FINAL REPORT

Title: Fire modeling and social science analysis of fire managers' use of fire weather data across the US

JFSP PROJECT ID: 15-1-06-8

August 2021

PI: Eric L. Toman (toman.10@osu.edu)
The Ohio State University, School of Environment and Natural Resources

Co-PI: Robyn S. Wilson
The Ohio State University, School of Environment and Natural Resources

Co-PI: W. Matthew Jolly
USDA Forest Service, Rocky Mountain Research Station, Fire Sciences Lab

Co-PI: Christine S. Olsen (original lead PI)
Formerly of: Oregon State University, Dept. of Forest Ecosystems & Society

Table of Contents

List of Tables

List of Abbreviations

FMO: Fire Management Officers
IMT: Incident Management Team
NFDRS: National Fire Danger Rating System
NDFD: National Digital Forecast Database
WFDSS: Wildland Fire Decision Support System
USFS: United States Department of Agriculture Forest Service

Keywords

Fire management; decision making; weather; planning

Acknowledgments

We would like to thank the many interviewees and survey respondents who contributed their time and thoughts to this project. We would also like to thank David Calkin, Michael Hand, and Matthew Thompson for their review of drafts of our survey instruments.

Abstract

Fire weather tools, such as the National Fire Danger Rating System (NFDRS) and the Wildland Fire Decision Support System (WFDSS), have been developed to support wildland fire management decisions. However, little is known about how these tools are used in practice, the sensitivity of fire management decisions to fire weather variables, or the sensitivity of fire-weather tools to input errors. This project was designed to address these gaps in current knowledge.

Objectives: This project sought to achieve four main objectives:

1) Consider how fire-weather models are used to support strategic and tactical decisions.
2) Consider the sensitivity of fire-weather tools to various sources of input error.
3) Assess the sensitivity of fire management decisions to fire-weather variables.
4) Consider implications of these results to improve support for fire management decisions.

Methods: Project methods included:

1) Semi-structured interview with 27 full and part-time Incident Management Team (IMT) members, district rangers, fire management officers, regional fire management coordinators, fire management and fuels specialists, and others in the western and southern United States.
2) Leveraging concurrent work to explore the sensitivity analysis fire behavior modelling tools to explore how fire weather inputs affect model outputs. This phase identified critical fire weather inputs that heavily impact model predictions from fire modeling systems that are used in Decision Support Systems throughout the United States and this guided the development of fire management scenarios for subsequent phases of the project. While our original objectives included plans to complete a sensitivity analysis, the project was modified due to 1) a loss of the portion of project funds intended to support this analysis due to fire borrowing (funds were not returned to the project), and 2) another research team was commissioned to complete a similar analysis concurrently with our project during the same timeframe.
3) Web-based survey with federal fire managers (e.g., Fire Management Officers or FMOs) working for US Department of Agriculture Forest Service (USFS) including an embedded choice experiment designed to evaluate the influence of fire-weather and other key variables in a decision regarding whether to engage in direct or indirect attack.

Key Results: Results from the interviews indicated that, in practice, models are being used differently than intended (e.g., to inform operational decisions), confidence in model outputs differs between managers and technical specialists and is influenced by both social and technical characteristics. Participants have lower confidence in precipitation and wind forecasts than humidity or general weather forecasts. In general, participants appeared to express a preference for indirect attack. Decisions to switch to direct attack was strongly influenced by the timing of the fire even (e.g., early in the fire season). Participants were more likely to decide to switch to indirect attack when the combination of variables suggested the potential for extreme fire behavior.

Conclusions: Overall, these results emphasize the importance of designing decision support tools with the decision strategies used by managers in mind. Results also suggest the importance of both social and technical components in developing manager confidence in models. This emphasizes the importance of communication and relationship-building by technical specialists on IMTs. Moreover, our results suggest that wind and precipitation forecasts merit particular attention in further efforts to improve model accuracy and build confidence in existing models.

Objectives

This project sought to achieve four main objectives. Each objective is listed below with related questions explored under each.

1) Consider how fire-weather models are used to support strategic and tactical decisions.
   a. What are the primary tools and data sources used to support operational fire management decisions at different spatial and temporal scales and how confident are decision makers in these tools?
   b. What would improve the utility of fire danger and behavior information (e.g., more detail, higher levels of confidence in predictions)?
   c. Are current strategic and tactical decisions aligned with fire management objectives?
   d. Can improved model information result in decisions that are more aligned with objectives?

2) Consider the sensitivity of fire-weather tools to various sources of input error.
   a. What sources of observed and forecast weather data are used to support operational fire danger and fire behavior assessment tools?
   b. For each of these tools, what fire weather variables most heavily impact calculated values?
   c. What are the natural ranges of errors for these key variables?

3) Assess the sensitivity of fire management decisions to fire-weather variables.
   a. To what extent would fire model outputs have to change to lead to different decisions?
   b. What tipping points exist in fire danger and behavior information that lead to new fire management decisions?
   c. What information causes a tipping point?

4) Consider implications of these results to improve support for fire management decisions.
   a. How can tools be improved to be more useful for fire managers>
   b. What fire weather data is key to providing the information desired by managers?
   c. Where could future research and development efforts be focused to improve fire danger and behavior modeling?

