	shared socioeconomic pathways
TAC	technical advisory committee
UAP	upper air profiler
UCB	University of California, Berkeley
UCLA	University of California, Los Angeles
UCM	University of California, Merced
UCSB	University of California, Santa Barbara
UCSD	University of California, San Diego
USF	University of San Francisco
USFS	United States Forest Service
USGS	United States Geological Survey
VIIRS	Visible Infrared Imaging Radiometer Suite
WG	workgroup
WRF	Weather Research and Forecasting (model)
WTs	weather types
WUI	wildland-urban interface

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Project Deliverables

Following is a list of major project product deliverables and associated links to the products. Other project deliverables, including interim project reports, are available upon request by emailing pubs@energy.ca.gov and providing the project agreement number (EPC-18-026).

Overarching Tasks and Deliverables

- Task 2 - Project Team and Product Management Plan
 - Product Management Plan
- Task 8 - User Engagement Workshops: Phase 1
 - User Needs Assessment Summary
- Task 11 - User Engagement Workshops: Phase II
 - Integration Workshop Summary
- Task 13 – Technology/Knowledge Transfer Activities
 - Technology/Knowledge Transfer Report

Technical Tasks by Workgroup

- Workgroup 1 – Tasks 3 (Optimal Configuration of Weather Stations)
 - Site Recommendation Methodology Framework and Baseline Needs Assessment Summary
 - Weather Station Network Dataset
 - Inventory Dataset
 - Upper-air Profiler Test Plan
 - Upper-air Profiler Report
 - Weather Station Network Optimization Data Archive
 - Optimal Location of Weather Stations Report
- Workgroup 1 - Task 4 (Extreme Weather Historical Analysis)
 - Extreme Weather Historical Pre-Analysis Spatial Dataset
 - Extreme Weather Historical Data Archive
 - Extreme Weather Historical Analysis Report
 - Publication (Prein et al. 2022)
 - Publication (Coen 2026)
 - CAWFE Model Animations

- Workgroup 2 – Task 5 (Advancing Wildfire Science of Tree Mortality)
 - State of Wildfire Science Report
 - Tree Mortality Fuel Projection Dataset
 - Contemporary Tree Mortality Archive/Dataset
 - Map Data - Salo Sciences
 - Map Data - EDART
 - Tree Mortality Evaluation Summary
 - Publications
- Workgroup 3 – Task 6 (Near-term Risk Forecast Model Development: Phase I)
 - Near-Term Risk Forecast Baseline Needs Assessment Summary
 - Near-Term Risk Forecast Data Archive
 - Near-Term Risk Forecast Dataset
 - Near-Term Risk Forecast Modeling Framework Summary
 - Decision-Support Tool Brief
 - Near-Term Risk Forecasts User's Guide
 - Near-Term Risk Forecast Outputs
 - Publications
- Workgroup 3 – Task 9 (Near-Term Risk Forecast Integration - Phase II)
 - Near-Term Risk Forecast Integration Workplan - Phase II
 - Near-Term Risk Forecast Cost-Benefit Analysis Factsheet
 - Near-Term Risk Forecast: Evaluation of Performance and Recommendations Summary
 - Near-Term Risk Forecast Data Archive - Phase II
- Workgroup 4 – Task 7 (Next-Generation of Long-term Fire Risk Projection Models - Phase I)
 - Long-Term Risk Projections Baseline Needs Assessment Summary
 - Long-Term Risk Projections Modeling Framework Summary
 - Long-Term Risk Projections Dataset
 - Long-Term Risk Projections Data Archive
 - Planning Support Tool Design Brief
- Workgroup 4 – Task 10 (Long-Term Wildfire Projections - Phase II)

- Long-Term Risk Projections Workplan - Phase II
- Long-Term Risk Projections Report (Task 10)
 - Machine Learning Model Report – Hawbaker et al. (forthcoming publication)
 - Publications
 - Scenario Memos
- Long-Term Risk Projections Data Archive - Phase II
 - See Appendix C



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APPENDIX A: PyreCast Data and Code Repositories

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Appendix A:

PyreCast Data and Code Repositories

The PyreCast data and archive consists of two main components: open-source code repositories and real-time data outputs.

Open-Source Repositories:

The PyreCast system is powered by several open-source repositories, which have been made publicly available. These include the ELMFIRE and GRIDFIRE fire spread models, the PyreCast web application, and various helper scripts like Geosync. These repositories provide the foundational software and tools that run the PyreCast web application and its associated data feeds. PyreCast is powered by software contained in the following open-source repositories that are publicly available:

Description	URL
ELMFIRE fire spread model	Code - https://github.com/lautenberger/elmfire Instructions and tutorials - https://elmfire.io
GRIDFIRE fire spread model	Code - https://github.com/pyregence/gridfire
PyreCast web application	Code - https://github.com/pyregence/pyregence
Geosync helper scripts	Code - https://github.com/pyregence/geosync

Real-Time Outputs:

The real-time outputs from PyreCast can be accessed through multiple online platforms, including the PyreCast web application, Application Program Interfaces (APIs), and a dedicated web server. These resources offer real-time data related to active fires and other relevant layers, making it possible for users to obtain up-to-date wildfire risk information.

Description	URL
Web application	Pyre Cast https://pyrecast.org/
Application Program Interface (API) – active fires	GeoServer https://geoserver-usw1.pyrecast.org/geoserver02/web/
Application Program Interface (API) – all other layers	GeoServer https://geoserver-usw1.pyrecast.org/geoserver01/web/
Data repository	Pyre Cast https://data.pyrecast.org/



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APPENDIX B: Long-term Projections - Data and Code Repositories

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Appendix B:

