EXHIBIT A

SCOPE OF WORK

☒ Contract ☐ Grant

Does this project include Research (as defined in the UTC)? ☒ Yes ☐ No

PI Name: Michael Kleeman

Project Title: Using Integrated Observations and Modeling to Better Understand Current and Future Air Quality Impacts of Wildfires and Prescribed Burns

Project Summary/Abstract

Prescribed fire has been promoted as a tool for management of fire-resilient ecosystems and mitigation of risk for catastrophic wildfires. However, prescribed fires also have potentially significant consequences for air quality and public health. Therefore, new scientific studies are needed to better understand the relative emissions, chemistry, and transport of smoke from wildfires versus prescribed burns. These scientific studies will support policies that are likely to influence the pace and scale of prescribed burns in the state of California, including through the Action Plan of the Wildfire and Forest Resilience Task Force. In support of this effort, we propose to quantify the relative magnitude and timing of pollutant emissions, extent of chemical transformation, transport and dispersion, and resultant toxicity of smoke from wildfires and prescribed burns. We will use a combined measurement-modeling approach based on a mobile measurement system developed at UC Davis for rapid deployment during fires and chemical transport models (CTMs) developed at UC Davis and National Center for Atmospheric Research (NCAR) that have been enhanced to predict dispersion and chemical transformation in smoke plumes. The models chosen for this project allow prediction of air pollutants including particulate matter and hazardous air pollutants at 1-24 km resolution. This is an appropriate spatial scale to track the impacts of wildfires and prescribed burns on urban population centers in California and allows sufficient spatial and temporal resolution to understand trends in exposure, which is important given the inherent variability in fires and their impacts on air quality. The UC Davis and NCAR models will be used for a retrospective analysis of wildfire smoke in the context of air quality, present-day measurement-model comparisons of the composition and health impacts of smoke from wildfires and prescribed burns, and a forecasting analysis of the differential air quality impacts of wildfires and prescribed burns. Emissions inventories and plume rise parameterizations will be updated in both models to reflect the state-of-the science. This approach builds on more than a decade of wildland fire research by each investigator/subcontractor, and represents a new collaboration to provide the broad expertise needed to address the interdisciplinary problems inherent in wildfires.

If Third-Party Confidential Information is to be provided by the State:

☐ Performance of the Scope of Work is anticipated to involve use of third-party Confidential Information and is subject to the terms of this Agreement; ***OR***

☐ A separate CNDA between the University and third-party is required by the third-party and is incorporated in this Agreement as Exhibit A7.

Scope of Work

Introduction

The most severe air pollution events in recent California history have all been associated with extreme wildfires, exposing millions of residents to unhealthy levels of combustion gases, primary particulate matter (PM) and secondary reaction products. Exposure to wildfire smoke increases cardiac mortality risk in the short term[1] and contributes to increased cancer risk in the long term[2]. Climate change will amplify cycles of extreme precipitation followed by drought, worsening wildfire risk[3–6]. Since there is no practical way to prevent the most dangerous ignition events, managing fuel loads and forest structure through prescribed burning has received renewed attention as an approach to mitigate future wildfire risk[7–9].

Historically, frequent controlled fires were used by Indigenous populations to assist hunting, promote desired vegetation growth, and prevent catastrophic wildfires[10]. Prescribed burning also served a cultural role and is called cultural burning by some Indigenous leaders[11]. There have been significant efforts in California in recent years to expand cultural and prescribed burning and revitalize Indigenous culture, though needs and opportunities remain[11–13].

The severity of forest fires can be described on a spectrum based on fuels consumed and associated emissions factors. A typical wildfire burns into the forest canopy while a typical prescribed burn only consumes fuel on the forest floor, but the mildest wildfires and the most aggressive prescribed burns may consume similar amounts of fuel. Even under ideal conditions, some population exposure to smoke is inevitable during prescribed burns and so important research questions need to be answered before prescribed burning is widely used and accepted to manage and restore California's forests. These questions include:

> (1) How do differences in consumed fuels (including non-biomass fuels in the wildland-urban-interface (WUI)) and meteorological conditions affect the emissions and chemical composition of fresh and aged smoke from prescribed burns versus wildfires?
> (2) How does the transport and dispersion of smoke plumes differ between prescribed burns and wildfires?
> (3) What are the resulting implications for public health in the context of these other questions?
> (4) Do models accurately predict the differences in smoke plumes from prescribed burns versus wildfires, and their atmospheric interactions, to provide a realistic assessment of possible health impacts?

Critical knowledge gaps and scientific needs in these areas are briefly described below.

Fuel Composition and Meteorology Fire emissions at a given location depend highly on factors such as fuel composition and meteorological conditions that differ between wildfires and prescribed burns. Wildfires typically burn under hot, dry, and windy conditions, which increase the likelihood of consuming canopy fuels, large woody fuels, and soil duff. In addition, wildfires that burn in the WUI combust non-biomass fuels that must be represented in emissions inventories. By contrast, prescribed burns are conducted during more moderate weather conditions with higher fuel moisture, resulting in less overall biomass consumed. Even though prescribed burns have lower overall emissions than wildfires, the reduced energy released from prescribed burns may translate to reduced plume injection height, which may increase ground-level smoke concentrations in the immediate vicinity around the fire. <u>The differing fuel consumption between wildfires and prescribed burns must be characterized and applied to emissions models to analyze differences in total emissions and plume injection height.</u>

> **Hypothesis 1:** Prescribed burns will emit lower amounts of fine particulate matter ($PM_{2.5}$) mass and toxic compounds per unit of burn area compared to wildfires, but reduced plume rise and reduced atmospheric mixing downwind of prescribed burns will result in similar ground-level concentrations in the immediate vicinity of the fire. We will test this hypothesis using a combination of measurements and model simulations downwind of prescribed burns and wildfires.

Smoke Composition and Toxicity. Prescribed burns are ideally carried out under calm-to-moderate conditions that encourage predictable fire behavior and high dilution of the resulting smoke plumes. In contrast, wind-driven wildfires rapidly consume dead material on the forest floor and then spread into the forest canopy where they consume living material. These different fuel components can result in differences in smoke composition. Wildfires can also move into the WUI where they can burn building materials, furniture, plastics, petroleum products, etc. that can release a broad range of toxic compounds. <u>The detailed chemical composition and toxicity of smoke generated from prescribed burns and wildfires must be measured using state-of-the-science methods to understand potential differences in near-field smoke toxicity.</u>

> **Hypothesis 2:** Ground-level concentrations of toxic compounds will be enhanced downwind of fires that burn in the WUI compared to prescribed burns. We will attempt to test this hypothesis using field measurements at locations downwind of both fire types if we have the opportunity to sample downwind of a WUI fire. We will also compare differences in predicted smoke composition at longer time scales using the UCD and NCAR models with updated emissions to reflect differences between wildfires that combust material in the WUI and prescribed burns.

Smoke Dispersion and Aging. The fuel characteristics (e.g., fuel composition) and burn conditions (e.g., combustion efficiency) of a fire determine the concentration and composition of the precursor species that participate in the downwind chemical reactions. Many of the chemical reaction products are semi-volatile, which may cause them to evaporate or condense depending on local conditions. Condensation of semi-volatile compounds to form additional $PM_{2.5}$ as the smoke plume ages increases the immediate public health risk associated with $PM_{2.5}$ exposure. <u>The degree of aging in smoke plumes from prescribed burns and wildfires must be characterized using chemical fingerprinting techniques and advanced model simulations to understand impacts on nearby population centers.</u>

> **Hypothesis 3:** Prescribed burns will produce less secondary $PM_{2.5}$ than wildfires for the same approximate burn area. We will test this hypothesis using measured and modeled chemical composition and markers of aging in smoke from prescribed burns and wildfires.

Smoke Exposure Frequency, Duration, and Intensity. The association between PM exposure and public health risk is non-linear, with a steeper concentration-response at low levels of PM exposure and a muted concentration response at high levels of PM exposure. Simply stated, multiple exposures to low-levels of smoke may be just as damaging, or more damaging, than a single exposure to a high level of smoke. <u>A detailed modeling study based on realistic scenarios for the frequency, duration, size, design (broadcast vs. pile), and intensity of prescribed burns must be carried out to analyze impacts on smoke exposure and public health.</u>

> **Hypothesis 4:** Population-weighted exposure over multi-year timeframes will be reduced in scenarios that manage forest fuel loads using prescribed burns compared to scenarios that do not increase the use of prescribed burns and therefore continue to experience catastrophic wildfires. We will test this hypothesis using model simulations combined with a health impact analysis using BenMap.

Proposed Methods to Address Prescribed Fire Knowledge Gaps

Our measurement-modeling approach to assess the air quality and public health implications of prescribed burning relies on (i) a mobile measurement platform specifically designed for rapid deployment during fires and (ii) chemical transport models (CTMs) that include fire-specific refinements. For measurements, the Rapid Response Mobile Research Unit (2RMRU) developed at UC Davis is a fully contained, self-powered mobile research laboratory designed for *in situ* measurement and sampling of smoke during active wildfires. It was successfully deployed several times throughout the 2017-2020 fire seasons. For models, the UCD/CIT CTM developed at UC Davis has been used to evaluate source contributions to primary and secondary PM in California for more than 20 years. The Multi-Scale Infrastructure for Chemistry and Aerosols version 0 (MUSICAv0) model developed at NCAR is a multi-scale version of the CAM-Chem global model with regional refinement down to ~6 km resolution[14,15]. MUSICAv0 has recently been used to model smoke and air quality impacts from fires during the 2019 FIREX-AQ (Fire Influence on Regional to Global Environments and Air Quality) and 2018 WE-CAN (Western wildfire Experiment for Cloud chemistry, Aerosol absorption and

Nitrogen) field campaigns[16]. These measurement and modeling tools will be used to carry out five Research Tasks to address the proposed hypotheses and build the scientific understanding to support future public policy for prescribed burns. Figure 1 illustrates the project workflow.

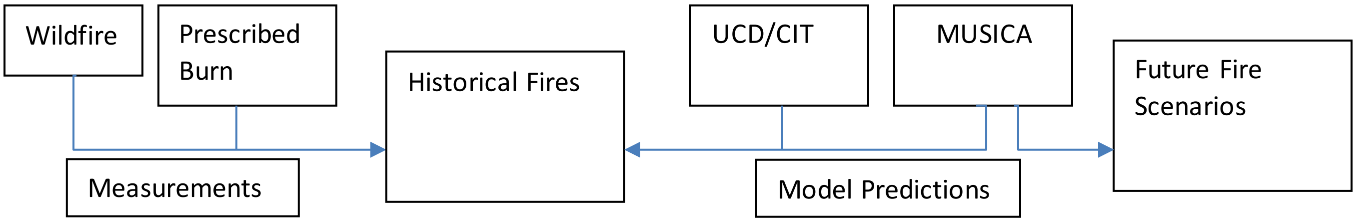


Figure 1: Workflow diagram

Measurement Platform

Rapid Response Mobile Research Unit (2RMRU). The UCD mobile measurement system 2RMRU consists of a base station and two electric vehicles (EVs) that are sequentially cycled between active and recharging states to provide continuous, emissions-free power for the on-board instrumentation. The recharging station is assembled ~0.5 miles from the sampling zone and consists of a portable 9.5 kW generator and residential EV charger. The entire system is transported via an 18-foot aluminum two-car open hauler easily towed by a ¾ ton truck.

Figure 2. Photo montage of the 2RMRU deployed in a decimated neighborhood during the 2018 Carr Fire.

Continuous Emissions Monitoring. Real-time gas-phase measurements include CO_2 [Thermo Scientific (TS) 410i], CO (TS 48i), NO_x (TS 42i), SO_2 (TS 5020i), and total VOCs (ppbRAE 3000). Real-time particle size distributions from 10nm to 10µm will be measured using a NanoScan SMPS (TSI 3910) coupled to an optical particle sizer (TSI 3330) while PM at four size cuts (PM_1, $PM_{2.5}$, PM_4, PM_{10}) and total suspended particulate (TSP) mass concentrations are provided by multichannel DustTraks (TSI 8533 DRX) and real-time black carbon (BC) via an aerosol absorption photometer (DST ObservAir). DustTrak measurements will be calibrated against offline filter-based measurements of $PM_{2.5}$ mass. Depending on instrument availability, CH_4/NMHC (TSM 55i) and real-time PM metal (TARTA[17]) may also be measured.

Offline Gas and PM Sampling. Nonadsorbing volatile organic compounds (VOCs) will be collected into 150-mL cylinders and adsorbing semi-volatile/volatile organic compounds (S/VOCs) will be collected onto sorbent-packed sampling columns using six-port solenoid valve manifolds (SVMs), which allows sequential sampling that can provide time resolution and avoid potential overloading. Media can be changed in situ to extend sampling duration. $PM_{2.5}$ will be collected onto filters through an inline cyclone using three parallel six-port SVMs, which provides sufficient samples for the wide range of offline analyses described below.

Chemical Characterization. VOCs from cylinders will be analyzed by headspace gas chromatography-mass spectrometry (GC-MS) for C_2-C_{12} *n*-alkanes, C_4-C_{10} isoalkanes, C_5-C_8 cycloalkanes, C_2-C_8 alkenes, C_6-C_{10} aromatics, C_2-C_7 carbonyls, ethyne, and relevant gas-phase US EPA-listed hazardous air pollutants (HAPs). SVOC samples will be solvent extracted and analyzed via high-resolution GC-MS (GC-HRMS). Target analyte will include halocarbons (including methyl chloride), amines, mono- and polycyclic aromatic hydrocarbons (PAHs), relevant HAPs, and polyhalogenated biphenyls, diphenyl ethers, and dibenzo dioxins and furans (PXBs, PXDEs, PXDDs, and PXDFs, where X = Cl/Br). Nontargeted analysis will identify additional compounds and unknown spectral features and guide selection of further targeted analysis[18]. Formaldehyde, and other low molecular weight carbonyls, will be sampled on DNPH coated silica gel and analyzed via HPLC with UV/Vis detection. One of the three PM sampling manifolds will be loaded with stretched Teflon® filters for routine analysis performed for the Interagency Monitoring of Protected Visual Environments (IMPROVE) network[19]. This includes gravimetric analysis, elements via X-ray fluorescence, organic functional groups and EC/OC via Fourier Transform Infrared Spectroscopy[20,21], and optical absorption by Hybrid Integrating Plate/Sphere. The other two sampling manifolds will be loaded with Pallflex® Emfab™ filters: one set will be archived, and the other extracted according to the protocols of Bein et al.[22,23]The extracts will be analyzed for elemental composition via inductively coupled plasma-mass spectrometry and molecular organics via targeted and nontargeted GC-HRMS. Target analytes will include a standard set of C_{15}-C_{40} linear, branched, and cyclic hydrocarbons, PAHs, PXBs, PXBEs, PXDDs, and PXDFs.

Modeling Platforms

Emissions Algorithms. Both CTMs used in the current project will describe emissions from wildfires and prescribed burns using algorithms updated to reflect the state-of-the-science in wildland fire emissions, particularly incorporating emission factors from recent field and laboratory campaigns (e.g., FIREX-AQ) and non-biomass fuels in the WUI.

The UCD/CIT model typically obtains wildfire and prescribed burn emissions using the open source BlueSky smoke modeling framework[24,24]. BlueSky will be used here with support from CALFIRE for all UCD/CIT model simulations and some MUSICAv0 simulations. BlueSky will be modified to reflect the most recent updates for fuel loads, fuel consumption, emission factors and fuel moisture. Area burned will be derived from historically mapped perimeters from the CAL FIRE Fire and Resource Assessment Programs GIS database. We will then use satellite-based active fire products (MODIS, VIIRS, GOES-ABI) to apportion the area burned within specific days. Fuel loading will be mapped at 30-m resolution using the Fuels Characterization and Classification System (FCCS[25]) LANDFIRE 2020 update.

Biomass consumption rates are highly dependent on fuel moisture content, including dead woody fuels, live fuels, and soil or duff. Figure 3 shows this relationship as modeled by the Consume fire effects model for Douglas Fir/Poderosa Pine forest common in the Sierras under different moisture regimes (as defined by BlueSky and presented in Table 1). The difference in moisture conditions is critical to quantifying relative emissions between wildfires and prescribed burns.

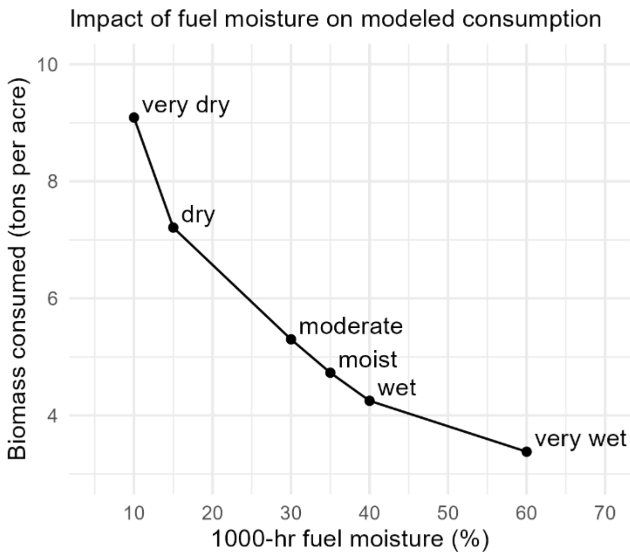


Figure 3: Biomass combustion rates as a function of fuel moisture.

