Wildfire Interdisciplinary Research Center

SJSU SAN JOSÉ STATE UNIVERSITY

Written Statement of


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Before the House Committee on Science, Space, and Technology hearing on
"Enhancing Fire Weather Prediction and Coordination"

July 12, 2023

I am an Assistant Professor of Mechanical Engineering, Director of the Thermo-Fluids Complexity Laboratory, and Co-Principal Investigator of the Wildfire Interdisciplinary Research Center (WIRC) at San José State University (SJSU). In this testimony, I present a concise overview of wildfire physics and modeling approaches focusing on the role of fire behavior as the central piece for developing the next generation of wildfire models. I then elaborate on some of the identified challenges by the fire science community and provide recommendations to overcome these challenges and improve our fundamental understanding of wildfire behavior and its impacts on the environment.

## 1. Background

Wildfires are an important part of the ecosystems globally and nature's tool for regulating the health of the wildlands (McLauchlan et al. 2020; Shuman et al. 2022). Indigenous people have also used fire for land management through millennia (Shuman et al. 2022). However, detrimental effects of climate change, poor land management practices such as fire exclusion, and continuous growth of the Wildland Urban Interface (WUI) areas have transitioned wildfire regimes to the extreme, leading to loss of lives, severe disturbances in the biological systems that the well-being of people depends on, and cause billions of dollars in damages. For instance, just in the U.S., the adjusted impacts of wildfires exceeded $100 Billion over the past 22 years (Smith 2020). These impacts are projected to increase in severity and magnitude ("Spreading like Wildfire: The Rising Threat of Extraordinary Landscape Fires" 2022). While similar to other natural hazards, wildfires cannot and shouldn't be excluded from our ecosystems, in the short term, our communities need to become resilient to their impacts and, over time, adapt and learn to coexist with wildfires.

A community resilient to wildland fires can prepare for anticipated scenarios, take mitigating actions, adapt to changing conditions, minimize losses during the response to an event, and rapidly recover (Scott, Thompson, and Calkin 2013). To this end, a key component in forming these actions is the ability to understand and accurately estimate the potential progression of the fire through the landscape and the community zones. The fire weather prediction models are central in providing this information to the stakeholders. Accurate predictions (here interchangeably forecasts) are crucial for response operations, such as issuing timely evacuation orders to at-risk communities and resource allocation for suppression operations. Also, accurate models may lead to better estimates of the overall risk in the landscape and the development of more effective and efficient mitigation and preparedness practices, such as designing and optimizing the egress routes for WUI communities. Moreover, fire weather models are essential for quantifying the full extent of the wildfire impacts on human health and biological systems across large spatiotemporal scales.

## 2. Physics of Wildfire Spread

First, it is important to distinguish between fire behavior and fire impacts. Fire behavior aims to characterize and quantify the wildfire perturbation(s) to the environment, i.e., humans, the built environment, and the ecological and climate systems. In contrast, the fire impacts' objective is to characterize these systems' response to the wildfire effects. Fire behavior is a multi-physics and multi-scale phenomenon, generally parametrized by the rate of spread of the fire line (front), the fire intensity, the topology of the flame and smoldering regions through the boundary layer, burning dynamics of the fuels, the fire plume dynamics, and emission factors (volatile gases, and particulates as black carbon and/or organic carbon, etc.). Second, it is worth recognizing that fire behavior (here, interchangeably dynamics) occurs at the scales of flame dynamics, namely at the meter and second scales.

The field (Clements et al. 2007; 2019), laboratory observations (Finney et al. 2015; J. D. Cohen and Finney 2022; J. Cohen and Finney 2022), and post-fire investigations (Maranghides et al. 2015) show that wildland fire spread is driven by two main mechanisms: (1) the spread of the local fire front through heat transfer from flames and hot gases to unburnt combustibles (Rothermel 1972; Scott and Burgan 2005; Balbi et al. 2020), and (2) firebrand shower also known as ember attacks (Tarifa, Notario, and Moreno 1965; Fernandez-Pello 2017; Koo et al. 2010; Tohidi and Kaye 2017a). Firebrand shower is arguably the fastest and most complex mechanism of wildfire spread involving firebrand generation (Manzello, Maranghides, and Mell 2007; Suzuki et al. 2012), firebrand transport through the interaction of the fire plume with the boundary layer, and firebrand accumulation and ignition of spot fires far ahead of the main fire front (Sardoy et al. 2007; Tohidi and Kaye 2017a). This mechanism is also known to be responsible for most losses in the WUI areas (Caton et al. 2017).

