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Fire behavior modeling for operational decision-making

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Summary
Simulation frameworks are necessary to facilitate decision-making to many fire agencies. An accurate estimation of fire behavior is required to analyze potential impact and risk. Applied research and technology together have improved the implementation of fire modeling, and decision-making in operational environments.

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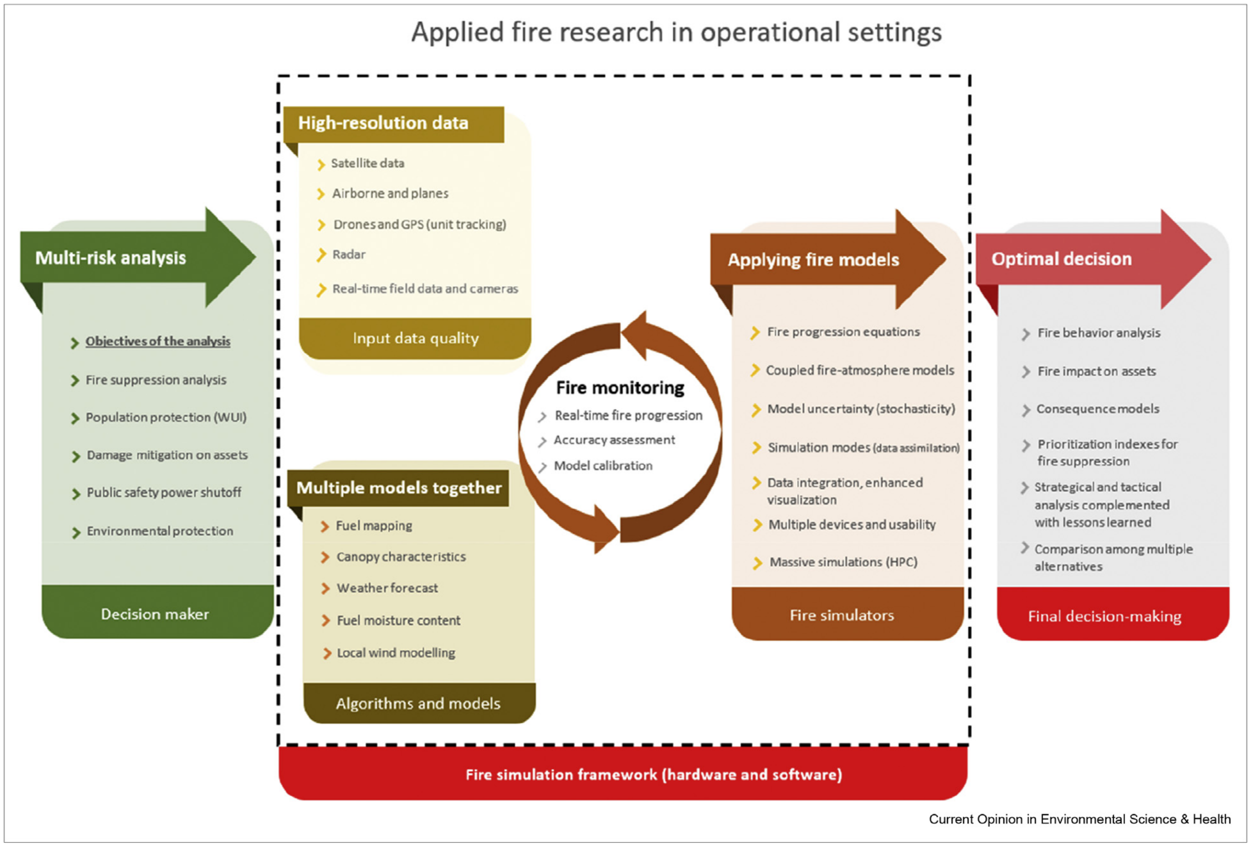
Introduction