Details of Long-term Model Components

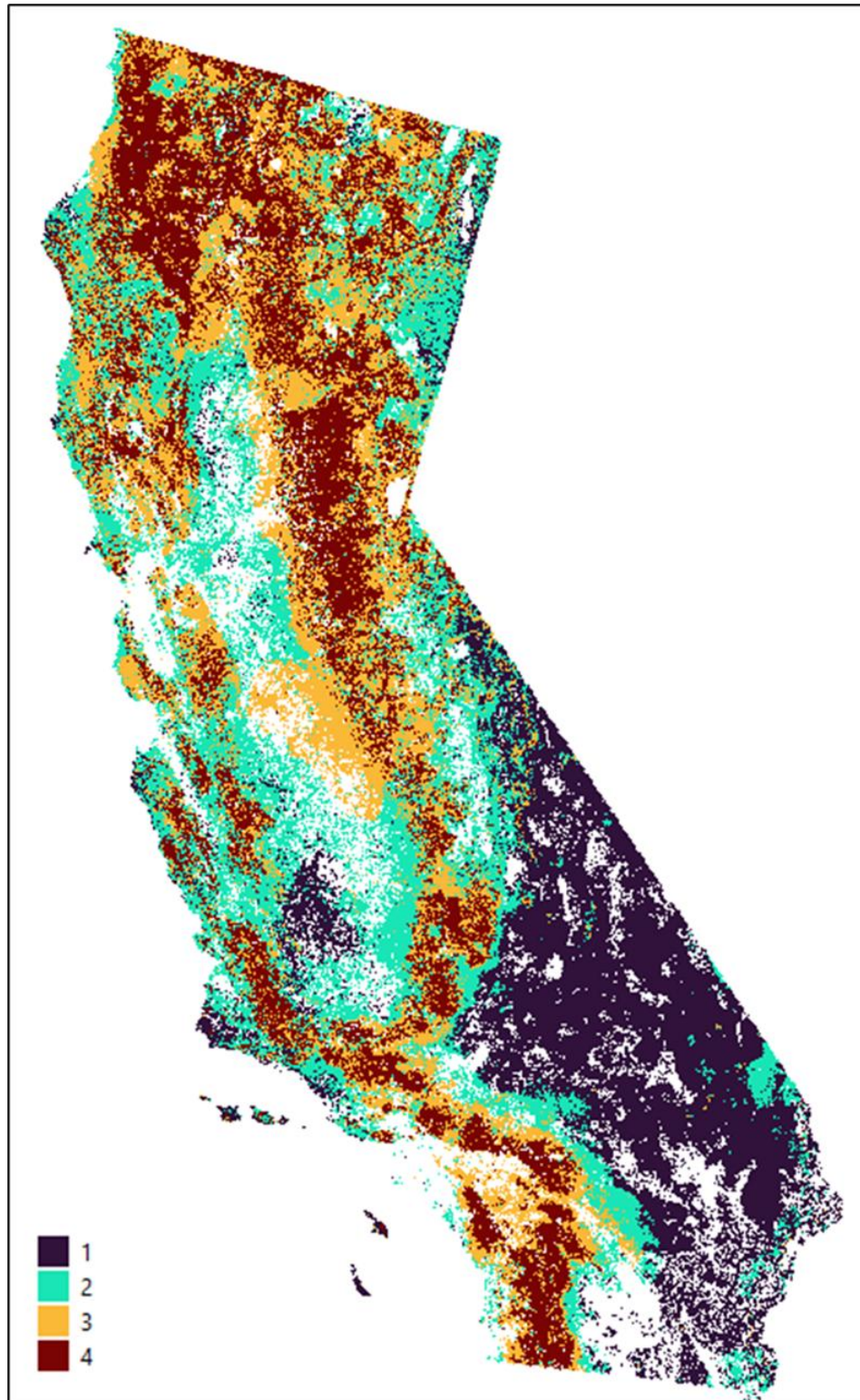
Vegetation Management Scenarios

The identification of vegetation management scenarios focused on reducing wildfire hazard in California through 2100. Two scenarios were assessed: a 'high ambition' regime treating one million acres per year, aligned with 2021 policy, and a 'business-as-usual' regime treating about 140,000 acres per year, reflecting 2010-2019 averages. The summary below outlines definitions, assumptions, results for both scenarios across different management zones, and the vegetation data used in wildfire projections.

High Ambition Vegetation Treatment Scenario

This scenario aims to achieve the one million acres per year treatment goal from the [2021 California Wildfire and Forest Resilience Action Plan](#), focusing on areas with 'moderate' and 'high' wildfire hazard as mapped by Vogler et al. (2021; Figure B1). With high treatment rates, some management areas can be fully treated in 15 years, but manual-only regions - except state-owned lands - won't reach full coverage in that timeframe. Federal lands eligible for mechanical methods would be entirely treated within 15 years, while those needing manual treatment would not. At a rate of 111,000 acres/year for WUI Interface lands, all would be treated in 18 years; accessible WUI Intermix lands with mechanical treatments would be completed in 20 years. Only 28% of high hazard WUI Intermix lands requiring manual treatment would be covered in 15 years. Treatable areas exclude those inaccessible due to jurisdiction, administration, or natural barriers. Table B1 summarizes forested acres and annual treatment by management zone

Figure B-1. Current Wildfire Hazard Potential (WHP) across California based on data produced by Vogler et al. 2021. WHP classes included in the map are Very Low = 1, Low = 2, Moderate = 3, High = 4.



Source: Vogler et al. (2021)

Table B-1. Summary of all forested acres and annual treatment acres by classes of wildfire hazard potential under the 'High Ambition' vegetation management scenario.

Management Zone	Mechanically Operable?	Wildfire Hazard Potential (WHP) Class (Acres)				Total Acres	Target Annual Treatment Acres
		Very low	Low	Moderate	High		
Federal (includes USDA Forest Service, BLM)	Yes	4,038,187	2,674,987	3,852,379	4,631,706	15,197,259	380,000
	No	295,571	345,050	652,050	1,489,189	2,781,859	145,000
	Federal Totals^a	4,333,758	3,020,037	4,504,428	6,120,894	17,979,118	640,000
Non harvestable (NH; includes Protected Areas, Non-vegetated Areas)	Yes	2,816,144	7,708,890	4,634,042	2,119,623	17,278,698	0
	No	12,030,084	4,461,104	4,125,794	4,648,486	25,265,467	0
	NH Total	14,846,227	12,169,993	8,759,836	6,768,109	42,544,165	0
Private Industrial Forestry (PIF)	Yes	110,409	865,648	1,816,618	2,282,487	5,075,162	95,000
	PIF Total	110,409	865,648	1,816,618	2,282,487	5,075,162	95,000
Private Non-industrial Forestry (PNIF; small landowners)	Yes	33,888	528,618	1,395,064	1,623,783	3,581,353	20,000
	No	3,469	46,259	159,790	376,997	586,514	0
	PNIF Total	37,357	574,876	1,554,854	2,000,779	4,167,867	20,000
State (includes CalParks, CalFWS)	Yes	166,158	478,509	350,120	240,341	1,235,128	37,000
	No	18,135	56,230	58,811	58,693	191,868	15,000
	State Total^b	184,293	534,739	408,930	299,034	1,426,997	102,000
Utility Lands	Yes	224,932	351,503	265,499	135,711	977,645	30,000
	Utility Total	224,932	351,503	265,499	135,711	977,645	30,000
WUI (includes Interface and Intermix)	Yes	801,781	2,859,989	3,225,504	2,017,472	8,904,745	129,500
	No	95,086	241,720	342,204	427,225	1,106,235	55,500
	WUI Total	896,867	3,101,708	3,567,708	2,444,697	10,010,980	185,000
Totals		61,901,533	61,855,513	62,633,621	60,155,134	82,181,934	1,072,000

a – An additional 115,000 acres/year in prescribed fire treatment is assumed for Federal lands.

b - An additional 50,000 acres/year in prescribed fire treatment is assumed for State lands.

Source: Pyregence Consortium

Assumptions

The major assumptions to prioritize treatments included:

- Treatment of the WUI Interface takes precedence over WUI Intermix at a 60%/40% split.
- This Interface to Intermix precedence would result in a 70%/30% split between mechanical treatment over manual treatment¹⁹.
- Timber harvesting on private lands will count towards the acreage target of treatments on private lands.

