Towards Data-Driven Operational Wildfire Spread Modeling

A REPORT OF THE NSF-FUNDED WIFIRE WORKSHOP
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Summary

This report presents a record of the discussions that took place during the workshop entitled "*Towards Data-Driven Operational Wildfire Spread Modeling*" held on January 12-13, 2015, at the University of California, San Diego. The workshop was organized as part of WIFIRE, a collaborative project sponsored by the National Science Foundation (NSF) between San Diego Supercomputer Center, Calit2's Qualcomm Institute and Jacobs School of Engineering at the University of California at San Diego (UCSD) and the Department of Fire Protection Engineering at the University of Maryland (UMD). The objective of WIFIRE is to build a cyberinfrastructure for real-time and data-driven simulation, prediction and visualization of wildfire behavior (see *http://wifire.ucsd.edu*). WIFIRE is funded by NSF Award #1331615 as part of the Interdisciplinary Research in Hazards and Disasters (Hazards SEES) program.

The objectives of the WIFIRE workshop were: (1) to identify technical barriers and milestones that need to be overcome in order to develop validated data-driven wildfire spread models and make them operational; and (2) to bring together leading representatives of the wildfire research community, the geosciences community and the fire science community. The wildfire research community has relevant expertise on wildfire operations; the geosciences community has relevant expertise on large-scale effects in wildfires (e.g., the coupling with atmospheric phenomena); the fire science community has relevant expertise on flame-scale effects in wildfires (e.g., the response of the fire to changing local conditions). The workshop was organized around four main topical areas and corresponding breakout groups, including operational rate-of-spread models for wildfire spread, CFD models, wildfire data, and data assimilation (see Appendix A for a description of the WIFIRE workshop program). Our goal in this report is to document and share the substance and scope of the workshop discussions and to thereby invite the wider research community to support, engage in, and contribute to the general effort to develop operational data-driven tools for wildfire spread predictions.

Michael Gollner and Arnaud Trouvé
(workshop organizers)

Introduction

Providing accurate predictions of the spread of wildland fires has long been a goal of the fire research community. Whether used as a planning tool prior to prescribed burning or as an operational tool to predict the growth of current or potential uncontrolled wildfires, the accuracy of wildland fire spread models and their ability to provide useful information in a timely manner are of paramount importance. Despite the development of a plethora of fire models, their use has been relatively limited operationally. Some of this stems from the fact that all models are by nature approximate, simplified versions of reality. Available data to initialize and parametrize these models, such as fuels, topography, weather, *etc.*, are also subject to large uncertainties and limited resolution. A new approach to this problem is to couple existing models and real-time observations, with the objective of reducing the uncertainties in model fidelity and input data by using real-time observations of the wildland fire dynamics. This approach is called "data-driven modeling." Data-driven modeling allows an optimal use of available information and leads to improved forecasts of system dynamics.

Long since used for weather predictions, data-driven modeling relies on the coupling of numerical model predictions and real-time observations, in essence nudging approximate simulations toward more accurate observations of the system state. While the potential for data-driven fire modeling is clear [1–6], numerous challenges are still present. This workshop has addressed these challenges from different angles, focusing on existing operational tools and numerical models, data collection and data assimilation techniques, hoping to identify technical barriers and milestones that need to be overcome in order to make data-driven wildfire spread models operational.

It is our hope that this workshop and the WIFIRE project as a whole will serve as a catalyst for the community to continue working on this problem. Numerous challenges must be addressed, such as the development of improved algorithms, access to remote sensing data with higher spatial and temporal resolution, and improvement of cyberinfrastructure. However, new technologies such as high performance computing, unmanned aerial vehicles (UAVs), commercial satellites, *etc.*, are becoming a reality and are helping to overcome some of the current technical barriers. The fire research community should be prepared to utilize these new technologies as they become available. This workshop and the WIFIRE project make some preliminary steps in that direction.

1. Operational Rate of Spread Models

In this section, we define operational models as simulators that are used as tools to respond to actively burning fires. These models are often computer applications that rely on simplified analytic models to predict the propagation of a fire as a function of time. Underlying these numerical tools, simplified mathematical models must be relied upon to solve for fire propagation faster than real time. These may be physical models based upon a simplification of known processes, empirical models, which rely on correlations to observed data, or semi-physical models, combining the two [7-9]. Almost all operational models are empirical or semi-physical in nature, requiring adjustments from real observations to account for unknowns in the models such as fuels, wind, unknown physics, *etc*., as the true physical nature of how fires spread does not yet seem to be well known [10,11].

The most common parameter calculated is the rate-of-spread (ROS) of the fire. This parameter enables a model to predict the propagation of a fire between time intervals, based upon specified conditions. In the most common model used in the United States, the Rothermel Model [12], information characterizing the fuel (moisture content, density, packing ratio, *etc*.), weather (wind speed, direction), and terrain (slope, aspect ratio) must be provided to the model which then calculates a constant ROS for the given conditions. Due to its wide use, the Rothermel model has been correlated with the surface ROS of many fuel types common in the US [13]. Many different models are available worldwide, which are mostly empirical, such as Cheney *et al*. or McArthur's model to predict fire spread in Australian Grasslands [14,15].

While all ROS models are dependent on the fuel type, *surface* fire spread models, which include grasses, shrubs and other low-lying vegetation, have not been shown to extend to represent fire spread through a tree canopy. For such purposes, models for transition between the surface to the canopy are used, such as Van Wagner's model [16], followed by adjustments to surface models to account for the drastically different fire spread regimes in crown fuels [17,18]. While Van Wagner's transition model is semi-physical, models for the ROS in crown fires are almost all empirically-based.

Because fuels ignite and burnout over a short distance, the depth of the "front" of the fire is often neglected and the fire is treated as an infinitesimally thin front (the fireline). Numerical models interpret ROS model predictions as values of the rate of spread in the direction of the wind or steepest slope and propagate the fireline or fire front over a two-dimensional landscape. The area enclosed by this fireline then grows with time as the fire propagates. Because models for fire spread can only provide the ROS in the fastest direction (head fire ROS), correlations must be used to propagate the fire to the sides or flanks. In some models, such as FARSITE, a Huygens' wavelet model which assumes both an ellipsoidal fireline shape [19, 20] and correlations for the width of a fire [21,22] are used to spread the fire at the flanks. With this empirical description of the fire flanks ROS, one-dimensional correlations can be used operationally to predict two-dimensional fire propagation.

While the full physical equations for the fluid dynamics and thermo-chemistry of fires can be formulated and solved numerically (*e.g.*, Computational Fluid Dynamic approaches), this high-resolution physics-based approach is (so far) computationally prohibitive and so has yet to be used operationally. One such model that intends to become operational in the future, WRF-Fire, still relies on the Rothermel model for fire spread. Therefore ROS models will remain critically important in many scenarios [23]. More discussion on CFD models for fire spread will be presented in Section 2.

Other types of models, such as mathematical analogues or statistical approaches appear in the literature [9], however since none has been used extensively on an operational basis, they will not be covered here. A recent review by Sullivan of physical and quasi-physical [7], empirical and quasi-empirical, [8] and simulation and mathematical analogue [9] models for fire spread is an excellent source for further details.

For the WIFIRE project, using the greater San Diego region as a testbed, simplistic models must be used because they can run quickly enough to be implemented as decision making tools. In Southern California, fire events are often of relatively short duration (up to 3 days) and are driven by wind conditions that are relatively well understood (Santa Ana wind conditions) [24]. Very few active fires here utilize modeling (or deploy fire behavior analysts) because the fires remain small and are contained rapidly. The fires that would benefit from modeling are those that escape initial attack, get out of control, become large and last for several days or longer: these fires are often termed "extreme fires." A difficulty is that some of these extreme fires appear strongly affected by phenomena beyond the assumptions of the operational models (plume down bursts, canyons, interactions among several fire fronts) but documentation of such cases is difficult to acquire. While proposed data-driven modeling may improve these types of predictions in the future, the majority of fire modeling today is used for estimating fire risk and assist long term planning [25].

1.1. *Operational Model Usage*

Two common operational tools used in the US are FARSITE and WFDSS-FSPro. FARSITE or the Fire Area Simulator is a semi-empirical model that calculates fire growth in two-dimensional, deterministic simplified test conditions [19]. It is the most widely used fire growth simulator in the US and is used by both CAL FIRE and the US Forest Service for training and operations during large wildfire events [20]. FARSITE can be used to simulate fire growth using forecasted wind-weather scenarios but offers no information on the probability of an area being impacted under multiple wind and weather scenarios. WFDSS-FSPro, a model that calculates spatial probability of fire spread, overcomes this limitation by generating thousands of potential wind and weather scenarios (based on the current season's weather as well as historic weather) and incorporates this information by simulating thousands of individual fires. By accounting for uncertainty in the weather and running a large ensemble of simulations, long-term analyses using FSPro provides risk-based assessments for strategic decision-making [26].

Typically, these fire codes are not programmed to incorporate real-time data as they progress. However, the inputs for the atmospheric and vegetation parameters could be automated to accept real-time data instead of manually inputted.