Background

Over the last decade, 7.5 million acres have been burned annually in the United States (NIFC 2014), endangering our natural resources, infrastructure, homes, and lives. Wildland fire managers are frequently required to make decisions that attempt to maximize firefighting readiness and effectiveness while minimizing risk and ensuring the safety of firefighting personnel and the public. These decisions are made both well before a fire starts as well as during fire events when deciding on what resources to adopt and operational tactics to employ. Despite the magnitude of these decisions, little is known about how these decisions are made, what factors are most influential to the decisions, and what role fire weather-based prediction tools play in supporting the decision-making process.

Many modeling and forecast programs have been developed over the last several decades to support fire managers as they make these complex decisions. In the early 1970's, the US National Fire Danger Rating System (NFDRS) was developed to aid wildland fire managers in preparing for and responding to wildland fires (Deeming 1977). The system is built upon a network of weather stations that record and report hourly weather data nationwide. NFDRS has been used operationally for decades and it is the foundation for many daily fire management decisions. In the late-2000's, the Wildland Fire Decision Support System (WFDSS) was created to provide managers with resources to manage extended attack fires. Fire behavior prediction tools were integrated into this system to provide fire spread predictions from one day to up to two weeks. Many of the fire modeling tools in WFDSS build upon the fuel moisture and fire danger indices from NFDRS. WFDSS further extends its weather inputs by leveraging data from the National Weather Service National Digital Forecast Database to provide seven day forecast weather scenarios. Both of these systems have become an integral component of local, state and federal wildland fire management decision-making (Calkin et al. 2011).

However, despite a long tradition of use and application by fire managers, neither of these systems has undergone extensive sensitivity testing. As such, little is known about what weather parameters are most influential to predicted outputs. This information is critical to both the decision-makers and the data providers. A clear and comprehensive sensitivity analysis of both the fire danger and fire behavior prediction tools could assist partners, such as the National Weather Service, to focus their efforts to improve critical fire weather forecast variables. Additionally, these sensitivity analyses would help fire managers to better understand the abilities and limits of the current system.

Moreover, despite substantial investments in the development of tools such as NFDRS and WFDSS, there has been limited assessment of how these tools are used. Federal fire management policies clearly indicate that these tools are required to be used to inform decision-making (NWCG 2014) but it is not clear how influential the fire model outputs are in the decision-making process. Ultimately, fire management decisions are characterized by substantial uncertainty with multiple interacting variables (Steelman and McCaffrey 2011, Thompson 2014, Thompson and Calkin 2011). Little is known about how output from fire models is weighed against other considerations when making decisions. This project sought to address these gaps and improve our understanding of how managers use the currently available tools and their outputs, how they perceive the quality of the provided information, and how the tools could be modified to increase their perceived utility and adoption by fire managers.

Materials and Methods

This project was implemented in four phases with each phase building upon the previous steps to systematically address our research objectives.

Phase one
In the first phase of the project we conducted semi-structured interviews with fire managers and technical specialists from several federal agencies across the western and southern US. We purposefully selected participants to represent a broad range of fire management positions and agencies (see Table 1 and 2 for additional information about interview participants). The

research team drew on our working knowledge of this population, local fire science network contacts, and publicly available employee information to identify the initial list of potential participants. We used a snowball approach to identify additional participants; at the conclusion of each interview, we asked the participant to recommend relevant personnel for further interviews.

Table 1: Study sample by agency

Agency	Participants
USDA Forest Service (USFS)	10
National Park Service (NPS)	4
Bureau of Land Management (BLM)	3
Fish and Wildlife Service (FWS)	3
US state agencies	5
National Oceanic and Atmospheric Administration, National Weather Service (NWS)	2

Table 2: Expertise of study sample

Agency	Participants
Planning: Technical specialists	15
Planning: other	3
Operations	5
Command	2
Non-IMT (e.g., line officer, regional coordinator, predictive services manager)	4

Between March and May 2017, we completed 27 interviews in person and over the phone. Interviews lasted between 30 and 60 minutes on average, with the longest taking 110 minutes. Interviewees included full and part-time IMT members, district rangers, fire management officers, regional fire management coordinators, fire management and fuels specialists, and others. Interviewees may have held multiple titles; for example, an interviewee may have been a fire management officer who served as a fire behavior analyst on an IMT.

We used an interview protocol to guide these interviews (full interview protocol available on the JFSP website; saved under “other products” associated with this project), but conversation was not confined to those questions and was allowed to proceed organically (Patton 2002). Interviews explored the flow of information during fire incidents, such as fire model outputs and weather forecasts, and decisions during incidents. Participants addressed many of the questions unprompted during the interviews.

All interviews were audio-recorded and transcribed. Analysis was completed using the data analysis software MaxQDA. The research team developed a detailed codebook based on initial research questions, guiding theory, and themes that emerged within the interviews (Rubin and Rubin 2005; Saldana 2010; Creswell and Poth 2018) to guide the coding process. A portion of these transcripts were coded by two researchers and discussed until intercoder reliability (measures the percent of matching codes assigned by two or more coders working in isolation) and intercoder agreement (involves discussion between coders to reconcile discrepancies through discussion and measures final agreement after arbitration) reached 99% (intercoder agreement requires coders to reconcile any discrepancies through discussion and arbitration) (Campbell et al. 2013). Both researchers coded and discussed 40% of the interviews (10 transcripts) to reach agreement on the coding approach before the remaining transcripts were coded independently. Complex sections were discussed on a case-by-case basis for the remaining transcripts.