¹⁹ This assumption would mean that of the total acres allotted to WUI treatments, there would be 300,000 * 40% * 70% = 84,000 of mechanical treatments in the WUI Intermix (where slopes are less than 30%).

- Prescribed fires can occur on any slope class and harvestable areas occur only where mechanical treatment is possible (areas with slopes less than 30%).
- For State and federally managed lands, harvesting will be based on ecological harvest methods, which would leave a high residual of remaining basal area and standing snags.
- For Private lands, harvesting will be consistent with current practices.
- Any areas with a protected status—such as roadless areas, PACs, wilderness, national monuments, etc. (totaling 40 percent of acres considered)—would not be treated by mechanical or manual means.
- High fire suppression effort would be emphasized everywhere except in roadless and wilderness areas where fire would serve as a restoration action.
- Corporations would be responsible for reducing the fire risk on their lands; corporately-held lands would harvest at business-as-usual rates of a 36-year return interval.
- For family-owned forests, the continuation of present harvest rates would indicate a 200+ year return interval.
- For transmission infrastructure, investor-owned utilities would perform significant additional vegetation control around their respective transmission infrastructure up to 175 ft from transmission lines (totaling a 350 ft buffer, centered on transmission poles), following Liberty CalPeco and the California Tahoe Conservatory's Powerline Resilience Corridor Strategy.

Treatment Schedule

The vegetation treatments followed a wildfire hazard potential order where areas mapped as 'high' hazard would be prioritized for treatment first, descending through 'moderate,' 'low' and eventually any 'very low' hazard areas if time and resources permit. Locations of treatment were randomly drawn based on assumptions detailed above.

Retreatment would occur on a 15-year rotation for WUI areas (both Interface and Intermix) and State managed areas.

After 15 years, for federally managed lands, prescribed fire would supplant mechanical and manual treatments at a rate of 50% to maintain the "treated" status, such that annual treatments would be 335,000 acres of prescribed fire, 190,000 acres of mechanical treatments, and 72,500 acres of manual treatments.

Results

Using the described schema:

- At a rate of 111,000 acres treated per year for the WUI Interface zone, all areas in State Responsibility Areas would be treated within 18 years, regardless of fire risk level.

- At a rate of 51,800 acres treated per year for the WUI Intermix areas that allowed for mechanical treatment, all eligible areas would be treated within 20 years.
- At a rate of 22,200 acres treated per year for the WUI Intermix areas only eligible for manual treatment, only 28% of the extremely high hazard area would be treated after 15 years, leaving a potential shortfall of over 840,000 acres.

At the proposed rate of treatment of 50,000 acres per year, all State Park lands, excluding protected areas, could be treated within 15 years, potentially allowing for treatment of 500,000 acres of land under local or tribal management in the same timeframe.

For federally managed lands, while all the eligible mechanically treatable areas could be treated within 15 years at a rate of 380,000 acres per year, lands receiving manual treatment at a rate of 145,000 acres per year for 15 years would leave close to four million acres untreated. Because most of the funding comes from the State of California, it is assumed that treatments on federal land would follow SRA risk prioritization. Using this approach, the rate of treatment would be sufficient to treat all the lands in the elevated hazard risk areas and could feasibly be distributed differently depending on annual priorities.

For corporate and family-owned forest lands treated at a rate of 115,000 acres per year (95,000 corporate, 20,000 family), a substantial deficit of nearly four million acres would remain after 15 years.

Based on a treatment rate of 10,000 acres per year around transmission lines, it would take almost 30 years for all the areas in the elevated fire risk classes to be treated, or 16 years for the high and very high-risk areas to be treated. Increasing the treatment rate to 30,000 acres per year allows for a retreatment interval of 10 years.

Business-As-Usual (Low Ambition) Treatment Scenario

This scenario represents an attempt to perpetuate the vegetation management/treatment approach from the previous decade (2010-2019). As such, the total average annual treatment rate across the state is approximately 140,000 acres per year, or 86% less activity than the high ambition scenario. Treatment levels are based on completed activities reported by departments and agencies and averaged across the decade. Rather than specifically targeting areas of the landscape, treatments are opportunistic and scattered across the landscape. High fire suppression efforts were applied across the entire landscape. All the assumptions from the high ambition scenario apply to this scenario as well.

Vegetation Data Used for Modeling

Two sources of vegetation data were used to inform vegetation management scenarios and train projected vegetation outputs, including:

TreeMap

TreeMap 2016 provides a tree-level model of the forests of the conterminous United States. Forest plot data from [Forest Inventory and Analysis](#) (FIA) are matched to a 30x30 meter (m) grid. Beyond the Pyrengence project, TreeMap is used in the private and public sectors for

projects including fuel treatment planning, snag hazard mapping, and estimation of terrestrial carbon resources. TreeMap uses a random forests machine-learning algorithm to impute the forest plot data to a set of target rasters provided by Landscape Fire and Resource Management Planning Tools ([LANDFIRE](#)). Predictor variables consisted of percent forest cover, height, and vegetation type, as well as topography (slope, elevation, and aspect), location (latitude and longitude), biophysical variables (photosynthetically active radiation, precipitation, maximum temperature, minimum temperature, relative humidity, and vapor pressure deficit), and disturbance history (time since disturbance and disturbance type) for the landscape circa 2016.

In the attribute table of this raster, a set of attributes drawn from the FIA databases, including forest type and live basal area are included. The raster map of plot identifiers can be linked to the FIA databases available through the [FIA DataMart](#) or the text and SQL files included in the [data publication](#) (also referenced below) to produce tree-level maps or to map other plot attributes. The accompanying database files included in the below referenced publication also contain attributes regarding the FIA plot CN (or control number, a unique identifier for each time a plot is measured), the subplot number, the tree record number, and for each tree: the status (live or dead), species, diameter, height, actual height (where broken), crown ratio, number of trees per acre, and a code for cause of death where applicable. The TreeMap dataset has been validated for applications including percent live tree cover, height of the dominant trees, forest type, species of trees with most basal area, aboveground biomass, fuel treatment planning, and snag hazard. Of these available attributes, only species, age, biomass, and location data were used in developing the Landis II inputs. More information can be found [here](#):

Landscape Ecology, Modeling, Mapping, and Analysis

Landscape Ecology, Modeling, Mapping, and Analysis (LEMMA) data is produced by an informal team comprised of employees of the USDA Forest Service, Pacific Northwest Research Station, and the Department of Forest Ecosystems and Society, Oregon State University (OSU), based at the Forestry Sciences Lab on the OSU campus.

For wildfire projections, the team used LEMMA's Gradient Nearest Neighbor (GNN) data product to validate vegetation data outputs produced by [Landis II](#) (see <https://lemma.forestry.oregonstate.edu/data/home>). GNN data are multivariate, imputed maps of forest attributes based on 30-m Landsat imagery, [Forest Inventory and Analysis \(FIA\) data](#), and other geospatial data products, such as climate and topography. GNN models apply only to forested land (areas currently or with the potential to support at least 10% tree cover), because a consistent regional plot sample of non-forest areas is not available. These [data](#) can be downloaded from: <https://lemmdownload.forestry.oregonstate.edu/>

Long-term Wildfire Models

The long-term wildfire modeling framework integrates three complementary models (LUCAS, FRSM, and separately LANDIS-II) to represent interacting processes of land use, vegetation dynamics, carbon cycling, and wildfire disturbance.