1.2. *Limitations*

Operational fire models do not capture true fire physics. They represent fire behavior using equations that relate simplified parameters of the most common fire behaviors [11]. There are many behaviors not addressed by these models, including mass ignition and mass fire, interactions among multiple fire fronts, fire whirls and ember transport from fire whirls, thresholds for spread, and meteorological feedbacks on large fires (down bursts). The inputs to these models – vegetation, wind and topography – are roughly defined to drive a conceptual output of what to expect. For instance, the fuel model utilized by FARSITE is a standardized representation of the real fuel specifically adjusted for the Rothermel spread equation [12]. That input is not specifically describing the actual vegetation and is derived from a static product that is updated every 2 or 3 years. The Landfire product, where most spatially-resolved fuel and topography data are derived from in the US, does not have annual adjustments for areas that have been burned, grazed, *etc*. [27]. Error in static fuel maps where major fires have occurred often require individual analysts to make modifications before modeling.

In order to improve the accuracy and utility of fire modeling, the physics must eventually be better understood. However, ongoing research to this end will require many years before it is included in operational tools [10]. Even then, this information will still be subject to inherent inaccuracies in input data. Because understanding the physics in various regimes remains difficult, ensembles of varying conditions have often been used to accommodate for the lack of fidelity and accuracy. The ensemble-averaged predictions result in probabilities for fire growth. Data-driven modeling offers the opportunity to improve upon this statistical-ensemble-based approach by taking advantage of real-time sensor data. In the meantime, there are several opportunities for increased cyberinfrastructure to provide resources to fire managers with existing tools, as described below.

1.3. *First Steps towards Data-Driven Operational Wildfire Spread Modeling*

We present below three examples in which enhanced cyberinfrastructure and new workflows are affecting wildfire safety strategies. The first two examples are based on work performed by the PHOENIX Rapidfire research team at the University of Melbourne, Victoria, Australia [28].

Systematic wildfire spread simulation triggered by ignition reports

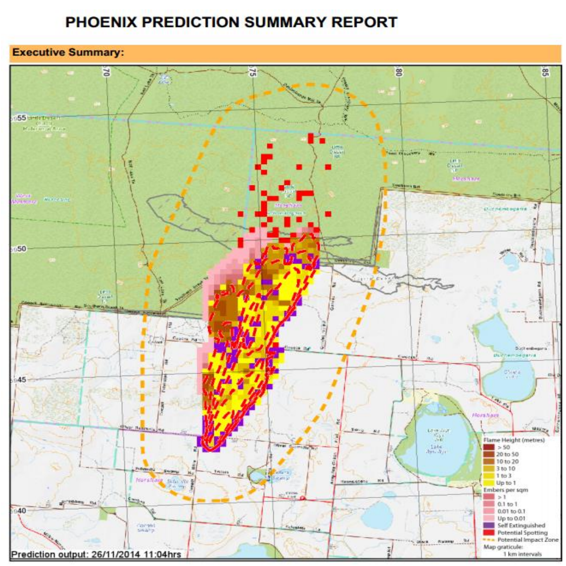
The state of Victoria in Australia has developed a new operational standard for running PHOENIX automatically for every ignition event that is reported at their emergency phone number. The intent in this new standard is to provide a systematic estimate of where the fire may go within 5 minutes of its initial reporting. That assessment is presented with an uncertainty boundary. An ensemble-based approach captures the uncertainty in exact ignition location and start time. See Figure 1 below.

This new standard eliminates the process of waiting to determine if a model is necessary, and provides a preliminary assessment of intensity and impact over the first few hours of the fire spread.

Systematic wildfire spread simulation triggered by new weather forecasts

Another innovative approach being tested with emergency services in the state of Victoria is to use daily weather forecasts (produced twice a day) and run the PHOENIX RapidFire model with a 5 km ignition grid across the State of Victoria in order to generate fire risk maps (Figures 2(a)-(b)). Once processed, results can be quickly queried for response and/or planning. Results can be used to describe relative potential exposure to fire spread. If a real fire is reported during this time, analysis can be done using existing pre-processed model outputs.

One key question to be answered by fire models during a potentially damaging fire is to quantify how much area will burn and how many houses and/or infrastructure are at risk of being lost. This problem cannot be solved by a traditional approach as it is difficult to define a threshold indicating which regions of interest will be involved in the fire, so instead an uncertainty barrier (fire affected area) has been implemented. Assets falling in the impact zone need to be considered for protection or evacuation. Initial rate of fire spread gives a good indication of fire risk to firefighters.



Name:	COOACK MITRE RD		
Prediction start time(24hr):	26 Nov 2014 11:11:00	**Prediction end time(24hr):**	26 Nov 2014 17:00:00
Area burnt:	1466 ha	**Criticality score:**	0
Max spotting distance:	0 km	**Ignition pt: Lat/Long**	-36.66, 141.81

Figure 1: PHOENIX Rapidfire automated prediction report showing an estimate of the fire location (dotted orange line) and intensity, at a given time, through an ensemble of simulations that accounts for uncertainties in ignition location and timing [28].

Figure 2(a): PHOENIX Rapidfire automated prediction report showing an estimate of the fire probability through an ensemble of simulations that corresponds to varying ignition location [28].

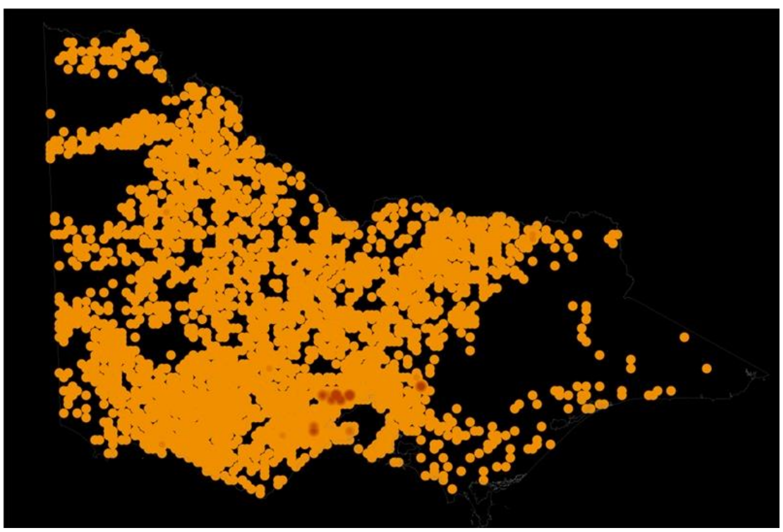


Figure 2(b): See caption of Fig. 2(a). This map shows the potential property loss. Ignition points are in yellow, endangered assets are in red [28].

Educating the public

A persistent theme in operational fire response is that the public is not sufficiently educated in the hazards of wildfire in fire-prone regions. Florida is an interesting case because the government there has made significant efforts to inform communities on the fire problem, including fire hazards, frequencies, laws and regulations [29]. This is especially critical in places like Florida and California where much of the population is not native to the area. One goal of the modeling effort is to create educational communication tools to describe fire as a scientific process and help influence adaptation and preparedness at the community level.

In Australia, there is a growing focus on the social aspects of managing wildfires and a growing use of spread models for planning [30]. Investment in spread models by fire agencies is now more weighted towards model inputs and impact modeling rather than understanding and improving the description of spread mechanisms. In general, fires agencies struggle with investing in basic research on fire physics.

1.4. *Conclusion and Implications for WIFIRE*

The three examples presented in this section are good candidates to be considered by WIFIRE for evaluating the potential of an enhanced cyberinfrastructure on fire prevention and/or firefighting in San Diego County. Under weather conditions that are well understood and predictable, operational wildfire spread models can be used and preprocessed to generate fire risk maps. The forecast products can then be used to generate messages/warnings as is already done with numerical weather prediction outputs.

The greater challenge is with fires under extreme or unpredictable weather conditions. Research workflows should be developed for extreme fire events.

2. CFD Models for Wildfire Spread

2.1. *Domain of Application of CFD-Based Wildfire Models*

Computational Fluid Dynamics (CFD) models are three-dimensional numerical flow solvers based on the Navier-Stokes equations and the basic principles used in fluid mechanics and heat transfer of conservation of mass, momentum and energy. CFD models are routinely used in many areas of science and engineering, including geosciences and aerospace, mechanical and chemical engineering. Over the past twenty-five years, CFD models have also been adapted and applied to building fire and wildland fire problems. These models typically have a restricted domain of validity/application and are designed to simulate some specific aspects and processes of fire phenomena: partly because of current limitations in computational power, and partly because fire dynamics at the fine scales of combustion and heat transfer are still not fully understood, CFD-based wildfire models do not provide a complete and accurate description of all scales relevant to the fire dynamics. Despite these limitations, a strength of CFD-based wildfire models is that they provide a description of the strong coupling between the fire and its environment: for instance, the fire dynamics are affected by environmental conditions, in particular the three-dimensional wind conditions; environmental conditions are affected in turn by the release of large amounts of heat associated with combustion processes (see an illustration in Fig. 3). This coupling between the fire and the atmosphere is considered critical to a basic understanding of erratic and/or extreme wildfire behavior.