We will develop best estimates of fuel moisture inputs by fusing data from three sources: 1) soil moisture from the WRF model, 2) 10- and 1000-hour woody fuel moisture from NFDRS algorithms driven by data from the WRF model, and 3) available observations from RAWS. The 10-hour fuel moisture can be computed from temperature, relative humidity and cloudiness, while the 1000-hour fuel moisture is computed from rainfall, season, and daily temperature and humidity ranges. We will develop a preprocessor to the BlueSky fire emissions model to produce spatially and temporally resolved fuel moisture conditions from WRF and observed inputs.

Table 1: Fuel moisture values for different fuel moisture categories, assigned in BlueSky based on soil moisture ranges.

Soil moisture m^3/m^3	**<0.1**	**0.1 - 0.15**	**0.15 - 0.25**	**0.25 - 0.3**	**0.38 - 0.38**	**>0.38**
Fuel moisture category (based on BlueSky)	Very dry	Dry	Moderate	Moist	Wet	Very Wet
1000 hr fuel moisture % (based on BlueSky)	10	15	30	35	40	60
Duff fuel moisture % (based on BlueSky)	20	40	75	100	130	180

Consumption will be modeled with the Consume model, which uses FCCS fuels information and fuel moisture parameters to estimate flaming and smoldering consumption. Daily fuel assignments will be done in one of two ways. If daily progression maps are available, we will intersect those with fuel maps to produce daily area burned by fuel bed. If only final perimeters are available, we will use satellite fire detects to apportion overall burning into daily activity. In that case, each detection will be intersected with the fuel map to produce a representative sample of fuel beds. We will incorporate recently compiled emission factors (g/kg of fuel burned) from the Smoke Emissions Repository Application (SERA[26], Prichard et al., 2020) and the Next-generation Emissions Inventory expansion of Akagi (NEIVA[27]) to calculate speciated emissions from biomass fuels for wildfires and prescribed burns. In addition, emission factors from non-biomass fuels in the WUI will be incorporated based on the recent publication of Holder et al.[28] PM emissions will be assigned particle size and composition profiles based on measurements made during biomass burning experiments[29].

Table 2 illustrates differences in emission factors for different fuel components and for different combustion efficiencies. The emissions factors are from the First Order Fire Effects Model (FOFEM)[30] and are based on

Urbankski et al.[31], which are also included in the SERA database. The higher $PM_{2.5}$ emission factors for wildfires (WF) reflects the consumption of canopy fuels during wildfires, which does not occur during prescribed burns. The non-biomass values (structure, vehicle) are from Holder et al.[28]

Table 2: Emission factors (g/kg) of pollutants as a function of fuel type and combustion conditions, where STSF = short term flaming and smoldering and RSC = residual smoldering, and Rx = prescribed and WF = wildfire.

Cover Type	CO_2	CO	CH_4	NO_x	SO_2	$PM_{2.5}$	PM_{10}	NH_3	NMOC
Western Forest – Rx STSF	1598	105	5	2	1	18	22	1.5	27
Western Forest – WF STSF	1600	135	7	2	1	23	27	1.5	34
Shrubland STSF	1674	74	4	2	0.7	7	8	1.5	18
Grassland STSF	1705	61	2	2	0.7	9	10	1.5	18
Woody RSC	1408	229	14	0	0	33	39	0.5	45
Duff RSC	1371	257	8	0.7	1.8	35	42	2.7	62
Structure	1325	69	-	0.3	0.06	-	39	0.82	-
Vehicle	1827	48	3	4	1.9	-	57	0.4	-

MUSICAv0 typically uses the updated Fire INventory from NCAR version 2.5 (FINNv2.5)[32] for emissions from wildfires and prescribed burns. FINNv2.5 uses satellite-based active fire products from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Visible Infrared Imaging Radiometer Suite (VIIRS) to determine fire perimeter and area. Emissions of each pollutant In FINNv2.5 are calculated as the product of the area burned at location x and time t, the biomass at location x, the fraction that is burned, and the EF for each pollutant. The burned area, as a function of time, is based on individual fire detection and in this way, prescribed fires and wildfires in present-day simulations can be easily separated. Because FINN is a global model, fuel loading is assigned by generic vegetation type (e.g., temperate forest) and global region (similar to earlier versions of FINN with updates from van Leeuwen et al.[33]). Biomass (i.e., fuel) is based on the International Geosphere-Biosphere Programme (IGBP) classification and includes 16 cover types. FINNv2.5 also will be updated in this project to reflect recent emission factor compilations for biomass and non-biomass fuels based on updates to the BlueSky emissions framework and an independent review of the literature. A previous comparison of total emissions from California wildfires showed similar results for FINN and emissions generated using FCCS classifications and FOFEM emission factors (which would be similar to those generated using BlueSky)[30]. Further comparisons in total emissions and emissions composition will be performed as part of this project.

Plume Rise Predictions. Predicting plume rise and vertical profiles for smoke modeling is one of the most important but difficult tasks in the chain of calculations to predict downwind smoke exposure. The UCD/CIT model uses the Bluesky Pouliot-Godowitch plume rise algorithm[34], which estimates the energy released by the biomass burned. As part of this project, a machine-learning based approach for predicting plume rise will be developed and tested. Recent studies have combined observations of wildfire plumes from the Multi-angle Imaging SpectroRadiometer (MISR) satellite with the Random Forest Regression (RFR) method to predict the fraction of the wildfire plume that will rise above the PBL height. Building on these recent studies, in this project, a RFR training dataset will be created for wildfires in California using all available satellite observations of plume rise, webcam observations of plume rise, radar observations of plume rise, the predictions of wildfire emissions (with updated emission factors), meteorological parameters from WRF, and FCCS land cover information. Plume rise observations will be divided into training and verification datasets to enable a statistical analysis of the updated plume rise model.

In MUSICAv0, four approaches for deriving plume-rise profiles were recently evaluated[16]. These included two plume-rise climatologies[35] and two plume-rise parameterizations[36,37]. Results show that for fires sampled during FIREX-AQ model simulations with the two plume-rise parameterizations generally performed better than the model simulations with the two plume-rise climatologies (Figure 4). In the proposed work, we will compare the previously evaluated plume-rise parameterizations and the new RFR-based parameterization, and will select the best parameterization(s) for simulating California wildfires and prescribed burns for the MUSICAv0 simulations.

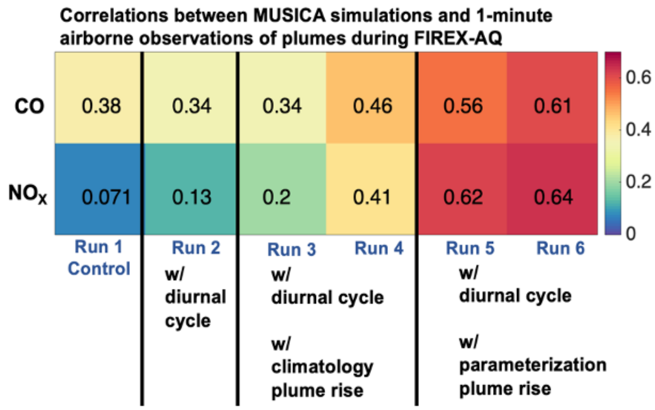


Figure 4. Correlations between MUSICA and FIREX-AQ airborne measurements. Runs 2-6 use diurnal cycle from Li et al. [2019]. Runs 3 and 4 use two different plume-rise climatology approaches [Val Martin et al., 2010]. Runs 5 and 6 use two different plume-rise parameterizations [Freitas et al., 2007; Sofiev et al., 2012]. Model agreement with observations increases from the control run to runs with improved fire representations (left to right).

UCD/CIT CTM. The UCD/CIT CTM is a reactive 3-D model that predicts the evolution of gas- and particle-phase pollutants in the atmosphere in the presence of emissions, transport, deposition, chemical reaction, and phase change as represented by Eq. (1)

$$\frac{\partial C_i}{\partial t} + \nabla \cdot uC_i = \nabla K \nabla C_i + E_i - S_i + R_i^{gas}(C) + R_i^{part}(C) + R_i^{phase}(C)$$ (eq**Error! Reference source not found.**)

where C_i is the concentration of gas or particle phase species *i* at a particular location as a function of time *t*, *u* is the wind vector, *K* is the turbulent eddy diffusivity, E_i is the emissions rate, S_i is the loss rate, R_i^{gas} is the change in concentration due to gas-phase reactions, R_i^{part} is the change in concentration due to particle-phase reactions and $R_i^{phase}$is the change in concentration due to phase change[38]. Loss rates include both dry and wet deposition. Phase change for inorganic species occurs using a kinetic treatment for gas-particle conversion[39] driven towards the point of thermodynamic equilibrium[40]. Phase change for organic species is also treated as a kinetic process with vapor pressures of semi-volatile organics calculated using the 2-product model[41].

The basic capabilities of the UCD/CIT model are similar to the CMAQ model maintained by the US EPA, but the UCD/CIT model has several source apportionment features and more particle size resolution, which makes it attractive for the current project. The UCD/CIT model explicitly tracks the mass and the number concentration of particles in 15 discrete size bins spanning the range from 10 nm through 10 µm, with tracer species used to quantify source contributions to the primary particle mass in each bin. A moving sectional bin approach is used[42] so that particle number and mass can be explicitly conserved with particle diameter acting as the dependent variable.

The emissions of particle source tracers are empirically set to be 1% of the total mass of primary particles emitted from each source category, so they do not significantly change the particle radius and the dry deposition rates. For a given source, the simulated concentration of artificial tracer directly correlates with the amount of PM mass emitted from that source in that size bin. The corresponding number concentration attributed to that source can be calculated using Eq. (2)

$$num_i = \frac{tracer_i \times 100}{\frac{\pi}{6} Dp^3 \rho}$$ (eq **Error! Reference source not found.**)

where $tracer_i$ represents the artificial tracer mass in size bin *i*, *Dp* is the core particle diameter, and *ρ* is the core particle density. Core particle properties are calculated by removing any condensed species to better represent the properties of the particles when they were emitted. More details describing the source apportionment technique in UCD/CIT model are provided in previous studies[43–47].

A total of 50 particle-phase chemical species are included in each size bin. Gas-phase concentrations of oxides of nitrogen (NOx), volatile organic compounds (VOCs), oxidants, ozone, and semi-volatile reaction products are predicted using the SAPRC-11 chemical mechanism[48].

Recent innovations in the UCD/CIT model particularly relevant to this work include the ability to predict source contributions to airborne ultrafine particles (D_p<100nm) common in wildfire plumes[47]and the development of new source apportionment techniques for formaldehyde[49]. New aging mechanisms for phenolic compounds common in fire smoke also will be added to the SAPRC chemical mechanisms used by the UCD/CIT model as a way to quantify the chemical aging of smoke plumes.

NCAR MUSICAv0. MUSICA is a newly developed community modeling capability for simulations of large-scale atmospheric phenomena in a global modeling framework that still resolves chemistry at emission- and exposure-relevant scales[14]. MUSICAv0 is a configuration of the Community Atmospheric Model with chemistry (CAM-chem)[50,51], using a spectral element dynamical core (which is an unstructured grid mesh based on a cubed sphere) with regional refinement down to ~10 kilometers[52] . MUSICAv0 accounts for both fine-scale activities at the WUI (with a resolution of up to 6 km) and large-scale transport and impacts. Recent studies have shown that MUSICAv0 is capable of simulating wildfire effects including smoke. For example, fire plumes were modeled during FIREX-AQ using the default model grid resolution of 14 km over the continental U.S. A case study of the Williams Flats Fire (17:00, August 7th 2019, over Washington), Figure 5, shows that the spatial resolution of MUSICAv0 is comparable to the fire plume and the 1-minute-merged airborne observations. While the example shown in Figure 5 has a resolution of 14 km, for the proposed project we will run MUSICAv0 at higher resolution (6 km over selected regions), to resolve more features of fire impacts on atmospheric composition.

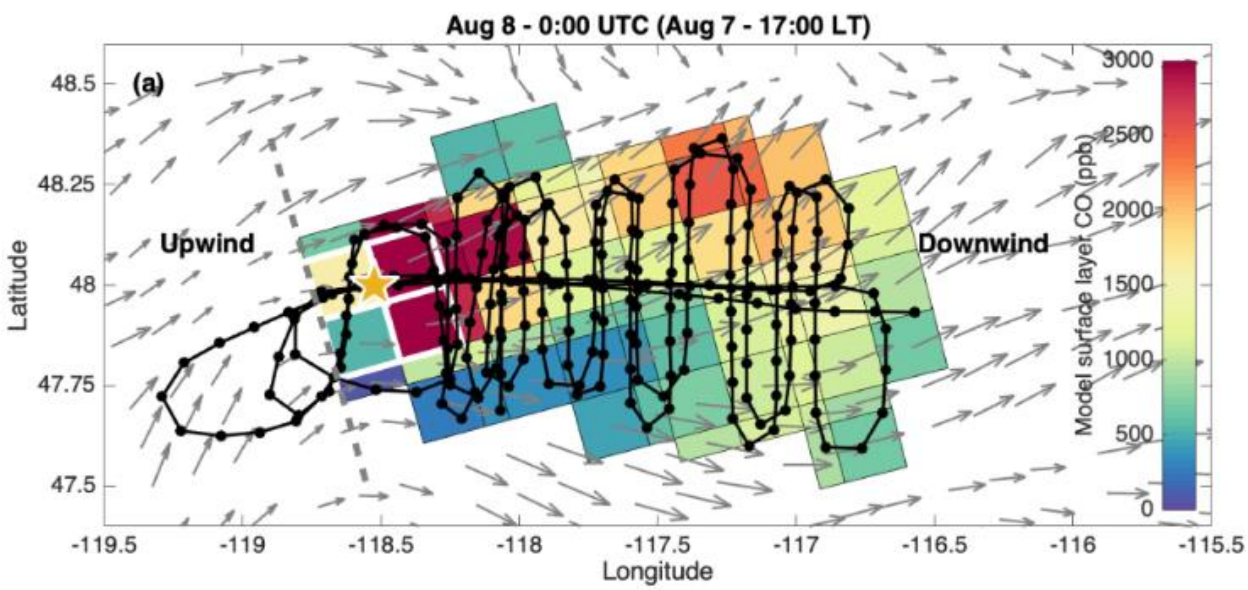


Figure 5. (a) DC-8 aircraft flight track (black line) and 1-minute-merged observation locations (black dots), and sampled model fire plume (colored region) over the Williams Flats Fire at 17:00 on August 7th, 2019 Local Time (LT). Modeled carbon monoxide (CO; ppb) within the plume at model surface layer is shown by the color and the modeled wind at model surface layer is shown by gray arrows. The location of the Williams Flats Fire is marked by the star and the four model grid cells with fire emissions are highlighted by white rectangles.

Recent updates to MUSICAv0 particularly relevant to this work include new plume rise representations, the addition of diurnal cycles for fire emissions, and improved representation of the WUI and associated emissions. In addition, the free running option of MUSICAv0 allows modeling smoke impacts under future conditions and design scenarios.

Table 3: MUSICA and UCD/CIT configuration for this work.

Model Feature	MUSICAv0	UCD/CIT
Resolution of the refined urban regions	~6 km	4km/1km
Global resolution	~1degree (111 km)	24km
Biomass burning emissions	FINNv2.5[32]	BlueSky[24,53]
Anthropogenic emissions	CAMS-GLOB-ANT_v5.1	CARB
Biogenic emissions	MEGAN[54]	MEGAN[54]
Gas-phase chemistry	MOZART-TS1[51]	SAPRC11[48]
Aerosols	MAM4[55]; Volatility Basis Set[50]	ISOROPIA ; n-product model[56,47]
Plume rise	MUSICA plume-rise parameterizations and development of RFR approach in this proposal.	BlueSky and development of RFR approach in this proposal.

Table 4: Research tasks 1-3 and the associated hypotheses and measurement and modeling platforms. Rx=prescribed and WF=wildfire.

Task	Hypothesis	Platform(s)
Design a Research Plan/Field Deployment Plan for Characterizing Wildfire Smoke	#1: $PM_{2.5}$ WF vs. Rx burns, #2: smoke composition and toxicity of WF vs. Rx burns	2RMRU
Design Multiple Scenario-Based Modeling Frameworks for Prescribed Burning Activities	#1: $PM_{2.5}$ WF vs. Rx burns, #2: smoke composition and toxicity of WF vs. Rx burns, #3: Secondary $PM_{2.5}$ WF vs Rx burns; #4: Population-weighted exposure for WF vs Rx burns	NCAR MUSICAv0 + UCD/CIT FINNv2.5 + BlueSky
Data Analysis of Ambient Observations and Corroboration with Scenario-Based Modeling	#1: $PM_{2.5}$ WF vs. Rx burns, #2: smoke composition and toxicity of WF vs. Rx burns	2RMRU, UCD/CIT, NCAR MUSICAv0

Task 1 Design a Research Plan / Field Deployment Plan for Characterizing Wildfire Smoke

Fire Selection and Sampling Strategies. Measurements will be made in at least two wildfires and two prescribed burns over the first two years of the project as recommended by an advisory board, and as conditions permit. The random nature of wildfires precludes defining specific sampling events, but locations will be prioritized based on prevalence of recent catastrophic wildfires, wildfire hazard index, and proposed efficacy of prescribed burns. Northern California (North Coast, Klamath, Modoc, Sierra Nevada), with > 87% of the area burned in the largest wildfires over the past 6 years[57], is one region of priority. However, opportunities to sample in Southern California (South Coast, Transverse) will also be pursued. WUI wildfires will be prioritized over all other fires given current knowledge gaps and limited opportunities and inherent challenges in sampling these events.