Land Use and Carbon Scenario Simulator (LUCAS)

The Land Use and Carbon Scenario Simulator (LUCAS) is a model system that tracks changes in land use, land cover, land management, and disturbance, and their impacts on ecosystem carbon storage and flux. The LUCAS model combines a State-and-Transition Simulation (STMS) model to simulate changes in land-use across a range of geographic scales, a Stock and Flow Model to track the movement of carbon between different “pools” including interactions between land and atmosphere.

The STMS model is used to simulate changes in land use and land cover classes resulting from changes due to urbanization, agricultural expansion and contraction, forest harvest, wildfire and other processes. Monte Carlo methods are used to capture and reflect model and data uncertainties. Ecoregions are used to stratify the landscape into discrete units.

LUCAS carbon modeling is done using a stock-flow modeling approach. Carbon pools are defined as a set of stocks, and flows are used to move carbon between stocks over time. Two primary types of flows are defined - automatic flows occur every year and include transfers of carbon from growth, mortality, and emission. Event-based flows are used to move carbon between stocks when a change in the land system occurs, such as removal of biomass from vegetation management or urbanization. To parameterize the stock-flow model, the researchers used the CBM-CFS3 and methods described in Sleeter et al. (2022).

For LUCAS, initial inputs included California Farmland Mapping and Monitoring Program (FMMP) data to initialize urbanization and agricultural transitions, USFS Aerial Detection Surveys for insect and drought mortality, and LANDFIRE forest harvest data. Protected lands are delineated using the USGS Protected Areas Database, and land-cover classifications are taken from the National Land Cover Database (NLCD). County and ecoregion boundaries (EPA Level III/IV ecoregions, U.S. Census Bureau TIGER Line files) can be used for summarizing results.

UC Merced Fire Risk Simulation Model (FRSM)

The FRSM integrates statistical fire models with dynamically evolving vegetation and climate inputs, providing a forward-looking tool for evaluating how wildfire regimes may respond to climate change, land use, and ecosystem dynamics.

The FRSM operates at a 3 km spatial resolution and semi-monthly temporal scale and is built around a hierarchical modeling pipeline implemented in R. It combines three core components: (1) probabilistic modeling of large fire occurrence, (2) extreme value modeling of fire size, and (3) fractional estimation of burn severity. Fire occurrence is modeled using generalized additive models (GAMs) that relate ignition likelihood to climate variables (for example, temperature, precipitation, humidity, wind), vegetation structure derived from the LUCAS (Land Use and Carbon Scenario Simulator) model, and topographic features. Fire sizes are simulated using a Generalized Pareto Distribution to capture the heavy-tailed nature of large wildfire events, while burn severity is estimated as proportional fractions across severity classes using sequential statistical models informed by climate and fuel conditions.

A key innovation of FRSM is its coupling with the LUCAS landscape simulation model, allowing vegetation composition and biomass to evolve dynamically over time and feed back into fire

behavior predictions. This enables the system to capture interactions between climate-driven vegetation change and wildfire activity, which are critical for long-term risk assessment. The framework is also designed to ingest multiple climate projection datasets, including dynamically downscaled WRF outputs and statistically downscaled LOCA2-Hybrid scenarios, supporting analysis across a range of future climate pathways.

Model evaluation demonstrates that the system reproduces broad spatial and temporal patterns of wildfire occurrence and burned area across California. Simulated annual burned area shows strong agreement with observed historical variability, with statistically significant correlations across multiple metrics. While the model does not explicitly represent lightning variability, resulting in underestimation of extreme fire years, it captures overall trends and variability in wildfire activity and provides a robust probabilistic representation of wildfire outcomes.

A critical methodological challenge addressed in this work is the mismatch between observed and climate model–projected relative humidity, which could otherwise lead to unrealistic projections of declining fire activity. To resolve this, the study developed statistical models to reconstruct relative humidity from temperature and precipitation, enabling more accurate representation of drying trends and fire-conducive conditions under future climates.

The FRSM modeling system represents an advancement in California’s ability to assess future wildfire risk. By generating ensembles of plausible wildfire futures rather than single deterministic outcomes, the framework explicitly captures uncertainty in both climate projections and fire processes. The modular design supports ongoing refinement, scenario exploration, and integration with broader land-use, carbon accounting, and infrastructure planning efforts. These capabilities make the FRSM a valuable decision-support tool for evaluating long-term wildfire risk, informing mitigation strategies, and supporting climate resilience planning for California’s landscapes and communities.

[Code](https://github.com/pyregence/WesterlingFireModels) for the coupled FRSM modeling framework can be found at <https://github.com/pyregence/WesterlingFireModels>

LUCAS/FRSM Fire Simulation System

The codebase developed for the LUCAS/FRSM model framework implements a stochastic fire simulation model (FRSM) for projecting wildfire occurrence, size, and severity under future climate scenarios. The system uses a three-stage hierarchical modeling pipeline written in R, integrating climate projections, dynamic vegetation data from the LUCAS (Land Use and Carbon Scenario Simulator) model, and topographic variables. The framework is designed to operate at a 3 km grid-cell resolution on a semi-monthly time step across the western United States. By coupling statistical fire models with scenario-driven climate and vegetation inputs, the system enables forward-looking assessments of how wildfire regimes may shift under changing environmental conditions.

The first stage involving the FRSM determines where and when fires ignite and how large they grow. Fire occurrence is modeled as a binary presence/absence outcome using a Generalized Additive Model (GAM) built with the mgcv R package. This model, based on the approach developed by LeRoy Westerling, relates the probability of fire in a given grid cell and time

period to a suite of climate, vegetation, and topographic predictors. Climate variables include 1000-hour and 100-hour fuel moisture indices, minimum relative humidity, wind speed, maximum temperature, precipitation, and a water-year precipitation variable that captures antecedent moisture conditions. Vegetation inputs come from the LUCAS model and include logit-transformed proportional cover of extensive land-cover types (forest, shrubland, grassland, agriculture, developed, barren, and wetland) as well as biomass stocks (aboveground biomass, foliage, deadwood, litter, and snag components). Topographic predictors include elevation, log-transformed slope, and southwest aspect from LANDFIRE. The GAM produces a probability surface, and fire presence is then determined stochastically by sampling against these probabilities.

For grid cells where fire is determined to be present, fire size is modeled using a Generalized Pareto Distribution (GPD), an extreme value distribution well-suited to the heavy-tailed nature of fire size data. The GPD is fit using the VGAM package with scale and shape parameters estimated via maximum likelihood (stable BFGS optimization). Fire sizes in hectares are generated by drawing from this distribution with a location parameter anchored at $\log(404)$, reflecting the minimum detectable fire size in the observational record. The predictor set for fire size overlaps substantially with the occurrence model, ensuring physical consistency between the drivers of ignition and growth.

