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In Box

Improving the Science for Wildland Fire Prediction at S2S Scales

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ABSTRACT: The size, duration, impact, and cost of wildland fire is increasing over the last several decades. A recent Interagency Council for Advancing Meteorological Services (ICAMS)-sponsored workshop focused on the scientific questions and challenges associated with subseasonal-to-seasonal wildfire outlooks. Opinions from this workshop, including recommended cross-agency motivation and activities, are provided.

SIGNIFICANCE STATEMENT: Skillful hazardous wildland fire outlooks on the subseasonal-to-seasonal time scale are desperately needed to enable better preparation for these potentially impactful events. This is a clear area where progress could be made more quickly via interagency collaboration.

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Wildfire is among the most impactful natural disasters, with annual costs over the last 40 years averaging over $57 billion. Additionally, the annual disaster costs are increasing with time along with the size and duration of fires, with the costs associated with wildfire for 2020, 2021, and 2022 being in the top 6 over that 40-yr period (https://www.ncei.noaa.gov/access/billions/).

Fire managers and communities use longer-range outlooks of hazardous wildfire conditions (e.g., the 1-month fire-weather outlooks provided by the National Interagency Fire Center and National Weather Service) as part of their planning process. In particular, subseasonal-to-seasonal (S2S) forecasts, which we define here as ranging from 3 weeks to 2 years, are particularly useful for decision-makers in proactive wildland fire management, e.g., suppression resource prepositioning, fire prevention actions, and prescribed fire planning. These proactive activities are able to protect lives and property, reduce firefighting costs, and improve firefighting efficacy. However, it is well recognized that S2S outlooks have relatively low skill for predicting temperature or precipitation anomalies (relative to shorter-range forecasts out to a week), and S2S models have not been truly evaluated for hazardous wildland fire applications.

Soliciting input from researchers and stakeholders from private, public, and university sectors on various wildland fire-weather topics, the Interagency Council for Advancing Meteorological Services (ICAMS; Droegemeier and Jacobs 2022) Committee on Research and Innovation (CoRI) organized a series of wildland fire workshops. In order, these workshops focused on interagency science coordination/collaboration activities, fire-weather interface with fire behavior modeling, and improving the science of S2S prediction of wildland fire. We focus on the third of these workshops, which was held virtually on 12 October 2022. We consider S2S prediction ripe for interagency coordination because S2S modeling is at the intersection of weather and climate, which naturally span multiple agencies, and because improvements in these predictive modeling systems could benefit the meteorological community and a range of stakeholders. Over 90 people participated in this workshop, which included two breakout sessions that enabled all participants to provide their input. This paper captures the main opinions expressed by the group, as synthesized by the authors. The S2S focus of this workshop complements other interagency efforts, such as the PCAST (2023) report and other efforts.

S2S forecast skill is influenced by a complex array of processes including land–atmosphere interactions (especially for subseasonal and improved spatial resolution of predictions), ocean–atmosphere interactions (for both subseasonal to seasonal), stratospheric–tropospheric dynamics, and sea ice variability; thus, S2S modeling requires an integrated Earth system approach (e.g., Merryfield et al. 2020). Most S2S modeling systems use horizontal grid spacings ranging from 50 to 100 km, which adds additional challenges to provide skillful forecasts, especially in complex terrain. Traditionally, the S2S prediction has been focused on the prediction of near-surface temperature and precipitation anomalies. Some studies have shown that there is enhanced skill in predicting these anomalies during specific teleconnection patterns (e.g., Mariotti et al. 2020; Meehl et al. 2021). However, at 3–4 weeks time scales, the modeling systems in use today show marked forecast differences (e.g., Pegion et al. 2019) that make the practical use of these outlooks questionable. We see these forecast differences at the longer time scales as both a challenge and an opportunity for better interagency collaboration and improved actionable predictions—and the focus of this article.

Wildland fire is often a compound condition wherein antecedent precipitation leads to the rapid growth of grasses and other undergrowth, which then dries over time and provides the fine fuel load for the potential fire. The drying of surface fuels is related to the atmospheric conditions; indeed, the Hot-Dry-Windy index (Srock et al. 2018) is one of the tools used to evaluate the potential for the atmosphere to affect a fire for short-range decision support. Thus, to truly evaluate how the S2S models capture the potential fire behavior (i.e., ignition, spread, and intensity), we will need to evaluate more than temperature and precipitation anomaly, but also humidity and wind conditions. These models need to represent any past fire suppression activities as well. Further, while many S2S models are designed for other applications, there is the need for more complex treatment of the vegetation and terrain to capture ecosystem dynamics that are sensitive to the evolving weather; this may require much finer horizontal model grid spacings. S2S model predictions could enhance vegetation predictions that are needed to provide information on when and how vegetation seasonally cures, the mortality of the vegetation due to drought and interacting factors, the extent of herbaceous vegetation growth, and the potential to revegetate after a fire. Consequently, this would include both the initialization of models to include more complete information on the current vegetation state and improving the representation of vegetation before, during, and after fires.

