

Review

Recent Advances in Wildland Fire Smoke Dynamics Research in the United States

Yongqiang Liu ^{1,*} , Warren E. Heilman ², Brian E. Potter ³, Craig B. Clements ⁴ , William A. Jackson ^{5,†}, Nancy H. F. French ⁶ , Scott L. Goodrick ¹ , Adam K. Kochanski ⁴ , Narasimhan K. Larkin ³, Pete W. Lahm ⁷, Timothy J. Brown ⁸, Joshua P. Schwarz ⁹ , Sara M. Strachan ¹⁰  and Fengjun Zhao ^{1,11}

¹ Center for Forest Health and Disturbance, USDA Forest Service, 320 Green St., Athens, GA 30602, USA; scott.l.goodrick@usda.gov (S.L.G.); zhaofengjun1219@163.com (F.Z.)

² Northern Research Station, USDA Forest Service, 2601 Coolidge Rd., Suite 203, East Lansing, MI 48823, USA; warren.heilman@usda.gov

³ Pacific Wildland Fire Sciences Laboratory, USDA Forest Service, 400 N 34th St., Seattle, WA 98103, USA; brian.potter@usda.gov (B.E.P.); sim.larkin@usda.gov (N.K.L.)

⁴ Department of Meteorology and Climate Science, San Jose State University, 1 Washington Sq., San Jose, CA 95192, USA; craig.clements@sjsu.edu (C.B.C.); adam.kochanski@sjsu.edu (A.K.K.)

⁵ National Forests in North Carolina, USDA Forest Service, Asheville, NC 28802, USA; bill.jackson@emberalliance.org

⁶ Michigan Tech Research Institute, Michigan Technological University, 1400 Townsend Dr., Houghton, MI 49931, USA; nhfrench@mtu.edu

⁷ Fire and Aviation Management, USDA Forest Service, 201 14th Street, SW, Washington, DC 20024, USA; peter.lahm@usda.gov

⁸ Desert Research Institute, 2215 Raggio Pkwy, Reno, NV 89512, USA; tim.brown@dri.edu

⁹ Earth System Research Laboratory, National Oceanic and Atmospheric Administration, 325 Broadway, Boulder, CO 80305, USA; joshua.p.schwarz@noaa.gov

¹⁰ Idaho Department of Environmental Quality, 1410 N Hilton St., Boise, ID 83706, USA; sara.strachan@deq.idaho.gov

¹¹ Ecology and Nature Conservation Institute, Chinese Academy of Forestry, 2 Dongxiaofu, Xiangshan Road, Haidian District, Beijing 100091, China

* Correspondence: yongqiang.liu@usda.gov; Tel.: +1-706-559-4240

† This author was retired.



Academic Editors: Kyu-Myong Kim and Alexandros Papayannis

Received: 15 July 2025

Revised: 18 September 2025

Accepted: 28 September 2025

Published: 22 October 2025

Citation: Liu, Y.; Heilman, W.E.; Potter, B.E.; Clements, C.B.; Jackson, W.A.; French, N.H.F.; Goodrick, S.L.; Kochanski, A.K.; Larkin, N.K.; Lahm, P.W.; et al. Recent Advances in Wildland Fire Smoke Dynamics Research in the United States.

Atmosphere **2025**, *16*, 1221. <https://doi.org/10.3390/atmos16111221>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Abstract

Smoke plume dynamics involve various smoke processes and mechanics in the atmosphere and provide the scientific foundation for the development of tools to simulate and predict smoke and its environmental and human impacts. The increasing occurrence of wildfires and the demands for more extensive application of prescribed fires in the U.S. have posed great challenges and immediate actions for advancing smoke plume dynamics and improving smoke predictions and impact assessments to mitigate smoke impacts. Numerous efforts have been made recently to address these needs and challenges. This paper synthesizes advances in smoke plume dynamics research mainly conducted in the U.S. in the recent decade, identifies gaps, and suggests future research needs. The main advances include smoke data collections from comprehensive field campaigns, new satellite products, improved understanding of smoke plume properties and chemistry, structure and evolution, evaluation and improvement of smoke modeling and prediction systems, the development of coupled smoke models, and applications of machine-learning techniques. The major remaining gaps are the lack of comprehensive simultaneous measurements of smoke, fuels, fire, and atmospheric interactions during wildfires, high-resolution coupled modeling systems of these components, and real-time smoke prediction capacity. The findings from this synthesis study are expected to support smoke research and management to meet various challenges under increasing wildland fires and impacts.

Keywords: wildland fire; emission; smoke plume; field measurement; modeling

1. Introduction

Smoke plume dynamics is a discipline of wildland fire science connected with smoke features and processes and their interactions with the atmosphere and fires. Smoke plume dynamics provide the scientific principles for developing smoke modeling and prediction. For example, plume rise is an important smoke property that determines how far the species emitted from fires can be transported. A low plume rise indicates that the species likely remain within the atmospheric planetary boundary layer (PBL), a layer above the ground with dominant vertical mixing processes due to turbulence, eddies, and convections, and mainly affect local air quality. In contrast, a high plume rise indicates that the species likely penetrate the free atmosphere, the atmosphere layer above the PBL, dominated by horizontal movement, and are transported over a long range to affect regional air quality. Regional air quality models such as the Community Multiscale Air Quality (CMAQ) model [1] require specification of plume rise as an initial condition so that the species can be appropriately distributed at model layers above the fires, and the chemistry occurring within the smoke can advance under appropriate dilution/temperature/light-exposure conditions. In addition to heat flux from a fire, plume rise is dependent upon the buoyancy of smoke and the complex processes inside smoke plumes (e.g., merging of multiple updrafts), interactions with the ambient atmosphere (wind, thermal stability), fire-induced circulation, and interactions with the canopy (dragging, turbulence). Smoke plume dynamics research improves plume rise modeling by providing a sound scientific understanding of these processes.

Smoke plume dynamics can provide an understanding of smoke processes and allow for improvements in smoke and air quality impact modeling. Smoke particles, predominantly in the form of black carbon (BC) and organic carbon (OC), contribute remarkably to atmospheric particulates, while their gaseous emissions contribute substantially to the formation of secondary aerosols, which are also important to air pollution and haze [2,3]. The manner in which smoke is vertically and horizontally distributed via dynamical motions is thus also critical to influencing the chemical evolution not only of ozone, but also secondary aerosol species that have strong impacts on health [4]. Studies, such as the PM_{2.5} (particulate matter with diameter of 2.5 μm or smaller) and ozone concentrations in Eastern U.S. cities modified by smoke transport from Canada and the Western U.S. [5], the BC transport and deposition to the Arctic or to other snow and ice covered regions such as the high mountains [6], smoke penetration in the tropopause and mixing into the stratosphere [7], and smoke plume led photochemical reaction rates for ozone production [8,9], have shown regional and global air quality and climate impacts [10].

Modeling the smoke plume dynamics of wildland fires has broad impacts on decision-makers and society. Fire smoke has been associated with health issues of different population groups [11] and reduced visibility. Concerns about human health, work and school attendance, and visibility can impact the practices of land managers using prescribed fires to manage fuel loads and ecosystems. Air quality and land management agencies need to forecast ground-level concentrations of smoke-generated pollutants, identify smoke-sensitive targets, and communicate smoke-related air quality impacts to the public [12]. An understanding of plume dynamics and smoke chemistry is necessary to answer the public questions of “Where is the smoke coming from? How long will it last? How high are the concentrations? Should I worry?”. Accurate smoke forecasts help people change their behavior to mitigate smoke impacts on their health.

Wildfires have increased dramatically in North America in recent decades [13–15], leading to more severe smoke impacts, such as the closing of highways and schools [16]. Measurements and analyses of individual fire cases, including the 2023 Canada fires, and long-term fire activity have provided more evidence for the important contributions of fire emissions to air pollution in the U.S. [17–19]. Also, wildfire smoke has influenced PM_{2.5} trends from 2000 to 2022 in nearly three-fourths of the contiguous U.S. (CONUS) states [20].

The improvement of plume dynamics modeling capabilities is urgently required, and yet, it is a great challenge to improve the smoke modeling needed to support operational decision-making for assessing and mitigating smoke impacts, especially in regions with complex terrain and urban areas. Great efforts have been made recently to address this challenge. Many comprehensive field campaigns were implemented to collect smoke data together with fuels, fire behavior, and meteorology. Recent campaigns include the Western Wildfire Experiment for Cloud Chemistry, Aerosol Absorption and Nitrogen (WE-CAN) (https://www.eol.ucar.edu/field_projects/we-can, accessed on 14 July 2025), the Biomass Burning Fluxes of Trace Gases and Aerosols (BB-FLUX) (<https://volkamergroup.colorado.edu/timeline/field/bb-flux>, accessed on 14 July 2025), the Fire Influence on Regional to Global Environments and Air Quality (FIREX-AQ) [21], the Fire and Smoke Model Evaluation Experiment (FASMEE) [22,23], and the FIRELAB laboratory effort that advances understanding of the chemical processes occurring within plumes [21]. New satellite smoke products have been released with improved capabilities and resolutions in space and time. The data collected from field campaigns, laboratories, and satellites have been used to improve fire emission estimates, analyze smoke properties and evolutions, and evaluate and improve smoke modeling tools. Smoke modeling has been improved with the development and application of coupled modeling systems and machine-learning techniques [24,25].

This paper reviews the smoke plume dynamics research mainly conducted in the U.S. during the recent decade. The objectives are to describe advances in smoke measurement and modeling and identify knowledge gaps and future research needs. The findings are expected to support smoke plume research and applications to meet the current challenges of increased wildfire occurrence and intensity, prescribed fire needs, and smoke impacts.

2. Advances in Smoke Measurements

Figure 1 shows the major processes of smoke dynamics and plume chemistry, together with atmospheric interactions and environmental impacts. After being emitted from fires, smoke particles and gases move through the vegetation canopy, PBL, and sometimes into the free atmosphere via the processes of eddies, turbulence (see [26] for a comprehensive review of turbulence and wildland fires), dispersion and transport, plume rise, and chemistry. These processes are controlled by and feed back to atmospheric conditions and processes. Measurement and modeling studies of these processes are described in this and the following sections, respectively.

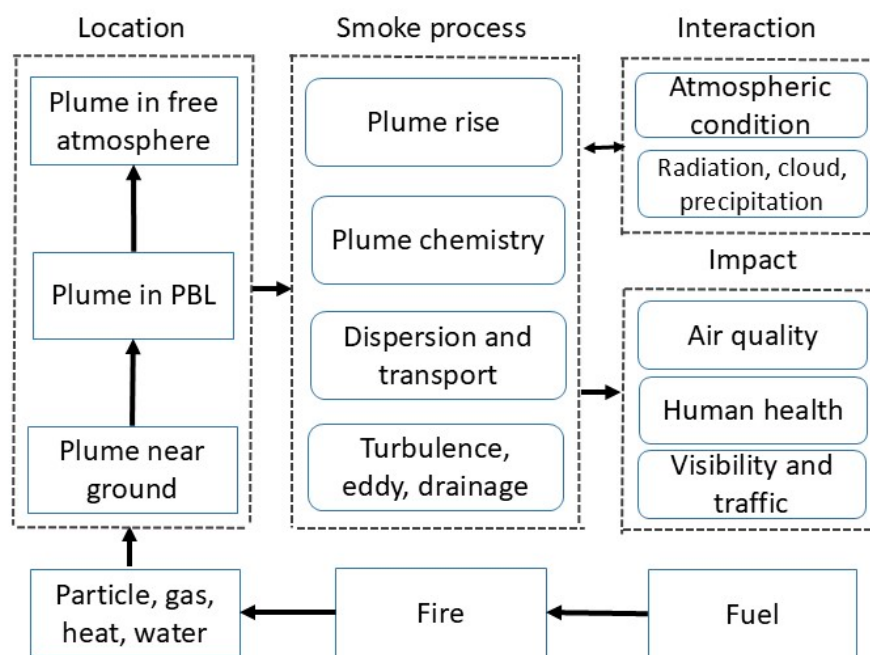


Figure 1. A schematic illustration of smoke plume processes, as well as atmospheric processes that interact with smoke processes, and the environmental impacts of smoke. (Modified from [27]).

2.1. Field Campaigns

Major progress in smoke measurements in the United States in the last decade, using various instruments, has occurred via several comprehensive wildland fire field campaigns. Ground-based and airborne monitors and samplers are used in these campaigns to measure gas and particles [28] and smoke structures. Mobile and high-resolution 3D mobile Doppler light detection and ranging (Lidar) and dual-polarized (or Dual pol) Doppler radars are extensively used to detect plume dynamics and winds [29]. Lidar allows for the ambient wind profiles to be measured intermittently, while plume structures are sampled with range height indicator (RHI) scans. Dual-polarized Doppler radars offer an advantage through transmitting and receiving both horizontal- and vertical-oriented beams and providing measurements of the size and shape of particles (pyrometeors, ash, and debris) within the plume [30–32]. In comparison, the Doppler lidar is a great tool for observing the plume dynamics of a wildfire, while Doppler radar has a lower attenuation effect of optically thick plumes, a much faster scan speed, and beam polarization.

Table 1 lists the major campaigns, as well as laboratory experiments, conducted in the past decade. WE-CAN and BB-FLUX conducted measurements of western wildfire emissions of particles, carbonaceous and nitrogen gases, and volatile organic compounds (VOCs) using instruments onboard aircraft. The data was used to analyze the physical, chemical, and optical properties, and the temporal variations of smoke gases and particles, and their interactions with clouds. FIREX-AQ and the National Aeronautics and Space Administration (NASA)’s FireSense [33] used advanced technology and instruments onboard satellites and aircraft. FIREX-AQ focused on smoke during fires, while FireSense measured the fuels, fires, and smoke before, during, and after fires.

Table 1. Wildland fire field campaign and laboratory experiment programs. CSU, CU, UGA, NASA, NOAA, USFS, and DoD represent Colorado State University, University of Colorado, University of Georgia, National Aeronautics and Space Administration, National Oceanic and Atmospheric Administration, US Forest Service, and Department of Defense, respectively.

Program	Description	Implementation	Program and/or Data Websites
We-CAN	Airborne; nitrogen, absorbing aerosols, and cloud activation; smoke focused on chemistry; to characterize emissions and evolution.	Western U.S. in 2018, led by CSU	https://www.eol.ucar.edu/field_projects/we-can , accessed on 14 July 2025 https://data.eol.ucar.edu/master_lists/generated/we-can/ , accessed on 14 July 2025
BB-FLUX	Airborne and in situ measurements; trace gases and particles; to quantify total emission and evolution	20 wildfires in Western U.S. in 2018, led by CU	https://volkamergrupp.colorado.edu/timeline/field/bb-flux , accessed on 14 July 2025 https://www.uwyo.edu/atsc/research-facilities/uwka/projects-data.html , accessed on 14 July 2025
FireSense	Airborne measurement of various fire phases; deliver unique Earth science and technological capabilities to operational agencies and address challenges in US wildland fire management.	9 and 3 wildland fires in Western US in 2023 and 2024, respectively, and 3 in Southeastern U.S. in 2025, led by NASA	https://cce.nasa.gov/firesense/ , accessed on 14 July 2025 https://www-air.larc.nasa.gov/missions/firesense/index.html , accessed on 14 July 2025
FIREX-AQ	Airborne and ground measurements; smoke composition and chemistry; to better understand the impact of smoke on air quality and climate	Wildfires in Western U.S. and prescribed fire in Eastern U.S. in 2019, led by NOAA and NASA	https://csl.noaa.gov/projects/firex-aq/ , accessed on 14 July 2025 https://www-air.larc.nasa.gov/cgi-bin/ArcView/firexaq , accessed on 14 July 2025
FASMEE	Mainly ground-based; fuels, fire behavior, emission and smoke, and meteorology; smoke focused on structure; to evaluate and advance operational-use fire and smoke models.	Planning: 2016–2018; prescribed fires at Fishlake NF, UT, in 2019 and 2023. Led by USFS	https://research.fs.usda.gov/pnw/centers/fasmee , accessed on 14 July 2025 https://www-air.larc.nasa.gov/missions/fasmee/index.html , accessed on 14 July 2025
WFSI	Measurement of fuels, fire behavior, smoke, and meteorology data; evaluate and accelerate operational availability and use of next-generation physics-based fire behavior and smoke models.	Prescribed fires in Southeastern U.S. in each year during 2022–2025 (joint with FireSense in 2025), led by DoD and USFS	https://serdp-estcp.mil/page/4f3816cb-f84e-4935-b8fd-896381e98f1b , accessed on 14 July 2025 https://wfsidata.org/data , accessed on 14 July 2025
FireLab	Measurement of nitrogen, VOC, and carbon emissions from fuel combustion in lab; understanding optical and photochemical properties and processes.	Characteristic fuels of the Western U.S. burned in 2016 at Missoula Fire Lab, led by NOAA and USFS	https://csl.noaa.gov/projects/firex/firelab/ , accessed on 14 July 2025
G-WISE	Link smoke emission rates and properties to fire dynamics; understanding dependence of fire emissions on fuel properties and moisture conditions.	Fuels collected from different Georgia ecoregions and burned in Athens Fire Lab in 2022 and 2025, led by UGA and USFS.	https://rawad85.wixsite.com/g-wise , accessed on 14 July 2025

FASMEE and the Wildland Fire Science Initiative (WFSI) have focused on measuring prescribed fires from the ground. FASMEE is a multi-agency, interdisciplinary collaborative effort following the Prescribed Fire Combustion and Atmospheric Dynamics Research Experiment (RxCADRE) [34,35] to measure fuels, fire behavior, fire energy, meteorology,

smoke, and fire effects. The data are used to evaluate and advance operational-use fire and smoke models [36]. FASMEE implemented the Southwest Campaign to measure the stand replacement fires in Fishlake National Forest, Utah. WFSI conducted similar data collections to FASMEE, but for understory burns in the Southeast. There were also other measurements of prescribed fires, including sub-canopy fire experiments sponsored by the U.S. Joint Fire Science Program (JFSP) and the U.S. Department of Defense Strategic Environmental Research and Development Program (SERDP), conducted in New Jersey and North Carolina [37–41], and the grassfire experiments conducted over flat terrain in Texas (FireFlux) [42] and in areas of complex terrain in California [43].

There have been extensive collaboration and coordination among various field measurement programs. For example, FASMEE conducted the Western Wildfire Campaign of fuel measurements to support WE-CAN and FIREX-AQ studies. FASMEE and WFSI conducted field measurements together with FireSense in Fishlake, UT, in 2023 and Fort Stewart, GA, in 2025, respectively.

These comprehensive field campaigns provided valuable and comprehensive data for smoke research in many ways. First, smoke was one of the components of these campaigns. The collected data can be used directly to understand smoke processes and evaluate and improve smoke models. Second, the fuel and fire behavior data that were also collected during these campaigns can be used to obtain fire emissions of gases, particles, heat, water, etc., as inputs for smoke modeling. Third, smoke is one of the ultimate products of fuel combustion and fire behavior modeling. Thus, the measured smoke properties are useful for validating fuel and fire behavior modeling. Also, all the data of smoke, fuel, fire behavior, and meteorology provide necessary information to understand the interactions among the fire and environmental components and develop coupled modeling systems.

2.2. Laboratory Experiments

To explore the chemical and physical processes that interplay with both smoke dynamics and the ultimate impacts on radiation and health, laboratory studies are extremely valuable. Such experiments explore, for example, reaction rates, smoke composition from various fuels under different burning conditions, aging, and fire dynamics. Many studies are carried out at universities [44], national labs (e.g., Sandia National Laboratory Thermal Test Complex), and internationally [45]. Two notable examples in the last decade (Table 1) are the NOAA FIRELAB experiment of 2016 [21], which provided laboratory-based insights to some of the science topics to focus on in the NOAA/NASA FIREX-AQ field campaign discussed above, and the Georgia Wildland-fire Simulation Experiment (G-WISE), which burned fuels from Georgia's Coastal Plain, Blue Ridge, and Piedmont ecoregions in a lab to understand fire and smoke dynamics [46].