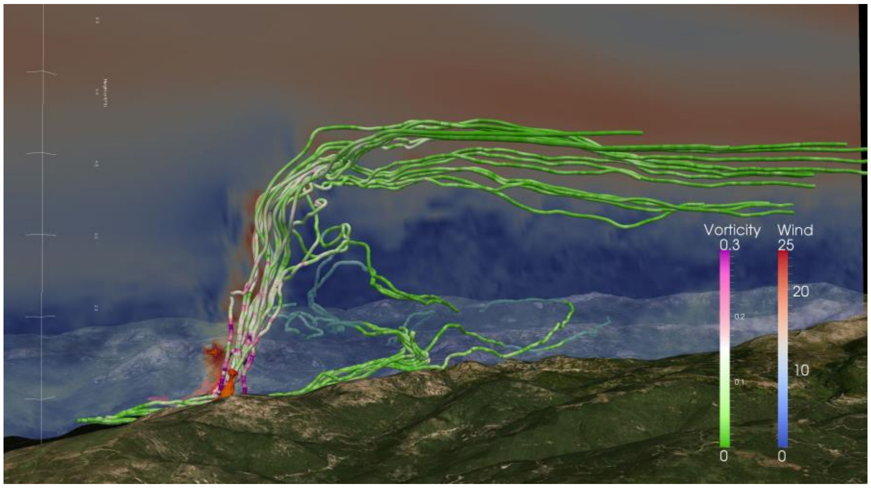


Figure 3: Illustration of current coupled fire-atmosphere capabilities: instantaneous snapshot from a mesoscale (several tens of kms) wildfire simulation using Meso-NH/ForeFire. The three-dimensional image shows wind speed in red/blue colors in a vertical slice along with vorticity in green/purple colors along spaghetti-like streamlines (the streamlines are positioned in the vicinity of the fire plume). Picture taken from Ref. [31].

CFD models have been used successfully over the past two decades to bring fundamental insights into wildfire dynamics and have thereby contributed to increase our basic understanding of the mechanisms that control wildfire spread. They have also been used to simulate and help interpret laboratory-scale and field-scale wildfire experiments. It is worth emphasizing, however, that despite the significant progress that has been made to date, there is a large consensus in the wildfire research community that a fundamental understanding of wildfire spread is still lacking. Because of this incomplete understanding of wildfire spread mechanisms, the exact level of fidelity and accuracy provided by CFD models remains an open question. This question is a barrier to a more widespread application of CFD in wildfire research and to a possible integration into operational models.

2.2. *The Multi-Scale Problem in CFD Modeling Applied to Wildfire Behavior*

The dynamics of wildfires are determined by interactions between pyrolysis, combustion, heat transfer, near-flame flow dynamics as well as atmospheric flow dynamics. These interactions occur at: vegetation scales that characterize the biomass fuel; flame scales that characterize the combustion and heat transfer processes; geographical scales that characterize the terrain topography and land cover; and meteorological regional/global scales that characterize atmospheric conditions. Figure 4 gives a schematic representation of the different length scales that are believed to play a role in fire behavior: the vegetation scales, denoted $L_{\text{vegetation}}$; the flame scales represented by a characteristic flame height and width, L_{flame} and W_{flame}; the length of the fireline, $L_{fireline}$; the geographical scales represented by a characteristic topographical scale and a land cover scale, $L_{topography}$ and L_{land_cover}; and the meteorological scales represented by the depth of the atmospheric boundary layer (ABL), L_{ABL}. In addition, the fire plume has scales that can be represented by a characteristic height and width, L_{plume} and W_{plume}; the plume scales take a large range of values as they grow from flame scales to geographical scales and then to meteorological scales. In wildfire problems, $L_{\text{vegetation}}$ is on the order of a few millimeters or centimeters; L_{flame} and W_{flame} are on the order of a few meters; $L_{fireline}$, $L_{topography}$ and L_{land_cover} are typically on the order of a few tens or hundreds of meters; and L_{ABL} is on the order of kilometers.

CFD models have the potential to provide detailed information on the interactions between physical phenomena occurring at all these different scales. However, because of computational cost, the domain of application of CFD models is typically limited to a particular range of scales. Thus, current CFD-based wildfire models are scale-specific and belong to one of the following three classes (see Fig. 5): *combustion solvers* aimed at describing the coupling between pyrolysis, combustion, radiation and flow occurring at the vegetation and flame scales; *wildfire solvers* aimed at describing the coupling between combustion and flow occurring at fireline scales and/or geographical scales; and *atmospheric boundary layer solvers* aimed at describing the coupling between combustion and flow occurring at meteorological scales.

Examples of combustion solvers that have been developed for wildfire dynamics applications include a group of models known as multiphase models [32-35]. These solvers use a computational grid resolution of order 1-10 cm and provide a fine-grained treatment of the pyrolysis, combustion and heat transfer processes that are responsible for flame spread through a first-principles-based model. Simulations with these solvers are typically performed in small domains (a few tens of meters in two-dimensional simulations or a few meters in three-dimensional simulations).

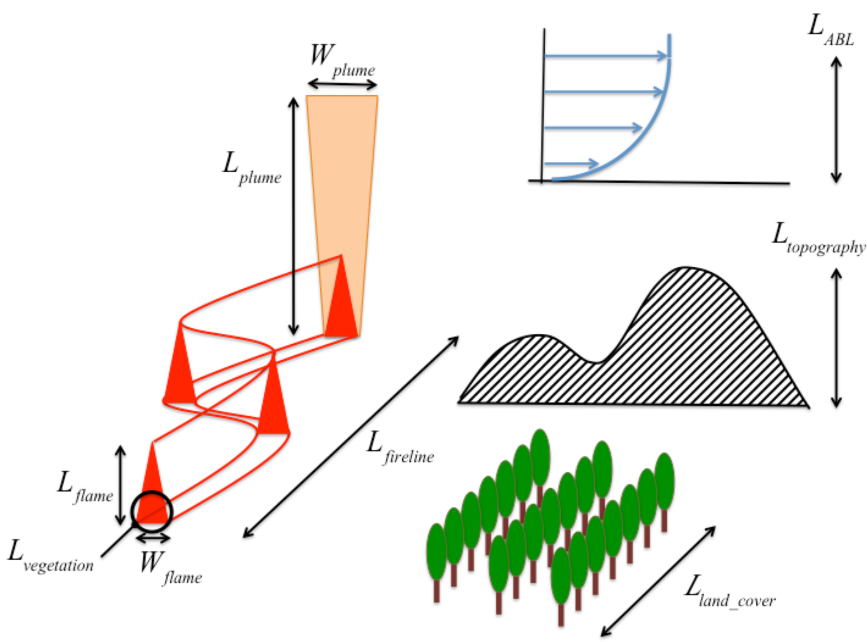


Figure 4: The different length scales that contribute to determining wildfire behavior: vegetation scales, flame scales, fireline scales, geographical scales (i.e. topographical scales and land cover scales) and meteorological scales.

Examples of wildfire solvers include FIRETEC [36] and WFDS [37] (WFDS is based on FDS [38], a well-established solver originally developed for fire plume dispersion and building fire applications). These solvers use a computational grid resolution of order 1 m and provide a coarse-grained treatment of unresolved vegetation-scale and flame-scale processes through a simplified (but physics-based) combustion model. Simulations with these solvers are typically performed in intermediate-size field-scale domains (*e.g.*, one kilometer in size).

Examples of atmospheric boundary layer (ABL) solvers that have been developed for wildfire dynamics applications include WRF-SFIRE and WRF-Fire [23, 39-41] as well as MESO-NH/ForeFire [42,43]. These solvers use a computational grid resolution of order 10-100 m and provide a macroscopic-level treatment of unresolved vegetation-scale, flame-scale, fireline-scale and topographical-scale processes through a parametrized semi-empirical rate-of-spread wildfire model. Simulations with ABL solvers are typically performed in arbitrary-size field-scale domains (from a few kilometers to several tens of kilometers and beyond). The atmospheric boundary layer solvers feature nesting capabilities that allow for multi-scale simulations in which an outer domain of coarse resolution captures the large synoptic-scale (larger than 1000 km) flow and feeds a set of nested higher-resolution inner domains that describe the mesoscale (between 1 km and 1000 km) and microscale (smaller than 1 km) flows. The rate-of-spread wildfire model operates on a separate surface model with grid resolution typically more than 10 times finer than that used on the finest inner domain of the atmospheric flow model. A strength of ABL solvers is that they are integrated with research-level or operational-level numerical weather prediction capabilities (i.e., WRF and MESO-NH) and therefore incorporate detailed descriptions of the fuel maps, topographic maps and weather conditions.

