Smoke Models and Applications

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Abstract

In this synthesis, we reviewed various models used to simulate smoke transport, dispersion, and deposition. We looked at the box, Gaussian plume, puff, particle, and Eulerian models. We went on to include their applications, performances, and limitations. This paved the way for smoke modeling frameworks like BlueSky and the National Air Quality Forecasting Capability system, as they incorporate a set of comprehensive tools comprised of various models capable of handling the complex aspects of smoke. Despite all the existing research and available models, we observed that much work needs to be done, particularly regarding adequately characterizing the emissions source term, as this is the chief challenge of smoke modeling.

1 Introduction

Wildfires are unexpected fires that start in rural or urban regions and can last long over a vast land area (Team & Group 2017). Unlike prescribed or controlled burns, which are fires intentionally started for agricultural use or to prevent wildfires themselves from occurring, wildfires are uncontrollable, and the extent to which they burn ranges from mild to severe. Although wildfires have been argued to benefit flora and fauna that evolved with fire (Heidari et al. 2021), we can say from a rational standpoint that those benefits do not exactly cater to humans. Not only do wildfires destroy property, but they also emit smoke, which contains chemicals that impair air quality (Bravo et al. 2002), thereby jeopardizing human health and well-being (Liu et al. 2017), and also the full functionality of the climate system (a build-up of the emissions) (Liu 2005). Wildfire emissions include but are not limited to carbon dioxide (CO_2), carbon monoxide (CO), methane (CH_4), nitrogen oxides (NOx), volatile organic compounds (VOCs), and particulate matter (PM) (Spracklen et al. 2007). Because of its chemical complexity, wildfire smoke differs significantly from conventional industrial pollution and thus requires much study to assess it. Out of all the wildfire emissions, most studies are chiefly concerned with accurately estimating concentrations of fine particulate matter with a diameter of 2.5 micrometers, commonly known as $PM_{2.5}$ because of its aggravating health

impacts (Xie et al. 2018). It can easily flow to the respiratory and circulatory systems since it is tiny, causing breathing complications, cardiovascular morbidity, neonatal defects, and sometimes death in sensitive groups (Liu et al. 2017, Klepac et al. 2018).

Wildfires are a common natural disaster in many parts of the world, especially the Western United States, Australia, and Siberia (Australia 2017, Machemer 2020). In the United States, California is famous for its wildfires, with the largest fire since 1932 being the August Complex fire of 2020, said to be caused by lightning and recorded to have burned over a million acres (California 2021). Apart from the elements of nature, humans are also the culprits of wildfires, as carelessness, arson, and certain land-use practices are critical contributors to fires in some areas (Balch et al. 2017). Since the climate system is highly complex and the components are interconnected, as wildfires increase and burn for long periods, a negative feedback loop is formed, which releases carbon that has been captured by vegetation back into the atmosphere, contributing to more global warming and the consequences that follow it (Parmesan et al. 2021).

The effects of smoke vary over temporal and spatial scales; hence several models have been built to simulate its past and present behavior (Liu et al. 2019), predict its impacts, and also make regulatory decisions in smoke management. Most of these models often focus on one or several aspects of the underlying physics of wildfires, such as the emissions source term, the effects of wind on the dispersion of smoke particles, the height of the plume, rate of heat release, temperature inversion, mixing height/depth, and concentration of particulate matter. The emissions source is a significant factor to consider in the transport of smoke, as it plays a massive role in estimating the concentration of smoke effluents such as particulate matter (Goodrick et al. 2013). In general, it is simply any forcing that causes smoke to be injected into the atmosphere. Some models go further to include the chemical changes that occur as the gases are emitted and are vital for addressing a variety of air quality concerns, including ozone generation (Goodrick et al. 2013).

However, there are multiple challenges found in modeling smoke transport, but the most prevalent, as we observed while going through the seed papers, are issues encountered while attempting to estimate the emissions source term. The start of a fire is usually spontaneous or random, so it is difficult to quantify it adequately. This difficulty led the researchers to make assumptions to evaluate the rate at which the effluents are dispersed (Goodrick et al. 2013). Because of these, many uncertainties exist, as each researcher's assumptions are independent of another's. Some of the assumptions imposed on the models often make them very simple and unrealistic, leading to under/over-predictions (Strand et al. 2012, Goodrick et al. 2013). Apart from the difficulties encountered in accurately describing the emissions source, the models applied to wildfire smoke transport are often restricted by the location of smoke monitors, dependence on fire estimates, intricate complexities, and the inability to estimate smoke effluents accurately. For these reasons, researchers have recently developed modeling frameworks incorporating several models to describe the components of smoke modeling, such as dispersion, plume rise, heat release, and time rate (Langmann et al. 2009, Cleland et al. 2020). To take a step further, researchers posit that combining observations from many sources frequently overcomes the limitations of utilizing individual observations and allows for a more accurate estimation of $PM_{2.5}$ concentrations compared to using a single observation (Cleland et al. 2020, Reid et al. 2021).