2.3. Satellite Products and Applications

Satellites are advanced remote-sensing technology that provide data and information on the Earth system with varied resolutions and frequencies. The satellites that are available at an early time for fire and smoke detection include Landsat (global, 30 m, 16 days, since 1972) based on post-fire land cover change, the Moderate Resolution Imaging Spectroradiometer (MODIS) (global, 250/500 m, daily, since 2000), the Visible Infrared Imaging Radiometer Suite (VIIRS) (global, 375/750 m, since 2012), and GOES-R series (western hemisphere, 4 km, 30 min, since 2016) [47].

Satellites play important roles in global and regional fire and smoke monitoring and detection. They provide wildfire information (locations, perimeters, areas, intensity, severity, and other properties) based on heat signatures, hot spots, fire radiative power (FRP), and vegetation changes. The detected fuel, fire, FRP, and other information are

used to estimate fire emissions. Satellites equipped with lidar/radar detection, imaging, and plume-sampling technologies, such as the Cloud-Aerosol LIDAR with Orthogonal Polarization (CALIOP) [48] and the Multiangle Imaging SpectroRadiometer (MISR) [49], can detect the height of smoke plumes. Finally, satellite techniques such as TEMPO provide air pollutants and aerosol optical depth (AOD). Also, inversion methods and various algorithms are used to convert optical retrievals of satellites to pollutant concentrations by applying complex algorithms to optical reflections. In addition, satellites can track smoke plume dispersion and transport.

Satellites also provide information other than on fire and smoke, such as fuels, weather, topography, and terrain, for understanding the relationship between fire and smoke and their environment, the causes and effects of fire and smoke, and the influence of weather on fire and smoke dynamics [50]. Both the spatial fire distributions and the weather conditions that affect fire activities have been mapped using remote-sensing data, which, together with fire and smoke information, is used by models to predict the fire and smoke dynamics and the environmental impact.

Satellite-derived data of fire emissions and smoke properties cover large spatial areas and long temporal periods. They provide useful information for smoke and air quality modeling. However, the evaluation of satellite remotely sensed smoke products has been a challenge. Recent wildland fire and smoke field campaigns provide useful data to address this challenge. The MISR instrument was used to detect smoke particle properties and their evolution in a wildfire during FIREX-AQ [51]. Similar particle property evolution with smoke age is found between the MISR detection and the in-situ data. The differences in sampling and changes in the plume geometry between sampling times lead to most of the key differences in particle size and absorption. VIIRS detected FRP, and in situ observations of smoke aerosols and trace gases during FIREX-AQ were used to obtain changes in conserved CO₂, CO, and BC [52]. Good agreement in fire NO_x emissions is found between the high-spatial-resolution TROPospheric Monitoring Instrument (TROPOMI) and the aircraft observations from WE-CAN and FIREX-AQ [53]. There are strong linear relationships in the high-resolution emission rate estimates in aggregate among satellite-based top-down approaches, traditional fuel-based bottom-up approaches, and a novel approach based entirely on integrated airborne and in situ measurements using data collected during FIREX-AQ. However, no single approach can capture the emission characteristics of every fire [54].

Satellite instruments, especially those with multi-angle cameras, are extensively used to obtain plume rise. Some satellite plume-rise products were compared with lidar measurements during WE-CAN [55]. In comparison with the lidar measurements, the values over mountainous terrain were mostly close for the MISR/Enhanced Research and Lookup Interface products, routinely lower for the MODIS/Multi-Angle Implementation of Atmospheric Corrections products, and show great potential for a single homogenous aerosol-rich layer for the VIIRS/Aerosol Single-scattering albedo and Height Estimation and the TROPOMI/aerosol layer height product, which, however, overestimate and underestimate in the near-fire-event region and an underestimation of smoke plume height in the downwind region still prevails, respectively (Figure 2).

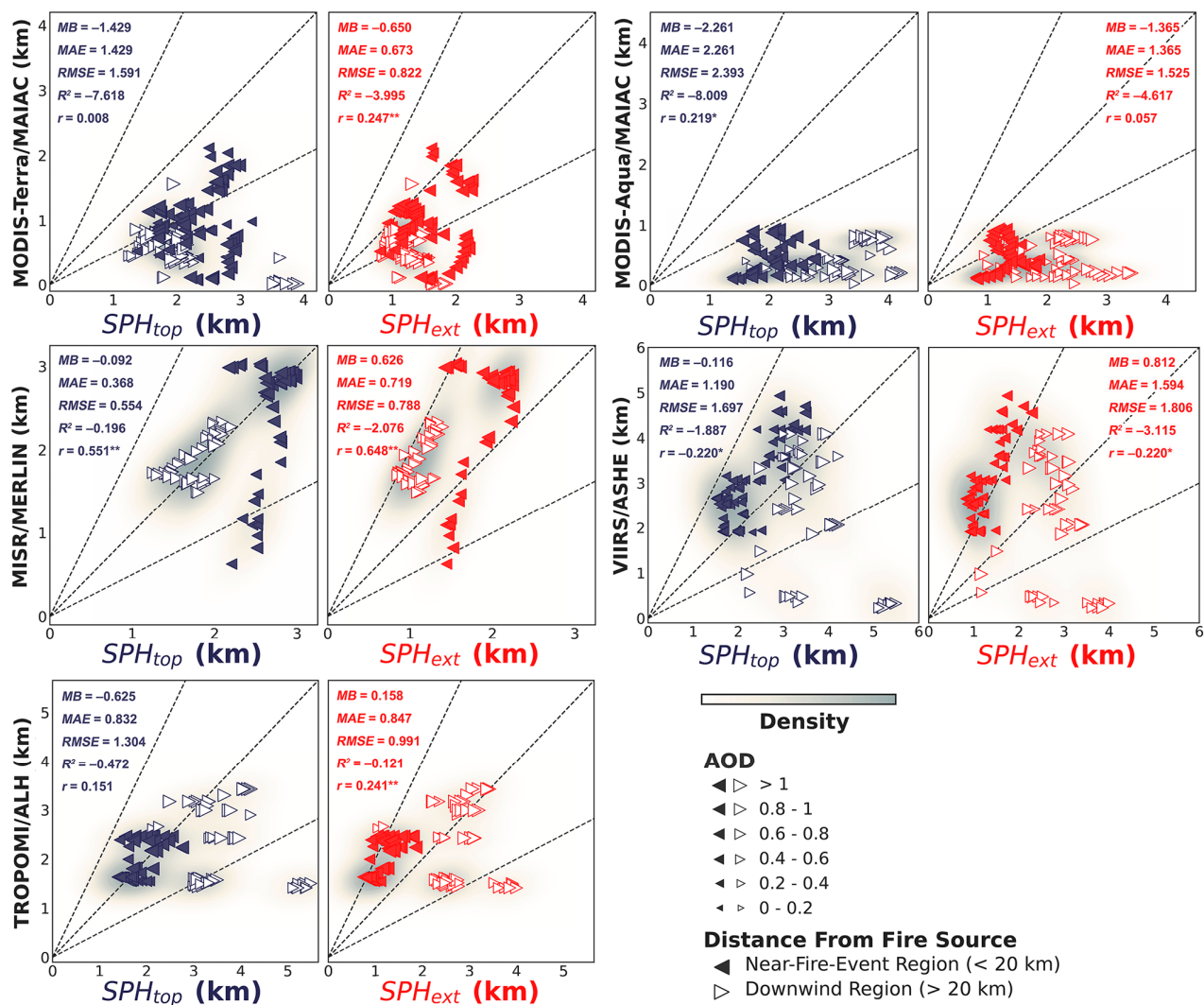


Figure 2. Comparisons of smoke plume height (SPH) detected by satellite techniques and measured using the airborne Wyoming Cloud Lidar technique during BB-FLUX with two different definitions: SPH_{top} (left, blue) and SPH_{ext} (right, red). Dotted lines denote the ratios of 2:1, 1:1, and 1:2 for reference. The shaded areas show the estimated density of the collocated pairs. Evaluation metrics are MB (km)—mean bias; MAE (km)—mean absolute error; RMSE (km)—root-mean-square error; R^2 (unitless)—coefficient of determination; and r (unitless)—Pearson correlation coefficient (* and ** indicate $p < 0.05$ and $p < 0.01$, respectively) (From [55]. The publisher, the Copernicus Publications, is licensed under the Creative Commons Attribution 4.0 License under which the authors retain the copyright. Permission to use this figure was granted by the corresponding author).

Satellite products provide crucial support for smoke and air quality modeling by developing fire emission inventories. MODIS products, such as hot spots and land cover, were used as the inputs for the Global Fire Emission Database (GFEDv1) two decades ago, and VIIRS data were used for the recent version (GFEDv5) [56,57]. MODIS and VIIRS products are also used in the early and recent versions of the Fire Inventory from NCAR version 1.0 (FINN) [58] and the recently developed Global Forest Fire Emissions Prediction System (GFFEPS) [59]. FRP, another very useful satellite product, is also used to develop fire emission inventories. For example, VIIRS FRP data are used for the VIIRS-based Fire Emission Inventory (VFEI) that provides emission data from early 2012 to 2019 for more than 40 species of gases and aerosols at spatial resolutions of around 500 m [60]. It is found that VFEI produces similar results when compared to other major inventories in many regions of the world.

Different from polar-orbiting satellites that carry MODIS and VIIRS instruments with global coverage and high resolution but low frequency, geostationary satellites such as the Geostationary Operational Environmental Satellite (GOES) provide continuous observation of a particular region. Thus, their products are especially valuable for regional smoke and air quality prediction. The GOES-R series covers CONUS at 0.5–2 km resolution and frequencies of 0.5–10 min [61]. The Warn-on-Forecast System for Smoke (WoFS-Smoke), an ensemble-based forecast system for wildfire smoke aerosols, runs the High-Resolution Rapid Refresh-Smoke (HRRR-Smoke) model using GOES-R products at a 2 km resolution at 5 min intervals [62]. For tropospheric emissions, Monitoring of Pollution (TEMPO) is another instrument from geostationary orbit to measure air quality (gases such as ozone, NO_x , and HCHO are available now and aerosols are available soon) over the Northern Hemisphere [63]. It has an hourly interval and 2 km spatial resolution at its nadir. It can also detect gases in a layer near the ground. Extensive applications to smoke are expected.

Satellite technology also provides useful information for tackling some urgent fire and smoke challenges, including WUI fires (to be discussed in Section 4.3). In comparison with wildfires in rural areas, WUI fire and smoke dynamics and impacts are more difficult to detect, assess, and predict due to different fire behaviors, which are often more intense because of structure combustion, emissions of more toxic materials and other emission sources such as traffic, impacts of urban conditions on wind, temperature and other atmospheric conditions, and dense population. All of these features vary extremely in space. Satellite remotely sensed datasets and informatics provide high-resolution detection of fire behavior, atmospheric chemical compositions, and urban atmospheric and other natural conditions. They can be effectively integrated to detect WUI fires and smoke, as suggested to deal with the climatic challenges at the urban scale [64].

2.4. Smoke Properties

2.4.1. Fire Emissions

Fire emissions of nitric oxide (NO), nitrogen dioxide (NO_2), sulfate dioxide (SO_2), VOCs, ammonia (NH_3), nitrous acid (HONO), carbon monoxide (CO), and particulates are extensively measured for various fuel types for wildfires in the Western U.S. and agricultural fires in the Southeastern U.S. during wildland fire campaigns, including SO_2 [65] and NH_3 , and NH_x [66] emission factors and secondary O_3 production [67] during FIREX-AQ, the ratio of changes in HONO to changes in CO for WE-CAN wildfires [68], and $\text{PM}_{2.5}$ emission factors [69] and bacterial emissions [70] during the 2019 FASMEE. It is found that reduced N compounds measured during WE-CAN comprised a majority of the total reactive nitrogen [71]. The VOC mixing ratio of 11 fires during FIREX-AQ was approximately 1000 ppbv for two fires, 700 for one fire, and below 400 for the other fires [72]. The Northern California fires in October 2017 emitted over 2000 tons of CO h^{-1} [73]. Refs. [72,74] developed fire emission parameterizations based on the FIREX-AQ measurements. They will be used to provide more accurate boundary conditions for fire plume chemistry and evolution modeling and satellite studies to predict transport and formation of ozone and SOC.

The FIREX FireLab experiment measured nitrogen emissions through the burning of characteristic Western U.S. fuels in a laboratory [75]. The experiment obtained individual components of reactive nitrogen (Nr) and compared them with other chemical properties, such as carbon emissions from fires. CO_2 , hydrogen cyanide, and the ratio of ammonia to particle ammonium are recommended as markers for combustion Nr, high-temperature pyrolysis factor, and low-temperature pyrolysis factor, respectively. Ref. [76] found strong dependences of CO, CO_2 , and other gaseous and particulate effluents emissions from common wildlife–urban interfaces (WUI) fuel oxygen concentrations and heat fluxes in laboratory conditions.

2.4.2. Processes and Evolution

There has been an improvement in the quantity and quality of ambient measurements of organic matter [77]. Advanced instruments are available for offline analyses to separate SOA from POA, including the Particle in Liquid Sampler (PILS), aerosol chemical speciation monitor (ACSM), extractive electrospray ionization–time of flight–MS (EESI-TOF-MS), Proton transfer–reaction mass spectrometry (PTR-MS), and chemical ionization MS (CIMS). The online techniques often used to reduce the errors introduced by filter-based measurements, such as the latter, are performed over several hours to days, making it challenging to differentiate atmospheric processes.

Figure 3 shows an example of the variations in reactive oxidized nitrogen species measured during WE-CAN [78]. NO_x and HONO are rapidly converted after emission to more oxidized forms with an average e-folding time of approximately 90 min and a distance of approximately 40 km [71]. The extent of oxidation increases significantly with time through chemistry and dilution [79]. When a plume dilutes by a factor of 5 to 10, up to one-third of the primary organic aerosol (OA) has evaporated and subsequently reacted to form biomass-burning secondary organic aerosol (SOA) with near unit yield, while the reactions of measured biomass-burning SOA precursors contribute to only 13 percent of the total biomass burning SOA [80]. The median particle diameter increases faster in smoke with a higher initial OA concentration [81]. However, smoke particles evolve in complex patterns. The brown carbon (BrC) mass absorption coefficient varies with plume age and with flights [82]. The ratio of BrC to CO emissions enhanced, depleted, or remained constant during the aging period [83]. Plume PM age may be different. In a comparative laboratory and field study of smoke aging impacts on PM, the measured PM varies from net decreases to net increases, with most showing little to no change, while the lab result shows significant increases [84].

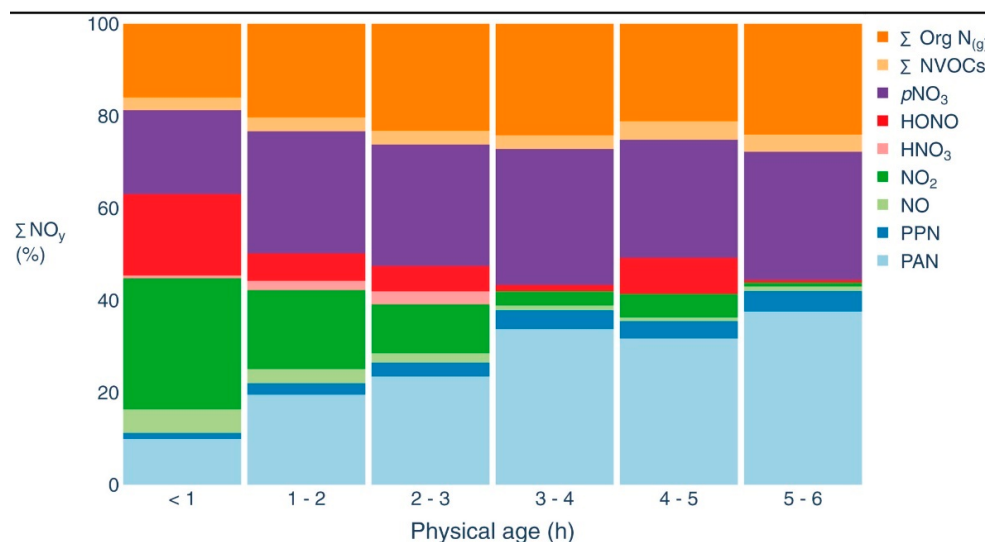


Figure 3. Partitioning of reactive oxidized nitrogen species as a function of physical age (h) measured during WE-CAN (From [78]. Permission to use this figure was granted by the corresponding author).

Chamber measurement is another widely used approach. The short-term (within 12 h, mainly near the emission sources) photochemical evolution of biomass-burning OA has been extensively studied in laboratory experiments using environmental chambers. A novel approach of dual chambers was used to examine the evaluation of the oxidation chemistry of biomass burning and the related mechanisms. Emissions were added to both chambers, but only one chamber had perturbation from exposure to UV, O_3 , and NO which was added to change the ratio of VOC to NO_x and the other chamber served as a control [85]. The OA

mass enhancement was found but was insensitive to the perturbation performed. A further chamber measurement showed that VOCs were responsible for most of the observed SOA. A majority of the SOA formed in the chamber experiments was found to be from the oxidation of the oxygenated aromatic and heterocyclic VOCs [39]. Long-term chamber measurements at a daily scale are very limited. An analysis of the experiments with different fuels finds a much larger enhancement in OA mass concentrations compared to a previous similar measurement. The higher enhancement could be explained by differences in photochemical age and accounting for measurement artifacts. The OA mass enhancement correlated with fresh emissions of non-methane organic compounds, in contrast to the previous measurement.

2.4.3. Optical Properties

Field measurements provided optical features of smoke particles, which are necessary to calculate the short-wave radiative and climate effects of smoke. The fresh smoke extinction coefficients and AOD during a BB-FLUX fire event were 2–10 times larger than the background values [86]. Mid-visible smoke mass extinction efficiency (MEE) measured during FIREX-AQ can change by a factor of 2–3 between fresh smoke (<2 h old) and one-day-old smoke [87]. The average single-scattering albedo (SSA) for individual smoke peaks at 870 nm increased from ~0.9 to ~0.96 during a month-long smoke event in 2017, measured in Missoula, MT [17]. Meanwhile, the Ångström absorption exponent (AAE) decreased significantly with smoke aging. Measurements of smoke show a strong decrease in total absorption, which decreased significantly at 405 nm and slightly at 660 nm with aging during WE-CAN due to decreasing OA mass and water-soluble OC (WSOC) [88]. In addition to BC, BrC contributed to smoke absorption, each accounting for about half the absorption, at 401 nm on average. Dark BrC contributed three-fourths and one-half of the short and long visible-light absorption, respectively [89]. The AAE and SSA of biomass-burning aerosol from the combustion of fuel beds were measured in a laboratory during the G-WISE experiment [90]. Fuel-bed composition and moisture content are found to be significant factors for smoke aerosol optical properties.

2.4.4. Contributions to Clouds

New observational evidence for the roles of smoke particles in modifying cloud properties and generating clouds is obtained from field campaigns. Ref. [91] investigated the cloud impacts of smoke particles by comparing ice-nucleating particles (INPs) inside and outside smoke plumes during WE-CAN and found that smoke plumes enhanced INPs. Ref. [92] conducted a statistical analysis of sampled small cumulus clouds during WE-CAN and compared them with smoke aerosol properties and found increases in cloud droplet concentrations and decreases in size due to smoke. Pyrocumulonimbus (pyroCb) was observed over the Williams Flats fire, measured during FIREX-AQ [93].

2.5. Plume Structure

Smoke from wildfires usually rises into the free atmosphere and interacts strongly with atmospheric processes. Smoke particles cool the surface due to their scattering and absorption of solar radiation, which generates surface flow decoupled from the upper-level winds and advecting smoke in the opposite direction to ambient smoke-free flow [94]. Ref. [95] used a new mobile millimeter-wave (Ka band) Doppler radar system to measure the fine-scale kinematics and microphysical properties of two wildfires in California and a prescribed fire during the 2019 FASMEE field campaign. Figure 4 shows the measured reflectivity, radial velocity, Doppler spectrum width, differential reflectivity, and copolarized correlation coefficient.