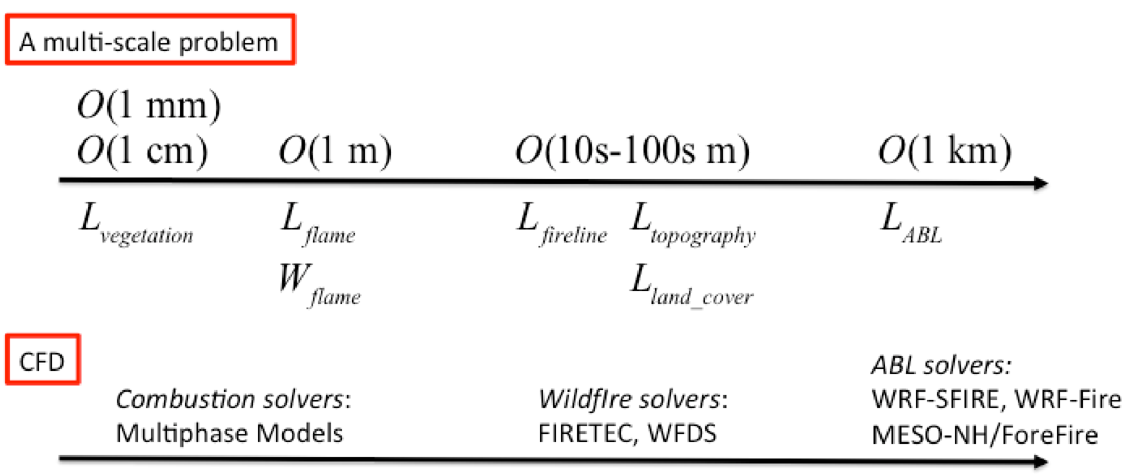


Figure 5: The different classes of CFD models used for wildfire spread simulations: combustion solvers resolve dynamics at the vegetation and flame scales; wildfire solvers resolve dynamics at the fireline and geographical scales; atmospheric boundary layers (ABL) solvers resolve dynamics at the meteorological scales.

Thus, combustion solvers are limited to the lower range in the spectrum of relevant length scales and their domain of application is restricted to fundamental studies of local flame dynamics and/or comparisons with laboratory experiments. Wildfire solvers focus on intermediate-scale fireline-flow-topography/land-cover interactions and their domain of application includes fundamental studies of fireline dynamics and/or comparisons with field-scale prescribed fires or experiments. Finally, atmospheric boundary layer solvers consider the upper range in the spectrum of relevant length scales and their domain of application includes fundamental studies of wildfire-atmosphere interactions and/or comparisons with real fire incidents. The atmospheric boundary layer solvers have also the potential to be used as a component of operational models.

2.3. *CFD-Based Wildfire Models for Operational Applications*

As pointed earlier, the exact level of fidelity and accuracy provided by CFD models in general, and atmospheric boundary layer (ABL) solvers in particular, remains an open question and there is a widespread concern that these models may not be mature enough (yet) for a possible integration into operational models. A key concern involves assumptions required to accommodate fire-atmosphere coupling with the explicitly uncoupled fire behavior model of Rothermel [12]. The Rothermel spread equation assumes airflow in the absence of the fire and therefore requires highly subjective parameters to force the model to capture effects of feedback between fire-induced airflows and flame spread. Nevertheless, the main arguments favoring an ABL modeling approach to fire disaster management tools are:

1) ABL models are already in use for weather forecasting applications and provide valuable forecasts of meteorological conditions, *e.g*., possible changes in prevailing wind directions, air temperature and humidity;
2) ABL models can incorporate high-resolution topographical and land cover information and thereby provide accurate estimates of near-fireline environmental conditions, in particular surface wind conditions and ambient levels of humidity, which are dominant factors in determining the rate of wildfire spread;
3) ABL models can incorporate high-resolution flow-plume interaction models and thereby provide accurate estimates of the fire plume dynamics and smoke composition (*i.e*., toxicity levels and atmospheric pollutants).

There is also some interest in applying the power of CFD to incorporate fire spread due to spotting, without which the dynamics of the largest fires are difficult to model. Figure 6 presents an illustration of the importance of providing better descriptions of surface wind conditions alone. As stated above, the objective of providing accurate descriptions of environmental conditions that control the local wildfire dynamics can be met by developing validated CFD models.

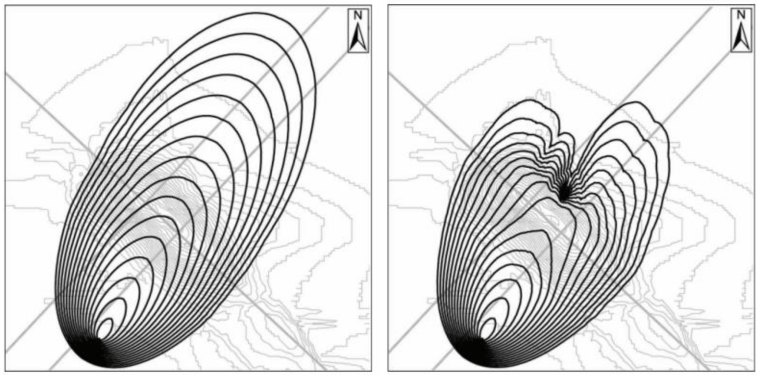


Figure 6: Simulation of wildfire spread using FARSITE with uniform wind (left picture) versus spatially-resolved wind (right picture). Reproduced from Ref. [44].

3. Wildfire Data

Whether collected from prescribed burns or uncontrolled wildfires, the types and the spatial and temporal resolution of data collected are paramount to the development and use of wildland fire spread models. With the exception of satellite remote sensing or ground-based point-source wind, temperature and humidity measurements, wildland fire data have primarily been collected via prescribed burn experiments requiring significant time and resources.

Early data collection efforts began with single goals in mind (*e.g.*, Fireflux to evaluate coupled fire/atmosphere modeling [45]), however more recent data collection efforts have tried to collect data on prescribed burns that serve multiple user groups (*e.g.*, RxCADRE [46]). Because the focus of the workshop is real-time fire modeling, our review will restrict itself to experiments focused on fire behavior and spread rather than fire emissions, even though these studies are also important for many other user groups [47,48]. Other data reviewed will include available remote sensing resources and fuel and weather feeds. A review of the need for data collection, types of data available, remote-sensing products available and several large data sets and future recommendations will also be covered.

3.1. *Purpose of Experimental Data Collection*

It is often difficult to justify the large expense and effort of a wildland fire experiment. Two primary needs have motivated most studies collecting data on wildland fires in the literature. First, sets of data have been collected to help understand wildland fire phenomena and to develop either empirically- or physically-driven models to describe the process. Early laboratory-scale experiments from Rothermel *et al*. provided a needed data set culminating in the development of semi-empirical steady rate-of-spread (ROS) models for fire spread through dead, surface wildland fuels [12]. Later field experiments in Australia produced a similar model for surface spread through grassland fuels [14]; that model was almost entirely empirically-based. Laboratory-scale or field-scale experiments must be conducted with a specific scientifically-driven hypothesis in order to become as efficient and practically useful as possible, providing a framework from which to frame potential results. With the advent of numerical modeling, more properties have begun to be collected during experiments with the intent to both increase our basic understanding of physical phenomena and validate newer, high-fidelity numerical models.

Second, data are often desired for model evaluation or validation. Originally developed as steady rate-of-spread models and validated using limited laboratory- and field-scale experimental data, ROS models are in great need of more diverse and more realistic data to demonstrate their validity for a range of wildland fire scenarios. For semi-empirical models, results from experimental tests are statistically incorporated with an underlying physics-based theoretical framework and fit to results. This was done by Rothermel for surface fire models [49] and later by Cruz *et al*. for crown fire models [18]. For CFD models, the 3D weather and fuel data are much more complex than the data provided to 1D or 2D empirical models. Simplifications, therefore, become absolutely necessary for all of the above models, but the trade-off between model performance and degree of simplification is not known.

Validation attempts to evaluate the level of agreement between a real-world system and a model. Validation may be undertaken for purposes of determining the "correctness" of model formulation, which is almost impossible for wildfires under field conditions because of the uncertainty of a large number of initial and boundary conditions. Alternatively, for validating the operational utility of a model, the contribution of model error must be quantified separately from user- and data-error sources. In wildland fires, this has also proven extremely difficult, even for the simplest fire model.

Models can, however, provide useful information within a domain of application even with considerable sources and degrees of uncertainty, as operational empirical models are now used, with essential input of the expertise and judgement of a human analyst. It is within this domain, therefore, that they can be tested with field-based data. Choosing the right variables to evaluate (rate of spread, fireline location, flame length, fire intensity, *etc*.) is important in properly verifying or validating models.

3.2. *Types of Experimental Data*

There is no simple answer to the question of what type of data is necessary for model evaluation because each model has a different objective (fire science, investigation, consulting, land management, real-time emergency response, *etc.*), with some having multiple objectives depending on their specific application. A different set of data needs to be measured for each application, with different spatial and temporal resolutions. With the limited resources available to conduct large-scale outdoor experiments, it is best that the experiments are designed with the most overlap possible without sacrificing accuracy, benefiting both physical model development and model evaluation. The interaction between modelers and experimentalists is therefore needed, something recently demonstrated in the RxCADRE experimental campaign.