The development of smoke models has gone through a series of complexities, from the most basic box model to the more sophisticated BlueSky, with each successive model trying to address the limitations of the one before it. This study aims to review articles that elucidate models for wildland fires (encompassing wildfires and prescribed burns), their various physics,

applications, analyses, uncertainties, and future aspects.

2 Models for Smoke Transport and Dispersion

Here, the models for smoke are described in order of complexity, from the simplest to the ones that rely on fewer assumptions, listing the advantages and pitfalls of each one of them and also giving examples of such models applied to wildland fire smoke research. The models to be discussed are; box, Gaussian plume, puff, particle, Eulerian grid, and full physics-based models. We shall also talk about two smoke modeling frameworks; BlueSky and NAQFC.

2.1 Box Model

According to Lettau (1970), the box model is the most fundamental method for forecasting emission concentrations in an airshed (volume of air over a specified geographical region). He proposed that a simple box can represent an airshed, the vertical extent of which is specified by the top of the mixed layer and the horizontal dimensions of which are determined by the airshed's spatial area, with the bottom of the box serving as the emissions source (Goodrick et al. 2013). The box model posits that pollutants are instantly and uniformly spread within the box. This instantaneous distribution of smoke prevents the model from accounting for plume rise and diffusion as the buoyant nature of smoke concentrates most of the particles at the top of the mixing layer, which then mixes farther downstream. This single assumption limits the box model, leading to its oversimplification. As a result of this assumption, the box model overestimated smoke concentrations within 100 km of the fire (Pharo et al. 1976). Research has shown that near-field estimations of smoke concentrations, often marred by inaccuracies due to the absence of diffusion, can be improved by increasing the distance between the mixing layer and the source (Goodrick et al. 2013).

The box model has been used to predict short- and long-term thermal and PM changes in small and big cities but excludes the option of analyzing the spatial specifics of emission dispersal (Lettau 1970). Another application of the box model is the Ventilated Valley Box (VALBOX) Model developed by M. L. Sestak, W. E. Marlatt, and A. R. Riebau in an unpublished report in 1988 is one example of a box model (Goodrick et al. 2013). It is a simple screening model designed to estimate surface concentrations of $PM_{2.5}$ and other pollutants in mountain valleys. The VALBOX model developed by M. L. Sestak, W. E. Marlatt, and A. R. Riebau in an unpublished report in 1988 is one example of a box model (Goodrick et al. 2013). It is a simple screening model designed to estimate surface concentrations of $PM_{2.5}$ and other pollutants in mountain valleys. The VALBOX model received negative reviews after it was analyzed by researchers in the United States Environmental Protection Agency (EPA). The technique used by the authors in defining box heights appeared to have certain flaws, as described by Robert E. Eskridge of the EPA. Although they specified that there is a temperature inversion that prevents vertical mixing, the fact that the boxes are one layer thick implies that they are often deeper than the flow, and thus the pollutants will be mixed vertically, going against the governing assumptions. It was also difficult for the model to predict the surface concentrations for which it was built.

The box model does not cover fine temporal scales, as dividing the box into smaller boxes is computationally intensive, thereby removing the model's simplicity, which is its forte (Goodrick et al. 2013). Despite the model's shortcomings, Brown & Bradshaw (1994) in their study noted that it came in handy when analyzing the total smoke loading in a valley for a multi-day AQ

incident. The box model also neglects some aspects of the meteorological data entered, such as wind speed and mixing height, as these variables are constants.