Phase two

In this phase, we leveraged the fire spread model sensitivity analysis that was published by Page et. al. (2018) to develop fire spread scenarios for the choice experiments that exploited known model sensitivities to variables such as windspeed, relative humidity and rainfall. We chose a relatively small but complex fire from Central Utah as our example fire. We produced fire spread simulations using LANDFIRE fuels data, the FlamMap fire modeling package and weather from a local Remote Automated Weather Station. We compared observed and forecast weather data for 30 days previous to the fire simulation initiation date and we determined the forecast mean absolute error over that time period for temperature, relative humidity, rainfall and windspeed. We then created a factorial set of simulations that encompassed the weather forecast and its potential error over that time period for a 72-hour period. This allowed us to leverage model sensitivity to various weather inputs in the scenarios for the choice experiments.

Phase three

The third objective was addressed by developing a web-based survey sent to federal fire managers working for the USFS. Surveys were conducted using Sawtooth, a web-based survey and choice experiment platform. For this survey, we specifically targeted fire management officers (FMOs) (i.e., assistant fire management officers, forest fire management officers, etc.). To be an FMO, individuals must have several years of operational firefighting experience and hold qualifications to serve as division supervisors, operations section chiefs, or incident commanders on IMTs.

We developed our initial list of FMOs from internal email lists and augmented this by contacting individual Forest Supervisors to check that our list was up-to-date for their forests. After removing invalid emails, we had a final list of 669 potential respondents. Of these, 243 respondents, or 36% responded. After removing respondents who did not complete the choice experiment, the final sample included 182 respondents for an adjusted response rate of 27%. This response rate is in line with previous online surveys of federal fire managers, which typically have a response rate between 25 – 50% (e.g., Hand, Wibbenmeyer, Calkin, & Thompson, 2015; Wibbenmeyer, Hand, Calkin, Venn, & Thompson, 2012; Wilson, Winter, Maguire, & Ascher, 2011).

The survey (survey available on the JFSP website) included questions about participant characteristics (including length of time they had worked in fire, time in their current job, as well as their gender, education, and what role they served in most frequently on IMTs). The survey also included a series of questions about the perceived risk and agency culture regarding the use of direct and indirect attack fire management strategies. Additionally, we measured respondent confidence in weather models.

The main portion of the survey was dedicated to an embedded choice experiment designed to test whether participants would choose to engage in direct or indirect attack to manage an ongoing wildfire. Choice experiments provide a method to test the influence of included variables on participant decisions. Specifically, choice experiments allow examination of how different levels of a given attribute, such as the varying probability of wetting rain, influence which tactics fire managers believe are best for a fire. Choice experiments also allow comparisons of the relative importance of different attributes, for example whether fire managers are more sensitive to changes in precipitation or changes in wind speed when making tactical decisions.

Before beginning the choice experiment, all respondents were provided the same introduction to a potential wildfire (see survey for full description). The introduction was intended to be ambiguous such that it was not immediately clear whether direct or indirect attack was more appropriate. That said, there are substantial challenges in designing a wildfire scenario that is realistic in light of the real-world complexity associated with such decisions. To develop the scenario presented here, we sought feedback on draft scenarios from a group of FMOs from one USFS region as well as from several USFS scientists with extensive experience working on these issues. While some simplification is required given the limitations posed by experimental research, we sought to develop a context for the subsequent decisions that included or controlled for the primary variables that influence decisions about whether to engage in direct versus indirect attack to allow us to specifically consider the unique effect of weather information.

After reviewing the introduction, respondents were asked whether they would prefer to engage in direct or indirect attack given the information provided. Respondents were then randomly assigned to one of two conditions. Those assigned to the first condition (n = 103) were informed that the initial attack team had decided to indirectly attack the fire in the first 48 hours. In the second condition, respondents (n = 79) were told the initial attack team had decided to directly attack the fire during the first 48 hours. The choice experiment asked participants to consider when they would switch away from the initial approach to managing the fire.

In the text below, we report a study-specific measure of "importance" for each attribute. As used here, importance provides a measure of the relative influence of a given attribute compared to other attributes in the choice experiment. Importance scores were calculated from the results of the choice experiment analysis. Part-worth utilities were calculated using hierarchical Bayesian analysis; to calculate importance, the relative range of part-worth utility for each attribute for each respondent is calculated as a percent of the total range across attributes, and then averaged across respondents (Orme 2010). Thus, the importance measures of all attributes sum to 100%, and measures of importance are ratio-scaled, which is to say an attribute with an importance of 50% is twice as important as an attribute with an importance of 25%.

Results and Discussion

Results are organized below according to our project objectives. Objective 4 is primarily addressed in our conclusion.

1) Consider how fire-weather models are used to support strategic and tactical decisions.

The utility of fire weather and behavior models to support decisions depends on a number of variables and may vary across a fire event.

In the early stages of a wildfire there is a high need for immediate information to inform initial decisions. In these cases, fire-weather models were generally described as being more useful than fire behavior models. Decisions during these early stages of initial attack are largely scripted based on predefined guidelines (pocket guides) and run cards informed by NFDRS thresholds. Thus, information about weather conditions and resource availability are drawn on to inform these early decisions. Detailed results generated through WFDSS are not generally available when initial decisions need to be made.

Interview participants also indicated that when WFDSS becomes mandatory, the initial output may not be immediately available or helpful to support decision-making. In particular, they noted that the outputs are often delayed and unable to keep up with the pace of incidents during the early stages of an extended fire. They also noted that the quality of these outputs is heavily dependent on the quality of the underlying information on local conditions and management objectives previously included in WFDSS. Interview participants noted that units have a responsibility to keep WFDSS up to date before a fire ignites; however, in some cases they found this may not be realistic for under-resourced or overworked units that have to make tradeoffs about where they place their time. In such cases, there may be some additional time needed to update the foundational information within WFDSS including fuel layers, geospatial layers, or management plans before WFDSS can be run.