Once onsite in an active fire zone, all sampling efforts will be coordinated through incident command and will originate at base camp. Any subsequent movement within the fire zone will be at the discretion and direction of onsite personnel. Existing and new relationships with CALFIRE, Cal/OSHA, the UC Davis and Santa Rosa Fire Departments, and the UC Agriculture and Natural Reserve (UC ANR) will be leveraged to facilitate sampling of both wildfires and prescribed burns following incident-specific safety protocols. An advisory committee will be formed with individuals from these stakeholder agencies, as well as CARB, local District Staff, and an Air Resource Advisor, to consult on the selection, location, and duration of sampling events. For wildfires, we anticipate a minimum of two days per sampling event but will be equipped for a maximum of ten consecutive sampling days. The intent is to remain at the sampling site until the emissions subside sufficiently for background measurements to be made. A secondary objective is to measure the full spectrum of combustion phase (flaming to smoldering) for specific fires as opportunity allows, which may require additional time or relocation. In this case, additional supplies and samples can be ferried to and from UC Davis as needed. Prescribed burns will be sampled for the duration of the event. Ambient background conditions will be measured immediately prior to ignition for prescribed burns and upwind of wildfires using the same sampling and analysis techniques. When intercomparing wildfire and prescribed burn measurements, data will be normalized by total, background-corrected carbon measured (CO_2 + CO + CH_4 + NMHCs + particulate C) as a proxy for carbon consumed by the fire.

Task 2 Design Multiple Scenario-Based Modeling Frameworks for Prescribed Burning Activities

Model Wildfires in Northern California and Southern California, Past 10 Years. PI Kleeman has support under NIH/NIEHS R01ES031701, USDA 2021-51181-35862, and EPA RD84048401 to simulate smoke exposure during all major wildfires in California over the past 10 years using a combination of advanced emissions models, CTMs (source-oriented UCD/CIT model for this project), and machine learning models.

For these retrospective simulations, wildfire area burned will be derived from historically mapped perimeters from the CAL FIRE Fire and Resource Assessment Programs GIS database. We will then use satellite-based active fire products (MODIS, VIIRS, GOES-ABI) to apportion the area burned within specific days. Emissions will be generated as described under emissions algorithms above.

Hourly meteorology inputs to drive the regional chemical transport model at 1km resolution will be simulated using the WRFv3.4 model (www.wrf-model.org). The model will have 31 vertical layers from the ground level to the top pressure of 100 hPa. Initial and boundary conditions for meteorological simulations will be taken from North American Regional Reanalysis (NARR), which has a spatial resolution of 32 km and a temporal resolution of 3 h. The Yonsei University (YSU) boundary layer vertical diffusion scheme[58] and Pleim-Xiu land surface scheme[59] will be adopted in this study. Four-dimensional data assimilation will be applied to anchor the model predictions to observed meteorological patterns.

The base 2020 emission inventory produced by the California Air Resources Board will act as the starting point for CTM anthropogenic emissions. CARB provided the 2020 emissions inventory based on a CEPAM 2019v1.03 Planning Inventory. The yearly changes to these emissions inventories can be estimated using emissions trends available on the CEPAM website (https://ww2.arb.ca.gov/applications/cepam2019v103-standard-emission-tool). This inventory will represent all mobile, point, and non-point (area) sources with 4 km spatial resolution across California. This inventory will first be downscaled to 1 km spatial resolution over selected subdomains of California using more detailed location information for sources or their spatial surrogates. This method should be accurate when averaging over sufficiently large areas, but may be inaccurate over smaller domains. Many aspects of the emissions inventory are based on “average day” time patterns that do not account for accidents, unusual weather patterns, etc. Once again, these emissions are considered to be accurate when averaged over sufficiently long time periods, but they may be inaccurate over shorter times.

Random Forest Regression (RFR) will be used to combine CTM predictions with measurements from satellites and ground-based monitors to improve the accuracy of the predicted exposure fields. RFR is a statistical machine learning (ML) approach that has been shown to be a powerful tool for air quality modeling compared to traditional statistical methods such as bias correction (BC) and multiple linear regression (MLR)[60–63]. Four major support elements will be used in the RFR approach: surface monitoring data from US EPA and Purple Air, Moderate Resolution Imaging Spectroradiometer optical depth (AOD) retrievals, meteorology data from WRF, and CTM results from the UCD/CIT model.

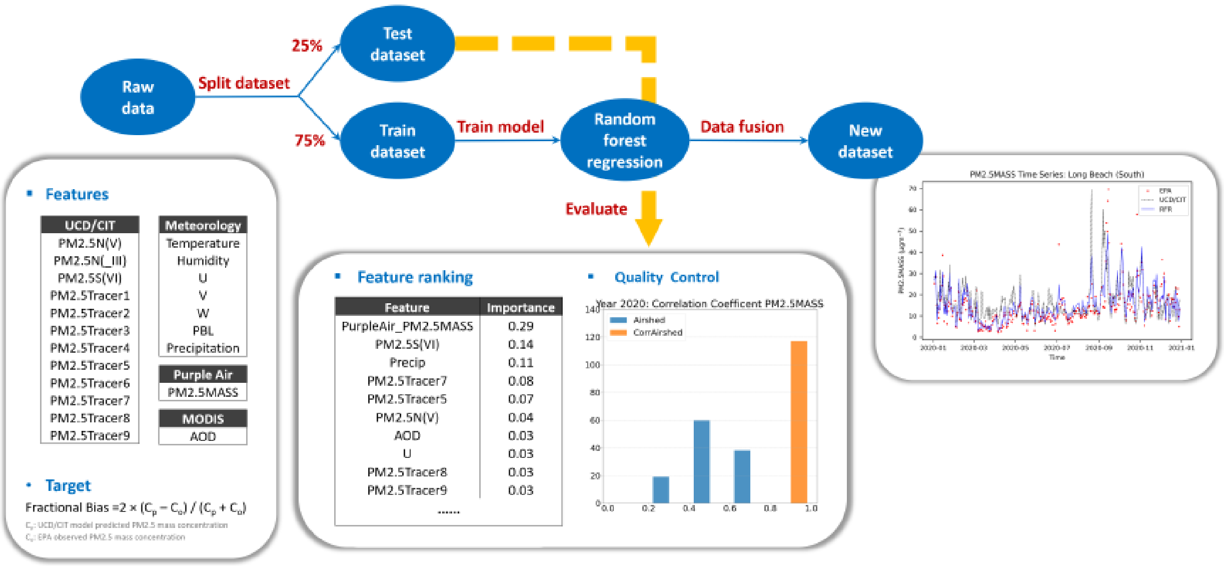


Figure 6. Flow chart of random forest algorithm.

The fractional bias (FB) values between UCD/CIT PM2.5 variables and EPA daily average observations will be calculated as training targets in the RFR approach. Fractional bias is defined as

$$FB = 2\left(\frac{M - O}{M + O}\right)$$

where *M* is the model prediction and *O* is the measured value. The equation cannot take on values outside the range of +2 and -2. Figure 6 illustrates the basic steps of how the RFR technique will be employed in this study, using $PM_{2.5}$ mass as an example. The FB between predicted and measured $PM_{2.5}$ mass concentrations will be calculated first. The dataset will then be randomly split into a training set (75%) using the training features listed in Figure 6 and a test set (25%). During training, the RFR algorithm constructs a large number of decision trees, and then combines the predictions from all the trees to arrive at a final prediction for output data. In order to evaluate model accuracy, the RFR model derived from the training dataset is applied to the test dataset. Once trained, the RFR model is used to predict the FB for $PM_{2.5}$ mass in every model grid cell. The RFR predictions are independent of the original FB equation, and so any extreme FB values must be limited to the range between +2 and -2. The correction factor (CF) will then be applied to the UCD/CIT PM2.5 mass prediction is $CF_{PM2.5MASS} = (2 + FB_{PM2.5MASS}) / (2 - FB_{PM2.5MASS})$.

The training process summarized above for $PM_{2.5}$ mass will be applied to five additional predicted concentrations including $PM_{2.5}$ OC, $PM_{2.5}$ EC, $PM_{2.5}$ ammonium ion, $PM_{2.5}$ nitrate and $PM_{2.5}$ sulfate. Some of these species also appear as training support variables. The RFR training procedure is modified in these cases to remove the target variable from the list of training support variables. The final step of the RFR method involves calculating the mean CF based on the weighted fraction average of the CF values derived from the six sets of RFR training. This approach optimizes improvements across all PM variables. Figure 7 summarizes the performance of the RFR approach during simulations for the year 2020 at the Bakersfield, CA, monitoring site. Peak concentrations in the fall months are associated with wildfire events.

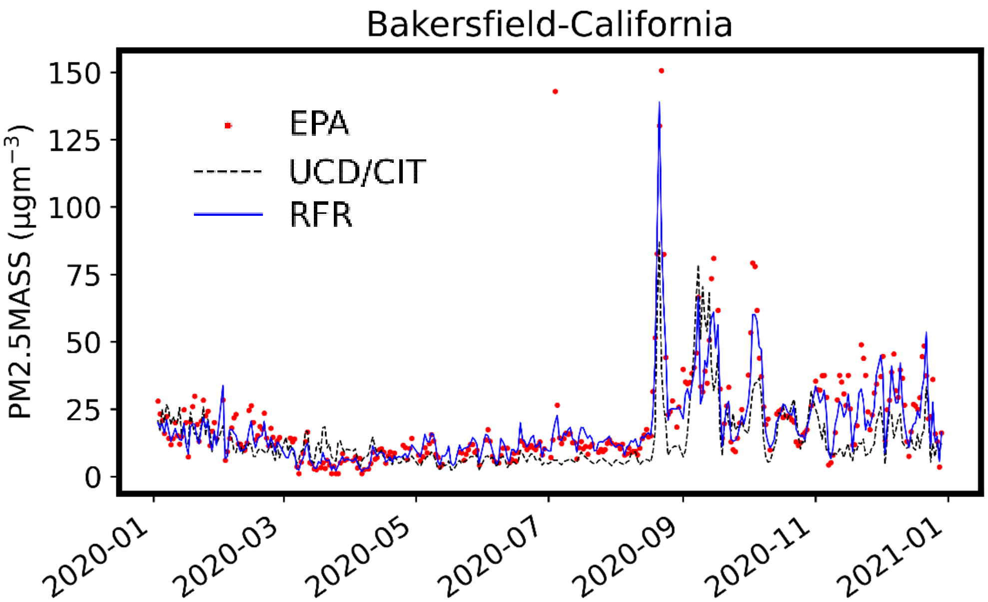


Figure 7. Predicted $PM_{2.5}$ mass concentrations with and without RFR correction at Bakersfield, CA, during the year 2020. Peak concentrations in fall months are associated with wildfire events.

In the current study, wildfire smoke will be tracked separately from routine sources of airborne PM such as mobile sources, industrial sources, etc. using source tagging features inherent in the UCD/CIT CTM. Smoke generated from natural vegetation will be tracked separately from smoke generated from the urban interface where buildings, vehicles, and other infrastructure may be burned. The products from this externally funded research will act as a comparison point for scenarios that use prescribed burns to mitigate wildfire risk.

Design Prescribed Burn scenarios to Mitigate Wildfire Risk. Prescribed burn scenarios will be modeled using MUSICAv0 and the UCD/CIT model based on emissions from FINNv2.5 and BlueSky. Building on existing collaborations and recent research projects (Barsanti as co-PI on UC Lab Fees-Banerjee and CARB 19RD008), prescribed burn scenarios will be developed in coordination with UC ANR, CALFIRE, and CARB to hypothetically reduce fuel load in locations where wildfires occurred or are likely to occur. Each prescribed burn scenario will stipulate the exact days on which prescribed burns would have been or future days when burns could be carried out, the ignition points, and the target burn area. Prescribed burn days in each scenario will be selected based on actual meteorological predictions for each day of the calendar year in current/historical simulations. As an example, ideal conditions for prescribed burns in coniferous forests include clear sunny days (< 30 °C) with low winds (< 5 m/s) and moderate humidity (0.25-0.45) during a time of the year when soil moisture is relatively high (0.15-0.03 m^3/m^3)[64]. Each of these parameters is available from existing WRF simulations for California archived by PI Kleeman's research group with hourly time resolution and 4 km spatial resolution over California between the years 2000-2023.

From the retrospective modeling led by UC Davis, we will have statistical representations of historical wildfires including location, size (daily acres), emissions, duration, and air quality impacts. We will use these representations to design and conduct a set of model simulations representing the observed range of historical fires over a five-year time period. We will then rerun these simulations gradually increasing prescribed burns and gradually decreasing wildfires over the same time period. We will consult with Rob York of UC Berkeley/UC ANR to develop realistic prescribed burn scenarios including location, duration, and timing of the burns, as well as the extent to which they are likely to reduce the frequency and severity of wildfires over that time period. This analysis will attempt to represent the stochastic nature of both wildfires and prescribed burns within the resource constraints of the project.

We will evaluate changes in air quality between the wildfire and prescribed burn scenarios, particularly $PM_{2.5}$, and the associated health impacts. These changes will be evaluated at different temporal (e.g., 1-hr, 24-hr, annual) and spatial scales (e.g., 4-100s km) accessible using MUSICAv0 and the UCD/CIT model that are appropriate to understand trends in exposure, which is important given the inherent variability in both wildfires and prescribed burns and their resultant impacts on air quality. Statistical analyses will be performed to determine the extent to which wildfires and prescribed burns results in differential health impacts within the variability of the predictions generated by the two modeling systems. The mean and standard deviation of population exposure to smoke will be calculated during multiple wildfires and prescribed burns. Hypothesis tests and confidence intervals will be used to determine if population exposure to smoke is reduced during scenarios that adopt prescribed burns.

Compare Population Exposure in Wildfire and Prescribed Burn Scenarios. One of the approaches for estimating the health impacts of smoke is to calculate a daily short-term excess mortality from fires, which accounts for the relative risk of exposure to daily $PM_{2.5}$ concentrations with and without fires, accounting for both the change in concentration and the potential increase in toxicity associated with $PM_{2.5}$ from smoke[66,67]. This approach for estimating relative risk and short-term mortality is at the foundation of the EPA BenMap[65] model, and has been used previously for fires in the US and other countries[67]. BenMap encodes concentration response functions from high quality epidemiological studies and provides a convenient tool to estimate health effects due to changing burdens of $PM_{2.5}$ and ozone. Unfortunately, BenMap does not directly predict public health impacts from toxic compounds, and so these effects will be described through changes in population exposure.

A key consideration in the evaluation of prescribed burning scenarios will be the requirement that changes in air pollution exposure do not disproportionately increase the health burden on any group, especially those from historically disadvantaged communities. Population-weighted concentrations of wildfire smoke will be calculated for each race/ethnicity group using demographic information obtained from the American Community Survey (ACS). The relative toxicity of each unit of fire smoke exposure will be considered based on the composition measurements made during prescribed burn and wildfire events (Task 1). The potential changes to the health burdens carried by each race/ethnicity group will be carefully considered in the final evaluation of public health impacts.

Task 3 Data Analysis of Ambient Observations and Corroboration with Scenario-Based Modeling

Compare Predicted and Measured Concentrations in Plumes Downwind of Wildfires and Prescribed Burns. We will conduct simulations of the wildfires and prescribed burns measured during Task 1 of the current study using both the UCD/CIT and MUSICAv0 models, and then evaluate model predictive accuracy for those events. We will characterize each burn by total smoke emissions (kg/hr) to help put the results in context relative to the spectrum of current wildfires. The evaluation will focus on $PM_{2.5}$ mass, PM chemical composition, and HAPs. We will develop specific metrics to evaluate model accuracy that are relevant for exposure and health outcomes and take advantage of the extensive measurement capabilities of the 2RMRU platform. We will also evaluate model results using PurpleAir, EPA AQS, and satellite retrievals of aerosol optical depth. Both the UCD and NCAR teams have experience with such measurement-model evaluations for fires.

The CTMs used in the current study employ a first-order closure method for turbulent transport in which the pollutant turbulent flux is assumed to be proportional to the mean gradient of the pollutant concentration (K-theory). It is important to recognize that this form of closure model only matches measurements over sufficiently large averaging operations in space and/or time. First order closure models cannot predict the instantaneous behavior of the random turbulent processes in the atmosphere. For example, Figure 8a illustrates a hypothetical snapshot of a narrow smoke plume viewed from above, while Figure 8b illustrates the time-averaged concentration field downwind of the wildfire. The concentrated instantaneous narrow plume follows a random path dictated by individual turbulent eddies (random process that cannot be exactly predicted), while the long-term average concentration assumes the standard Gaussian profile (follows predictable behavior). CTMs are based on the timescales inherent in Figure 8b, and so model-measurement comparisons must be carried out in that regime.

Measurements during prescribed burns and wildfires will be collected over times that range from minutes to hours depending on the sampling media and target analytical method. Measurements from multiple samples will be averaged in time and/or location to create a comparison point for model evaluation. CTM predictions with and without RFR corrections will be combined at corresponding times and locations for comparison to measurements. Model performance statistics will include fractional bias, fractional error, Pearson Correlation

Coefficient, and root mean square error. The accuracy of model predictions during historical fires will be used as an estimate of the accuracy of model predictions under prescribed burn scenarios.