Once fires are placed on the landscape, the second stage assigns burn severity. Each fire is classified into three severity classes including low, moderate, and high, following standard protocols from the Monitoring Trends in Burn Severity (MTBS) program. Rather than assigning a single severity to each fire, the model estimates the fractional area burned at each severity level. This approach, developed by Jonathan Sam at UC Merced, uses logistic regression models trained on observed severity distributions.

The severity fraction models use a sequential estimation strategy. High-severity fraction is predicted first, followed by moderate severity (conditioned on the remaining unburned-at-high fraction), and finally low severity (as the complement). Predictors for the severity models include vapor pressure deficit, synthetic relative humidity metrics, wind speed, and a composite fuel moisture index, all aggregated to semi-monthly intervals. Vegetation structure from LUCAS, particularly biomass and dead organic matter stocks, also informs severity predictions, capturing how fuel loading and forest structure influence burn outcomes.

A third modeling stage, developed at UC Merced, extends severity predictions to statewide wall-to-wall mapping using GAMs. This stage includes an innovative iterative component: an initial model (i0) predicts severity based on climate, vegetation, and topographic variables, while a dynamic model (i1) incorporates distance-weighted kernels (11×11 and 21×21 cell windows) that account for the influence of recent nearby burns on current fire severity. Wind direction adjustments are applied via focal filters to capture directional fire spread effects. This iterative approach allows the simulation to represent landscape-level feedbacks where recent fire history modifies subsequent fire behavior.

The framework is explicitly designed to operate under multiple future climate scenarios. Climate inputs can be sourced from Scripps Institution projections, UCLA climate data, or GridMET observational grids. The modular data-loading architecture allows seamless

substitution of different climate scenarios, enabling the system to project fire regimes under a range of greenhouse gas emission pathways. All predictor variables are standardized using z-score normalization with scaling parameters derived from the historical training period, ensuring that model predictions remain well-calibrated when applied to future climate conditions that may fall outside the historical range.

A distinguishing feature of this framework is its coupling with the LUCAS landscape simulation model. Rather than treating vegetation as static, the system ingests annually updated vegetation state variables from LUCAS, including land-cover composition and carbon stock estimates. This coupling means that as climate change alters vegetation distributions and biomass accumulation patterns, these changes feed back into fire probability, size, and severity predictions. The logit transformation applied to LUCAS proportional cover data ensures numerical stability near boundary values while preserving the nonlinear relationships between land cover and fire behavior.

The modeling framework is calibrated against two observational fire datasets: MTBS, which provides mapped burn perimeters and severity classifications for large fires across the United States, and the Calibrated Burn Severity Estimates (CBSE), which offer refined severity metrics. Topographic data are sourced from LANDFIRE. The system supports multiple model versions (2019 and 2025 variants) with conditional loading, allowing for model intercomparison and progressive refinement as new observational data and improved climate projections become available.

This LUCAS/FRSM fire simulation system represents an integrated, multi-stage approach to projecting wildfire under climate change. By combining probabilistic fire occurrence modeling, extreme value theory for fire size, sequential severity fraction estimation, and dynamic vegetation feedbacks, the framework captures the key dimensions of wildfire regimes relevant to national climate assessments. The stochastic design produces ensembles of plausible fire futures rather than single deterministic projections, appropriately representing the deep uncertainty inherent in both climate trajectories and fire behavior. The modular R-based architecture facilitates ongoing model development, scenario exploration, and integration with broader land-use and carbon accounting frameworks.

[Code and data](https://data.pyrengence.org/wg4/Coupled_LUCAS_FRSM/) for the coupled LUCAS/FRSM modeling framework can be found at - https://data.pyrengence.org/wg4/Coupled_LUCAS_FRSM/.

LANDIS-II

The second-generation landscape disturbance and succession (LANDIS-II) model LANDIS-II is a spatially dynamic mechanistic simulation model. It simulated species- and age-specific forest succession, growth, mortality, carbon cycling, wildfire, and insect outbreaks. LANDIS-II provided an independent but complementary representation of vegetation and disturbance dynamics to the coupled FRSM/LUCAS models, emphasizing ecological processes and fine-scale heterogeneity rather than statewide fire probability. LANDIS-II simulates forest or shrub species as cohorts within and among a grid of cells allowing spatial interactions among processes over large areas (1,000 to 1,000,000+ ha) and intermediate time frames (1-100

years). These processes include growth and succession, management actions like harvesting and prescribed fire, and natural disturbances.

Initial vegetation conditions were derived from TREEMAP (Riley et al. 2021) and then updated through 2020 based on a combination of the eDART mortality product (Slaton et al. 2021) and rapid assessment of vegetation data (RAVG).

Carbon dynamics within the LANDIS-II model were simulated by the Net Ecosystem Carbon and Nitrogen (NECN) extension (v. 6.6) (Scheller et al. 2011). NECN simulates aboveground processes (growth, succession, regeneration, mortality) and belowground processes (decomposition, turnover). The carbon pools that were tracked include live, dead (duff, litter, coarse woody debris), and soil organic matter. Weather inputs drive forest growth and decomposition as well as place limits on possible regeneration. Landscape level net primary productivity and net ecosystem exchange are the result of individual species-age cohorts' response to weather. Thirty-nine tree species and three shrub type groups were simulated.

The model was run at a 150m resolution, with climate data being fed in at a 12km grid. Due to computational limitations, most of the forested acres in the state were broken up into six large regional tiles.

Disturbances

Wildland fire was simulated using the SCRPPLE extension (v.2.3) (Scheller et al. 2019). The extension simulates fire based on ignitions, fuels, topography, and weather. Ignitions are spatially allocated stochastically but weighted by a probability surface based on prior wildfire ignition data and temporally allocated by a poisson regression with the Canadian Fire Weather Index (FWI) as an independent variable. The ignition probability surfaces were derived using a kernel density estimation function (in QGIS 3.18) based on data from Short et al. (2019) wildfire occurrence data. Fire severity is a two-step algorithm, with site level fire intensity calculated from six variables (site soil clay content, previous year's potential evapotranspiration, wind speed, climatic water deficit, fine fuels, and ladder fuels) and the site level mortality based on the species present in the site, the age of the cohorts, and their approximate bark thickness.

Insect outbreaks were simulated using the Biomass BDA extension (V2.2). Four insects were modeled that represent the majority of damage across the landscape (Fettig et al. 2019): fir engraver (*Scolytus ventralis*), Jeffrey pine beetle (*Dendroctonus jeffreyi*), mountain pine beetle (*Dendroctonus ponderosae*), and western pine beetle (*Dendroctonus brevicomis*). The annual timing of insect outbreaks were simulated as a function of drought stress, as measured by climatic water deficit, and warm winter temperatures. The probability of the outbreak spreading and the outbreak severity reflect the density of hosts at a given site, which is calculated from the amount of biomass of a specific host in a given cell (Sturtevant et al. 2004).