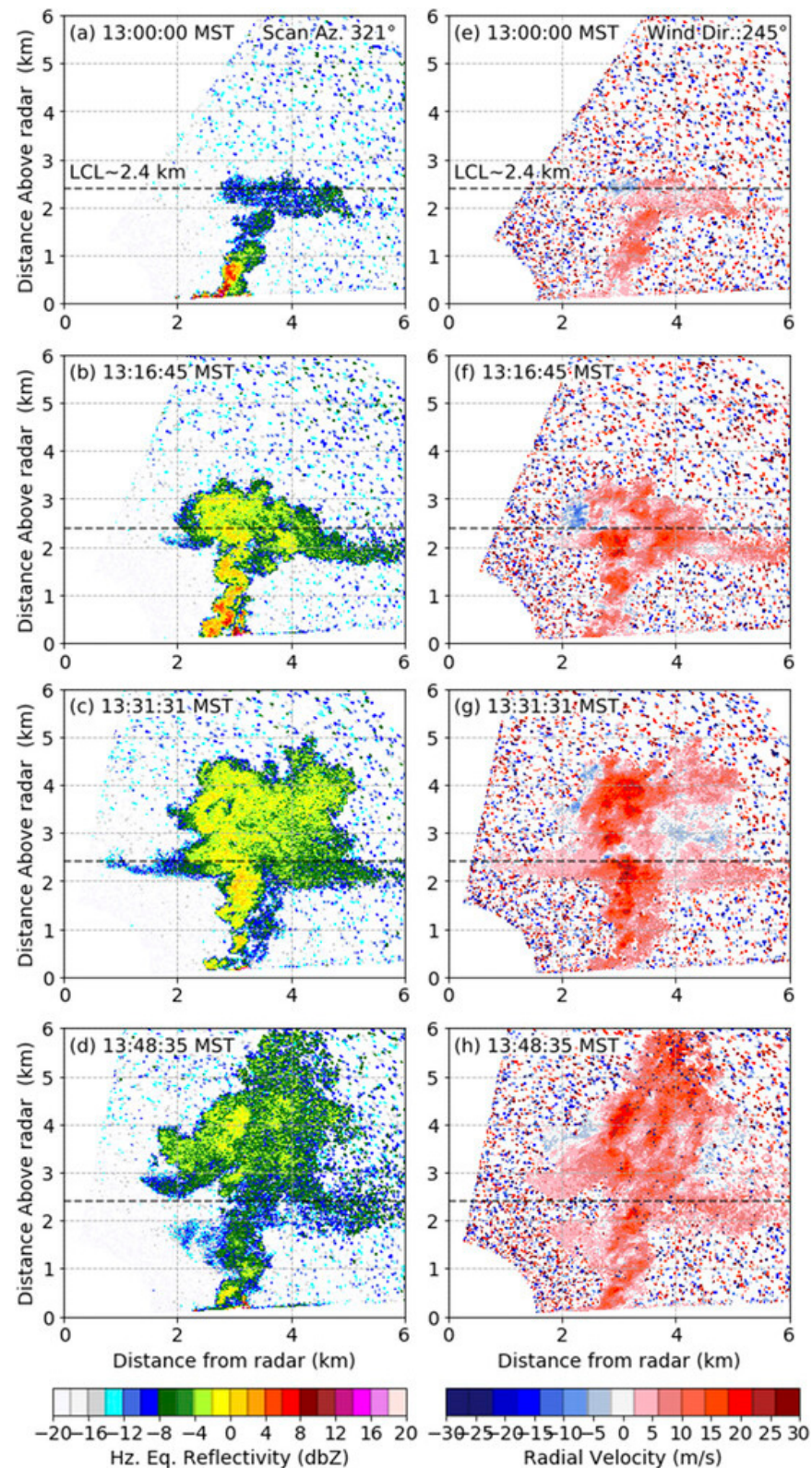


Figure 4. KASPR radar signatures from the South Monroe prescribed burn of (a–d) horizontal equivalent reflectivity factor and (e–h) radial velocity (m s^{-1}) beginning at 1300 MST 7 November 2019. (From [95] © American Meteorological Society. Used with permission).

The dynamics and the environmental impacts of plumes often differ between prescribed fires and wildfires because of different intensities [96]. A prescribed fire is often carried out near communities and in WUI and can potentially linger for relatively long periods of time. Smoke from prescribed burning occurs mostly on the ground and within

the PBL and often affects local air quality. Studies on the plume dynamics during prescribed fires have provided several key findings on smoke processes within the canopy and PBL, including maximum increases in the energy of turbulent circulations near the top of forest canopies induced by fire, thereby enhancing the dispersion of smoke plumes there, which are often stronger horizontal than vertical smoke mixing within forest vegetation layers due to turbulent circulations; highly skewed distribution of turbulent velocity in the vicinity of fires in forested environments, making overall turbulence regimes in such environments non-Gaussian and calling into question the application of smoke modeling tools that assume Gaussian turbulence for diffusing smoke; and sweep-ejection dynamics for turbulent heat and momentum flux occurrence above fire fronts in forested environments, suggesting that the presence or absence of overstory vegetation may have an impact on the way heat, momentum, and smoke particles are redistributed by turbulence [37,38].

2.6. Plume Rise

Early studies using MISR detections show that the mean plume heights are 2 km for wildfires in the Northwest Pacific region, 3 km for wildfires in the Rocky Mountain, intermountain, and Southwest regions, and nearly 0.8 km for wild and prescribed fires (mainly latter) in the Southeast region [97]. The average plume height of prescribed fires measured in the Southeast using a ceilometer is approximately 1 km [98]. The detected smoke plume rise depended on fire cases and methods used to define plume height, ranging between 2.8 and 5.5 km for seven fires [99] and 1.0 and 2.5 km for the other five wildfires [55] during BB-FLUX. Smoke from about one-third of the measured data during FIREX-AQ was injected above PBL height [100]. Satellite remote-sensing data have been used together with modeling techniques to form long-term plume rise datasets. For example, a global hourly fire plume rise dataset was formed for 2002–2012 based on simulation with a dynamic smoke plume rise model [101] and satellite-detected fire size and FRP [102].

3. Advances in Smoke Modeling

3.1. Smoke Models

Smoke modeling is conducted using dynamical or statistical models. Dynamical models are mathematical models constructed around the full set of primitive dynamical equations that govern smoke motions and concentration variations. Dynamical models often consist of the conservation laws of mass, momentum, and energy, which are nonlinear and need to use numerical methods to obtain approximate solutions through time and/or space integration. The Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model [103] and CMAQ are examples of Lagrangian trajectory and Eulerian grid models, respectively. The chemistry version of the Weather Research and Forecasting model (WRF-Chem) [104] is an example of weather–chemical coupled models. Statistical smoke models are developed based on the empirical relationships between smoke and fire emissions and meteorological variables. They usually require no time or space integration.

3.2. Evaluation and Improvement of Smoke Dynamics and Chemistry Modeling

The massive new data from the field campaigns and satellite products described above have been used to evaluate and improve smoke-modeling skills. In particular, ref. [105] evaluated and intercompared one-day wildfire smoke forecasts of fire emissions, AOD, PM_{2.5}, plume rise, and ratio of PM_{2.5} to AOD from 12 modeling systems using the measurements of the Williams Flats fire during FIREX-AQ. Refs. [106–108] validated simulated fire emissions, vertical profiles of OA, SOA, and VOC based on the WE-CAN and FIREX-AQ measurements and GEOS-Chem fire emission inventories, and smoke transport and PM_{2.5} concentrations. The MODIS/MAIAC product and the AeROsol RObotic NETwork

(AERONET) stations were used to evaluate the simulated AOD, and the FIREX-AQ data were used to evaluate the simulated smoke gases and particles using WRF-Chem for North America during July–August 2019 and the VFEI fire emission inventory [59]. Ref. [109] investigated the chemistry driving O_3 production using a box model and photo-chemical measurements during FIREX-AQ. Refs. [85,110] use a kinetic process-level model and a one-dimensional Lagrangian chemical transport model to simulate the photochemical evolution of SOA. The connections between modeling and measurements are summarized below.

Ref. [105] reveals some major discrepancies in smoke modeling. The solid black line with dots stands for Fuel2Fire emissions. The daily OC emissions from Fuel2Fire (black line in Figure 5), obtained a bottom-up emission dataset derived using information on fuels and satellite and ground-based intelligence, were below 500 tC/day on the first five days, jumped to about 3000 tC/day in the next two days, and dropped to nearly zero in the final two days. The predicted emissions follow the daily variations with most models, despite increasing too soon and dropping too late. The satellite products that were used to estimate the model fire emissions are a major uncertainty, with the models using the FRP product (solid lines), producing much larger emissions than those using the hotspot product (dashed lines). The model predicted the daily total biomass-burning OC emissions from the Williams Flats fire. Solid and dashed-dotted lines are the models that obtain emissions from the FRP and hotspot, respectively. The max-to-min ratios of model emissions (grey bars in Figure 5) range from 20 on 7 August and 60 or more on 3 and 10 August. Furthermore, the AOD magnitude and smoke plume area were overall underpredicted for nearly all models, while the night surface $PM_{2.5}$ concentrations were over-predicted for the models that obtain emissions from FRP. The plume rise ranges were narrower in prediction than those observed for all models, which tend to overpredict plume rise for the shallower injections and underpredict for the days with deeper injections.

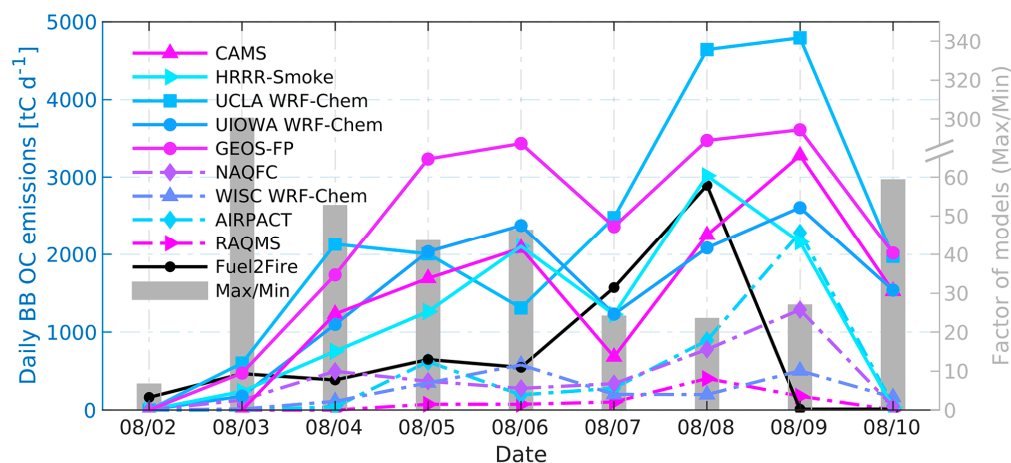


Figure 5. Model-predicted daily total biomass burning OC emissions from the Williams Flats fire. Solid and dashed-dotted lines are the models that obtain emissions from FRP and hotspot, respectively. The solid black line with dots stands for Fuel2Fire emissions analysis. Grey bars are factors between the maximum and minimum for all models. (From [105]. Permission to use this figure was granted by the corresponding author).

The vertical VOC profiles were found to be several times lower in the simulations using GEOS-Chem and several fire emission inventories and applied various injection height assumptions than the WE-CAN and FIREX-AQ measurements, suggesting that these inventories underestimated BB emissions [108]. Although the modeling with a plume version of a kinetic model that simulates the dilution, oxidation chemistry, thermodynamic properties, and microphysics of OA reveal the relationships of the roles of dilution-driven evaporation of primary organic aerosol (POA) and simultaneous photochemical production of SOA to the observed evolution in OA mass with physical age, the model substantially underestimated the change in the oxygen-to-carbon ratio of the OA compared to the measurements for four large wildfire plumes during WE-CAN [111,112]. The evaluation of the CMAQ simulation of the smoke plume from a wildfire event in the Northwestern US using satellite and ground measurements indicates that the model was able to reproduce heavy and prolonged smoke over major smoke population centers, such as the Seattle and Portland metropolitan areas, and a PM_{2.5} concentration magnitude [113].

The WRF-Chem simulations were found to be able to reproduce the AOD magnitudes accurately and the inter-diurnal variations in smoke concentration [60]. However, the biases for CO and BC simulations were higher because the model was not able to reproduce the timing, shape, and location of individual plumes over complex terrain (Rocky Mountains) during the FIREX-AQ campaign period. Ref. [114] did a similar simulation study but used the global chemical transport model, GEOSChem, using GFED4s for WE-CAN fire cases. The model generally captures the observed vertical profiles of carbonaceous BB aerosol concentrations, while FIREX parameterizations based on the BC to OA ratio improve model-observation agreement in some regions. They do not sufficiently differentiate the absorption characteristics at short wavelengths. Also, photochemical whitening substantially decreases the burden and direct radiative effect of BrC. The compatibility of smoke models in modeling and prediction of smoke dynamics and chemistry has improved remarkably in the past decade. An ensemble technique that runs multiple models has been used to reduce smoke modeling uncertainties. Ref. [106] conducted simulations of the Western U.S. wildfires during August–September 2020 using regional air quality models, global air quality models, and global ensemble and evaluated model performance with MAIAC and VIIRS-Suomi National Polar-orbiting Partnership retrieved AOD and AirNow surface PM_{2.5} measurements. They found that the ensemble technique significantly reduced biases and produced more consistent and reliable forecasts during extreme fire events in comparison to individual models.

Research-level chemical modeling of smoke evolution often occurs in “box models” that evaluate the chemistry within a single “box” of smoke without necessarily including the complexities of transport and dilution. This approach allows for focused study of various chemical processes (or many) relevant to important impacts on smoke, such as secondary aerosol production, oxidation of gases and aerosol constituents, and ozone production [4,107,108]. The simulated day maximum O₃ was almost double the night mixing ratio. Also, there was a rapid transition from VOC-sensitive to NO_x-sensitive chemistry in the afternoon and a slower transition in the opposite direction in the evening [108].

SOA in the smoke plume mainly originates from the aging of intermediate and semi-volatile organic compounds and is an important contributor to total OC. Chemical modeling helps estimate the SOA production rate and the related processes. Ref. [109] uses a kinetic, process-level model to simulate the photochemical evolution of OA observed from multiple chamber experiments and reproduces the time-dependent evolution of the OA mass concentration during the first day. This study further reveals that smoke evolution in the following days is more dominated by SOA than POA, and particle and vapor wall losses are much more important in influencing the OA evolution than dilution, hetero-

geneous chemistry, and oligomerization reactions. Ref. [110] simulates the changes in the concentration and composition of biomass-burning OA of a major wildfire using the one-dimensional Lagrangian chemical transport model PMCAMx-Trj. The results indicate the importance of the intermediate VOC fragmentation to predict SOA products, in addition to functionalization.

3.3. Development of Interactive and Integrated Smoke Modeling Tools

Typical plume rise models, especially those used operationally, attempt to estimate plume rise and smoke dispersion as standalone processes. For the sake of simplicity and computational efficiency, they rely on external models to estimate fire heat release, emissions, and ambient atmospheric conditions, assuming that the last observed fire growth can be projected to the future and provide a forecast of the burned area. As fire emission is generally estimated on a daily basis, fractioning into hourly emissions is performed based on typical daily fire activity profiles, with emissions peaking in the late afternoon. The operational requirements of rapid output mean that all these systems use parameterizations of plume rise and do not predict the fire, atmosphere, and smoke interactions and feedbacks within the plume structure.

Dynamically modeling fire plumes requires understanding of the integrated nature of fire, air, and smoke as an integrated physical system. Thus, improving plume dynamics science will require the use of physics-based, coupled fire–atmosphere or fire–atmosphere–chemistry models. Either such models will need to be adapted for operational use, or a new generation of plume rise models will need to be developed based on categorizing and approximating the more complex fully coupled model outputs. To do so, data on fuel structure and variability, fire behavior, and fire meteorology will need to be collected to advance our ability to accurately model the underlying complex dynamics of the fire–smoke system. High-resolution spatial and temporal measurements of these elements will be needed to inform the development of improved algorithms for modeling plume dynamics. The goal is to create coupled models with the capability to fully predict the fire, atmosphere, and smoke interactions and feedbacks within the plume structure.

Efforts have been made toward developing coupled models. An example of such models is the WRF-SFIRE-CHEM (WRFSFC), which couples the chemical transport model WRF-CHEM [104] with the fire module SFIRE [115]. WRFSFC is a hybrid model that couples a computational fluid dynamics (CFD)-type weather model of WRF with an empirical fire model. It simulates fire progression, calculates emissions, and simulates smoke's physical processes (plume rise, dispersion, and transport) and chemistry based on the local meteorological and fuel conditions affected by the fire itself. Figure 6 shows the application of WRFSFC to smoke–radiation interactions and the impacts on air quality from several 2015 Northern California wildfires [116]. The results reveal positive smoke–radiative feedback. That is, reduced solar radiation due to smoke, cooling air temperature, reduced surface winds, elevated smoke concentration, and further reduction in solar radiation.

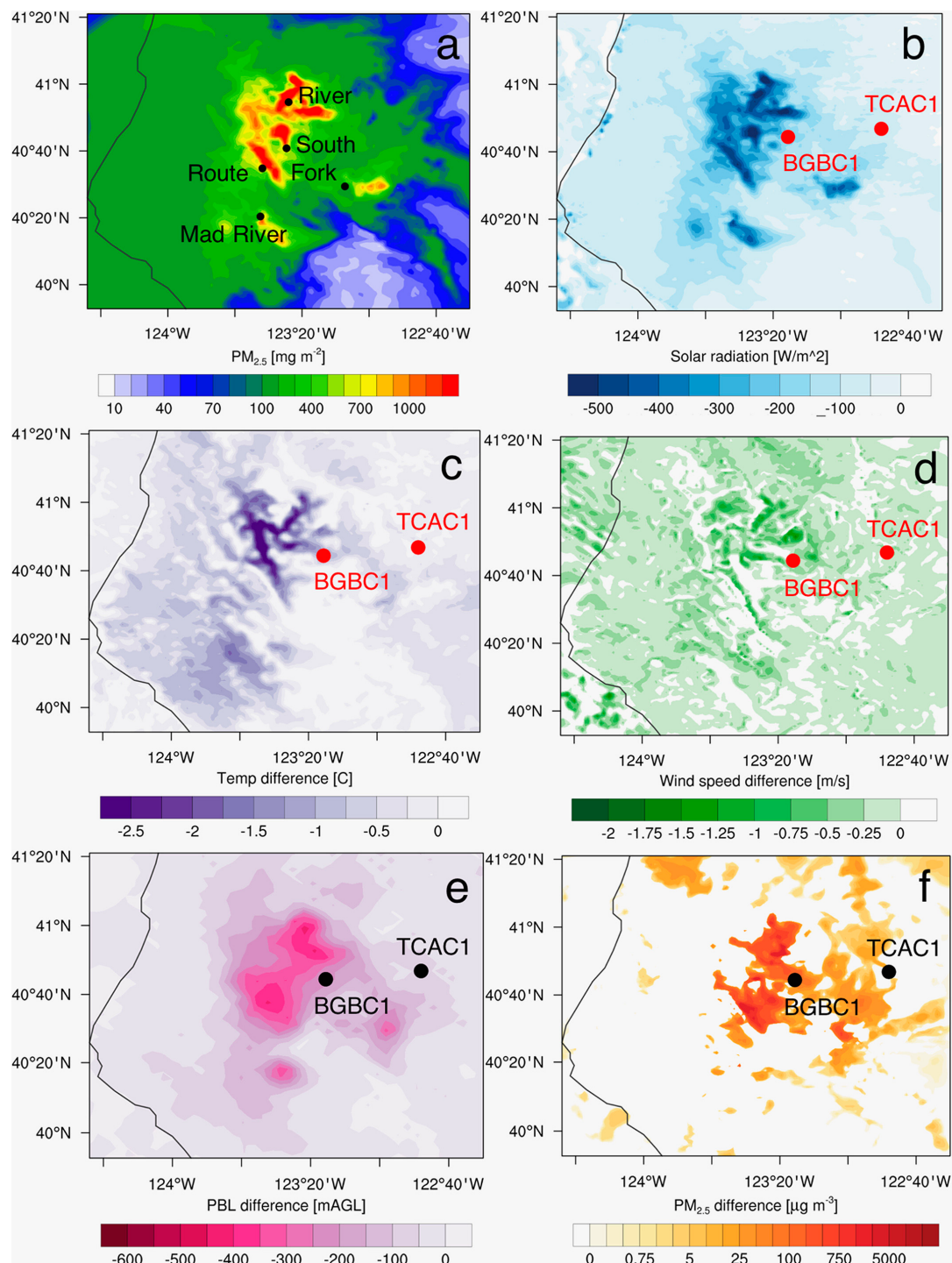


Figure 6. WRF-SFC simulation of a Northern California wildfire on 19 August 2019. (a) Column-integrated PM_{2.5} concentrations with smoke-radiative aerosol radiative feedback. (b–f) Differences in solar radiation, 2 m temperature, surface wind, PBL, and surface PM_{2.5} between modeling with and without feedback. (From [116], whose publisher, John Wiley & Sons publications, grants permission to an author to reuse own article in a new co-authored publication. The corresponding author of [116] is a co-author of this review paper).

