**Study Plan**

**Background**

Increasing wildfire activity in the Western United States has placed heavy economic and logistical burdens on federal firefighting agencies. The US Forest Service spent more money suppressing the 2021 Dixie Fire than it spent for all fire suppression in 2010 [1], [2]. In the coming years and decades, climate change may bring even harsher fire seasons [3]–[5] and force fire managers into difficult decisions for allocating their scarce suppression resources [6]. For this reason, we propose developing data-driven optimization algorithms to improve dispatch and prioritization decisions toward effective wildfire suppression.

The primary aim of this research is to improve upon an integer optimization model by Belval et. al. [7] for assigning Interagency Hotshot Crews (IHCs) to requests, which replicates historical daily crew allocations while decreasing driving time and crew fatigue. In particular, we will incorporate the “rotational queueing” constraint, which requires that IHCs stationed in a single Geographic Area Coordination Center (GACC) take turns on assignments outside of their home region. We will also seek to improve the model will by predicting the likely locations of future crew assignments, which has been found to improve routing efficiency and working conditions for firefighting crews [8]. The model will allow us to examine the impacts of the current hierarchical dispatch system on efficiency, in comparison to centralized dispatch.

Upon completion of this objective, future work will aim to use causal machine learning to model resource effectiveness at the fire level based on fire weather conditions and relevant geographic features. This would assist with large fire prioritization, where decision-makers choose which resources to send to each fire without controlling the details of the fire-level suppression strategy. Most existing research on resource efficacy is at the fireline level [9], [10] since this is fundamentally how fire is suppressed. It is possible that inference at the fire level will be intractable, so proof of concept will be required early in the project.

**Primary objective:** Integer optimization model for dispatching Interagency Hotshot Crews to decrease travel distance and fatigue.

There is substantial research on optimal dispatch of suppression resources for initial attack. Haight and Fried [11] formulate the initial attack problem as a two-stage stochastic integer optimization problem, where resource deployment is decided before the fire season and dispatch decisions occur each fire day. Extensions of this work include simultaneous dispatch of multiple resource types, resources shared among planning units, richer models of the interplay between suppression efforts and fire growth, and chance constrained objective functions [12]–[14].

The body of research on initial attack implicitly makes decisions about prioritization; each day the model decides how many resources each fire will receive. However, especially for large fires that have escaped initial attack, fire managers have complicated and dynamic objectives that affect prioritization decisions, which may be difficult to encode reliably into the optimization formulation. For this reason, Belval et. al. [7] take a new approach to optimizing dispatch for IHCs. Rather than letting the model decide the number of crews assigned to each fire, they interpret the resource allocation quantity as fixed data and propose a simple integer optimization model that can be executed each day (or more frequently) to decide the specific crew assignments. They find that historical allocations could have been replicated while decreasing total driving distance and crew fatigue.

Our objective will be to build on this approach to account for the rotational queuing rule underlying assignments out of an IHC’s home region. Using historical IHC assignment data from the Resource Ordering and Status System (ROSS; in place 2008-2019) and the Interagency Resource Ordering Capability (IROC; in place 2020-present), we will develop a dispatch model that matches historical allocations efficiently while adhering to the rotational queuing rule. Through experimentations, the model will be used to evaluate the impact of this constraint on travel time and crew fatigue and determine whether the efficiency gains found in [7] remain once the rotational queueing rule is enforced. Furthermore, the model will be augmented by predicting where future crew assignments are more or less likely, by incorporating sources such as Visible Infrared Imaging and Radiometer Suite (VIIRS) fire observations [15] and Severe Fire Danger Index [16]. Ultimately, the optimization model developed in this research can provide a decision tool to support firefighting crew assignments, while ensuring consistency with historical decisions and with practical requirements.

With only minor modifications to this model, we will also be able to examine the inefficiencies created by a hierarchical IHC dispatch system, in which routing decisions are made mostly at the GACC level, with the National Multi Agency Coordinating group (NMAC) allocating resources across GACCs in periods of critical shortages. To examine the impact of this decentralized dispatch system, we will run a family of fire season simulations to optimize dispatch for each GACC, with assignments outside the GACC encoded as constraints into the model. Then we will aggregate travel costs and fatigue for crews across all GACCs and compare the results to the original model, which optimizes over all IHCs at once. The analysis will quantify the inefficiencies created by hierarchical dispatch, in terms of the total fatigue and travel distance that would be prevented by using a centralized IHC dispatch system.