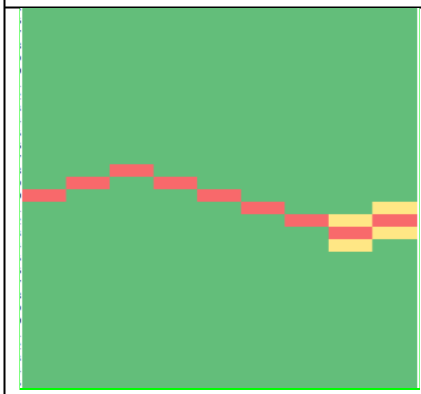
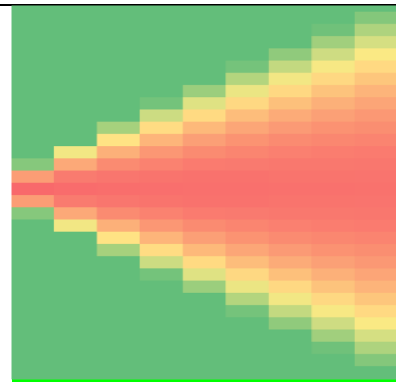
(a) instantaneous concentration of a narrow plume originating from the left	(b) time-averaged Gaussian concentration profile originating from the left
	

Figure 8. (a) Instantaneous vs. (b) time-averaged smoke concentration downwind of a wildfire.

Evaluate the Model's Ability to Predict Chemical Aging of Smoke. The CTMs chosen for this project represent gas-phase chemistry and secondary organic aerosol (SOA) formation with sufficient complexity to investigate differences in chemical aging of smoke between wildfires and prescribed burns. The models will be modified as needed to incorporate recent updates in emissions, chemical mechanisms, and SOA parameterizations that may impact predictions of plume chemistry and chemical aging of smoke. Models also will be modified as needed to better represent the differences between prescribed burns and wildfires that aren't routinely captured by the existing CTMs. We will develop specific metrics to evaluate if the models accurately predict changes in smoke concentration and composition that are relevant for exposure and health outcomes. This will allow us to systematically evaluate the public health burden of wildfires and prescribed burns in the modeling scenarios.

Task 4 Communication and Coordination with CALFIRE/CARB to Improve Comparative Analysis

The project team will regularly communicate with CALFIRE/ CARB staff members as relevant to optimize prescribed burns and wildfires targeted for measurements and model analysis. The project team will also regularly communicate with CALFIRE/CARB staff as relevant when designing prescribed burn scenarios to ensure that the location, frequency, and size of the prescribed burn scenarios capture the range of options being considered in California. Early and frequent communication throughout the project will ensure that the results provide useful information for future policy decisions.

Task 5 Final Report and Sharing of Results

Project results will be compiled as a final report and as peer-reviewed articles in scientific journals. Plain-language summaries will be published on a website every 6 months and at the conclusion of the project to inform interested members of the general public about project results. A final seminar to summarize the project findings will be held in coordination with the project sponsor to provide an interactive forum where the scientific findings and policy implications can be fully discussed.

Conclusion

Advancing the representation of smoke from wildfires and prescribed burns in state-of-the science air quality models, evaluating model predictions using state-of-the science measurements, and developing prescribed burn scenarios representative for California are critical for evaluating the public health impacts of prescribed burns relative to wildfires. Addressing current knowledge gaps and informational needs in these areas, including as highlighted in the SOW, requires a project team with interdisciplinary experience. To that end we have assembled a new collaborative team and have outlined an approach that combines measurements and models to specifically address the most critical knowledge gaps in the areas of emissions, chemical transformation, and exposure to smoke generated from prescribed burns and wildfires. The results of the proposed project will provide a scientific foundation for prescribed burn policies that improve air quality and public health outcomes in California.

Deliverables

The deliverables produced in the proposed research include the database of measured concentrations downwind of prescribed burns and wildfires, emissions estimated for historical fires, predicted exposure fields downwind of prescribed burns and wildfires, and a final report synthesizing the results into overall conclusions.

Measured concentrations will be archived in comma separated value (csv) format with date, time, location, and value for each record. Method detection limits (MDLs) will be reported for each analyte. Standard Operating Procedures (SOPs) will be provided for each measurement and analysis method.

Predicted exposure fields downwind of prescribed burns and wildfires will be archived in either csv format or netcdf format. Each exposure field will contain meta-data summarizing the model version, the map projection, date, time, and pollutant concentrations.

The final report will use the measurement data and model predictions to test the hypotheses described in this proposal in order to better understand the potential impact of prescribed burns on air quality in California. The final report will be amended based on comments received from CARB and CALFIRE.

Project Schedule

Task 1: Field Measurements (completed by year 2 if possible, continued in year 3 if necessary)
Task 2: Model Simulations
Task 3: Reconciliation Between Measurements and Models
Task 4: Communication and Coordination with Agencies
Task 5: Final Reporting

Task	Year 1				Year 2				Year 3			
1												
2												
3												
4												
5												
	m,p	p	m,p	p	m,p	p	m,p	p	m,p	m,p,dfr	fr	

m=meeting
p=progress report
dfr=draft final report
fr=final report

Project Management Plan

Dr. Kleeman (UCD) will act as PI. He will coordinate project activities and serve as the primary contact point with the funding agency. Dr. Kleeman will also contribute to the modeling objectives by generating exposure fields for airborne particles in the PM0.1, PM2.5, and PM10 size fractions. Dr. Kleeman will contribute to the interpretation of exposure results and write reports and peer-reviewed papers documenting the project results. Dr. Kleeman will supervise a postdoctoral research scholar at UC Davis who will carry out various project activities.

Dr. Bein (UCD) will act as co-Investigator leading the project measurement activities. He will coordinate with all project stakeholders to select measurement locations / time periods, collect samples, send samples to the laboratory for analysis, interpret results, and write reports and peer-reviewed papers documenting the findings.

Sean Raffuse (UCD) will act as co-Investigator leading the development of prescribed burn and wildfire emissions using the BlueSky modeling framework. He will update inputs to BlueSky using the latest published results and apply the model to recreate emissions historical wildfires and predict emissions during prescribed burn scenarios. He will contribute to written reports and peer-reviewed journal articles documenting the project findings.

Dr. Wenfu Tang (UCAR) will apply the FINNv2.5 emissions system and the MUSICAv0 CTM during historical and prescribed burn simulations. Dr. Tang will help to compare predictions from MUSICAv0 to the UCD/CIT model and to measured concentrations. She will work with other team members to implement prescribed burn scenarios and help interpret the public health implications of the resulting concentration fields.

Dr. Barsanti (UCAR) will act as co-Investigator leading the development of prescribed burn scenarios and interpreting comparisons of air quality under prescribed burn vs. wildfire scenarios. Dr. Barsanti will compare the chemical composition of smoke from wildfires and prescribed burns. She will work with the team to interpret the public health implications of exposure predictions and write reports and peer-reviewed papers documenting project results.

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Project Tasks

Meetings

A. Initial meeting. Before work on the contract begins, the Principal Investigator and key personnel will meet with the CARB Contract Project Manager and other staff to discuss the overall plan, details of performing the tasks, the project schedule, items related to personnel or changes in personnel, and any issues that may need to be resolved before work can begin.

B. Progress review meetings. The Principal Investigator and appropriate members of his or her staff will meet with CARB's Contract Project Manager at quarterly intervals to discuss the progress of the project. This meeting may be conducted by phone.

C. Technical Seminar. The Contractor will present the results of the project to CARB staff and a possible webcast at a seminar at CARB facilities in Sacramento or El Monte.

CONFIDENTIAL HEALTH DATA AND PERSONAL INFORMATION (OPTIONAL)

CARB will not be provided access to and will not receive any confidential health data or other confidential personal information under this contract. Further, CARB will have no ownership of confidential health data or other confidential personal information used in connection with this contract. The entities conducting the research in this contract will follow all applicable rules and regulations regarding access to and the use of confidential health data and personal information, including the Health Insurance Portability and Accountability Act (HIPAA) and requirements related to the Institutional Review Board (IRB) process. CARB will not be a listed entity with authorized access to confidential information pursuant to the IRB process for this contract.

HEALTH AND SAFETY

Contractors are required to, at their own expense, comply with all applicable health and safety laws and regulations. Upon notice, Contractors are also required to comply with the state agency's specific health and safety requirements and policies. Contractors agree to include in any subcontract related to performance of this Agreement, a requirement that the subcontractor comply with all applicable health and safety laws and regulations, and upon notice, the state agency's specific health and safety requirements and policies.

EXHIBIT A1

SCHEDULE OF DELIVERABLES

List all items that will be delivered to the State under the proposed Scope of Work. Include all reports, including draft reports for State review, and any other deliverables, if requested by the State and agreed to by the Parties.

If use of any Deliverable is restricted or is anticipated to contain preexisting Intellectual Property with any restricted use, it will be clearly identified in Exhibit A4, Use of Preexisting Intellectual Property & Data.

Unless otherwise directed by the State, the University Principal Investigator shall submit all deliverables to State Contract Project Manager, identified in Exhibit A3, Authorized Representatives.

Deliverable	**Description**	**Due Date**
Initial Meeting	Principal Investigator and key personnel will meet with CARB Contract Project Manager and other staff to discuss the overall plan, details of performing the tasks, project schedule, items related to personnel or changes in personnel, and any issues that may need to be resolved before work can begin.	Month 1
Progress Reports & Meetings	Quarterly progress reports and meetings throughout the agreement term, to coincide with work completed in quarterly invoices.	Quarterly
Draft Final Report	Draft version of the Final Report detailing the purpose and scope of the work undertaken, the work performed, and the results obtained and conclusions.	Six (6) months prior to agreement end date.
Data	Data compilations first produced in the performance of this Agreement by the Principal investigator or the University's project personnel.	Two (2) weeks prior to agreement end date.
Technical Seminar	Presentation of the results of the project to CARB staff and a possible webcast at a seminar at CARB facilities in Sacramento or El Monte.	On or before agreement end date.
The following Deliverables are subject to paragraph 19. Copyrights, paragraph B of Exhibit C		
Final Report	Written record of the project and its results. The Final Report shall be submitted in an Americans with Disabilities Act compliant format. The Public Outreach Document, as described in Exhibit A1, Section 2, shall be incorporated into the Final Report.	Two (2) weeks prior to agreement end date.

EXHIBIT A2

KEY PERSONNEL

List Key Personnel as defined in the Agreement starting with the PI, by last name, first name followed by Co-PIs. Then list all other Key Personnel in alphabetical order by last name. For each individual listed include his/her name, institutional affiliation, and role on the proposed project. Use additional consecutively numbered pages as necessary.

Last Name, First Name	**Institutional Affiliation**	**Role on Project**
Principal Investigator (PI):		
Michael Kleeman	UC Davis	Air Quality Modeling and Measurements
Co-PI(s) – if applicable:		
Other Key Personnel:		
Kelley Barsanti	National Center for Atmospheric Research	Atmospheric Chemistry
Keith Bein	UC Davis	Wildfire Exposure Measurements
Sean Raffuse	UC Davis	Wildfire Emissions

EXHIBIT A3

AUTHORIZED REPRESENTATIVES & NOTICES

The following individuals are the authorized representatives for the State and the University under this Agreement. Any official Notices issued under the terms of this Agreement shall be addressed to the Authorized Official identified below, unless otherwise identified in the Agreement.

State Agency Contacts	University Contacts
Agency Name: **CARB**	University Name: University of California Davis
Contract Project Manager (Technical) Name: Address: Research Division 1001 I Street, 7th Floor Sacramento, CA 95814 Telephone: (916) Email: @arb.ca.gov	***Principal Investigator (PI)*** Name: Michael Kleeman Address: Civil & Environmental Engineering Dept. UC Davis, Ghausi Hall 1 Shields Ave. Davis, CA 95616. Telephone: 530-752-6900 Email: mjkleeman@ucdavis.edu Designees to certify invoices under Section 14 of Exhibit C on behalf of PI: 1. TBN 2. <Name>, <Title>, <EmailAddress> 3. <Name>, <Title>, <EmailAddress>

Authorized Official (contract officer)	Authorized Official
Name: Alice Kindarara, Chief Address: Acquisitions Branch 1001 I Street, 19th Floor Sacramento, CA 95814 ***Send notices to (if different):*** Name: Address: Research Division 1001 I Street, 7th Floor Sacramento, CA 95814 Telephone: (916) Email: @arb.ca.gov	Name: Grace Liu Address: Sponsored Programs 1850 Research Park Drive Davis, CA 95618 ***Send notices to (if different):*** Name: SPO Awards Analyst Address: Sponsored Programs 1850 Research Park Drive Davis, CA 95618 Telephone: 530-754-7700 Fax: 530-752-0333 Email: awards@ucdavis.edu
Administrative Contact Name: Address: Research Division 1001 I Street, 7th Floor Sacramento, CA 95814 Telephone: (916) Email: @arb.ca.gov	***Administrative Contact*** Name: Gregory Zebouni Address: Civil & Environmental Engineering Dept. UC Davis, Ghausi Hall 1 Shields Ave. Davis, CA 95616. Telephone: 530-752-6900 Email: gzebouni@ucdavis.edu
Financial Contact/Accounting Name: Accounts Payable Address: P.O. Box 1436 Sacramento, CA 95814 Email: AccountsPayable@arb.ca.gov **Send courtesy copy to: rd.invoices@arb.ca.gov**	***Authorized Financial Contact/Invoicing*** Name: James Ringo Address: Contracts & Grants Accounting 1441 Research Park Drive Davis, CA 95618 Telephone: (530) 757-8523 Email: jaringo@ucdavis.edu Designees for invoice certification in accordance with Exhibit C – University Terms and Conditions, Section 14 on behalf of the Financial Contact: 1. 2. 3.

EXHIBIT A4

USE OF PREEXISTING INTELLECTUAL PROPERTY & DATA

If either Party will be using any third-party or pre-existing intellectual property (including, but not limited to copyrighted works, known patents, trademarks, service marks and trade secrets) "IP" and/or Data with restrictions on use, then list all such IP and the nature of the restriction below. If no third-party or pre-existing IP/Data will be used, check "none" in this section.

A. State: Preexisting Intellectual Property (IP)/Data to be provided to the University from the State or a third party for use in the performance in the Scope of Work.

☒ None or ☐ List:

Owner (State Agency or 3rd Party)	Description	Nature of restriction:

B. University: Restrictions in Preexisting IP/Data included in Deliverables identified in Exhibit A1, Deliverables.

☒ None or ☐ List:

Owner (University or 3rd Party)	Description	Nature of restriction:

C. Anticipated restrictions on use of Project Data.
If the University PI anticipates that any of the Project Data generated during the performance of the Scope of Work will have a restriction on use (such as subject identifying information in a data set), then list all such anticipated restrictions below. If there are no restrictions anticipated in the Project Data, then check "none" in this section.

☒ None or ☐ List:

Owner (State Agency or 3rd Party)	Description	Nature of restriction:

EXHIBIT A5

RÉSUMÉ / BIOSKETCH

NAME Kleeman, Michael J	POSITION TITLE Professor
eRA COMMONS USER NAME MJKLEEMAN	

EDUCATION/TRAINING *(Begin with baccalaureate or other initial professional education, such as nursing, and include postdoctoral training.)*

INSTITUTION AND LOCATION	DEGREE *(if applicable)*	YEAR(s)	FIELD OF STUDY
University of Waterloo, Canada	B.A.Sc.	1993	Mechanical Engineering
California Institute of Technology, Pasadena	M.S.	1994	Env. Eng. Science
California Institute of Technology, Pasadena	Ph.D.	1998	Env. Eng. Science

A. Personal Statement

Dr. Kleeman is a recognized expert in urban / regional air pollution problems with experience acting as Principal Investigator for more than $10M of externally-funded research and co-Investigator for another +$20M of externally-funded research during his 27 year career. Dr. Kleeman has pioneered measurement methods for ultrafine particles and developed source apportionment techniques to quantify the ambient ultrafine contributions from different source types. He has also pioneered the development of source apportionment techniques for primary and secondary particulate matter within regional chemical transport models. Using these methods, Dr. Kleeman has conducted extensive studies on the health effects of ultrafine particles in California and across the United States. He has also extended these methods to analyze the intersection of air-climate-energy in California in order to quantify the $20B/yr public health savings through clean air associated with the adoption of low-carbon energy sources. Dr. Kleeman has published more than 160 manuscripts in leading scientific journals that have been cited more than 15,000 times.

Selected major contributions:

a. 2000 **Kleeman, M.J**., J.J. Schauer, and G.R. Cass. Size and Composition Distribution of Fine Particulate Matter Emitted from Motor Vehicles. Environmental Science, and Technology, 34:1132-1142.
b. 2008 **Kleeman, M.J.,** Riddle, S.G., Robert, M.A., Jakober, C.A., Fine, P.M., Hays, M.D., Schauer, J.J. and Hannigan, M.P. Source Apportionment of Fine (PM1.8) and Ultrafine (PM0.1) Airborne Particulate Matter During a Severe Winter Pollution Episode. Environmental Science and Technology, DOI: 10.1021/es800400.
c. 2015 J. Hu, H. Zhang, Q. Ying, S. Chen, F. Vandenberghe, and **M.J. Kleeman**. Long-term Particulate Matter Modeling for Health Effects Studies in California – Part I: Model Performance on Temporal and Spatial Variations. Atmospheric Chemistry and Physics, 15(6), pp3445-3461.
d. 2019 X. Yu, M. Venecek, A. Kumar, J. Hu, S. Tanrikulu, S. Soon, C. Tran, D. Fairley, and **M.J. Kleeman**. Regional Sources of Airborne Ultrafine Particle Number and Mass Concentrations in California. Atmospheric Chemistry and Physics, 19, pp 14677-14702.
e. 2022 Y. Li., A. Kumar, Y. Li, and **M.J. Kleeman**. Adoption of Low-Carbon Fuels Reduced Race/Ethnicity Disparities in Air Pollution Exposure in California. Science of the Total Environment, 15;834:155230. doi: 10.1016/j.scitotenv.2022.155230. Epub 2022 Apr 12. PMID: 35427611.