2.2 Plume Models

Unlike the box model, which considers the fire to be a source that spreads instantly throughout the whole volume of the box, Gaussian plume models specify the emissions source as a point or a narrow region containing the fire. In addition, atmospheric transport and dispersion mechanisms are studied in greater depth, with the transport of smoke being determined by trajectory winds, which are assumed to be constant in both space and time, and concentrations crosswind of the plume are assumed to disperse in a Gaussian distribution pattern (Achtemeier et al. 2001, Goodrick et al. 2013). As a result, the plume model improves on the box model and moves us closer to a more realistic method of estimating $PM_{2.5}$ concentrations.

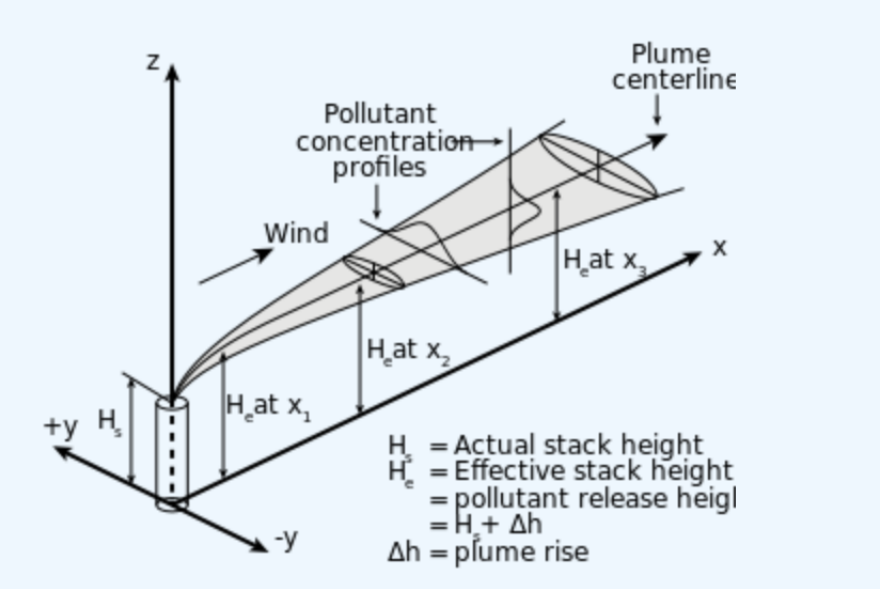

Figure 1: Visualization of a buoyant Gaussian plume (source: link)

The dispersion of a smoke pollutant is calculated using the plume's centerline height above ground level, which is the sum of the plume rise, ΔH, and the height of the plume's emission source point, H_s. Plume rise due to buoyancy is determined using Briggs (1975) equations for bent-over, hot, buoyant plumes, given by

$$C = \frac{Q}{u} \cdot \frac{f}{\sigma_y \sqrt{2\pi}} \cdot \frac{g_1 + g_2 + g_3}{\sigma_z \sqrt{2\pi}}, \tag{1}$$

where:

f = crosswind dispersion parameter = $\exp\left(\frac{-y^2}{\sigma_y^2}\right)$

g = vertical dispersion parameter = $g_1 + g_2 + g_3$

g_1 = vertical dispersion with no reflections = $\exp\left(-\frac{(z-H)^2}{2\sigma_z^2}\right)$

g_2 = vertical dispersion for reflection from the ground = $\exp\left(-\frac{(z+H)^2}{2\sigma_z^2}\right)$

g_1 = vertical dispersion for reflection from an inversion aloft

$$= \sum_{m=1}^{\infty} \left\{ \exp\left(-\frac{(z-H-2mL)^2}{2\sigma_z^2}\right) + \exp\left(-\frac{(z+H+2mL)^2}{2\sigma_z^2}\right) + \exp\left(-\frac{(z+H-2mL)^2}{2\sigma_z^2}\right) + \exp\left(-\frac{(z-H+2mL)^2}{2\sigma_z^2}\right) \right\}$$

C = concentration of emissions, in g/m^3, at any receptor located:

x meters downwind from the emissions source point

y meters crosswind from the emissions plume centerline

z meter above ground level

Q = source pollutant emission rate, in g/s

u = horizontal wind velocity along the plume centerline, in m/s

H = height of emission plume centerline above ground-level, in m

σ_y = horizontal standard deviation of the emission distribution, in m

σ_z = vertical standard deviation of the emission distribution, in m

L = height from the ground-level to the bottom of the inversion aloft, in m

Briggs (1975) equations above are useful because they account for upward reflection from the ground and include downward reflection from the bottom of any inversion lid present in the atmosphere.