One respondent explained that fuel layers may only be updated every few years, and thus incoming IMTs may not have access to up-to-date information on local fuels.

> *"We have a real issue with workload. Workload and capacity … That definitely has an impact on the WFDSS process … we're having trouble getting the data in from our other specialists that we want. Some of it might be not a priority, don't care, but I think most of it is they've got other things that are far more pressing to get done."*

Belief about the value of the output of the tools varied between managers and technical specialists.

The technical specialists that participated in our interviews generally expressed confidence in the reliability of the models, including those that may have considerable uncertainty. For example, one specialist stated:

> *"Even if these basic models are only 50% accurate, it gets you in the ballpark."*

While another indicated:

> *"I always caution people, when you look at models, is that it's useful information, but don't look at it as a for-sure thing. So, you should always question it, and – they are good though for helping guide your decisions, and looking at values out there that may be threatened."*

Managers generally expressed moderate confidence in the models. They recognized that the resulting forecasts would not likely be perfect leading to some hesitancy to rely on the models in their decision-making. As one manager stated:

> *"I think overall, if you just did any of the fire spread models and let it run … if you've got reasonable weather and field moisture input, it's probably going to overpredict what is actually happening out there."*

Managers described a range of different ways they used models to inform their decisions. Managers described model output as providing one type of information they could use to consider potential decisions. Many described models as "telling a story" of different potential scenarios that could occur and what may drive those different outcomes. Some described using model output to test their intuition about what might occur and the outcomes associated with particular decisions. As one manager stated:

> *"But we do look at that, going if we did nothing, where's this gonna go? Where's the most likely spot this thing is gonna grow? And where's our thread area out there? Where's our values that we need to protect? The model shows this going here, and we have something of value there. That is a high priority. We better focus here."*

Another noted:

> *"So, you're taking a model which – our models are good and our models are bad, right? But they're another tool that helps guide tactics or I look at them as a – kind of a gut check or a reference check to see if they're tracking with what you think is occurring."*

There are a number of barriers to using models to using fire weather and behavior models. Participants described a number of barriers that may limit the ability for models to effectively support fire management decisions.

Participants described the potential to become desensitized to forecasts of extreme events. They referred to "red flag fatigue" where managers may become less sensitive to red flag warnings that have been in place for an extended period of time. Some suggested this may be addressed by revising the warning system with additional detail (such as adding an "orange flag" or "super red" levels). As one participant stated:

> *"There's a chronic red flag on the [location] to the point where damn near all summer is a red flag warning – or a big chunk of the fire summer anyway – and the problem is that if you hear that every single day and every time, it becomes less meaningful."*

One participant described this as a particular concern for early-career firefighters.

> *"What I have found is that [first-year firefighters] just start glossing over the importance of some of those products like ERC [energy release component] or red flag y because every day we're just getting another set of super extreme conditions y so you just stop worrying about it as much."*

Participants also described concern about whether the models were capable of providing reliable forecasts given changing weather conditions. Technical specialists in particular expressed concern that there may be a "new normal" where more extreme conditions are common and models based on historical data may not be capable of providing reliable forecasts going forward. As one stated:

> *"We're potentially looking at 1 in like 1700-year kinds of weather events. And we're relying*

on either a 10-year or a 30-year data capture and extrapolating the right-hand tail."

Some also described a conflict between beliefs about what makes a good operations chief and a willingness to use model forecasts. Some referenced a culture that emphasizes experience and intuition in making decisions. In such cases, some expressed concern that models were only viewed as useful if they confirmed pre-existing beliefs. One technical specialist noted:

> *"If we tell them something that they already have concluded, they love it. If we tell them something that's not quite the same, they're highly questionable [questioning]."*

Similarly, an operations chief stated:

> *"I don't need the spread models as much as I, I need – because if I don't – if I don't have a pretty good idea of what the fire's gonna do over the next 48 hours, then I'm not a very good ops chief."*

Some described this as having the potential to create some challenges as operations personnel may not be willing to adjust their approach when model forecasts may suggest plans will not be successful.

Methods to increase adoption of tools.

The technical specialists we interviewed recognized that effective decision support involved more than simply providing information. They described a number of different ways they encouraged use of model results to more effectively support decision-making.

For example, several participants described adjusting model inputs to calibrate the models and improve forecasts. Some described situations where they had reduced the accuracy of some of the input variables to improve the overall functioning of the model. These respondents described the importance of having an in-depth understanding of how the models function to do this effectively.

Several technical specialists also noted the importance of developing relationships with others on the IMT to build trust and credibility. They described this as contributing to increased confidence in the models and a greater willingness to consider model output. They indicated it takes time to build these relationships. Some indicated they found success when they were able to work with the same operations chief or incident commanders on different fire events. While Fire Behavior Specialists can work remotely in some cases, some participants emphasized the importance of being physically present on the fire event and having face-to-face interactions with the IMT. They noted that being present on the fire allowed them to learn about local conditions and better calibrate their models while also providing an opportunity for direct interactions with the rest of the IMT, to describe and discuss the rationale for the models, and to develop relationships.