Wildfire models aim to simulate these mechanisms and can generally be divided into detailed and operational categories. The detailed models refer to the type of simulators that solve conservation laws characterized by fire behavior principles and are mostly developed using Computational Fluid Dynamics (CFD) methods (Koo et al. 2012; Linn et al. 2002). While these models have the potential to provide high-fidelity forecasts of fire progression and fire line intensity, their operational use is currently impractical. This limitation is primarily due to the heterogeneity of the fuels and their condition throughout the landscape and, most importantly, the large spatial and temporal scales of wildfires that make them computationally expensive.

To tackle the computational costs and complexities of wildfire modeling, wildfire scientists have worked on operational models for decades. The seminal work of Rothermel (Rothermel 1972), also known as the Rothermel Rate of Spread (ROS) model, is the central piece to many operational flame spread models such as FARSITE (Finney 1998). While this model has benefited the wildfire science community and stakeholders for many years and significant improvements have been made (Andrews 2018), it is originally a one-dimensional and semi-empirical equation based on an incomplete description of the physics (Scott and Burgan 2005; W. Mell et al. 2007; W. E. Mell et al. 2010; Balbi et al. 2020). Briefly, these limitations are that the operational models mostly do not fully account for the interactions of the fire with the atmospheric boundary layer, and, to the best of my knowledge, none of the operational and even detailed models have a physics-based representation of the firebrand shower spread mechanism. Only a few models account for the transport of firebrands using a probabilistic approach (Albini, Alexander, and Cruz 2012); also see ElmFire (https://elmfire.io/). Yet, the current probabilistic models do not account for the contribution of the spot fire ignitions in the rate of spread of wildfires. There is a crucial need to fundamentally understand the underlying physics of wildfire spread mechanisms across different scales and efficiently implement them in the next generation of fire weather forecast systems.

In this regard, recent advances in operational models have focused on improving the two-way coupling between local fire spread, terrain, and various weather phenomena leading to the development of coupled fire-atmosphere models such as WRF-SFIRE (Mandel, Beezley, and Kochanski 2011). Within the Research and Applications Laboratory at the National Center for Atmospheric Research (NCAR), efforts have been made to extend the functionality of the Weather Research and Forecasting (WRF) community model to enable coupled simulations of weather conditions and fire behavior. Also, new developments at WIRC leverage the WRF-SFIRE model (Mandel, Beezley, and Kochanski 2011; Mandel et al. 2014; Kochanski et al. 2019), making it the only fire-atmosphere model that is operational for the nation and has been used internationally; for instance, it is recently used to model the Canadian wildfires. In addition, with the new and cross-disciplinary developments in this model, WRF-SFIRE is now, to the best of our knowledge, the only fire model that is fully coupled with firebrand generation (Tohidi, Kaye, and Bridges 2015) and firebrand transport (Tohidi and Kaye 2017a; 2017b; 2017c) models. In the Thermo-Fluids Complexity Laboratory, efforts are being made to better understand the heat transfer mechanisms from the firebrands to the recipient surface and implement the first version of the spot ignition modules in the model. These fundamental studies—supported by the National Science Foundation (NSF) and the Industry Advisory Board of WIRC—can help create full feedback from the firebrand shower mechanism to the rate of spread models for the next-generation simulators.

Despite significant advancements in our understanding of fire behavior, e.g., see a very small subset of the studies (Finney et al. 2015; Tohidi, Gollner, and Xiao 2018; Manzello et al. 2020; Tao et al. 2021; Palacios and Bradley 2022; Ahmed and Trouvé 2021; Seto and Clements 2011), delivering a high-fidelity operational forecast remains challenging. The primary reason for the incompleteness of the operational models and, consequently, the inaccuracies in forecasts, particularly for high-impact events, is information loss by oversimplification of the fire dynamics to gain computational performance. Our current fire models and their input layers are developed to conduct simulations at large spatiotemporal scales (often at spatial scales of hundreds of meters and long temporal scales of several hours, which are more appropriate for wildland fires but not the WUI fires), whereas the fire dynamics, as mentioned, occurs at flame scale. Additionally, field and experimental observations at the appropriate scales for wildfires are difficult to conduct, and it is very challenging to expand these observations to cover all variations in the parameter space of the problem. As a result of sparse observations and often coarse data from simulations, there are knowledge gaps in our understanding of the processes that govern how fires scale up from a single ignition point to large-scale fire weather systems such as Pyrocumulonimbus (PyroCb) fires

(Rodriguez et al. 2020).

## 3. Knowledge Gaps and Challenges in Wildfire Modeling

The critical knowledge gaps include (a) how extreme fire weather conditions lead to high-intensity and high-impact wildfire events; (b) how, during wildfires, thermal degradation of the biomass (vegetation and structural components in the case of WUI conflagrations) and the subsequent heat transfer processes transition from vegetation scale (at sub-meter length) to landscape scales (at kilometers in length); (c) what role and contribution firebrand showers have in the fire rate of spread and transition of wildfires from small to large-scale regional events; (d) There is very little understanding of how wildfires propagate through WUI areas and the differences between the released energy from structural burns versus vegetation clusters. In fact, none of the current fuel layers that serve as input for the operational models consider the structures and urban developments as flammable. This limitation has deterred us from leveraging the provided risk analysis platforms for estimating the wildfire risk at WUI (Mahmoud and Chulahwat 2018; Masoudvaziri et al. 2021) to its full potential.