3.4. Interactions with Canopy and Topography

Atmosphere, canopy, and particle dispersion-coupled models have been used to simulate smoke interactions with canopy and PBL processes. One example is the Advanced Regional Prediction System with canopy submodel (ARPS–Canopy) [117] coupled with the FLEXPART particle dispersion model. Modeling has shown that forest overstory and

understory vegetation act as a drag on ambient and fire-induced winds within vegetation layers [118–120]. Horizontal and vertical wind-shear patterns related to the drag and thermal dynamics affected by vegetation generate or modify atmospheric turbulence, which affect smoke dispersion and upright processes [119,121].

Modeling studies have shown the important smoke impacts of topography and landscape types through modifying atmospheric dynamics and thermodynamics (e.g., wind, temperature, and moisture), generating local flows such as katabatic winds or drainage flows, anabatic winds, föhn and chinook winds, terrain channeling of flows, land/sea breezes), and generating an urban heat island effect that changes smoke transport and dispersion [122]. Ref. [123] provides observational and modeling evidence for the impacts of small-scale topographical flows on smoke transport near the Utah Valley.

Plume dynamics at night can differ dramatically from those during the daytime. One phenomenon related to night smoke is the so-called superfog. A superfog case was simulated using Planned Burn-Piedmont (PB-P) during the smoldering phase of a prescribed burn on 18 October 2016, in the Kaibab National Forest, AZ [124]. The simulation produced drainage/slope flows and superfog along Highway I-40 where a traffic accident was reported. Ref. [125] simulated a pair of historic superfog events using a thermodynamic model with a 2D PBL model. The coupled model was able to simulate smoke transport and turbulent mixing processes that control the persistence of superfog as it disperses from the burned area. The results were verified with laboratory experiments.

3.5. Plume Rise

Accurate simulation and prediction of smoke plume rise and vertical structure are critical for understanding smoke dynamics and assessing smoke impacts. For example, overestimating plume rise by models would lead to more transport in the free atmosphere by winds with a more active plume chemistry but reduce the impacts of turbulence, eddy, canopy, and terrating in the PBL and the ground PM concentration, which, therefore, underestimates the human health risk.

Several types of modeling tools for the smoke plume rise of wildland fires are available. One is dimensionless empirical schemes based on field and lab data using statistical and similarity theory, including the widely used Briggs scheme [126]. It was originally developed for stack plumes and has been converted for wildfire plume by replacement with fire heat release [127]. A regression model for prescribed fire plume rise was developed based on measured plume rise data [128]. Another type is to use satellite remote sensing information, including measured plume rise from multiple-angle instruments and fire emission/intensity detection such as FRP [129–132]. The third type is 1D dynamical models that explicitly simulate the time evolution of plume rise processes and determine the final injection layer [101,133]. There are also 3D models, such as WRFSFC and Daysmoke [134], which simulate smoke processes and provide plume rise directly if a high resolution is used.

Smoke plume rise models have been evaluated, and sensitivity tests of air quality modeling to plume rise have been conducted in many studies. Ref. [135] evaluated smoke vertical distributions simulated using the Freitas model coupled with WRF-Chem for three wildfires during FIREX-AQ. They found that more than 80% of smoke emissions penetrated into the free atmosphere, much larger than the chance of less than 50% from the WRF-Chem default plume rise option. The updated emission profiles improved the simulation of the downwind transported smoke. Ref. [136] compared performances of the Briggs, Sofiev, and Freitas plume rise models in CMAQ simulations against the MISR and CALIPSO aerosol heights over the CONUS during a two-month period and found substantial differences among the models. The simulations, however, provide quantitative impacts of smoke plume rise simulations on air quality prediction. If the plume rise height is

higher in modeling than observation, the CMAQ simulations underpredict local AOD and surface PM_{2.5} by approximately 20–30% and overpredict downwind by 5–10% on average. Ref. [137] analyzed the effects of plume rise on U.S. air quality using the Multi-Scale Infrastructure for Chemistry and Aerosols Version (MUSICAv) model during FIREX-AQ and WE-CAN and found that including plume rise improves the model agreement between the modeling and observations of CO and NO_x by including plume rise parameterizations in smoke simulations.

To address the issue of limited plume rise measurements, a technique is used to produce plume rise data using high-resolution smoke models such as WRF-SFIRE. The “data” are then used to develop plume rise models together with meteorological and emission properties. Ref. [138] used WRF-SFIRE with a large-eddy simulation (LES) mode to develop a plume dataset, which was then used to develop a plume rise modeling tool based on a simple energy balance. Ref. [139] used the High-Resolution, Rapid Refresh (HRRR) with LES to develop a plume dataset, which was then used to develop a plume rise modeling tool based on ML technology.

3.6. Smoke Decision Support Systems

Smoke modeling tools can be converted into smoke decision support systems (SDSSs) and are available to assist managers, decision-makers, and society in evaluating and mitigating the impacts of smoke. SDSSs also assist managers in planning and/or successfully implementing prescribed fires. HYSPLIT and other transport models are widely used by managers in real time to assess the potential smoke impacts of prescribed fires. A major advancement over the last decade is the development and applications of operational smoke prediction systems, which, in addition to smoke models, also include all or parts of the components to determine fuels, burned areas, fire emission, and plume rise. The BlueSky framework [140] uses the Fuel Characteristic Classification System (FCCS) [141] to specify fuels across the contiguous US and HYSPLIT to predict smoke transport and particle concentrations. The HRRR-Smoke air quality modeling system (<https://rapidrefresh.noaa.gov/hrrr/HRRRsmoke/>, accessed on 14 July 2025) estimates emissions from wildfires detected by the VIIRS/JPSS satellite fire product and makes 36 h smoke predictions every 6 h over the CONUS using WRF-Chem. Other examples of smoke forecasting systems include the Washington State University AIRPACT system [142], which utilizes CMAQ and the HRRR-Smoke system.

It is essential to estimate fire emissions and predict smoke transport when fires are burning so that response measures can be implemented in time to protect human health and predict traffic impacts. The use of satellite data, including FRP, can improve the performance of operational smoke prediction systems. The application of high-frequency satellite GOES products has provided instant burn information and allows for real-time smoke prediction [143]. Atmosphere models with simplified fire spread models are developed to improve operational smoke forecasting capabilities [144–146].

3.7. Applications of ML/DL

Artificial intelligence (AI) and its subsets of machine learning (ML) and deep learning (DL) have been extensively applied to wildland fire and smoke events in recent decades. AI can process and analyze fire, smoke, and related information, such as fuel, meteorology, air quality, and human interactions, for developing prediction models. In a review on ML applications in wildfire science and management, ref. [25] provides a detailed description and evaluation of approaches with their advantages, limitations, and applications to wildfire problems, including fire and smoke impacts.

ML has been a useful tool to obtain fire information, including emissions. Refs. [147–149] used ML models to analyze and predict monthly high-resolution burned area and emissions over the CONUS and predict their future trends. The predictors for burned area include atmospheric, land surface, and socioeconomic conditions, and the atmospheric circulation patterns conducive to wildfires. The ML emission model was found to be able to reproduce the major features of fire emissions, including spatial distributions, seasonal, and interannual variability (Figure 7). Note a significant difference in model performance, with $R = 0.97$ in Figure 7b and $R = 0.07$ in Figure 7c. The poor performance with CLM may reflect a limitation with many global dynamic vegetation models (GDVMs). CLM and other GDVMs are vegetation-based, which respond to atmospheric forcing much smaller than atmosphere-based models. As a result, GDVMs often have low skills in predicting interannual fire variability (especially extremely large fires) in many regions, including the South, which is shown in [149].

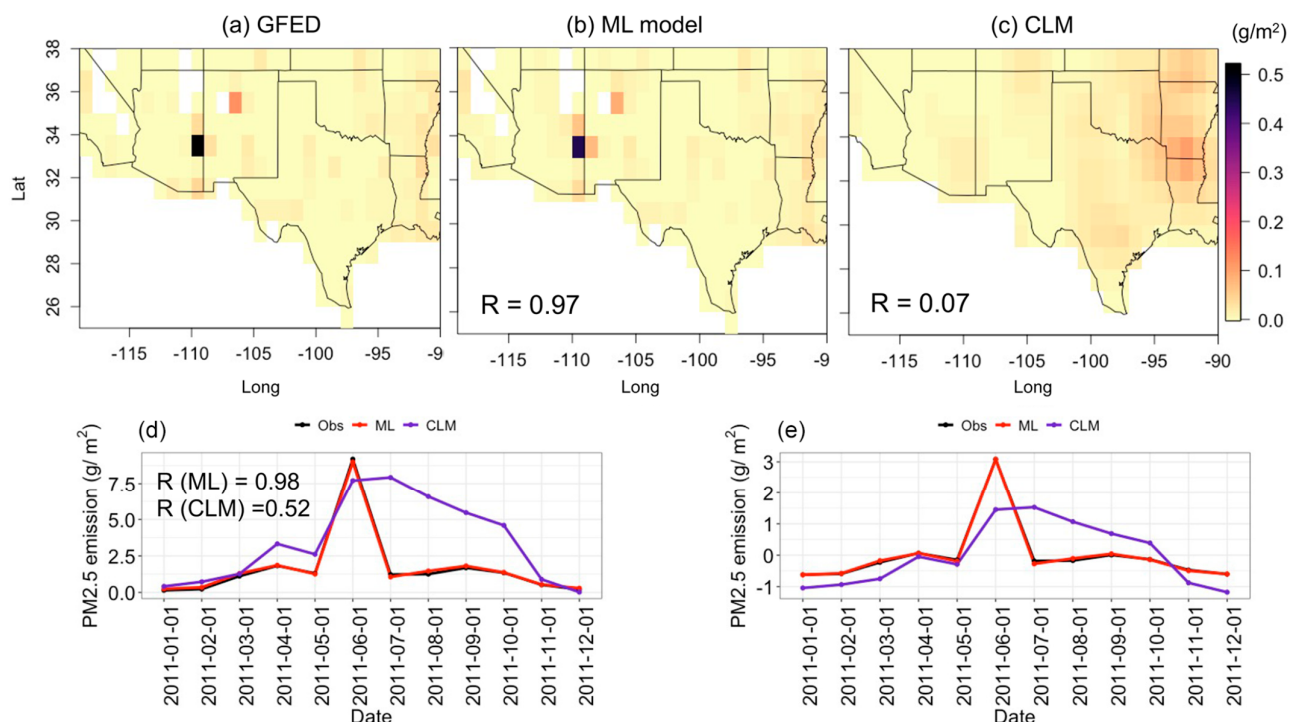


Figure 7. Comparisons of 2011 fire emissions among models. (a–c): spatial distributions of the annual mean fire PM2.5 emissions for GFED, the ML model, and CLM. (d,e): time series of the domain-averaged total and normalized fire PM2.5 emissions. (From [149]. The publisher, the Copernicus Publications, is licensed under the Creative Commons Attribution 4.0 License under which the authors retain the copyright. Permission to use this figure was granted by the corresponding author).

ML is a useful tool to obtain smoke data for smoke and impact modeling. Ref. [150] integrated smoke simulations and observations using ML for regional health impact assessments. ML-based data are fused with coupled WRF and CMAQ. The results showed improved surface PM2.5 estimation for the regional fire events in the Pacific Northwest during two 2017 summer and fall months. Ref. [151] used ML to predict smoke plume rise using the CALIPSO satellite products. Ref. [152] used an ML model to simulate a CCN from simulated aerosol, trace gas, and atmospheric elements. Ref. [153] used ML to provide rapid wildfire smoke exposure estimates through fusing data from multiple sources, including air quality monitoring, low-cost sensor networks, satellite measurements, and meteorological and smoke modeling.

In comparison with empirical models, including regression, correlation, and time-series analysis, which are also data-based approaches like ML models and rely on a statistical

analysis of historical data, and physical models, which simulate the processes governing fire and smoke dynamics using physical laws and mathematical algorithms, AL (including ML and DL) models use computational algorithms to identify patterns and predict wildfire and smoke with the capacity of processing massive data, self-learning, using human experience, and physical rules [50]. AI models are more complex, with the ability to incorporate a broad array of variables and often find the most significant and optimal factors for fire and smoke analyses [154]. Ref. [155] compared the performance of the three types of models in simulating fire behavior in Australia and found that some traditional wildfire simulators excel in real-time operational applications, while ML techniques demonstrate superior accuracy in handling complex datasets.

There are many issues with ML fire applications [25]. First, a massive amount of historical data is needed to train models. Thus, ML is best suited to problems where there is sufficient high-quality data. This may not be the case, for example, for fire management and for fire predictions where no analog exists in the observed data. Second, ML models often include a large number of drivers with complex relationships with fires and between themselves, which are often not intuitive and clear. Some contributing but not major drivers may show irrational relationships with fires (e.g., positive correlations between moisture and fires). While ML models are powerful interpolators, they can be poor extrapolators at the same time. Thus, caution is needed when using ML techniques because they are usually like a black box. Third, a major obstacle for ML model applications is the lack of interpretability or explainability of the model outputs, and the model interpretability varies significantly across the different types of ML models. Finally, there are also limitations with ML applications to certain fire issues. Ref. [25] connects descriptive, diagnostic, predictive, and prescriptive analytics to the fire risk issues of past fires, their drivers, future fires, and fire risk mitigation, respectively. It seems that ML fire applications were predominantly associated with descriptive or diagnostic analytics focused on fire detection and mapping using classification methods, and on fire susceptibility mapping and landscape controls on fire using regression approaches.

4. Gaps and Research Needs

4.1. Measurement

- Measurements of smoke plume from large wildfires

There are limited simultaneous observations of fire behavior and deep plumes from large wildfires because they are difficult to measure or quantify, whereas most instrumented burns are prescribed fires with a less intense plume. Lack of direct measurements of vertical velocities in deep wildfire plumes and datasets linking airborne infrared imagery of fire front properties to vertical velocities limit our understanding of plume structures. Fire emission data (including water vapor) are also useful to understand pyro-cumulus clouds possibly generated by big wildfires. Some fire and smoke programs (FASMEE, FIRE-AX, FireSense, etc.) have been working together to measure fire behavior and smoke during stand replacement prescribed fires. Despite a much bigger challenge, there is a need to explore the feasibility of conducting such measurements for large wildfires.

There is also a need to use different techniques to develop integrated fire and smoke datasets. Ref. [156] illustrates a compilation pipeline to integrate ground- and satellite-based telemetry tracking wildlife datasets. It includes the phases of dataset pre-processing, formatting individual datasets to a common template, dataset binding, error checking, and filtering. Such a pipeline could be instrumental for developing integrated fire and smoke datasets.

- Plume rise

Satellite remote-sensing products have been widely used to estimate plume rise. Evaluation using measurements obtained during recent field campaigns identified many advantages and disadvantages of various satellite techniques. The products using multi-angle imaging, such as MISR, are most accurate but at weekly intervals. Algorithms based on temperature contrast, UV radiometry, or oxygen absorption estimate plume rise on a daily basis for regular satellite techniques such as MODIS and VIIRS, but they still have large errors and need further improvement. Also, similar algorithms are needed for relatively new satellite products at hourly or even minute intervals, such as GOES-R and TEMPO. A new methodology to estimate plume rise directly from imagery from MODIS imagery applied to the new geostationary GOES-R ABI imagery provides a glimpse of how a plume changes from moment to moment, which will likely lead to a new understanding of plume evolution. Future field campaigns have the potential to utilize multiple synchronized ground lidar units set such that their directional measurements intersect at the fire, with the intersection providing a virtual vertical tower that can detail the movement of air and aerosols at the center of the plume.

- Smoke from duff burning

Measurement and modeling results have emerged to indicate that the burning of the duff layer during the flaming phase contributed substantially to air pollution episodes in remote metropolitan areas of the Southeastern US [157,158]. The results have large uncertainty because of the lack of emission factor measurements of duff burning during the flaming phase. The related smoke plume structure, which is expected to be much different from duff burning during the smoldering phase, has not been well understood. There is a need to measure emission factors and smoke plume structure from duff burning during both smoldering and flaming phases to improve current fuel tools, such as FCCS and global fire emission databases.

- Differences between prescribed fire and wildfire

Smoke dynamics are different between prescribed fire and wildfire in many ways. A prescribed fire is ignited intentionally by fire managers, while a wildfire is ignited as an incident by lightning or human factors, such as arson. A prescribed fire is implemented mostly in rural forests and range lands, while a wildfire occurs mostly in rural areas. But there are increasing trends in WUI areas. A prescribed fire lasts for hours, while a wildfire could range between days and months. Fire behavior is usually much less intense for a prescribed fire than for a wildfire. Smoke stays within the PBL and affects local areas near a burn site for most prescribed fires but penetrates the troposphere (even the stratosphere) and is transported long distances for wildfires. The ozone and SOC of a prescribed fire are less concerning than those of a wildfire because prescribed fires are implemented mainly during late winter and early spring, with a short smoke lifetime. Because of these differences, field campaigns of prescribed fires focus on local measurement using presetting tower-based instruments rather than aircraft along the smoke in downwind areas, and the findings obtained from prescribed fire campaigns may not apply to wildfires. Further field measurements and analyses are needed to understand the similarities and differences in smoke dynamics between a prescribed fire and a wildfire.

4.2. Modeling

- Evaluation and improvement of smoke modeling

The recent field campaigns have obtained a large amount of smoke data for wildland fires. They are extremely valuable for the evaluation and improvement of existing smoke modeling tools. For example, multiple synchronized ground lidar units were used to detect smoke movement, and satellite, airborne, and tower-based platforms were used to measure

fire behavior and energy during FASMEE, providing fire and smoke information for evaluating and advancing modeling of smoke plume rise and the complex fire–smoke–atmosphere interactions. More efforts are needed to evaluate the modeling of processes inside plumes and understand the causes for the discrepancies revealed in previous model evaluation and intercomparison studies, explore the impacts on and improvements in long-range smoke transport, and improve the understanding and modeling of interactions of smoke plumes with fire, fuel, and the atmosphere.

- Coupling with dynamic fire modeling

Physics-based CFD fire models can resolve the fire dynamics. However, it is difficult to couple them with the atmosphere for operational applications because of their computational costs and input data requirements. As a result, the plume-driven fire dynamics related to the combustion environment and ambient atmospheric conditions are not well understood in current smoke models. To overcome the fire dynamics-related gap, continuous efforts are needed to develop high-resolution dynamical coupled systems among the fire, smoke, and atmosphere [159]. Figure 8 is a schematic diagram for next-generation smoke research and forecasting systems. The core of such systems is CFS models to simulate and predict smoke's physical processes of plume rise, transport, dispersion, and deposition, and the chemical processes that lead to the generation of secondary species. These processes are determined by fire emissions of gases, particles, heat and water, and meteorological conditions. Meanwhile, smoke particles feed back to the atmosphere and fire and fuel dynamics by modifying atmospheric radiation, cloud, circulation, and thermal structure. Thus, such systems will simulate complex interactions among the atmospheric and smoke processes, fire behavior, and emissions, and need comprehensive and coordinated measurements across the fields of fuels, fire behavior and energy, smoke and meteorology, and emission and chemistry for their development and evaluation. Also, there is a need for more powerful computational capacity, especially for operational real-time applications of such systems. The proliferation of cloud-computing capabilities, the ever-increasing computational abilities of computer processors, and more extensive applications of AL/ML techniques offer near-term potential. The CFD modeling outputs of pollutant concentrations, smoke structure and evolution, and modified meteorology will be used to evaluate smoke impacts on air quality, human health, ecosystem health, traffic, and climate.