Calibration

LANDIS-II was calibrated using detailed, spatially explicit initial conditions derived from TREEMAP (Riley et al. 2021), updated with observed drought, insect, and fire mortality through 2020. Species-specific growth, mortality, and carbon cycling parameters were tuned using regional ecological literature and prior western U.S. applications. Fire behavior and severity were calibrated using Monitoring Trends in Burn Severity fire severity data, while insect disturbance dynamics were calibrated against national forest health datasets. Validation involved comparing modeled biomass, carbon stocks, and net ecosystem carbon balance against forest inventory data, remote sensing products, and flux-based datasets (1984–2020). At regional scales, LANDIS-II outputs aligned closely with observations of biomass and vegetation and with parallel LUCAS results.

These components formed a multi-scale modeling system in which FRSM emphasizes probabilistic wildfire behavior, LUCAS emphasizes land-use and carbon outcomes, and LANDIS-II emphasizes detailed forest succession and disturbance ecology.



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APPENDIX C: Long-term Projections - Data and Code Repositories

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Appendix C:

Long-term Projections - Data and Code Repositories

Climate Data

Historical Climate Data

[Historical ERA5-WRF climate data](https://analytics.cal-adapt.org/data/catalog/) (1950-2021) used in this project can be accessed from the Cal Adapt: Analytics Engine Data Catalog - <https://analytics.cal-adapt.org/data/catalog/>.

Simulated Future Climate Data

[Downscaled and bias corrected simulated future climate data](https://analytics.cal-adapt.org/data/catalog/) used in this project can be accessed from the Cal Adapt: Analytics Engine Data Catalog - <https://analytics.cal-adapt.org/data/catalog/>. Datasets are organized by climate scenarios as follows:

Dynamically Downscaled / WRF bias corrected climate scenarios, including:

- CESM2_ssp370_r1i1p1f1
- CNRM-ESM2-1_ssp370_r1i1p1f2
- EC-Earth3-Veg_ssp370_r1i1p1f1
- FGOALS-g3_ssp370_r1i1p1f1

Hybrid-Statistically Downscaled / LOCA2-Hybrid bias corrected climate scenarios, including:

- ACCESS-CM2_ssp245_r1i1p1f1
- ACCESS-CM2_ssp370_r1i1p1f1
- ACCESS-CM2_ssp585_r1i1p1f1
- CNRM-ESM2-1_ssp370_r1i1p1f2
- CNRM-ESM2-1_ssp585_r1i1p1f2
- EC-Earth3-Veg_ssp245_r5i1p1f1
- EC-Earth3-Veg_ssp370_r1i1p1f1
- EC-Earth3-Veg_ssp370_r4i1p1f1
- EC-Earth3-Veg_ssp585_r4i1p1f1
- EC-Earth3_ssp370_r1i1p1f1
- HadGEM3-GC31-LL_ssp585_r1i1p1f3
- HadGEM3-GC31-LL_ssp585_r3i1p1f3
- INM-CM5-0_ssp245_r1i1p1f1

- MIROC6_ssp370_r1i1p1f1
- MPI-ESM1-2-HR_ssp245_r1i1p1f1
- MPI-ESM1-2-HR_ssp370_r3i1p1f1
- MRI-ESM2-0_ssp370_r4i1p1f1

Synthetic Relative Humidity Data

Synthetic relative humidity datasets were necessary because the downscaled, bias-corrected global climate model projections used for California’s Fifth Climate Change Assessment systematically overestimated near-surface moisture and failed to reproduce the observed long-term decline in relative humidity across California’s arid regions. This discrepancy meant that projected climate data did not reflect the same physical behavior as historical observations, particularly during the dry season when wildfire risk is most sensitive to minimum humidity. As a result, fire models calibrated to observed relative humidity produced unrealistic declines in projected fire activity when driven by the wetter GCM-based relative humidity projections. Because standard bias correction cannot resolve errors in long-term trends, a synthetic relative humidity product was developed using a statistical model grounded in observed relationships among temperature, precipitation, and site characteristics. The goal was to generate daily minimum and maximum relative humidity fields that better align with observed historical trends, thereby restoring consistency between historical calibration data and future projections, and enabling more credible wildfire and vegetation modeling outcomes.

Daily synthetic relative humidity raster datasets provide spatially explicit, statewide estimates of maximum and minimum synthetic relative humidity in a raster format, enabling consistent analysis across historical and future climate scenarios. These datasets are available from multiple climate modeling sources - including historical ERA5 WRF (1950–2021, used to fit statistical model), UCLA WRF Bias-Corrected projections, and LOCA2-Hybrid projections - all delivered as Cloud-Optimized GeoTIFFs using the original source data’s projection and grid. Data are organized for efficient access, with historical ERA 5 WRF available directly by date, and UCLA WRF Bias-Corrected and LOCA2 datasets structured by climate scenario (GCM/SSP/ensemble run ID), year, and date-specific files (YYYY_MM_DD). Together, these resources support climate and wildfire research, hydrological modeling, and other environmental applications by providing daily humidity estimates across a range of temporal and scenario contexts. The following provides additional details on where to access the datasets.

Daily Synthetic Relative Humidity Rasters (ERA 5 WRF) – This dataset is historical ERA 5 WRF data (1950 to 2021), provided as a daily, statewide rasters (Cloud-Optimized GeoTiff) using the same projection and grid as the ERA 5 WRF data source. [Data](https://data.pyregence.org/wg4/CEC-Submitted/era5wrf/) can be accessed from the following link - <https://data.pyregence.org/wg4/CEC-Submitted/era5wrf/>.

Daily Synthetic Relative Humidity Rasters (UCLA WRF_Bias Corrected) - This dataset is organized by climate scenario, including:

- CESM2_ssp370_r1lip1f1
- CNRM-ESM2-1_ssp370_r1i1p1f2

- EC-Earth3-Veg_ssp370_r1i1p1f1
- FGOALS-g3_ssp370_r1i1p1f1

The data is a daily, statewide raster (Cloud-Optimized GeoTiff) using the same projection and grid as UCLA WRF Bias Corrected source data. [Data](https://data.pyregence.org/wg4/CEC-Submitted/wrf_bc/) can be accessed from the following link - https://data.pyregence.org/wg4/CEC-Submitted/wrf_bc/. The directory is structured by gcm/ssp/runid name set and then by Daily/<year>/synrh<max/min>_<date>.tif. The files are synrh (synthetic relative humidity) followed by max or min. The filename is organized by YYYY_MM_DD.