In addition to the knowledge gaps in our understanding of (wild)fire behavior, there exist challenges that limit further development and use of current models. The following lists some of the identified challenges,

1. Current models do not account for human interactions and their effects on fire dynamics. One of the most challenging aspects of fire weather modeling is to account for the suppression activities and their effectiveness during the events. This lack of information is particularly important during the emergency response phase and for stakeholders who need accurate estimates and situational awareness.
2. Most detailed (CFD-based) models are siloed in disciplinary sciences, in institutions and/or national laboratories, and very few can access and contribute to their development, testing, and validation of their capabilities in a truly open-source and reproducible fashion.
3. Model inputs, including vegetation properties, fuel categories, terrain characteristics, and weather data, are generally required to be in the 30 meters spatial resolution; see the LANDFIRE dataset (https://landfire.gov/). While this might be an acceptable trade-off between the model's accuracy and computational cost for wildland fires in remote areas, in the case of WUI fires, it deters us from meaningfully characterizing the fire spread and, consequently, the risk. There is a crucial need, in particular for WUI areas, to develop high-resolution fuel (vegetation) maps that are frequently updated and ensure that the data is accessible to the wildfire science community.
4. Fuel Moisture Content (FMC), provided once a day by the National Fire Danger Rating System (NFDRS), plays a fundamental role in determining the flammability of the vegetation in the landscape. Accurately estimating and validating this parameter over large spatial scales with high spatial and temporal resolutions is challenging. But if done correctly and updated frequently, it will benefit all stakeholders. The Wildfire Interdisciplinary Research Center at SJSU has ongoing efforts to collect and improve the FMC dataset over a limited geographic area in California.
5. The lack of high-quality multi-spectral observational data at the flame scale has created a major gap in our scientific understanding of fire behavior and impacts across scales. Thus, there is an urgent need to support more field campaigns and flame-scale observational data

collection efforts. For instance, in 2022, a coordinated wildfire dynamics observation was conducted by the National Oceanic and Atmospheric Administration (NOAA), San José State University, University of Nevada, Reno, and the National Aeronautics and Space Administration (NASA) Goddard, named CalFiDE. More recently, WIRC led an international collaboration with stakeholders such as CAL FIRE for conducting a prescribed burn and collecting flame scale data on the spatial and temporal evolution of wildfires; for more information on the partners and project, see The California Canyon Fire Experiment (https://blogs.sjsu.edu/newsroom/2022/sjsu-wildfire-scientists-trailblaze-unprecedented-canyon-fire-research/). Such observations are invaluable for the development and validation of fire weather models and improving our understanding of wildfire dynamics.

6. Lack of canonical cases, community exposure data (Caton et al. 2017), and limited rigorous quantitative metrics for the validation and verification of wildfire models over large spatiotemporal scales (Rochoux et al. 2014; 2015; 2018; Mittermaier 2021). Canonical cases should be created under controlled mid- to large-scale laboratory experiments (Finney, Grumstrup, and Grenfell 2020) or managed and instrumented prescribed burns (Clements et al. 2007; 2019; Prichard et al. 2019). More support for large-scale experimental measurements and observations is needed. Also, the relevant metrics/scores should be coproduced with stakeholders as the definition of a reliable forecast (success) may differ between the stakeholders. The Measurement and Computation of Fire Phenomena Database (MacFP-DB), coordinated and maintained by the National Institute of Standards and Technology (NIST), can be a good example to expand on.
7. Communication and interpretation of the fire weather model outputs, e.g., risk maps, to stakeholders remains difficult. This may be due to the limited coproduction of the fire models with stakeholders. Coproduction can directly address the stakeholders' immediate and most relevant needs and create opportunities for incorporating their domain knowledge in the model development phase (Shuman et al. 2022).
8. Just as critically important and challenging are the information delivery systems in remote areas that fit the needs and objectives of diverse first responders and at-risk communities during high-impact events.