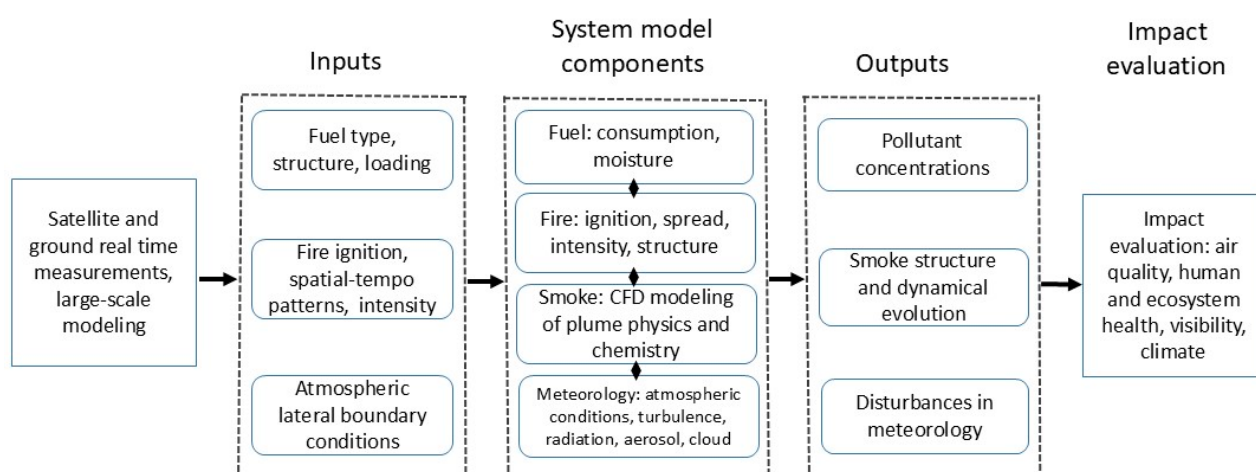


Figure 8. A schematic diagram of high-resolution dynamic coupled systems among fire, smoke, and atmosphere.

In-time and high-resolution wildfire information is one of the inputs for coupled systems. Wildfire detection and prediction have advanced recently [160]. Statistical techniques like logistic regression, frequently used in binary data analysis, have been widely

applied to predicting the probabilities of fire occurrence and building a relationship with the predictor variables. The same as smoke dynamics research, numerous studies have explored ML's applications across various fields, including the forecast and detection of forest fires, and have shown great promise. However, wildfire prediction and detection are facing many challenges, including finding appropriate models with complex factors of weather conditions, physical terrain, vegetation cover, and human activities to predict the occurrence of fires and the timely monitoring and detection of wildfires that are constantly changing their spatial extent and intensity over time, especially in remote areas where there could be few permanent infrastructures for surveillance, aggregating and analyzing data coming from different sources, and dealing with certain aspects such as the scalability and the interoperability of the systems used in the wildfire predictions.

- Plume rise

While many tools are available to estimate wildland fire plume rises, few of them can be used to obtain vertical concentration profiles. Also, most models do not include the plume rise impacts of multiple, simultaneous updrafts, which often produce less-efficient vertical smoke transport than a single-core updraft due to smaller updraft velocities and diameters and larger entrainment impact. While fire–smoke coupled dynamical models can explicitly simulate multiple-core structure and process, they are not parameterized in most plume rise models. Many issues with multiple-updraft cores need to be resolved, including the development of schemes to determine updraft numbers and understanding the contributors.

- Future smoke under a changing climate

Climate change due to the increasing atmospheric CO₂ concentrations is an urgent issue facing the world. Climate change is expected to affect smoke dynamics by modifying wildfire occurrence and size, fuel loading, and moisture (and therefore fire emissions). Atmospheric conditions contributing to plume rise, smoke transport, and dispersion [161,162] need to be projected. Earth system models are powerful tools that include atmospheric and vegetation models to provide environmental conditions for wildfires [150,163,164]. Research efforts on these issues using climate, ecosystem, and Earth Systems models are underway. For example, MUSICA has been under development to become the next-generation WRF-Chem and couple to other Earth system components, including dynamic vegetation with fire prediction and emission estimation capacities [165], and the US Department of Energy Exascale Earth System Model has been coupled with Freitas's plume rise model [166].

4.3. The Unique Challenge of WUI Smoke Dynamics

Wildfires in WUI have increased remarkably in recent decades. The fuel source changes from biomass to a complex mixture of building materials, plastics, vehicles, and household chemicals, which results in a completely different emission profile, and WUI fires and smoke represent a fundamentally different combustion regime and dynamics. Fires in WUI often burn structures, vehicles, and their contents, in addition to biomass in the natural landscape, emitting numerous toxic species, toxic organic compounds, and metals [167–169]. WUI areas showed at least 60% higher increase in moderate air quality days and greater sensitivity than non-WUI areas [170]. The smoke plume composition changes over time due to atmospheric chemistry and physical processes [171]. WUI fires may also lead to higher human exposures than wildland fires because of their proximity to communities [172].

However, WUI fire emission species and factors, and their differences from wildfire emissions, are not well understood. Data on smoke compositions specifically associated with WUI fires and how they are transformed over short and long distances are very sparse.

The impact of the unique WUI emissions and chemistry on regional exposures is not well understood. The capacity of smoke systems is limited in providing accurate information for wildfires in WUI. Model developments are needed to deal with smoke wildfires in the WUI, with two differences among others to be considered. In addition to the different smoke dispersion and transport between urban and rural areas mentioned above, heat release and fire spread are different between structure burning and vegetation burning, and structure will affect winds and other meteorological conditions. These differences suggest the need to add the components of structure fire and urban modeling to the current smoke decision systems.

There is a need to use interdisciplinary approaches to incorporate estimating emissions, collect chemical data, evaluate human health impacts, and improve modeling tools for WUI fire, smoke, and impacts. This approach requires the involvement of multidisciplinary research teams from multiple governmental agencies and institutions [171]. The efforts to be made include identifying risky communities and vulnerable populations, characterizing fuel and combustion, estimating fire emissions of natural fuels and structure materials, analyzing plume chemistry, especially toxics related processes, simulating and predicting smoke transport and transformation, evaluating smoke exposure and health impacts, which returns to the first effort and help identifying the communities most impacted.

4.4. ML/DL Technology

There are many gaps with potential opportunities in ML applications to wildfire research and management. As indicated above, ML fire applications are currently more closely aligned with descriptive and diagnostic analytics but insufficiently with predictive (e.g., predicted fire behavior) or prescriptive analytics (e.g., optimizing fire management decisions). ML applications in these problem domains have merged and will continue to be new opportunities for ML applications. Research effort is needed to develop methods that allow for greater interpretability of ML methods [25]. As these models often operate as black boxes, increasing transparency in their decision-making processes is essential for building trust and confidence among stakeholders. The development of interpretable machine learning [173] and hybrid models that combine process-based models and ML methods [174] are possible solutions. These hybrid models have the potential to offer more robust predictions by incorporating both physical principles and statistical patterns. ML can also be applied to improve ML fire model drivers, such as weather information [25]. Ref. [175] indicates the potential of ML and DL to automate the detection and counting of wildlife individuals with higher detection rates than conventional surveys, while significantly reducing costs and analysis time. This suggests the great value and capabilities of ML and DL in processing massive satellite fire and smoke data.

There is a need to develop integrated systems of statistical, physical, and ML models. Each of these models has advantages and disadvantages [173]. For example, the empirical/statistical Rothermel Model is a useful tool for predicting the spread of wildland fires with a few critical factors of fuel, wind, and topography, but is limited in its ability to account for unpredictable variables and fire feedback to the atmospheric variable. Physics-based models such as FIRETEC are highly customizable but computationally intensive. As described above, ML and DL models are able to identify major predictors among a large number of factors, capture spatial and temporal patterns in wildfire dynamics, and integrate efficiently, but their performance and actual values vary depending on data availability and physical interpretability. One of the focuses of the modeling study is to develop hybrid modeling approaches that integrate multiple methods to harness their combined strengths and, in the meantime, minimize their weaknesses [173].

4.5. Smoke Health Impacts

Numerous studies have indicated the severe short- and long-term impacts of wildland fire smoke on human health [176,177]. As shown in Figure 3, outputs of the smoke prediction systems will be used to evaluate and predict such impacts. The recent advances in smoke measurement and modeling, as synthesized in this review, can enable better health impact studies. The improved fire air pollutant emission factors, plume rise modeling, and O₃, SOC, and other secondary products generated in the plume will provide more accurate estimates of ground air pollutants and their evolution, which will further improve the quantitative evaluation of the smoke impacts on human health. The findings and uncertainties of smoke studies suggest that some areas need special attention. First, it was found that WUI fires often lead to greater human health impacts than wildfires. Emissions of many toxic materials from building burning and dense populations in the WUI are among the major contributors. In addition, air pollutant emissions from other sources, such as traffic [178], are also a contributor. Thus, there is a need to monitor and measure emissions from all of these sources to accurately evaluate the health impacts during a WUI fire period. Second, the smoke modeling systems discussed above do not cover urban components. As discussed above, urban areas can significantly affect local meteorology and, therefore, smoke dynamics. Thus, an urban model should be a part of the smoke prediction systems for WUI fire and smoke modeling and their health impacts. In addition, ML has been widely applied in predicting health outcomes [179]. It is valuable to explore ways to integrate ML modeling and the prediction of fire smoke and health impacts.

4.6. Management

- Smoke management of prescribed fire

Two issues will need additional development for technical specialists and fire managers working together to effectively implement smoke prediction models in the field for prescribed fires. The first issue is the ability to estimate plume rise, which provides information to know if and how much smoke particles will travel a long distance instead of being deposited downward into a populated area. The second issue is the ability of a manager to estimate emissions and plume rises from co-occurring multiple wildland fires. These events complicate the overall smoke environment that needs to be considered for prescribed burning to have minimal smoke impacts.

- Smoke decision support systems

Current SDSSs are based on smoke modeling tools mainly for local smoke from prescribed fires and regional and continental smoke from wildfires. However, there are still large uncertainties in smoke modeling. Ref. [180] compares the performance of the Simple Smoke Screening Tool, VSmoke, and HYSPLIT, the tools popularly used to help prescribed fire planning, in simulating smoke dispersion from prescribed fires in North Carolina. They found that the total smoke area predicted by the three tools shows low spatial agreement, differing in total smoke area by thousands of square kilometers, and varying by an order of magnitude in the numbers of residents potentially exposed to smoke. More such model intercomparisons are needed to improve model performance.

4.7. New Approaches and Support

Due to the variability of fire plume shapes and sizes, the paucity of existing observations, and the complexities of the underlying controlling dynamics, any approach to substantially improving our understanding of smoke plume dynamics likely needs to be multi-pronged and integrated across both modelers and field researchers. Because fires and fire plumes are highly variable due to the existing atmospheric and fuel conditions at the

time of the fire and because fire behavior is different in different areas, advances in plume dynamics will have to utilize broadly obtained observations of intensively observed fires. Because the required observational and modeling efforts are large, partnerships will be needed, both for funding and for implementation. The scale of the effort needed is beyond any one group or institution and beyond any one model, observational technique, or study. Coordination will be paramount, with the free sharing of ideas and datasets.

The National Cohesive Wildland Fire Management Strategy (NCWFMS), initiated in 2009, continues to work collaboratively among stakeholders and across all ecosystems in the U.S. by utilizing the best science in addressing the roles of fire and the significant impacts of wildfire smoke. The USDA Shared Stewardship Strategy (SSS) is another critical policy direction that provides an impetus for improved knowledge regarding plume dynamics. A broad understanding of plumes, from fumigation to well-dispersed plumes, is needed to successfully support well-intended strategies. The translation of current and future research into plume dynamics and chemistry that occurs within plumes and smoke as it moves and ages is of critical concern to all who seek greater public health protection from wildland fire smoke.

5. Conclusions

Large wildfires have increased dramatically in the Western U.S. in the last three decades. Fires and smoke are increasingly impacting air quality, human health, and visibility in urban areas, necessitating fire and smoke researchers and managers to provide fire and smoke information and operational decisions more rapidly and accurately to assess and mitigate the impacts of smoke. Advances in the past decade in smoke measurement, modeling, and the implementation of operational systems have greatly increased our understanding of smoke dynamics and capabilities to support fire management and evaluate fire and smoke impacts:

- Field experiments have changed their focus recently from fire behavior to smoke–atmosphere interactions and further to comprehensive field measurements of fuel, fire behavior, emission, smoke, and meteorology. Massive data have been collected using measurement techniques from the ground and onboard aircraft and satellite, and new knowledge and uncertainties about fire emissions, smoke properties, evolution, structure, plume chemistry, and atmospheric interactions have been achieved. Long-term global smoke plume height datasets have been developed using satellite multiple-angle detection and modeling techniques for research on smoke impacts and fire–climate interactions.
- Smoke, fire, atmosphere, and canopy-coupled models, smoke operational prediction and decision support systems, plume-rise models, and ML wildland fire and smoke models have been developed and/or improved. The recent comprehensive field campaigns provided extremely valuable datasets of the physical, chemical, and optical properties of smoke, fuels, fire behavior, and meteorology for smoke model evaluation and improvement. Applications of these models have improved our understanding and prediction of smoke processes and mechanisms, their control factors and feedback to ambient conditions, and future smoke and air quality impact trends.
- Major gaps in smoke dynamics research exist and need to be filled to better address the challenges facing smoke dynamics research. Observational data across multiple times and spaces for large wildfires, plume vertical structure, and duff burning are needed to improve smoke modeling and prediction. There is a need to understand the differences in measured smoke properties between prescribed fire and wildfire. There is also a need for high-resolution, dynamic fire, smoke, and atmospheric-coupled systems, integrated systems of statistical, physical, and ML models, and the simultaneous

measurements of these components for wildfires and WUI fires. It is important to develop “physics-informed” or “explainable AI” (XAI) models that respect physical laws, as ML techniques applicable in wildfire simulation are not only limited in data fitting, but have to consist of scientific content. Schemes are needed for vertical plume distributions and multiple updrafts. There is also a need to improve nighttime smoke modeling, smoke processes in Earth system models, and operational smoke prediction skills.

Author Contributions: This review paper is developed from a book chapter (see Acknowledgments). Book chapter—Conceptualization, Y.L., W.E.H., B.E.P., C.B.C. and W.A.J. Writing: current science state, B.E.P.; measurement, C.B.C., Y.L., W.E.H., N.H.F.F. and J.P.S.; modeling, A.K.K., Y.L., W.E.H., S.L.G. and F.Z.; decision support systems, W.A.J., N.H.F.F., N.K.L., S.M.S. and S.L.G.; management, S.L.G., P.W.L. and T.J.B. Review paper—Modification, Y.L. (most work), W.E.H. (smoke–canopy interaction), and J.P.S. (laboratory measurement); Editing, W.E.H. and S.M.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data was created or analyzed in this study.

Acknowledgments: This review paper is developed from a book chapter [27] as part of a USDA Forest Service Smoke Assessment Project. The chapter is licensed under the terms of the Creative Commons Attribution 4.0 International License (<http://creativecommons.org/licenses/by/4.0>, accessed on 14 July 2025). The major additions in the review paper include recent studies on field campaigns, laboratory experiments, satellite product applications, model evaluation and improvement using the collected data, and ML applications to fire emission and smoke modeling.

Conflicts of Interest: The authors declare that they have no conflicts of interest.

Abbreviations

AAE	Ångström absorption exponent
ACSM	Aerosol chemical speciation monitor
AERONET	Aerosol RObotic NETwork
AI	Artificial Intelligence
AOD	Aerosol optical depth
ARPS	Advanced Regional Prediction System
BB-FLUX	Biomass Burning Fluxes of Trace Gases and Aerosols
BC	Black carbon
BrC	Brown carbon
CALIOP	Cloud-Aerosol LIDAR with Orthogonal Polarization
CALIPSO	Cloud-Aerosol LIDAR and Infrared Pathfinder Satellite Observations
CCN	Cloud condensation nuclei
CFD	Computational fluid dynamics
CIMS	Chemical ionization MS
CMAQ	Community Multi-Scale Air Quality model
DL	Deep learning
EESI-TOF-MS	Extractive electrospray ionization–time of flight–MS
FASMEE	Fire and Smoke Model Evaluation Experiment

FCCS	Fuel Characteristic Classification System
FINN	Fire inventory from NCAR
FIREX-AQ	Fire Influence on Regional to Global Environments and Air Quality
FRP	Fire radiative power
GFED	Global Fire Emission Database
GFFEPS	Global Forest Fire Emissions Prediction System
GOES	Geostationary Operational Environmental Satellite
G-WISE	Georgia Wildland-fire Simulation Experiment
HRRR	High-Resolution Rapid Refresh model
HYSPLIT	Hybrid Single-Particle Lagrangian Integrated Trajectory
INP	Ice-nucleating particles
JFSP	Joint Fire–Science Program
LES	Large eddy simulation
Lidar	Doppler Light Detection and Ranging
MEE	Mass extinction efficiency
MISR	Multi-angle Imaging SpectroRadiometer
ML	Machine learning
MODIS	Moderate Resolution Imaging Spectroradiometer
MUSICA	(Multi-Scale Infrastructure for Chemistry and Aerosols)
NCWFMS	National Cohesive Wildland Fire Management Strategy
OA	organic aerosol
OC	Organic carbon
PBL	Planetary boundary layer
PB-P	Planned Burn-Piedmont
PILS	Particle in Liquid Sampler
POA	Primary organic aerosol
PTR-MS	Proton-transfer-reaction mass spectrometry
RHI	Range Height Indicator
RxCADRE	Prescribed Fire Combustion and Atmospheric Dynamics Research Experiment
SDSS	Smoke decision support system
SERDP	Strategic Environmental Research and Development Program
SOA	Secondary organic aerosol
SOC	Secondary organic carbon
SSA	Single scattering albedo
SSS	Shared Stewardship Strategy
TEMPO	Tropospheric Emissions: Monitoring of Pollution
TROPOMI	TROPOspheric Monitoring Instrument
VFEI	VIIRS-based Fire Emission Inventory
VIIRS	Visible Infrared Imaging Radiometer Suite
VOC	Volatile organic compounds
WE-CAN	Western wildfire Experiment for Cloud chemistry, Aerosol absorption, and Nitrogen
WFSI	Wildland Fire Science Initiative
WoFS-Smoke	Warn-on-Forecast System for Smoke
WRF	Weather Research and Forecasting
WUI	Wildlife–urban interface

References

1. Byun, D.; Schere, K.L. Review of the governing equations, computational algorithms, and other components of the Models-3 Community Multiscale Air Quality (CMAQ) Modeling System. *Appl. Mech. Rev.* **2006**, *59*, 51–77. [[CrossRef](#)]
2. Larkin, N.K.; Raffuse, S.M.; Strand, T.M. Wildland fire emissions, carbon, and climate: U.S. emissions inventories. *For. Ecol. Manag.* **2014**, *317*, 61–69. [[CrossRef](#)]