Along these lines, one respondent noted:

> *"I try to gather information from them on what they're seeing, then I validate it, and then I fold that into my analysis and forecast in such a way that that Superintendent or the other crew's Superintendent can see that guy took the information we provided and is using it. There's nothing that builds street cred with the ground pounders [more] than seeing their information being used."*

Another stated:

> *"If they can get a good justification from someone, such as myself, on why I'm forecasting that [winds gusting to 40 miles an hour], what leads me to believe that that's gonna happen, and I can tell them in plain terms that they can understand and they can ask questions and get answers and there's a good understanding, they're gonna run with my assessment and they will make changes accordingly on their operational tactics."*

2) Consider the sensitivity of fire-weather tools to various sources of input error.

As part of this project, we collaborated with other fire weather researchers to leverage results from a concurrent study that explored the sensitivity of fire weather forecasts on fire behavior predictions (Page et. al. 2018). Specifically, they found that forecasts of air temperature and relative humidity performed well with root-mean-square errors (RMSEs) of about 2°C and ~10%, respectively. However, they found a strong sensitivity of fire spread models to wind speed errors and they also found that wind speed was consistently underpredicted when observed wind speeds exceeded about 4 m s−1, with mean fractional bias (MFB), and mean bias error (MBE) values of approximately −15% and −0.5 m s−1, respectively. The same fire spread model and underlying algorithms are used in both the US Fire Behavior Prediction System and the US National Fire Danger Rating System and the results from this concurrent study were sufficient to provide the scientific basis for the development of the fire behavior scenarios used in the choice experiments. We leveraged this information about fire model input sensitivity to design scenarios for an example wildfire that varied temperature, relative humidity and windspeed inputs into FlamMap to produce fire spread maps for the next 72 hours and these scenarios were included into the choice experiments to explore the sensitivity of weather inputs on decision making.

3) Assess the sensitivity of fire management decisions to fire-weather variables.

To address this objective, we implemented a web-based survey to examine how decisions about whether to engage in direct or indirect attack. Survey respondents were FMOs within the USFS (n = 182). Respondents were very experienced in fire management; they had an average of 24 years of experience in fire management overall and had served in their current position for an average of 8 years. Respondents had served in multiple different roles; 32% indicated they most frequently served as division supervisors, 26% as incident commanders (Type 1 – 3), 18% as operations section chiefs, and 24% in other roles (e.g., technical specialists, safety officers, and task force leaders). Most of our respondents (88%) identified as male and a majority (69%) had completed a bachelor's degree or higher level of formal education.

On average, respondents were more likely to indicate the USFS encourages direct than indirect attack and they felt both approaches were equally risky. Respondents had moderate to high confidence in all weather forecasts, indicating that forecasts were reliable 51 – 75% of the time. However, we did find that average confidence differed significantly across models (df = 3, $F = 16.003$. $p < .001$) and respondents indicated less confidence in precipitation and wind forecasts than humidity forecasts or weather forecasts in general (pairwise t-test; $p < .05$).

After reading the introduction to the fire scenario, participants were asked to indicate whether they believed direct or indirect attack would be preferable for the described scenario. Our intention was for the description to be ambiguous and we expected roughly equal numbers to prefer each option. In practice, two-thirds (68%) of respondents indicated a preference for indirect attack as a means of managing our described scenario.

At this point in the survey, respondents were told whether the initial team had decided to engage in direct or indirect attack. Respondents were randomly assigned to this experimental condition; 103 were assigned to the first condition and informed that the initial attack team had decided to indirectly attack the fire during the first 48 hours while 79 respondents were assigned to the second condition and were told the initial attack team had decided to engage in direct attack. In each case, participants were then presented with different sets of forecast conditions and asked to indicate under which set of conditions they would switch from the initial tactical approach employed by the original management team. These forecasts varied five attributes – forecasted precipitation, forecasted humidity, forecasted wind, time in fire season in which the fire was occurring, and the energy release component.

Condition 1: Switching from indirect to direct attack

In the first condition, respondents chose whether to switch from indirect to direct attack. Seasonality (the time in year when the fire event was described as occurring) was the most important attribute influencing decision to switch from indirect to direct attack (average importance score = 37.40; see Table 3). Respondents indicated a stronger preference to switch to direct attack when it is early versus middle or late in the season. Wind was the second-most important attribute (average importance score = 19.31 indicating it is approximately half as important as seasonality), with respondents preferring to switch to direct attack when the forecasted wind was low (described as slightly windy) compared to when the forecasted wind was high (described as very windy). Precipitation was the third most important attribute (average importance = 18.74). Respondents have a stronger preference for switching to direct attack when wetting rain is forecasted compared to no rain in the forecast. ERC was the fourth most important attribute (average importance = 16.15). Interestingly respondents did not have clear linear preferences with regards to ERC. Humidity was the least important attribute (average importance = 8.41), with respondents preferring to switch to direct attack when humidity was high (described as humid) compared to when forecasted humidity was low (described as dry).

Responses indicated that the ideal conditions for switching to direct attack would be a fire occurring early in the fire season with wetting rain, high humidity, and slight wind forecasted, with ERC trending towards 90%. This combination of weather factors suggests moderate fire behavior early in the fire season.

Additionally, respondents indicated they preferred to continue to indirectly attack all three fires presented to them in nearly half of all cases (48% of all choice sets). Indeed, only some combinations of attributes led to scenarios where switching to direct attack was viewed as preferable to continuing to engage in indirect attack. For example, while the ideal conditions for switching to direct attack described above had a greater utility than continuing to engage in indirect attack, if these same sets of forecasted conditions occurred in the middle or late in the season, respondents then indicated a preference to continue to engage in indirect attack.