Fuel characteristics are often determined before any prescribed fire in order to know the properties of the fuel that will burn. Measurements of pre- and post-fire fuels using destructive (*e.g.*, clipping and weighing) and non-destructive (*e.g.*, LIDAR) techniques allow an evaluation of the fuel consumption. Variables measured and sampling techniques from different disciplines are shown in Table 1.

Table 1: In-situ measurements available during fire experiments based on disciplines as defined for the RxCADRE experiments [46].

Discipline	Variables Measured	Sensing Technique(s)
Fuel Characteristics	Mass	Mass scale, sampling, LiDAR
	Cover	
	Depth	
	Moisture	Drying/sampling, hydrometer
Fuel Consumption	Mass consumed by fuel component	Direct measurements, LiDAR, IR
Fire Effects	Thermal radiometry	Visible and IR videography, heat flux gauges
	HD visual imagery	
	Stem temperatures	
Local Event-Scale Meteorology	Plume Properties	3-D sonic anemometers, thermocouples, thermisistor/hygristors, Doppler SoDAR, Doppler Lidar, Doppler mini SoDAR, cup and vane anemometers
	Fine-scale wind and thermodynamic fields	
Fire Behavior	Fire intensity	Heat flux gauge, thermocouples, pressure probes, videography (IR/visible)
	Rate of spread	
	Convective/radiative heat flux	
	Soil heating	
	Wind/flame velocity	
	IR imagery	
Event-scale Fire Mapping	Fire radiative power and energy	IR imagery (tower, UAV, satellite)
	Flame front development	
	Satellite imagery of fire and effects	
Emissions and Event-Scale Plume Behavior	Emissions of CO, CO_2, H_2O, $PM_{2.5}$	Gas sensors, particle sensors, Doppler SoDAR, Doppler Lidar, Doppler mini SoDAR
	Black Carbon	
	Plume Height	

Fire/atmosphere modelers are often interested in data beyond the fireline (at the scale of the atmospheric boundary layer) for model evaluation. These could be defined as local event-scale meteorology. During experiments the majority of measurements are ground based (vane or sonic anemometers); however, other measurements within the atmospheric boundary layer such as Sodar and upper-air soundings are also taken. Some of these measurements can also be taken to assess the convective plume, which relates to emission and transport of effluents from the fire. There are a host of effluents that can be measured, including gaseous species (*e.g.*, CO, CO_2), black carbon, particulate matter (*e.g.*, $PM_{2.5}$), *etc*. Fireflux I and II were experiments specifically designed to measure these features, mainly in order to evaluate coupled fire-atmospheric CFD modeling tools [41,43,45].

For fire behavior analysis, most data collected in both prescribed and accidental wildland fires have come from instruments on the ground. Many studies are interested in improving models for wildland fire spread, focusing on flame scales to larger fire line behavior. Other outcomes such as effective distances for firefighter safety zones and effects on ecological systems are also considered before conducting measurements [50]. These often consist of point measurements of convective and radiative heat fluxes, temperature, vertical and horizontal velocity, video imagery and relative humidity. Overhead measurements of infrared (IR) images to map the fire or provide fire radiative power estimates are often recorded. These overhead IR images can be processed to track the fireline for use with real-time fire modeling techniques and also assess the accuracy of remote sensing applications comparing readouts to those taken by satellites or unmanned aerial vehicles (UAVs). These are often coupled with measurements of the surrounding winds and atmosphere necessary to properly initialize CFD models. Collected point data (such as heat fluxes) are sometimes meant to inform CFD modelers, but are more often used for development of physical fire models (*e.g*., the dominance of convective or radiative heat fluxes) or firefighter safety (*e.g*., firefighter safety zones).

For coupled fire-atmosphere modeling, multiple data sets are needed for comparison with the weather model components, such as WRF. These data include upper-air observations of both the atmospheric thermodynamics and winds. These data can be obtained from in situ radiosonde systems or remote sensing instruments; however, the stochastic nature of turbulence makes using these data and properly initializing atmospheric CFD models a difficult task.

3.3. *Wildfire Sensing Products for Near Real-Time and Archival Applications*

Remote sensing, particularly airborne and satellite-based measurements, detect fire location and may provide an estimate of the fire intensity for each pixel (fire radiative power, or FRP). While polar orbiting satellites such as Terra, Aqua, and S-NPP (with MODIS and VIIRS sensors, respectively), provide autonomous, synoptic observations of fire activity, both day and night, nominally twice a day from each sensor, this temporal resolution, and the corresponding spatial resolution, may not be adequate for real-time fire modeling. NOAA's Geostationary Operational Environmental Satellite system (GOES) offers greater temporal resolution, but suffers in terms of spatial resolution. This applies to both *post hoc* model evaluation of a fire event or real-time predictions of fire spread. Therefore data fusion with various sources of remotely sensed data, as well as downscaling techniques, could improve remotely sensed data resolution to fill gaps. A summary of satellite-based remote sensing sources is provided in Table 2 while Table 3 presents popular online products for remote sensing and ground-based inputs needed for modeling.

Table 2: Satellite-based remote sensing sources for fire detection and soil moisture content.

Source	Description	Resolution	Frequency	Link
MODIS	Fire detection (IR)	1 km	6 h	http://modis.gsfc.nasa.gov
VIIRS	Fire detection (IR)	750 m	12 h	http://npp.gsfc.nasa.gov/viirs.html
GOES	Fire detection (IR)	4 km		http://www.goes.noaa.gov/
Landsat	Fire detection (IR)	30 m	16 h	http://landsat.usgs.gov
AVHRR	Fire detection (IR)	1 km	8 h	http://www.ssd.noaa.gov/PS/FIRE/Layers/FIMMA/fimma.html
S-MAP	Soil moisture content (IR)	1-3 km	2-3 days	http://smap.jpl.nasa.gov/

Spatial information, particularly regarding the fireline location and fire intensity (radiative heat flux), and a measure of the data uncertainty are all necessary for fire spread modeling. Questions arise particularly in the use of the data, *i.e*. what remotely sensed data (*e.g*., satellite-based for wildland fire applications) are "good enough" for modeling? For example, what is the upper level of temporal latency and spatial resolution required for particular applications? Is 6 nominal "looks" per day of a fire event at 750-1000 m nominal resolution too coarse? Can this be downscaled through interpolation methods such as kriging or incorporating burned area with hot spots?

Data assimilation relies on real-time information to improve predictions operationally, however extensive datasets from previous efforts can be utilized to test the applicability of this technique for real-time fire modeling. The most valuable data are firelines (or fire locations). These data can be collected from manual entries (such as NIROPS, night observations of firelines during active wildfires), satellite data, UAVs, *etc*. Other information on the fire is important to initialize the simulation. Fuel moisture could also be useful as well as real-time weather conditions.

The Direct Broadcast community provides the best source of near-real time data for operational modeling and situational awareness. The network of receiving stations within the U.S. and globally continues to expand and as new satellites are launched and products developed these stations have evolved to keep pace. Many of these resources are available to the public with some delay online, see Table 3.

While an assortment of sensing products is available, these products do not yet provide firelines at the kind of spatial and temporal resolution that seem to be required for real-time wildfire spread modeling. Data with good spatial resolution of fuel and topography are available in localized areas, typically performed by LIDAR; however, they are not yet available in a nationwide database. Due to activities changing this fuel over time, the database would have to be updated frequently. Note that the data assimilation technique may make up for inaccuracies in input data.

Table 3: Popular fuel, weather and fire detection products available online.

Source	**Description**	**Link**
Fire perimeters and incident data		
USFS Active Fire Mapping	Large federal (US) fire incidents including remote fire detection maps	*activefiremaps.fs.fed.us*
GeoMAC	Geospatial Multi-Agency Coordination: reports of fire progression from GIS, incorporates NIROPS IR flights at night (lag in posting)	*http://www.geomac.gov/*
Incident Information System	Incident information system for large wildland fires from the NWCG	*http://inciweb.nwcg.gov/*
NICC	Different incident command centers - links	*http://www.nifc.gov/nicc*