B. Positions and Honors

Positions

1999–2003 Assistant Professor, Department of Civil and Environmental Engineering, UC Davis, Davis CA.

2003–2006 Associate Professor, Department of Civil and Environmental Engineering, UC Davis, Davis CA.

2006–pres. Professor, Department of Civil and Environmental Engineering, UC Davis, Davis CA.

Honors

1993-1994 California Institute of Technology Knapp Fellowship

2007 California Air Resources Board Silver Superior Accomplishment Award

2008 United States Environmental Protection Agency Scientific and Technological Achievement Award Level III

C. Contributions to Science

1. Dr. Kleeman has carried out a series of emissions characterization experiments to measure the size and composition distribution of airborne particles immediately after release from dominant sources. These measurements provide vital input data for chemical transport models and they also provide the basis for chemical fingerprints that can be recognized in the downwind atmosphere. The source profile measurements that he has made are used by the California Air Resources Board for atmospheric simulations and planning in the heavily polluted San Joaquin Valley and the South Coast Air Basin surrounding Los Angeles. Collectively, these regions account for 7 of the top 10 polluted cities in the US. The source profile measurements have contributed to our improved understanding of the air pollution problem and the design of effective control strategies.

References:

1999 Kleeman, M.J., J.J. Schauer, and G.R. Cass. Size and Composition Distribution of Fine Particulate Matter Emitted from Wood Burning, Meat Charbroiling and Cigarettes. Environmental Science, and Technology, Environmental Science, and Technology, 33:3516-3523.

2000 Kleeman, M.J., J.J. Schauer, and G.R. Cass. Size and Composition Distribution of Fine Particulate Matter Emitted from Motor Vehicles. Environmental Science, and Technology, 34:1132-1142.

2007 Robert, M.A., C.A. Jakober, and M.J. Kleeman. Size and Composition Distribution of Particulate Matter 2. Heavy -duty Diesel Vehicles. Journal of the Air and Waste Management Association, 57, pp1429-1438.

2007 Robert, M.A., C.A. Jakober, S. VanBergen, and M.J. Kleeman, Size and Composition Distribution of Particulate Matter 1. Light-duty Gasoline Vehicles. Journal of the Air and Waste Management Association, 57, pp1414-1428.

2008 Kleeman, M.J., M.A. Robert, S.G. Riddle, P.M. Fine, M.D. Hays, J.J. Schauer, and M.P. Hannigan. Size Distribution of Trace Organic Species Emitted From Biomass Combustion and Meat Charbroiling. Atmospheric Environment, 42 pp3059-3075.

2. Dr. Kleeman has developed and applied receptor-based source apportionment calculations for ultrafine particles (D_p<0.1µm) through a series of source profile measurements and community monitoring. By developing new methods to chemically analyze particles in the ultrafine size range, he was able to extend the source apportionment tools traditionally used for PM2.5 into the PM0.1 size fraction. This included the development of molecular marker libraries used in Chemical Mass Balance (CMB) models and the development of efficient elemental analysis techniques for Inductively Coupled Plasma Mass Spectrometry (ICPMS) that can be used to support Positive Matrix Factorization (PMF) models. These source apportionment methods for ultrafine particles have been demonstrated in roadside and community receptor environments throughout California.

References:

2007 Riddle SG, M.A. Robert, C.A. Jakober, M.P. Hannigan, M.J. Kleeman. Size distribution of trace organic species emitted from light duty gasoline vehicles. Environmental Science and Technology, 41, pp7464-7471.

2008 Kleeman, M.J., S.G. Riddle, and C.A. Jakober. Size Distribution of Particle-Phase Molecular Markers During a Severe Winter Pollution Episode. Environmental Science and Technology, 42, pp4697-4703.
2008 Kleeman, M.J., Riddle, S.G., Robert, M.A., Jakober, C.A., Fine, P.M., Hays, M.D., Schauer, J.J. and Hannigan, M.P. Source Apportionment of Fine (PM1.8) and Ultrafine (PM0.1) Airborne Particulate Matter During a Severe Winter Pollution Episode. Environmental Science and Technology, DOI: 10.1021/es800400.
2013 T. Kuwayama, C.R. Ruehl, and M.J. Kleeman. Daily Trends and Source Apportionment of Ultrafine Particulate Mass (PM0.1) over and Annual Cycle in a Typical California City. Environmental Science and Technology, dx.doi.org/10.1021/es403235c.

Complete List of Published Work in MyBibliography:
http://faculty.engineering.ucdavis.edu/kleeman/publications/

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EDUCATION

University of California, Davis	Ph.D.	Atmospheric Sciences	2007
California State University, Chico	B.S.	Chemistry	2001
California State University, Chico	B.S.	Physics	2001

CURRENT AND PREVIOUS POSITIONS

Air Quality Research Center, U.C. Davis	Professional Researcher	2023-present
Caldecott Tunnel Exposure Facility, U.C. Davis	Scientist in Charge	2018-present
Air Quality Research Center, U.C. Davis	Assoc Professional Researcher	2016-2023
Center for Health & the Environment, U.C. Davis	Research Professor	2012-present
Air Quality Research Center, U.C. Davis	Assist Professional Researcher	2009-2016
Air Quality Research Center, U.C. Davis	Postdoctoral Scholar	2007-2009
Dept. Land, Air and Water Resources, U.C. Davis	Research Assistant	2001-2007

RECENT HONORS AND AWARDS (last 3 years)

- Environmental Health Perspectives Editor's Choice Award, 2021
- National Institute of Environmental Health Sciences Extramural Paper of the Month, July 2020

RECENT PUBLICATIONS (last 3 years)

Kado SY, **Bein KJ**, Castaneda AR, Pouraryan AA, Garrity N, Ishihara Y, Rossi A, Haarmann-Stemmann T, Sweeney CA, Vogel CFA (2023). Regulation of IDO2 by the aryl hydrocarbon receptor (AhR) in breast cancer. *Cells*, 12: 1433. DOI: 10.3390/cells12101433

Badley J, Cossaboon J, Malany K, McNabb NA, Mouat JS, Parenti M, Sharifi O, Stevens NC, Thongphanh K, Xu J, **Bein KJ**, Van Winkle LS, Lein PJ (2022). Forged in Fire: Environmental Health Impacts of Wildfires, Open Access Government, eBook

Dutta M, Weigel KM, Patten KT, Valenzuela AE, Wallis CD, **Bein KJ**, Wexler AS, Lein PJ, Cui JY (2022). Chronic exposure to ambient traffic-related air pollution (TRAP) alters gut microbial abundance and bile acid metabolism in a transgenic rat model of Alzheimer's disease. T*oxicology Reports*, 9: 432-444. DOI: 10.1016/j.toxrep.2022.03.003.

Bein KJ, Wallis CD, Silverman JL, Lein PJ, Wexler AS (2022). Emulating near-roadway exposure to traffic-related air pollution via real-time emissions from a major freeway tunnel system. *Environmental Science & Technology*, 56(11): 7083-7095. DOI: 10.1021/acs.est.1c07047.

Ishihara Y, Kado S, **Bein KJ**, He Y, Pouraryan AA, Urban A, Haarmann-Stemmann T, Sweeney C, Vogel CFA (2022). Aryl hydrocarbon receptor signaling synergizes with TLR/NF-kb-signaling for induction of IL-22 through canonical and non-canonical AhR pathways. *Frontiers in Toxicology*, 3: 787360. DOI: 10.3389/ftox.2021.787360.

Yuan W, Velasquez SC, Wu CW, Fulgar CC, Zhang Q, Young DE, **Bein KJ**, Vogel CFA, Li W, Cui LL, Wei HY, Pinkerton KE (2022). Pulmonary health effects of wintertime particulate matter from California and China following repeated exposure and cessation. *Toxicology Letters,* 354: 33-43. DOI: 10.1016/j.toxlet.2021.10.014.

Patten KT, Valenzuela AE, Wallis C, Berg EL, Silverman JL, **Bein KJ**, Wexler AS, Lein PJ (2021). The effects of chronic exposure to ambient traffic-related air pollution on Alzheimer's disease phenotypes in wildtype and genetically predisposed male and female rats. *Environmental Health Perspectives* 129 (5): 057005. DOI: 10.1289/EHP8905.

Edwards S, Zhao G, Tran J, Patten KT, Valenzuela A, Wallis C, **Bein KJ**, Wexler AS, Lein PJ, Rao X (2020). Sex-specific cardiopulmonary pathological changes in response to chronic traffic-related air pollution exposure in rats.

Environmental Health Perspectives, 128(12): 127003. DOI: 10.1289/EHP7045.

Dahlem C, Kado SY, He F, **Bein KJ**, Kado N, Wu D, Haarmann-Stemmann T, Vogel CFA (2020). AHR signaling interacting with nutritional factors regulating the expression of markers in vascular inflammation and atherogenesis. *International Journal of Molecular Sciences*, 21(21): 8287. DOI: 10.3390/ijms21218287.

Berg EL, Pedersen LR, Pride MC, Petkova SP, Patten KT, Valenzuela AE, Wallis C, **Bein KJ**, Wexler AS, Lein PJ, Silverman JL (2020). Developmental exposure to near roadway pollution produces behavioral phenotypes relevant to neurodevelopmental disorders in juvenile rats. *Translational Psychiatry*, 10(289): 1-16. DOI: 10.1038/s41398-020-00978-0.

D'Evelyn SM, Vogel CFA, **Bein KJ**, Lara B, Laing EA, Abarca RA, Zhang Q, Li L, Li J, Nguyen TB, Pinkerton KE (2020). Differential inflammatory potential of particulate matter (PM) size fractions from Imperial Valley, CA. *Atmospheric Environment*, 244: 117992. DOI: 10.1016/j.atmosenv.2020.117992.

Patten KT, González EA, Valenzuela A, Berg E, Wallis C, Garbow JR, Silverman JL, **Bein KJ**, Wexler AS, Lein PJ (2020). Effects of early life exposure to traffic-related air pollution on brain development in juvenile Sprague-Dawley rats. *Translational Psychiatry*, 10(1): 166. DOI: 10.1038/s41398-020-0845-3.

Yuan W, Fulgar CC, Sun X, Vogel CFA, Wu CW, Zhang Q, **Bein KJ**, Young DE, Li W, Wei H, Pinkerton KE (2020). In vivo and in vitro inflammatory responses to fine particulate matter ($PM_{2.5}$) from China and California. *Toxicology Letters*, 328: 52-60. DOI: 10.1016/j.toxlet.2020.04.010

Kaur R, Labins JR, Helbock SS, Jiang W, **Bein KJ**, Zhang Q, Anastasio C (2019). Photooxidants from brown carbon and other chromophores in illuminated particle extracts. *Atmospheric Physics and Chemistry*, 19: 6579. DOI: 10.5194/acp-19-6579-2019

OTHER RELEVANT PUBLICATIONS

Bein KJ, Wexler AS (2015). Compositional variance in extracted particulate matter using different filter extraction techniques. *Atmospheric Environment*, 107: 24-34.

Bein KJ, Zhao YJ, Wexler AS (2015). Retrospective source attribution for source-oriented sampling. *Atmospheric Environment*, 119: 228-239.

Bein KJ, Zhao YJ, Wexler AS (2009). Conditional sampling for source-oriented toxicological studies using a single particle mass spectrometer. *Environmental Science & Technology*, 43(24): 9445-9452.

Bein KJ, Zhao Y, Johnston MV, Evans GJ, Wexler AS (2008). Extratropical waves transport boreal wildfire emissions and drive regional air quality dynamics. *Journal of Geophysical Research – Atmospheres*, 113: D23213.

Bein KJ, Zhao Y, Johnston MV, Wexler AS (2008). Interactions between boreal wildfire and urban emissions. *Journal of Geophysical Research – Atmospheres*, 113(D7): D07304.

SYNERGISTIC ACTIVITIES

Caldecott Tunnel Exposure Facility – Designed, developed, and currently operate a measurement and exposure facility adjacent to a major freeway tunnel system in the California Bay Area for *(1)* continuous emissions monitoring (CEM) of gases and particulate matter under real-world changes in the vehicular fleet mixture and *(2)* conducting real-time inhalation exposure studies on the neurological, cardiovascular, and epigenetic health impacts of traffic-related air pollution. All the CEM instrumentation, sampling trains and equipment, hardware-software interfacing, data acquisition, sample processing and preparation methods, and analytical techniques proposed for the current study are also employed at this facility.
Rapid Response Mobile Research Unit (2RMRU) – Designed and developed a fully contained, self-powered mobile research unit for rapid deployment to active wildfires to measure and sample particle and gas phase emissions. PM and gas samples are chemically and toxicologically characterized offline while real-time measurements of particle size distribution, PM mass concentration, and combustion gas concentrations are provided by continuous emissions monitoring instrumentation. Integrated electric vehicles (EVs) are sequentially cycled between powering the equipment and recharging, providing a continuous power source. The EVs and all associated systems are contained on a two-car open hauler that is easily towed by a ¾ ton truck. The unit has been deployed at several wildfires throughout the 2017-2020 California wildfire seasons.

Grant Reviewer – Standing member of the Scientific Review Committee for the National Institute of Health’s Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) programs

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Atmospheric Chemistry Observations and Modeling (ACOM) National Center for Atmospheric Research (NCAR)
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A. Education

Ph.D. Environmental Science & Engineering, 2006, Oregon Health & Science University
M.S. Environmental Science & Engineering, 2011, Oregon Health & Science University
B.A. Environmental Biology and Environmental Studies, 1996, Univ. of Colorado-Boulder

B. Professional Experience

2022-	Scientist, ACOM, National Center for Atmospheric Research
2019-2022	Associate Professor, Chem. & Env. Engineering, Univ. of CA-Riverside 2015-2019
	Assistant Professor, Chem. & Env. Engineering, Univ. of CA-Riverside
2011-2015	Research Assistant Professor, Civil & Env. Engineering, Portland State University 2010-2011
	Senior Research Associate, Civil & Env. Engineering, Portland State University 2008-2010
	Research Assistant, Mechanical Engineering, Univ. of Colorado-Boulder
2008-2010	Visiting Scientist, National Center for Atmospheric Research
2006-2008	ASP Postdoctoral Fellow, National Center for Atmospheric Research

C. Relevant Scientific Accomplishments and Synergistic Activities

· Fulbright to study linkages between fire behavior, fire emissions, and smoke at Scion NZ with T. Strand in 2023 ·Two biomass burning laboratory campaigns (FLAME-IV, FIREX), one wildfire field campaign (FIREX-AQ), and two prescribed burning campaigns (Blodgett Research Forest) · First application of two-dimensional gas chromatography with time-of-flight mass spectrometry (GC×GC-TOFMS) for analysis of gaseous organic compounds in smoke (Hatch et al., 2015) · Most comprehensive emissions database to date of gaseous non-methane organic compounds in smoke (Hatch et al., 2017) · Developed NEIVA: Next-generation Emissions InVentory expansion of Akagi (NEIVA) a biomass burning database that integrates emissions factors from multiple laboratory and field studies, links them with physical and chemical properties important for understanding their fate and transport, and maps them to model surrogates (Shahid, B. S. et al., in prep.) · Developed, tested, and published a new gas-phase chemical mechanism for furans, an abundant organic compound in smoke (Jiang et al., 2020) · Member Scientific, Technical, and Modeling Peer Review (STMPR) Advisory Group, California Air Resources Board (2020-) · Chair (2019) and Member (2015) of External Review Panel for the EPA Community Multiscale Air Quality (CMAQ) model

D. Relevant Publications (underline indicates primary advisee/mentee)

Liang, Y., Stamatis, C., and Coauthors, 2022: Emissions of organic compounds from western US wildfires and their near-fire transformations. *ATMOSPHERIC CHEMISTRY AND PHYSICS*, **22**, 9877–9893, https://doi.org/10.5194/acp-22-9877-2022. (Liang and Stamatis co-lead authors)

Stamatis, C., and K. C. Barsanti, 2022: Development and application of a supervised pattern recognition algorithm for identification of fuel-specific emissions profiles. *ATMOSPHERIC MEASUREMENT TECHNIQUES*, **15**, 2591–2606, https://doi.org/10.5194/amt-15-2591-2022.

Li, Q., J. Jiang, I. K. Afreh, K. C. Barsanti, and D. R. Cocker III, 2022: Secondary organic aerosol formation from camphene oxidation: measurements and modeling. *ATMOSPHERIC CHEMISTRY AND PHYSICS*, **22**, 3131–3147, https://doi.org/10.5194/acp-22-3131-2022. (Jiang and Li co-lead authors)

Decker, Z. C. J., and Coauthors, 2021: Nighttime and daytime dark oxidation chemistry in wildfire plumes: an observation and model analysis of FIREX-AQ aircraft data. *ATMOSPHERIC CHEMISTRY AND PHYSICS*, **21**, 16293–16317, https://doi.org/10.5194/acp-21-16293-2021.

Robinson, M. A., and Coauthors, 2021: Variability and Time of Day Dependence of Ozone Photochemistry in Western Wildfire Plumes. *ENVIRONMENTAL SCIENCE & TECHNOLOGY*, **55**, 10280–10290, https://doi.org/10.1021/acs.est.1c01963.

