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Title: Initial Attack Fire Suppression, Spatial Resource Allocation, and Fire Prevention Policy in California, the United States, and the Republic of Korea

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Heidi J. Albers

In this dissertation, I combined a scenario-based, standard-response optimization model with a stochastic simulation model to improve the efficiency of the deployment of initial attack firefighting resources on wildland fires in California and the Republic of Korea. The optimization model minimizes the expected number of fires that do not receive a standard response—defined as the number of resources by type that must arrive at the fire within a specified time limit—subject to budget and station capacity constraints and uncertainty about the daily number and location of fires. The simulation model produces a set of fire scenarios in which a combination of fire count, fire locations, fire ignition times, and fire behavior occur. Compared with the current deployment, the deployment obtained with optimization shifts resources from the planning unit with the

highest fire load to the planning unit with the highest standard response requirements. Resource deployments that result from relaxing constraints on station capacity achieve greater containment success by encouraging consolidation of resources into stations with high dispatch frequency, thus increasing the probability of resource availability on high fire count days. I extended the standard response framework to examine how a policy priority influences the optimal spatial allocation and performance of initial attack resources. I found that the policy goal of a fire manager changes the optimal spatial allocation of initial attack firefighting resources on a heterogeneous landscape, especially, for the socio-economic value of a potential fire location. Furthermore, I investigated the tradeoff between the number of firefighting resources and the level of fire ignition prevention efforts mitigating the probability of human-made fires in the Republic of Korea where most fires are caused by human activities. I found that fire ignition prevention is as cost-effective as initial attack resources given the current budget in the Republic of Korea on reducing the expected number of fires not receiving the standard response. From the comparison of the California and Republic of Korea cases, I can identify “rules of thumb” to be followed when allocating IA resources in particular ecological and policy settings.

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Initial Attack Fire Suppression, Spatial Resource Allocation, and Fire Prevention Policy in California, the United States, and the Republic of Korea

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I understand that my dissertation will become part of the permanent collection of Oregon State University Libraries. My signature below authorizes release of my dissertation to any reader upon request.

Yohan Lee, Author

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"Shout for joy to the LORD, all the earth. Worship the LORD with gladness; come before him with joyful songs. Know that the LORD is God. It is he who made us, and we are his; we are his people, the sheep of his pasture. Enter his gates with thanksgiving and his courts with praise; give thanks to him and praise his name. For the LORD is good and his love endures forever; his faithfulness continues through all generations (*Psalm* 100)"

CONTRIBUTION OF AUTHORS

Jeremy S. Fried, Albers J. Heidi, and Robert G. Haight contributed to the writing and preparation of the manuscript “Deploying Initial Attack Resources for Wildfire Suppression: Spatial Coordination, Budget Constraints, and Capacity Constraints” (California case, Chapter 4 and 5 in this dissertation).

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1. INTRODUCTION

Over the past several decades, the area burned by large wildfires in the United States and the associated suppression costs have increased dramatically (Calkin *et al.* 2005; Littell *et al.* 2009). This increase in the size and cost of wildfires has presented a challenge to fire management agencies charged with protecting human life, property, and natural resources (Gebert *et al.* 2007). For example, in southern California recent fires, such as the CEDAR fire (2003) and the WITCH fire (2007) in San Diego, and the STATION fire (2009) in Los Angeles, burned extensive areas (i.e., 273,246 acres, 197,990 acres, 160,557 acres, respectively) and resulted in substantial suppression costs and property losses (i.e., 2,820, 1,650, and 209 structures, respectively). Furthermore, the synchrony of large wildfires across broad geographic regions often contributes to budget shortfalls when suppression costs exceed the Congressional funds designated for these actions (Holmes *et al.* 2008, see Table 1-1). This threat to human communities and important ecosystems extends beyond the United States to many other countries, including the Republic of Korea (ROK)[1].

[1] The Republic of Korea is synonymous with South Korea. In this dissertation, I denote the name as ROK.

Table 1-1 CALFIRE E-Fund for emergency fire suppression: actual versus budgeted expenditures (unit: millions).

	2005-06	2006-07	2007-08	2008-09	2009-10
Budgeted amount	95	95	82	69	182
Actual amount	93	169	372	437	256
Amount Over/Under Budget	-2	74	290	368	74

(Source: Legislative Analyst's Office (LAO), 2010)

Fuel build-up over several decades, as a result of effective fire suppression, is a contributing factor to the severity of fires in the western United States. High densities of people and high structural values throughout an extensive wildland-urban interface leads fire managers to prioritize aggressive initial attack fire-fighting as the preeminent strategy for preventing large and costly wildfires. Although a combination of demographic, topographic, and meteorological factors makes the problem of regional wildfire management difficult, the issues facing all types of forest owners are qualitatively similar around the world.

Initial attack (IA) is the strategy most relied upon to prevent large and costly wildfires. It has long been understood that vigorous, rapid IA can contain a fire quickly before it becomes large and causes substantial damage (Parks1964). IA is generally defined as the first one to eight hours of fire suppression effort, during which the primary objective is containment of the fire at a small size in the shortest possible time (National Wildfire Coordinating Group, 2008). Examples of fire suppression resources used for initial attack include fire engines, bulldozers, hand crews, and water-dropping helicopters. The types and numbers of suppression resources used in initial attack vary depending on the difficulty of building fire-line through vegetation fuels at a fire location and the fire weather (humidity, temperature, wind speed) that drives fire behavior on a given day.

For IA resources, fire planners and managers make three types of allocation decisions: locating bases, deploying resources to those bases, and dispatching resources to fires (Martell 1982). First, they allocate fire-fighting resources to their home bases at the start of the fire season. Then, they deploy resources to meet expected demand for fire suppression in the coming days, weeks, or months. As fires occur, fire managers dispatch those resources to achieve the earliest possible containment, while taking into account the possibility of overlapping fire ignitions. In my dissertation, I focus on deploying resources to bases and dispatching them to fire locations on a daily basis over a landscape. While most fire managers have a clearly defined goal of minimizing the amount of unwanted fire loss, they face substantial uncertainty about the number, location, and intensity of fires and they have limited funds to acquire new suppression resources or construct new operating bases. As a result, fire managers must efficiently deploy costly firefighting resources across dispersed locations with considerable uncertainty about where fires will occur and how difficult they will be to control.

Both simulation and optimization models aid resource deployment and dispatch (Martell 1982; Martell 2007). Location specific deployment and dispatch rules are evaluated using simulation models that include stochastic properties of fire suppression tactics, dispatch policies, fire behavior, and fire-line production rates (Fried and Gilless 1999; Fried *et al.* 2006). Consequently, simulation results may include infrequent but consequential combinations of conditions that can lead to highly undesirable outcomes. While simulation models are excellent for exploring the impact of marginal changes to the system, or even for "test-driving" entirely new system designs, they are not suited for identifying optimal deployment and dispatch policies because their complex, non-linear and stochastic structures are difficult to include in optimization algorithms.

Optimization models often address deployment and dispatch decisions as separate problems. Deployment models distribute suppression resources to stations in order to minimize operating costs while meeting predefined resource requirements in surrounding areas (Hodgson and Newstead 1978; Greulich and O'Regan 1982). Dispatch models typically address a single fire and determine the number and type of suppression resources to dispatch in order to minimize suppression cost plus damage subject to resource availability constraints (Kourtz 1989; Mees *et al.* 1994; Donovan and Rideout 2003). Neither of these types of optimization models account for uncertainties in fire occurrence or behavior.

Recent studies developed a two-stage stochastic integer programming (SIP) model that optimizes both deployment and dispatch decisions while accounting for uncertainty in number, location, and intensity of fires (Haight and Fried 2007; Hu and Ntaimo 2009). The model includes the locations of fire stations and possible locations of fires along with travel times between stations and fires. Ignition uncertainty is characterized with a set of fire scenarios, each listing the location and intensity of fires that could occur in a single day. Resources are deployed to fire stations before the number, location, and intensity of ignitions are known and dispatch takes place contingent on the fire scenario. These SIP models are an example of scenario optimization (or robust optimization) in a maximal covering problem for emergency service deployment. In this dissertation, I combine a scenario-based, standard optimization model with a stochastic simulation model of initial attack to improve the efficiency of the deployment of fire suppression resources. The objective is to minimize the expected number of fires that do not receive a standard response – defined as the required number of IA firefighting resources that can reach the fire within a maximum response time – subject to a deployment budget.

Although IA fire suppression is effective, it is costly. Fire prevention activities can improve the efficiency of active fire management by reducing the daily demand for fire suppression resources. In general, the fire prevention policy implies three types of activities: fuel management, structure protection, and ignition prevention. Fuel management implies the modification of wildland vegetation by area-wide or strip (fuel break) conversion to reduce the rate of fire spread or the intensity of a fire. Within this class of activities are the prescribed-burn and let-burn policies, which have received more attention recently because of the recognition of the constructive role of fire in natural ecosystems (Turner 2003). Structure protection reduces property loss (e.g., housing) through creating defensible space[2]. Ignition prevention activities include the use of education, laws, penalties, inspections, and activity regulation by restricting the number and kinds of users on public wildlands during high fire season. A fire ignition prevention policy is adopted differently across regions because some fire prevention policy is infeasible due to social costs or a lack of cooperation from nearby human communities.

The core objective of this dissertation is to investigate the optimal spatial allocation of IA resources to bases given limited budgets in California and the ROK. I assess how deployment and dispatch decisions obtained with the optimization model affect IA success relative to the performance of an existing resource deployment that is based on expert knowledge and experience. Then, I examine how changes in station capacity and budget constraints affect resource

[2] "Defensible space" improves a home’s chance of surviving a wildfire. Defensible space is the buffer a home(or other types of structure) owner creates between a building on the property and the grass, trees, shrubs, or any wildland area that surround it. This space is required to slow or stop the spread of wildfire and it protects a home from catching fire.

deployment decisions and IA success. Furthermore, I investigate forest fire management in the ROK by applying sophisticated models developed to inform policy in California. California and the ROK share important policy goals for containing and suppressing fires, but differ in terrain, vegetation, and current policy settings. This analysis brings insights from the ROK experience to bear on western US forest fire policy and explores the general applicability of the modeling framework to other ecological, fire, and policy settings in the two regions. I also extend the optimization framework to examine how a policy priority influences the optimal spatial allocation and performance of IA resources. Finally, I investigate the trade-offs between investments in fire ignition prevention for reducing the rate of fire ignitions caused by human and IA firefighting resources for reducing the number of fires that do not receive a standard response, by conducting sensitivity analyses on parameters (e.g., seasonal rate of fire ignition).

The main purpose of my study is to provide information to fire managers about how to effectively deal with changes in the suppression budget and how those changes will affect their measures of performance for IA. In the era of declining budgets, this study has a critical importance because IA resources are costly despite their usefulness. This study also examines how fire prevention efforts influence the effectiveness of IA fire suppression, which allows me to measure the tradeoffs between IA fire suppression and fire ignition prevention. In particular, I look at a specific fire prevention activity in the ROK: fire ignition prevention, achieved by restricting human access on wildlands, as a representative fire prevention policy. Thus far, no study to date has attempted to clarify the relationship between fire ignition prevention mitigating the probability of fire ignitions, and IA firefighting for assessing the trade-off between them in a real setting.

In chapter 2, I summarize the relevant economics and forestry literature on wildland fire suppression, operations research methods, natural hazards, and wildfire policies in the United States (US) and the ROK. The conceptual framework of my study is described in chapter 3. A synergistic, stochastic simulation and an optimization model to improve the efficiency of the spatial allocation and configuration of resources for IA on wildland fires are described in chapter 4. Results from the model for the base case and from the sensitivity analysis are presented in chapter 5. I describe the policy implications for international wildland fire management in chapter 6. Finally, a discussion and conclusions are described in chapter 7.

2. LITERATURE REVIEW

2.1. Overview

To optimize the spatial allocation of IA firefighting resources in California and the ROK, I developed a scenario-based, standard response model that builds upon previous studies modeled IA fire suppression planning and forest management decisions under fire risk. I used both an economic framework and operations research techniques to show hot effectiveness could be improved for a given budget. A thorough analysis of the effect of IA fire suppression planning and fire prevention decisions on the effectiveness of wildland fire suppression in California and the ROK requires the width of an understanding of literature in the following subjects: wildfire economics, simulation and optimization modeling of assignment of IA firefighting resources, California Fire Economics Simulator Version 2 (CFES2), endogenous wildfire and natural hazards, and wildfire policy in the US and the ROK.

I gained insight from literature on the least cost plus loss analysis framework and advanced economic models of wildfire risk in the field of wildfire economics. Operations research models provide information on advanced simulation and optimization methods to address questions of finding strategic IA resource deployments for the Californian and Korean cases. CFES 2 captures stochastic properties of firefighting tactics, dispatch policies, fire behavior, fire-line production rates, and the marginal changes to the system of IA fire suppression in California. Previous research on wildfire and natural hazards provide insight for how to incorporate fire risk into my model. The international wildfire policy literature offers insight into the current and potential role of government regulation in California and the ROK in order to mitigate the risk of wildland fires growing large and damaging. The contributions of this dissertation derive from applying the combination of simulation and optimization models for multiple purposes on a flammable landscape for effective fire protection.

2.2.Wildfire Economics

In the early stages of wildland fire planning in the United States, economic theory contributed to the rationale for planning public wildfire management budgets. In response to a 1978 congressional mandate that requires benefit-cost analysis of future budget plans, the USDA Forest Service developed the National Fire Management Analysis System (NFMAS)[3] (Pyne *et al.* 1996). NFMAS was

[3] W.N. Sparhawk (1925) laid the early foundation for the NFMAS. He established the basic efficiency principles, based on least protection costs plus losses ($LC+L$) incurred by wildfire (Sparhawk 1925). However, it ignored what was known about the beneficial effects of wildfires, which may result in overestimated damages. The NFMAS refines Sparhawk's approach and estimates the most cost efficient fire management program mix, which meets resources management objectives and provides the necessary level of protection to life, property, and resources. Costs include both preparedness and suppression; net value change accounts the benefits and damages of wildfire on natural resources and improvements.

the first operational model based on the Cost Plus Net Value Change (*C+NVC*) theoretical framework (Baumgartner and Simard 1982; Donovan and Rideout 2003a), which minimizes suppression costs and fire damage as a trade-off against pre-suppression costs. NFMAS is designed to assess the most efficient mix of fire-fighting resources for a given preparedness budget level. Since NFMAS was developed, other wildfire planning models that are less closely tied to economic theory have been developed. Mendes (2010) indicates that economic thought has been absent from fire suppression despite abundant operational fire studies. The previous wildfire literature failed to apply a multi-disciplinary approach to their studies, or even deduce how and where, economic tools may improve firefighting.

During the last decade, some economists have proposed model improvements to the long-enduring *LC+L* minimization model to the *C+NVC* model (Donovan and Rideout 2003a; Donovan and Brown 2005; Donovan *et al.* 2008). Donovan and Rideout (2003a) identified two errors in the *LC+L* model formulation: (1) suppression is illogically treated as a model output; (2) suppression and primary protection are incorrectly modeled as negatively correlated. They suggest a corrected graphical conceptual model of those different expenditure types which helps to identify the optimal level of fire management expenditure. By applying the *C+NVC* model framework, Donovan and Rideout (2003b) determined the specific mix of firefighting resources for a given fire that minimizes *C+NVC*. They showed that the most efficient wildland firefighting organization can be characterized mathematically utilizing an integer programming model. Furthermore, Donovan and Brown (2005) demonstrated that an alternative incentive system can encourage fire managers to contain costs and consider the beneficial effects of wildfire, as they work to limit wildfire damages.

Even though the *C+NVC* model is widely accepted, empirical studies were rarely conducted to solve real problems until 2006 (Lankoande and Yoder 2006). Empirical economic approaches often require large datasets because many different variables influence the decision-making process. The need to design more efficient forest fire management practices and the advances in computing power have led economic researchers to develop empirical studies that emphasize the use of economic models in the design and implementation of efficient and cost-effective prevention and forest fire management strategies (Kline 2004; Riera and Mogas 2004; Loomis *et al.* 2003; Prestemon *et al.* 2001; Cleaves *et al.* 2000).

Recently, some economists have investigated wildfire issues that include three themes: spatial externalities associated with fires, institutional incentives (e.g., liability, insurance, and regulations) for private and public landowners' decisions under fire risk, and the development of decision tools for optimal fire management. Spatial externalities arise because fire spreads. Any fire management or harvesting decisions that are made in a unit affect the fire risk associated with adjacent units (Konoshima *et al.* 2008; Crowley *et al.* 2009;

Konoshima *et al.* 2010; Busby and Albers 2010). Studies of efficient institutional incentive systems on fire manager's (or forest owner's) activities are further complicated by the fact that fire management in a landscape, especially around the Wildland Urban Interface (WUI), involves multi-stakeholders with different preferences and financial goals (Yoder *et al.* 2003; Yoder 2004; Donovan and Brown 2005). Risk-based decision support tools for fire management have contributed to mitigating wildfire risks in highly valued resources (Thompson and Calkin 2011).

2.3. Operations Research in Deployment and Initial Attack Dispatch Decision-making Problems for Fire Suppression

Researchers in the area of Operations Research (OR) have actively developed simulation and optimization models that support fire managers in decisions regarding deployment and dispatch of IA resources to wildland fires. In order to address fire management problems in practice, simulation and optimization models are becoming more sophisticated with the advance of computational technology. Deployment and dispatch of IA firefighting resources represent a spatial queuing system that includes probabilistic fire occurrence and growth, policies for dispatching resources to fire locations, and stochastic fire line production rates (Martell *et al.* 1998; Haight and Fried 2007).

Deploying and dispatching suppression resources have been considered as separate problems with insufficient consideration given to stochastic fire occurrence and behavior (Martell 2007). Deployment models assign suppression resources to stations so as to minimize operational costs while meeting resource requirements within stations' service areas (MacLellan and Martell 1996). Dispatch models determine the number and type of suppression resources to send to fire locations in order to minimize the sum of suppression costs and fire damages, subject to resource availability constraints (Kourtz 1984; Mees *et al.* 1994; Donovan and Rideout 2003). Still, resolution of deployment and dispatch problems is critical to fire managers, especially, given the increasing centralization of fire protection agencies, as fire agencies are compelled to “do more with less” (Martell 2007). Recent models attempt to employ a scenario-based, standard response framework that optimizes both daily deployment and dispatch decisions, while simultaneously accounting for uncertainty surrounding the number, location, and intensity of fires (Haight and Fried 2007, Lee *et al.* 2013).

Incorporating IA simulation models into optimization algorithms poses challenges to OR researchers due to the complexity of the IA system that resists distillation to a few core variables and relationships. Fire simulation models include detailed representations of the IA process (e.g., Islam and Martell 1998; Fried and Gilless 1999), whereas fire suppression optimization models have been developed to address the deployment and dispatch of fire-fighting resources (Martell 1982). Even though recent studies try to develop an integrated model that includes both simulation and optimization processes in an effort to address deployment and dispatch decision problems for IA firefighting resources, the simulation aspect of the integrated model tends to be oversimplified and misses potentially important details, which produces unreliable results (Hu and Ntaimo 2009). Haight and Fried (2007) suggest that using a scenario-based standard response model allows them to avoid the issue by assuming that a fire is less likely to be a large fire if the fire gets a standard response within a defined window of time.

In my dissertation, a scenario-based, standard-response optimization model is combined with a stochastic simulation model to improve the efficiency of resource deployment for IA on wildland fires across a landscape. Current studies address the problem of dimensionality by ignoring the spatial and temporal correlation of weather (MacLellan and Martell 1996, Martell 1998). My model considers spatial factors by assuming that the chiefs of different fire planning units are cooperative, and will allocate firefighting resources to fire bases across a landscape to improve the effectiveness of IA firefighting resources.

2.4.The California Fire Economics Simulator Version 2

CFES2 is a computer program that performs a stochastic simulation analysis of the IA system on wildland fires (Fried and Gilless 1999). CFES2 includes considerable operational detail and is designed to support decision-making in wildland fire protection through the quantitative analysis of the potential effects of changes to the wildland fire management system (Fried *et al.* 2006). Examples of parameters that can be varied include the availability and stationing of resources; rules for the level of dispatch; schedules for when fire-fighting resources are staffed and available; and deployment and fireline-building tactics. The CFES2 model can be used to evaluate the effectiveness of several types of IA resources, alternative allocations and dispatching rules for suppression resources, and multi-unit and multi-agency cooperation.

CFES2 contains five program modules: occurrence (Fried and Gilless 1988), behavior (Gilless and Fried 1999), dispatch, fire-line production rate (Fried and Gilless 1989; Gilless and Fried 2000), and containment (Fried and Fried 1996). To generate the key parameters for each modeled fire, Monte Carlo selections (i.e., random draws) are used from mathematical frequency distributions generated from the historical data. Occurrence, behavior, and fire-line production rates are represented as stochastic processes, using parameters estimated from historical data. While containment and dispatch use data generated by the stochastic modules, those processes are modeled as deterministic in

CFES2. CFES2's emphasis on stochastic representation reflects its purpose of explicitly considering the variability in IA effectiveness from fire to fire, day to day, and year to year.

As an event-driven, clock-based simulator, CFES2 produces IA information one day at a time, progressing through the calendar year (Fried *et al.* 2006). For each simulated fire day, the occurrence module determines whether or not fires occur. The simulation clock changes to the next day if no fires occur. Once any fires occur, the occurrence module determines the number of fires, and the time(s) of day when they start. To generate a time-of-day adjusted rate of spread and dispatch index for each fire, the behavior module selects a 2 p.m. behavior index for the day. As each fire occurs, the dispatch module identifies the closest IA resources to dispatch, while considering resources unavailable due to earlier commitment to another fire or to maintenance. Resource response times are calculated from each firefighting resource station to each fire location. As dispatched IA resources arrive at a fire, the fire-line production rate module assigns a production rate to each resource, and the containment module evaluates the cumulative interaction of fire behavior and containment efforts. A final fire size is calculated and reported for fires that would be contained within simulation size and time limits, along with total fire-line production. When all of the day's fires have been contained or escaped, the simulation clock is advanced to the next day and the process repeated for a calendar year. At the end of a year of simulated fire activity, the simulation clock is reset to January first. Fried *et al.* (2006) showed that statistical characterizations of natural variation in fire occurrence, fire behavior, and the effectiveness of IA efforts under different stationing and dispatch policies, conditions of resource availability and fuel management programs can be assessed by examining the results of many simulated years in CFES2.

2.5.Endogenous Wildfire and Natural Hazard Risk

In environmental and resource economics literature, many studies account for the risk of natural hazards in their decision models (Ehrlich and Becker 1972, Shogren and Cocker 1991, Shogren and Crocker 1999, Finnoff *et al.* 2005). Endogenous risk implies that a decision maker can affect the risk he or she faces through control variables. Ehrlich and Becker (1972) build a model for endogenous risk by defining self-protection, which reduces the probability of a hazardous event, and self-insurance, which reduces the severity of damage coming from the hazardous event. Shogren and Crocker (1999) suggest that human actions and reactions have impacts on the likelihood and the severity of events. Considering individuals’ ability to manage the risk they face in an endogenous risk model has a critical importance in order to avoid making sub-optimal management decisions (Shogren and Cocker 1991; Finnoff *et al.* 2005).