Virtually all groups working on S2S applications are using an ensemble of models (e.g., Merryfield et al. 2020). Very often, these models are using different physics parameterizations across the ensemble members to represent the uncertainty within these parameterizations. This results in spread in the forecasts from the ensemble members, and can be used to estimate the probability of a specific outcome occurring (i.e., by the number of members forecasting the outcome divided by the total number of members). However, it has been observed that members that share the same physical parameterizations tend to clump together (e.g., as shown in Pegion et al. 2019), which reduces the value of the ensemble. Additional work is needed within these ensemble modeling systems to evaluate and ultimately improve the skill of the spread of the ensemble.

A prevailing thread throughout the workshop's discussion was the need for better verification observations and methods. The verification approach may need to be tailored for different regions, as any given forecast product may have different utility across different climatic conditions. Clearly, we need to continue evaluating the predictions of temperature and precipitation anomalies, as well as the evolution of fuel conditions (which may require the evolution of the atmospheric boundary layer over time, so that the feedbacks between the vegetation and atmosphere are correctly represented). This requires that we evaluate other variables, such as near-surface relative humidity and winds, against observations.

The ability of S2S models to predict wildfire potential, not wildfire occurrence, needs to be considered. Straightforward evaluation of S2S outlooks using acres burned or fire intensity may not indicate true skill in predicting wildfire potential, especially given the range of prefire mitigation efforts that might be conducted (e.g., lack of a triggering event even though there is plenty of dry fuel, prescribed fires, mechanical fuel reduction, prepositioning of fire suppression resources, etc.). There is also a need to validate the evolution of the atmosphere and surface properties against observations to demonstrate;

for example, if S2S-predicted compound events that lead to a high potential for wildfire are represented properly.

Another common theme was the potential that advanced statistical techniques, including machine learning (ML), offer. There have already been multiple studies showing how ML and other empirical models can be used to better understand the sources of predictability (e.g., Nardi et al. 2020), including the key drivers of wildfires (e.g., Wang et al. 2021), and provide ensemble S2S prediction systems (e.g., Weyn et al. 2021). Machine learning can also help to expedite analysis of S2S forecasts, which has traditionally been driven by expert interpretation; fill in gaps in available observations and inform data collection activities that are necessary for verification; and downscale information from relatively coarse model grid cells. There was a strong consensus that ML approaches will be increasingly important in advancing S2S science, both via model development and interpretation as well as providing insightful ways to understand and verify model predictions. While ML-based models are computationally expensive to train, they are markedly more computationally efficient when used for predictions (e.g., Lam et al. 2023). Like other S2S models, ML-based prediction systems need to be extensively validated with observations to ensure that they are able to capture the more complicated compound conditions that are associated with hazardous wildland fire conditions. However, the participants noted a relative paucity of long-term observations, especially collocated fuel state and atmospheric variables, that could be used for either model development or explainable ML methods.

Improving S2S-scale wildfire outlooks should be a multiagency priority, and coordinated across agencies, for these reasons:

- Improved multiweek to seasonal hazardous wildfire outlooks are sorely needed by predictive services, forest managers, and other stakeholders to improve their ability to prepare communities and save lives.
- S2S forecasting lies at the intersection of weather and climate modeling, making it sensitive to both initial and boundary conditions, and continued efforts are needed to bring these two previously separate communities together.
- Hazardous wildfire conditions are typically associated with compound activities (e.g., above-normal precipitation before a lengthy dry-down condition resulting in a heavy fine-fuel load coupled with strong winds), and thus model improvement and verification needs to be aimed at connecting these compound conditions.
- New and improved observations of vegetation conditions, meteorological surface layer and atmospheric boundary layer conditions, soil moisture, and precipitation, especially in drought-prone areas, are needed.
- Improved verification approaches are required to evaluate wildfire potential, as well as other geophysical variables that are not typically output by these modeling systems. These verification approaches likely will depend on climatic regime, and may include evaluation via teleconnection patterns and other analog methods.
- Advances in ML may both improve the representation of physical phenomena, provide a better understanding of the limits of predictability, and lead to new approaches to evaluate these models spatially and from a process-oriented perspective.
- Ensemble systems are needed to provide the probabilistic outlooks. These ensemble systems should include a mixture of physical models with physics diversity and statistical models. However, a significant effort needs to be made to understand and improve the spread/skill relationships provided by these ensemble systems.
- The S2S approach to forecast wildfire potential could also be applied to the postfire environment to improve predictions of and warning for postfire cascading hazards, such as debris flow and flood events, and to support mitigation actions for emergency stabilization and recovery of vegetation.

Multiple agencies work in all of these areas, and at a variety of different levels on the "research to operations" spectrum. Coordination across the activities will more rapidly advance the skill in these modeling systems. However, we urge the agencies to also include research on how land managers and other stakeholders are using these modeling systems, so that future improvements can be targeted directly at improving the decision support aspects of these modeling systems.

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