Porter, W. C., J. L. Jimenez, and K. C. Barsanti, 2021: Quantifying Atmospheric Parameter Ranges for Ambient Secondary Organic Aerosol Formation. *ACS EARTH AND SPACE CHEMISTRY*, **5**, 2380–2397, https://doi.org/10.1021/acsearthspacechem.1c00090.

Hallar, A. G., and Coauthors, 2021: Coupled Air Quality and Boundary-Layer Meteorology in Western US Basins during Winter: Design and Rationale for a Comprehensive Study. *BULLETIN OF THE AMERICAN METEOROLOGICAL SOCIETY*, **102**, E2012–E2033, https://doi.org/10.1175/BAMS-D-20-0017.1. (section lead author)

Afreh, I. K., B. Aumont, M. Camredon, and K. C. Barsanti, 2021: Using GECKO-A to derive mechanistic understanding of secondary organic aerosol formation from the ubiquitous but understudied camphene. *ATMOSPHERIC CHEMISTRY AND PHYSICS*, **21**, 11467–11487, https://doi.org/10.5194/acp-21-11467-2021.

Pfister, G. G., and Coauthors, 2020: The Multi-Scale Infrastructure for Chemistry and Aerosols (MUSICA). *BULLETIN OF THE AMERICAN METEOROLOGICAL SOCIETY*, **101**, E1743–E1760, https://doi.org/10.1175/BAMS-D-19-0331.1. (section co-lead author)

Jiang, J., W. P. L. Carter, D. R. Cocker III, and K. C. Barsanti, 2020: Development and Evaluation of a Detailed Mechanism for Gas-Phase Atmospheric Reactions of Furans. *ACS EARTH AND SPACE CHEMISTRY*, **4**, 1254–1268, https://doi.org/10.1021/acsearthspacechem.0c00058.

Hatch, L. E., and Coauthors, 2019: Highly Speciated Measurements of Terpenoids Emitted from Laboratory and Mixed-Conifer Forest Prescribed Fires. *ENVIRONMENTAL SCIENCE & TECHNOLOGY*, **53**, 9418–9428, https://doi.org/10.1021/acs.est.9b02612.

Ahern, A. T., and Coauthors, 2019: Production of Secondary Organic Aerosol During Aging of Biomass Burning Smoke From Fresh Fuels and Its Relationship to VOC Precursors. *JOURNAL OF GEOPHYSICAL RESEARCH-ATMOSPHERES*, **124**, 3583–3606, https://doi.org/10.1029/2018JD029068.

Jen, C. N., and Coauthors, 2019a: High Hydroquinone Emissions from Burning Manzanita (vol 5, pg 309, 2018). *ENVIRONMENTAL SCIENCE & TECHNOLOGY LETTERS*, **6**, 378, https://doi.org/10.1021/acs.estlett.9b00315.

Jen, C. N., and Coauthors, 2019b: Speciated and total emission factors of particulate organics from burning western US wildland fuels and their dependence on combustion efficiency. *ATMOSPHERIC CHEMISTRY AND PHYSICS*, **19**, 1013–1026, https://doi.org/10.5194/acp-19-1013-2019.

Decker, Z. C. J., and Coauthors, 2019: Nighttime Chemical Transformation in Biomass Burning Plumes: A Box Model Analysis Initialized with Aircraft Observations. *ENVIRONMENTAL SCIENCE & TECHNOLOGY*, **53**, 2529–2538, https://doi.org/10.1021/acs.est.8b05359.

Hatch, L. E., A. Rivas-Ubach, C. N. Jen, M. Lipton, A. H. Goldstein, and K. C. Barsanti, 2018: Measurements of I/SVOCs in biomass-burning smoke using solid-phase extraction disks and two-dimensional gas chromatography. *ATMOSPHERIC CHEMISTRY AND PHYSICS*, **18**, 17801–17817, https://doi.org/10.5194/acp-18-17801-2018.

Jen, C. N., and Coauthors, 2018: High Hydroquinone Emissions from Burning Manzanita. *ENVIRONMENTAL SCIENCE & TECHNOLOGY LETTERS*, **5**, 309–314, https://doi.org/10.1021/acs.estlett.8b00222.

Bian, Q., S. H. Jathar, J. K. Kodros, K. C. Barsanti, L. E. Hatch, A. A. May, S. M. Kreidenweis, and J. R. Pierce, 2017: Secondary organic aerosol formation in biomass-burning plumes: theoretical analysis of lab studies and ambient plumes. *ATMOSPHERIC CHEMISTRY AND PHYSICS*, **17**, 5459–5475, https://doi.org/10.5194/acp-17-5459-2017.

Barsanti, K. C., J. H. Kroll, and J. A. Thornton, 2017: Formation of Low-Volatility Organic Compounds in the Atmosphere: Recent Advancements and Insights. *JOURNAL OF PHYSICAL CHEMISTRY LETTERS*, **8**, 1503–1511, https://doi.org/10.1021/acs.jpclett.6b02969. (invited Perspective)

Hatch, L. E., R. J. Yokelson, C. E. Stockwell, P. R. Veres, I. J. Simpson, D. R. Blake, J. J. Orlando, and K. C. Barsanti, 2017: Multi-instrument comparison and compilation of non-methane organic gas emissions from biomass burning and implications for smoke-derived secondary organic aerosol precursors. *ATMOSPHERIC CHEMISTRY AND PHYSICS*, **17**, 1471–1489, https://doi.org/10.5194/acp-17-1471-2017.

Hatch, L. E., W. Luo, J. F. Pankow, R. J. Yokelson, C. E. Stockwell, and K. C. Barsanti, 2015: Identification and quantification of gaseous organic compounds emitted from biomass burning using two-dimensional gas chromatography-time-of-flight mass spectrometry. *ATMOSPHERIC CHEMISTRY AND PHYSICS*, **15**, 1865–1899, https://doi.org/10.5194/acp-15-1865-2015.

Li, J., M. Cleveland, L. D. Ziemba, R. J. Griffin, K. C. Barsanti, J. F. Pankow, and Q. Ying, 2015: Modeling regional secondary organic aerosol using the Master Chemical Mechanism. *ATMOSPHERIC ENVIRONMENT*, **102**, 52–61, https://doi.org/10.1016/j.atmosenv.2014.11.054.

Barsanti, K. C., A. G. Carlton, and S. H. Chung, 2013: Analyzing experimental data and model parameters: implications for predictions of SOA using chemical transport models. *ATMOSPHERIC CHEMISTRY AND PHYSICS*, **13**, 12073–12088, https://doi.org/10.5194/acp-13-12073-2013.

Pankow, J. F., W. Luo, A. N. Melnychenko, K. C. Barsanti, L. M. Isabelle, C. Chen, A. B. Guenther, and T. N. Rosenstiel, 2012: Volatilizable Biogenic Organic Compounds (VBOCs) with two dimensional Gas Chromatography-Time of Flight Mass Spectrometry (GC x GC-TOFMS): sampling methods, VBOC complexity, and chromatographic retention data. *ATMOSPHERIC MEASUREMENT TECHNIQUES*, **5**, 345–361, https://doi.org/10.5194/amt-5-345-2012.

Barsanti, K. C., and J. F. Pankow, 2006: Thermodynamics of the formation of atmospheric organic particulate matter by accretion reactions - Part 3: Carboxylic and dicarboxylic acids. *ATMOSPHERIC ENVIRONMENT*, **40**, 6676–6686, https://doi.org/10.1016/j.atmosenv.2006.03.013.

Barsanti, K., and J. Pankow, 2005: Thermodynamics of the formation of atmospheric organic particulate matter by accretion reactions - 2. Dialdehydes, methylglyoxal, and diketones. *ATMOSPHERIC ENVIRONMENT*, **39**, 6597–6607, https://doi.org/10.1016/j.atmosenv.2005.07.056.

Barsanti, K., and J. Pankow, 2004: Thermodynamics of the formation of atmospheric organic particulate matter by accretion reactions - Part 1: aldehydes and ketones. *ATMOSPHERIC ENVIRONMENT*, **38**, 4371–4382, https://doi.org/10.1016/j.atmosenv.2004.03.035.

Book Chapters

Alvarado, M. J., Barsanti, K. C., Chung, S. H, Jaffe, D. A., Moore, C. T. Chapter 6: Smoke Chemistry in Wildland Fire Smoke in the United States: A Scientific Assessment. Peterson, D. L., McCaffrey, S. M., Patel-Weynand, T. eds., Springer, 2021

Carlton, A., Barsanti, K., Wiedinmyer, C., Afreh, I. Detailed Characterization of Organic Carbon from Fire: Capitalizing on Analytical Advances to Improve Atmospheric Models. In: Multiphase Environmental Chemistry in the Atmosphere, A. Laskin ed., ACS Books, 2018

F. Relevant Invited Talks (since 2015)

Atmospheric Chemical Mechanisms Conference, Keynote. Title: *Considering Multiple Dimensions of Complexity in Atmospheric Chemistry Models*, December 2022

Telluride Science Meeting on Organic Particles in the Atmosphere. Title: L*inking Gas-Phase Chemistry and SOA Formation in Model Parameterizations*, July, 2022

University of California Irvine Seminar. Title: *Linking Comprehensive VOC Measurements, Secondary Pollutant Formation, and Highly Parameterized Air Quality Models*, virtual, April 2021

University of Colorado Boulder Seminar. Title: *Managing Chemical Complexity in Highly Parameterized Air Quality Models*, virtual, March, 2021

American Geophysical Union. Union Session. Title: *Early Implications of the COVID-19 Shelter-in-Place Restrictions on Urban Air Quality in the Los Angeles Basin*, virtual, December, 2020

CMAS: Community Modeling and Analysis System. Plenary. Title: *New Methods for Achieving a Detailed Chemical Inventory of Wildland Fire Emissions,* virtual, October, 2020

California Fire Science Seminar Series. Title: *Managing the Chemical Complexity of Wildland Fire Emissions in Highly Parameterized Air Quality Models,* virtual, October, 2020

NOAA Climate Program Office.Title: *Fingerprinting Fires to Improve Predictions of Air Pollutants*, virtual, November, 2019

Mountain Studies Institute. Title: *Fingerprinting Fires to Improve Predictions of Air Pollutants*, Durango, CO, November, 2019, (presentation and panel discussion)

Atmospheric Chemistry Gordon Research Conference. Discussion Leader. Title: *The Chemical Evolution of Aerosol Physical Properties*, Newry, ME, July 2019

Atmospheric Chemical Mechanisms Conference. Title: *Developing Reactivity- and Source-Based Monoterpene Parameterizations for Secondary Organic Aerosol Modeling*, Davis, CA, December 2018

Society of Environmental Toxicology and Chemistry (SETAC) Annual Speaker, Baylor University Student Chapter. Title: *Embracing Chemical Complexity in Predictive Models of Secondary Organic Particulate Matter from Biomass Burning*. Baylor, TX, April 2018

Informal Symposium on Kinetics and Photochemical Processes in the Atmosphere. Title: *Managing Chemical Complexity in Predictive Models of Secondary Organic Aerosol*. Pasadena, CA, March 2018

Living the Promise UCR Development Campaign Chancellor’s Event. Title: *Transformational Changes in Air Quality Science and Engineering Research*, San Francisco, CA, March 2018

Mountain Studies Institute. Title: *Smoky Air: Should We Care?* Pagosa Springs, CO, March 2018 (presentation and panel discussion); Durango, CO, March 2018 (presentation)

UCR Board of Trustees. Title: *Understanding Impacts of Wildfires and Vehicles to our Environment and Health*, Riverside, CA, February 2018

Horiba CONCEPT Meeting. Title: *Developing New Resources to Meet Future Air Quality Management Challenges and Requirements*. Riverside, CA, February 2018

International Aerosol Modeling Algorithms Conference. Title: *Integrating Biomass Burning Emissions Measurements and Predictive Models of Secondary Organic Aerosol Formation*, Davis, CA, December 2017

Berkeley Atmospheric Science Center Seminar. Title: Embracing Chemical Complexity in Biomass Burning Emissions and Mechanistic Models. Berkeley, CA, February 2017

Gordon Research Conference-Biogenic Hydrocarbons and the Atmosphere. Title: *Partitioning of Speciated Organics from Breathing to Burning*. Girona, Spain, July 2016

Department of Atmospheric Sciences Seminar, Colorado State University. Title: *Exploring Chemical Complexity in Biomass Burning Emissions and Air Quality Models*. Fort Collins, CO, March 2016

American Geophysical Union Annual Conference. Title: *Incorporating Detailed Chemical Characterization of Biomass Burning into Air Quality Models*. San Francisco, CA, December 2016

Sean M. Raffuse

Associate Director – Software and Data

University of California Davis, Air Quality Research Center

EDUCATION

Washington University in St. Louis, M.S., Environmental Engineering	2003
Washington University in St. Louis, B.S., Chemical Engineering	2001
Lewis and Clark College, B.A., Chemistry	2001

EXPERIENCE AND QUALIFICATIONS

Mr. Raffuse serves as the Principal Investigator for UC Davis' operation of the Chemical Speciation Network (CSN), which measures speciated particulate matter at over 130 sites across the United States. He oversees data management, data validation, and software development for the CSN, IMPROVE, and ASCENT programs. He has led the design and management of several large, complex web applications and software frameworks in the domains of air quality, smoke modeling, data validation, and data analysis.

Mr. Raffuse's research has focused on developing, improving, and applying fire and smoke models through the use of new data sets, research, and information systems, and developing and using satellite-derived data products. Mr. Raffuse is an expert on the modeling of pollutant emissions from fires. He has produced wild and prescribed fire emissions inventories (including greenhouse gases) for the U.S. Environmental Protection Agency (EPA), the U.S. Fish and Wildlife Service, and the U.S. Department of the Interior. He also served as Co-Investigator on the Smoke and Emissions Model Intercomparison Project (SEMIP), which was conducted to assess the uncertainties inherent in current wildland fire emissions and air quality modeling.

SELECT PUBLICATIONS

Raffuse, S., O'Neill, S., Schmidt, R. (2023) A model for rapid wildfire smoke exposure estimates using routinely-available data – rapidfire v0.1. *Geoscience Model Development* (preprint) 10.5194/egusphere-2023-1031

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EXHIBIT A6

CURRENT & PENDING SUPPORT

PI: M. Kleeman

Status (active or pending)	**Award #** (if available)	**Source** (name of the sponsor)	**Project Title**	**Start Date**	**End Date**
PROPOSED PROJECT		CARB	Using Integrated Observations and Modeling to Better understand Current and Future Air Quality Impacts of Wildfires and Prescribed Burns	1/1/2024	12/31/2027
ACTIVE	R01-ES031701	NIH/NIEHS	The CHARGE Study Phase II	5/1/2020	1/31/2025
ACTIVE	4979-RFA20-1B/21	HEI	Ambient Air Pollution and COVID-19 in California	4/1/2021	12/31/2023
ACTIVE	R01-ES033413-01	NIH/NIEHS	Extreme weather, air pollution, and stroke among an aging female population	1/1/2021	12/31/2023
ACTIVE	R01-AG074347-01	NIH/NIEHS	Extreme weather-related events and environmental exposures in the risk for Alzheimer's disease and related dementias		
ACTIVE	NOA 1RF1NS130659-01	NIH/NIEHS	Do atmospheric ultrafine particles lodge in the brain and cause cognitive decline leading to Alzheimer's Disease Related Dementias?	12/1/2022	11/30/2027
ACTIVE	2021-51181-35862	USDA	Smoke taint risk from vineyards exposed to wildfire smoke: Assignment and management strategies.	1/1/2022	12/31/2025
ACTIVE	RD84048401	EPA	Early Life Vulnerability to Climate-driven Wildfire Events on Pregnancy and Child Development Health Outcomes in Underserved Populations		

ACTIVE		Climateworks	Alternative Jet Fuel in California – Modeling LCFS Policy Scenarios and Air Quality Impact Considerations in the 2030 Timeframe	8/1/2021	12/31/2023
ACTIVE	19-RD012	CARB	Direct Measurements of Ozone Sensitivity to Oxides of Nitrogen and Volatile Organic Compounds in the South Coast Air Basin	8/1/2019	8/31/2023
ACTIVE	21-TTD004	CARB	Updated welding toxic emissions estimates in California	7/1/2022	6/30/2024
ACTIVE	22-ISD010	CARB	Evaluation of Air Toxics, Metals, and VOCs Found in Biogas, Biomethane, and their Combustion Products	6/1/2023	5/30/2026
ACTIVE		LADPH	Aliso Canyon Community Exposure and Health Study	11/1/2022	10/31/2025
ACTIVE	22AQP001	CARB	Updating California Temporal Profiles	7/1/2022	6/30/2024

PI: K. Bein					
Status (active or pending)	**Award #** (if available)	**Source** (name of the sponsor)	**Project Title**	**Start Date**	**End Date**
PROPOSED PROJECT		CARB	Using Integrated Observations and Modeling to Better understand Current and Future Air Quality Impacts of Wildfires and Prescribed Burns	1/1/2024	12/31/2027
ACTIVE	R01ES02667 0	NIH/NIEHS	Air pollution, atherosclerosis, and the role of the aryl hydrocarbon receptor	3/1/2019	2/28/2024
ACTIVE	P30ES02351 3	UCD NIEHS Environmental Health Sciences Center	Wildfire toxicology: fingerprinting toxicological triggers in wildfire emissions	4/1/2021	9/30/2023
ACTIVE	RF1AG07470 9	NIH/NIEHS	Traffic-related air pollution exacerbates AD-relevant phenotypes in a genetically	5/1/2021	4/30/2026

			susceptible rat model via neuroinflammatory mechanism(s)		
ACTIVE	R21ES033460	NIH/NIEHS	Epigenetic crossroads of environmental exposures and early-life adversity	10/1/2021	9/30/2023
ACTIVE	P30CA093373	UCD P30 Comprehensive Cancer Center	Assessment of wildfire smoke exposures and the risk of lymphoma development: possible role of the Ah-receptor as a central mediator	9/1/2022	8/31/2024
ACTIVE	U54OH-007550-21	National Institute of Occupational Safety & Health	Assessing the impact of co-exposure to agricultural and wildfire emissions on California farmworker health	9/30/2022	9/29/2027
ACTIVE	R01NS130659-01	National Institute of Neurological Disorders and Stroke	Do atmospheric ultrafine particles lodge in the brain and cause cognitive decline leading to Alzheimer's disease related dementias?	12/1/2022	11/30/2027
ACTIVE	R01ES033472	National Institute of Environmental Health Sciences	Synergistic effects of stress and traffic-related air pollution on cardiovascular health	2/1/2023	1/31/2026

PI: K. Barsanti

Status (active or pending)	**Award #** (if available)	**Source** (name of the sponsor)	**Project Title**	**Start Date**	**End Date**
PROPOSED PROJECT		CARB	Using Integrated Observations and Modeling to Better understand Current and Future Air Quality Impacts of Wildfires and Prescribed Burns	1/1/2024	12/31/2027
ACTIVE		UC Lab Fees	Transforming Prescribed Fire Practices for California	3/1/2020	2/28/2024
ACTIVE		CARB	Understanding and Mitigating Wildfire Risk in California	1/1/2020	12/31/2023
ACTIVE		NSF	Mechanistic Studies of Secondary Organic Aerosol Production from Biomass Burning Derived Precursors	1/1/2018	8/31/2023

EXHIBIT A7

THIRD PARTY CONFIDENTIAL INFORMATION REQUIREMENT

CONFIDENTIAL NONDISCLOSURE AGREEMENT

(Identified in Exhibit A, Scope of Work – will be incorporated, if applicable)

If the Scope of Work requires the provision of third party confidential information to either the State or the Universities, then any requirement of the third party in the use and disposition of the confidential information will be listed below. The third party may require a separate Confidential Nondisclosure Agreement (CNDA) as a requirement to use the confidential information. Any CNDA will be identified in this Exhibit A7.