In the forestry literature, wildfire researchers recently began adopting endogenous fire risk frameworks in their studies (Amacher *et al.* 2005; Konoshima *et al.* 2008; Crowley *et al.* 2008). Previous studies suppose fire risk is exogenously given (Martell 1980, Routledge 1980, Reed 1984). The consideration of fire risk as endogenous in a model can result in a different solution from studies that assume that fire risk is exogenous.

Furthermore, Konoshima *et al.* (2008), Crowley *et al.* (2008), and Busby and Albers (2010) extend their models to incorporate multiple stands in order to address the spatial dimension of fire risk across a landscape. Konoshima *et al.* (2008) take into account the spatial externalities associated with fuel treatments across stands and uses a spatially explicit, dynamic optimization model to find the optimal spatial allocation and level of harvest and fuel treatment effort, in particular, for a small, stylized landscape. Crowley *et al.* (2008) and Busby and Albers (2010) build spatially explicit game theoretic models to explore the strategic interaction of fuel treatments between stakeholders' choices on a landscape with multiple types of landowners. In those studies, authors have simplified either the landscape or the representation of fire behavior to reduce the computational load of optimization approaches.

To optimally manage natural resources under the risk of hazard, recent studies suggest reducing the risk of hazard through proactive hazard management

(Amacher *et al.*2005; Finnoff *et al.*2007). Finnoff *et al.* (2007) suggest that managers need to take a risk with regards to prevention in order to maximize social welfare. In wildfire management literature, previous studies have focused on the effects of fuel treatments on forest management and wildfire suppression (Amacher *et al.* 2005; Konoshima *et al.* 2006; Crowley *et al.* 2008; and Busby and Albers 2010). However, the implication of other preventative fire management actions, such as ignition prevention, on the current risk of fire and varying types and levels of fire suppression effort remain unexplored.

In my dissertation, the probability of fire is first considered exogenous, but later the probability of fire is assumed to be controllable by fire prevention efforts, specifically where human-made fires are dominant like the ROK. My model supposes that fire ignition prevention efforts directly influence the probability of fire ignition caused by human activities, which implies that fire risk can be altered by human choices.

2.6. International Fire Policy: the United States and the Republic of Korea

US fire policy

The suppression of forest fires dominated early US Forest Service policy. For example, in 1935, the 10 AM policy indicates (Gorte and Gorte 1979, p. 2):

> "*The approved protection policy of the National Forests calls for fast, energetic, and thorough suppression of all fires in all locations, during possibly dangerous fire weather. When immediate control is not thus attained, the policy calls for prompt calculating of the problems of the existing situation and probabilities of spread, and organizing to control every such fire within the first work period. Failing in this effort, the attack each succeeding day will be planned and executed with the aim, without reservation, of obtaining control before ten o'clock the next morning*."

However, the suppression policy that was adopted after the 1910 fires, in conjunction with the 10am policy, produced forests with high fuel loads, and, as a result, forests fires have trended towards higher intensity and larger size. This result instigated a series of policy changes in the 1970's (Stephens and Ruth 2005). The realization that not all (Calkins *et al.* 2005) suppression expenditures could be economically justified, along with an increasing awareness of the ecological importance of wildfire, led the US Forest Service to adopt the Wilderness Prescribed Natural Fire Program in 1972 (Dale *et al.* 2005).

Federal forest-fire policy in the US has been modified since recognizing and embracing the role of fire as an essential ecological process in the mid-1990's

(Stephens and Ruth, 2005). Stephens and Ruth (2005) emphasize that multiple legislative administrative efforts, such as the National Fire Plan (USDA-USDI 2000), the Healthy Forest Initiative (2002), and the Healthy Forests Restoration Act (HFRA 2003), provided support for reducing fuels to mitigate the risk of wildfires. Nevertheless, there is little in the way of comprehensive policy to deal with fire and fuels, nor is such policy in development (Franklin and Agee 2003). This emphasizes the need for research on the tradeoffs between the costs and benefits of wildfire risk reduction. Moreover, only a few studies are available to provide credible information on the range of feasible strategies for decreasing the risk of wildfires through fuel treatments.

In summary, recent US fire policy has emphasized not only the effectiveness and efficiency of fire suppression, but also its impacts on ecosystems. IA is still the dominant management approach applied to fire-prone landscapes because it is very effective to contain fires quickly and prevent them from becoming large fires, albeit expensively (approximately 97 – 99% of all wildland fires are successfully suppressed during IA (Arienti *et al.* 2006)), although other fire management strategies such as prescribed burning and mechanical thinning are employed in practice. Dale *et al.* (2005) suggest that fire policy should be changed to reflect a more refined index of threats, potential harm, and possible effectiveness by regional conditions. As public fire agencies spend increasingly large sums on fire suppression, the budgetary problem has become more urgent (Donovan *et al.*2008). O'Toole (2006) indicates that most fires will be allocated an excessive amount of suppression resources as long as there is a blank check for emergency fire suppression expenditures. To achieve fire management goals efficiently, Donovan *et al*. (2008) suggested that incentive systems for fire prevention activities such like fuel treatment need to be applied and also studied further. In 2009, the most up-to-date national fire policy, the Federal Land Assistance, Management, and Enforcement (FLAME) Act[4] was enacted to address problems with excessive wildfire suppression emergency costs, yet the effect of FLAME Act has not yet been observed in studies. The policy may contribute to anticipating actual funding requirements fully for wildland fire suppression and preventing future borrowing from non-fire programs.

Korean fire policy

Since the establishment of the ROK in 1948, the Korean government has maintained an effective suppression policy on wildland fires because they pose a serious threat to human lives and property (Yoo 2006). Korean forests are highly susceptible to fires because of their ecological structure and topographic and climatic conditions (Lee 2005; Lee *et al.* 1999; Lee *et al.* 2006). The Korean

[4] Federal Land Assistance, Management, and Enhancement Act of 2009 (FLAME), Public Law 111-88, Title IV, enacted October 30, 2009. This Act authorizes the establishment of the FLAME Wildfire Suppression Reserve Fund for the Department of Agriculture. Many Congressional organizations interested in solving the ongoing and increasing issues with wildfire suppression emergency costs helped the FLAME Act to be enacted.

Forest Service (KFS) has established a systematic and cooperative system for forest fire control by focusing on the reduction of forest fires started by people, and the early detection of, and rapid response to, forest fires by helicopters and crews (KFS 2005).

The causes of forest fires are mainly anthropogenic (e.g., visitors to the mountains and graves (>50%), burning rice fields and farms (>18%), cigarette smoking (>10%)) (KFS 2010). In particular, to prevent fire ignitions precautionary policies by central and local governments include the prohibition on bringing flammable materials into forests, controls on forestland access by closing forest roads during the peak fire season, and the use of a forest fire warning system in certain weather conditions (Yoo 2006). Once a fire ignites the early detection of forest fires and quick initial response play a crucial role in the successful suppression of a fire before it escapes. Through patrolling, the Korean Forest Service can control human access to forest areas and detect fire ignitions more quickly.

Despite of the need for research in the field of fire economics and policy, few studies have been conducted in the ROK (Youn 2000). Thus far, most studies focus on the ecological impacts of forest fires on forest lands, and fire behavior and its characteristics (Lee *et al.* 2006; Kwak *et al.* 2010; Lee *et al.* 2009). In particular, Lee *et al.* (2009) classified potential fire locations into 5 clusters by fire susceptibility, which were based on fire occurrences, burned area, rate of spread, and burned area per fire between 1991-2007. Recently, some researchers have begun to look at the economic impacts of forest fires on local communities and their economies (Lee *et al.* 2007; Youn 2000). However, these studies do not address fire policy and management issues. Because of the ROK's mountainous terrain and poor forest roads, the KFS focuses on using helicopters to suppress fires quickly (Kim and Lee 2006). Thus, the urgent need to improve the effectiveness of IA firefighting with helicopters calls for investigation. Furthermore, the economic tradeoff between preventative fire management benefits and costs remains unexplored in the ROK.

2.7.Summary

In the field of wildfire studies, fire researchers have addressed many realistic problems using available science, in particular using economics and operations research (OR). In the OR studies, simulation and optimization models have been used to address fire management problems. Due to the computational requirements, fire simulation models have not been incorporated into optimization algorithms. The next step in this progression of research is to study the operational plan of initial-attack firefighting on a landscape by using a synergistic, combined optimization model with simulation. In addition, investigating the tradeoffs between the benefits and costs of wildfire risk reduction remains open. Thus, another step in the progression of research is the study of the tradeoff models between alternative fire management strategies on a landscape. Decision models, including endogenous fire risk, may determine the optimal level of fuel treatment and ignition prevention in a flammable landscape where human caused fires are dominant. The results of these sophisticated fire management decision models can provide new insight into optimal fire management policy. Taking the next step within this body of work will shed light on the area of wildfire management and planning on flammable landscapes to address wildfire risk.

3. CONCEPTUAL FRAMEWORK

In order to maximize the number of fires that are successfully contained before unacceptable costs and damages occur, fire managers deploy firefighting resources to stations and then dispatch the resources to fires. Fires that are not contained in the early stages of fire suppression are more likely to become large fires, which cause the most damage. For instance, most of the area that burns occurs in the large fire classes; large fires, which include only 1.1% of all fires, account for 97.5% of the area burned in the US (Calkin *et al.* 2005). A strong and prompt IA is most effective in successfully containing a fire within a prescribed time window, which increases the chance of preventing the fire from escaping and becoming a large fire (Arienti *et al.* 2006). However, because IA resources are costly, fire managers need to allocate and operate IA firefighting resources efficiently in the face of uncertainties surrounding the timing and location of fires.

Deploying IA resources to satisfy the expected demands for fire suppression is critical to achieving the fire manager’s goal. In this study, the capability for IA is represented by the ability to provide a "standard response," defined as the required number of resources that can reach the fire within a maximum response time (e.g., 30 minutes or 60 minutes), to potential fire locations. Thus, the objective in the optimization problem is to minimize the expected number of fires that do not receive a standard response subject to resource availability constraints.

3.1. Basic Framework

In this section, I develop a conceptual framework that allocates IA firefighting resources across stations in order to minimize the number of fires that do not receive a standard response with a budget constraint. First, I assume that a single fire manager makes a decision on a fire planning unit (FPU). Then, I investigate whether sharing suppression resources between FPUs affect the optimal allocation of resources among stations by extending the optimization model for multiple FPUs. Previous optimization models that address initial attack are designed to address a single planning unit (e.g., Donovan and Rideout 2003; Haight and Fried 2007). Modeling planning units as independent may result in a sub-optimal solution, when resources are, in reality, widely shared among adjacent fire planning units. The probability of fire in the FPU is exogenous.

3.1.1. A single fire planning unit

The fire manager's objective is to minimize the expected number of fires that do not receive a standard response within a given budget limit for a single FPU. Mathematically, the objective function is represented as follows:

$$\min_{x_{ij}} NFNSR = f\left(x_{ij}\right) \quad (3\text{-}1)$$

$$s.\ t.\ c_i * \sum_{j=1}^{J} x_{ij} \leq B \quad (3\text{-}2)$$

Where:

i denotes the index of IA resource types;

j denotes the index of IA stations;

$NFNSR$: number of fires not receiving a standard response;

x_{ij}: amount of IA resources by type and station;

c_i: unit cost of IA resource by type.

In the optimization problem, a fire manager chooses the number of IA resources by type and station. By determining the optimal level of resources, the fire manager can maximize the effectiveness of IA fire suppression for a given budget. To find the optimal number of IA resources by type and station, the first order conditions are derived for the minimization as follows:

$$\mathcal{L} = f(x_{ij}) + \lambda(B - c_i * \sum_{j=1}^{J} x_{ij}) \tag{3-3}$$

$$x_{ij}: \quad \frac{\partial f}{\partial x_{ij}} = \lambda c_i \tag{3-4-1}$$

$$\lambda: \quad B - c_i * \sum_{j=1}^{J} x_{ij} = 0 \tag{3-4-2}$$

The first order conditions (FOC) state that the last unit *i* of IA firefighting resources that the decision maker obtains will yield the same level of marginal contribution (or marginal benefit) to the IA capability per dollar spent on other IA resources, as far as the budget is a binding constraint (i.e., $B = c_i * \sum_{j=1}^{J} x_{ij}$). This implies that the fire manager will choose the number of IA resources by type such that the marginal contribution per dollar on IA capability will be equal across all types of resources with the budget limit. For example, if the marginal contribution of a helicopter is larger than for other types of resources (e.g., engines and dozers) in the current allocation, the fire manager is willing to employ more helicopters by removing other types of resources that have a lower marginal contribution. When it comes to trade-offs among stations, the implication is also clear and simple: the fire manager will choose the number of IA resources by station such that the marginal contribution per dollar on IA capability will be equal across stations when the last unit of resources is added to a station.

3.1.2. Multiple fire planning units

The single FPU model is adjusted to determine the effect of modeling a single planning unit independently on the optimal solution, when, in reality, suppression resources are widely shared with adjacent fire-planning units. By constructing a multiple FPU model, I consider not only IA resources in an FPU, but also all available resources that reach any fire locations in the FPU from stations in adjacent FPUs. In the multiple FPU model, I first assume that FPUs are not cooperative, thus they do not share any resources. Second, I assume that FPUs are cooperative, thus they share any available resources between FPUs and also budgets.

No sharing of resources between FPUs

When I extend the framework to consider multiple FPUs, the model includes all available IA resources and stations in multiple fire planning units. The decision maker takes into account tradeoffs between IA resources by type and station within an FPU, as well as tradeoffs among FPUs. I assume that IA firefighting resources are not shared between FPUs. The model is modified as follows:

$$\min_{x_{iju}} \sum_{u=1}^{U} f_u(x_{iju}) \tag{3-5}$$

$$s.t.\ c_i * \sum_{j=1}^{J} x_{iju} \leq \sum_{u=1}^{U} B_u \tag{3-6}$$

Where:

u is the index of FPUs.

In the optimization problem, a fire manager determines the optimal number of IA resources by type, station, and unit. The optimality conditions are the same as they were in the case of a single, except they are expanded to account for multiple FPUs. The optimality conditions hold across multiple FPUs. That is, the marginal contribution per dollar on IA capability will be equal across resource types, stations, and units for the last IA resource (i.e., $\frac{\partial \sum f}{\partial x_{iju}} = \frac{\partial \sum f}{\partial x_{iju'}}$ (when $u \neq u'$)).

Sharing IA resources across FPU's

In this section, I assume that FPUs are cooperative and IA firefighting resources are actively shared between FPUs. I suppose that IA firefighting resources are shared only between adjacent FPUs because IA firefighting resources in a planning unit cannot arrive at a fire location in remote FPUs within the maximum response time. When IA firefighting resources are shared among adjacent FPUs, the marginal benefit of an IA resource in a management unit may be different from that of the previous case. Mathematically, the model is modified as follows:

$$\min_{x_{iju}} \sum_{u=1}^{U} f_u\left(x_{iju}, x_{iju'}\right) \tag{3-7}$$

$$s.t.\ c_i * \sum_{u=1}^{U} \sum_{j=1}^{J} x_{iju} \leq \sum_{u=1}^{U} B_u \tag{3-8}$$

Where:

u is the index of FPUs;

u' represents an FPU adjacent to u.

To find the optimal number of IA resources by type, station, and unit, the first order conditions are derived for the minimization problem with multiple fire planning units as follows:

$$\mathcal{L} = \sum_{u=1}^{U} f_u\left(x_{iju}, x_{iju'}\right) + \lambda\left(\sum_{u=1}^{U} B_u - c_i * \sum_{u=1}^{U} \sum_{j=1}^{J} x_{iju}\right) \tag{3-9}$$

$$x_{ij}: \quad \frac{\partial \sum_u f_u}{\partial x_{iju}} = \frac{\partial f_u}{\partial x_{iju}} + \frac{\partial \sum_{u'} f_{u'}}{\partial x_{iju}} = \lambda c_i \tag{3-9-1}$$

$$\lambda: \quad \sum_{u=1}^{U} B_u - c_i * \sum_{u=1}^{U} \sum_{j=1}^{J} x_{iju} = 0 \tag{3-9-2}$$

When the objective of a fire manager is to minimize the total number of fires that do not receive a standard response for multiple planning units (like Figure 3-1), IA resources are allocated between FPUs such that the last unit of IA firefighting resources will yield the same level of marginal contribution to the IA capability per dollar spent on other IA resources across FPUs (i.e., $\frac{\partial \sum f}{\partial x_{iju}} = \frac{\partial \sum f}{\partial x_{iju'}}$ (when u $\neq$ u')). For example, if $\left|\frac{\partial \sum f}{\partial x_{ij2}}\right| > \left|\frac{\partial \sum f}{\partial x_{ij1}}\right|$ (i.e., $\left|\frac{\partial f_3}{\partial x_{ij2}}\right| > 0$), more IA resources should be allocated to FPU 2 (Figure 3-1). Thus, ignoring the effects of sharing IA resources between management units may result in a sub-optimal allocation.

Two types of calculation problems can arise from modeling a single FPU. First, a fire manager can overlook the effect of sharing resources when, in reality, IA resources are widely distributed between adjacent units. As a result, the number of required resources in the model can be over-estimated. Second, if the framework assumes that resources in adjacent FPU's are always available, the fire manager fails to consider competition for them when fires occur in both units. Competition for resources should be represented properly in the model to avoid the under-estimation of required resources.

FPU 1	FPU 2	FPU 3
MB1: $\left|\frac{\partial f_1 + \partial f_2}{\partial x_{ij1}}\right|$	MB2: $\left|\frac{\partial f_1 + \partial f_2 + \partial f_3}{\partial x_{ij2}}\right|$	MB3: $\left|\frac{\partial f_2 + \partial f_3}{\partial x_{ij3}}\right|$

Figure 3-1 Three FPU's sharing IA firefighting resources with an adjacent unit.

3.1.3. Application to landscapes in California and the Republic of Korea

To apply the conceptual model to a landscape in California and the ROK, I built a mixed-integer programming model that optimizes both daily deployment and dispatch decisions, while accounting for uncertainty about the number, location, and intensity of fires. The model includes the locations of fire stations and the potential fire locations, along with the time required for travel between stations and fires. Ignition uncertainty is characterized by a set of fire scenarios, each listing the location and intensity of the fires that occur in a single day. In the next chapter, I will describe the simulation model to explain how I produced the set of fire scenarios. Resource deployment and dispatch decisions are included in a two-stage decision-making process. Deployment takes place at the beginning of the day or the fire season before the number, location, and intensity of ignitions are known. Dispatch takes place during each day of the fire season, contingent on the fire scenario. Due to dimensionality, it is impossible to solve the problem analytically at the landscape level with several types of resources. Instead I applied the optimization model to a real problem at a landscape scale and demonstrate the model by producing numerical solutions.

Furthermore, two extensions were also added to the analysis. First, the case when the value of the fire location to be protected is heterogeneous across a landscape is considered. I employed two weight systems: population and ecological importance. Second, I explored the relationship between IA fire suppression budget and subsequent fire prevention budge by considering the case when the probability of fire is reduced by fire prevention efforts. Based on the conceptual framework, I developed a theoretical model that includes IA fire suppression and fire ignition prevention as decision variables, and used the model to demonstrate the tradeoffs between IA fire suppression and fire ignition prevention. In particular, I conducted an empirical study that emphasizes the use of fire ignition control for implementing efficient and cost-effective fire prevention and forest fire management strategies in the ROK fire regimes by estimating the effect of fire ignition control policy on IA fire suppression.

3.2. Tradeoffs between IA fire suppression and fire ignition prevention

In this section, I investigate the tradeoffs between fire suppression and ignition prevention activities. First, I assume that the probability of fire ignition is decreased by fire ignition prevention efforts. Ignition prevention is effective on a landscape where most fires are caused by human activities and those fires can be controlled by restricting human activities in wildlands during a fire season. I constructed a conceptual tradeoff model of fire suppression and ignition prevention. Using the standard-response optimization framework, I verified the relationship between fire suppression and ignition prevention. To date, only a few researchers have studied the economic tradeoffs between fire suppression and fuel treatment for fire prevention (Amacher *et al.* 2006). However, no one has studied the economic tradeoffs between fire suppression and ignition prevention policy where human-caused fires are dominant.

The causes of forest fires are various, including both anthropogenic and natural drivers like lightning. As human demands increase on wildlands for recreational and residential development, the problem of human-caused fires is also expanding in many populated countries, including the ROK (Figure 3-2). In my dissertation, I focus on human-caused fires because only human-caused fires can be controlled, for example, by legal enforcement that can directly restrict the number of users and their activities in wildlands. For instance, it is common for fire observers to patrol forested areas during a fire season in the ROK in order to restrict human access to wildlands or limit their use of flammable equipment (e.g., cigarettes, lighters, and other cooking tools) in wildlands.

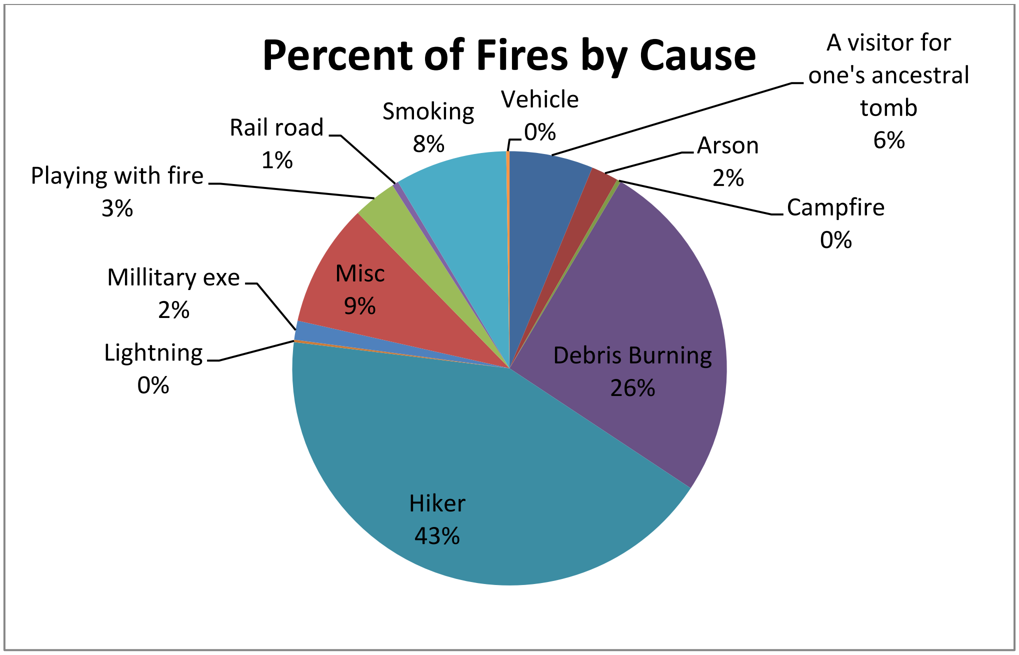


Figure 3-2 Percent of Wildland Fires by Cause during 1991 - 2007 (Source: KFS 2007)

3.2.1. Fire Risk and Fire Ignition Prevention Effort

My conceptual model posits that the probability of fires decreases as fire ignition prevention efforts, φ, grow. The parameter "probability of fire", P, describes the probability that a fire occur and is determined by the level of fire ignition prevention effort in the fire management unit:

$$\text{Probability of fire: } P = g(\varphi).$$

I assumed that the function of ignition prevention effort is convex because the marginal effect of ignition prevention effort decreases as the total amount of ignition prevention effort increases (Figure 3-3). Thus, the probability of fires decreases at an increasing rate, as ignition prevention expenditures increase (i.e., decreasing return to ignition prevention efforts).