3. Larkin, N.K.; Raffuse, S.M.; Huang, S.; Pavlovic, N.; Lahm, P.; Rao, V. The Comprehensive Fire Information Reconciled Emissions (CFIRE) Inventory: Wildland Fire Emissions Developed for the 2011 and 2014 U.S. National Emissions Inventory. *J. Air Waste Manag. Assoc.* **2020**, *70*, 1165–1185. [\[CrossRef\]](#) [\[PubMed\]](#)
4. Decker, Z.C.J.; Robinson, M.A.; Barsanti, K.C.; Bourgeois, I.; Coggon, M.M.; DiGangi, J.P.; Diskin, G.S.; Flocke, F.M.; Franchin, A.; Fredrickson, C.D.; et al. Nighttime and daytime dark oxidation chemistry in wildfire plumes: An observation and model analysis of FIREX-AQ aircraft data. *Atmos. Chem. Phys.* **2021**, *21*, 16293–16317. [\[CrossRef\]](#)
5. Wilkins, J.L.; de Foy, B.; Thompson, A.M.; Peterson, D.A.; Hyer, E.J.; Graves, C.; Fishman, J.; Morris, G.A. Evaluation of stratospheric intrusions and biomass burning plumes on the vertical distribution of tropospheric ozone over the midwestern United States. *J. Geophys. Res. Atmos.* **2020**, *125*, e2020JD032454. [\[CrossRef\]](#)
6. Evangeliou, N.; Balkanski, Y.; Hao, W.M.; Petkov, A.; Silverstein, R.P.; Corley, R.; Nordgren, B.L.; Urbanski, S.P.; Eckhardt, S.; Stohl, A.; et al. Wildfires in northern Eurasia affect the budget of black carbon in the Arctic—A 12-year retrospective synopsis (2002–2013). *Atmos. Chem. Phys.* **2016**, *16*, 7587–7604. [\[CrossRef\]](#)
7. Katich, J.M.; Apel, E.C.; Bourgeois, I.; Brock, C.A.; Bui, T.P.; Campuzano-Jost, P.; Commane, R.; Daube, B.; Dollner, M.; Fromm, M.; et al. Pyrocumulonimbus affect average stratospheric aerosol composition. *Science* **2023**, *379*, 815–820. [\[CrossRef\]](#)
8. McClure, C.D.; Jaffe, D.A. Investigation of High Ozone Events Due to Wildfire Smoke in an Urban Area. *Atmos. Environ.* **2018**, *194*, 146–157. [\[CrossRef\]](#)
9. Lim, C.Y.; Hagan, D.H.; Coggon, M.M.; Koss, A.R.; Sekimoto, K.; de Gouw, J.; Warneke, C.; Cappa, C.D.; Kroll, J.H. Secondary organic aerosol formation from biomass burning emissions. *Atmos. Chem. Phys.* **2019**, *19*, 12797–12809. [\[CrossRef\]](#)
10. Heilman, W.E.; Liu, Y.; Urbanski, S.; Kovalev, V.; Mickler, R. Wildland fire emissions, carbon, and climate: Plume rise, atmospheric transport and chemistry processes. *For. Ecol. Manag.* **2014**, *317*, 70–79. [\[CrossRef\]](#)
11. Reid, C.E.; Brauer, M.; Johnston, F.H.; Jerrett, M.; Balmes, J.R.; Elliott, C.T. Critical review of health impacts of wildfire smoke exposure. *Environ. Health Perspect.* **2016**, *124*, 1334–1343. [\[CrossRef\]](#)
12. Waldrop, T.A.; Goodrick, S.L. *Introduction to Prescribed Fires in Southern Ecosystems*; Science Update SRS-054; US Department of Agriculture Forest Service, Southern Research Station: Asheville, NC, USA, 2012; p. 80.
13. Holden, Z.A.; Swanson, A.; Luce, C.H.; Jolly, W.M.; Maneta, M.; Oyler, J.W.; Warren, D.A.; Parsons, R.; Affleck, D. Decreasing fire season precipitation increased recent western US forest wildfire activity. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, E8349–E8357. [\[CrossRef\]](#) [\[PubMed\]](#)
14. Wilmot, T.Y.; Mallia, D.V.; Hallar, A.G.; Lin, J.C. Wildfire activity is driving summertime air quality degradation across the western US: A model-based attribution to smoke source regions. *Environ. Res. Lett.* **2022**, *17*, 114014. [\[CrossRef\]](#)
15. Carreras-Sospedra, M.; Zhu, S.; MacKinnon, M.; Lassman, W.; Mirocha, J.D.; Barbato, M.; Dabdub, D. Air quality and health impacts of the 2020 wildfires in California. *Fire Ecol.* **2024**, *20*, 6. [\[CrossRef\]](#)
16. Mass, C.F.; Ovens, D. The Northern California wildfires of 8–9 October 2017: The role of a major downslope wind event. *Bull. Am. Meteorol. Soc.* **2018**, *100*, 235–256. [\[CrossRef\]](#)
17. Selimovic, V.; Yokelson, R.J.; McMeeking, G.R.; Coefield, S. In situ measurements of trace gases, PM, and aerosol optical properties during the 2017 NW US wildfire smoke event. *Atmos. Chem. Phys.* **2019**, *19*, 3905–3926. [\[CrossRef\]](#)
18. Li, Y.; Tong, D.; Ma, S.; Zhang, X.; Kondragunta, S.; Li, F.; Saylor, R. Dominance of wildfires impact on air quality exceedances during the 2020 record-breaking wildfire season in the United States. *Geophys. Res. Lett.* **2021**, *48*, e2021GL094908. [\[CrossRef\]](#)
19. Dinavahi, S.; Archer, C.L. Air quality in the U.S. during the 2023 wildfire season. *Bull. Atmos. Sci. Technol.* **2025**, *6*, 6. [\[CrossRef\]](#)
20. Burke, M.; Childs, M.L.; de la Cuesta, B.; Qiu, M.; Li, J.; Gould, C.F.; Heft-Neal, S.; Wara, M. The contribution of wildfire to PM_{2.5} trends in the USA. *Nature* **2023**, *622*, 761–766. [\[CrossRef\]](#)
21. Warneke, C.; Schwarz, J.P.; Dibb, J.; Kalashnikova, O.; Frost, G.; Al-Saad, J.; Brown, S.S.; Brewer, W.A.; Soja, A.; Seidel, F.C.; et al. Fire Influence on Regional to Global Environments and Air Quality (FIREX-AQ). *J. Geophys. Res. Atmos.* **2023**, *128*, e2022JD037758. [\[CrossRef\]](#)
22. Prichard, S.; Larkin, N.S.; Ottmar, R.; French, N.H.; Baker, K.; Brown, T.; Clements, C.; Dickinson, M.; Hudak, A.; Kochanski, A.; et al. The Fire and Smoke Model Evaluation Experiment—A Plan for Integrated, Large Fire–Atmosphere Field Campaigns. *Atmosphere* **2019**, *10*, 66. [\[CrossRef\]](#) [\[PubMed\]](#)
23. Watts, A.C.; Varner, J.M.; Soltanaghai, E.; Calle, L.; Alipour, M. An Interdisciplinary Approach to Coordinated Data Collection for Wildland Fire Science: The Fire and Smoke Model Evaluation Experiment (FASMEE). In Proceedings of the IGARSS 2024—2024 IEEE International Geoscience and Remote Sensing Symposium, Athens, Greece, 7–12 July 2024; pp. 2588–2592.
24. Kochanski, A.K.; Jenkins, M.A.; Yedinak, K.; Mandel, J.; Beezley, J.; Lamb, B. Toward an integrated system for fire, smoke and air quality simulations. *Int. J. Wildland Fire* **2015**, *25*, 534–546. [\[CrossRef\]](#)
25. Jain, P.; Coogan, S.C.P.; Subramanian, S.G.; Crowley, M.; Taylor, S.; Flannigan, M. A review of machine learning applications in wildfire science and Management. *Environ. Rev.* **2020**, *28*, 478–505. [\[CrossRef\]](#)
26. Heilman, W.E. Atmospheric turbulence and wildland fires: A review. *Int. J. Wildland Fire* **2023**, *32*, 476–495. [\[CrossRef\]](#)

27. Liu, Y.Q.; Heilman, W.E.; Potter, B.E.; Clements, C.B.; Jackson, W.A.; French, N.H.F.; Goodrick, S.L.; Kochanski, A.K.; Larkin, N.K.; Lahm, P.W.; et al. Smoke Plume Dynamics. In *Wildland Fire Smoke in the United States: A Scientific Assessment*; Peterson, D.L., McCaffrey, S.M., Patel-Weynand, T., Eds.; Springer International Publishing: Cham, Switzerland, 2022; pp. 83–119. ISBN 9783030870454.
28. Yokelson, R.J.; Burling, I.R.; Gilman, J.B.; Warneke, C.; Stockwell, C.E.; de Gouw, J.; Akagi, S.K.; Urbanski, S.P.; Veres, P.; Roberts, J.M.; et al. Coupling field and laboratory measurements to estimate the emission factors of identified and unidentified trace gases for prescribed fires. *Atmos. Chem. Phys.* **2013**, *13*, 89–116. [[CrossRef](#)]
29. Clements, C.B.; Oliphant, A.J. The California State University Mobile Atmospheric Profiling System: A facility for research and education in boundary layer meteorology. *Bull. Am. Meteorol. Soc.* **2014**, *95*, 1713–1724. [[CrossRef](#)]
30. Lang, T.J.; Rutledge, S.A.; Dolan, B.; Krehbiel, P.; Rison, W.; Lindsey, D.T. Lightning in wildfire smoke plumes observed in Colorado during summer 2012. *Mon. Weather. Rev.* **2014**, *142*, 489–507. [[CrossRef](#)]
31. Lareau, N.P.; Clements, C.B. Environmental controls on pyrocumulus and pyrocumulonimbus initiation and development. *Atmos. Chem. Phys.* **2016**, *16*, 4005–4022. [[CrossRef](#)]
32. McCarthy, N.; McGowan, H.; Guyot, A.; Dowdy, A. Mobile X-pol radar: A new tool for investigating pyroconvection and associated wildfire meteorology. *Bull. Am. Meteorol. Soc.* **2018**, *99*, 1177–1195. [[CrossRef](#)]
33. Falkowski, M.; Shuman, J.; Boland, J.; Kauffman, T.; Lefer, B.; Martin, M.M.; Riris, H. The NASA FireSense Project: Responding to Stakeholder Needs Across the Fire Life Cycle. In Proceedings of the IGARSS 2024—IEEE International Geoscience and Remote Sensing Symposium, Athens, Greece, 7–12 July 2024.
34. Ottmar, R.D.; Hiers, J.K.; Butler, B.W.; Clements, C.B.; Dickinson, M.B.; Hudak, A.T.; O'Brien, J.J.; Potter, B.E.; Rowell, E.M.; Strand, T.M.; et al. Measurements, datasets and preliminary results from the RxCADRE project—2008, 2011 and 2012. *Int. J. Wildland Fire* **2016**, *25*, 1–9. [[CrossRef](#)]
35. Peterson, D.L.; Hardy, C.C. The RxCADRE study: A new approach to interdisciplinary fire research. *Int. J. Wildland Fire* **2016**, *25*, i. [[CrossRef](#)]
36. Ottmar, R.; Varner, M.; Hiers, K.; Cornwell, E.; Kling, J. Research and management: Working together for the common good. *Wildfires* **2021**, *30*.
37. Heilman, W.E.; Bian, X.; Clark, K.L.; Zhong, S. Observations of turbulent heat and momentum fluxes during wildland fires in forested environments. *J. Appl. Meteorol. Climatol.* **2019**, *58*, 813–829. [[CrossRef](#)]
38. Heilman, W.E.; Banerjee, T.; Clements, C.B.; Clark, K.L.; Zhong, S.; Bian, X. Observations of sweep-ejection dynamics for heat and momentum fluxes during wildland fires in forested and grassland environments. *J. Appl. Meteorol. Climatol.* **2021**, *60*, 185–199. [[CrossRef](#)]
39. Heilman, W.E.; Clark, K.L.; Bian, X.; Charney, J.J.; Zhong, S.; Skowronski, N.S.; Gallagher, M.R.; Patterson, M. Turbulent momentum flux behavior above a fire front in an open-canopied forest. *Atmosphere* **2021**, *12*, 956. [[CrossRef](#)]
40. Desai, A.; Heilman, W.E.; Skowronski, N.S.; Clark, K.L.; Gallagher, M.R.; Clements, C.B.; Banerjee, T. Features of turbulence during wildland fires in forested and grassland environments. *Agric. For. Meteorol.* **2023**, *338*, 109501. [[CrossRef](#)]
41. Seitz, J.; Zhong, S.; Charney, J.J.; Heilman, W.E.; Clark, K.L.; Bian, X.; Skowronski, N.S.; Gallagher, M.R.; Patterson, M.; Cole, J.; et al. Atmospheric turbulence observed during a fuel-bed-scale low-intensity surface fire. *Atmos. Chem. Phys.* **2024**, *24*, 1119–1142. [[CrossRef](#)]
42. Clements, C.B.; Kochanski, A.K.; Seto, D.; Davis, B.; Camacho, C.; Lareau, N.P.; Contezac, J.; Restaino, J.; Heilman, W.E.; Krueger, S.K.; et al. The FireFlux II experiment: A model-guided field experiment to improve understanding of fire-atmosphere interactions and fire spread. *Int. J. Wildland Fire* **2019**, *28*, 308–326. [[CrossRef](#)]
43. Clements, C.B.; Seto, D. Observations of fire-atmosphere interactions and near-surface heat transport on a slope. *Bound.-Layer Meteorol.* **2015**, *154*, 409–426. [[CrossRef](#)]
44. Deegan, A.M.; Glenn, C.K.; El Hajj, O.; Anosike, A.; Kumar, K.; Abdurrahman, M.; Bai, B.; Liu, P.; O'Brien, J.; Saleh, R.; et al. Properties of surface-active organics in aerosol particles produced from combustion of biomass fuels under simulated prescribed-fire and wildfire conditions. *ACS Environ. Sci. Technol. Air* **2025**, *2*, 264–276.
45. Czech, H.; Popovicheva, O.; Chernov, D.G.; Kozlov, A.; Schneider, E.; Shmargunov, V.P.; Sueur, M.; Rüger, C.P.; Afonso, C.; Uzhegov, V.; et al. Wildfire plume ageing in the photochemical larger aerosol chamber (PHOTO-LAC). *Environ. Sci. Process. Impacts* **2024**, *26*, 35–55. [[CrossRef](#)]
46. Saleh, R.; O'Brien, J. Overview of the Georgia Wildland-fire Simulation Experiment (G-WISE). *ACS EST Air* **2025**, *2*, 979–981. [[CrossRef](#)]
47. Yang, S.X.; Huang, Q.Y.; Yu, M.Z. Advancements in remote sensing for active fire detection: A review of datasets and methods. *Sci. Total Environ.* **2024**, *943*, 173273. [[CrossRef](#)] [[PubMed](#)]
48. Winker, D.M.; Hunt, W.H.; McGill, M.J. Initial performance assessment of CALIOP. *Geophys. Res. Lett.* **2007**, *34*, L19803. [[CrossRef](#)]
49. Kahn, R.A.; Chen, Y.; Nelson, D.L.; Leung, F.; Li, Q.; Diner, D.J.; Logan, J.A. Wildfire smoke injection heights: Two perspectives from space. *Geophys. Res. Lett.* **2008**, *35*, L04809. [[CrossRef](#)]

50. Singh, H.; Ang, L.-M.; Lewis, T.; Paudyal, D.; Acuna, M.; Srivastava, P.K.; Srivastava, S.K. Trending and emerging prospects of physics-based and ML-based wildfire spread models: A comprehensive review. *J. For. Res.* **2024**, *35*, 135. [\[CrossRef\]](#)
51. Junghenn Noyes, K.T.; Kahn, R.A.; Limbacher, J.A.; Li, Z.; Fenn, M.A.; Giles, D.M.; Hair, J.W.; Katich, J.M.; Moore, R.H.; Robinson, C.E.; et al. Wildfire Smoke Particle Properties and Evolution, From Space-Based Multi-Angle Imaging II: The Williams Flats Fire during the FIREX-AQ Campaign. *Remote Sens.* **2020**, *12*, 3823. [\[CrossRef\]](#)
52. Wiggins, E.B.; Soja, A.J.; Gargulinski, E.; Halliday, H.S.; Pierce, R.B.; Schmidt, C.C.; Nowak, J.B.; DiGangi, J.P.; Diskin, G.S.; Katich, J.M.; et al. High temporal resolution satellite observations of fire radiative power reveal link between fire behavior and aerosol and gas emissions. *Geophys. Res. Lett.* **2020**, *47*, e2020GL090707. [\[CrossRef\]](#)
53. Griffin, D.; McLinden, C.A.; Dammers, E.; Adams, C.; Stockwell, C.E.; Warneke, C.; Bourgeois, I.; Peischl, J.; Ryerson, T.B.; Zarzana, K.J.; et al. Biomass burning nitrogen dioxide emissions derived from space with TROPOMI: Methodology and validation. *Atmos. Meas. Tech.* **2021**, *14*, 7929–7957. [\[CrossRef\]](#)
54. Wiggins, E.B.; Anderson, B.E.; Brown, M.D.; Campuzano-Jost, P.; Chen, G.; Crawford, J.; Crosbie, E.C.; Dibb, J.; DiGangi, J.P.; Diskin, G.S.; et al. Reconciling assumptions in bottom-up and top-down approaches for estimating aerosol emission rates from wildland fires using observations from FIREX-AQ. *J. Geophys. Res.* **2021**, *126*, e2021JD035692. [\[CrossRef\]](#)
55. Huang, J.; Loria-Salazar, S.M.; Deng, M.; Lee, J.; Holmes, H.A. Assessment of smoke plume height products derived from multisource satellite observations using lidar-derived height metrics for wildfires in the western US. *Atmos. Chem. Phys.* **2024**, *24*, 3673–3698. [\[CrossRef\]](#)
56. van der Werf, G.R.; Randerson, J.T.; Giglio, L.; van Leeuwen, T.T.; Chen, Y.; Rogers, B.M.; Mu, M.; van Marle, M.J.E.; Morton, D.C.; Collatz, G.J.; et al. Global fire emissions estimates during 1997–2016. *Earth Syst. Sci. Data* **2017**, *9*, 697–720. [\[CrossRef\]](#)
57. Chen, Y.; Hall, J.; van Wees, D.; Andela, N.; Hantson, S.; Giglio, L.; van der Werf, G.R.; Morton, D.C.; Randerson, J.T. Multi-decadal trends and variability in burned area from the fifth version of the Global Fire Emissions Database (GFED5). *Earth Syst. Sci. Data* **2023**, *15*, 5227–5259. [\[CrossRef\]](#)
58. Wiedinmyer, C.; Kimura, Y.; McDonald-Buller, E.C.; Emmons, L.K.; Buchholz, R.R.; Tang, W.F.; Seto, K.; Joseph, M.B.; Barsanti, K.C.; Carlton, A.G.; et al. The Fire Inventory from NCAR version 2.5: An updated global fire emissions model for climate and chemistry applications. *Geosci. Model Dev.* **2023**, *16*, 3873–3891. [\[CrossRef\]](#)
59. Anderson, K.; Chen, J.; Englefield, P.; Griffin, D.; Makar, P.A.; Thompson, D. The Global Forest Fire Emissions Prediction System version 1.0. *Geosci. Model Dev.* **2024**, *17*, 7713–7749. [\[CrossRef\]](#)
60. Ferrada, G.A.; Zhou, M.; Wang, J.; Lyapustin, A.; Wang, Y.; Freitas, S.R.; Carmichael, G.R. Introducing the VIIRS-based Fire Emission Inventory version 0 (VFEIv0). *Geosci. Model Dev.* **2022**, *15*, 8085–8109. [\[CrossRef\]](#)
61. Hoff, R.M.; Kondragunta, S.; Ciren, P.; Xu, C.; Zhang, H.; Huff, A. Development of synthetic GOES-R ABI aerosol products. *Atmos. Meas. Tech.* **2014**, *7*, 10131–10157.
62. Jones, T.; Ahmadov, R.; James, E.; Pereira, G.; Freitas, S.; Grell, G. Prototype of a Warn-on-Forecast System for Smoke (WoFS-Smoke). *Weather Forecast.* **2022**, *37*, 1191–1209. [\[CrossRef\]](#)
63. Naeger, A.R.; Newchurch, M.; Liu, X.; Chance, K. The NASA Tropospheric Emissions: Monitoring of Pollution (TEMPO) Satellite Mission: Early Adopters Program and Applied Science Activities. In Proceedings of the IGARSS 2022—2022 IEEE International Geoscience and Remote Sensing Symposium, Kuala Lumpur, Malaysia, 17–22 July 2022; pp. 7178–7181.
64. Mak, H.W.L. Application of satellite informatics in mitigating climatic challenges within the atmosphere: Selected case studies of Asian cities. In *Asia-Pacific Tech Monitor: Innovative Technologies for Building Climate-Resilient Cities in Asia and the Pacific*; ESCAP: Asian and Pacific Centre for Transfer of Technology: New Delhi, India, 2025; pp. 36–47.
65. Rickly, P.S.; Guo, H.; Campuzano-Jost, P.; Jimenez, J.L.; Wolfe, G.M.; Bennett, R.; Bourgeois, I.; Crounse, J.D.; Dibb, J.E.; DiGangi, J.P.; et al. Emission factors and evolution of SO₂ measured from biomass burning in wildfires and agricultural fires. *Atmos. Chem. Phys.* **2022**, *22*, 15603–15620. [\[CrossRef\]](#)
66. Tomsche, L.; Piel, F.; Mikoviny, T.; Nielsen, C.J.; Guo, H.; Campuzano-Jost, P.; Nault, B.A.; Schueneman, M.K.; Jimenez, J.L.; Halliday, H.; et al. Measurement report: Emission factors of NH₃ and NH_x for wildfires and agricultural fires in the United States. *Atmos. Chem. Phys.* **2023**, *23*, 2331–2343. [\[CrossRef\]](#)
67. Xu, L.; Crounse, J.D.; Vasquez, K.T.; Allen, H.; Wennberg, P.O.; Bourgeois, I.; Brown, S.S.; Campuzano-Jost, P.; Coggon, M.M.; Crawford, J.H.; et al. Ozone chemistry in western U.S. wildfire plumes. *Sci. Adv.* **2021**, *7*, eabl3648. [\[CrossRef\]](#)
68. Peng, Q.; Palm, B.B.; Melander, K.E.; Lee, B.H.; Hall, S.R.; Ullmann, K.; Campos, T.; Weinheimer, A.J.; Apel, E.C.; Hornbrook, R.S.; et al. HONO Emissions from Western U.S. Wildfires Provide Dominant Radical Source in Fresh Wildfire Smoke. *Environ. Sci. Technol.* **2020**, *54*, 5954–5963. [\[CrossRef\]](#)
69. Aurell, J.; Gullett, B.; Holder, A.; Kiros, F.; Mitchell, W.; Watts, A.; Ottmar, R. Wildland fire emission sampling at Fishlake National Forest, Utah using an unmanned aircraft system. *Atmos. Environ.* **2021**, *247*, 118193. [\[CrossRef\]](#)
70. Kobziar, L.N.; Lampman, P.; Tohidi, A.; Kochanski, A.K.; Cervantes, A.; Hudak, A.T.; McCarley, R.; Gullett, B.; Aurell, J.; Moore, R.; et al. Bacterial emission factors: A foundation for the terrestrial-atmospheric modeling of bacteria aerosolized by wildland fires. *Environ. Sci. Technol.* **2024**, *58*, 2413–2422. [\[CrossRef\]](#)