Or

Exhibit A7 is not applicable for this Agreement.

EXHIBIT E

SPECIAL CONDITIONS FOR SECURITY OF CONFIDENTIAL INFORMATION

If the Scope of Work or project results in additional legal and regulatory requirements regarding security of Confidential Information, those requirements regarding the use and disposition of the information, will be provided by the funding State agency in Exhibit E. (Please see section 8.E of Exhibit C.)

OR

Exhibit E is not applicable for this Agreement.

Attachment A

UCD Response to Reviewers' Comments

Responses to Reviewer Comments on UCD proposals

"Using Integrated Observations and Modeling to Better Understand Current and Future Air Quality Impacts of Wildfires and Prescribed Burns"

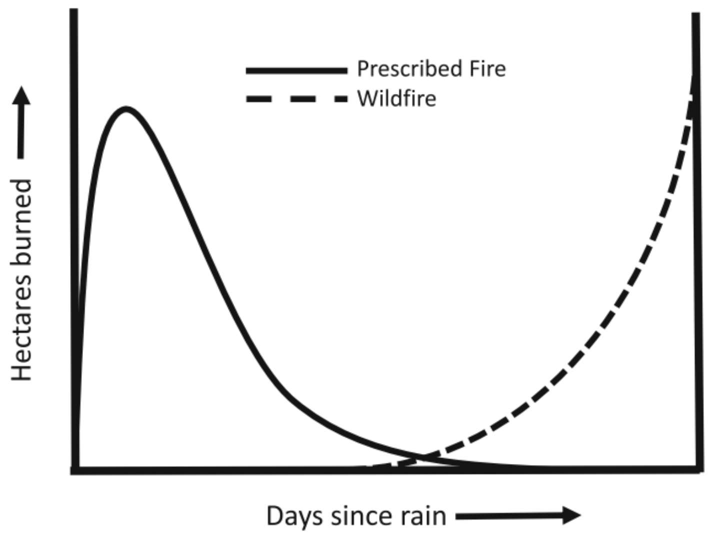
October 10, 2023

Reviewer #1

General comments:

R1C1: Prescribed fire (Rx) vs. wildfire (WF): For the purposes of this analysis, I think it work considering keeping the distinction between Rx fire and wildfire specific and physically based. Recommend being more specific about the physical process (e.g., spread rate, fire intensity/behavior, and/or daily emissions) if generalizing about the differential effects of Rx vs Wildfire, and building into the analysis and conclusions the principle that Rx fire is really just a planned subset of that larger wildfire-driven spectrum of fire behavior and smoke impacts from fire that occurs on the wildlands. For example, any quantitative work trying to make concrete distinctions between Rx vs wildfire should focus on the days of WF spread that truly would never occur under planned Rx conditions. Impacts that occur during days/periods that are intermediate on that fire spread/behavior spectrum, where either "sporty" Rx fire or "mellow" wildfire could have caused them, should be identified. This will make the results of this research more useful as agencies consider upping the pace and scale of prescribed burns.

Response: In the context of this proposal, clear distinctions between wildfires and prescribed fires can be made based on fuels consumed and associated emission factors and, as noted, meteorological conditions. For the specific example of fuel consumption, there is statistically significant differences in the amount of canopy consumed during prescribed fires vs. wildfires, which results in different emission factors for prescribed burns and wildfires. In the context of meteorological conditions, the figure below from Hiers et al. nicely demonstrates the clear distinction between key meteorological indicators (e.g., temperature, RH, wind, **precipitation**) and area burned in prescribed fires vs. wildfires. Consultations with Cal Fire and UC Berkeley ANR, particularly Rob York, will also be useful in this regard.



These concepts have been summarized in statements added to the introduction paragraph three.

Specific Comments:

R1C2: Page 5, "support from CalFire": should be defined-- hopefully that operational assistance Calfire will provide can include an operational assessment of what portions of the fuelbeds being fed into the BlueSky framework are likely to burn, and which are not, so that the inputs reflect realistic fuel consumption and resulting emissions. Otherwise, we risk some substantial overestimation of emissions, especially on the Rx side. Recommend postfire confirmation of those assumptions with some of the monitoring work that Joe Restaino et al. do for CalFire, if possible.

Response: The evaluation of vegetation maps / models and of consumption models is beyond the scope of this project. That said, the contractors have some experience in these areas and can bring that knowledge to bear in this project. Emissions inputs can be modified prior to their use in the modeling simulations to account for any known under/overestimates associated with fuel loading and/or consumption. These objectives are added to the second paragraph of the "Modeling Platforms / Emissions Algorithms" section.

R1C3: Page 5, "Consumption will be modeled with the Consume model": The older smartfire algorithms don't integrate the different fuelbeds in a polygon across space, but instead "pick" a representative 30x30 pixel at the centroid of a polygon (e.g., the daily growth polygons that presumably will be the basis for the modeling). Sometimes in heterogeneous areas, or over large polygons, this can result in erroneously high or low emissions estimates that also diverge from reality. If this is an issue with the estimates being used, how will it be dealt with?

Response: One of the benefits of the SMARTFIRE/BlueSky frameworks is the modularity: the description of the fuels is independent of the choice of consumption model in SMARTFIRE/BlueSky. For this contract, we will not be using polygon centroids to assign fuels. Daily fuel assignments will be done in one of two ways. If daily progression maps are available, we will intersect those with fuel maps to produce daily area burned by fuel bed. If only final perimeters are available, we will use satellite fire detects to apportion overall burning into daily activity. In that case, each detection will be intersected with the fuel map to produce a representative sample of fuel beds. These points are clarified in the second paragraph of the "Modeling Platforms / Emissions Algorithms" section.

R1C4: Page 5, Table 1: The study appears to assume fuel moistures from soil moistures…These assumptions should be checked against representative operational RAWs and fuels stick data commonly available during the management of the chosen Rx and wildfire events to ensure they are in the right ballpark.

Response: This is an excellent idea. Fuel moisture is a critical difference between Rx and WF emissions. Within the limited scope of this project, we will develop the best available fuel moisture information given the combination of soil moisture, operational RAWs, and meteorological models. This objective is added to the second paragraph of the "Modeling Platforms / Emissions Algorithms" section.

R1C5: Page 6, Plume Rise Predictions: Sanity checks for plume rise from these two modeling approaches can often come from alert wildfire webcams that now cover most of California's flammable landscapes. Also, incident meteorologists routinely track plume height on the most extreme wildfires with radar-based tools—for the operational portion of this work, it would be a good idea to make sure the modeling is reasonably tracking such observations.

Response: We have updated the section "Plume Rise Predictions" to acknowledge these additional potential data sources and to clarify that the input data will be divided into training a verification datasets to enable a statistical analysis of the updated plume rise model.

R1C6: Page 9, Task 1, general sampling locations: I don't see mention of the Sierra Nevada here…is it the intent of this project only to cover the north and south, but not Central California? Lots of the largest, most serious impacts have occurred when smoke fills the Central Valley from Sierra Nevada fires, so might be worth reconsidering.

Response: Thank you for pointing this out, it was not an intended omission. We are certainly interested in sampling wildfires throughout the Sierra Nevada's and will actively pursue those opportunities as they arise and as appropriate. Sierra Nevada added to Task 1 description.

R1C7: Page 9, Task 1, sampling strategies/advisory committee/"Upwind": Impacts of the larger wildfires (and even some large Rx fires) can manifest far away, so an important pillar of the sampling strategy should be that you try to figure out where the longer-range impacts are likely to go. Recommend ensuring that an Air Resource Advisor (https://www.wildlandfiresmoke.net/ara) is connected to this advisory group and that both localized and regional impacts beyond the immediate area are sampled, where and when possible. Also note that, especially for wildfires, "upwind" sampling of wildfire will also need to key off of the smoke forecast coming from wildfires, especially the larger ones where "upwind" might be out of state! Finally, most large fires seem to be occurring in concert with other large fires, and the plumes often merge. How will apportionment between the different fires be handled if that's the case?

Response: This point is well taken, and an ARA will be included on the advisory board as suggested (description added in second paragraph of Task 1). Resource constraints dictate that we can only collect samples with a single team. We have a two-tiered sampling strategy: *(1)* onsite at the discretion and direction of incident command and *(2)* downwind of plume touchdown based on smoke forecasting models and real-time data. The former tends to de-risk the probability of sampling success but may not always be viable. In that case, the second approach will be pursued. In fact, that has been the strategy in previous deployments and experience has shown that it is common for areas to be heavily impacted by wildfire emissions for periods of days, making it an easy sampling target. Ultimately, these decisions will be made at the time of the incident based on the best available information and under advisement from the board. Our strategy for measuring background concentrations will be to either remain onsite until plume impact subsides or use an historical average of measured and modeled data. Both approaches have been used in previous studies. Plumes merging, in general, should not be an issue for onsite sampling but could potentially be a factor otherwise. In the case of clustered wildfires, the sum over all active burn areas contributing to the plume will be used as the normalizing factor. Large plumes merging from very distinct wildfires, although possible, is less likely and not a sampling priority so will be avoided as conditions allow.

R1C8: Page 11, second to last paragraph, Rx scenarios to mitigate wildfire impacts: Will the statistical representation also include daily acres and emissions for the wildfire vs the Rx fire? This would be important to have to understand how realistic the scenarios would be.

Response: Yes. To the extent that these differences are well understood and clearly differentiable between wildfires and prescribed burns, these will be taken into account when defining the scenarios. Clarified in the second to last paragraph.

R1C9: Page 11, last paragraph-top of page 12: For practitioners, it might be useful to summarize the degree to which reducing daily emissions reduces concentrations and public health impacts downwind. Often the mitigations proposed for reducing smoke impacts is reducing emissions, but sometimes this is not effective. And sometimes doubling acres/emissions doesn't necessarily increase impacts. Quantitative demonstrations of this principle from the data being produced would be potentially useful for operations and planning.

Response: We agree with the reviewer that the wildfire impacts may not be proportional to the wildfire size for all of the reasons discussed in the proposal. Our measurements and modeling will attempt to quantify impacts under wildfire and Rx burn scenarios.

R1C10: Page 12, top of page: Per my general comments at the top, daily emissions and spread rates overlaps at the upper end of the Rx scale and the lower end of the wildfire scale, so it might be useful make sure that we summarize impacts by the spectrum of daily emissions/smoke production as well as by fire type (e.g., Rx vs. WF)

Response: We can summarize the total smoke emissions (kg/hr) for all wildfires and Rx burns to help put the results in context relative to the spectrum of current wildfires. Clarified in paragraph.

R1C11: Page 14, Deliverables: Recommend daily emission (even hourly) emission also be archived so we have a good start in putting future fires in context with these intensively studied fires on that yardstick. Also, documenting whether and when impacts were linearly related to emissions (e.g., emissions reduction would have caused significant impact reduction) vs when and where impacts were somewhat decoupled from daily emissions (and why) would help immensely from an operational perspective as a deliverable that could directly inform operations and planning.

Response: All emissions inventories produced in the project will be archived and made available to CARB for wider distribution (clarified in Deliverables Section). We will analyze the relationship between emissions and impacts for all the wildfire and Rx burn scenarios, but it may not be possible to derive a simple relationship since there are multiple complex factors at play.

Reviewer # 2

The research proposal demonstrates a comprehensive understanding of the topic, and the research questions are well-defined and relevant to the field of study. The researcher's prior experience in conducting field studies and working with complex models is evident, providing confidence in the team's ability to execute the project successfully. The research proposal shows promise in comparing smoke from prescribed burns and wildfires.

However, there are some areas that could benefit from further clarification and elaboration. Specifically:

R2C1: Page 2: The proposal mentions studying the emissions and chemical composition of both fresh and aged smoke from prescribed burns and wildfires. However, it's not clear from the proposal if there are specific plans for measuring aged smoke. It would be helpful to provide more details on the methodology and instruments that will be used to measure aged smoke and how it will be differentiated from fresh smoke.

Response: Sampling primary wildfire emissions is the priority objective of this study. However, we do recognize the potential for atmospheric processing when sampling downwind of plume touchdown. Smoke plume aging depends on transport times and background conditions. Ultimately, smoke plume age will be evaluated post hoc. We will differentiate chemical signatures of primary versus aged wildfire emissions to the degree possible, but the measurement program will not be designed around this objective. We will also rely on our modeling efforts and prior measurement-modeling efforts concerning fresh vs. aged smoke from fires to address this dimension of the research.

R2C2: Page 6: FINN model uses satellite-based active fire products. Providing more information on how the model will generate separate emissions estimates for wildfires and prescribed burns.

Response: Emissions of each pollutant In FINNv2.5 are calculated as the product of the area burned at location *x* and time *t*, the biomass at location *x*, the fraction that is burned, and the EF for each pollutant. The burned area, as a function of time, is based on individual fire detection and in this way, prescribed fires and wildfires in present-day simulations can be easily separated. Biomass (i.e., fuel) is based on the International Geosphere-Biosphere Programme (IGBP) classification and includes 16 cover types. Currently, the EFs do not account for differences in wildfires and prescribed burns, but these can easily be changed in the FINNv2.5 model framework. These points updated in last paragraph of "Emissions Algorithms" Section.

R2C3: Page 9: The proposal mentions conducting measurements in at least two wildfires and two prescribed burns over the first two years of the project. However, it might be beneficial to discuss with the research team the potential scenarios of different fire numbers and assess if these scenarios align with the overall scope of the project. This could ensure that the study's objectives are adequately addressed and that sufficient data are obtained for robust conclusions.

Response: The timeline and budget of the project limits that number of fire events that can be sampled. We recognize that the measurements alone will likely not cover the full spectrum of fires that occur in California. We will quantify the uncertainty in our measurements and recommend additional future measurements if they would strengthen the analysis. We will certainly attempt to sample as many fires as funds allow but are confident that at least two wildfires and two prescribed burns can be achieved.

R2C4: Page 9: The proposal mentions the field deployment plan for wildfires, with a minimum of two days per sampling event and the ability to sample for up to ten consecutive days. It would be helpful to provide a rationale for selecting this specific duration. Explaining the reasoning behind the chosen sampling duration would add clarity to the research design.

Response: Thank you for bringing this to our attention. This range is based on past experiences sampling wildfires where the impact at a specific sampling location has lasted anywhere from 2 to 10 days. For example, the 2017 Northern California Firestorm impacted the Bay Area for only a couple of days while the Camp Fire impact lasted 10 days. The intent is to remain at the sampling site until the emissions subside sufficiently for background measurements to be made. A secondary objective is to measure the full spectrum of combustion phase (flaming to smoldering) for specific fires as opportunity allows, which may require additional time or relocation. In this case, additional supplies and samples can be ferried to and from UC Davis as needed. Clarified in the last paragraph of the "Fire Selection and Sampling Strategies" Section.

R2C5: Page 9: The proposal mentions conducting retrospective simulations, but it is not explicitly stated which wildfires or time periods will be used for these simulations. Providing more details about the selection criteria for the wildfires and the time period under consideration would enhance the proposal's coherence.

Response: The 10-year retrospective simulations period will consider all wildfires in the previous 10 years (Clarified in first sentence of Task 2). This window includes most of the largest wildfires in recent California history. The project will focus on a subset of fires that had the most accurate model representation based on a comparison to ground based measurements and the greatest public health impact based on BenMap calculations.