NWCG	National Wildfire Coordinating Group coordinates activities between different US fire agencies	*http://www.nwcg.gov/*
NIFC	National interagency fire center coordinates US Fire activities and updates daily statistics	*http://www.nifc.gov*
USFS RSAC	USFS remote sensing applications center	*http://www.fs.fed.us/eng/rsac/*
NIROPS	USFS National Infrared Operations, flown over major fires once per evening as requested	*http://nirops.fs.fed.us/*
Avenza	Smartphone application used by wildfire-fighting crews to record updates to fireline	*http://www.avenza.com/pdf-maps*
Fuel Data		
LandFIRE	Vegetation, fuel, topography, etc.	*http://www.landfire.gov*
Live Fuel Moisture	Based on NVDI Data	*http://wfas.net*
Emissions Data		
NOAA Hazard Mapping System	Aerosol thickness, etc.	*http://www.ospo.noaa.gov/Products/land/hms.html*
IDEA - NOA	Aerosol optical thickness coupled with fire detections	*http://www.star.nesdis.noaa.gov/smcd/spb/aq/*
WRAP FETS	Fire emissions tracking on the US west coast	*http://wrapfets.org/*
Weather Data		
HRRR	High resolution rapid refresh from NOAA of their atmospheric/wind model	*http://ruc.noaa.gov/hrrr/*
MESO-WeST	Real-time weather station data (RAWS and others)	*http://mesowest.utah.edu/*
RAWS	Remote Automated Weather Station (RAWS) data	*http://raws.wrh.noaa.gov/roman/*
NOAA Land Station Data	NOAA National Climate Data Center land based data	*http://www.ncdc.noaa.gov/oa/land.html*
Atmospheric Sounding	Atmospheric Soundings of Upper Air	*http://weather.uwyo.edu/upperair/sounding.html*
NOMADS	The NOAA National Operational Model Archive and Distribution System	*http://nomads.ncdc.noaa.gov/*
NOAA Env. Prot. Prod.	NOAA National Center for Environmental Prediction model products	*ftp://ftpprd.ncep.noaa.gov/pub/data/nccf/com/*
MADIS	MADIS is a meteorological observational database and data delivery system that provides observations that cover the globe.	*https://madis.ncep.noaa.gov/*

Firelines with spatial resolution of approximately 10 m and temporal resolution of approximately 10 minutes are desired to achieve a reliable forecasting tool with accurate enough predictions for local-scale fires [6]. These requirements can theoretically be met with current satellite technology; however, these requirements may also be cost-prohibitive at the moment. Some of these problems could be alleviated with the deployment of UAVs over a fire. However, the use of UAVs has separate jurisdictional issues which to date have limited their use for prescribed fires.

NIROPS have shown that it is possible to capture firelines at good spatial resolution using an airborne infrared sensor. However, the low frequency of the fireline mapping (maps are made only once per night) is a limitation. Part of the problem is that the process is not automated. The use of drones, for instance the use of an MQ-1 Predator Remotely Piloted Aircraft (RPA) on the Rim fire in California, was successful in observing particular locations, but no permanent program has been established, most likely because of the high cost and UAV safety concerns[1].

Several changes in the near future may change this picture. Smaller and cheaper sensors, new satellites funded by private industry and advancements in sparsely networked data may provide new means for data to be captured from multiple sources and automatically compiled together. This could come from public and commercial satellites, equipped firefighting aircraft that already span a fireline and UAVs which are advancing in popularity and decreasing in cost. Obviously, without procedures for UAVs to deploy during a fire and relay that information in a timely manner to modelers, data-driven operational fire spread modeling may not be feasible. However, advancements in technology and policy are coming so quickly that we foresee that real-time fireline data will be available within a decade.

3.4. *State of the Science - Experimental/Prescribed Fire Data*

A number of data sets exist from experimental fires for model validation (see Table 4). Some of these experiments were designed specifically for model evaluation applications (*e.g.*, RxCADRE, FireFlux II), while others were conducted for basic fire behavior monitoring. The advantage of controlled experimental fires as compared to active wildfires is the ability to control the environmental conditions for burn operations, optimized sensor placement, number of sensor platforms and types, and timing with satellite overpasses. In addition, fuels can be well characterized and thereby respond to the needs of fire models.

Controlled fire experiments are, however, plagued with several problems. One problem is that the data are typically not publicly available: only Fireflux I and RxCADRE have datasets that can be found online and in both cases, the data sets are not yet complete. Another problem is that experiments are generally conducted under low wind and in relatively flat terrain, *i.e.*, under conditions that are not representative of actual uncontrolled wildfires. A third problem is the control of initial and boundary conditions. High-fidelity CFD results are very sensitive to input data such as atmospheric winds, which typically are only measured at the surface at one or a few points. During modeling studies, it is often found that choosing different inputs for wind will drastically alter the simulated fire dynamics. This problem can be overcome in part in real-time modeling applications by using data assimilation techniques. The question of how to characterize initial and boundary conditions in field-scale fire experiments remains an open one.

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[1] *http://www.fs.fed.us/science-technology/fire/unmanned-aircraft-systems*

FireFlux II

The FireFlux II campaign was conducted as a follow up experiment to the first FireFlux experiment conducted in 2006 on a coastal tall-grass prairie in southeast Texas, USA [53]. The FireFlux campaign dataset has become an international standard for evaluating coupled fire-atmosphere model systems[2]. While FireFlux is one of the most comprehensive field campaigns to date, the dataset does have some major limitations: especially the lack of sufficient measurements of fire spread and fire behavior properties. FireFlux II (FF2), was conducted on 30 January 2013. The experiment was designed to allow an intense head fire to burn directly through an extensive instrumentation array including one 42-m and three 10-m micro-meteorological towers. Each tower was equipped with a variety of sensors, including 3D sonic anemometers, pressure sensors, heat flux radiometers, and an array of fine-wire thermocouples to measure plume temperatures. The experiment was carried out under red flag warning conditions with strong winds of 8 m/s and relative humidity of approximately 24%. Instrumentation also included a scanning Doppler wind LIDAR, microwave temperature profilers, radiosonde balloons for upper-air soundings, a full suite of air quality instrumentation located downwind, and multiple ground- and tower-mounted infrared and visible video cameras. In addition, the fire spread was monitored from the air using helicopter mounted infrared and visible video cameras. Fireline progression was also recorded by a grid of thermocouples and small data loggers buried underground and in the path of the fire. Measured fire spread rates were approximately 1.5-2.5 m/s for the head fire while the flanks spread at 0.7 m/s.

RxCADRE

The number of integrated, quality-assured datasets is small in wildland fire research, thereby limiting the general ability to evaluate models and tackle fundamental questions. To help fill this gap, the Prescribed Fire Combustion and Atmospheric Dynamics Research Experiment (RxCADRE) was proposed as an effort to collect, reduce, and complete a preliminary analysis of data. Data were collected in 2008, 2011 and 2012, on small replicate and large operational prescribed fire burn blocks, corresponding to longleaf pine ecosystems located at Eglin Air Force base in Florida and at the Joseph Jones Ecological Research Center in Georgia [46]. The goal was to develop synergies between measurements of fuel, atmospheric conditions, fire behavior, radiative energy, smoke generation, and fire effects for fire model development and validation.

The RxCADRE project organized its data collection around a stepwise hierarchical structure with 6 major discipline areas: fuels, meteorology, fire behavior, radiative power and energy, emissions, and fire effects. These were presented earlier in Table 1. The burn block selection targeted grass, grass/shrub, and managed southern pine forest fuelbeds at both fine- and operational-scales. Each discipline employed data collection techniques ranging from in-situ instrumentation to mapping fire progression with manned and unmanned aircraft. Once collected, data were reviewed, reduced, analyzed and linked to metadata. Over 125 datasets and accompanying metadata are being uploaded and stored in the US Forest Service Research Data

Archive[2] and will be available in the near future to all scientists and managers for purposes of evaluating and improving fire models, and advancing knowledge in the area of wildland fire science. Ten papers have been submitted for review and publication as a special issue of the *International Journal of Wildland Fire*.

Table 4: Selected prescribed fire datasets. Note that for almost all experiments, fuel information (e.g., loading, relative humidity, curing, etc.) is available but is not indicated in the table, focusing instead on the instrumentation used. See the citations for more information.

Experiment	**Fuel**	**Conditions**	**Plot Size**	**Measurements**	**Location**	**Citations**
FireFlux I	Grass	Flat, Low Wind	0.63 km^2	Fireline estimate, 3D wind, flame/fuel temperature plume temperatures	La Marque, TX, USA	[41,43,45, 51-52][3]
FireFlux II	Grass	Flat, Mod. Wind	350×850 m^2	Fireline (IR), 3D Wind, flame/fuel temperature, plume thermodynamics, etc.	La Marque, TX, USA	[53][4]
Wooster et al.	Grass	Flat, Low Wind	1.5×1.2 m^2	Fireline (IR), FRP, Wind	Lifted plot	[54]
RxCADRE	Grass/ Shrub	Flat, Mod. Wind	200×200m^2 (multiple plots)	All disciplines described in Table 1.	Eglin AFB, FL, USA	[46][5]
Henry W. Coe State Park	Grass/ Shrub	Slope, Low Wind	4.5 km^2	Atmospheric data such as 3D wind, flame/fuel temperature plume temperatures	Northern CA, USA	[55]
Camp Swift	Grass	Flat, Mod. Wind	100×100m^2 (3 plots)	Heat flux, ROS, flame geometry, anemometer data, sodar, air temp, etc,	Bastrop County, TX, USA	[56]
Cheney et al.	Grass	Flat, Low Wind	25 km^2 (121 plots)	ROS, mean wind speed, fuel loading, fireline size	Northern Territory, Australia	[14]
ICFME	Jack Pine/Black Spruce	Flat, Low Wind	(18 plots)	ROS,	Northwest Territories, Canada	[57]
NJ Pine Barrens	Pitch Pine/Oaks/Shrub	Flat, Low Wind	16 acres	Fuel loading, firebrands, fireline intensity (IR), heat flux	Pinelands National Reserve (NJ, USA)	[58]

[2] http://www.fs.usda.gov/rds/archive/Catalog?freesearch=RxCadre&searchfield=#
[3] http://www.fireweather.org/fireflux-i
[4] http://www.fireweather.org/fireflux-ii
[5] http://www.fs.usda.gov/rds/archive/Catalog?freesearch=RxCadre&searchfield=#

International Crown Fire Modeling Experiment (ICFME)

The International Crown Fire Modeling Experiment (ICFME) was a cooperative international experiment that brought together fire modeling experts from Canada, the United States, and Russia, to address the prediction of high-intensity fire behavior [57]. The goal of ICFME was to conduct a replicated series of highly instrumented crown fires to quantify parameters essential to modeling the initiation and spread of crowning fires.