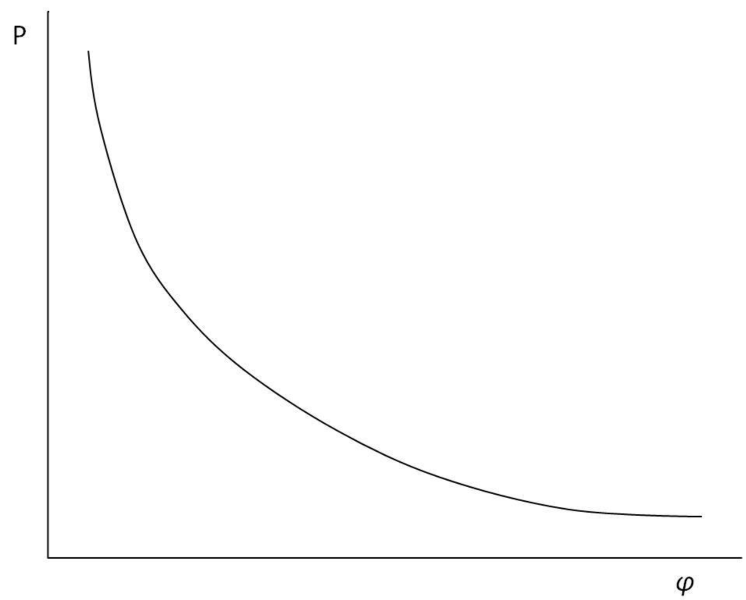


Figure 3-3 Probability of fire occurrence (*P*) is a decreasing function of ignition prevention effort (φ).

As the probability of fires, *P*, decreases, the number of fires not receiving a standard response decreases because a low probability of fire ignition increases the probability of resource availability, which allows IA firefighting resources to provide a standard response to a higher percentage of fires. Thus, I assume that the number of fires not receiving a standard response is an increasing function of the probability of fires. The function is modeled as a concave function of the probability of fire ignition (Figure 3-4). The number of fires not receiving a standard response increases at a decreasing rate, as the probability of fire ignition increases.

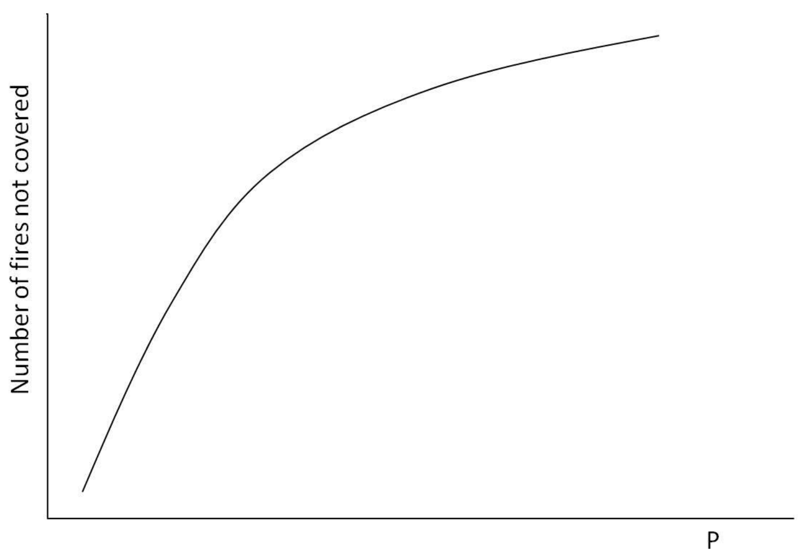


Figure 3-4 Number of fires not receiving a standard response is an increasing function of the probability of fires.

Consequently, an increase in ignition prevention effort reduces the number of fires that do not receive a standard response for a given level of suppression. Fire ignition prevention effort (φ) reduces the number of fire ignitions by limiting human-caused fires, thereby decreasing the demand on IA resources that provide a standard response to fire locations. With less demand, the percentage of fires that do not receive a standard response decreases because the availability of IA resources on a fire day increases for providing a standard response to fire locations. For example, the expected number of fires that do not receive a standard response increase in high fire count days, but decrease on lower fire count days with the same number of available IA resources. The objective value, f, describes the expected number of fires not receiving a standard response and is determined by fire ignition prevention effort, φ, on a landscape where human caused fires are dominant. For the objective value, $f'(\varphi) < 0$ and $f''(\varphi) > 0$ where prime denotes the derivative with respect to fire ignition effort, φ. The first and second order conditions imply that as effort increases, the expected number of fires not receiving a standard response decreases at an increasing rate[5]. The fire

[5] In this section, I assumed that the expected number of fires not receiving a standard response decreases at an increasing rate (a decreasing return to scale) as the amount of fire ignition prevention effort increase. From multiple optimization runs, I demonstrated this relationship in the results section (Figure 5-4). Otherwise, the expected number of fires not receiving a standard response may decrease at a constant rate or a decreasing rate (an increasing return to scale). If the fire ignition prevention policy has an increasing return to scale, the optimization problem has a corner solution and thereby a different result (Wu and Boggess 1999).

ignition effort describes the total effort for a given landscape. I assumed a constant cost of fire ignition prevention effort throughout this dissertation. As a result, the objective function is a decreasing return to fire ignition prevention expenditures, ε_{IP} (i.e., unit cost × amount of fire ignition prevention effort), which guarantees an interior solution (Figure 3-5).

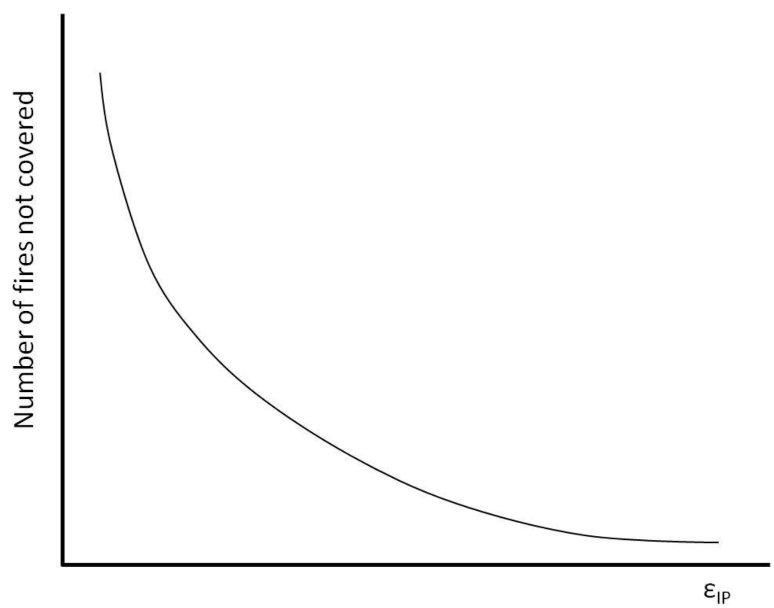


Figure 3-5 Number of fires not receiving a standard response is a decreasing function of the expenditures on fire ignition prevention (ε_{IP}).

3.2.2. Initial Attack Firefighting Resources

In this study, the IA capability is represented by the ability to provide a standard response to potential fire locations. As stated in the previous section, the objective is to minimize the number of fires that do not receive a standard response within the maximum response time limit (e.g., 30 minutes or 60 minutes). The capability for IA is enhanced by employing more IA firefighting resources, x. With more available firefighting resources, the fire manager can provide a standard response to more fire locations. For the objective value, I have $f'(x) < 0$ and $f''(x) > 0$ where prime denotes the derivative with respect to the number of IA firefighting resources, x. As a fire manager employs more IA resources, the expected number of fires not receiving a standard response decreases at an increasing rate, which was demonstrated in Figure 3-5. I also assume a constant cost of an IA firefighting resource throughout this dissertation. I denote the expenditures on IA resources as ε_{IA} (i.e., unit cost × number of resources). Then, the objective function is a decreasing return to the expenditures on IA resources, ε_{IA}, which guarantees an interior solution (Figure 3-6).

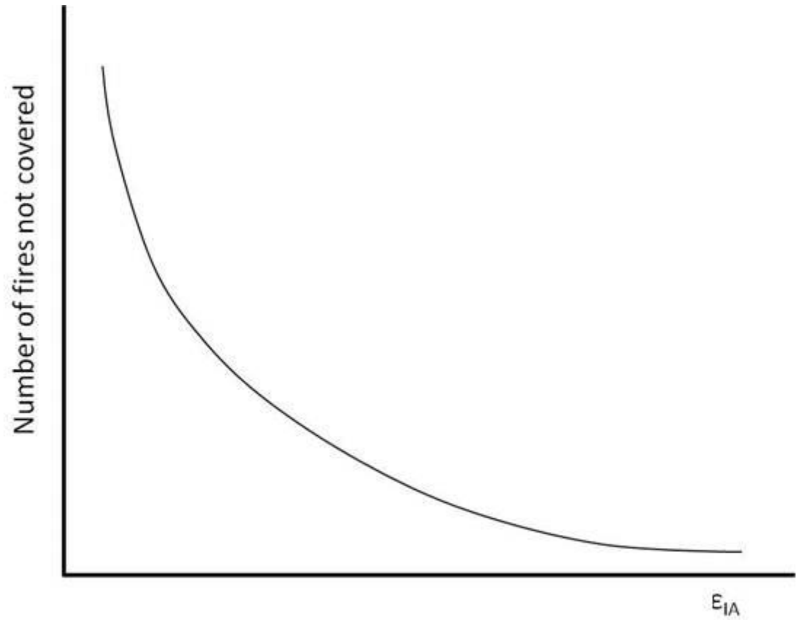


Figure 3-6 Number of fires not receiving a standard response is a decreasing function of the expenditures on IA resources (ε_{IA}).

3.2.3. Objective function

The objective is to minimize the number of fires that do not receive a standard response within a given budget. Mathematically, the objective function is represented as a function of the number of IA resources (x) and the amount of ignition prevention effort (φ) as follows:

$$\min_{x,\varphi} NFNSR = f(x, \varphi) \tag{3-10}$$

$$s.t.\ c_{IA} * x + c_{IP} * \varphi \leq B \tag{3-11}$$

where

$NFNSR$: number of fires not receiving a standard response;

x: number of IA resources;

φ: amount of ignition prevention effort;

c_{IA}: unit cost of IA resource;

c_{IP}: unit cost of fire ignition prevention effort;

B: budget.

The fire manager or other decision maker chooses the level of expenditures on IA resources and fire ignition prevention. By determining the optimal level of those expenditures, the decision maker can maximize the capacity for IA fire suppression for a given budget. To find the optimal level of those expenditures, the first order conditions are derived for the minimization as follows:

$$\mathcal{L} = f\ (x, \varphi) + \lambda(B - c_{IA} * x - c_{IP} * \varphi) \tag{3-11}$$

$$IA\text{:}\ \ \frac{\partial f}{\partial x} = \lambda c_{IA} \tag{3-12}$$

$$IP\text{:}\ \frac{\partial f}{\partial \varphi} = \lambda c_{IP} \tag{3-13}$$

The first order conditions (FOC) state that the last unit of fire ignition prevention efforts the decision maker obtains will yield the same level of marginal benefit (MB) on the IA performance per dollar spent on IA resources. This implies that the fire manager will choose the number of IA resources and the level of fire ignition prevention such that the marginal contribution per dollar on IA performance will be equal across all types of decisions.

In Figure 3-7, the optimal number of IA resources, x^*, changes as the level of fire ignition prevention effort alters the probability of fires. Thus, the optimal number of IA resources (x) can be represented as a function of the level of fire ignition prevention effort (φ). The functional relationship, *locus*, is modeled in Figure 3-7.

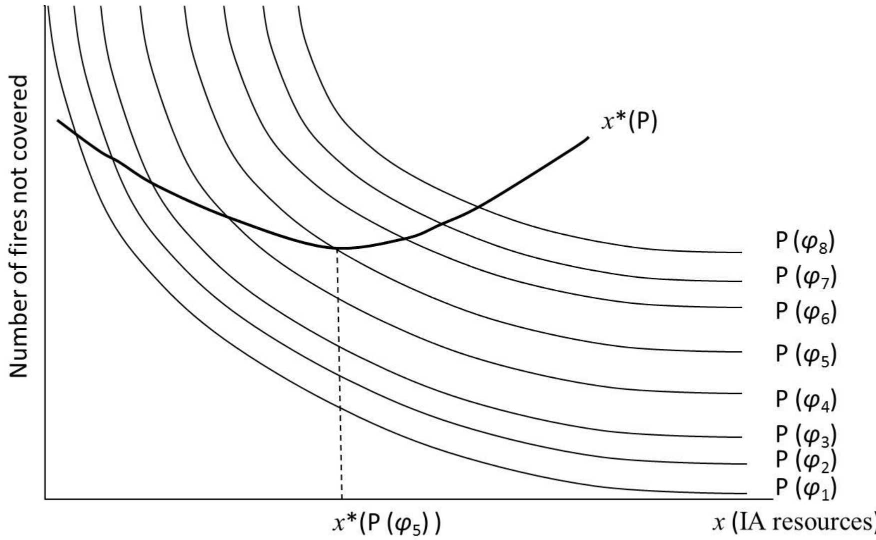


Figure 3-7 Relationship between number of fire not covered and IA resources for each level of fire ignition effort (where $\varphi_1 > \varphi_2 > \cdots > \varphi_3$ and $P_1 < P_2 < \cdots < P_8$).

3.2.4. Tradeoff between IA and IP

Given a budget (B), I define a tradeoff relationship between the expenditure of IA resources and the expenditure of IP as follows:

$$\varepsilon_{IA} + \varepsilon_{IP} = B$$

Where:

ε_{IA} represents the portion of the budget spent employing IA resources;

ε_{IP} represents the portion of the budget spent on fire ignition prevention activities.

As the fire manager spends more money on more IA firefighting resources, the number of fires not covered by IA standard response decreases due to an increase in available IA resources that can arrive at potential fire locations quickly. However, this reduces the number available for ignition prevention, which results in an increase in the number of fires not receiving a standard response. As more of the budget is allocated to employing IA resources, less of the budget is allocated to conducting fire ignition prevention, and vice versa. This relationship can be represented by the following figure (Figure 3-8).

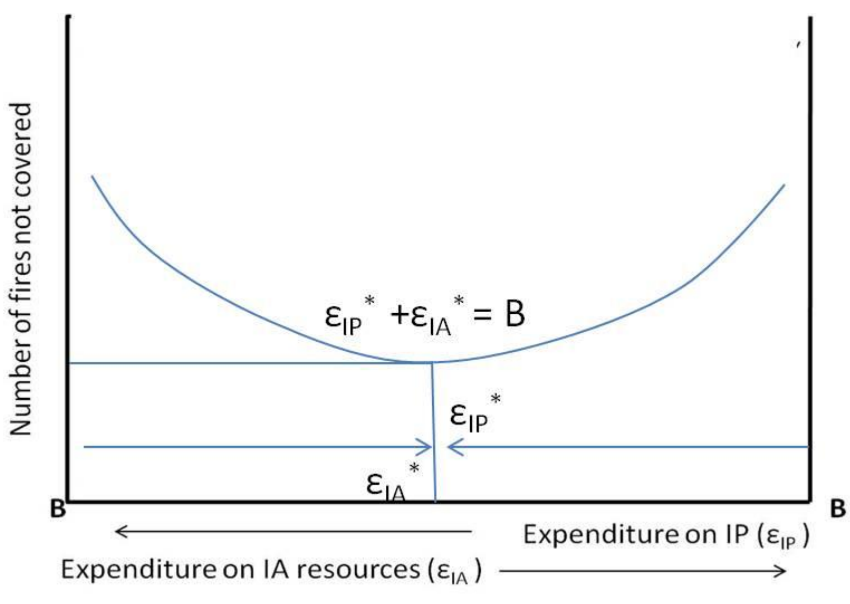


Figure 3-8 Tradeoff between the expenditure of employing IA resources (ε_{IA}) and the expenditure of implementing fire ignition prevention (ε_{IP}).

3.2.5. Finding the optimal solution

To derive the optimal conditions, I used a general functional form for the number of fires that do not receive a standard response as follows:

$$NFNSR = f(x, \varphi) = \kappa(x+1)^{-\eta}(\varphi+1)^{-\xi};\text{[6]} \tag{3-14}$$

Where:

$$\text{k} > 0,\ x \geq 0,\ \varphi \geq 0,\ \eta \geq 0, \text{ and } \xi \geq 0. \tag{3-15}$$

η and ξ represent the exponents of x and φ, respectively, which determine the extent of the marginal impacts of x and φ on the number of fires that do not receive a standard response.

Then, the objective function becomes as follows:

$$\min_{x,\varphi} f(x, \varphi) = \kappa(x+1)^{-\eta}(\varphi+1)^{-\xi} \tag{3-16}$$

$$s.t.\ \ c_{IA} * x + c_{IP} * \varphi \leq B \tag{3-17}$$

$$x, \varphi \geq 0$$

[6] This function satisfies $f'(x, \varphi)<0$ and $f''(x, \varphi)>0$.

The optimal conditions are derived by solving the optimization problem in terms of the fire manager's decision variables, including the amount of IA firefighting forces and the level of fire ignition prevention efforts. Based on the FOCs from equation (1), three equations are derived as follows:

$$\frac{\partial f}{\partial x}: \kappa(-\eta)(x+1)^{-\eta-1}(\varphi+1)^{-\xi} = \lambda c_{IA} \tag{3-18}$$

$$\frac{\partial f}{\partial \varphi}: \kappa(-\xi)(x+1)^{-\eta}(\varphi+1)^{-\xi-1} = \lambda c_{IP} \tag{3-19}$$

$$c_{IA} * x + c_{IP} * \varphi = B \tag{3-20}$$

Then, the optimal levels of IA and IP are derived as follows:

$$x^* = \frac{\xi B - \eta C_{IP} + \xi C_{IA}}{(\xi+\eta)C_{IP}} \tag{3-21}$$

$$\varphi^* = \frac{\eta B - \xi C_{IA} + \eta C_{IP}}{(\eta+\xi)C_{IA}} \tag{3-22}$$

These equations show that the optimal level of fire ignition prevention increases as the exponent (ξ) and budget (B) increased, while the optimal level of fire ignition prevention decreases as the unit cost of fire ignition prevention increases. Also, from the same assumptions, the optimal number of *IA* resources increases as the exponent (η) and the budget (B) increase, while the optimal level of *IA* resources decreases as the unit cost of *IA* resources increases. The optimal amounts of *IP* (φ*) and *IA* (x*) depend not only on C_{IP} but also on C_{IA}. The unit cost of IP, C_{IP}, positively effects the amount of *IA*(x), whereas the unit cost, C_{IA}, negatively effects the amount of *IA*(x). The impacts of C_{IP} and C_{IA} on the optimal amount of *IP*(φ) are determined by the exponents of x and φ (i.e., η and ξ, respectively) in the objective function. If η is big relative to ξ, the level of C_{IP} is critical to determining φ^*. On the other hand, if η is small relative to ξ, the impact of C_{IP} is mitigated when determining φ^*. Thus, the absolute amounts of IA resources and ignition prevention efforts are determined by a given budget and unit costs for *IA*(x) and *IP*(φ), while the exponents of x and φ, that represent the attributes of a landscape (e.g., terrain, climate, infrastructure, and socio-economic aspects) and determine the extent and effects of the fire management policies in the landscape, affect the relative importance of *IA*(x) and *IP*(φ) on the optimal allocation of a budget.

3.2.6. Spatial allocation on a landscape with multiple fire planning units

Fire ignition prevention policy reduces the daily demand of firefighting resources by mitigating the rate of fire ignitions across a landscape with multiple FPUs. Fire managers decide not only the number of IA firefighting resources and amount of fire ignition prevention efforts, but also where to employ IA resources and implement ignition prevention activities. In this section, I extend the model by assuming that the levels of fire ignition prevention efforts are different across the landscape with multiple FPUs, depending on the fire manager's goal. The manager's objective function is mathematically represented as follows:

$$\min_{x,\varphi} NFNSR = \sum_{u \in U} f_u(x_u, x_{u'}, \varphi_u) \tag{3-23}$$

$$s.t.\ c_{IA} * \sum_{u=1}^{U} x_u + c_{IP} * \sum_{u=1}^{U} \varphi_u \leq B \tag{3-24}$$

where:

$NFNSR$: number of fires not receiving a standard response;

x_u: number of IA resources in the unit *u*;

$x_{u'}$: amount of IA resources in the adjacent unit of *u*;

φ_u: unit of ignition prevention effort in the unit *u*.

The number of fires that do not receive a standard response depends on the number and location of IA resources and fire ignition prevention efforts employed in the FPUs. If IA firefighting resources are shared with adjacent units, the marginal effect of an IA firefighting resources is $\frac{\partial f_u}{\partial x_u} + \frac{\partial f_{u'}}{\partial x_u}$. If $\frac{\partial f_{u'}}{\partial x_u} > 0$, the fire manager will continue to allocate more resources to FPU, *u*, until the marginal contribution of the last unit of IA resources is the same with the marginal contribution of the last unit of IA resources in other FPUs. For the ignition prevention policy, I assume that there is no effect of fire ignition prevention efforts in a unit to adjacent units[7]. When the objective of the fire manager is to minimize the total number of fires that do not receive a standard response for the entire landscape, the fire manager allocates fire ignition prevention efforts to the FPUs such that $\frac{\partial f_u}{\partial \varphi_u} = \frac{\partial f_{u'}}{\partial \varphi_{u'}}$. If $\left|\frac{\partial f_u}{\partial \varphi_u}\right| < \left|\frac{\partial f_{u'}}{\partial \varphi_{u'}}\right|$, more efforts should be allocated to fire management u', and vice versa.

3.2.7. Social optimum vs. Government optimum from fire prevention policy

In the optimization problem thus far, unit costs only account for internal costs to the fire manager. However, in reality, there exists an external cost, 'social cost', to the public from the fire prevention policy. For example, if a fire ignition prevention policy restricts human activities like hiking and camping in a forest, the policy creates a social cost that is the opportunity cost to a society for giving

[7] Fire ignition prevention efforts can impact adjacent units or units farther away from the treated unit because if human access is limited in the unit, people may move to another place to engage in outdoor activities. Thus, the policy in a unit can affect the probability of human-caused ignitions. This phenomenon is called "leakage".

up the use of the forest during a fire season. In my model, if the social cost of implementing IP (SC_{IP}) is large enough, the optimal amount of IP is close to zero.

$$\lim_{SC_{IP}\to\infty} \frac{\xi B-\eta(C_{IP}+SC_{IP})+\xi C_{IA}}{(\xi+\eta)(C_{IP}+SC_{IP})} \quad \to \quad IP^* = 0 \ or\ infeasible \qquad (3\text{-}25)$$

$$\frac{\xi}{\eta}(B+C_{IA})-(C_{IP})<SC_{IP}$$

When I consider the social cost of a fire ignition prevention policy, the efficient fire management policy of the government is not consistent with the efficient policy for a social manager. As the social cost of the fire ignition prevention policy rises, the gap between the government optimum solution and the social optimum solution increases. A large gap is likely to bring a conflict between the government and the society. Thus, the social cost reduces the optimal amount of fire ignition prevention, and further a high social cost may make the fire prevention policy impossible to implement.