R2C6: Page 10: The proposal mentions using the CARB emission inventory data as a base but lacks a specific reference to this data source. It would be essential to provide the appropriate reference for the emission inventory used. Additionally, a justification for selecting the 2020 emission inventory as the base year should be included. Furthermore, details about the dataset and any potential limitations, would strengthen the proposal.

Response: The UCD research team actively collaborates with CARB emissions and modeling groups on multiple projects related to emissions inventory development. CARB provided the 2020 emissions inventory based on a CEPAM 2019v1.03 Planning Inventory. The yearly changes to these emissions inventories can be estimated using emissions trends available on the CEPAM website (https://ww2.arb.ca.gov/applications/cepam2019v103-standard-emission-tool). Clarified in third paragraph of Task 2.

Base emissions inventories use spatial surrogates to allocate area-source emissions to geographic locations. This method should be accurate when averaging over large areas, but may be inaccurate over smaller domains. Many aspects of the emissions inventory are based on "average day" time patterns that do not account for accidents, unusual weather patterns, etc. Once again, these emissions are considered to be accurate when averaged over sufficiently long time periods, but they may be inaccurate over shorter times. Clarified in third paragraph of Task 2.

Further details of the CARB emissions inventories can be provided by the CARB emissions group.

R2C7: Page 10: The proposal states that FB values (fractional bias) will be limited to the range between +2 and -2. It is important to explain the rationale behind this specific range selection. Justifying this choice will help readers understand the significance and implications of the selected FB range for evaluating model performance.

Response: Fractional bias is defined as

$$FB = 2\left(\frac{M-O}{M+O}\right)$$

Where *M* is the model prediction and *O* is the measured value. The equation cannot take on values outside the range of +2 and -2. RFR predictions for fractional bias do not use the equation above, but rather they predict fractional bias based on an internal decision tree that may occasionally predict values outside the constrained range. In these cases, the predicted FB must be constrained to theoretical limits prior to correcting the model prediction. Clarified in the Task 2 description.

R2C8: Page 14: It is recommended to encourage the authors to consider making their code open-source, if possible. Open-source code promotes transparency and reproducibility, allowing other researchers to verify and build upon the study's findings.

Response: We will publish all model input data and output files in a public repository for use by other researchers. Certain model codes are community tools that are freely available to the public (BlueSky, SMOKE, WRF, MUSICA). The UCD/CIT CTM was developed as a research tool and so it does not currently have training / instruction manuals that would be needed for new users. We are happy to provide a copy of the UCD/CIT source code to expert modeling staff at any public agency, but we are not resourced to create a true public domain copy of this model.

Reviewer # 3

In reviewing the UCD-NCAR full proposal I used some scratch paper to diagram the workflow outlined in the SOW — Just to help me visualize. Including a workflow diagram would be helpful to reviewers.

Response: Project workflow diagram added as Figure 1.

R3C1: Page 3. Smoke Exposure Frequency, Duration, and Intensity. Comment: there are varieties of Rx burns. The basic split are broadcast vs pile burns. The acreages involved vary too. I don't have a feel for representative "acreage bins", but probably they can be gleaned from various the FRAP interagency Rxburn GIS layer in firep221.gdb ("Historic Fire Perimeters 2022" GIS Mapping and Data Analytics | CAL FIRE), CalFire's new permitting system, the USDA-FS FACTS geodatabase, etc. Rob York and Scott Stephens also may have insight into whether the public land managers envision deploying Rx burns whose acreages are larger than what they've traditionally done.

Response: These are good suggestions for getting representative ranges of acreages for broadcast and pile burns. Thank you. Text under "Smoke Exposure Frequency, Duration, and Intensity" updated to note these dimensions of the problem.

R3C2: Page 4: Biomass burning is an important source of methyl halides. Will this project include methyl chloride?

Response: Methyl chloride is represented in the MOZART gas-phase chemical mechanism that is used in the MUSICA model system. Haloalkanes in general, and methyl chloride specifically, will be included in the chemical analysis of the gas phase samples collected during wildfire sampling. Additional detail provided under section on "Chemical Characterization".

R3C3: Page 5. There's some text below Table 1, about Table 2 which reads "…The biomass values are from…" However, it doesn't appear that there are biomass values (aka fuel loading?) in Table 2. Emission factors, yes. It seems it got lost.

Response: This was a typo and we thank the reviewer for catching this error. The sentence should read:

The emission factors are from the First Order Fire Effects Model (FOFEM)[30] and are based on Urbankski et al.[31], which are also included in the SERA database.

R3C4: Page 6. Plume Rise Predictions. Middle paragraph where it reads "…a RFR training dataset will be created for wildfires in California…" Might want to add that after the training, the PIs will test the smarter plume rise approach against some observations, say, MISR-based estimates. Another plume rises related question: will plume rise from Rx burns get looked at too?

Response: We agree with this suggestion and will conduct the tests against observations. Section on Plume Rise Predictions has been updated.

R3C5: Page 11 bottom. So just making sure I follow…the wildfire vs Rx burn scenario modeling - with chemistry, dispersion, plume rise & aging etc. (and feeding into BenMap)- will be done solely using MUSICAv0 (this I glean from Table 4). Also, further down the page, consulting with Rob York and other fire folks of UCB/UC ANR will be key, to figure out schema for assuming that Rx burn activity at level X can reduce probability of and extent of a future wildfire by factor Y. (Kind of like those SPLATS that Mark Finney envisioned: scattered treatments conferring protection to adjacent untreated areas, in that treated areas can serve to slow wildfire spread).

Response: That is correct. Thank you also for the reminder about the SPLATS concept from Mark Finney.

Reviewer # 4

R4C1: Page 5 says, "Satellite-based active fire products (MODIS, VIIRS, GOES-ABI) will be used to determine area burned" within CTM emission algorithms. Page 9 says that "wildfire area burned will be derived from historically mapped perimeters," with satellite-based active fire products used only to apportion the area burned within specific days.

The latter method described on Page 9 is much more appropriate for fire emissions than the method on Page 5, particularly for small fires like prescribed burns. Satellites often detect false positives and have low spatial resolution. Can you please articulate when the satellite-only method on page 5 will be used for fire perimeters?

Response: Thank you for spotting this. There is an error in the description on page 5 and the language on page 9 is correct. Area burned will be derived from historically mapped perimeters from the CAL FIRE Fire and Resource Assessment Programs GIS database. We will then use satellite-based active fire products (MODIS, VIIRS, GOES-ABI) to apportion the area burned within specific days.

R4C2: Have you looked into using GridMET data to augment your meteorological model initialization? https://www.climatologylab.org/gridmet.html

Response: Thank you for the suggestion – we will consider GridMET data in our analysis.

R4C3: Page 9: Field Deployment: How will prescribed fires be selected? Prescribed fires come in a range of sizes, intensities, ecosystems, etc. Your results will vary depending on which Rx fires are chosen.

Response: Prescribed fires will be targeted based on input from an advisory board, and as opportunity allows, with the primary objective of being as broadly representative of projected burn scenarios as possible, including frequency, area burned, and biotic zone. As stated above, we are ultimately constrained by the budget but will pursue as many sampling opportunities as funds allow. Clarified in first paragraph of Task 1.

R4C4: What is the plan for field sampling in terms of how close the sampling will occur to the fires and how the researchers will choose where to drive during the fires? The vehicles used for mobile sampling do not look like all-terrain vehicles. What's the plan if it is difficult to sample near the fires with low-clearance vehicles?

Response: Our sampling strategy is detailed in the response to comment 7 from reviewer 1 (R1C7).

R4C5: Page 11: "We will consult with Rob York of UC Berkeley/UC ANR to develop realistic prescribed burn scenarios including location, duration, and timing of the burns, as well as the extent to which they are likely to reduce the frequency and severity of wildfires over that time period."

I highly suggest you model a range for each of those parameters, as the true values are uncertain and dependent on stochastic events. For example, catastrophic wildfire may occur in an area that was previously prescribe burned if the weather conditions are extreme, the upstream fire behavior is intense, and/or the prescribed fire was low intensity.

Response: While we completely agree with your comments and suggestions, the number of modeling scenarios is constrained by the resources available for this contract. We will do our best to represent the stochastic nature of both wildfires and prescribed burns. Clarified in second last paragraph of "Design Prescribed Burn Scenarios to Mitigate Wildfire Risk".

R4C6: Page 12: "Statistical analyses will be performed to determine the extent to which wildfires and prescribed burns result in differential health impacts within the variability of the model predictions."

What types of statistical analyses are you planning to perform? Interpretation of statistical results like P-values can be tricky when you're testing model results rather than raw data.

Response: The mean and standard deviation of population exposure to smoke will be calculated during multiple wildfires and prescribed burns. Hypothesis tests and confidence intervals will be used to determine if population exposure to smoke is reduced during scenarios that adopt prescribed burns. Clarified in last paragraph of "Design Prescribed Burn Scenarios to Mitigate Wildfire Risk".

Reviewer # 5

R5C1: Identifying prescribed fire testing locations — strongly recommend using the same locations (if possible) as that of the wildfire testing sites. In doing so the potential variability in types of vegetations burned and other factors could be reduced to better compare emissions from the two types of fires.

Response: We appreciate this reviewer's suggestion and understand the concern. Based on our prior efforts, the differences in emissions between wildfires and prescribed fires due to differences in vegetation is likely small relative to other variables (e.g., wind speed and direction), particularly when considering total pollutant levels and exposure. We believe that developing a set of scenarios that represents the parameter range(s) for wildfires and prescribed burns, as a function of time, will give the best estimate of the extent to which wildfires and prescribed burns result in differential health impacts.

R5C2: Compositions and concentrations of compounds vary with distance from sources. Suggest taking this into account when measuring pollutants during wildfires and prescribed fires to allow better comparison.

Response: Please see response to comment 1 from reviewer 2 (R2C1). Also, when intercomparing wildfire and prescribed burn measurements, although not a priority objective of our sampling efforts, data will be normalized by total, background-corrected carbon measured (CO_2 + CO + CH_4 + NMHCs + particulate C) as a proxy for carbon consumed by the fire (Clarified in last paragraph of Task 1). Note also that the modeling efforts will include analysis of fresh and aged smoke.

R5C3: For continuous emissions monitoring, among others, TSI DustTraks (TSI 8533 DRX) is planned to be used to measure concentrations of four PM fractions including PM2.5. For chemical characterization, PM samples will be collected on Teflon filters for gravimetric and other analysis. Caution should be used that PM2.5 concentrations using TSI DustTracks (TSI 8543 DRX) is about twice as that of federal equivalent method. TSI 8533 is the earlier version of DRX with slightly higher than twice compared to the federal equivalent method.

Response: This is a good point, and we are aware of these measurement biases for optical particle counters in general and the DustTrak specifically. As noted, we will be collecting filter samples in parallel to the real-time measurements and gravimetric analysis of those filters will be used to calibrate the DustTrak data post-hoc, as recommended by the manufacturers (clarified in first paragraph of "Continuous Emissions Monitoring"). The gravimetric-based correction factor for PM2.5 will be applied to the other size fractions measured by the DustTrak based on the real-time ratios of those data to the PM2.5 channel with the assumption that the correction factors are linear with zero offset.

R5C4: We at CARB had issue with PM sampling during wildfires due to very high loading on filters resulting in instruments failure just when the most important data was needed. Suggest having a backup plan to get the most of this critical time if similar issue is encountered.

Response: We have encountered this issue previously as well and as discussed in the proposal, have incorporated multiport valve manifolds that actuate between a bank of PM and gas samplers in series based on timed sampling protocols to address this issue, as well as add temporal resolution to our composition measurements. For example, there is a bank of six PM2.5 samplers connected to a common valve manifold and the valves are programmed to actuate successively to allow four hours of sampling per channel over a 24-hr period. Filter samples are removed, and new filters inserted *in situ* to allow for continuous sampling. Sampling duration per channel can be varied according to conditions as necessary. Clarified in section on "Offline Gas and PM Sampling".

R5C5: The project describes the formation of an advisory committee which include CARB staff on the selection of locations and sampling events. Strongly suggest consulting district staff as they have a very good idea on site selections based on their experiences during the many wildfires they responded to. CARB staff follow district staff recommendations where to place mobile monitors during wildfire events.

Response: We agree that district staff would make a valuable contribution to the advisory committee. We will work with CARB/Calfire to choose geographic locations of particulate interest, and then invite district staff from those regions to join our advisory committee. Clarified in second paragraph of Task 1.

Reviewer # 6

R6C1: How will point one with respect to WUI fires be assessed? Selecting examples of where fires entered the WUI or one to one comparisons with non-WUI fires?

Response: The 10 year retrospective (described under Task 2) will capture both WUI and non-WUI fires. Single fire events have significant variability thus limiting the utility of one-to-one comparisons.

R6C2: It's not as simple as this because of the spatial and temporal aspect of exposure. How is this accounted for the study? Is it just a one to one comparison of prescribed fire smoke vs wildfire smoke?

Response: One of the advantages of the chemical transport modeling is that we are able to capture the spatial and temporal aspects of smoke. As noted above, due to variability in single fire events, we need to capture a range of fires (which can be done with the 10-year retrospective analysis) and capture characteristics of wildfires and of prescribed burns in the scenario modeling.

R6C3: In light of the recent study by Johnson and Garcia Menedez that showed high variability in predicting prescribed fire smoke how does this model compare to this? I make this comment based on the word "accurately".

Response: Johnson and Garcia-Menendez looked at uncertainty in smoke constituent concentrations, specifically PM2.5, and health-response functions. They found that both can be a significant source of uncertainty. We will rely on published health-response functions (e.g., in BenMap), but will address uncertainty in smoke-derived PM2.5 concentrations. By modeling a large number of fires, rather than individual fires, we will have a range of spatially- and temporally-resolved PM2.5 concentrations associated with fires. This will provide useful information to describe exposure on average as a function of fire/atmosphere characteristics, including those which differentiate wildfires and prescribed burns. The two models used in the Johnson and Garcia-Menendez manuscript were dispersion models, which do not include the same level of detail in emissions and do not include any secondary pollution formation. This is in contrast to the chemical transport modeling we will be doing. We may additionally benefit from a denser monitoring network, including PurpleAir sensors, in CA.

R6C4: Holder et al. just published a WUI emissions factor paper focusing mostly on WUI fires in CA. I saw this paper was referenced further down.

No response needed.

R6C5: Agreed, but one thing we've (EPA) has tried to stress is that this type of work ultimately informs public health messaging and the interventions we tell people to employ to reduce exposure.

Response: We agree that the scientific measurements and analyses eventually will need to be distilled into a public health message.

R6C6: This has only been initially demonstrated for long-term exposures and not short-term and the evidence is not entirely within the concentration ranges observed in the U.S.

Response: We acknowledge the health-response uncertainties associated with smoke exposure, including uncertainties associated with spatial and temporal aspects. We appreciate the epidemiological perspective, and we will keep these comments in mind as we evaluate hypothesis 4.

R6C7: The single exposure to high concentrations is more than likely over weeks in many cases.

Response: Please also see responses above. The modeling will allow us to capture these longer time periods.

R6C8: While informative, the CAIF study in some ways showed that the total AQ and health impacts of prescribed fire are less than wildfire. This seems a little similar to that. What we need to know or understand now is what are the total smoke and health impacts communities experience from the combination of prescribed fire and wildfire.

Response: We can certainly look at the summed exposure associated with wildfire + prescribed burn smoke. We hope to get a more realistic look with the future scenarios, in which the number of prescribed fires and areas burned increase in time, while the number of wildfires and areas burned decrease in time.

R6C9: How does this differ from CaDoH? They did the same thing in the Kramer et al. (2023) paper.

Response: The Kramer et al. manuscript provides some useful metrics that we can build on in the context of expanding prescribed burns to target levels. Similarly to the Johnson and Garcia-Menendez manuscript, Kramer et al. use a dispersion model (no chemistry). Our use of chemical transport modeling as described in the proposal adds multiple dimensions. To highlight some of those: we will use a detailed fire emissions inventory that differentiates wildfire and prescribed burn emissions, and we will track emissions of WUI fuels (Kramer et al. used the National Emission Inventory (NEI) and does not include most recent information on WUI emission factors), we will scale wildfire emissions in response to prescribed burns (Kramer et al. did not scale wildfire emissions), we will consider secondary chemistry and the formation of toxic compounds (which can't be considered in a dispersion model), and we will track ultrafine particulate matter and fine particulate matter (the former was not included in Kramer et al.).

R6C10: The exposure durations (i.e., length of exposures could be vastly different)..

Response: We agree. We can quantify exposure aspects like average, max, and duration, but we may not able to quantify mortality effects for short term exposures. We may be able to quantify ER visits, asthma incidence, etc. depending on what is available in BenMap.

R6C11: Focusing on short-term PM2.5 exposure and mortality doesn't seem like the correct outcome to focus on. While it's the one with the biggest public health impact, the more sensitive outcome is asthma ED visits. A better rationale as to why to focus on mortality in this case is probably needed.

Response: We agree that we should have listed other health effects beyond mortality. We will analyze all the public health outcomes that BenMap enables, including asthma, ER visits, etc.

R6C12: What types of differences between RX and wildfire are not routinely captured by other modeling systems?

Response: Differences in emissions between prescribed burns and wildfires are not routinely captured. This can include differences in injection height, diurnal profile, and the amounts and identities of compounds emitted (as represented by emission factors). These differences will subsequently affect predicted concentrations of PM2.5 and air toxics.