Table 3: Importance of attributes across choice experiments

	Condition 1: Indirect to direct attack		Condition 2: Direct to indirect attack	
Attribute	**Average importance**	**Standard deviation**	**Average importance**	**Standard deviation**
Precipitation	18.74	12.46	31.46	14.23
Humid	8.41	3.42	10.97	4.97
Wind	19.31	7.71	12.44	5.42
Seasonality	37.40	12.85	23.15	16.35
Energy Release Component	16.15	7.50	21.97	8.69

Condition 2: Switching from direct to indirect attack

Forecasted precipitation was the most important attribute (average importance = 31.46; see table 3) when deciding whether to switch from direct to indirect attack. Specifically, respondents preferred to switch to indirect attack when there was no rain in the forecast. Seasonality was the second most important attribute (average importance = 23.15) with respondents preferring to switch to indirect attack later in the season. ERC was the third most important attribute (average importance = 21.97), primarily driven by the relatively low utility associated with the attribute level where ERC was described as trending towards 60% compared to the other levels (stable at 80% or trending towards 90%). Wind was the fourth most important attribute (average importance = 12.45) and respondents did not express clear linear preferences regarding the influence of wind on decisions to switch to indirect attack. Humidity was the least important attribute (average importance = 10.97) and respondents preferred to switch to indirect attack when forecasted humidity was low (i.e., dry) compared to when forecasted humidity was high (i.e., humid).

These results indicate that the ideal conditions to switch to indirect attack would be a fire with no rain forecasted, low humidity and high wind, occurring late in the season with ERC trending towards 90%. This combination of weather and fuel factors suggests extreme fire behavior, with a higher chance of a season-ending event on the horizon.

In most of the choice sets (92%), respondents chose to switch to indirect attack for at least one of the described scenarios. Respondents preferred to stay with direct attack for only a few limited combinations of attributes. For example, respondents preferred to stick with direct attack when there was forecasted rain, conditions were described as humid and windy, early in the season with the lowest ERC. However, if the same scenario were presented but without rain forecasted, responses suggest a preference to switch to indirect attack. Put another way, respondents were only willing to continue with direct attack for some scenarios where wetting rain was forecasted, otherwise they preferred to switch to indirect attack.

Prefer status quo

For some scenarios, respondents preferred to continue the original approach in both conditions. For example, for some scenarios where wetting rain was forecasted and it was not early in the season, respondents in both conditions preferred to continue with the initial strategy regardless of whether the initial team had engaged in direct or indirect attack. It is unclear why respondents preferred the default in these cases. It may be that the relative gain in utility was not believed to be worth the cost of changing tactics, or it may be that the fire managers did not have a preferred tactic in those circumstances and defaulted to the previous team's tactics.

Influences on switching

In an open-ended question, respondents were asked to indicate what had influenced their decision regarding switching approaches. In both conditions, the most commonly mentioned attribute influencing the decision to switch to direct or indirect attack was the time in the season the fire occurred (noted by 47% in condition 1 and 54% in condition 2). Respondents in condition 1 (switch to direct attack) then mentioned wind (28%) while ERC (16%), precipitation (15%), and humidity (8%) were mentioned less frequently. Respondents in condition 2 (switch to indirect attack) cited precipitation (27%), wind (26%), and ERC (19%) with a relatively small number mentioning humidity (8%).

Besides comments on weather and seasonality, respondents also indicated their decisions were based on perceived impacts to firefighter safety (21% condition 1, 11% condition 2) and considerations regarding the size and behavior of the current fire (11% condition 1, 20% condition 2).

Conclusions and Implications for Management/Policy and Future Research

Results developed through this project have a number of implications for how to provide weather information to decision makers in general and how to improve weather forecast models to support wildfire management decisions.

First, our results highlight the importance of considering how information is actually used by fire managers. While previous researchers have highlighted the types of information necessary for an operations-focused decision support tool (Dunn, Thompson, & Calkin, 2017), results from this project highlight that decision support tools should be designed and evaluated with the decision strategies used by fire managers in mind. Tools should be designed with the decision strategies of fire managers in mind. It is important to understand what information they use and how they make use of it to develop tools that successful meet their needs.

Weather information can be an important influence on tactical decision-making and success in wildfire management (Countryman, 1972; Rapp et al., 2020). However, our results highlight that weather information may not be used or interpreted consistently across decision-makers. Rather, what information fire managers use and what they learn from it depends on the context; weather information does not exist in a vacuum. The relative importance of different variables appears to change across the fire season. That said, our results did suggest there was a relatively consistent lack of confidence in wind and precipitation forecasts. This is particularly important as wind and precipitation were the most important pieces of weather information for decision-making. Thus, we suggest prioritizing efforts to improve the forecast accuracy where possible in these variable and increase confidence in the resulting forecast as appropriate. Typical fire weather forecasts are derived from the National Digital Forecast Database (NDFD) which are produced continuously across the United States by the US National Weather Service (Glahn & Ruth, 2003). A recent study has shown that the NDFD consistently underpredicts windspeeds when the winds are stronger than about 4 m/s (~9 mi/hr) (Page, Wagenbrenner, Butler, Forthofer, & Gibson, 2018). Winds are particularly difficult to forecast due in part to local terrain influences and extensive work is ongoing to improve wind forecasts in complex terrain. Models that downscale wind forecasts to correct for terrain influences, such as WindNinja (Wagenbrenner, Forthofer, Lamb, Shannon, & Butler, 2016), show promise in improving local-scale wind forecasts. While it is reasonable to expect increased confidence in the models as their accuracy improves, such improvements are not guaranteed to occur automatically. In addition to improving model accuracy, it will also be important to understand the specific concerns held by fire management personnel. Beyond model accuracy, personnel may be resistant to using models and prefer to rely on their own intuition as a symbol of competence and expertise (Noble & Paveglio, 2020; Rapp et al., 2020). In other cases, managers may not view the models as problematic but may have concerns about the perceived competence of the modelers (Noble & Paveglio, 2020; Rapp et al., 2020). Addressing these different concerns will require different approaches; potentially including how users relate model use and perceived job competency, providing updates on improvements in model accuracy, or providing opportunities to develop relationships between managers and technical specialists.