Moreover, the social cost helps the fire manager to employ more IA resources by restricting the use of the fund from alternative fire prevention activities. To my knowledge, few studies account for the social costs of fire prevention policy like fire ignition prevention in the ROK, even though the social costs may significantly affect the welfare of a society in reality. Further studies are needed to examine how social costs have an influence on the decision-making process for public fire policies.

4. SIMULATION, OPTIMIZATION, AND APPLICATION

This chapter begins with a description of two study areas: California and the ROK. Then, I introduced the simulation models, including CFES2 and a Korean stochastic fire simulation model, and explained how to incorporate the information from these models into the optimization model. I also described the standard response optimization model and an extension by adopting a weighting scheme. Finally, I described how I applied the simulation-optimization framework to the California and ROK cases.

4.1. Study Area

The study areas contain information on the regional attributes, stations and their locations, representative fire locations, and administrative borders for multiple planning units. In order to apply the standard response model in those study areas, the traveling times required for resources to reach potential fire locations from stations are known. Terrain and infrastructure like forest road systems significantly affect the traveling times. Sometimes, tough terrain limits the access of ground resources, which increases demand for air resources for initial attack. The probability of fire ignitions and the fire intensity, which influence the required number of resources, vary across the study area.

4.1.1. California

The study area consists of the central portions of three adjacent CALFIRE administrative units in the central Sierra region of California—Amador-El Dorado (AEU), Nevada-Yuba-Placer (NEU), and Tuolumne-Calaveras (TCU). CALFIRE has the primary responsibility for wildfire suppression in these areas (Figure 4-1). This 1.2 million hectare study area includes rolling hills and steep, rugged river canyons with elevation ranging from 300–1200 m, west to east. The area contains an array of vegetation types from annual grasslands, shrub lands, oak savannas, and open pine woodlands in the west, to short- and long-needled coniferous forests in the east, reflecting the effects of elevation and precipitation gradients. Vegetation cover, stratified by life form, is 42% herbaceous, 39% shrub, and 19% forest (Franklin *et al.* 2000). Before European settlement, these vegetation types supported low-intensity fires with high-frequency return intervals (2-16 years) (Barbour *et al.* 2007). Since 1900, fuels have increased as a result of fire suppression, and wildfires that occur under high fuel loads burn at a higher intensity. Low fuel moisture and severe fire weather combine to create the greatest potential for large fires during the period from June-October. The area experienced rapid population growth during the 1990's, greatly increasing the value at risk in buildings and infrastructure (e.g., power lines, cell towers, parks, fencing). From 2005 to 2008, CALFIRE had 45 stations for engines and dozers, four hand crew camps, and six air bases available to serve the study area (Figure 4-1).

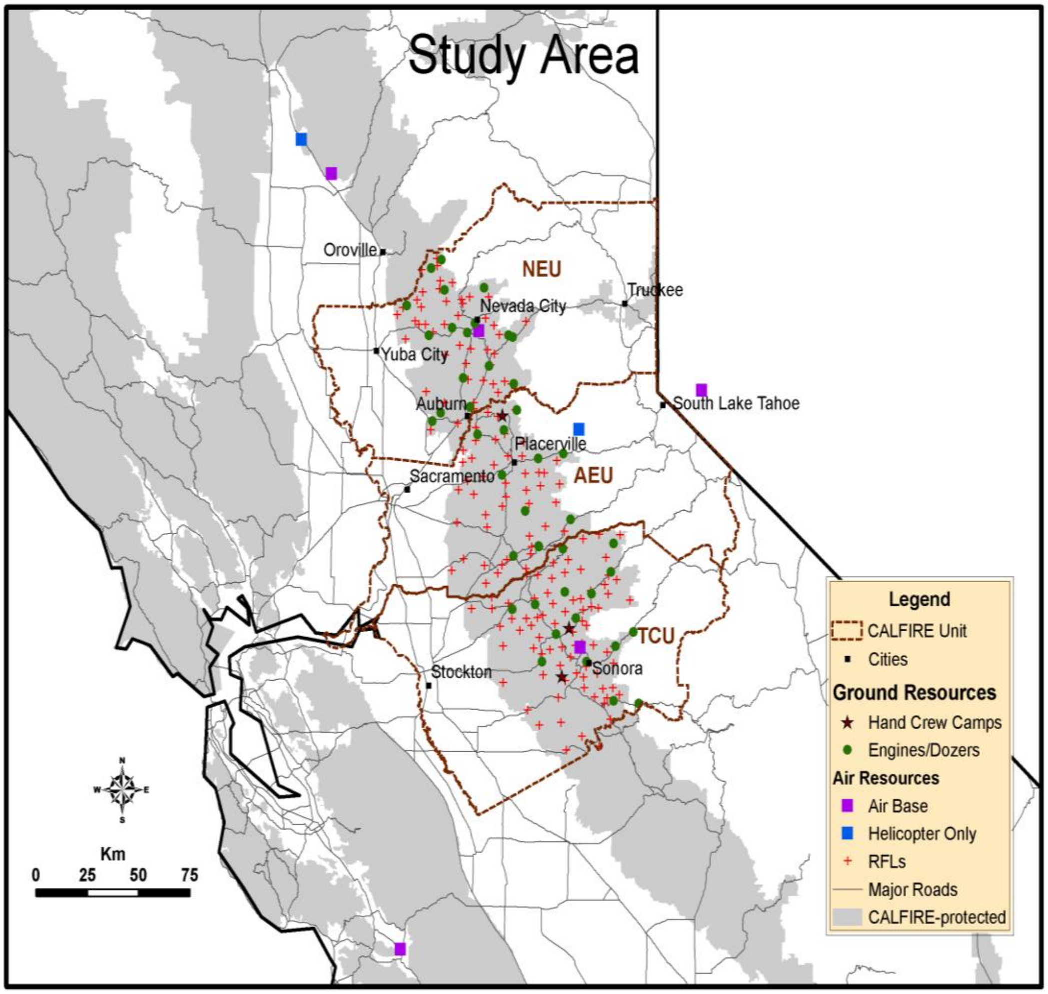


Figure 4-1 CALFIRE administrative units in the central Sierra region of California—Amador-El Dorado (AEU), Nevada-Yuba-Placer (NEU), and Tuolumne-Calaveras (TCU). The study area is the CALFIRE-protected area (shaded) in the central portions of the three units. Representative Fire Locations (RFL) are selected by CALFIRE. I excluded the CALFIRE-protected area in the eastern portion of NEU (shaded area surrounding Truckee) because it is too far away from other CALFIRE-protected areas to send or receive ground resources and depends primarily on US Forest Service and local suppression resources through mutual aid agreements.

CALFIRE uses CFES2 as a tool for strategic planning. The department stratified these three administrative units into 27 fire management analysis zones (FMAZ) that are described by a combination of fuel type (an indicator of the fire regime) and population density (an indicator of issues associated with the wildland-urban interface). CALFIRE relies on representative fire locations (RFL) for modeling fire potential within an FMAZ. These locations are selected according to historical fire locations, each of which is characterized by a particular fire behavior fuel model, slope class, herbaceous vegetation type, climate class, and most representative fire weather station. Each FMAZ is considered homogenous with respect to some of these variables: weather station, climate class and herbaceous vegetation class. However, the specific fuel model and slope class are allowed to differ among RFLs within an FMAZ. There are a total of 173 RFLs in the three units (Figure 1).

Fuel models used in the study area are from the National Fire Danger Rating System (narrative descriptions can be found in Deeming *et al.*, 1977). Percent slope, a key value in predicting fire behavior, is classed 1 (0 to 25%) through 5 (>75%). Herbaceous vegetation, which has varying effects on fire behavior depending on fuel type, is classified as annual throughout the fire planning units. Because of the Mediterranean climate, which is characterized by cold, wet winters and hot, dry summers, climate class is coded as 2 (sub-humid, savanna). Fire weather stations used for fire behavior prediction in the study area are located at Wolf Creek, White Cloud, Bald Mountain, Georgetown, Groveland, and Eliza Mountain.

4.1.2. The Republic of Korea

My study area in the ROK is comprised of the entire country (Figure4-2). The forested area in the ROK is approximately 6.4 million ha (i.e., approximately 64 % of the total land area), in which conifers cover 2.7 million ha; broad leaves, 1.7 million ha; and mixed forest, 1.9 million ha (KFS 2005). These lands are highly susceptible to forest fires because the area is currently characterized by thick growth due to insufficient past fuel management, and its thick layer of fine surface fuels, which ignite and spread fire easily. Forest fires can spread rapidly in these mountainous areas in part because fires spread more rapidly on steep slopes than on flat ground (Weise and Biging 1997). Spring is the most dangerous season for wildfires (i.e., March, April, and May) because the weather is dry and high winds are common; 68% of all forest fires and most large fires occur in the spring. In the ROK, the causes of forest fires are mainly anthropogenic (see Figure 3-2).

When a fire is reported, the Korean Forest Aviation Headquarters (KFAH) has the responsibility to provide a rapid and appropriate initial response to the ignition location. KFAH includes eight forest aviation bases. As the ROK is a small country with a high population density, concerns about large fires threatening human lives and property dominate fire suppression policy. Mountainous terrain in the ROK precludes timely access for ground-based IA resources; thus, there is great reliance on helicopters. Suppression by air is supported by the central government (i.e., the Korean Forest Service) because most local governments cannot afford to maintain expensive air firefighting resources. However, the main authority for forest fire suppression belongs to local governments. Local administrative units (e.g., Si, Gun, and Gu) are responsible for protecting private forests and mountain villages in their areas from natural hazards. A field command center coordinates human resources, evacuation control, and access to helicopters, depending on the size of the forest fire.

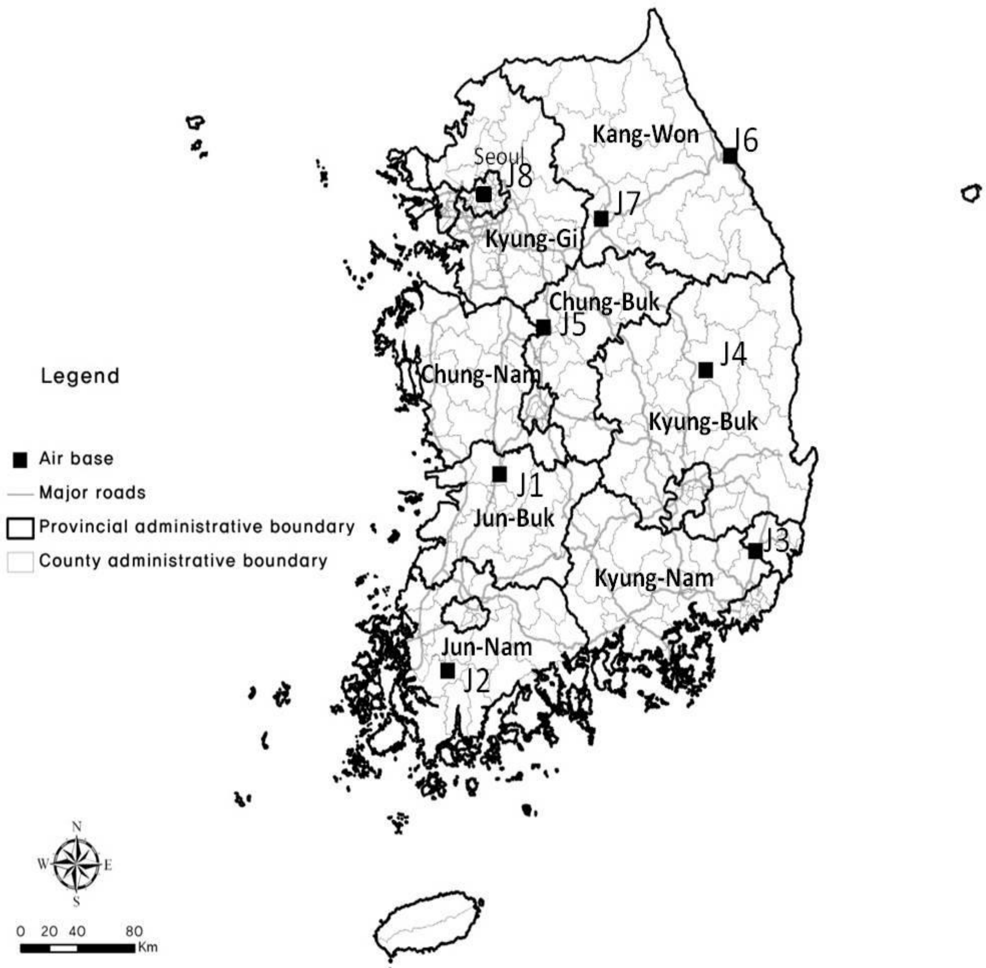


Figure 4-2 Provincial administrative boundary and Korean forest aviation bases located in the ROK.

4.2. Simulation

In this section, I describe two simulation models, including CFES2 and a Korean stochastic fire simulation model. Fire simulation models produce information on the number of daily fire ignitions, each fire location, and the intensity of each fire in California and the ROK, which construct a set of fire scenarios. By using the fire scenarios, I incorporate the information of these simulation models into the optimization model as a tractable framework.

4.2.1. California Fire Economics Simulator version 2 (CFES 2)

CFES2 is a computer program that performs a stochastic simulation analysis of the IA system to support fire managers' decision-making in wildland fire protection through the quantitative analysis of the potential effects of changes to the wildland fire management system (Fried *et al*. 2006). I used CFES2 to simulate IA and evaluate the performance of resource deployment and dispatch decisions. The CFES2 model uses stochastic simulation of fire occurrence, fire behavior and fire suppression productivity in combination with a mathematical model of perimeter containment (Fried and Fried 1996) to take into account the probabilistic properties of wildland fires (Fried and Gilless 1999). It includes considerable operational detail and is designed to support decision-making in wildland fire protection through quantitative analysis of the potential effects of changes to the wildland fire management system. Examples of parameters that can be varied include availability and stationing of resources; rules for how many resources to dispatch, by kind, at each fire dispatch level; criteria for setting the fire dispatch level; schedules describing when firefighting resources are staffed and available; and fireline-building tactics. The CFES2 model can be used to evaluate the contribution of several types of IA resources, alternate deployment of and dispatching rules for suppression resources, and multi-unit and multi-agency cooperation to IA effectiveness (Fried *et al.* 2006).

An important feature of CFES2 is the stochastic simulation of fire occurrence and behavior. The occurrence model contains random variables for number and location (RFL) of fires occurring on a given day, and the ignition time for each fire (Fried and Gilless 1988). The behavior model contains random variables for fire spread rate and fire intensity level depending on weather and time of day (Gilless and Fried 1999). I used these fire occurrence and behavior models to generate 5,814 fire scenarios for the three planning units combined. The models were parameterized with data from 15 years of historical fire occurrences and 8-21 years of fire weather observations between 1990 and 2010. Each scenario represents a day in which a particular combination of weather, fire count, fire locations, fire ignition times, fire behavior (e.g., intensity and rate of spread) and availabilities of firefighting resources occur. I selected fire scenarios with high fire-counts (defined as at least four fires in any unit in one day) and high fire season (defined as the period when fire behavior is most severe). The fire scenarios included 5,814 high-fire-season days with high fire-counts ($\geq$4 in any one planning unit and no more than one fire at any RFL), representing 16% of the days on which any fire occurred in any of the three units, and accounting for 42,835 fires, of which 43% were in NEU, 2% in AEU, and 29% in TCU. These fire scenarios are the basis for evaluating alternative deployment and dispatch decisions during severe fire days when multiple fires may occur. In the California case, I use the 5,814 high-fire-season scenarios in two ways: 1) to generate a sequence of fire scenarios to find an optimal resource deployment using the standard response optimization model, and 2) to simulate the performance of the resource deployment using CFES2.

4.2.2. Korean Stochastic Fire Simulation Model

To construct fire scenarios in the ROK, I developed a Korean stochastic fire simulation model of fire occurrence, by season and region, based on the historical fire data from Lee *et al.* (2011; See Appendix D for details). The model generates sequences of fire events that are consistent with Korean fire history. A three-stage approach is employed (Fried and Gilless 1988). First, a random draw from a Bernoulli distribution is used to determine if any fire occurs for each day of a simulated fire season. Second, if a fire occurs, a random draw from a geometric multiplicity distribution determines their number. Last, ignition times for each fire are randomly drawn from a time of day distribution. These specific distributional forms were chosen after analyzing historical fire data from Korea. Maximum Likelihood Estimation was used to estimate the primary parameters of the stochastic models. Fire sequences generated by the model appear to follow historical patterns with respect to diurnal distribution and total number of fires per year.

Thus, the simulation model includes fire occurrence models for generating fire scenarios, and contains random variables for the probability of fire occurrence and the number of fires occurring on a given day along with the location and the ignition time for each fire. The short duration of most fires fought by fire agencies in the ROK and the previous forest fire occurrence prediction work suggests an alternative structure for fire simulation, in which fire ignition on each day is generated independently of ignitions for preceding or subsequent days (Cunningham and Martell 1976, Haines *et al.* 1983). This structure requires the estimation of not one but several distributions, which together are used to generate a sequence of fire ignitions over the course of a day. Although more complex, this structure has the capability of producing a pattern of fires with a more reasonable distribution by time of day.

In addition, I use the existing regional fire susceptibility model (Lee and Lee 2009) to determine the fire dispatch level in the ROK, which provides the information on fire behavior and on fire location. The standard response to each fire in the ROK depends on the fire susceptibility index, which is derived from the historical fire behavior (e.g., the rate of spread) for the fire location and scaled by a regional cluster index (ranged by 1-5). The higher the susceptibility index, the more firefighting resources are required in the standard response.

To generate fire scenarios in the ROK for the optimization problem of IA resource deployment, I used the fire occurrence and susceptibility modules that were parameterized with historical fire data from 1991 to 2007. Each scenario represents a fire day in which a particular combination of fire count, fire locations, fire ignition times, and fire behavior occurs. I randomly selected fire scenarios with high fire-counts (defined as at least two fires in one day) and high fire season from March to May (defined as the period when fire behavior is most severe).

4.3. Optimization Model

I developed a scenario-based, standard-response optimization model to deploy IA resources to stations at the beginning of each fire season, and dispatch them to fires as they occur. The optimization model is for a landscape with multiple fire planning units. The model includes integer decision variables for the number of IA firefighting resources deployed to each station and the number of resources dispatched from each station to each fire in each scenario. Furthermore, I extended the standard response optimization model by adopting a weighting scheme across fire locations with different policy goals.

4.3.1. Scenario-based, Standard-response Optimization Model

The optimization model is a linear integer formulation with the objective: minimizing the expected number of fires that do not receive a standard response subject to budget and station capacity constraints (Haight and Fried 2007). The standard response is the number of resources by type that must arrive at a fire within a specified time limit. A standard response is defined for each of three dispatch levels for IA resources by fire management experts in each unit. The standard response varies among units due to differences in the number of resources by type stationed in the unit and the degree of reliance on air resources. The data include the locations of fire stations and representative fires. The number and locations of available fire stations are given (fixed). Each station has a capacity to house IA resources, and time required for resources to reach each representative fire location is known. The data also include fire scenarios, each representing a set of fire locations during a single day. To represent the uncertainty in fire location and behavior, the model includes multiple fire scenarios. Each scenario defines the number, location, and standard response requirements of fires that may occur during a single day. The model deploys resources to stations in the first stage and dispatches them to fires in the second stage, contingent on the fire scenario.

My standard-response framework relies on some simplification relative to the real world. The model will not send more resources to a fire than are defined in the standard response requirement because once the requirement is met it is assumed that no further benefit is obtained by sending additional resources. Further, the model will not send a partial response because benefit is contingent on the full standard response having been delivered. Finally, while the standard response is a pre-defined number of resources arriving within a response time threshold for each fire, the dispatch decisions that compose a standard response to a fire can vary – identical fires (location, severity, etc.) on different days may receive resources from different stations and planning units, depending on the other fires that occur on those days.

The model addresses deployment and dispatch decisions within multiple FPUs and is described with the following notation:

Indices:

u, U = index and set of fire planning units;

i, I = index and set of suppression resource types;

j, J^u = index and set of fire stations in unit u;

k, K^u = index and set of potential fire locations in unit u;

s, S = index and set of fire scenarios.

Parameters:

B = annual budget for the total operating cost across all fire planning units;

c_i = annual cost of operating resource type i;

C_{iju} = upper limit on the number of resources of type i at station j in unit u;

p_s = probability that fire scenario (fire day) s occurs;

r_{ikus} = number of resource type i required at location k in unit u during fire day s to satisfy the requirements for a standard response;

$t_{iju'ku}$ = response time of resource type i from station j in unit u' to fire location k in unit u;

T_{iku}= maximum response time for resource type i to fire location k in unit u to satisfy a standard response requirement;

$N_{iku}^{u'}$ = set of stations j in unit u' from which resources of type i can reach location k in unit u within the maximum response time;

i.e., $N^{u'}_{iku} = \{ j \in J^{u'} \mid t_{iju'ku} < T_{iku} \}$.

Decision variables:

y_{ju} = 1 if station *j* in unit *u* is hosting firefighting resources, 0 otherwise;

x_{iju} = integer variable for number of resources of type *i* at station *j* in unit *u*;

$d_{iju'kus}$ = integer variable for number of resources of type *i* at station *j* in unit *u'* that are dispatched to fire location *k* in unit *u* during fire day *s*;

z_{kus} = 1 if fire location *k* in unit *u* receives a standard response during fire day *s*, 0 otherwise.