Wildfire is an integral component of many ecosystems, often necessary for habitat renewal and biodiversity. However, as recent events in the western United States and elsewhere have shown, wildfires can also inflict severe damage and impacts on to communities, infrastructure, and the environment [1–3]. Many environmental variables can simultaneously influence a wildfire's behavior, of which the rate of spread (ROS) and flame length are the most critical and valuable estimations for scientists, first responders, and fire management agencies involved in decision-making. It is widely recognized that (1) fuels, (2) topography, (3) weather, and (4) the fire itself play the most significant roles in influencing wildland fire behavior [4]. Over the years, several fire spread models have been developed using a host of empirical, physical, and mathematical approaches—all designed with the aim of accurately predicting fire progression both spatially and temporally across the landscape [5–8]. Among the different types, empirical and quasi-empirical models are the most widely used in operational settings due to their relatively low computational complexity and resource requirement [7]. These models have been encapsulated in different applications ranging from rules of thumb [9] and 'pocket or field guides' to full-fledged software suites [10]. The most representative ones include Farsite [11], FlamMap [12], BehavePlus [13], ForeFire [14], WFDSS [15], Prometheus [16], Phoenix [17], Spark [18], and Wildfire Analyst [19,20]. These modeling systems are the direct result of decades of intense research and experimentation both in the laboratory and field and their implementation allows for an improved decision-making aiming to minimizing the adverse impacts of wildfires (Figure 1).

Many public and private entities, such as natural resource agencies, electrical utilities, insurance, and forestry companies strongly rely on contemporary science-based decision-making systems based on fire simulation frameworks to facilitate optimal decision-making considering the analysis of multiple risks and agency's objectives [21] (Figure 1). In the last decade, new research and sweeping advancements in fire modeling technology such as rapid computational speed have allowed for the application of fire spread models in operational settings such as in fire suppression activities. In the event of wildfire emergencies, first responders require accurate estimation of fire progression and behavior [20], analysis of fire risk and impact on communities and assets [22], indices to optimize the different suppression alternatives (e.g. initial attack

Figure 1



Innovative fire simulation frameworks including enhanced fire modeling capabilities through high-input data quality, improved models and algorithms, and accurate fire monitoring allow agencies to make decisions in operational settings based on multi-risk analysis and specific objectives.

assessment indices to better dispatch resources based on expected fire behavior and suppression difficulty), and analysis complemented by lessons learned from past fire events [23,24]. All of this information must be processed rapidly to make informed decisions regarding evacuation, fire attack, asset protection, and resource management. In this article, we review and summarize the most important characteristics of fire simulation frameworks and the most prominent lines of research and technology to enhance operational decision-making (Figure 1). Also, we identify and discuss current challenges in the field of fire modeling as well as the required advances for use in operational environments to deal with the uncertainty of future wildfire events under a global environmental change context.

Fire simulation frameworks

Situational awareness and decision-making in incidents are enhanced combining real-time data integration (field cameras, satellite hotspots, remote sensing products, weather stations, geo-tracking of resources, information from incident management platforms, etc.), forecast weather services, high-resolution thematic cartography, improved fire modeling capabilities, and proper viewers to interpret the outputs. All of these resources combined with expertise of trained analysts and users can improve risk awareness before any incident and decrease the uncertainty in executive decisions during the emergency.

Fire simulation frameworks are becoming a critical tool to support strategic analysis in operational units of fire agencies, dispatch centers, incident command posts, and incident field crews [19,20,25]. Each type of user has different needs during and before any emergency. Although operational units predominantly need estimations of fire risk and potential impacts over large scales, dispatch centers require initial attack assessment indices based on expected fire behavior and suppression difficulty [26] to properly allocate and dispatch resources to incidents; incident command posts analyze the potential fire progression of individual fires to subsequently better develop strategies and tactics; and incident field crews estimate fire behavior in a specific section of a fire. Accordingly, these analyses use different types of hardware from high-performance computers to mobile devices suited to real-time operations. High-performance computing capabilities allow for fire behavior estimations and derived fire danger indices, the use of stochastic approaches to assess risk and potential impacts at large scales, and permitting the kinds of data-driven workflows required by urgent computing [27].