Daily Synthetic Relative Humidity Rasters (LOCA2) - These datasets are organized by climate scenario, including:

- ACCESS-CM2_ssp245_r1i1p1f1
- ACCESS-CM2_ssp370_r1i1p1f1
- ACCESS-CM2_ssp585_r1i1p1f1
- CNRM-ESM2-1_ssp370_r1i1p1f2
- CNRM-ESM2-1_ssp585_r1i1p1f2
- EC-Earth3-Veg_ssp245_r5i1p1f1
- EC-Earth3-Veg_ssp370_r1i1p1f1
- EC-Earth3-Veg_ssp370_r4i1p1f1
- EC-Earth3-Veg_ssp585_r4i1p1f1
- EC-Earth3_ssp370_r1i1p1f1
- HadGEM3-GC31-LL_ssp585_r1i1p1f3
- HadGEM3-GC31-LL_ssp585_r3i1p1f3
- INM-CM5-0_ssp245_r1i1p1f1
- MIROC6_ssp370_r1i1p1f1
- MPI-ESM1-2-HR_ssp245_r1i1p1f1
- MPI-ESM1-2-HR_ssp370_r3i1p1f1
- MRI-ESM2-0_ssp370_r4i1p1f1

For each dataset, data is a daily, statewide raster (Cloud-Optimized GeoTiff) using the same projection and grid as the LOCA2-Hybrid source data. [Data](http://ungoliant.ucmerced.edu/data/Climate-Data/loca2/) can be accessed from the following link - <http://ungoliant.ucmerced.edu/data/Climate-Data/loca2/>. The directory is structured by gcm/ssp/runid name set and then by Daily/<year>/synrh<max/min>_<date>.tif. The files are synrh (synthetic relative humidity) followed by max or min. The filename is organized by YYYY_MM_DD.

Coupled LUCAS/FSRM Simulation Outputs

This dataset consists of annual raster maps of projected future ecosystem carbon stocks and fluxes, land use and land cover (LULC) classes, and LULC transitions for California, U.S. from 2021-2065. Data are simulation model output from the Land Use and Carbon Simulator (LUCAS; Sleeter et al. 2022) run under different future climate and land management scenarios. LUCAS model simulations were conducted on an annual timestep at 1-km spatial resolution under 26 scenarios with 10 Monte Carlo realizations per simulation. The 26 scenarios are different combinations of nine future climate scenarios, two urbanization scenarios, and two vegetation management scenarios. Climate scenarios were based on downscaled output from seven CMIP6 Earth System Models (ACCESS-CM2, CNRM-ESM2-1, EC-Earth3-Veg, HadGEM3-GC31-LL, INM-CM5-0, MPI-ESM1-2-HR, MRI-ESM2-0) run under one to three different Shared Socioeconomic Pathways (SSPs; Tebaldi et al. 2021) assuming additional radiative forcing by 2100 of 4.5 W m⁻² (SSP2-4.5), 7 W m⁻² (SSP3-7.0), or 8.5 W m⁻² (SSP5-8.5). Climate data were downscaled using a hybrid statistical-dynamical downscaling approach (LOCA2-Hybrid) and are freely available to the public from the [Cal-Adapt Analytics Engine Data Catalog](https://analytics.cal-adapt.org/data/catalog/) - <https://analytics.cal-adapt.org/data/catalog/>. The two urbanization scenarios sampled from historical rates of urban development on an annual basis, with one scenario restricting all new urban development to Wildland Urban Interface (WUI) areas while the other urbanization scenario excluded new urban development from WUI areas (Infill). The two land management scenarios consisted of a "business as usual" (Low) scenario based on historic rates of tree thinning and prescribed burning, while the second land management scenario (High) implemented forest management treatments to reduce wildfire hazard potential that match area targets from California's Wildfire and Forest Resilience Action Plan (California Forest Management Task Force 2021). Note: burn severity (high, med, low) are coded in the individual "Transition" rasters from LUCAS. The pixel values refer to a severity class (found in the metadata). There are multiple iterations for each scenario/timestep in the Transitions data.

[Coupled LUCAS-FSRM datasets](https://data.pyregence.org/wg4/Coupled_LUCAS_FSRM/) were posted online in January 2026 and can be downloaded from USGS at the following link - <https://doi.org/10.5066/P14EHY3V> (Projected future land change and ecosystem carbon stocks and fluxes for California (ver. 2.0, January 2026). [Code and data](#) used for this project can be found at: https://data.pyregence.org/wg4/Coupled_LUCAS_FSRM/.

LANDIS-II Model Simulation Outputs

The LANDIS-II model produced outputs such as fire event records, burn probability maps, and vegetation type transitions, reflecting the combined influence of climate and disturbance on ecosystem structure. Each climate projection was simulated under one of two vegetation management scenarios: a Business-as-Usual (BAU) case that maintained historical annual treatment levels (~150,000–180,000 acres per year), and a High Ambition scenario representing California's goal of treating one million acres annually to reduce fuels in high-risk wildfire zones. For each scenario and climate projection, LANDIS-II was run for two (or more) iterations ("replicates") for each management scenario and climate projection to generate

statistics on fire probability. The repository includes sample outputs from a single replicate for each WRF model and both vegetation management scenarios.

Model runs were performed on annual timesteps from 2001 to 2100 at 150-meter resolution, using either dynamically downscaled Weather Research and Forecasting (WRF) data from UCLA and statistically downscaled LOCA2-Hybrid datasets from Scripps.

Each scenario includes replicate model runs to capture variability. Notably, for the 'BAU' vegetation management scenario simulations, 5 replicates were completed representing treatment being applied annually for the time period 2001 to 2099 (replicates 110, 111, 112, 113 114). For the 'High Ambition' vegetation management scenario simulations, 5 replicates were completed representing treatments being applied annually for 2001 to 2045 (replicates 110, 111, 112, 113 114); and 3 replicates (replicates 120, 121, 122) were completed representing treatment being applied annually for 2001 to 2099.

Output variables include aboveground net primary productivity (AG_NPP), net ecosystem exchange (ANEE_proc), total carbon (Total C), aboveground biomass, biomass removed by management, and categorical maps of forest type, fire severity, and management activity type. Results are stored as georeferenced raster (tif) files organized by climate model, bias-correction method, and management scenario. [Outputs data](https://data.pyregence.org/wg4/CEC-Submitted/) can be accessed on the Pyregence data repository – <https://data.pyregence.org/wg4/CEC-Submitted/>.

Uncoupled Model Simulation Outputs

Uncoupled LUCAS Outputs

Historical and projected future land change and ecosystem carbon stocks for California dataset consists of annual raster maps of ecosystem carbon stocks, land use and land cover classes, and transition probabilities for California during historical (1985-2020) and projected future (2021-2100) time periods (Sleeter and Selman 2024). Data are simulation model output from LUCAS (Sleeter et al. 2022) was run under different future climate and land management scenarios. LUCAS model simulations were conducted on an annual timestep at 1-km spatial resolution with 40 Monte Carlo realizations per simulation. For the projected future time period, the model was run under all combinations of four climate scenarios, two urbanization scenarios, and two vegetation management scenarios. The climate scenarios were based on downscaled output from four CMIP6 Earth System Models (CESM2-LENS, CNRM-ESM2-1, EC-Earth3, and FGOALS-g3) all run under Shared Socioeconomic Pathway 3 assuming additional radiative forcing of 7 W m^{-2} by the year 2100 (SSP3-7.0; see Tebaldi et al. 2021). Climate data were downscaled using a hybrid statistical-dynamical downscaling approach (LOCA2-Hybrid). The two urbanization scenarios sampled from historical rates of urban development on an annual basis, with one scenario restricting all new urban development to Wildland Urban Interface (WUI) areas while the other urbanization scenario excluded new urban development from WUI areas. The two vegetation management scenarios consisted of a "business as usual" (low treatment intensity) scenario based on historic rates of tree thinning and prescribed burning ($\sim 180,000$ acres/year), while the second 'high ambition' vegetation management scenario (high treatment intensity) implemented forest management treatments to reduce wildfire hazard potential that match area targets from California's Wildfire and Forest

Resilience Action Plan (~1 million acres treated/year; California Forest Management Task Force 2021). Historical land change was based on trends in the National Land Cover Database (NLCD) and historical climate was based on annual output data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM).