**Follow-up work:** Causal machine learning model of resource effectiveness based on fire weather conditions and relevant geographic features.

There are many examples in the literature of optimization models for the containment of a single fire [17]–[21], which encode resource suppression effectiveness as deterministic or stochastic data variables. For example, the model may include parameters for “amount of fireline constructed per resource unit per unit time” or “probability of fireline holding.” Some work has been done to estimate these parameters empirically [9], [10]; however, these studies are limited by the availability and reliability of historical fireline data. Further fireline level analyses on a large scale are still limited by data constraints; data on use of resources at the fireline level is only available for a small subset of fires, and even that data suffers from incompleteness, inconsistency, and inaccuracy.

We will attempt to model resource effectiveness more coarsely, at the fire level. In preliminary work, we have developed a tool to generate daily fire footprints from VIIRS data and merged them with topographic, vegetation, and weather data. Based on daily situation 209 reports of resources assigned to each fire (possibly supplemented with ROSS/IROC data), this dataset will be leveraged to estimate the impact of each resource unit in preventing future fire spread.

Modeling resource effectiveness at the fire level creates significant (and possibly intractable) inferential challenges, since fires are suppressed with different goals and suppression inherently occurs at the fireline level. However, an estimate of resource effectiveness at the fire level that even improves marginally from a baseline constant would benefit any optimization approach to large fire prioritization.

Furthermore, estimating resource efficacy from observational data presents a challenge because historical resource allocation is determined in part by the risks of the fires, which includes the expected rate of spread. If fire managers indeed sent more resources to high-risk fires, a naïve model might infer that the resources increase fire spread. Accordingly, this research will draw on machine learning methods devised to measure treatment effects in the presence of confounding variables [9], [22], and will generalize these methods to convolutional neural networks, which are more appropriate to capture the spatial structure of the data.

If this project is successful, it will enable further research to create an end-to-end pipeline for wildfire suppression. Future work can focus on formulating a multistage stochastic optimization model to support prioritization and routing decisions for combatting wildfires within a region. At each time step, the model would evaluate the current conditions of the fires, their expected propagation, and the risk of new ignitions. It would then optimize the deployment or redirection of suppression resources.

**Roles and Responsibilities**

Data processing: Given the idiosyncrasies of the ROSS/IROC data, MIT researchers will communicate regularly with Dr. Belval about data preprocessing decisions to avoid pitfalls. As an intermediate step, they will share preprocessed data for her review. Furthermore, they will consult with her on judgments about the formulation that depend on specialized knowledge of the data generation process.

Data security: Shared data will be kept on the Forest Service Box drive whenever possible. When data must be stored locally for computing, it will be kept on a password-protected USB drive. If extra computing resources are needed for large-scale optimization models, the data will be transferred through secure copy protocol (SCP) to a password-protected drive on MIT Sloan’s internal computing cluster.

**Project Timeline**

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| Milestone | Description | Anticipated completion date |
| Redact and share IHC assignment data | Dr. Belval shares historical IHC assignment data from ROSS/IROC via Forest Service Box | April-May 2022 |
| Preprocess IHC assignment data | MIT researchers, in consultation with Dr. Belval, tidy up and process historical fulfilled requests into a format that can be fed as data to an optimization model | May-June 2022 |
| Preliminary results | Basic IHC routing analysis complete (evaluation of rotation queuing rule, centralized vs. hierarchical dispatch), presented to WRMS team at a weekly meeting for follow-up ideas | Early July 2022 |
| Present results at SSFARS | Present results at SSFARS; aim to incorporate predictions of future requests into dispatch model by this time | Late July 2022 |
| Paper submitted | Conduct follow-up research on IHC routing and submit paper (time commitment very dependent on amount of follow-up research) | Fall 2022 |
| Follow-up work on fire-level resource effectiveness model | Develop clean data pipeline incorporating historical fire data, weather observations, weather forecasts, topography, and suppression resource allocations  Build causal machine learning model of fire-level resource effectiveness. If proof of concept is achieved here, incorporate the model into an optimization formulation that makes prioritization recommendations. | Fall 2022-TBD |

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