## 4. Emerging Opportunities

With recent technological advancements in sensor design and deployment, expansion of the sensor networks, cloud and data storage infrastructures, and remote sensing capabilities (see NIROPS at https://fsapps.nwcg.gov/nirops/), the volume and ease of access to wildfire-related data has been increased dramatically. There also exists multidisciplinary field and laboratory datasets on fire behavior, smoke, and emissions at different scales, for instance, FASMEE (Prichard et al. 2019), MOYA (Barker et al. 2020), and WE-CAN (Palm et al. 2020) to name a few. In addition, there are a multitude of satellites with various sensors deployed that can be leveraged to study the landscape and fire weather conditions before, during, and after the events. Despite the abundance of satellite and remote sensing data, it is difficult to leverage them for understanding wildfire behavior and improving the current state of fire weather models. This is mainly due to their coarse spatial and temporal resolutions, often larger than the flame scale. In the case of airborne remote sensing data, the main issue is the over-saturation of the fire line intensity and difficulties in pre-processing and georeferencing the datasets (Valero et al. 2017). More support is needed to design and deploy scientific-grade sensors appropriate for capturing high-resolution (at flame scale) data over large spatiotemporal scales. Also, there is a need to establish an infrastructure to centralize, standardize the data formats, integrate the datasets, and provide ingestion portals and/or Application Programming Interface (API) to the scientific community such that the data can be adopted for fire weather model development more efficiently and effectively.

The advancements in machine learning, particularly in scientific machine learning (ML) and artificial intelligence (AI), can be leveraged to solve some of the foregoing challenges in fire weather modeling, such as providing closure and/or sub-models for solvers, reducing their dimensionality and computational complexities, and providing high-resolution and continuous observational data for situational awareness (McCarthy et al. 2021). While the research opportunities for such applications are very exciting and need to be supported, it is paramount to acknowledge the inherent limitations of ML models and always cross-validate their results with analytic, semi-analytic, experimental, and field observations. The same or even stricter standards conventionally used for CFD model validation and verification must be adopted. In the context of wildfire modeling, some of the limitations of ML models are,

- Existence of aleatoric and epistemic uncertainties in both input data and fire models, which may be propagated in the results of ML models. Please see the previous sections' discussions on the spatiotemporal resolution of the wildfire data, particularly fuel and satellite observations.
- Model interpretability, particularly in the case of using complex neural networks (Naser 2021; Cramer et al. 2022).
- Overfitting or underfitting due to the limited number of data that is not contaminated with effects of human interactions such as suppression campaigns. Wildfires are being contained and suppressed for good reasons, and this is reflected in the observations made by satellites and airborne imagery. In such cases, it is difficult to determine whether the observations truly capture the wildfire dynamics and not the altered dynamics with suppression activities. Uninformed use of this data in ML models, without accounting for suppression activities, may lead to biased wildfire forecast models with unreliable results.

## 5. Closing Remarks

The need for a rigorously validated and reliable wildfire model is increasing, and accurate estimation of the fire behavior across scales leads to (1) better and more accurate initial conditions for biological and meteorological studies, (2) reduction of uncertainties in the short and long-term projections of the wildfire risk throughout the landscape which in turn can better inform the mitigation, preparedness, response, and recovery for at-risk communities, and lastly (3) more precise quantification of the direct and indirect fire effects on the environment and biological systems, e.g., air quality, watershed health, and water quality. The key to the development of models with better and more reliable forecasts is the comprehensive application of the fundamentals of fire behavior and safety sciences, leveraging insights from field and experimental observations at the appropriate spatiotemporal scales (flame scale) and efficient implementation of the findings in the fire weather model development.

## 6. Summary of Recommendations

Given the focus of my testimony, the identified challenges, and elaborated opportunities and solutions in this document, I have summarized and listed the recommendations below:

- Investment in multi-scale laboratory infrastructures, controlled (managed) field campaigns, and rapid data collection teams nationwide to study wildfire dynamics at appropriate scales. These measurements and observations are crucial for defining the canonical cases of wildfires and fire weather model development, validation, and verification.
- Investment in improving the quality, frequency, and resolution of the current data layers for fire weather models.
- Investment in the transdisciplinary initiative(s) to design and deploy sensors to observe and measure wildfire behavior at flame scales with unsaturated, clean, and high-resolution data in space and time. Additionally, such continuous and high-resolution measurements nationwide can serve as a reliable situational awareness platform for responders and other stakeholders.
- Establish and support initiatives to address information and data delivery challenges faced by first responders and at-risk communities in remote areas with limited or unreliable access to conventional networks such as the Internet.
- Support data collection efforts on (1) the community and infrastructure exposure to wildfires, (2) post-incident damages, and (3) data on the suppression activities during events. These are key information to inform the fire weather and subsequent risk models, particularly in WUI areas.
- Support establishing infrastructure to centralize, standardize, and integrate the datasets and provide access to the scientific community to develop fire weather models.
- Encourage and support the development of open-source, community-driven wildfire models that coproduce with relevant stakeholders. Additionally, support is needed to make these models more accessible, less complex, and optimized for the scientific community to use in their wildfire-related studies.
- Promote transdisciplinary and international collaborations for studies on wildfires.

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