Second, results here also indicate the complex nature of decision support. Effective decision support is about much more than simply providing information or even providing accurate and reliable information. Ultimately, increasing the use of models will not only rely on improving their accuracy but also increasing the confidence that fire managers have in model output and the utility they see in how the provided information contributes to improving their decisions. The complexity in decision support was recognized by many of the technical specialists that participated in this study. Through their experiences, they found that model results could be improved through tailoring them to local conditions. Moreover, they recognized managers were more likely to consider the models when the output was not simply provided to managers but, rather, where models were calibrated based on ongoing dialogue between the technical specialists and fire managers and where they could discuss the rationale for decisions made in the models. Several of the specialists included here recognized that these discussions were more likely to occur when they were in the field with the IMTs rather than providing remote support.

These results suggest the importance of training the technical specialists not just in the technical aspects of the models but also in communication and other soft skills. While such skills may be seen as tangential to the developing the depth of expertise needed to run the models effectively, they may be as important to supporting decisions as the quality of the provided information.

Literature Cited

Calkin, David, Mark Finney, Alan A. Ager, Matthew Thompson, and Krista Gebert. 2011. "Progress towards and Barriers to Implementation of a Risk Framework for US Federal Wildland Fire Policy and Decision Making." *Forest Policy and Economics* 13 (5): 378–89. https://doi.org/10.1016/j.forpol.2011.02.007.

Campbell JL, Quincy C, Osserman J, Pedersen OK (2013) Coding in-depth semistructured interviews: problems of unitization and intercoder reliability and agreement. Sociological Methods & Research 42, 294–320. doi:10.1177/0049124113500475

Countryman, C. M. 1972. "The Fire Environment Concept," 15.

Creswell JW, Poth CN (2018) 'Qualitative inquiry & evaluation methods.' (Sage Publications, Inc.: Thousand Oaks, CA, USA)

Deeming JE, Burgan RE, Cohen JD (1977) The National Fire-Danger Rating System--1978. USDA Forest Service General Technical Report INTUS (USA). no. 39.

Dunn, Christopher J., Matthew Thompson, and David Calkin. 2017. "A Framework for Developing Safe and Effective Large-Fire Response in a New Fire Management Paradigm." *Forest Ecology and Management* 404 (June): 184–96. https://doi.org/10.1016/j.foreco.2017.08.039.

Glahn, Harry R., and David P. Ruth. 2003. "The New Digital Forecast Database of the National Weather Service." *Bulletin of the American Meteorological Society* 84 (2): 195–202.

Hand, Michael, Matthew Wibbenmeyer, David Calkin, and Matthew Thompson. 2015. "Risk Preferences , Probability Weighting , and Strategy Tradeoffs in Wildfire Management." *Risk Analysis* 35 (10): 1876–91. https://doi.org/10.1111/risa.12457

National Wildfire Coordinating Group (2014) Interagency Standards for Fire and Fire Aviation Operations. NFES 2724.

Noble, Peter, and Travis B. Paveglio. 2020. "Exploring Adoption of the Wildland Fire Decision Support System: End User Perspectives." *Journal of Forestry* 118 (2): 154–71. https://doi.org/10.1093/jofore/fvz070 .

Orme, Bryan. 2010. "Interpreting the Results of Conjoint Analysis." In *Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research*, 77–88. Madison, WI: Research Publishers LLC. http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Interpreting+the+Results+of+Conjoint+Analysis#0.

Page, Wesley G., Natalie S. Wagenbrenner, Bret W. Butler, Jason M. Forthofer, and Chris Gibson. 2018. "An Evaluation of NDFD Weather Forecasts for Wildland Fire Behavior Prediction." *Weather and Forecasting* 33 (1): 301–15. https://doi.org/10.1175/WAF-D-17-0121.1.

Patton MQ (2002) 'Qualitative research & evaluation methods.' (Sage Publications, Inc.: Thousand Oaks, CA, USA).

Rapp, Claire, Emily Rabung, Robyn Wilson, and Eric Toman. 2020. "Wildfire Decision Support Tools: An Exploratory Study of Use in the United States." *International Journal of Wildland Fire* 29 (7): 581–94. https://doi.org/10.1071/WF19131.

Rubin RJ, Rubin IS (2005) 'Qualitative interviewing: the art of hearing data.' (Sage Publications, Inc.: Thousand Oaks, CA, USA)

Saldana J (2010) 'The coding manual for qualitative researchers.' (Sage Publications, Inc.: Thousand Oaks, CA, USA)

Steelman, Toddi A, and Sarah McCaffrey. 2011. "What Is Limiting More Flexible Fire Management-Public or Agency Pressure?" *Journal of Forestry* 109 (8): 454–61.