One major Gaussian plume model to have been developed is SASEM, which is the Simple Approach Smoke Estimation Model. It was created as a screening tool for assessing the AQ consequences of prescribed fires on federal lands (Sestak & Riebau 1988). SASEM was also designed to calculate the maximum surface-level concentration of particulate matter and the distance from the fire source at which it would occur, resulting in reduced visual range. The model calculates the emission rates based on fuel types like; sagebrush, wood, litter and grass (Sestak & Riebau 1988, Achtemeier et al. 2001, Goodrick et al. 2013).

Plume models are advantageous because they do not require so much weather information. However, they are greatly limited by the assumption that smoke moves in a straight path under steady-state conditions (assuming that mixing height is constant). Because smoke particles move randomly, coupled with adverse weather conditions and complex topographies, the assumption would not be justified, so the results obtained might be invalid. Another downside of plume models is that if meteorological conditions change during a burn period, the models will not detect altering trajectories or corresponding concentrations. Furthermore, plume estimations become incorrect when smoke spreads beyond an acceptable distance for steady-state assumptions, often around 50 km (30 miles). Despite this restriction, plume models can be effective when plumes rise beyond the impact of the topography or when plumes are contained in a straight line that follows a vast valley with dispersion limited to the valley walls (Achtemeier et al. 2001, Goodrick et al. 2013).

2.3 Puff Models

Puff models simulate smoke dispersion by creating a sequence of puffs emitted at equally spaced intervals throughout the burn. These puffs are advected along the trajectory of their central location and grow with time, which is a function of the turbulent component until they surpass the size of the meteorological grid cell both horizontally and vertically, and then break into multiple new puffs, with each puff indicating a volume containing a certain amount of pollutant (Goodrick et al. 2013).

Unlike Gaussian plume models, puff models have highly varying winds in space and time and, as such, are a substantial improvement over plume models. They are presently employed in smoke management because they account for complex terrains where winds fluctuate, and smoke trajectory patterns are influenced, a drawback of the previous models discussed. Famous examples of puff models are CALPUFF (Scire et al. 2000), TSAR+, and NFSpuff (Harrison 1995, Hummel & Rafsnider 1995, Breyfogle & Ferguson 1996).

CALPUFF is a generalized non-steady-state air quality modeling system for regulatory purposes. It comprises three major components: CALMET, CALPUFF, and CALPOST. CALMET is a three-dimensional gridded modeling domain that generates hourly wind and temperature fields by interpolating at least one surface-wind and one upper air observation. In addition, CALMET generates two-dimensional meteorological variables such as mixing height and dispersion. CALPUFF, on the other hand, is a non-steady-state Lagrangian-Gaussian puff model that simulates dispersion processes using CALMET's output. Like in other models, CALPUFF analyzes plume rise using Briggs' equations as modified by Manin. The modification was necessary to assess partial plume penetration above the top of the mixing layer (Goodrick et al. 2013). CALPUFF can optionally simulate diurnally variable slope winds when upper-level winds are decoupled from the surface if there are inadequate data, with which it can indicate local inversions.

Choi & Fernando (2007) implemented the CALPUFF modeling system to simulate smoke plumes from a prescribed burn. The authors applied their research to predict PM_{10} dispersion from agricultural fires in Yuma/San Luis along the US/Mexico border to evaluate fires' local and regional air quality implications. Their findings indicate that the challenges encountered while simulating PM plumes using CALPUFF are centered around agricultural fire-activity observations. Because activities such as fuel type, fuel loading, burning procedures, and burn length are not often documented, researchers are forced to guess, introducing errors to the results. To minimize the errors, most of the input data items necessary for their study were roughly extrapolated from published research (Choi & Fernando 2007).

In general, puff models address time-varying variables and emission sources, allowing for a more realistic description of the burn's ramp-up, maximum combustion, and ramp-down phases. However, puff models are challenged by their inability to adequately define a fire as an emissions and heat source to calculate plume rise and emission distribution over this depth appropriately. In areas of extreme turbulence, they are constrained by the assumption that puffs grow via parameterized diffusion and entrainment; puffs grow as the polluted air mixes with ambient air.