Assumptions and limitations of fire spread models and input data with increasingly complex fire environments can result in uncertainty and errors in fire behavior model predictions [28,29]. Cruz and Alexander [30] analyzed the error of operational fire models and discovered a mean percent error in the fire ROS estimation ranging between 20% and 310%. The authors reported that this range of deviation may vary among regions depending on many factors such as input data quality, ability of models to accurately estimate gridded inputs derived from raw data (i.e. fuel maps, local weather, fuel moisture, etc.), calibration of fire spread models to the study area, and complexity of the analyzed fire event. Recent efforts in the field of fire science and technology have been made toward increasing the accuracy of fire simulations in many regions by a continued development and improvement of input data quality and models [28,29,31] (Figure 1). In this sense, accurate monitoring of fire progression across the landscape is key to calibrate and validate fire behavior model outputs [31] and further improve the whole fire simulation frameworks as a continued and iterative process [32]. Although wildfire behavior is difficult to quantify during active events, remotely sensed observations derived from sensors on satellite, manned aircraft, and unmanned aerial vehicle (UAV) platforms are fundamental to the systematic measurement and analysis of fire behavior [33,34]. Fire detection ('hotspots') and progression metrics (i.e. ROS) are predominately acquired from satellite-based thermal-infrared sensors [35]. The most popular being the Visible Infrared Imaging Radiometer Suite (VIIRS) and the Moderate Resolution Imaging Spectroradiometer (MODIS) - Active Fire and Burned Area products [36,37]. Other satellites commonly used for monitoring wildfire progression include geostationary satellites, such as the Himawari-8 [38] and the Geostationary Operational Environmental Satellite [39]. From an operational standpoint, satellite-based active fire products are the most timely and readily available. VIIRS and MODIS data have been used to generate fire spread maps [40], validate fire spread models [41], and adjust simulations [42]. Although satellite active fire products prove useful for operational monitoring and simulation calibration/validation, they are subject to inherent limitations notably the return rate, spatial resolution, and atmospheric obstructions (e.g. fire smoke plumes, suspended particulates, etc.) [37]. However, this might be subject to change with the launch of the WildFireSat program which will monitor active wildfires to capture essential characteristics such as ROS. Classically, gaps in the limitations of satellites have been filled by manned aircraft systems but more recently UAVs have shown their effectiveness in operational settings [43].

Raw data and models to derive inputs

Errors in input data may lead to a cascade of larger errors in the fire behavior prediction results [8,28,29]. New technologies, platforms, and sensors to derive inputs for fire modeling at proper spatiotemporal resolutions allow fire models to better capture the natural variability of data [44]. Uncertainties in weather (especially wind speed and direction), fuel model assignment, location, and timing of ignitions are the variables with the highest influence on ROS prediction accuracy [29].

Accurate and updated spatial data of wildland fuels, canopy characteristics, and their distribution are a prerequisite for fire behavior models [45]. In this regard, improvements in remote sensing methods have provided an inexpensive and faster alternative to field surveys. Recently, studies have been combining spectral and lidar data to more accurately map and quantify fuel types not only based on their optical properties but also their vertical structure at multiple scales [46,47]. The NASA's Global Ecosystems Dynamics Investigation spaceborne lidar [48] launched in 2018 is currently collecting three-dimensional measurements of forest structure that will be used for estimating forest aboveground biomass globally, and could potentially be applied for estimating canopy fuel properties, including canopy fuel load and bulk density.

The implementation of weather forecasting models has also allowed for more accurate and dynamic fire spread [49]. Coen et al. [50] developed such a module coupled with the Weather Research and Forecasting numerical weather prediction model which has near-surface winds directing the fire spread rate and direction at each timestep. Coupled fire weather models have the capacity to simulate feedback loops between the fire and atmosphere commonly referred to as 'fire—atmosphere interactions' to characterize more complex and rapidly changing fire behavior [51]. Although these coupled models have come a long way, they are not yet ready for operational use due to their heavy computational demands, broader training requirements, and organizational challenges associated with intertwining weather and land management activities [52].

Improving fire behavior estimations and new fire simulation modes

The improvement in operational, empirical, and coupled fire spread models could allow for better estimation of fire behavior in the coming years given the limitations and assumptions of current fire spread models [31]. In this sense, the calibration of new algorithms to estimate fire behavior could be enhanced by increasing the amount of observations through the use of UAVs, ground temperature sensors, or satellite hotspots. Also, data-driven techniques aim to circumvent the lack of prediction accuracy by incorporating observed data into a running model to tune or calibrate the simulation of the observed fire patterns [31,53]. In the context of operational fire simulations, data assimilation has been proposed using Kalman filters to calibrate several parameters of the ROS equation [54], updating both fire perimeter and fuel adjustment factors using Ensemble Kalman Filters [55], particle filters, also called sequential Monte Carlo analysis, genetic algorithms aiming to adjust weather conditions [56], or genetic algorithms aiming to adjust other environment variables like canopy cover or ROS adjustment factors [57]. These optimization methods, however, usually rely on heavy recursive algorithms making them hard to be used in an operational context. Faster algorithms have been proposed based on Derivative-Free Optimization methods [58], gradient-based optimization techniques using automatic forward differentiation [59], or through a fast convergent least square problem to obtain ROS adjustment factors [31].