The experimental site was located near Fort Providence, Northwest Territories, in a dense, approximately 80-year old, jack pine stand. Aerial, surface, and forest floor fuels were sampled in ten burn plots. Firelines approximately 50 m wide were established around each plot, which involved cutting and removing standing trees, and bulldozing to mineral soil to facilitate access and control. Some fuel manipulation (pruning trees and/or removing surface fuel) was carried out on portions of some plots, but most of the area remained undisturbed. The ICFME project was carried out between 1995 and 2001.

A description of the experimental design, goals, objectives and links to the project publications and data collected are available online[6].

In-situ fire behavior measurements

The Fire Fundamentals Team at the Missoula Fire Science Laboratory has been collecting in-situ fire behavior and fire imagery data for several years. The team is currently compiling these datasets into a detailed database and will be posting these data at an accessible site. Data will include site location, date, fuel type, slope as well as 10 Hz data for total, radiant and convective heat flux, ambient air temperature and horizontal and vertical mass flow rates. Additionally, fire video imagery will be posted showing in-situ fire behavior footage.

3.5. *Recommendations on Infrastructure and Coordination*

Based on the user group meeting several key items were identified to improve infrastructure and coordination. Most importantly, there appears to be little coordination and standardization in the community on collection, storage and archival procedures for experiments. For instance, there is no common portal to post and share data. RxCADRE has just recently begun to post data with applicable metadata to the USFS archival system, however this is exclusive to data from federal experiments.

To date there is no infrastructure to guide the storage and dissemination of information from experimental campaigns. A framework should be developed to coordinate the efforts of the research community applicable to data and models. Coordination between modelers and experimentalists has begun; however, much remains to be done.

[6] *https://www.frames.gov/partner-sites/applied-fire-behavior/international-crown-fire-modeling-experiment-icfme/*

For data assimilation, a very important component, sometimes missing, is description and quantification of errors. Evaluation of errors and reporting accuracy with data, such as through metadata is critical for data assimilation and proper experimental interpretation. This is now being added to metadata from the RxCADRE experiments and the practice should be continued on future experiments. The development of some common portal to post and share data, along with guidelines for reporting of errors is needed.

Collection of the fire front progression as a function of time is also critical, if fireline data are to be assimilated. While some experiments have collected fireline data (*e.g.*, Fireflux II, RxCADRE), these data are very limited in scope. Data from real fires may also be useful for this purpose. However, satellite detections often occur at low resolution (> 1km) and low frequency (1-4 times/day). More finely-resolved measurements are available but are taken at most once per day (NIROPS). Foreseeable developments of UAVs and satellite technologies will allow significant progress in this area, but the needs of both the research and operational communities should be addressed as products and missions are developed. Also, some existing data are not made public and the development of an open-source repository is needed.

Finally, most experimental campaigns to date (prescribed burns) have not been conducted at conditions akin to extreme fires (high winds, steep slopes, low humidity, unstable atmospheric conditions). While current data are still useful for development of fire models, especially for applications to prescribed fires which occur under these milder conditions, there is an unmet need to document wildland fire dynamics under extreme conditions.

4. Data Assimilation

A data assimilation framework typically features the following main components (Fig. 7): a forward model that simulates the state of a physical system (with some modeling uncertainty) given some choices for a set of parameters or for some initial/boundary conditions, called control variables; a set of observations that describes the true state of the physical system (with some measurement/processing uncertainty); and an inverse model that calculates the distance between the simulated and observed states and modifies (*i.e*., updates) the control variables according to some algorithm that works to minimize that distance. In geosciences, the output of the forward model prior to a data assimilation update is called a forecast; the output of the forward model posterior to a data assimilation update is called an analysis. When applied to wildfire problems, and while there are some variations in the literature (see Table 5), the forward model is typically a fire spread simulator that uses an operational-level rate of spread (ROS) description; observations are generally fireline positions; the inverse model is some algorithm taken from the geoscience field accounting for both modeling and observation errors; and control variables are generally the parameters of the ROS model.

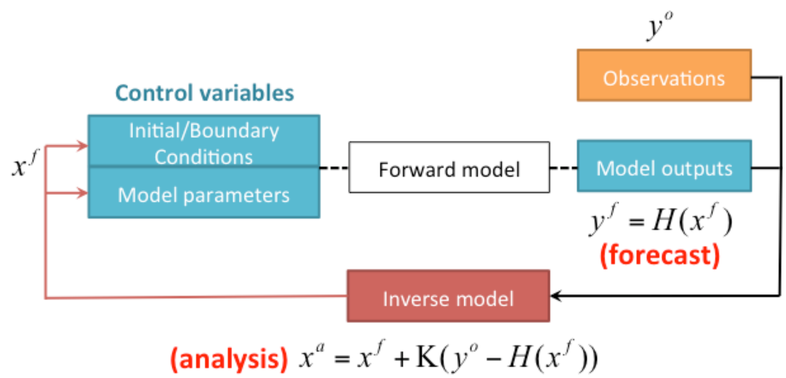

Figure 7: Data assimilation flow chart for a typical data-driven model.

4.1. *Data Sources and Uncertainty*

Wildfire rate of spread models require suitably accurate descriptions of the vegetation properties (*i.e.*, the fuel), the terrain topography and weather conditions. These descriptions have to be spatially-resolved; the description of the fuel has to be updated for seasonal changes; the description of weather conditions has to be time-resolved.

- Fuel maps in the US are available from Landfire. The Forest group at the Joint Research Centre (Ispra, Italy) translates Corine Land Cover to the US fuel categories[7]. Moisture is an important fuel property in wildfire dynamics and its description is quite complex: while live fuel moisture can be considered constant on the fire behavior scale, dead fuel moisture changes on an hourly scale and will respond to changes in atmospheric humidity.
- Terrain topography data are available in the form of digital elevation maps (DEM)[8]. These maps can be post-processed to give the aspect and slope angles that define the orientation of the ground surface and are inputs to fire spread models.
- Wind conditions are available from NOAAs 3-km High-Resolution Rapid Refresh (HRRR) model. The atmospheric data provided by the weather forecast center will be processed in different ways depending on the methodology used for data assimilation.

Note that while the available data already meet many of the needs of wildfire rate of spread models, the data are often provided without any error estimate. There is a general need for validation studies of remote sensing equipment and methodologies (for instance by comparisons with field measurements).

[7] http://forest.jrc.ec.europa.eu
[8] http://opentopography.org, http://landcover.ucsd.edu, https://asterweb.jpl.nasa.gov

4.2. *Current Data-Driven Systems for Wildfire Spread Forecasting*

Data-driven models are widely used for numerical weather prediction and numerical environmental prediction (*e.g.*, soil moisture analysis) applications. Wildfire applications are a recent target for data assimilation (see Table 5 summarizing the main contributions over the last decade). Studies using data-driven wildfire models are currently limited to theoretical tests (*i.e.*, Observation System Simulation Experiments - OSSE) and post-analysis of controlled burns and/or wildfire events. There is a need to extend the current scope of data assimilation developments to the monitoring of wildfire events at the operational level. It is worth noting that this need is being met in Europe: starting in Summer 2015, the European Forest Fire Information System (EFFIS) (using the FARSITE simulator) will be data driven and will deliver daily forecasts of wildfire spread.

An important limitation in current data-driven models is the lack of quantifiable uncertainty in both model and data. Data themselves are not useful if these data do not come with a quantification of the uncertainty (at least error bounds). It is important to account for both measurement errors and representativeness errors. Furthermore, models that are unnecessarily complex and depend on many unknown and to-be-estimated parameters may deteriorate the accuracy of the estimates of control variables. In data assimilation it is important to address the trade-off between complexity of the model and accuracy of the control variable updates.

Finally, it is important to define data format standards (similar to Geographic Projection, WGS84, or Web Map Services with Time layer, WMS-T) and interfaces between different standards to be able to come out with an operational data model.

4.3. *Methodology*

Data assimilation methods are methods in which the state of the system (*e.g.*, the fireline location) is modified through changes in the control variables (*e.g.*, changes in the parameters of the fire rate-of-spread model or changes in the initial fire location in a forecast calculation). One differentiates between methods that work with one simulation (*e.g.*, variational methods, optimization/control methods, methods based on the concept of the maximum aposteriori probability – MAP) and methods that work with a statistical ensemble of simulations (*e.g.*, ensemble Kalman filters – EnKF, particle filters, genetic algorithms).