The model is formulated as follows:

$$\text{Minimize: } O = \sum_{u \in U} \Big(\sum_{s \in S} p_s \sum_{k \in K^u} (1 - z_{kus}) \Big) \tag{4-1}$$

Subject to:

$$\sum_{u \in U} \sum_{i \in I} \sum_{j \in J^u} c_i x_{iju} \le B \tag{4-2}$$

$$x_{iju} \le C_{iju} y_{ju} \text{ for all } i \in I,\ j \in J^u, \text{ and } u \in U \tag{4-3}$$

$$\sum_{u' \in U} \sum_{k \in K^{u'}} d_{ijuku's} \leq x_{iju} \text{ for all } i \in I,\ j \in J^u,\ s \in S, \text{ and } u \in U \tag{4-4}$$

$$z_{kus} r_{ikus} \leq \sum_{u' \in U} \sum_{j \in N_{iku}^{u'}} d_{iju'kus} \text{ for all } i \in I,\ k \in K^u,\ s \in S, \text{ and } u \in U \tag{4-5}$$

$$z_{kus} \in \{0,1\} \text{ for all } k \in K,\ s \in S, \text{ and } u \in U \tag{4-6}$$

$$y_{ju} \in \{0,1\} \text{ for all } j \in J^u \text{ and } u \in U \tag{4-7}$$

Equation 4-1 minimizes the sum of the expected number of fires that do not receive the standard response across all planning units, where the weight p_s represents the probability of the occurrence of fire day s. Equation 4-2 requires that the total annual cost of operating suppression resources across the planning units is constrained by the budget. Equation 4-3 represents the capacity of each station for each type of suppression resource. Equation 4-4 requires that the number of each type of resource dispatched from each station during each fire day is less than or equal to the number of that type of resource deployed at the station. Equation 4-5 expresses whether a fire receives a standard response. A fire receives a standard response (z_{ksu} = 1) if, for each resource type i, the number of resources that are within the standard response time and are dispatched to the fire from all available stations, $\sum_{u' \in U} \sum_{j \in N_{iku}^{u'}} d_{iju'kus}$, is greater than or equal to the number of resources required, r_{iksu}. The variable $d_{iju'ku}$ allows resources to be dispatched to locations in planning units other than their home unit. If r_{iksu}= 0 for all resource types i, there is no fire at location k in unit u during fire day s and z_{ksu} is equal to one with no resource commitment.

4.3.2. Weights on Fire Location

With the consideration of important policy goals (e.g., protecting populated or ecologically sensitive areas), the optimal spatial allocation of IA resources from the optimization model changes in a heterogeneous landscape in terms of the importance (or value) of a threatened location. In the previous section, the optimization model does not account for the heterogeneity of fire locations because it works under the assumption that all fire locations have equal potential to cause damage and incur high suppression costs. However, if each fire location has a different value (importance) to be protected, IA firefighting resources concentrate on stations close to highly valuable areas in order to protect those places. Furthermore, when there are more fires than the maximum number of fires covered by available IA resources, the model must determine which limited resources to send to which fires to ensure a standard response for important locations first.

The standard response model is extended to include additional information to prioritize ignitions, such as proximity to threatened values (e.g., protecting a highly populated area or ecologically sensitive area). The model can prioritize ignitions by weighting potential fire locations in California and the ROK with information on the value to be protected (i.e., protection priority) at each fire location. For instance, if two fires occur, one near residential area and another in a wilderness area, the fire manager will send available IA resources for the standard response to the first one to protect the residential area.

For this analysis, I conducted a sensitivity analysis of weights on fire locations by modifying the optimization model to assume each fire location has a different weight based on its protection priority (Equation 4-8).

$$\text{Minimize: } \textit{Expected Cost} = \sum_{s \in S} p_s \sum_{k \in K} w_k (1 - z_{ks}) \tag{4-8}$$

Here, w_k is a weight vector that represents the value to be protected at the location k. If a fire at the fire location k doesn't get an appropriate IA response within a short time period, it is likely to escape and become a large fire. To construct the weight vector, I took demographic and ecological information into account in the model.

The weighting system provides a very useful and tractable tool to a fire manager who plans to deploy IA resources during a fire season. Using the currently available information and science, the fire manager tries to improve the effectiveness of IA resources. If a large fire occurred at a certain location last year, the fire manager may rule out that place from potential fire locations. On the other hand, if there are highly vulnerable places that contain heavy fuel loads, the fire manager may prioritize those places to send IA resources first. To address these issues, the weighting system in Equation 4-8 helps fire managers to adjust the spatial allocation of IA firefighting resources.

Two weighting schemes are developed to put an additional penalty on fire locations for two policy priorities: first, to protect populated areas and, second, to protect ecologically sensitive areas. The ROK is a highly-populated country (i.e., 1,271 people per sq mile) with high fire risk to populated areas. By using the population density at fire locations, I built a weight vector to prioritize highly populated locations. In addition to human communities, ecologically sensitive places (e.g., endangered species reserve, important riparian zone, and other protected areas for special purposes) need to be protected from severe fires, even though some aspects of fires are beneficial to forests. To do this, I construct an ecological importance index based on regional information on endangered species habitats (e.g., forest reserve for biodiversity) provided from the national agencies (e.g., Korea Forest Service). By using those indices, I explore how a policy priority change the optimal spatial allocation of IA firefighting resources across heterogeneous fire locations.

4.4. Application

I apply the simulation-optimization framework to real settings in California and the ROK. In this section, I first describe the key parameters and basic settings in each area. Then, I explain how I applied the framework to address the optimal deployment problem of IA firefighting resources in the California case. In addition, I explore the effects of employing the standard response model and the effects of budget and station capacity on the performance of IA firefighting resources. Then, I also describe how to apply the framework to find the optimal spatial allocation of IA firefighting helicopters in the ROK setting. Finally, I investigate the effects of a weighting scheme across heterogeneous fire locations in terms of value to be protected, and explore the tradeoff between IA fire suppression and fire ignition prevention in the ROK.

4.4.1. California Case

Across the optimization model applications, core parameters, including fire scenarios, standard response requirements, and resource costs, are held constant. Due to constraints imposed in undertaking the optimization, I used 100 fire scenarios for the optimization model to approximate the probability distribution of 4+ fire days during the high fire season (e.g., June, July, August, and September). Each of these 100 scenarios was randomly selected from the set of 5,814 scenarios that were developed with CFES2 to evaluate alternative deployment and dispatch decisions. Each scenario includes the location and dispatch level of each fire during a single day when there are at least four fires in any one of the three fire planning units. The mean daily number of fires for these 100 scenarios is 7.43, with a range of 4 to 12. Although I assumed that the scenarios are equally likely (i.e., $p_s = 0.01$, $s = 1 \ldots 100$) (Haight and Fried 2007, MacLellan and Martell 1996), their random selection from the larger set of 5814 implies that more likely fire scenarios are better represented in this sample of 100 than less likely fire scenarios. By assuming equal probability and aggregating the results, I was able to approximate the distribution of outcomes.

Table 4-1 The dispatch policy (number of resources by fire dispatch level) for initial attack in planning units AEU, NEU, and TCU.

Fire dispatch level[1]	Engine			Dozer			Hand crew			Helicopter		
	AEU	NEU	TCU	AEU	NEU	TCU	AEU	NEU	TCU	AEU	NEU	TCU
1	3	4	2	0	0	1	0	0	1	0	0	1
2	4	6	4	1	1	2	1	1	3	0	1	2
3	5	8	6	1	2	3	2	2	5	1	2	3

Resource type and planning unit (column group heading)

[1]Fire dispatch level, derived from modeled fire behavior parameters, ranges from 1 (low) to 3 (high) and is designed to ensure a suppression response that is well-matched to the challenge (e.g., growth rate or fire intensity) posed by a fire (Gilless and Fried 1999).

The standard response to each fire depends on the fire 's dispatch level, which ranges from 1 (low) to 3 (high) (Table 4-1). The fire dispatch levels are derived from the day maximum burning index and scaled by a diurnal adjustment factor specific to the time of fire occurrence (Gilless and Fried 1999). The dispatch levels assist CALFIRE personnel in determining how many resources of each type to dispatch for initial attack given the level of fire danger. In general, the higher the dispatch level, the more resources are required in the standard response. The number of required resources for the standard response is zero for any location that does not have a fire.

The optimization model deploys engines, bulldozers, hand-crews, and helicopters, from stations owned and operated by CALFIRE. Response times for ground resources to travel between their home station and every RFL were estimated using Google Earth. Response times for helicopters are based on air speed and distances between airbases and RFLs. In consultation with CALFIRE unit leaders, I established response time thresholds of 30 minutes for engines and 60 minutes for dozers, hand crews, and helicopters, beyond which a response would be considered unsatisfactory. Rapid response is critical because fast spreading fires are likely to escape and cause considerable damage if concerted initial attack is not applied within the first 30 minutes (Arienti *et al.* 2006; Haight and Fried 2007). For this application, I estimate the unit cost (i.e., annually operating costs) for each resource by type (Table 4-2).

Table 4-2 Crew size and operating costs of initial-attack resources

Attribute	Resource type			
	Engine	Dozer	Hand-crew	Helicopter
Crew	3	1	17	6
Hourly Cost ($)	143	188	390	1,051
Annual Cost[1] ($)	750,164	162,432	402,480	1,286,424

[1]Annual cost is based on hourly cost and estimated annual operating hours of each resource type obtained from consultation with CALFIRE personnel. Compared with engines, dozers have a higher hourly cost and lower annual cost because dozers are operated for fewer hours than engines.

Applications of the optimization model are solved on a Dell Pentium 4 desktop computer (CPU 2.4 GHz) with GAMS/CPLEX Solver. The termination criterion for the optimization runs is a combination of time limit and optimality: the solver is instructed to stop and report the solution after 16 hours of runtime or after proven optimality is achieved, whichever happens first.

The optimization model uses much simpler logic for determining whether or not an appropriate response is achieved for a fire than does the stochastic simulation model, CFES2. Therefore, in the applications described below, I measured the performance of the resource deployment and dispatch decisions obtained with the optimization model by simulating initial attack using CFES2 and counting the number of fires that are not successfully contained.

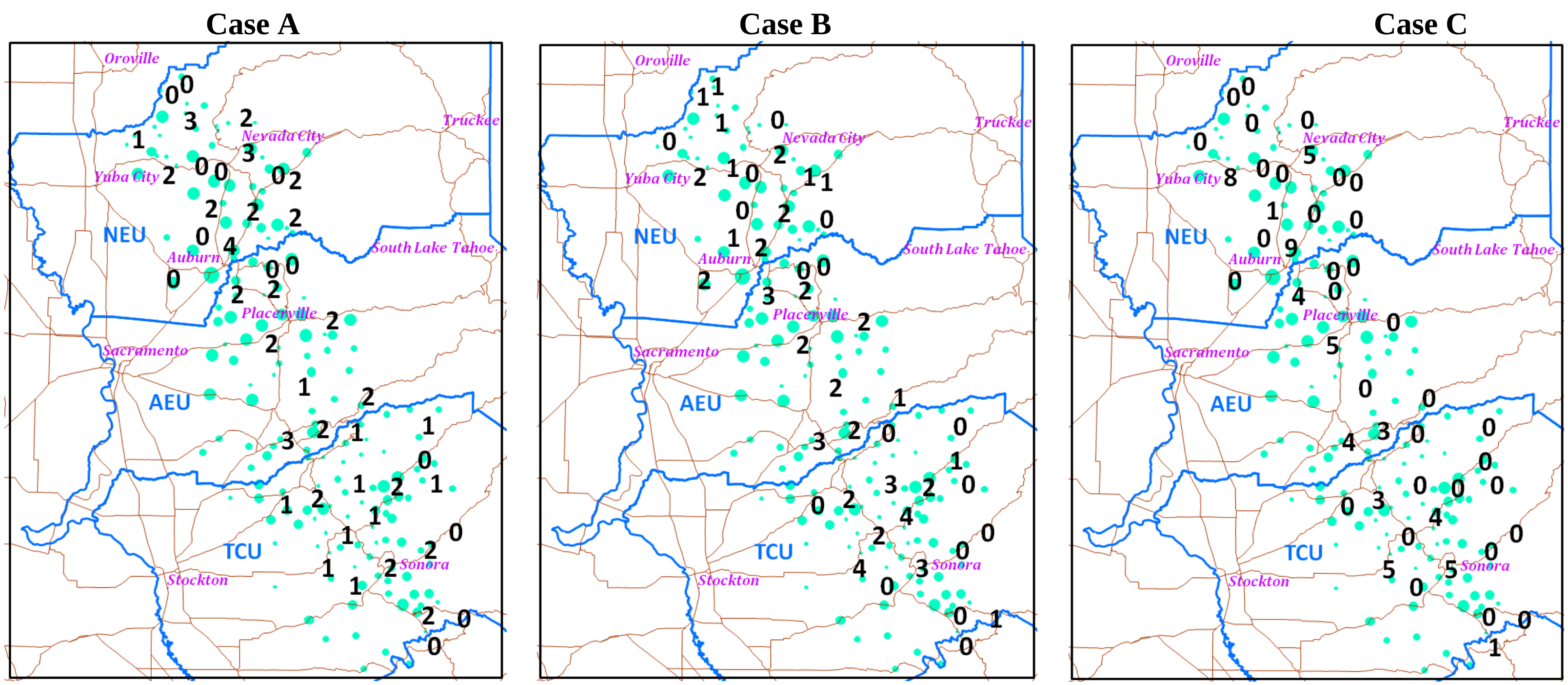
Table 4-3 Cases used for analysis in the California study

Case[1]	Station capacity				Budget
	Engine	Dozer	Crew	Helicopter	($million)
A. Base (CALFIRE deployment)	2	2	5	3	55.7
B. Low cap-current budget	2	2	5	3	55.7
C. High cap-current budget	Unlimited				55.7
D. Low cap-high budget	2	2	5	3	69.6
E. High cap-high budget	Unlimited				69.6
F. Low cap-low budget	2	2	5	3	41.8
G. High cap-low budget	Unlimited				41.8
H. Heuristic-current budget	Unlimited				55.7

[1]The Base case represents the current (2005-2008) deployment of resources in each planning unit with dispatch allowed between units. The other cases are resource deployments found by solving the scenario-based, standard-response optimization model with dispatch allowed between units and different budget and station capacity constraints.

Estimating the Effects of Employing a Standard Response Objective

In the case of California, I first explored how deployment and dispatch decisions obtained with an optimization model that minimizes the number of fires not receiving a standard response affect IA success. To address this issue, I formulated a base case using the CALFIRE resource deployment during the years 2005-2008 (Case A, Table 4-3). The deployment includes a total of 51 engines and seven dozers allocated among 32 of the 45 stations in the study area (Case A, Figure 4-3). In addition, 15 hand-crew teams are deployed at four camps, and eight helicopters are deployed at six air bases. The total annual operating cost of this deployment is $55.7 million. I assumed that resources are dispatched between units to suppress fires. This CALFIRE resource deployment has remained relatively stable for many years despite changes in fire load, fire severity, values at risk, and access. Small changes in deployment do occur from year to year as CALFIRE adapts to changes in funding.



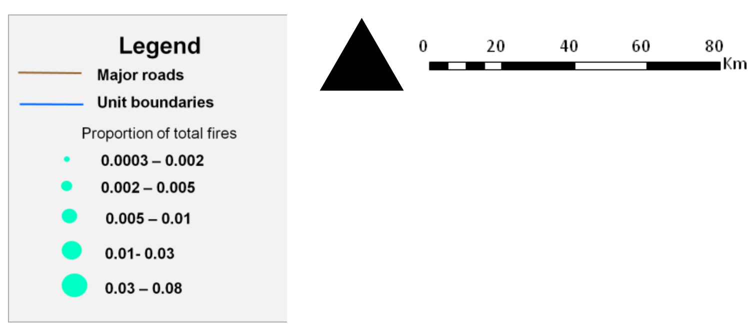


Figure 4-3 Deployment of engines and dozers in relation to representative fire locations in the current CALFIRE deployment (Case A); obtained with the optimization model with low station capacity and current budget (Case B); and obtained with the optimization model with high station capacity and current budget (Case C).

For comparison with the current CALFIRE deployment case, I used the standard-response optimization model to deploy resources among the three planning units given the same budget level ($55.7 million) and capacity constraints of the CALFIRE deployment, which I called the low capacity/current budget case (Case B, Table 4-3). The engine and dozer stations each house up to two engines and two dozers. Conservation camps each house up to five hand crews. Air bases each house up to three helicopter crews. The optimization model also assumes that resources may be dispatched between planning units.

I used CFES2, parameterized with the same inputs (e.g., fire occurrence, fire behavior, fire locations, resource productivities, response times) used in the simulations that generated the fire scenarios, to evaluate the performance of the resource deployments in each of these two cases. For each case, I modeled 400 years of initial attack using the model's pseudo-stochastic mode with deterministic fire-line production rates such that the sequence of fires in time and space, and their behavior, were identical for both cases. The main difference for each modeled fire between the cases was which resources arrived and when. Outcomes of initial attack on each of the thousands of fires modeled are determined by a mathematical containment module that accounts for rate of spread, timing of resource arrivals, fire-line production rates, and tactics deployed (e.g., head, tail or parallel attack) (Fried and Fried 1996).

Performance is measured by the number of fires that are not contained before they exceed simulation limits (ESL) on fire size or time. The size limit is 50, 100, or 300 acres, depending on the fuel type and the population density of the FMAZ where the fire occurs. The time limit is two hours. These limits can be thought of as addressing both a goal (no fires above a size limit or no fires with duration above a time limit) and a modeling constraint. A fire that exceeds either limit has likely transitioned from IA mode to extended attack mode, in which resources beyond the standard response are dispatched and the control strategy is adjusted (e.g., pulling back to the next ridge or setting backfires rather than direct containment). The performances of resource deployments are estimated using the 5,814 fire scenarios with high fire-counts (defined as at least four fires in any unit in one day) that occur during the high fire season which are extracted from the 400 years of daily simulation output. The difference in performance between the CALFIRE deployment case and the optimization model's low capacity/current budget deployment case represents the effect of changing the number and type of resources in administrative units to minimize the number of fires not receiving the standard response in those units. In both the simulation model and the real world, a standard response does not guarantee that a fire will be contained (or fail to become an ESL fire), though the vast majority of fires that receive a standard response are contained. Conversely, not receiving a standard response does not guarantee that a fire will become an ESL fire. From the perspective of fire managers and much of the public though, ESL rates are far more germane than standard response achievement.

CALFIRE relies on ESL rates as a performance measure rather than a potentially more useful economic statistic, like area burned, in part because no IA model yet devised is capable of accurately predicting the size of fires that exceed initial attack, and these fires almost always account for nearly all of the area burned. Past attempts to correlate average historic escaped fire sizes to ESL fires (e.g., USFS 1985) generated arbitrary results because such assignments are unavoidably an artifact of the period for which the average ESL fire size was computed. With increasing evidence that annual area burned is non-stationary, such assignments are also prone to bias.

Estimating the Effects of Station Capacity Constraints and Annual Operating Budgets

I also explore how changes in the station capacity and budget constraints affect resource deployment and IA success. To address this issue, I formulated and solved five additional optimization models with different combinations of constraints (Cases C-G, Table 4-3). In the first model (Case C), I removed the station capacity constraints while maintaining the existing budget of $55.7 million. The other four models (Cases D-G) were formulated with a different set of capacity and budget constraints in which budgets were increased or decreased by 25%, and capacity constraints either bound the solution or did not. In all five of these cases, I assumed that resources are dispatched between fire planning units. I used CFES2 to simulate the performance of the resource deployments obtained with each of the five models for comparison with the performance of the CALFIRE resource deployment. Performance is measured by the number of ESL fires per day based on the set of 5,814 fire scenarios with high fire counts and high fire season.

Testing the performance of a simulation optimization heuristic

Because the optimization model cannot minimize the number of ESL fires due to that problem's complexity, I developed a simple heuristic to find resource allocations that reduce the number of ESL fires from a base allocation. That heuristic model uses CFES2 simulations and re-deploys least-used IA resources from their current locations to other locations with a goal of increasing the number of fires that are successfully contained within the minimum time. The purpose of this analysis is to see if the heuristic, guided by simulated containment success, provides better deployments in terms of ESL fires than those obtained with standard response optimization. The algorithm is summarized as follows:

1) Use CFES2 to simulate the number of ESL fires for the current resource deployment.

2) Identify the least-used engine, dozer, and hand-crew and re-deploy them to stations nearest the RFLs with high frequencies of ESL fires.

3) Return to step 1 and repeat.

4) Stop and produce a solution (termination condition: 1% gap of improvement).

I applied this heuristic using the current CALFIRE deployment as the starting point and assumed that the number of resources by type remained fixed (Case H, Table 4-3). Thus, I looked at the trade-off between resource deployments at different stations but not trade-offs among resources types.

4.4.2. The ROK Case

Parameters and Settings

In the case of the ROK, my application focuses on the deployment of primary helicopters among eight stations, assuming that other resources such as hand crews and fire engines are retained in their current locations. The study area includes 228 representative fire locations defined as the centers of 228 distinct administrative places, which are the minimum fire management unit across the

Korean landscape (Figure 4-2). I estimated the response times for helicopters to travel from each station to each fire location and built a set of stations within 30 minutes of each fire location using GIS data. Because fires tend to escape if they do not receive an initial firefighting response at the early stage, I set a 30-minute response time threshold (Arienti *et al.* 2006; Haight and Fried 2007).

This analysis involves 100 fire scenarios for potential fire days, each with 2–26 fires occurring at different locations during high fire season. Because the draw-down of suppression resources on such fire days increases the probability that fires will escape initial attack, I constructed each scenario day that includes 2 or more fires. I generated those fire scenarios, using the Korean fire simulation model of fire occurrence and behavior in the ROK. The fire occurrence model contains random variables for whether or not any fires occur, and if so, the number of fires, fire location of each fire, and ignition time. I estimated probability distribution functions for these random variables from fire data recorded in the ROK during 1991 – 2007. The dispatch level of each fire, then, is determined by fire location and time of day (Lee and Lee 2009; Lee *et al.* 2006).

Table 4-4 Dispatch policy and operating costs for IA helicopters in the ROK

Resource type	Fire dispatch level[1]					Operating cost(KW)[2]	
	1	2	3	4	5	Hourly cost	Annual cost
Helicopter	0	1	2	3	4	7,000,000	616,000,000

[1]Fire dispatch index is defined as: 1(very low); 2(low); 3(medium); 4(high); 5(very high). The dispatch level of each fire, then, is determined by fire location (Lee and Lee 2009).
[2] KW denotes Korean Won; thus the hourly cost for a firefighting helicopter is about $7,000(USD); the annual cost is about $616,000(USD), which is provided from the Forest Aviation Headquarters of the Korean Forest Service (2011).

The parameters of the fire scenarios in the optimization model are derived from information on the fire days from stochastic simulation. Each fire scenario includes a set of fire locations where fires occur, together with the number of helicopters required for the initial attack of each fire. The daily number of fires ranges from 2 to 26 (on average 5.87 fires). The standard responses range from 0 to 4 helicopters reaching a fire within 30 minutes. The standard response to each fire varies by the fire's dispatch index (i.e., from 1 (very low) to 5(very high), Table 4- 4), which is derived from historical dispatch demand as in MacLellan and Martell 1996. A higher dispatch index requires more helicopters in the standard response. I assumed that each fire scenario was equally likely to occur (i.e., the probability of a fire day from the sample set for each of the 100 fire days = 0.01).

I focused on the optimization of helicopter deployment based on the maximal covering objective. The information on potential fire locations is used to calculate travel time from firefighting resource bases to RFLs in the ROK. For the application, I used spatially explicit GIS-based data from the Korea Forestry Research Institute regarding the ecology, fire behavior, and economic/cost characterizations that are important in the ROK. I used current data on helitack from the Forest Aviation Headquarters of the Korean Forest Service (KAHKFS 2011). The annual costs of initial attack resources from KAHKFS are utilized as unit costs in the application (Table 4-4).