Fire spread models can be used in various analyses or simulation modes. Uncoupled punctual models, where the ROS only depends on local variables, can be used in inverse mode to compute the time that any potential fire would take to reach an asset [28,60,61]. This is useful to create an evacuation perimeter around vulnerable assets or communities instead of creating fire perimeters around an ignition source. This model also allows for fire simulations to be run backwards in time to obtain the most probable location of ignition sources based on a final perimeter, or to define evacuation trigger points through firefighter's escape routes [61–63].

New challenges for fire modeling

Despite the progress of developments in the field of fire modeling, a changing climate with increased fuel loads and fuel continuity in most fire-prone areas requires further work to tackle fires in unprecedented locations as well as fires of greater magnitude in terms of size and behavior.

Extreme fire behavior

In recent years, there have been many instances of extreme fire behavior ranging from intense high temperatures, erratic and unpredictable spread, and rapid exponential growth of spot fires. Although many definitions of extreme fire behavior persist among the scientific community [64], the most widely accepted is that extreme fire behavior consists of "fire spread other than steady surface spread, especially when it involves rapid increases" [65]. The frequency of these extreme fire events is increasing [66,67]. These events bring new modeling challenges due to their erratic nature involving their capacity to influence their own fire environment. Pyroconvection activity within fire plumes can induce strong and sudden changes in wind velocity and direction and may even ignite new fires from pyrogenic lightning [68]. The term pyrocumulonimbus refers to these fire-induced or fire-augmented thunderstorm [69]. These events prove adverse challenges to fire behavior modeling due to changing input conditions unexpected for weather forecast models.

Fire in new regions

With increased warming, climate zones are projected to shift toward the poles in the middle and high latitudes resulting in traditionally non-fire-prone temperate regions experiencing fire events. An increase in fire activity in these temperate regions pose three major challenges for fire modeling, concerning (1) the availability of accurate landscape-wide fuel models, (2) knowledge of the meteorological conditions allowing fire spread in these fuels, and (3) the limited size of the fires preventing satellite-based monitoring. Regarding fuels, landscape-wide fire modeling is hampered because of the lack of accurate fuel maps; unlike in the European Mediterranean for instance, vegetation maps have not been translated to fuel maps. This process is challenging because of the lack of 1:1 resemblance between common temperate vegetation types and standard fuel types [70]. Some valuable work has been done on fuel characterization in temperate fuels but without insight into the accuracy of resulting fire behavior modeling. Moreover, a greater range of fuel types need characterization and testing to capture the large variability in vegetation types and allow off-the-shelf landscape-wide fire modeling. Assessment of the accuracy of fire spread modeling in temperate fuels is imperative to ensure trustworthy application of these models in emergencies. *Calluna vulgaris* (L.) heathland, a major fire-prone vegetation type in this region, can burn at higher fuel moisture contents than known for Mediterranean fires, and has also been reported to demonstrate surprisingly rapid drying capabilities, and even burning at subzero temperatures [71,72]. The way Calluna burns is furthermore significantly affected by its physiological development [71]. An added complexity in the adaption of fire models to temperate fuels is the paucity of good fire spread information. Fires in these regions are often so small and of such short duration that they cannot be detected by satellites (e.g. VIIRS or MODIS), hampering verification of modeling predictions such as outlined in the previous sections as these data are often not available from other sources.

Summary

Fire simulation frameworks are necessary to facilitate decision-making to many public and private agencies based on the analysis of multiple risks and agency's objectives. An accurate estimation of fire progression and behavior is required to analyze potential impact, risk, and better manage the emergencies. Applied research and technology together have improved the implementation of fire modeling, situational awareness, and decision-making in operational environments by the increasing power of user-friendly software interfaces that include real-time data integration, forecast weather services, high-resolution thematic cartography, improved fire modeling capabilities, and viewers to interpret the outputs. However, more research is needed to further evolve the current fire simulation frameworks and face the coming convective extreme wildfires and those occurring in non-traditionally fire-prone areas nowadays.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Some of the authors work in a private company which provides software solutions to fire agencies. However, the submitted manuscript summarizes the most important characteristics of fire simulation frameworks and the most prominent lines of research and technology to enhance operational decision-making without any bias in terms of cited researchers or works published by other authors.

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