2.4 Particle Models

A particle model predicts variations of a fixed number of particles (tiny air parcels) as they are advected throughout the model domain by the mean wind field and distributed by a turbulent component added at each step of the calculation, resulting in diffusion (Draxler & Hess 1998,

Goodrick et al. 2013, Liu et al. 2019). Particle models are frequently referred to as Lagrangian models because they employ coordinate systems that effectively track particles as they travel through space and time (Achtemeier et al. 2001, Goodrick et al. 2013). Hence, they assume that trajectory winds are not constant, so the dispersion patterns vary greatly. Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) (Draxler & Hess 1998, Stein et al. 2015), and FLEXPART (Stohl & Thomson 1999), are some examples of particle models which we shall briefly discuss.

The Hybrid Single-Particle Lagrangian Integrated Trajectory model (HYSPLIT), developed by collaborative efforts of the National Oceanic and Atmospheric Agency (NOAA) Air Resources Laboratory and the Australian Bureau of Meteorology Research Centre in 1998 (Draxler & Hess 1998), is a hybrid model that is widely used to calculate the trajectories, chemical transformations, dispersion and deposition of air pollutants in the atmosphere (Stein et al. 2015). HYSPLIT employs a technique involving puffs, particles, or both. The maximum emission rate, calculated by simulating a prescribed burn over the given geographical coordinates, is implemented as the constant emission rate for the wildfire (Draxler et al. 2022). Plume rise is computed by HYSPLIT using Briggs (1975) equations as modified by Arya (1999) under the assumption that the air parcel's rise is based on buoyancy terms while incorporating the value of the heat released during the emission, the wind velocity, and the frictional velocity, as well as the static stability at night. During the day, plume rise is confined to the top 75% of the mixed layer. However, at night, plume rise can reach up to twice the depth of the mixed layer (Draxler & Hess 1998).

FLEXPART is a Langrangian particle dispersion model designed by Stohl & Thomson (1999) to simulate the transport and dispersion of passive tracers in the planetary boundary layer (PBL). Most Langrangian dispersion models assume that the density within the PBL is homogeneous. This assumption neglects the fact that density decreases with height. In a shallow PBL, the assumption might hold; however, in deep PBLs, where the density at the top of the PBL may be lower than the ground by 20%, resulting in erroneous predictions of tracer concentrations, and in the presence of vertical wind shear, leads to incorrect calculations of tracer transport (Stohl & Thomson 1999). FLEXPART is advantageous over these models because it includes a density-correction term in the Langevin equation used to describe the velocity and position of the particle as a Markov process. With this, the model can account for variations in the density of the PBL and thus works for inhomogeneous Gaussian turbulence in the PBL, with relatively small computational costs.

2.5 Eulerian Models

Eulerian models, also known as grid models, calculate the transport and dispersion of smoke pollutants using coordinates fixed in space. With a fixed coordinate system, measuring the impact of individual plumes is difficult. Nonetheless, grid models allow for a more straightforward evaluation of the cumulative consequences of several plumes, hence their wide usage (Goodrick et al. 2013, Liu et al. 2019). They also evaluate the effects of chemical changes that may occur when effluents mix with one another within plumes and in the atmosphere.

A famous example of an Eulerian model is the Community Multiscale Air Quality (CMAQ) model. CMAQ, developed by the US EPA, is a comprehensive multi-pollutant chemical transport model (CTM) that can simulate dispersion, deposition, transformation, and dynamics of hazardous pollutants such as PM and ozone as they mix within plumes, as well as within the atmosphere (Goodrick et al. 2013). CMAQ has often been used to educate key stakeholders

and the general public about the potential consequences of emissions from all sources and to provide air quality forecasts (Appel et al. 2017).

CMAQ was implemented by Hu et al. (2008) to simulate the impacts on air quality of two large controlled fires in Atlanta, GA, on February 28, 2007. Comparing the results of the estimated concentration of $PM_{2.5}$ with observed hourly values, the authors noted that the values are highly correlated after 8:00 p.m., but the estimates are lower than the observed by 50 μgm^{-3} or more during the late afternoon times when the observations were at maximum. Apart from underestimating $PM_{2.5}$ concentrations, ozone was also underestimated, possibly due to inconsistencies in measuring the emissions of volatile organic compounds (VOCs), as well as secondary organic aerosols (SOA). Because of this, CMAQ has been handy for investigating the impact of smoke on regional haze (Achtemeier et al. 2001, Goodrick et al. 2013).