71. Lindaas, J.; Pollack, I.B.; Garofalo, L.A.; Pothier, M.A.; Farmer, D.K.; Kreidenweis, S.M.; Campos, T.L.; Flocke, F.; Weinheimer, A.J.; Montzka, D.D.; et al. Emissions of Reactive Nitrogen from Western U.S. Wildfires During Summer 2018. *J. Geophys. Res. Atmos.* **2020**, *126*, e2020JD032657. [[CrossRef](#)]
72. Sekimoto, K.; Coggon, M.M.; Gkatzelis, G.I.; Stockwell, C.E.; Peischl, J.; Soja, A.J.; Warneke, C. Fuel-type independent parameterization of volatile organic compound emissions from western US wildfires. *Environ. Sci. Technol.* **2023**, *57*, 13193–13204. [[CrossRef](#)] [[PubMed](#)]
73. Bela, M.M.; Kille, N.; McKeen, S.A.; Romero-Alvarez, J.; Ahmadov, R.; James, E.; Pereira, G.; Schmidt, C.; Pierce, R.B.; O'Neill, S.M.; et al. Quantifying carbon monoxide emissions on the scale of large wildfires. *Geophys. Res. Lett.* **2022**, *49*, e2021GL095831. [[CrossRef](#)]
74. Gkatzelis, G.I.; Coggon, M.M.; Stockwell, C.E.; Hornbrook, R.S.; Allen, H.; Apel, E.C.; Bela, M.M.; Blake, D.R.; Bourgeois, I.; Brown, S.S.; et al. Parameterizations of US wildfire and prescribed fire emission ratios and emission factors based on FIREX-AQ aircraft measurements. *Atmos. Chem. Phys.* **2023**, *24*, 929–956. [[CrossRef](#)]
75. Roberts, J.M.; Stockwell, C.E.; Yokelson, R.J.; de Gouw, J.; Liu, Y.; Selimovic, V.; Koss, A.R.; Sekimoto, K.; Coggon, M.M.; Yuan, B.; et al. The nitrogen budget of laboratory-simulated western US wildfires during the FIREX 2016 Fire Lab study. *Atmos. Chem. Phys.* **2020**, *20*, 8807–8826. [[CrossRef](#)]
76. Wang, S.; Bathras, B.L.; Cui, W.; Milazzo, M.; Goldstein, A.H.; Gollner, M.J. Laboratory Quantification of Emissions from Wildland-Urban Interface Fuels Using Fourier-Transform Infrared Spectroscopy. *Environ. Sci. Technol.* **2025**, *59*, 12843–12852. [[CrossRef](#)]
77. Srivastava, D.; Vu, T.V.; Tong, S.; Shi, Z.; Harrison, R.M. Formation of secondary organic aerosols from anthropogenic precursors in laboratory studies. *npj Clim. Atmos. Sci.* **2022**, *5*, 22. [[CrossRef](#)]
78. Calahorrano, J.F.J.; Lindaas, J.; O'Dell, K.; Palm, B.B.; Peng, Q.; Flocke, F.; Pollack, I.B.; Garofalo, L.A.; Farmer, D.K.; Pierce, J.R.; et al. Daytime Oxidized Reactive Nitrogen Partitioning in Western U.S. Wildfire Smoke Plumes. *J. Geophys. Res. Atmos.* **2020**, *126*, e2020JD033484. [[CrossRef](#)]
79. Garofalo, L.A.; Pothier, M.A.; Levin, E.J.T.; Campos, T.; Kreidenweis, S.M.; Farmer, D.K. Emission and Evolution of Submicron Organic Aerosol in Smoke from Wildfires in the Western United States. *ACS Earth Space Chem.* **2019**, *3*, 1237–1247. [[CrossRef](#)]
80. Palm, B.B.; Peng, Q.; Fredrickson, C.D.; Lee, B.H.; Garofalo, L.A.; Pothier, M.A.; Kreidenweis, S.M.; Farmer, D.K.; Pokhrel, R.P.; Shen, Y.; et al. Quantification of organic aerosol and brown carbon evolution in fresh wildfire plumes. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 29469–29477. [[CrossRef](#)]
81. June, N.A.; Hodshire, A.L.; Wiggins, E.B.; Winstead, E.L.; Robinson, C.E.; Thornhill, K.L.; Sanchez, K.J.; Moore, R.H.; Pagonis, D.; Guo, H.; et al. Aerosol size distribution changes in FIREX-AQ biomass burning plumes: The impact of plume concentration on coagulation and OA condensation/evaporation. *Atmos. Chem. Phys.* **2022**, *22*, 12803–12825. [[CrossRef](#)]
82. Washenfelder, R.A.; Azzarello, L.; Ball, K.; Brown, S.S.; Decker, Z.C.J.; Franchin, A.; Fredrickson, C.D.; Hayden, K.; Holmes, C.D.; Middlebrook, A.M.; et al. Complexity in the evolution, composition, and spectroscopy of brown carbon in aircraft measurements of wildfire plumes. *Geophys. Res. Lett.* **2022**, *49*, e2022GL098951. [[CrossRef](#)]
83. Zeng, L.; Dibb, J.; Scheuer, E.; Katich, J.M.; Schwarz, J.P.; Bourgeois, I.; Peischl, J.; Ryerson, T.; Warneke, C.; Perring, A.E.; et al. Characteristics and evolution of brown carbon in western United States wildfires. *Atmos. Chem. Phys.* **2022**, *22*, 8009–8036. [[CrossRef](#)]
84. Hodshire, A.L.; Akherati, A.; Alvarado, M.J.; Brown-Steiner, B.; Jathar, S.H.; Jimenez, J.L.; Kreidenweis, S.M.; Lonsdale, C.R.; Onasch, T.B.; Ortega, A.M.; et al. Aging Effects on Biomass Burning Aerosol Mass and Composition: A Critical Review of Field and Laboratory Studies. *Environ. Sci. Technol.* **2019**, *53*, 10007–10022. [[CrossRef](#)]
85. Tkacik, D.S.; Robinson, E.S.; Ahern, A.; Saleh, R.; Stockwell, C.; Veres, P.; Simpson, I.J.; Meinardi, S.; Blake, D.R.; Yokelson, R.J.; et al. A Dual-Chamber Method for Quantifying the Effects of Atmospheric Perturbations on Secondary Organic Aerosol Formation from Biomass Burning Emissions. *J. Geophys. Res. Atmos.* **2017**, *122*, 6043–6058. [[CrossRef](#)]
86. Deng, M.; Wang, Z.; Volkamer, R.; Snider, J.R.; Oolman, L.; Plummer, D.M.; Kille, N.; Zarzana, K.J.; Lee, C.F.; Campos, T.; et al. Wildfire Smoke Observations in the Western United States from the Airborne Wyoming Cloud Lidar during the BB-FLUX Project. Part I: Data Description and Methodology. *J. Atmos. Ocean. Technol.* **2022**, *39*, 545–558. [[CrossRef](#)]
87. Saide, P.E.; Thapa, L.H.; Ye, X.; Pagonis, D.; Campuzano-Jost, P.; Guo, H.; Schueneman, M.K.; Jimenez, J.; Moore, R.; Wiggins, E.; et al. Understanding the evolution of smoke mass extinction efficiency using field campaign measurements. *Geophys. Res. Lett.* **2022**, *49*, e2022GL099175. [[CrossRef](#)]
88. Shen, Y.J.; Pokhrel, R.P.; Sullivan, A.P.; Levin, E.J.T.; Garofalo, L.A.; Farmer, D.K.; Permar, W.; Hu, L.; Toohey, D.W.; Campos, T.; et al. Understanding the mechanism and importance of brown carbon bleaching across the visible spectrum in biomass burning plumes from the WE-CAN campaign. *Atmos. Chem. Phys.* **2024**, *24*, 12881–12901. [[CrossRef](#)]
89. Chakrabarty, R.K.; Shetty, N.J.; Thind, A.S.; Beeler, P.; Sumlin, B.J.; Zhang, C.; Liu, P.; Idrobo, J.C.; Adachi, K.; Wagner, N.L.; et al. Shortwave absorption by wildfire smoke dominated by dark brown carbon. *Nat. Geosci.* **2023**, *16*, 683–688. [[CrossRef](#)] [[PubMed](#)]

90. McQueen, Z.C.; Poland, R.P.; Glenn, C.K.; El Hajj, O.; Penland, R.; Anosike, A.; Kumar, K.V.; O'Brien, J.J.; Saleh, R.; Smith, G.D. Optical Properties of Biomass Burning Aerosols from Simulated Wildfires and Prescribed Fires with Representative Fuel Beds from the Southeast United States. *ACS EST Air* **2014**, *1*, 1137–1146. [\[CrossRef\]](#)
91. Barry, K.R.; Hill, T.C.J.; Levin, E.J.T.; Twohy, C.H.; Moore, K.A.; Weller, Z.D.; Toohey, D.W.; Reeves, M.; Campos, T.; Geiss, R.; et al. Observations of Ice Nucleating Particles in the Free Troposphere from Western US Wildfires. *J. Geophys. Res. Atmos.* **2021**, *126*, e2020JD033752. [\[CrossRef\]](#)
92. Twohy, C.H.; Toohey, D.W.; Levin, E.J.T.; DeMott, P.J.; Rainwater, B.; Garofalo, L.A.; Pothier, M.A.; Farmer, D.K.; Kreidenweis, S.M.; Pokhrel, R.P.; et al. Biomass burning smoke and its influence on clouds over the western U.S. *Geophys. Res. Lett.* **2021**, *48*, e2021GL094224. [\[CrossRef\]](#)
93. Peterson, D.A.; Thapa, L.H.; Saide, P.E.; Soja, A.J.; Gargulinski, E.M.; Hyer, E.J.; Weinzierl, B.; Dollner, M.; Schöberl, M.; Papin, P.P.; et al. Measurements from inside a Thunderstorm Driven by Wildfire: The 2019 FIREX-AQ Field Experiment. *Bull. Am. Meteorol. Soc.* **2022**, *103*, E2140–E2167. [\[CrossRef\]](#)
94. Lareau, N.P.; Clements, C.B. Cold smoke: Smoke-induced density currents cause unexpected smoke transport near large wildfires. *Atmos. Chem. Phys.* **2015**, *15*, 11513–11520. [\[CrossRef\]](#)
95. Aydele, T.B.; Clements, C.B. Mobile ka-band polarimetric Doppler radar observations of wildfire smoke plumes. *Mon. Weather. Rev.* **2021**, *149*, 1247–1264. [\[CrossRef\]](#)
96. Heilman, W.E.; Bian, X.; Clark, K.L.; Skowronski, N.S.; Hom, J.L.; Gallagher, M.R. Atmospheric turbulence observations in the vicinity of surface fires in forested environments. *J. Appl. Meteorol. Climatol.* **2017**, *56*, 3133–3150. [\[CrossRef\]](#)
97. Raffuse, S.M.; Craig, K.J.; Larkin, N.K.; Strand, T.T.; Sullivan, D.C.; Wheeler, N.J.M.; Solomon, R. An Evaluation of Modeled Plume Injection Height with Satellite-Derived Observed Plume Height. *Atmosphere* **2012**, *3*, 103–123. [\[CrossRef\]](#)
98. Liu, Y.Q.; Goodrick, S.; Achtemeier, G.; Forbus, K.; Combs, D. Smoke plume height measurement of prescribed burns in the southeastern United States. *Int. J. Wildland Fire* **2012**, *22*, 130–147. [\[CrossRef\]](#)
99. Deng, M.; Volkamer, R.M.; Wang, Z.; Snider, J.R.; Kille, N.; Romero-Alvarez, L.J. Wildfire Smoke Observations in the Western United States from the Airborne Wyoming Cloud Lidar during the BB-FLUX Project. Part II: Vertical Structure and Plume Injection Height. *J. Atmos. Ocean. Technol.* **2022**, *39*, 559–572. [\[CrossRef\]](#)
100. Thapa, L.H.; Ye, X.; Hair, J.W.; Fenn, M.A.; Shingler, T.; Kondragunta, S.; Ichoku, C.; Dominguez, R.A.; Ellison, L.; Soja, A.J.; et al. Heat flux assumptions contribute to overestimation of wildfire smoke injection into the free troposphere. *Commun. Earth Environ.* **2022**, *3*, 236. [\[CrossRef\]](#)
101. Freitas, S.R.; Longo, K.M.; Chatfield, R.; Latham, D.; Silva Dias, M.A.F.; Andreae, M.O.; Prins, E.; Santos, J.C.; Gielow, R.; Carvalho, J.A., Jr. Including the sub-grid scale plume rise of vegetation fires in low resolution atmospheric transport models. *Atmos. Chem. Phys.* **2007**, *7*, 3385–3398. [\[CrossRef\]](#)
102. Ke, Z.M.; Wang, Y.H.; Zou, Y.F.; Song, Y.; Liu, Y. Global wildfire plume-rise dataset and parameterizations for climate model applications. *J. Geophys. Res. Atmos.* **2019**, *126*, e2020JD033085.
103. Stein, A.F.; Draxler, R.R.; Rolph, G.D.; Stunder, B.J.B.; Cohen, M.D.; Ngan, F. NOAA'S HYSPLIT Atmospheric transport and dispersion modeling system. *Bull. Am. Meteorol. Soc.* **2015**, *96*, 2059–2077. [\[CrossRef\]](#)
104. Grell, G.; Freitas, S.R.; Stuefer, M.; Fast, J. Inclusion of biomass burning in WRF-Chem: Impact of wildfires on weather forecasts. *Atmos. Chem. Phys.* **2011**, *11*, 5289–5303. [\[CrossRef\]](#)
105. Ye, X.; Arab, P.; Ahmadov, R.; James, E.; Grell, G.A.; Pierce, B.; Kumar, A.; Makar, P.; Chen, J.; Davignon, D.; et al. Evaluation and intercomparison of wildfire smoke forecasts from multiple modeling systems for the 2019 Williams Flats fire. *Atmos. Chem. Phys.* **2021**, *21*, 14427–14469. [\[CrossRef\]](#)
106. Makkaroon, P.; Tong, D.Q.; Li, Y.; Hyer, E.J.; Xian, P.; Kondragunta, S.; Campbell, P.C.; Tang, Y.; Baker, B.D.; Cohen, M.D.; et al. Development and evaluation of a North America ensemble wildfire air quality forecast: Initial application to the 2020 Western United States "Gigafire". *J. Geophys. Res. Atmos.* **2023**, *128*, e2022JD037298. [\[CrossRef\]](#)
107. Decker, Z.C.J.; Novak, G.A.; Aikin, K.; Veres, P.R.; Neuman, J.A.; Bourgeois, I.; Bui, T.P.; Campuzano-Jost, P.; Coggon, M.M.; Day, D.A.; et al. Airborne observations constrain heterogeneous Nitrogen and Halogen chemistry on tropospheric and stratospheric biomass burning aerosol. *Geophys. Res. Lett.* **2024**, *51*, e2023GL107273. [\[CrossRef\]](#)
108. Robinson, M.A.; Decker, Z.C.J.; Barsanti, K.C.; Coggon, M.M.; Flocke, F.M.; Franchin, A.; Fredrickson, C.D.; Gilman, J.B.; Gkatzelis, G.I.; Holmes, C.D.; et al. Variability and time of day dependence of ozone photochemistry in western wildfire plumes. *Environ. Sci. Technol.* **2021**, *55*, 10280–10290. [\[CrossRef\]](#) [\[PubMed\]](#)
109. Dearden, A.; He, Y.; Akherati, A.; Lim, C.Y.; Coggon, M.M.; Koss, A.R.; de Gouw, J.; Warneke, C.; Yee, L.D.; Seinfeld, J.H.; et al. Multi-day photochemical evolution of organic aerosol from biomass burning emissions. *Environ. Sci. Atmos.* **2024**, *4*, 925–941. [\[CrossRef\]](#)
110. Patoulis, D.; Kallitsis, E.; Posner, L.; Pandis, S.N. Modeling biomass burning organic aerosol atmospheric evolution and chemical aging. *Atmosphere* **2021**, *12*, 1638. [\[CrossRef\]](#)