In the case of the ROK, I constructed a mixed-integer program using the two-stage maximal covering model framework such as in the Californian case. I employed the integrated solution package GAMS/CPLEX 12.0, which is designed for large and complex linear and mixed-integer programming problems. CPLEX solves a mixed-integer programming problem through a branch and cut algorithm, which solves a series of linear programming sub-problems.

Estimating the Effects of Weighting Fire Locations by Risk

In the case of the ROK, the first issue I address is to examine how the weights on fire locations affect the optimal deployment of IA firefighting helicopters. In the base case, I assumed that the expected loss due to a fire not receiving a standard response is homogenous across a landscape. However, in reality, damages and suppression costs from a fire vary by the fire location. I prioritized fire locations based on the value of the resource to be protected as reflected in two policy goals: prioritize areas of 1) population density and 2) high ecologically sensitivity.

To prioritize fire locations, I built indices that represent the resource value of fire locations as the proxy of the policy goals. First, I used the demographic statistics of the ROK to build the population index, ranging from 0 - 1. The total population of the ROK is about 50 Million. The population density (i.e., on average 491/km^2) varies greatly across the landscape, which ranges from 16,567/km^2 in Seoul to as little as 89/ km^2 in the province of Kangwon. Seoul has many people and little forested area, while Kangwon has fewer people and extensive forested area. Even though forest fires in Kangwon are more likely to be large due to abundant fuels, the policy goal to protect human lives and properties may concentrate IA firefighting resources in stations around Seoul. The population index ties directly to regional population density (e.g., Pop index =1, Seoul and Kangwon: 0.005). Second, I used the GIS information on forest reserves for biodiversity (i.e., endangered or threatened species habitats) to be protected from natural disturbances. I built the binary (0 or 1) ecological importance index of the representative fire locations account for whether the RFL fell in protected (1) or unprotected area (0). By using the indices, I solved Equation 4-8 and examined the effects of prioritizing fire locations given each policy goal.

Estimating the Tradeoffs between IA Firefighting Resources and Fire Ignition Prevention

In the case of the ROK, the trade-off relationship between IA firefighting resources and fire ignition prevention efforts was explored. As discussed in the theory section, the first step is to calculate the relationship between the number of helicopters and the expected number of fires not receiving a standard response for a given fire ignition level, and the relationship between the level of fire ignition prevention efforts and the expected number of fires not receiving a standard response for a given level of fire suppression. Then, a comparison can be made between the marginal contribution (benefit) of the last dollar invested in IA firefighting resources and fire ignition prevention efforts with the information on unit costs, and estimate the trade-offs between them for a given budget. The information on unit costs and the budget for IA firefighting helicopters is given from KAHKFS (2011). The unit cost of ignition prevention activities comes from KFS (2011)[8]. I calculated the cost of fire ignition prevention by multiplying unit cost by labor hours (i.e., \$40 (the unit cost per day (8 h)) × number of days × number of employed people). I assumed that the ignition prevention activities were only effective in controlling human-made fires, which are often caused by

[8] The main activity of fire ignition prevention in the ROK is to restrict human access on forests by installing a warning sign and imposing a high penalty to people who violate the rule. Every year, the KFS operates patrolling crews during a fire season and provides the information on the budget.

visitors to forests (e.g., hikers, foresters, and visitors to a cemetery in the mountains). Given the information on fire ignition rates, the location of each fire in the fire scenarios, and IA firefighting resources in the ROK, I calculated the marginal benefit for fire prevention and fire suppression investments on reducing the expected number of fires not receiving a standard response.

To estimate the effect of fire ignition prevention efforts in the landscape of the ROK, I first calculated the marginal contribution of ignition prevention policy across the whole landscape of the ROK by changing the rate of fire ignitions by ±5%, ±10%, ±15%, ±20%, ±25%, ±30%, ±35% and ± 40%. This shows how the ignition prevention policy affects the effectiveness of IA fire prevention in terms of the success rate of the standard response. Further, I estimated the effects of focusing the fire ignition prevention efforts on populated areas or remote areas with ecological values to be protected. The effect of fire ignition prevention activities may be different by region. For instance, fire ignition prevention activities are effective in populated areas in which most fires are caused by human activities, whereas these activities are less effective in remote areas in which fires do not frequently occur by human activities.

5. RESULTS

This chapter describes the results of the California case and the ROK case from applying the standard response model to address the real deployment problems of IA firefighting resources. I also explore a number of variations in the model parameters, such as budget and capacity, and the impact of those variations on the performance of IA firefighting resources through a sensitivity analysis. To examine how a policy priority influences the optimal spatial allocation of IA resources, I impose two policy weighting schemes on fire locations in the ROK: populated areas and ecologically important areas. Finally, I investigate the impact of fire ignition prevention on the performance of IA firefighting resources and show the tradeoff relationship between the amount of fire ignition prevention effort and the number of IA firefighting resources in the ROK.

5.1. California Case

Effects of Employing a Standard Response Objective

In the base case, the CALFIRE deployment of IA resources in 2005-2008 results in an average of 0.522 ESL fires per day for the days in which at least four fires occur in a single unit (Case A, Table 5-1). The average of 0.522 ESL fires per day represents 7.10% of the 42,835 fires included in the 5,814 scenarios. The 51 engines and seven dozers are divided among 32 of 45 stations (Figure 4-3) with the largest number of engines, dozers, hand-crews, and helicopters (40%) located in NEU, which has 43% of the fires.

The deployment obtained with the optimization model given the current budget and station capacity, (low capacity and current budget, Case B in Table 5-1), uses more dozers and helicopters and fewer engines than does the CALFIRE deployment in Case A. More dozers and helicopters are deployed to meet the relatively high standard response requirements in TCU (Table 5-1). Engines and dozers are deployed in 29 of the 45 stations, and they are shifted from NEU, which has the highest fire load, to AEU and TCU to meet the standard response requirements in those units (Figure 4-3). The optimal deployment averages 0.526 ESL fires per day (Table 5-1), which is not significantly different ($p<0.05$) than the mean number of ESL fires per day for the Case A deployment. However, the optimal deployment reduces the expected number of fires per day that do not receive a standard response by 40 percent, from 2.9 to 1.75 (Table 5-1) primarily because of the increased number of dozers and helicopters and the redeployment of engines and dozers from NEU to AEU and TCU.

Table 5-1 Performance and cost of alternative IA resource deployments

Case[1]	Number of resources deployed				Daily number of fires		Cost ($million)			Optimality
	Engine	Dozer	Hand crew	Helicopter	ESL[2]	Not covered[3]	AEU	NEU	TCU	gap[4]
A. Base (CALFIRE deployment)	51	7	15	8	0.522	2.90	16.9	20.7	18.1	---
B. Low cap-current budget[9]	45	11	15	11	0.526	1.75	16.2	18.7	20.8	0.03
C. High cap-current budget	46	11	13	11	0.478	1.36	15.4	23.9	16.4	0.08
D. Low cap-high budget	57	16	22	12	0.488	1.53	21.5	21.7	25.3	0.00
E. High cap-high budget	58	13	18	13	0.477	0.84	19.8	28.9	20.8	0.07
F. Low cap-low budget	34	9	11	8	0.537	2.32	13.5	13.0	15.2	0.05
G. High cap-low budget	35	10	9	8	0.531	2.11	13.7	18.9	9.2	0.10
H. Heuristic-current budget	51	7	15	8	0.490	2.56	17.4	22.6	15.7	---

[1]The Base case represents the current (2005-2008) deployment of resources in each planning unit with dispatch allowed between units. The other cases are resource deployments found by solving the scenario-based, standard-response optimization model with dispatch allowed between units and different budget and station capacity constraints.
[2]ESL (exceed simulation limits) fires are computed using CFES.
[3]Fires not covered (fires that do not receive a standard response) are computed using the optimization model.
[4]The optimality gap is the percentage difference between the best solution obtained with the optimization model after 16 hours of run time and the best possible solution.

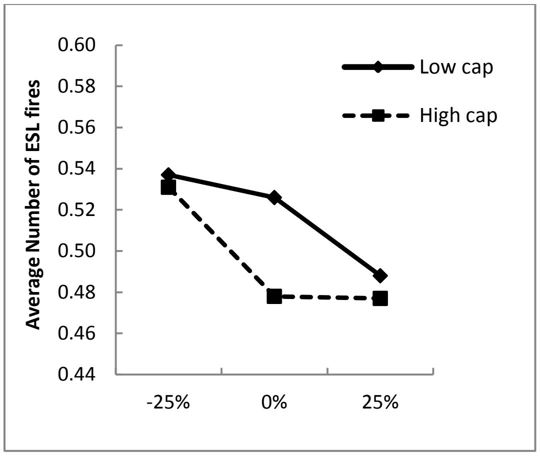
[9] To investigate how the number of scenarios used affects the optimal solution and objective function value, I estimate lower and upper bounds for the objective function value using the sample average approximation method suggested by Linderoth *et al.* (2006) (Appendix B). I conclude that 100 randomly selected scenarios adequately represent the distribution of severe fire days obtained with our fire ignition and intensity models. This result is consistent with previous studies that conclude that a relatively small sample of scenarios is sufficient to represent the distribution of scenarios in optimization problems (Snyder *et al.* 2004, Linderoth *et al.* 2006).

Effects of Station Capacity Constraints

When the current aggregate budget ($55.7 million) is re-allocated without station capacity constraints, the new deployment is designated as the high capacity and current budget Case C in Table 5-1. This deployment generates fewer ESL fires per day (0.478) and has fewer fires per day not receiving a standard response (1.36) compared with Case B. The 9% reduction in ESL fires is statistically significant ($p<0.05$) and represents an improvement in the predicted performance of a deployment for which station capacity is not limiting.

Relaxing the station capacity constraints in Case C changes the location of IA resources while leaving the optimal mix of resources across the three planning units almost the same as in Case B, which has low station capacity and current budget (Table 4-1). Engines and dozers are concentrated in 13 of the 45 stations (Case C, Figure 4-3). They are moved from TCU and AEU, which have the highest deployments in Case B, to NEU, which has the highest deployment in Case C. Further, with relaxed capacity constraints in Case C, seven of eleven helicopters can be deployed in a centrally located air base in NEU. The concentration of engines, dozers, and helicopters in stations in NEU is consistent with the relatively large fire load in NEU. These resources are well-positioned to contribute towards a standard response for many fires; they are within 30 or 60 minutes, depending on resource type, of many possible fire locations. This deployment also contributes to the reduction in the number of ESL fires and the number of fires not receiving a standard response relative to Case B (Table 5-1). Moreover, the improvement in containment success may be understated because more concentrated basing may reduce costs of maintaining station infrastructure and free up funds for suppression resources, though some of these funds might be needed to cover the cost of adjusting capacity at stations hosting more resources than current rated capacity (e.g., for additional buildings to house equipment or staff).

The capacity constraints affect the optimal allocation of funding among the planning units. For the cases with high station capacity (Cases C, E, and G, Table 5-1), NEU has the highest budget allocation because NEU has the highest fire frequency. In these cases, more engines, dozers, and helicopters are deployed in NEU to cover fires in NEU and across the border in AEU. For the cases with low station capacity (Cases B, D, and F, Table 5-1), the optimal budget allocation favors TCU. In these cases, the upper limits on engines, dozers, and helicopters in NEU shift those resources to TCU where there are more stations.



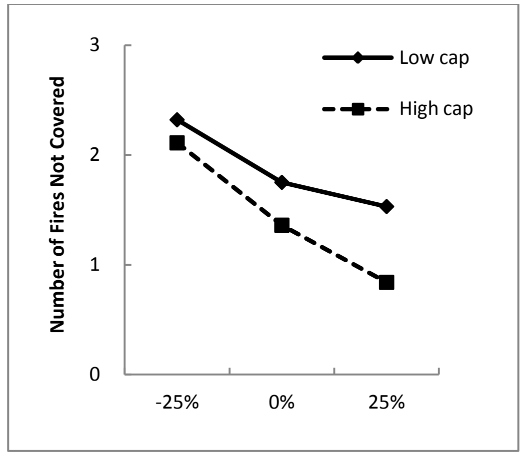


Figure 5-1 Expected number of ESL fires (left) and number of fires not receiving a standard response (right) as the budget constraint is varied relative to the current budget ($55.7 million).

Effects of the Budget Constraint

Budget constraints have significant impacts on the daily number of ESL fires and the number of fires not receiving a standard response (Figure 5-1). Increasing the budget level from -25% to +25% of the current level reduces the daily number of ESL fires on days with four or more fires in one of the CALFIRE units from 0.537 to 0.488 in the low station capacity cases and from 0.531 to 0.477 in the high station capacity cases. Increasing the budget also reduces the daily number of fires not receiving a standard response.

The low budget cases provide guidance on how to reduce resources in the event of a budget reduction. The cases with lower budgets (Cases F and G, Table 5-1) have 11 fewer engines, one or two fewer dozers, four less hand crews, and three fewer helicopters than the cases with the current budget (Cases B and C, Table 5-1). The case with low station capacity has nine fewer stations when the budget is reduced while the case with high station capacity has four fewer stations, though of course this case had fewer stations before the budget reduction. Thus, a budget cut in the capacity constrained case is more likely to cause a complete shutdown of some stations by removing one or two deployed engines. In contrast, a budget cut in the case with unconstrained capacity reduces resources in most stations without closing them.

With a 25% higher budget, the optimization model increases all four types of resources and their deployment depends on the station capacity constraints. With capacity constraints, 17 engines and dozers, seven hand crews and one helicopter are added to the three planning units (Cases B and D, Table 5-1). The new engines and dozers are added to eight new stations, mostly in TCU, which has 29 percent of the fires in the study area and the highest per fire standard response requirements for non-engine resources. Without station capacity constraints, 14 engines and dozers, five hand crews and two helicopters are added to the planning units (Cases C and E, Table 5-1). The new deployment of engines and dozers is scattered among the 16 stations with no net gain in the number of stations.

The performance of the optimization program is reported in the far right-hand column of Table 5-1. Case D reached a probably optimal solution in 1 hour.

The other five optimizations terminated at the 16 hour run time limit. Varying the run time limit led to stable and consistent results at slightly shorter and at longer run times, verifying the use of the 16 hour limit. For these five optimizations, the optimality gaps fell between 0.10 and 0.03, which characterizes these solutions as quite close to the optimal solution (Bixby and Rothberg 2007).

Testing the performance of a simulation optimization heuristic

I applied the simulation optimization heuristic described above using the CALFIRE deployment (Case A) as the starting point. After eight iterations, the heuristic's solution involves shifting eight engines and two dozers from stations on the edges of the study area, where fire frequency is low, to centrally located stations near Auburn and Placerville, where fire frequency is high. The new deployment (Case H, Table 4) reduced the number of ESL fires by 6.6% relative to the performance of Case A. While the new deployment violated the capacity constraints at four stations, it allowed slightly more ESL fires than the optimal deployment in Case C, which had no capacity constraints and involved more complex changes to the mix of resources and deployment among the fire planning units. In addition to not finding a superior resource allocation for reducing ESL fires over the optimization model, the simulation optimization heuristic is also time consuming. The deployment obtained after eight iterations required about 19.5 hours of execution time (2.4 hours per simulation times 8 simulations), slightly more than the execution time allowed for each application of the optimization model.

For comparison with results from the optimization model, I developed the simple deployment heuristic to apply with CFES2 simulations. Similar to the results of the optimization model without capacity constraints, the results of the heuristic suggest that I can improve the performance of IA resources by allocating them to stations with high fire loads, as these are also proximal to higher incidences of ESL fires.

5.2. The ROK Case

Optimal spatial allocation of initial attack

In the base case (BASE), the current deployment of IA helicopters in KFAH (2011) results in an average of 0.53 fires per day (9% of all fires) that do not receive the required response, considering the 2+ fire days (i.e., two or more fires per day) in which on average 5.87 fires per day occur in the Korean landscape (Table 5-2). Under the current budget and settings, the optimal deployment of helicopters (OPT) results in 0.47 fires per day that are not covered by the required response, which is an improvement of 11% over the base case. The optimal solution shifts helicopters to stations that are close to fire locations with the highest fire frequency (i.e., J1, J3, J6, and J8). Most fires are caused by human activity in the ROK, so high frequency fire locations tend to be close to metropolitan areas (i.e., J3 and J8), in accordance with previous studies (Lee *et al.* 2008). In addition, IA resources are deployed to stations near mountainous and coastal areas (i.e., J1, J2, J4, J6, and J7) because fires in mountainous and coastal areas have high spread rates and require more firefighting resources for rapid containment. However, the service area for J5 is dominated by unpopulated inland areas, moreover, the helicopters deployed at J1, J4 and J7 can cover most fire locations in J5's service area within 30 minutes. Thus, the number of helicopters deployed at J5 is small relative to other helicopter bases, despite the demand for IA resources (Figure 5-2). Moving IA helicopters from J5 to J1, J4, or J7 helps to reduce the expected number of fires that do not receive a standard response. The result also implies that the helicopters deployed at J1, J4, and J7 play an important role in cooperatively supplementing the demand of IA resources at J5.

Table 5-2 Number of helicopters deployed per station and number of fires that do not receive a predefined standard response from spatial optimization with different policy goals.

Case	Num. of helicopters deployed	Num. of fires not covered	Helicopter station							
			J1	J2	J3	J4	J5	J6	J7	J8
BASE[a]	27	0.53	3	3	4	3	3	3	4	4
OPT[b]	27	0.47	4	3	4	3	2	4	3	4
POP[c]	27	1.10	4	3	4	4	4	0	4	4
ECO[d]	27	0.99	4	3	4	4	2	4	4	2

[a] Existing allocation of currently available firefighting helicopters

[b] Optimal spatial allocation of helicopters through optimization with weights on fire locations with high fire load

[c] Optimal spatial allocation of helicopters through optimization with weights on populated places

[d] Optimal spatial allocation of helicopters through optimization with weights on ecologically sensitive (protected) places

Budget sensitivity analysis

Budget constraints have a significant impact on the expected number of fires not receiving a standard response. Increasing the budget level from -26% to +26% of the current level reduces the daily number of fires not receiving the standard response from 0.83 to 0.4. While budget increase allows to employ more IA firefighting resources and to enhance their availability when needed, budget decrease limits available IA resources even at core stations, thereby increasing the number of fires not receiving the standard response.

The low budget cases in Table 5-3 provide insights into how to reduce resources as the budget decreases. The case with an 11% reduction in the budget has three fewer helicopters than the OPT case with the current budget in Table 5-2, and results in removing helicopters from J6 and J8. This implies that maintaining the number of helicopters in other stations is more effective in reducing the number of fires that do not receive a standard response than maintaining the number of helicopters in J6 and J8. This is because IA helicopters at J7, which is located between the two stations, help to reduce the impact of removing the helicopters in J6 and J8 on the number of fires that do not receive the standard response because the service area of IA resources in J7 overlaps with those of J6 and J8 within the time limit. As budgets increase, the optimal allocation increases resources at all stations, but their deployment is limited by the current station capacity constraint (i.e., four helicopters per station).

The number of helicopters deployed to each station is limited by the capacity constraint, which may reduce the efficiency gains by limiting the maximum number of IA resources deployed at a core station (e.g., J3). Even though the marginal contribution of an additional IA resource at J3 is larger than that of additional IA resources at other stations, the capacity constraint results in an optimal spatial allocation that deploys all helicopters to stations up to the capacity limit, given that the resources are within the budget (Table 5-3). Once the number of helicopters in all stations reaches the capacity limit, the fire manager must increase the capacity of a station or build another station in order to decrease the number of fires not covered[10].

Table 5-3 Number of helicopters deployed per station and number of fires that do not receive a standard response from spatial optimization with budget changes.

Budget variation	Num. of helicopters deployed	Num. of fires not covered	Helicopter station							
			J1	J2	J3	J4	J5	J6	J7	J8
+26	34	0.4	4	4	4	4	4	4	4	4
+15	31	0.41	4	3	4	4	4	4	4	4
+11	30	0.42	4	3	4	4	4	4	3	4
+5	28	0.44	4	3	4	4	2	4	3	4
0	27	0.47	4	3	4	3	2	4	3	4
-5	26	0.49	4	3	4	3	2	4	3	3
-11	24	0.57	4	3	4	4	3	1	3	2
-15	23	0.6	4	3	4	3	2	1	4	2
-26	20	0.83	3	3	4	2	2	2	2	2

[10] The impact of capacity constraints in the allocation problem of firefighting resources on the effectiveness of initial attack resources may be an interesting issue. However, we do not focus on the problem in this study. It is an area recommended for future research.

5.3. Policy Preference: Weighting Scheme

When considering different policy goals, the optimal allocation of suppression resources changes depending on how each fire location is prioritized (Table 5-2). In the base case, above I assumed that all fire locations are equally important and must be protected. However, because potential fire locations are generally heterogeneous in terms of their characteristics and their values to be protected, I set a priority on important locations such as populated areas (POP) and ecologically sensitive places (ECO) (Table 5-2). When prioritizing fire locations that are ecologically sensitive, such as endangered-species habitat, the optimal deployment of helicopters required for initial attack allocates the 27 helicopters to cover fire locations with priority for those that contain fires in forest reserves (e.g., J1, J3, J4, and J6) (Figure 5-3). In contrast, when prioritizing the protection of populated areas, the optimal allocation of helicopters concentrates more helicopters on fire locations near big cities (e.g., J3 and J8) rather than on fire locations close to forest reserves (e.g., J6) (Figure 5-4). These results imply that policy goals are critical in determining the optimal fire policy for utilizing available firefighting resources, even in a small country. Thus, policy preferences and socio-economic values drive the optimal allocation of firefighting resources in a heterogeneous landscape.

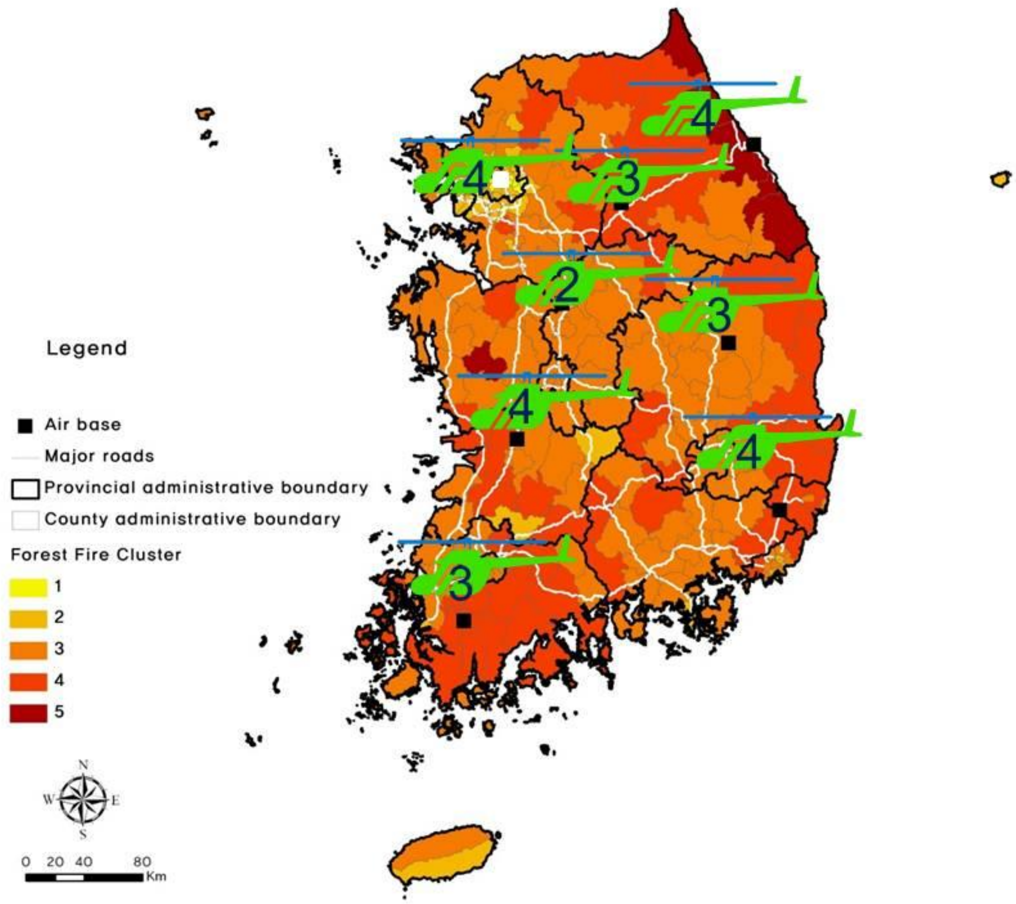


Figure 5-2 Optimal spatial allocation of IA helicopters with the consideration of spatial characteristics of fire locations to be protected for fire susceptibility.