CMAQ was also integrated into BlueSky to analyze the performance of BlueSky predictions during the 2007 and 2008 wildfires in California (Strand et al. 2012). More recently, $PM_{2.5}$ estimates from CMAQ were bias-corrected using the Constant Air Quality Model Performance (CAMP) and used in conjunction with observed and satellite-derived $PM_{2.5}$ to estimate smoke concentrations during the October 2017 California fires through data fusion (Cleland et al. 2020). This reduced the restrictions associated with CMAQ because of its inherent biases.

Another Eulerian model is the Ash3d model, a three-dimensional novel Eulerian advection and dispersion model, which makes use of finite volume methods that allow the concentration of tephra (volcanic ash) to be evaluated at every point throughout the model domain, leading to a more direct calculation of concentration than in Lagrangian models (Schwaiger et al. 2012). Ash3d solves for mass conservation in the atmosphere while accounting for turbulent diffusion and tephra settling during dispersion to estimate the trajectory of an ash cloud and predict the likely region impacted by it. It is intended for operational settings as it utilizes fast numerical methods and simple assumptions. With this model, the authors capitalized on the accuracy of Eulerian models and forwent speed.

Of all the papers studied, only Schwaiger et al. (2012) provided the mathematical equations for estimating the source term, in this case, of a volcanic eruption. It denotes the rate of mass influx per unit time ($kgm^{-3}s^{-1}$) into the plume. Although wildfire smoke and tephra (ash particles from a volcanic eruption) are different (wildfire smoke is caused by burning organic material, unlike tephra, which is not caused by burning), they have similar advective transport mechanisms, and hence the equations implemented by the authors can be applied in wildfire smoke models. A differential equation describing the source term $S(z)$ is given by

$$\frac{dS}{dz} = S(z)\frac{k^2\left(1-\frac{z}{H}\right)\exp\left[k\left(\frac{z}{H}-1\right)\right]}{H\left[1-(1+k)\exp(-k)\right]}, \tag{2}$$

where H is the plume height, S is the erupted mass at a given time, z is the vertical height, and mass distribution over height is controlled by k. Smaller k values result in an equal distribution of mass with height, whereas high values concentrate more mass at the top. Maximum concentration of ash occurs when $z = \frac{H(k-1)}{k}$. To keep the time reasonable, diffusion was evaluated via dimension-splitting with the Crank-Nicolson method, with the kinetic turbulent fluxes parametrized as proportional to the gradient of the fluctuating variable. When diffusion is not a constraint on the time step, it can be dealt with using an explicit method such as the forward Euler. In order to calculate the concentration of tephra, the emissions source, S, becomes the right-hand side of the advection equation. The governing equation is given by

$$\frac{\partial q}{\partial t} + \nabla \cdot [(\mathbf{u} + \mathbf{v}_s)\, q] - \nabla \cdot (\mathbf{K} \nabla q) = S, \tag{3}$$

where q is the concentration of a particular grain size, $\mathbf{u}$ is the wind field velocity, $\mathbf{v}_s$ is the settling (fall) velocity of the ash particles, $\mathbf{K}$ is the diffusivity in 3-D.

Studying CMAQ, Ash3d, and other grid models, we observed that grid sizes constrain grid models. By reducing the spaces within grids, which leads to a finer resolution, grid models can be better enhanced (Goodrick et al. 2013). Another technique for improving grid models is implementing adaptive model grids within existing models. The essence of adaptive grids is to dynamically modify their resolution in response to environmental gradients, resulting in more accurate simulations of spatial fields (Achteimer et al. 2011, Goodrick et al. 2013).

3 Smoke Modeling Frameworks

On many occasions, smoke models only scratch the surface of the complexity of the modeling problem. Although some of the models discussed in this study integrate information on emissions, meteorological conditions, and atmospheric chemistry to give easily available high-quality, accurate emission measurements at fine spatial and temporal resolutions, they are restricted when used alone. Their flaws include reliance on emission estimates and meteorological forecasts with wide error margins, poor capture of plume size and location, and weather-imposed constraints (Achtemeier et al. 2001, Strand et al. 2012, Goodrick et al. 2013, Cleland et al. 2020). Uncertainties also arise due to the models' inability to calculate fire size from aerial measurements accurately, discrepancies in the temporal resolution of the data, effects of synoptic patterns, and the use of a constant emission rate (Draxler & Hess 1998, Pan et al. 2020). As these uncertainties compound, errors are introduced into subsequent components of the models/frameworks (Pan et al. 2020).