111. Jin, L.; Permar, W.; Selimovic, V.; Ketcherside, D.; Yokelson, R.J.; Hornbrook, R.S.; Apel, E.C.; Ku, I.-T.; Collett, J.L., Jr.; Sullivan, A.P.; et al. Constraining emissions of volatile organic compounds from western US wildfires with WE-CAN and FIREX-AQ airborne observations. *Atmos. Chem. Phys.* **2023**, *23*, 5969–5991. [[CrossRef](#)]
112. Akherati, A.; He, Y.; Garofalo, L.A.; Hodshire, A.L.; Farmer, D.K.; Kreidenweis, S.M.; Permar, W.; Hu, L.; Fischer, E.V.; Jen, C.N.; et al. Dilution and photooxidation driven processes explain the evolution of organic aerosol in wildfire plumes. *Environ. Sci. Atmos.* **2022**, *2*, 1000–1022. [[CrossRef](#)]
113. Zou, Y.; O'Neill, S.M.; Larkin, N.K.; Alvarado, E.C.; Solomon, R.; Mass, C.; Liu, Y.; Odman, M.T.; Shen, H. Machine learning-based integration of high-resolution wildfire smoke simulations and observations for regional health impact assessment. *Int. J. Environ. Res. Public Health* **2019**, *16*, 2137. [[CrossRef](#)]
114. Carter, T.S.; Heald, C.L.; Cappa, C.D.; Kroll, J.H.; Campos, T.L.; Coe, H.; Cotterell, M.I.; Davies, N.W.; Farmer, D.K.; Fox, C.; et al. Investigating Carbonaceous Aerosol and Its Absorption Properties From Fires in the Western United States (WE-CAN) and Southern Africa (ORACLES and CLARIFY). *J. Geophys. Res. Atmos.* **2021**, *126*, e2021JD034984. [[CrossRef](#)]
115. Mandel, J.; Beezley, J.D.; Kochanski, A.K. Coupled atmosphere-wildland fire modeling with WRF 3.3 and SFIRE 2011. *Geosci. Model Dev.* **2011**, *4*, 591–610. [[CrossRef](#)]
116. Kochanski, A.K.; Mallia, D.V.; Fearon, M.G.; Mandel, J.; Sourì, A.H.; Brown, T. Modeling wildfire smoke feedback mechanisms using a coupled fire-atmosphere model with a radiatively active aerosol scheme. *J. Geophys. Res. Atmos.* **2019**, *124*, 9099–9116. [[CrossRef](#)]
117. Kiefer, M.T.; Zhong, S.; Heilman, W.E.; Charney, J.J.; Bian, X. Evaluation of an ARPS-based canopy flow modeling system for use in future operational smoke prediction efforts. *J. Geophys. Res. Atmos.* **2013**, *118*, 6175–6188. [[CrossRef](#)]
118. Massman, W.J.; Forthofer, J.M.; Finney, M.A. An improved canopy wind model for predicting wind adjustment factors and wildland fire behavior. *Can. J. For. Res.* **2017**, *47*, 594–603. [[CrossRef](#)]
119. Charney, J.J.; Kiefer, M.T.; Zhong, S.; Heilman, W.E.; Nikolic, J.; Bian, X.; Hom, J.L.; Clark, K.L.; Skowronski, N.S.; Gallagher, M.R.; et al. Assessing Forest canopy impacts on smoke concentrations using a coupled numerical model. *Atmosphere* **2019**, *10*, 273. [[CrossRef](#)]
120. Moon, K.; Duff, T.J.; Tolhurst, K.G. Sub-canopy forest winds: Understanding wind profiles for fire behaviour simulation. *Fire Saf. J.* **2019**, *105*, 320–329. [[CrossRef](#)]
121. Kiefer, M.T.; Heilman, W.E.; Zhong, S.; Charney, J.J.; Bian, X. Mean and turbulent flow downstream of a low-intensity fire: Influence of canopy and background atmospheric conditions. *J. Appl. Meteorol. Clim.* **2015**, *54*, 42–57. [[CrossRef](#)]
122. Miller, C.; O'Neill, S.; Rorig, M.; Alvarado, E. Air-quality challenges of prescribed fire in the complex terrain and wildland urban interface surrounding Bend, Oregon. *Atmosphere* **2019**, *10*, 515. [[CrossRef](#)]
123. Mallia, D.V.; Kochanski, A.K.; Kelly, K.E.; Whitaker, R.; Xing, W.; Mitchell, L.E.; Jacques, A.; Farguell, A.; Mandel, J.; Gaillardon, P.; et al. Evaluating wildfire smoke transport within a coupled fire-atmosphere model using a high-density observation network for an episodic smoke event along Utah's Wasatch Front. *J. Geophys. Res. Atmos.* **2020**, *125*, e2020JD032712. [[CrossRef](#)]
124. Liu, Y.; Goodrick, S.; Achtemeier, G. The Weather Conditions for Desired Smoke Plumes at a FASMEE Burn Site. *Atmosphere* **2018**, *9*, 259. [[CrossRef](#)]
125. Bartolome, C.; Princevac, M.; Weise, D.R.; Mahalingam, S.; Ghasemian, M.; Venkatram, A.; Vu, H.; Aguilar, G. Laboratory and numerical modeling of the formation of superfog from wildland fires. *Fire Saf. J.* **2019**, *106*, 94–104. [[CrossRef](#)]
126. Briggs, G.A. Plume rise predictions. In *Lectures on Air Pollution and Environmental Impact Analysis*; American Meteorological Society: Boston, MA, USA, 1975; pp. 59–111.
127. Pouliot, G.; Pierce, T.; Benjey, W.; O'Neill, S.M. Wildfire emission modeling: Integrating BlueSky and SMOKE. In Proceedings of the 14th International Emission Inventory Conference “Transforming Emission Inventories Meeting Future Challenges Today”, Las Vegas, NV, USA, 11–14 April 2005.
128. Liu, Y.Q. A regression model for smoke plume rise of prescribed fires using meteorological conditions. *J. Appl. Meteorol. Climatol.* **2014**, *53*, 1961–1975. [[CrossRef](#)]
129. Sofiev, M.; Ermakova, T.; Vankevich, R. Evaluation of the smoke-injection height from wild-land fires using remote-sensing data. *Atmos. Chem. Phys.* **2012**, *12*, 1995–2006. [[CrossRef](#)]
130. Sofiev, M.; Vankevich, R.; Ermakova, T.; Hakkarainen, J. Global mapping of maximum emission heights and resulting vertical profiles of wildfire emissions. *Atmos. Chem. Phys.* **2013**, *13*, 7039–7052. [[CrossRef](#)]
131. Val Martin, M.; Logan, J.A.; Kahn, R.A.; Leung, F.-Y.; Nelson, D.L.; Diner, D.J. Smoke injection heights from fires in North America: Analysis of 5 years of satellite observations. *Atmos. Chem. Phys.* **2010**, *10*, 1491–1510. [[CrossRef](#)]
132. Baker, K.; Woody, M.; Valin, L.; Szykman, J.; Yates, E.L.; Iraci, L.T.; Choi, H.D.; Soja, A.J.; Koplitz, S.N.; Zhou, L.; et al. Photochemical model evaluation of 2013 California wild fire air quality impacts using surface, aircraft, and satellite data. *Sci. Total. Environ.* **2018**, 637–638, 1137–1149. [[CrossRef](#)]
133. Paugam, R.; Wooster, M.; Freitas, S.; Val Martin, M. A review of approaches to estimate wildfire plume injection height within large-scale atmospheric chemical transport models. *Atmos. Chem. Phys.* **2016**, *16*, 907–925. [[CrossRef](#)]

134. Achtemeier, G.L.; Goodrick, S.A.; Liu, Y.; Garcia-Menendez, F.; Hu, Y.; Odman, M.T. Modeling smoke plume-rise and dispersion from southern United States prescribed burns with Daysmoke. *Atmosphere* **2011**, *2*, 358–388. [\[CrossRef\]](#)
135. Ye, X.; Saide, P.E.; Hair, J.; Fenn, M.; Shingler, T.; Soja, A.; Gargulinski, E.; Wiggins, E. Assessing vertical allocation of wildfire smoke emissions using observational constraints from airborne lidar in the western U.S. *J. Geophys. Res. Atmos.* **2022**, *127*, e2022JD036808. [\[CrossRef\]](#)
136. Li, Y.; Tong, D.; Ma, S.Q.; Freitas, S.R.; Ahmadov, R.; Sofiev, M.; Zhang, X.; Kondragunta, S.; Kahn, R.; Tang, Y.; et al. Impacts of estimated plume rise on PM_{2.5} exceedance prediction during extreme wildfire events: A comparison of three schemes (Briggs, Freitas, and Sofiev). *Atmos. Chem. Phys.* **2023**, *23*, 3083–3101. [\[CrossRef\]](#)
137. Tang, W.; Emmons, L.K.; Buchholz, R.R.; Wiedinmyer, C.; Schwantes, R.H.; He, C.; Kumar, R.; Pfister, G.G.; Worden, H.M.; Hornbrook, R.S.; et al. Effects of Fire Diurnal Variation and Plume Rise on the U.S. Air Quality During FIREX-AQ and WE-CAN Based on the Multi-Scale Infrastructure for Chemistry and Aerosols (MUSICAv0). *J. Geophys. Res. Atmos.* **2022**, *127*, e2022JD036650. [\[CrossRef\]](#)
138. Moisseeva, N.; Stull, R. Wildfire smoke-plume rise: A simple energy balance parameterization. *Atmos. Chem. Phys.* **2021**, *21*, 1407–1425. [\[CrossRef\]](#)
139. Wang, S.Y. Emulating Wildfire Plume Injection Using Machine Learning Trained by Large Eddy Simulation (LES). *Environ. Sci. Technol.* **2024**, *58*, 22204–22212. [\[CrossRef\]](#) [\[PubMed\]](#)
140. Larkin, N.K.; O'Neill, S.M.; Solomon, R.; Raffuse, S.; Strand, T.; Sullivan, D.C.; Krull, C.; Rorig, M.; Peterson, J.; Ferguson, S.A. The BlueSky smoke modeling framework. *Int. J. Wildland Fire* **2009**, *18*, 906–920. [\[CrossRef\]](#)
141. Prichard, S.J.; Sandberg, D.W.; Ottmar, R.D.; Eberhardt, E.; Andreu, A.; Eagle, P.; Swedin, K. *Fuel Characteristic Classification System Version 3.0: Technical Documentation*; USDA Forest Service General Tech. Rep. PNW-GTR-887; Pacific Northwest Research Station: Corvallis, OR, USA, 2013; 79p.
142. Chen, J.; Vaughan, J.; Avise, J.; O'Neill, S.; Lamb, B. Enhancement and evaluation of the AIRPACT ozone and PM_{2.5} forecast system for the Pacific Northwest. *J. Geophys. Res. Atmos.* **2008**, *113*, D14305. [\[CrossRef\]](#)
143. Schmit, T.J.; Griffith, P.; Gunshor, M.M.; Daniels, J.M.; Goodman, S.J.; Lebar, W.J. A closer look at the ABI on the GOES-R series. *Bull. Am. Meteorol. Soc.* **2017**, *98*, 681–698. [\[CrossRef\]](#)
144. Jiménez, P.A.; Muñoz-Esparza, D.; Kosović, B. A High Resolution Coupled Fire–Atmosphere Forecasting System to Minimize the Impacts of Wildland Fires: Applications to the Chimney Tops II Wildland Event. *Atmosphere* **2018**, *9*, 197. [\[CrossRef\]](#)
145. Giannaros, T.M.; Lagouvardos, K.; Kotroni, V. Performance Evaluation of an Operational Rapid Response Fire Spread Forecasting System in the Southeast Mediterranean (Greece). *Atmosphere* **2020**, *11*, 1264. [\[CrossRef\]](#)
146. Linn, R.R.; Goodrick, S.L.; Brambilla, S.; Brown, M.J.; Middleton, R.S.; O'Brien, J.J.; Hiers, J.K. QUIC-fire: A fast-running simulation tool for prescribed fire planning. *Environ. Model. Softw.* **2020**, *125*, 104616. [\[CrossRef\]](#)
147. Wang, S.S.-C.; Qian, Y.; Leung, L.R.; Zhang, Y. Identifying key drivers of wildfires in the contiguous US using machine learning and game theory interpretation. *Earth's Future* **2021**, *9*, e2020EF001910. [\[CrossRef\]](#)
148. Wang, S.S.-C.; Leung, L.R.; Qian, Y. Projection of future fire emissions over the contiguous US using explainable artificial intelligence and CMIP6 models. *J. Geophys. Res. Atmos.* **2023**, *128*, e2023JD039154. [\[CrossRef\]](#)
149. Wang, S.S.C.; Qian, Y.; Leung, L.R.; Zhang, Y. Interpreting machine learning prediction of fire emissions and comparison with FireMIP process-based models. *Atmos. Chem. Phys.* **2022**, *22*, 3445–3468. [\[CrossRef\]](#)
150. Zou, Y.; Wang, Y.; Ke, Z.; Tian, H.; Yang, J.; Liu, Y. Development of a REgion—Specific ecosystem feedback fire (RESFire) model in the Community Earth System Model. *J. Adv. Model. Earth Syst.* **2019**, *11*, 417–445. [\[CrossRef\]](#)
151. Yao, J.Y.; Raffuse, S.M.; Brauer, M.; Williamson, G.J.; Bowman, D.M.J.S.; Johnston, F.H.; Henderson, S.B. Predicting the minimum height of forest fire smoke within the atmosphere using machine learning and data from the CALIPSO satellite. *Remote Sens. Environ.* **2018**, *206*, 98–106. [\[CrossRef\]](#)
152. Nair, A.A.; Yu, F.; Campuzano-Jost, P.; DeMott, P.J.; Levin, E.J.T.; Jimenez, J.L.; Peischl, J.; Pollack, I.B.; Fredrickson, C.D.; Beyersdorf, A.J.; et al. Machine Learning Uncovers Aerosol Size Information from Chemistry and Meteorology to Quantify Potential Cloud-Forming Particles. *Geophys. Res. Lett.* **2021**, *48*, e2021GL094133. [\[CrossRef\]](#)
153. Raffuse, S.; O'Neill, S.; Schmidt, R. A model for rapid wildfire smoke exposure estimates using routinely-available data—Rapidfire v0.1.3. *EGUsphere* **2023**, *17*, 381–397.
154. Ejaz, N.; Choudhury, S. A comprehensive survey of the machine learning pipeline for wildfire risk prediction and assessment. *Ecol. Inform.* **2025**, *90*, 103325. [\[CrossRef\]](#)
155. Singh, H.; Ang, L.-M.; Paudyal, D.; Acuna, M.; Srivastava, P.K.; Srivastava, S.K. A comprehensive review of empirical and dynamic wildfire simulators and machine learning techniques used for the prediction of wildfire in Australia. *Technol. Knowl. Learn.* **2025**, *30*, 935–968. [\[CrossRef\]](#)

156. Wann, G.T.; Whipple, A.L.; O'Donnell, M.S.; Aldridge, C.L. A compilation pipeline for wildlife tracking datasets collected from ground-based and satellite-based telemetry transmission devices. *Ecol. Inform.* **2025**, *90*, 103220. [\[CrossRef\]](#)
157. Zhao, F.J.; Liu, Y.Q.; Goodrick, S.; Hornsby, B.; Schardt, J. The contribution of duff consumption to fire emissions and air pollution of the Rough Ridge Fire. *Int. J. Wildland Fire* **2019**, *28*, 993–1004. [\[CrossRef\]](#)
158. Zhang, A.; Liu, Y.; Goodrick, S.; Williams, M.D. Duff burning from wildfires in a moist region: Different impacts on PM 2.5 and ozone. *Atmos. Chem. Phys.* **2022**, *22*, 597–624. [\[CrossRef\]](#)
159. Liu, Y.; Kochanski, A.; Baker, K.R.; Mell, W.; Linn, R.; Paugam, R.; Mandel, J.; Fournier, A.; Jenkins, M.A.; Goodrick, S.; et al. Fire Behaviour and Smoke Modelling: Model Improvement and Measurement Needs for next-Generation Smoke Research and Forecasting Systems. *Int. J. Wildland Fire* **2019**, *28*, 570–588. [\[CrossRef\]](#)
160. Kolluru, V.K.; Chintakunta, A.N.; Nuthakki, Y.; Koganti, S. Advancements in wildfire prediction and detection: A systematic review. *Int. J. Multidiscip. Res.* **2022**, *4*, 1–15.
161. Ford, B.; Val Martin, M.; Zelasky, S.E.; Fischer, E.V.; Anenberg, S.C.; Heald, C.L.; Pierce, J.R. Future fire impacts on smoke concentrations, visibility, and health in the contiguous United States. *GeoHealth* **2018**, *2*, 229–247. [\[CrossRef\]](#)
162. Liu, Y.Q.; Liu, Y.; Fu, J.; Yang, C.-E.; Dong, X.; Tian, H.; Tao, B.; Yang, J.; Wang, Y.; Zou, Y.; et al. Projection of future wildfire emissions in western USA under climate change: Contributions from changes in wildfire, fuel loading, and fuel moisture. *Int. J. Wildland Fire* **2021**, *31*, 1–13. [\[CrossRef\]](#)
163. Andela, N.; Morton, D.C.; Giglio, L.; Chen, Y.; van der Werf, G.R.; Kasibhatla, P.S.; DeFries, R.S.; Collatz, G.J.; Hantson, S.; Kloster, S.; et al. A human-driven decline in global burned area. *Science* **2017**, *356*, 1356–1362. [\[CrossRef\]](#)
164. Liu, Y.Q. New development and application needs for Earth system modeling of fire–climate–ecosystem interactions. *Environ. Res. Lett.* **2018**, *13*, 011001. [\[CrossRef\]](#)
165. Pfister, G.G.; Eastham, S.D.; Arellano, A.F.; Aumont, B.; Barsanti, K.C.; Barth, M.C.; Conley, A.; Davis, N.A.; Emmons, L.K.; Fast, J.D.; et al. The Multi-Scale Infrastructure for Chemistry and Aerosols (MUSICA). *Bull. Am. Meteorol. Soc.* **2020**, *101*, E1743–E1760. [\[CrossRef\]](#)
166. Lu, Z.; Liu, X.; Ke, Z.; Zhang, K.; Ma, P.-L.; Fan, J. Incorporating an interactive fire plume-rise model in the DOE's energy exascale earth system model version 1 (E3SMv1) and examining aerosol radiative effect. *J. Adv. Model. Earth Syst.* **2024**, *16*, e2023MS003818. [\[CrossRef\]](#)
167. Holder, A.L.; Ahmed, A.; Vukovich, J.M.; Rao, V. Hazardous air pollutant emissions estimates from wildfires in the wildland urban interface. *PNAS Nexus* **2023**, *2*, pgad186. [\[CrossRef\]](#)
168. Boaggio, K.; LeDuc, S.D.; Rice, R.B.; Duffney, P.F.; Foley, K.M.; Holder, A.L.; McDow, S.; Weaver, C.P. Beyond particulate matter mass: Heightened levels of lead and other pollutants associated with destructive fire events in California. *Environ. Sci. Technol.* **2022**, *56*, 14272–14283. [\[CrossRef\]](#)
169. Villarruel, C.M.; Figueroa, L.A.; Ranville, J.F. Quantification of bioaccessible and environmentally relevant trace metals in structure ash from a wildland–urban interface fire. *Environ. Sci. Technol.* **2024**, *58*, 2502–2513. [\[CrossRef\]](#)
170. Jung, J.; Schollaert, C.L.; Masuda, Y.J.; Connolly, R.E.; Bonilla, E.; Samuel, K.; Elum, D.; Haugo, R.D.; Bandzuh, J.T.; Baek, B.H.; et al. Wildland fire smoke exposure disparities by wildland urban interface category and land ownership. *Landsc. Urban Plan.* **2025**, *263*, 105423. [\[CrossRef\]](#)
171. National Academies of Sciences, Engineering, and Medicine. *The Chemistry of Fires at the Wildland-Urban Interface*; The National Academies Press: Washington, DC, USA, 2022.
172. Tang, W.; Emmons, L.K.; Wiedinmyer, C.; Partha, D.B.; Huang, Y.; He, C.; Zhang, J.; Barsanti, K.C.; Gaubert, B.; Jo, D.S.; et al. Disproportionately large impacts of wildland-urban interface fire emissions on global air quality and human health. *Sci. Adv.* **2025**, *11*, eadr2616. [\[CrossRef\]](#) [\[PubMed\]](#)
173. Jia, Y.; Opabola, E.A. Interpretable machine learning insights into wildfire damage drivers in California, USA. *Int. J. Disaster Risk Reduct.* **2025**, *126*, 105610. [\[CrossRef\]](#)
174. Xu, Z.; Li, J.; Cheng, S.; Rui, X.; Zhao, Y.; He, H.; Guan, H.; Sharma, A.; Erxleben, M.; Chang, R.; et al. Deep learning for wildfire risk prediction: Integrating remote sensing and environmental data. *ISPRS J. Photogramm. Remote Sens.* **2025**, *227*, 632–677. [\[CrossRef\]](#)
175. Delplanque, A.; Théau, J.; Foucher, S.; Serati, G.; Durand, S.; Lejeune, P. Wildlife detection, counting and survey using satellite imagery: Are we there yet? *GIScience Remote Sens.* **2024**, *61*, 2348863. [\[CrossRef\]](#)
176. Rizzo, L.V.; Rizzo, M.C.F.V. Wildfire smoke and health impacts: A narrative review. *J. Pediatr.* **2025**, *101*, S56–S64. [\[CrossRef\]](#)
177. Grant, E.; Runkle, J.D. Long-term health effects of wildfire exposure: A scoping review. *J. Clim. Change Health* **2022**, *6*, 100110. [\[CrossRef\]](#)
178. Mak, H.W.L.; Ng, D.C.Y. Spatial and socio-classification of traffic pollutant emissions and associated mortality rates in high-density Hong Kong via improved data analytic approaches. *Int. J. Environ. Res. Public Health* **2021**, *18*, 6532. [\[CrossRef\]](#)

179. Dey, A.K.; Ma, Y.; Carrasco-Escobar, G.; Han, C.; Rerolle, F.; Benmarhnia, T. Two-stage interrupted time series analysis with machine learning: Evaluating the health effects of the 2018 wildfire smoke event in San Francisco County as a case study. *Am. J. Epidemiol.* **2025**, *194*, 2936–2944. [[CrossRef](#)]
180. Johnson, M.M.; Garcia-Menendez, F. A comparison of smoke modelling tools used to mitigate air quality impacts from prescribed burning. *Int. J. Wildland Fire* **2023**, *32*, 1162–1173. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.