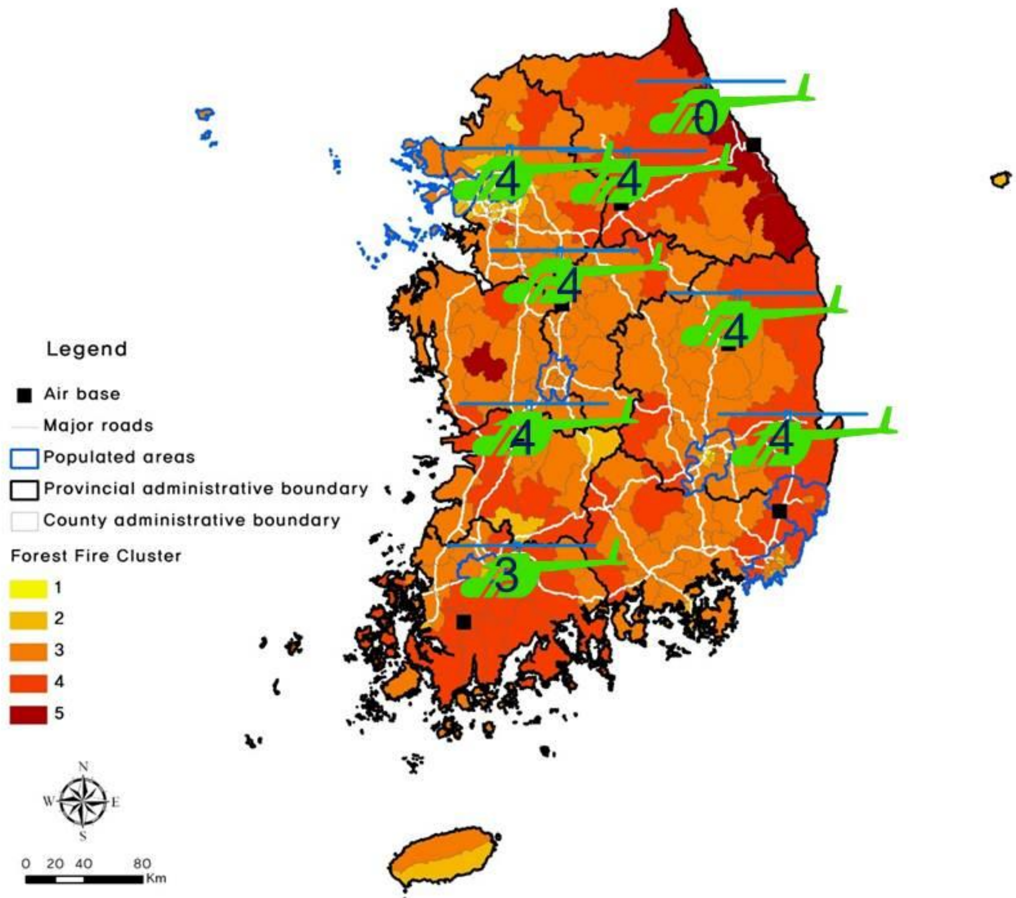


Figure 5-3 Optimal spatial allocation of IA helicopters with the consideration of spatial characteristics of fire locations to be protected for populated areas.

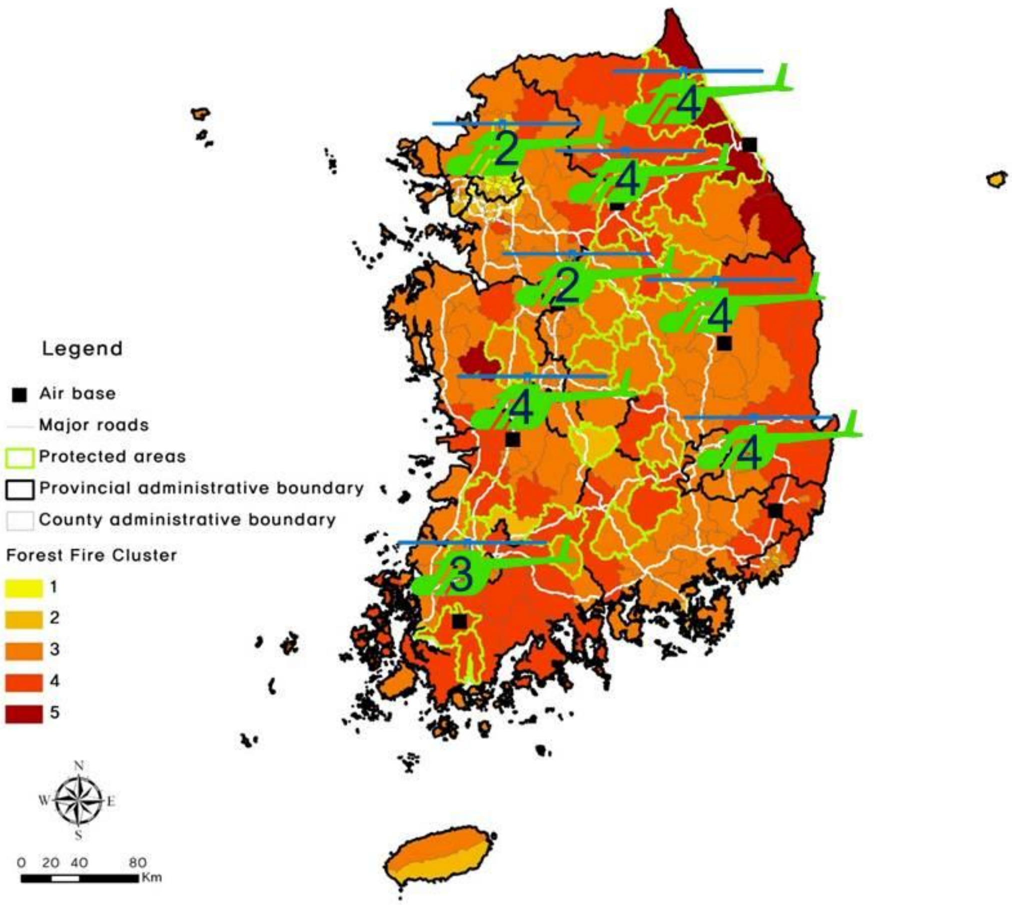


Figure 5-4 Optimal spatial allocation of IA helicopters with the consideration of spatial characteristics of fire locations to be protected for ecologically sensitive areas.

My results differ from those of previous IA optimization models that use the simple maximum set-covering framework (MacLellan and Martell 1996; Haight and Fried 2007; Hu and Ntaimo 2009). These models implicitly treat all fires that exceed IA size limits as equal; the deployments and dispatches do not reflect heterogeneity across space in either the magnitude of the damage or the eventual size of the escaped fire. In practice, fires located near large populations or particularly valuable resources may receive a higher priority for initial attack than identical fires in other locations. My model described here assumes that multiple fires may occur on one day, and fires occur on a heterogeneous landscape—not only in terms of fire susceptibility but also in terms of protection priority. My approach in this study is supplementary to the previous models by defining the standard response for each fire together with the resource and response-time requirements that are related to the expected fire intensity and priority of each fire depending on its location.

5.4. Returns to Fire Ignition Prevention

To investigate the tradeoff relationship between IA resources and fire ignition prevention policy, I derived two curves from optimization runs by varying the expenditure on employing IA resources and the level of fire ignition prevention effort. The first curve represents the relationship between the total number of helicopters deployed and the expected number of fires per fire day not receiving the standard response (Figure 5-5); the second curve represents the relationship between the level of fire ignition prevention efforts and the expected number of fires per fire day not receiving the standard response (Figure 5-6).

Figure 5-5 presents the functional relationship between the number of helicopters deployed and the expected number of fires per fire day not receiving the standard response. The points on the curve represent a non-dominated solution for each budget level. Without a budget increase, improvements cannot be achieved in terms of expected number of fires per fire day not receiving the standard response for each non-dominated solution. Consequently, the points on the curve in Figure 5-5 represent loci that describe the functional relationship.

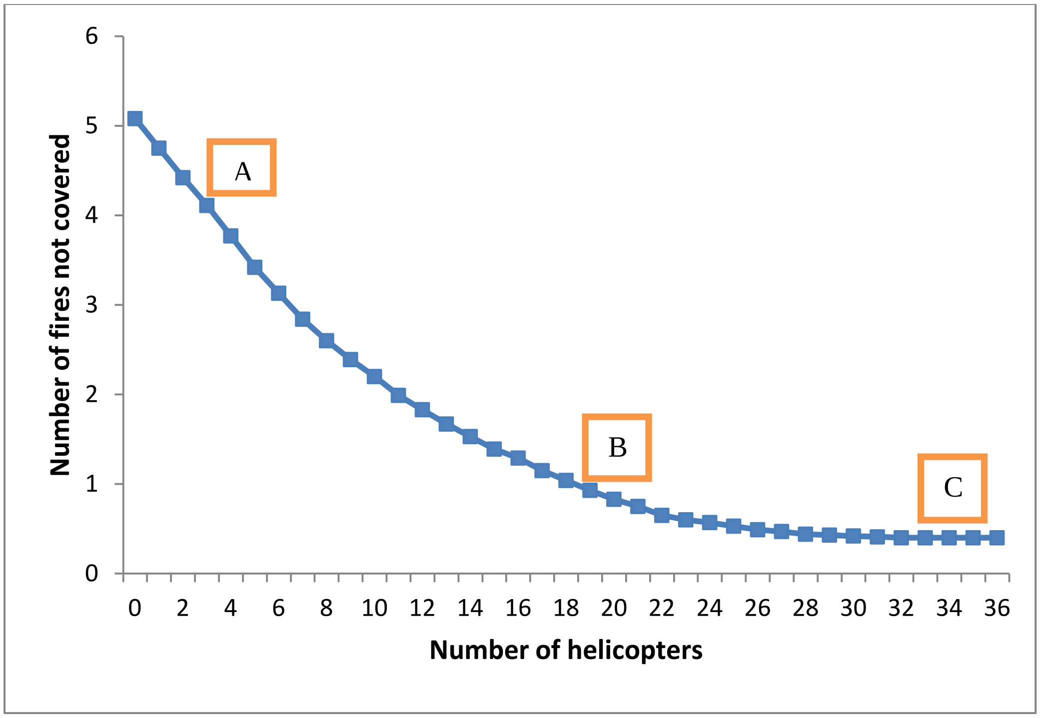


Figure 5-5 Relationship between the number of fires not covered and the number of helicopters deployed.

The deployment of helicopters depends on a given budget. When there are no available helicopters (i.e., the budget equals zero), the expected number of fires not receiving the standard response is equal to the average daily fire frequency of 5.87. As the budget increases and more helicopters are deployed, fewer fires are not covered. For instance, with 12 helicopters deployed, the expected number of fires left uncovered is 1.83 (31.1% of the average number of fires per fire day). Increasing the number of helicopters from 12 to 27 reduces the number of uncovered fires to 0.47 (23.0% of the daily average). The slope of the tradeoff curve, which represents the gain in the daily number of fires covered per unit increase in number of helicopters deployed, is relatively steep between the case of 0 helicopter deployed and that of 19 helicopters deployed. Between the case of 20 helicopters deployed and that of 32 helicopters deployed, on the other hand, the slop is relatively flat (0.04 fires / helicopter).

The relationship curve in Figure 5-6 can be used to evaluate the effectiveness of fire ignition prevention on reducing the number of fires not receiving a standard response. The vertical distance between points on the curves represents the reduction in expected number of fires not receiving the standard response resulting from changing the level of fire ignition prevention effort while maintaining a given helicopter force (i.e., 27 firefighting helicopters).

In Figure 5-6, the curve showing the relationship between the level of fire ignition prevention efforts and expected number of fires not receiving the standard response has a convex shape in which the expected number of fires not receiving the standard response decreases at an increasing rate as the level of fire ignition prevention efforts increases for a given level of IA fire suppression. The points on the curve represent non-dominated solutions with a given budget. For each non-dominated solution, improvements cannot be achieved without a budget increase, in terms of number of fires per fire day not receiving the standard response. As a result, the points on the curve represent loci that describe the functional relationship.

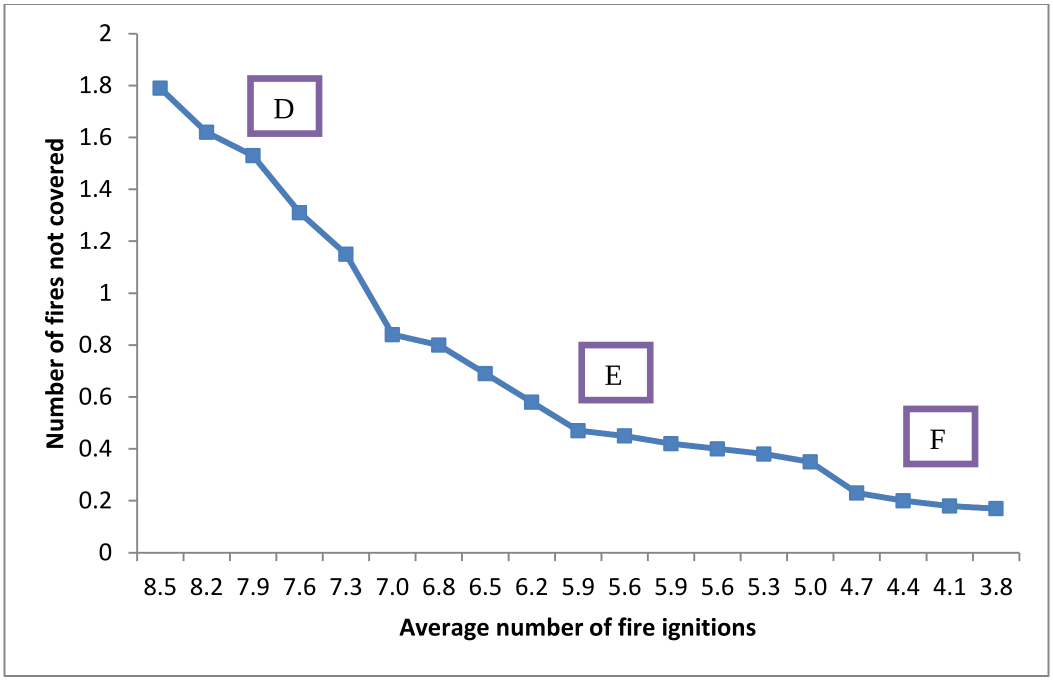


Figure 5-6 Relationship between the number of fires not covered and the daily average number of fire ignitions by the level of fire ignition prevention efforts.

The level of fire ignition prevention efforts determines the value of the objective function, i.e., expected number of fires not receiving the standard response. When there is no additional fire ignition prevention effort, the expected number of fires not receiving the standard response is equal to that of the optimal solution with helicopters optimally deployed for the current budget case (i.e., 0.47 fires per day). As more fire ignition prevention efforts are employed, fewer fires occur, and consequently a smaller number of fires remain uncovered by the standard response. For example, with the current level of ignition prevention efforts, the expected number of fires left uncovered is 0.47 (8.0% of the average number of fires per day). Increasing the level of fire ignition prevention efforts from the current level (5.87 fires/day) to 30% more than the current level (4.7 fires/day) reduces the number of uncovered fires to 0.24 (5% of the daily average). The slope of the tradeoff curve, which represents the gain in the daily number of fires covered per unit increase in level of fire ignition prevention efforts, is relatively steep - between -45% of the current level (8.51 fires/day) and the current level (5.87 fires/day). Between the current level and +45% of the current level (3.82 fires/day) of fire ignition prevention efforts, on the other hand, the slope is relatively flat (0.03 fires/5% ignition prevention effort increment).

In Figure 5-5, the slope of the tradeoff curve represents the benefit/input(cost) ratio of the reduction in the expected number of fires per increase in spending on helicopters deployed for initial attack; the slope of the tradeoff curve in Figure 5-6 is a benefit/input(cost) ratio showing the reduction in expected number of fires per increase in spending on fire ignition prevention activities[11]. In Figure 5-5, the slope is relatively steep between solutions A and B (< -1) indicating the benefits from deploying more helicopters are relatively big. Between solutions B and C, the slope is relatively flat (> -1) indicating that deploying more helicopters is not cost-effective in terms of reducing the expected

[11] The unit cost of operating a helicopter is $616,000(USD), and the unit cost of reducing the fire ignition rate by 5% is assumed as $1,824,000 (i.e., $40 (the unit cost per day) × 80 days × 228 persons for patrolling the areas). Those figures are obtained from consultation with KFS personnel.

number of fires not receiving a standard response. In the same context, the slope is relatively steep between solutions D and E (< -1) indicating the benefits of more fire ignition prevention efforts are relatively big in Figure 5-4. Between solutions E and F, the slope is relatively flat (> -1) indicating that additional fire ignition prevention efforts are not cost-effective in terms of reducing the expected number of fires not receiving a standard response.

By comparing the marginal contributions of additional helicopters deployed and additional fire ignition prevention efforts to reducing the expected number of fires not receiving a standard response, the tradeoff relationship between two fire management policies is shown in Figure 5-7. With the existing fire management policy in the ROK, there are 27 available firefighting helicopters for initial attack. The marginal decrease of the expected number of fires not receiving the standard response for the last dollar spent on an additional helicopter is 0.00003, while the marginal increase of the expected number of fires not receiving a standard response for the last dollar spent on an additional unit of fire ignition prevention effort (+5%) is 0.00009. Because the marginal benefit of fire ignition prevention per dollar spent is larger than that of IA firefighting helicopters per dollar spent, spending the additional unit on fire ignition prevention is more cost-effective than that on IA firefighting helicopters.

When fire ignition prevention is applied in the Korean landscape, the curve that shows the tradeoff between the cost of helicopters deployed and the cost of additional fire ignition prevention effort is relatively flat (Figure 5-7). With a small number of helicopters available for initial attack, fire ignition prevention efforts are as cost-effective as employing more helicopters. However, with more than 30 helicopters, additional helicopters produce little reduction in the expected number of fires not covered because those helicopters deployed to dispatch 1-4 helicopters to fires for initial attack are not able to cover the high number of fires caused by human activities. The greatest gain from fire ignition prevention in terms of reducing the expected number of fires not covered occurs when the current number of helicopters (i.e., 27 helicopters) is available.

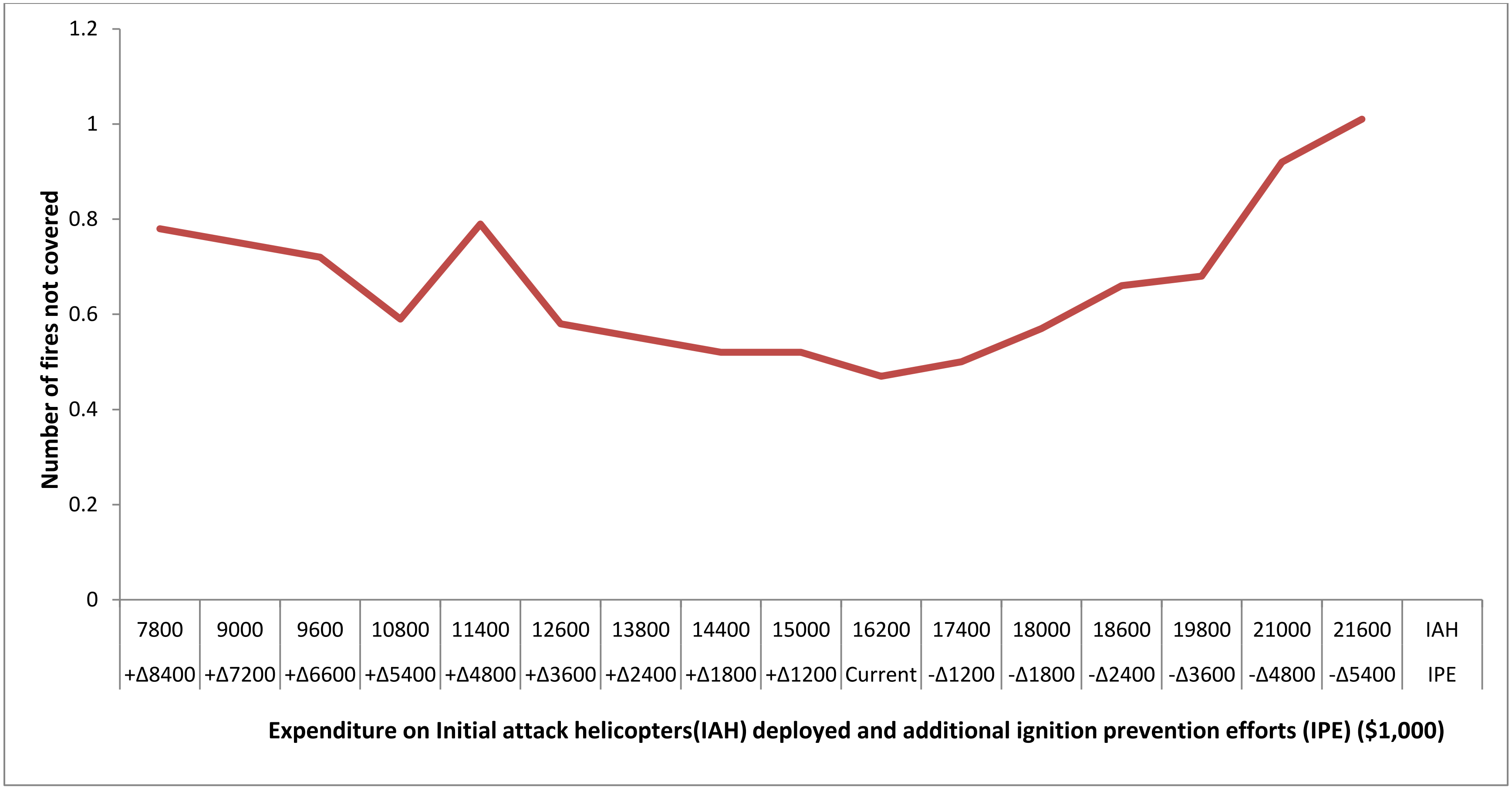


Figure 5-7 Tradeoff curve between the cost of basing helicopters (IAH) and the cost of fire ignition prevention efforts (IPE) in terms of the expected number of fires not covered by the standard response within a given budget.