To thoroughly address these challenges, methods for characterizing fuel loading, calculating fuel consumption and converting it to emissions, and predicting plume height are necessary. Smoke modeling frameworks are required because they incorporate a comprehensive set of tools comprised of various models capable of handling various aspects of smoke, decreasing complexity for end users (Goodrick et al. 2013). We shall briefly discuss two frameworks, BlueSky and NAQFC, and their performance compared with observational data.

3.1 BlueSky

Larkin et al. (2009) created the BlueSky Smoke Modeling framework (BlueSky) as part of a collaborative effort to model and predict emissions from wildland fires. In order to provide real-time forecasts of air quality and ground-level concentrations of $PM_{2.5}$ for the USA, BlueSky combines a smoke transport and dispersion model with off-the-shelf weather information, fuels, total fuel consumption, time rate, and emissions sources in a framework. BlueSky estimates $PM_{2.5}$ impacts from a single fire and the cumulative effects from numerous fires by collecting and analyzing data on all fire activity in the area. BlueSky has implemented the dispersion models CALPUFF, HYSPLIT, and CMAQ (Goodrick et al. 2013).

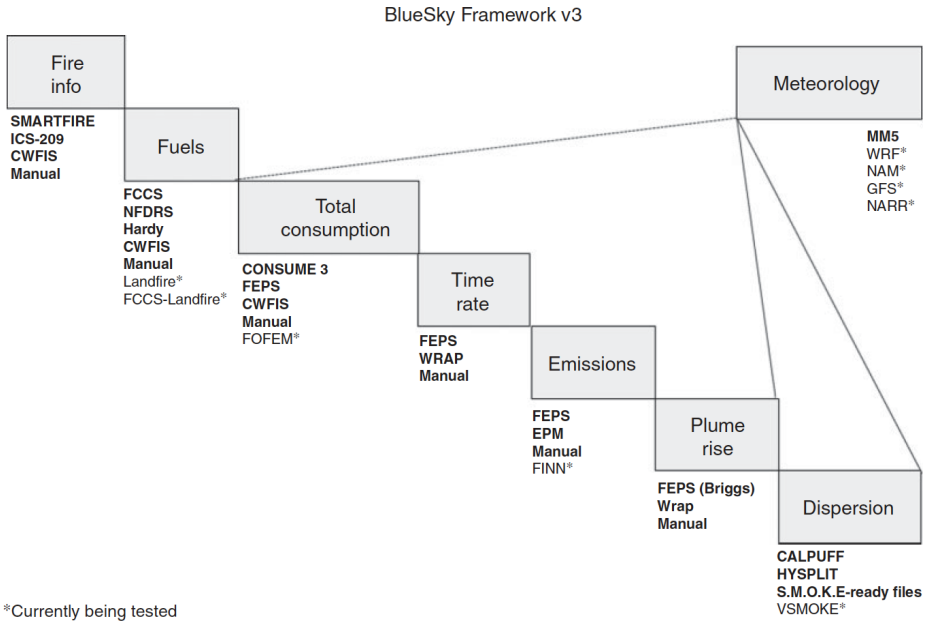

Figure 2: The BlueSky Framework shows the pathways used. The pathway presented information about fuel type and a consumption model, which was used to evaluate the fuels burned and the emissions model intended for it. The plume rise profile is based on research using wildfire data by the Western Regional Air Partnership (WRAP). (Larkin et al. 2009, Strand et al. 2012, Goodrick et al. 2013)

Because the prior version of BlueSky had a propensity to underestimate near-field surface smoke concentrations while potentially overestimating the far-field, it was critical to evaluate predictions using several observed concentrations in order to determine the performance of the framework, and also to ascertain the level of accuracy (Riebau et al. 2006, Strand et al. 2012). To that end, Strand et al. (2012) analyzed the performance of BlueSky using hourly $PM_{2.5}$ concentrations from two regional wildfires in southern and northern California in 2007 and 2008, respectively. The hourly meteorological fields obtained from the National Center for Atmospheric Research Mesoscale Model, Version 5 (MM5) were processed to make them compatible with CMAQ, the dispersion model integrated into BlueSky. The daily fire information was obtained from the SMARTFIRE v1 system consisting of both ground- and satellite-based data, while the fuel loadings are from the 1 km fuel loading map derived from the Fuel Characteristic Classification System. The total fuel consumption, extracted from the Emissions Production Model (EPM), a simplified version of the CONSUME model version 3 was used to calculate the consumption sums (Larkin et al. 2009, Strand et al. 2012, Pan et al. 2020). Plume rise along with the evolution of emissions were evaluated from the Fire Emissions Production Simulation (FEPS), which produces hourly emissions output (Larkin et al. 2009). When compared with observed values from the 2007 southern California wildfire, BlueSky under-predicted $PM_{2.5}$ concentrations due to insufficient characterization of the emissions source and the coarseness of the modeling grid.