While data assimilation methods have been available for several decades, their use tends to be problem dependent because of the nonlinearities associated with the system response to changes in the control variables and additional difficulties associated with non-Gaussian distributions of uncertainties (uncertainties in both the control variables and the measurements). The dimension of the control variable vector (*i.e.*, the number of control variables) is also an issue. Large numbers of control variables are possible but these large numbers require sufficient information in the data (this is related to the notion of identifiability and/or observability of the model).

In data assimilation schemes using computational-intensive models and/or large numbers of control variables and/or a large statistical ensemble, the use of high-performance parallel computing platforms becomes necessary. Another technical feature of data assimilation for operational applications is the need to establish robust automated schemes for input data retrieval and model set-up. Access to fuel maps, elevation maps and wind datasets has to be negotiated with the data provider in order to both facilitate and strengthen access. Furthermore, forward and inverse models used in the data assimilation loop have to meet minimum levels of reliability. An example of limited reliability with the forward model is found when using the Weather Research Forecast model – WRF – in the presence of sharp terrain gradients and occasionally observing the development of a numerical instability leading to simulation failure. An example of limited reliability with the inverse model is found when using EnKF with few observations and failing to obtain convergence of the data assimilation cycles. These issues are research problems in their own right.

Another robustness issue for data assimilation algorithms is that related to the quality of the observations obtained through sensors. Data assimilation algorithms need to provide reasonable estimates of the control variables even when incorrect information on sensor noise is used (this property is guaranteed for linear models but not non-linear models).

Table 5: A review of wildfire data assimilation methods found in the literature.

Ref.	Model/Control variables	Observation	Assimilation method
[59,60]	cell automata fire/no fire field	fire/no fire field	particle filter
[61,62]	cell automata ROS parameters	fire/no fire field	genetic algorithm
[63,64]	cell automata fire/no fire field	fire/no fire field	particle filter
[1,65]	reaction-diffusion eqn. temperature field	temperature field	EnKF
[1]	reaction-diffusion eqn. eqns. For coefficients	combustion front	best fit
[2,66]	coupled WRF-SFIRE & level-set horizontal morphing	fire/no fire field	EnKF
[3,67]	coupled WRF-SFIRE & level-set	fireline	fire re-play atmosphere spin-up
[68,69]	fuel moisture field	RAWS fuel moisture station data	trend surface, extended KF
[70]	coupled WRF-SFIRE fire arrival time	MODIS/VIIRS active fires detection	least squares atmosphere spin-up
[4,6,71]	level-set ROS parameters	fireline	EnKF, particle filter

[6,72]	level set fire front position	fireline	EnKF

5. Conclusion

The general objective of this workshop, also one of the main objectives of the WIFIRE project, is to develop the foundations for an operational wildfire spread forecasting capability. The workshop participants have identified numerous technical barriers on the road to developing such a capability; they have also shared a general optimistic sense that given the new (current or upcoming) remote sensing, computing, networking, storage, visualization technologies (*i.e.*, the new cyberinfrastructure), the goal of providing an operational wildfire spread forecasting capability may be achieved within approximately a decade.

Current challenges include:

- The limitations of current rate-of-spread models used to simulate wildland fire propagation. These models are based on limited understanding of the physics and have been calibrated against experimental data representing relatively mild (i.e., steady-state) conditions: they need to be based on a deeper understanding of the physics and include extreme fire behavior conditions (*i.e.*, high wind, low humidity, unstable atmospheric conditions as well as steep slopes).
- The limitations of current input data to wildland fire rate-of-spread models. Well-resolved information on vegetation, topography and weather is required and this information needs to be regularly updated and provided with spatial resolution on the order of 10 meters.
- The limitations of current remote sensing capabilities. The envisioned wildfire spread forecasting capability requires real-time observations of the fire front location (based on airborne or spaceborne mid-infrared observations) and these observations need to be made at fireline scales and/or geographical scales (*i.e.*, topographical scales and land cover scales), *i.e.*, with approximately 10 meter spatial resolution and 10 minutes temporal resolution.
- The limited scope of current experimental/field databases. The envisioned wildfire spread forecasting capability will have to go through an extensive trial period to demonstrate value and robustness. This will require a systematic effort to document prescribed fires and/or wildfire events, preferably including both mild and extreme conditions. The wildland fire research community needs to define standards on collection, storage and archival procedures of experimental/field data. In addition, data uncertainties need to be systematically quantified.

To meet these challenges, the wildland fire research community can build on preliminary work that has already demonstrated the potential of data-driven tools for fire spread predictions (see Table 5). It can also count on new remote sensing technologies using unmanned aerial vehicles (UAVs) or commercial satellites, as well as on existing methods developed in geosciences (*e.g.*, in the area of numerical weather prediction). With these assets, the question is not "if" wildfire spread forecasting tools will become available; the question is simply "when".

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Appendix A: WIFIRE workshop program

Monday, January 12 *(overview, breakout session, review of operational models)*

- 8:30-9:00 am – Welcome remarks and presentation of WIFIRE
  Ilkay Altintas
- 9:00-10:00 am – WIFIRE workflow structures
  Ilkay Altintas and Dan Crawl
- 10:00-10:30 am – Coffee Break
- 10:30-12:00 – Introduction session
  (5-minutes/5-slides presentation by each workshop participant)
  Ilkay Altintas; Jessica Block; Craig Clements; Anna Cortés; Raymond de Callafon; Evan Ellicott; Jean-Baptiste Filippi; Mark Finney; Michael Gollner; Kayo Ide; Marie Ann Jenkins; Dan Jimenez; Christopher Lautenberger; Jan Mandel; Sophie Ricci; Mélanie Rochoux; Albert Simeoni; Arnaud Trouvé
- 12:00-1:30 – Catered Lunch
- 1:30-3:30 – Breakout session
  - ***Operational rate-of-spread models for wildfire spread***
    Mark Finney (panel Lead); Ilkay Altintas; Jessica Block; Christopher Lautenberger; Albert Simeoni
  - ***CFD models for wildfire spread***
    Marie Ann Jenkins (panel Lead); Jean-Baptiste Filippi; Adam Kochanski; Arnaud Trouvé
  - ***Wildfire data***
    Craig Clements (panel Lead); Evan Ellicott; Michael Gollner; Dan Jimenez
  - ***Data Assimilation***
    Jan Mandel (panel Lead); Anna Cortés; Raymond de Callafon; Kayo Ide; Mélanie Rochoux; Sophie Ricci
- 3:30-4:00 – Coffee Break
- 4:00-5:00 – ***Operational rate-of-spread models for wildfire spread***
  Chair: Mark Finney
  (10-minutes review by Mark Finney (Lead) followed by open discussion)
- 6:00-8:00 – Dinner off site

Tuesday, January 13 *(review of CFD models, wildfire data, and data assimilation, report writing)*

- 8:30-9:30 – ***CFD models for wildfire Spread***
  Chair: Marie Ann Jenkins
  (10-minutes review by Marie Ann Jenkins (Lead) followed by open discussion)
- 9:30-10:00 – ***Wildfire Data***
  Chair: Craig Clements
  (10-minutes review by Craig Clements (Lead) followed by open discussion)
- 10:00-10:30 am – Coffee Break
- 10:30-11:00 – ***Wildfire Data*** (cont.)
  Chair: Craig Clements
  (open discussion)
- 11:00-12:00 – ***Data Assimilation***
  Chair: Jan Mandel
  (10-minutes review by Jan Mandel (Lead) followed by open discussion)
- 12:00-1:30 – Catered Lunch
- 1:30-2:30 – Data Driven Wildfire Spread Models
  Chairs: Michael Gollner, Arnaud Trouvé
  (open discussion)
- 2:30-3:30 – Report writing
  (all participants)
- 3:30-4:00 – Coffee break
- 4:00-5:00 – Continuation of report writing and closing remarks
  (all participants)

Appendix B: List of participants

WIFIRE participants:

Ilkay Altintas (UCSD)

Jessica Block (UCSD)

Daniel Crawl (UCSD)

Charles Cowart (UCSD)

Raymond de Callafon (UCSD)

Michael Gollner (UMD)

John Graham (UCSD)

Amarnath Gupta (UCSD)

Jeff Sale (UCSD)

Wei Tang (UMD)

Arnaud Trouvé (UMD)

Cong Zhang (UMD)

Invited Participants:

Derek Chong (University of Melbourne, Australia)

Craig Clements (San Jose State University)

Ana Cortes, (Universitat Autònoma de Barcelona, Spain)

Evan Ellicott (University of Maryland)

Jean-Baptiste Filippi (University of Corte, France)

Mark Finney (US Forest Service)

Kayo Ide (University of Maryland)

Marie Ann Jenkins (York University, Canada)

Dan Jimenez (US Forest Service)

Christopher Lautenberger (Reax Engineering Inc.)

Jan Mandel (University of Colorado)

Mélanie Rochoux (CERFACS, France)

Albert Simeoni (University of Edinburgh, UK)