Thompson M (2014) Social, institutional, and psychological factors affecting wildfire incident decision-making. Society & Natural Resources 27, 636–644. doi:10.1080/08941920.2014.901460

Thompson, Matthew, and David Calkin. 2011. "Uncertainty and Risk in Wildland Fire Management: A Review." *Journal of Environmental Management* 92 (8): 1895–1909. https://doi.org/10.1016/j.jenvman.2011.03.015

Wagenbrenner, N. S., J. M. Forthofer, B. K. Lamb, K. S. Shannon, and B. W. Butler. 2016. "Downscaling Surface Wind Predictions from Numerical Weather Prediction Models in Complex Terrain with WindNinja." *Atmospheric Chemistry and Physics Discussions* 2016 (January). https://doi.org/10.5194/acp-2015-761.

Wibbenmeyer, Matthew, Michael Hand, David Calkin, Tyron Venn, and Matthew Thompson. 2012. "Risk Preferences in Strategic Wildfire Decision Making: A Choice Experiment with U.S. Wildfire Managers." *Risk Analysis* 33 (6): 1021–37. https://doi.org/10.1111/j.1539-6924.2012.01894.x.

Wilson, Robyn S., Patricia L. Winter, Lynn A. Maguire, and Timothy Ascher. 2011. "Managing Wildfire Events: Risk-Based Decision Making among a Group of Federal Fire Managers." *Risk Analysis* 31 (5): 805–18. https://doi.org/10.1111/j.1539-6924.2010.01534.x.

Appendix A: Contact Information for Key Project Personnel

Eric L. Toman, Ph.D.
toman.10@osu.edu
The Ohio State University
School of Environment and Natural Resources
210 Kottman Hall
2021 Coffey Road
Columbus, OH 43210
614-292-7313

Robyn S. Wilson, Ph.D.
wilson.1376@osu.edu
The Ohio State University
School of Environment and Natural Resources
210 Kottman Hall
2021 Coffey Road
Columbus, OH 43210

W. Matthew Jolly
William.Jolly@usda.gov
USDA Forest Service
Rocky Mountain Research Station
Fire Sciences Lab

Christine S. Olsen (original lead PI)
Oregon State University
Department of Forest Ecosystems & Society (retired)

Claire Rapp
rapp.172@buckeyemail.osu.edu
The Ohio State University
School of Environment and Natural Resources
210 Kottman Hall
2021 Coffey Road
Columbus, OH 43210

Appendix B: List of Completed/Planned Scientific/Technical Publications/Science Delivery Products

1. *Articles in peer-reviewed journals*

   Rapp, C., E. Rabung, R. Wilson, and E. Toman. 2020. Wildfire decision support tools: an exploratory study of use in the United States. International Journal of Wildland Fire. 29(7): 581-594 https://doi.org/10.1071/WF19131

   Rapp, C., R. Wilson, E. Toman, and W.M. Jolly. In Review. Assessing the role of short-term weather forecasts in fire manager tactical decision-making: a choice experiment.

2. *Technical reports*

   Olsen, C., C.E. Rapp, E. Toman, R. Wilson, W.M. Jolly. 2018. Wildland fire managers' use of fire weather data in strategic and tactical decision-making across the US (Western focus): Phase One Interview Findings.

3. *Text books or book chapters*

   None

4. *Graduate thesis (masters or doctoral)*

5. *Conference or symposium proceedings scientifically recognized and referenced (other than abstracts).*

6. *Conference or symposium abstracts*

   Rapp, C.E., E.A.L. Rabung, R.S. Wilson, and E. Toman. 2019. Wildfire decision support tools in theory versus in the field: an exploratory study. Arlington, VA. Society for Risk Analysis Annual Meeting. (December)

   Rapp, C., Wilson, R., E. Toman and W.M. Jolly. 2021. Assessing the role of short-term weather forecasts in fire manager tactical decision-making. Presented at the Society for Risk Analysis Annual Meeting in the symposium "Managing and Reducing the Risk of Wildfire through Response and Fuel Treatment". Virtual Meeting. (December)

7. *Posters*

8. *Workshop materials and outcome reports*

9. Field demonstration/tour summaries

10. Website development

11. Presentations/webinars/other outreach/science delivery materials.

Rapp, C., E. Rabung, R. Wilson, and E. Toman. In Prep. Research brief - Wildfire decision support tools: an exploratory study of use in the United States. Lake States Fire Science Consortium Research Brief.

Appendix C: Metadata

1. Data Types

Our data included (1) qualitative data from in-depth interviews with fire management personnel, (2) quantitative data from structured surveys, and (3) fire weather climatology and simulated fire model values. The qualitative data will include interview audio files and transcripts (.doc files), which were coded to identify themes. Study participants were assigned a unique identifier and all identifying information was removed from the transcripts. Coding and theme building were completed using the qualitative data analysis software programs MaxQDA and NVivo. The quantitative data from the surveys will include spreadsheets of coded survey data that will be entered and stored in Excel. Analysis of the quantitative data will take place in the quantitative data analysis software programs SPSS and Latent Gold.

2. Long-Term Data Management

Data Repository

Qualitative data cannot be made anonymous and will not be released, but will be kept for at least five years on our restricted-access institutional servers, or as instructed by the Institutional Review Board.

De-identified survey data and all metadata documents will be deposited with the U.S. Department of Agriculture Research Data Archive (https://www.fs.usda.gov/rds/archive/). These data consist of de-identified survey responses from 182 USDA Forest Service Fire Management Officers who completed our web-based survey and embedded choice experiment. The data are available as .csv files and include numeric responses to likert-scale and multiple choice questions included in the survey.