3.2 National Air Quality Forecasting Capability (NAQFC)

NAQFC can be described as a fire signal-capturing algorithm that utilizes multiple models and observations from various sources. The models integrated into the system include BlueSky

and the Hazard Mapping System (HMS) fire detection algorithm of the NOAA National Environmental and Satellite Data and Information Service (NESDIS). It also employs the US EPA Sparse Matrix Operator Kernel Emission (SMOKE) to calculate plume rise. Simultaneously, it relies on the NOAA National Weather Service's (NWS) North American Multi-scale Model (NAM) and CMAQ for meteorological forecasts and chemical transport models. The emissions data from BlueSky are projected into a longitude-latitude map and converted to CMAQ-ready gridded emission files in SMOKE (Pan et al. 2020). The datasets are; ground observations from Interagency Monitoring of Protected Visual Environments (IMPROVE), Automated Smoke Detection and Tracking Algorithm (ASDTA) and HMS smoke plume satellite retrievals, and aircraft measurements from the southeast nexus (SENEX) campaign.

The fire-capturing capabilities of the NAQFC system are essential in smoke modeling because they form the basis of estimating the emissions source term. At the very least, the system identifies the location of wildland fires through the HMS. Beyond that, it analyzes their magnitude, start time, and duration of burn (Ruminski & Kondragunta 2006, Ruminski et al. 2008). However, adequately describing fire emissions and their impact on air quality is particularly difficult for NAQFC. According to Hu et al. (2016), one reason is that the detection accuracy of the HMS drops drastically when the geographical extent of the fire is small. Apart from that, HMS has a procedure for eliminating fire hotspots that do not have associated smoke plumes. This reduced the number of fire hotspots that BlueSky subsequently uses, thus decreasing the accuracy of the system. Another downside of the system is that its performance is inhibited by cloud cover (Pan et al. 2020). Uncertainties arose because it was incredibly challenging to determine plume rise from aerial measurements. Discrepancies in the temporal resolutions of the data created further uncertainty.

4 Research Gaps and Future Work

In this synthesis, we reviewed various models used to simulate smoke transport and dispersion, their strengths and weaknesses, performances, and the overall limitations of smoke modeling. However, we observed that to better simulate smoke and have more accurate predictions, certain aspects of smoke require more work. For instance, from the publications reviewed, Schwaiger et al. (2012) were the only authors who adequately described the transport model used in their work along with the governing equations. The other authors tried to describe the smoke dispersion models they used, but it was hard to visualize it without a given set of equations. Because of this, it is difficult, if not impossible, to replicate what has been done. Also, procuring smoke data proved to be a odious task as were often required to provide a security pass, and on two occasions, met with an obsolete server. The significant gaps and future work are outlined below:

1. Characterization of the emissions source term: in as much as researchers have tried to maneuver through smoke modeling with the assumptions put in place; it is still challenging to estimate the source term due to the randomness of fire, unfavorable weather conditions, the reliance on constant emission rates that subsequently introduce errors into the estimates, and the absence of one established model that is a go-to for source term estimation. While it is essential to develop novel modeling approaches, it is also important for researchers to delve deeper into the findings of others. Are there ways of modifying the source term from, say, Schwaiger et al. (2012) to account for smoke?

2. Some models, such as the box model, lack some fundamental physics to make for a more realistic model. It is possible to employ it to estimate the source term rather than having it as a stand-alone model.

3. Large domains and time scales: wildfires often spread over large areas and are represented on Eulerian grids using large grid sizes. This puts a strain on computational resources since not all locations on the physical domain have smoke. Employing adaptive mesh refinement (AMR) to simulate smoke dispersion over large spatio-temporal scales is cost-effective as only regions with smoke are targeted.

4. It is also pertinent to study the sensitivity analyses in greater detail. That way, we can understand the factors or parameters that must be in place to reduce uncertainties.

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