Three datasets were produced through this modeling effort, including:

- *Historical and projected future ecosystem carbon stocks for California* - provides annual raster maps of ecosystem carbon stocks for California, USA. Carbon stock estimates were derived by linking the Land Use and Carbon Scenario Simulator (LUCAS) model and the Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3).
- *Historical and projected future land change transition probabilities for California* - provides annual raster maps of land change transition probability (e.g., urbanization, wildland fire, timber harvest) for California. Land change transition probabilities are from Land Use and Carbon Scenario Simulator (LUCAS) simulations.
- *Historical and projected future land use and land cover for California* - provides annual raster maps of historical and projected future land use and land cover (LULC) for California. Changes in LULC over time were simulated using the Land Use and Carbon Scenario Simulator.

[Uncoupled LUCAS datasets](https://doi.org/10.5066/P13IZC92) were posted online in July 2025 and can be downloaded from USGS at the following link - <https://doi.org/10.5066/P13IZC92>.

Uncoupled Fire Risk Simulation Model Outputs

The historical and projected future wildfire disturbance dataset for California consists of annual raster maps of fire occurrence metrics during historical (1951-2020) and projected future (2021-2100) time periods. The model's primary data product is a tabular 'fire list' that includes data outputs related to a fire's identity (code), fire location (x and y coordinates), year, month, day the fire occurred, the model iteration, fire size, and fire severity class and fraction. The 'fire list' can be used to produce monthly and annual raster projections of fire area, ignition probability, smoke emission, and burn severity fractions (low, moderate, high). Historical fire list and annual burned area rasters were produced using daily historical ERA5-WRF climate data and vegetation data from LUCAS based on conditions that existed as of 2020. These [simulated historical data](https://data.pyregence.org/wg4/CEC-Submitted/era5wrf/WesterlingFireModel/) can be accessed from the Pyregence data repository - <https://data.pyregence.org/wg4/CEC-Submitted/era5wrf/WesterlingFireModel/>.

In a similar way, projected wildfire disturbance was modeled using uncoupled (e.g., based on 2020 vegetation conditions) using different projected climate data (2000 to 2100). Projected wildfire disturbance fire list, and fire presence and burned area rasters were completed for the following climate scenarios:

- ACCESS-CM2_ssp245_r1i1p1f1
- EC-Earth3-Veg_ssp245_r5i1p1f1
- HadGEM3-GC31-LL_ssp585_r3i1p1f3
- MRI-ESM2-0_ssp370_r4i1p1f1

- INM-CM5-0_ssp245_r1i1p1f1
- HadGEM3-GC31-LL_ssp585_r1i1p1f3
- ACCESS-CM2_ssp585_r1i1p1f1
- EC-Earth3-Veg_ssp370_r4i1p1f1
- CNRM-ESM2-1_ssp585_r1i1p1f2
- EC-Earth3-Veg_ssp585_r4i1p1f1
- CNRM-ESM2-1_ssp370_r1i1p1f2
- EC-Earth3-Veg_ssp370_r1i1p1f1
- EC-Earth3-Veg_ssp370_r1i1p1f1
- CESM2_ssp370_r1i1p1f1
- CNRM-ESM2-1_ssp370_r1i1p1f2
- FGOALS-g3_ssp370_r1i1p1f1

These wildfire disturbance datasets, representing bias corrected and downscaled (dynamically and LOCA2) climate data that can be accessed from the UC Merced data repository:

- [Dynamically downscaled FRSM model runs](https://data.pyregence.org/wg4/CEC-Submitted/wrf_bc/) - https://data.pyregence.org/wg4/CEC-Submitted/wrf_bc/.
- [LOCA2 downscaled data FRSM model runs](https://data.pyregence.org/wg4/CEC-Submitted/loca2/) - <https://data.pyregence.org/wg4/CEC-Submitted/loca2/>.

Code Repositories

Land Use and Carbon Scenario Simulator (LUCAS)

The [LUCAS code repository](https://data.pyregence.org/wg4/Coupled_LUCAS_FRSM/) is available through the Pyregence data portal at https://data.pyregence.org/wg4/Coupled_LUCAS_FRSM/. The codebase is tightly integrated with the associated data files, and as a result, it is not structured in a manner consistent with a conventional GitHub-system repository that separates code and documentation. Instead, the full code and data package are distributed together and can be accessed directly through the Pyregence data repository to ensure reproducibility and proper context for use.

Fire Risk Simulation Model (FRSM)

The [code](https://github.com/pyregence/WesterlingFireModels) for the FRSM model is available on GitHub in the WesterlingFireModels repository at <https://github.com/pyregence/WesterlingFireModels>. This repository includes the sub-models used in the FRSM model, the code to prepare input data (including climate, LUCAS vegetation, etc.), and the code to prepare data for recalibration of the model parameters. There is also a version of the WBSE model that has been updated to work within the WesterlingFireModels code framework, a set of prototype R scripts that were used in setting up the coupled LUCAS/FRSM models, and pre- and post-processing data for LANDIS-II.

Wildfire Burn Severity and Inventory (WBSE)

The Wildfire Burn Severity and Emission Inventory (WBSE) code provides estimates of 30-m resolution burn severity, and emissions of CO₂, CO, CH₄, non-methane organic compounds (NMOC), SO₂, NH₃, NO, NO₂, nitrogen oxides (NO_x = NO + NO₂), PM_{2.5}, OC, and BC. Day of burning and daily emissions information is provided for each fire during 2002-2020 at 500-m resolution. The project team implemented WBSE for large wildfires (> 404ha) during 1984-2020 in the state of California, U.S., on a per-fire event scale since 1984 and a daily scale since 2002. [Code](https://github.com/pyregence/WBSE) for WBSE can be found at <https://github.com/pyregence/WBSE>. See Xu et al. (2022a), Xu et al. (2022b), and Sam et al. (2022) for details on application of WBSE.

Landscape Disturbance and Succession Model (LANDIS-II)

The [code](https://github.com/LANDIS-II-Foundation) for the LANDIS-II model used in this project can be accessed from GitHub at <https://github.com/LANDIS-II-Foundation>.

[Code](#) to pre-process climate inputs from the source data (e.g. LOCA2) into a form ingestible by LANDIS-II preprocessing can be found in the WesterlingFireModels code repository (<https://github.com/pyregence/WesterlingFireModels>) in the LANDIS subdirectory. This subdirectory also contains the specific installers used for this project, the pre-processing steps to derive parameters for the model, and the code to post-process LANDIS-II outputs into the published formats.