When a fire manager implements a fire ignition prevention policy by focusing on some specific places with a policy goal, the optimal spatial allocation of helicopters deployed and the objective value have been changed (Table 5-4) from the previous results (Table 5-2) without the additional fire ignition policy. Because there are no human-caused fires if the fire manager conducts a strong fire ignition prevention policy in the potential fire locations (e.g., restricting human access to forest areas during a fire season) by laws or seasonal regulations, the expected number of fires not receiving a standard response significantly decreases, and the optimal solutions concentrate IA firefighting helicopters on fire stations away from the fire manager's policy target areas. With the priority on populated areas, the spatial allocation of IA firefighting helicopters distributes more resources to unpopulated areas because the fire ignition prevention efforts reduced the daily demand of firefighting helicopters for IA around populated areas. Also, with the priority on ecologically sensitive areas, the fire ignition prevention efforts on those areas allow the fire manager to move firefighting helicopters to populated areas by restricting human-caused fire ignitions in remote, unpopulated, and ecologically sensitive areas (Figure 5-8).

Table 5-4 Number of helicopters deployed per station and number of fires that do not receive a predefined standard response from spatial optimization with a fire ignition prevention for the different policy goals.

Case	Num. of helicopters deployed¶¶¶	Num. of fires not covered	Helicopter station							
			J1	J2	J3	J4	J5	J6	J7	J8
POP¶	27	0.39	4	3	4	4	2	4	4	2
ECO¶¶	27	0.34	4	3	4	4	4	4	0	4

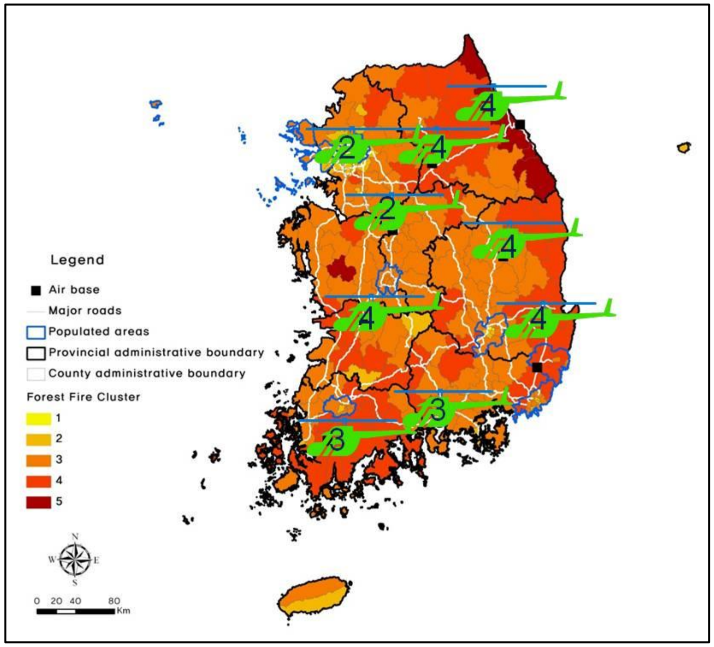
¶ Optimal spatial allocation of helicopters through optimization with fire ignition prevention on populated places

¶¶ Optimal spatial allocation of helicopters through optimization with fire ignition prevention on ecologically sensitive (protected) places

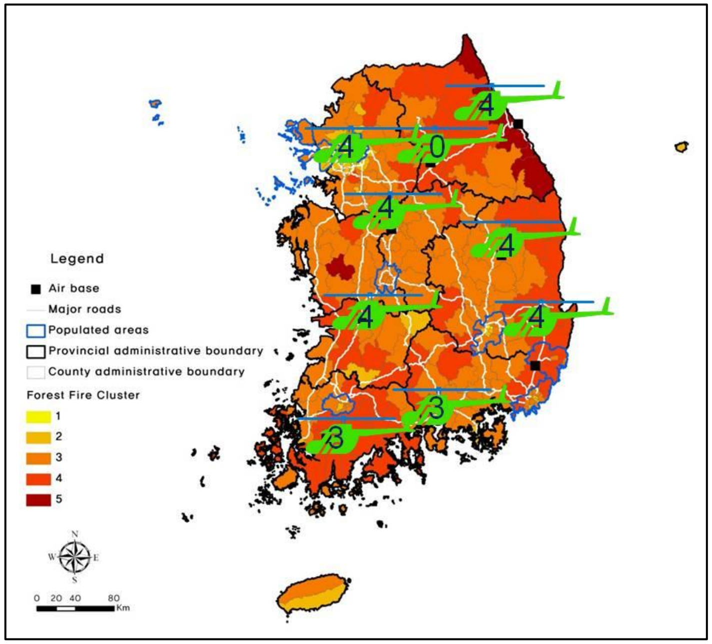
¶¶¶ In this case, there is no tradeoff between the expenditure on IA helicopters and the expenditure on the ignition prevention policy by assuming that the fire ignition prevention policy has no cost for implementing the regulation by the government.

When a fire manager implements the fire ignition prevention policy by focusing on specific locations based on a policy goal (e.g., protecting populated areas, or protecting endangered species habitats), there are two types of tradeoffs. First, there is a tradeoff between the expenditure on firefighting helicopters deployed and the cost of fire ignition prevention efforts, and second, there is a tradeoff among potential fire locations based on the weight of each location that is calculated from the value at risk in each area. This study, however, only focuses on the second tradeoff, and specifically, on fire ignition prevention efforts between populated areas and ecologically sensitive areas (Table 5-4). If the fire manager implements the fire ignition prevention policy for populated areas and ecologically sensitive areas with the same costs, concentrating the fire ignition prevention policy to ecologically sensitive areas is more cost-effective than populated areas in terms of reducing the expected number of fires not covered.

Because the fire ignition prevention policy on targeted areas helps fire managers utilize IA helicopters for other places, a fire manager gains some efficiency from the new policy. In particular, when a budget is limited, a fire ignition prevention policy provides an alternative option to the fire manager who may consider less expensive fire ignition prevention policies, such as barricading human access to susceptible forests during a fire season, where most fires are caused by hikers or forest workers. However, the strong fire ignition policy may create substantial social opportunity costs. Without any consideration of those social costs, the benefit of the fire ignition prevention policy may be over-estimated.



Populated Area



Ecologically Important Area

Figure 5-8 Optimal spatial allocation of IA helicopters with the consideration of spatial characteristics of fire locations to be protected under different policy goals.

6. DISCUSSION AND CONCLUSIONS

The contributions of my dissertation to the literature are in both the methodology and the application. As an extension to the methods in the literature on standard response based initial attack planning (Haight and Fried 2007), I combined an optimization model with stochastic simulation, and applied the model to a realistic setting by considering multiple fire planning units on a landscape, several types of firefighting resources, a priority rule for dispatching resources to fires by weighting fire locations, and two countries with different settings. This framework helps a fire manager to make decisions, particularly with regards to the strategic deployment of IA firefighting resources on a landscape under uncertainty in fire occurrence and behavior. The methodology results include deployment plans, scenario dispatch plans, expected number of fires that do not receive a standard response, and operational budget of each planning unit. The scenarios and tactics used in the operational phase are well defined and produced by a realistic fire-fighting simulator, such as CFES2 (Fried *et al.* 2006). I extended the model framework to examine the effect of budget and capacity constraints. Also, I modified the optimization model to incorporate the effect of fire ignition prevention efforts. In my application contribution, I applied the methodology to three planning units in California and to the entire ROK to effectively distribute several types of IA resources across available stations in the landscapes at the beginning of a fire season. The results provide insights into how to optimally allocate IA resources to improve their performance in standard response success for IA fire suppression in particular fire settings.

In this chapter, I discuss the objective function of my optimization model and potential alternative objectives, the effect of station capacity on the optimal spatial allocation of IA resources, the performance of heuristic analysis, the effect of fire ignition prevention policy on the performance of IA resources for IA standard response success, and the strength of the simulation-optimization framework. In addition, I describe some limitations and policy implications in this study. Then, I summarize the main findings and offer concluding remarks.

6.1. Objective Function for Initial Attack Firefighting Planning

The standard response model for IA firefighting planning provides a tractable tool for a fire manager to successfully contain fires in the early stages of fire suppression. The objective in the optimization model is to minimize the expected number of fires that do not receive a standard response - defined as the number of resources by type that must arrive at the fire location within a specified timeline - subject to budget and station capacity constraints and uncertainty about the daily number and location of fires. The standard response model for IA firefighting planning simplifies an IA system while retaining the essential goal of achieving the earliest containment by IA resources. CFES2 models the containment of fires as a relationship between fire-line production and fire perimeter growth, in order to evaluate the performance of the deployments obtained with optimization in the California case. CFES2 predicts the number of fires that exceed simulation limit (ESL) on fire size or burning time, which can be thought of as a proxy for fires that escaped from initial attack.

The IA optimization model aids a fire manager in achieving the goal to contain fires in the IA fire suppression stage and thereby prevent them from becoming large and costly fires. In particular, large fires, 1.1% of all fires, account for 97.5% of the area burned in the US (Calkin *et al.* 2005). A strong and prompt IA is most effective in containing a fire within a prescribed time window, which increases the chance of preventing the fire from escaping and becoming a large fire (Arienti *et al.* 2006).

Based on results from modeling the California case, when compared with the current CALFIRE deployment, the deployment obtained with optimization and the current budget and station capacities will result in fewer fires that do not receive a standard response and no change in the number of ESL fires. However, I found significant performance gains with the current budget, when station capacity was assumed not to limit the number of firefighting resources deployed at each location. While I expected that performance would scale with budget, the performance improvements associated with increasing station capacity were unexpected. Our optimization model with a standard response objective produced resource deployments that perform at least as well as the predicted performance of the existing resource deployment that is based on expert knowledge and experience.

Furthermore, the standard response optimization model provides a useful tool for a fire manager who considers protection priority by fire location. When the objective is to minimize ESL fires, all fires that exceed IA size are implicitly treated as equal. The deployments and dispatches do not reflect heterogeneity across space in the magnitude of the potential damage or the eventual size of the escaped fire. In practice, however, fires located near areas of high human population density and/or high value resources may receive a higher priority for initial attack than fires in other locations. The standard-response model can be easily extended to address this priority issue by accounting for the importance of fire location with respect to a policy goal such as protecting human lives, homes or the habitat of a threatened species.

One objective extensively discussed in the literature on wildfire planning models is minimizing the sum of Cost plus Net Value Change (C+*NVC*), which traditionally provides the theoretical foundation in wildfire economics. This model minimizes the sum of pre-suppression (expenditures on wildfire management prior to a fire season), suppression (direct wildfire suppression expenditures during a fire season), and *NVC* (net wildfire damage), which is negative when fire benefits exceed damages and nonnegative otherwise. Donovan and Rideout (2003b) suggested that their integer linear programming model successfully applied the theoretical framework to a single fire event, by identifying the specific fire-fighting resources that must be deployed to minimize the C+ *NVC* for the given set of model parameters. However, thus far the model's limitations prevent it from being extended to address a portfolio of sometimes temporally overlapping fire events occurring throughout a planning area. Lightning storms can generate multiple fire starts in a very short time. It would be beneficial if the model were to be extended to address spatial and temporal issues when determining the optimal mix of firefighting resources, as little research has been conducted to address realistic landscape level wildfire planning. Ntaimo *et al*. (2012) incorporated the C+ *NVC* model into the standard response optimization framework to achieve the minimum value of cost plus net value change. This study also showed a limitation to the current *NVC* framework. The *NVC* component assumes that an average *NVC* per acre is given for escaped fires and it is constant across space.

6.2. Effects of Station Capacity Constraints

Previous studies about IA firefighting planning focused on dispatching several types of resources to a single fire location or deploying a single type of resource across homogeneous fire stations with a given station capacity

(MacLellan and Martell 1996; Donovan and Rideout 2003; Haight and Fried 2007; Ntaimo *et al*. 2012). Donovan and Rideout (2003) use an integer programming model to determine the optimal mix of firefighting resources to dispatch to a given fire to achieve containment with minimal resultant cost and damages but do not consider the effect of a station capacity on the efficient operation of firefighting resources. In a similar framework to that used here, Haight and Fried (2007) consider a scenario-based standard response model to optimize both deployment and dispatch of engines for IA firefighting with a given capacity constraint for each station but do not consider multiple types of firefighting resources nor do they address capacity constraints directly. Unlike these previous studies, I considered a model that includes many types of firefighting resources in multiple fire planning units and examines the effect of capacity constraints. Because my framework includes all of these dimensions, it is uniquely capable of examining the impact of expanding station capacity and determining the characteristics of stations for which the expansion would prove most useful in achieving the goal of standard response.

The impact of relaxing station capacity constraints on the number of fires receiving the standard response varies across stations due to differences in response times and the probability of fire within the station's response area. Resource deployment resulting from relaxing all constraints on station capacity achieves greater containment success by consolidating resources into stations with high standard response requirements. Because a location's probability of fire and characteristics such as fuel determine its dispatch frequency, expanding station capacity to put more resources in stations with high standard response requirements increases resource availability during high fire frequency periods. Expanding stations located in central areas, or near main roads that increase the speed with which road-based resources can get to fires, improves the effectiveness of a given level of IA resources because those stations have larger maximum service areas than other stations. Also, because the rate of fire spread, which is determined by fuel, wind, and slope (Finney 2003), critically affects the fire dispatch level of a fire location, expanding stations and locating IA resources in high dispatch areas also puts resources close to areas with fast spreading fires. A fire manager can achieve the goal of increasing the number of fires receiving the standard response by expanding station capacity in stations with high dispatch frequency.

Budget declines in places like California underscore the need to make the most efficient use of limited initial attack fire fighting resources. The results here demonstrate that relaxing station capacity constraints in particular locations and increasing their allocation of IA resources can improve the outcome from a given set of resources. This analysis, however, does not consider the feasibility nor the costs of expanding station capacity. In view of declining budgets and catastrophic fires, managers could benefit from further research that assesses the costs of expanding stations and compares those costs to the benefits of the improved resource allocation through that expansion using a framework such as that presented here.

6.3. Heuristic Method

I developed a simple deployment heuristic to work in conjunction with the CFES2 simulation to allocate suppression resources across stations in the California study area and compared the results against those provided by the optimization framework. A heuristic is a technique designed for solving large problems with less time and effort when classic methods like optimization are too slow or costly to find an exact solution. The heuristic analysis explicitly provides the information on the marginal change of reallocating an IA resource to another station in the value of the objective function because the heuristic is initialized with the current allocation. The deployment obtained from the heuristic analysis performs as well as the optimal deployment obtained from optimization model without capacity constraints in reducing the rate of ESL fires. By trading optimality, completeness, and accuracy for time and cost, the heuristic analysis in the California study produces a solution that is acceptable when compared with the optimization results.

The spatial allocation of IA resources obtained from the heuristic differs from the optimal spatial allocation of IA resources across stations. From the current actual allocation, the heuristic moves IA resources from a station with the lowest fire load to a station with the highest fire load, whereas the optimization model shifts all available IA resources from stations with the highest fire load to stations with the highest standard response requirements. In the optimization model, stations with the highest standard response requirements are supposed to respond to all fire locations in which IA resources can arrive within the maximum response time of 30 minutes for IA engines. However, during the CFES2 simulation, IA resources are free to respond to fire locations across a relatively broad area because IA resources can continue to respond to new fires until a fire exceeds simulation limits. For example, IA engines that are able to arrive at a fire location in 100 minutes can contribute to the containment of the fire within the IA time window, even though the effectiveness of IA fire suppression on wildfires is affected by timing (Arienti *et al*. 2006). The results of the heuristic imply that, under the current budget constraint, a range of deployments may perform equally well in terms of the rate of fire containment success.

I found that a fire manager can improve the performance of IA firefighting resources as compared to the current CALFIRE deployment of IA resources by allocating them to stations with high fire loads, which are also proximal to high incidences of ESL fires. Because high fire loads demand many IA firefighting resources, which increases the probability of resource shortages on high fire count days, allocating IA resources to stations with high fire loads can enhance the resource availability on such days. I found that the new deployment of IA resources obtained from the heuristic significantly improved the rate of fire containment success as compared to the current actual deployment of IA resources, although it is not a superior resource allocation for reducing ESL fires over the optimization model. The heuristic method provides an alternative way for a fire manager to improve the performance of IA firefighting resources without an optimization process.

6.4. Tradeoff between Initial Attack Firefighting and Fire Prevention Policy

Fire ignition prevention improves the performance of IA resources by decreasing the frequency of human-caused fires. First, the relationship between the expected number of fires not covered and the average number of fire ignitions over fire scenarios during high fire season, and second, the tradeoff relationship between the number of firefighting helicopters and the level of fire ignition prevention efforts suggest that fire ignition prevention is as cost-effective as IA firefighting helicopters in the ROK, given the current budget. The relationship between the fire ignition prevention effort and the expected number of fires not covered shows a decreasing return to scale. If a fire manager already has a strong fire ignition prevention policy, as is true in the ROK, the marginal benefit of a fire ignition prevention effort is relatively small. However, if there was no, or very limited, fire ignition prevention effort, a fire manager may be able to improve the performance of IA resources by implementing a policy of fire ignition prevention.

In addition to the benefits to successful IA rates, however, the fire ignition prevention policy may create social costs that affect the optimal level of fire ignition prevention efforts (Walters 1961; Hazzila and Kopp 1990). In my dissertation, the optimal levels of IA firefighting resources and fire ignition prevention were determined without the consideration of social costs. In order to optimize the social welfare for a human community, a policy maker should consider the social cost of a fire prevention policy before implementing the policy. If the policy restricts the communities' recreational activities in a wildland, lack of public support may make the policy hard to implement (Hazilla and Kopp 1990). In the same context, fuel treatment policies such as prescribed burning and mechanical thinning may not be applicable in many places due to the opportunity costs to human communities and the low tolerance for such policies (Winter *et al*. 2002). Despite these social costs, fire prevention policies may still be cost-effective in avoiding potentially destructive fires.

While human-caused fires usually occur close to populated areas and therefore are detected and attacked decisively and quickly when they occur, lightning fires occur across a broad landscape. Fires caused by lightning can occur in remote areas where they may be not detected until they become a relatively large fire. Given their tendency to occur in clusters of fires that start at nearly the same time, such lightning fires can overwhelm suppression capacity both spatially and temporally (Flanningan and Wotton 1991). In the ROK, lightning occurs primarily in conjunction with rain storms. However, in northern California, a lightning storm may cause several fire ignitions simultaneously during a dry season. Furthermore, in California, a combination of aggressive suppression and effective fire prevention programs have allowed higher levels of fuels to develop, thereby increasing fire hazard. In this case, extra ignition prevention efforts for human-caused fires may increase, rather than decrease, future fire danger. When fires do occur, they are more likely to grow large, escape, and incur substantial damage.

In California, fuel reduction treatments are an important part of fire prevention policy that affect wildfire behavior and enhance fire suppression capabilities (Finney and Cohen 2003). In particular, fuel treatments are effective in reducing the risk of crown fire, which is the most concerning fire behavior for fire managers (Reinhardt *et al.* 2008). Crowley *et al.* (2008) examine the tradeoff between fuel treatment and suppression, and suggest that the inefficiencies in fire management are caused by free-riding on public provision of fire suppression effort. Mercer *et al.* (2008) also study the tradeoffs between expenditures for fuels management and suppression resources. However, it is difficult to reach general conclusions about optimal levels of investment in fuel treatment and fire suppression due to the complexity of fire behaviors. There are uncertainties concerning the impact that different types of fuel treatments have on wildfire behavior (Reinhardt *et al.* 2008).

In this dissertation, I focused specifically on the tradeoffs between fire ignition prevention and IA fire suppression by assuming fuel treatment effort is exogenously given. The effect of ignition prevention on fire suppression is more explicit than that of fuel treatment because fire ignition prevention efforts directly reduce the demands on firefighting resources by limiting the number of ignitions on a landscape. However, modeling the relationship between fire suppression and fuel treatment (i.e., prescribed fires and mechanical thinning) is potentially a fruitful area for future study because fuel treatment can not only alter wildfire behavior but also substantially improve the effectiveness of fire suppression tactics (Finney and Cohen 2003). By decreasing fire intensity, it also has the potential to decrease the losses on acres that do burn by reducing tree mortality and the probability that a home will ignite.

6.5. Simulation-Optimization Framework

In this study, I combined a scenario-based, standard-response optimization model with stochastic simulation to improve the efficiency of resource deployment for initial attack on wildland fires in California and the ROK. Optimization for IA firefighting planning and simulation of firefighting tactics in previous studies have been developed with a different purpose (Martell 1982;

Martell 2007). In general, the optimization algorithm determines firefighting resource deployment and dispatch plans without considering many of the details of firefighting tactics. However, prudent fire managers will want to validate an "optimal" plan before implementing it in the field. Wildfire suppression simulation models can assist them in this aim by demonstrating the potential effects of changes in key components of wildland fire systems. In particular, stochastic simulation models of initial attack such as CFES2 are utilized to generate an outcome with more realistic representation of fire growth, deployment and dispatching of firefighting resources, fire containment, and evaluating IA effectiveness. Although fire managers use stochastic simulation models to evaluate changes in the spatial distribution of fire-fighting resources for initial attack, fire simulation models for fire suppression have not been incorporated into optimization models due to their computational requirements and software (Hu and Ntaimo 2009). My model structure that combines a decision model with stochastic simulation provides a tractable decision tool for deploying and dispatching multiple types of firefighting resources on a landscape by incorporating simulation information into an optimization model.

The simulation-optimization framework may be useful for addressing other natural resource management problems that include spatial components. Previous studies address the problem of dimensionality by ignoring the spatial and temporal correlation between events (Martell 1998). However, the absence of spatial components may result in a sub-optimal solution because spatial aspects like topography, spatial pattern, and spatial relationship have a critical impact on the occurrence and the behavior of an event (Konoshima *et al.* 2008; Busby and Albers 2010). By generating scenarios about events with spatial information through simulation, my model contains spatial detail on a landscape, including locations of fire stations, suppression resources, and potential fires, and practical decision criteria such as minimizing the expected number of fires not receiving a standard response. For example, the simulation-optimization model can be applied to address the problem of optimizing the location and area (sum of the area of each location) of fuel treatment on a landscape, by incorporating fuel treatment into an IA optimization model with a given type and level of treatment[12].

6.6. Limitations

My dissertation contains three important modeling assumptions that may affect results. First, an representative fire location (RFL) in my model is a map point that represents a proportion of the average annual fire load together with a particular mix of fuels, topography, and distance to fire stations. In practice, the mix of resources that are dispatched to fires, and the timing of their arrivals, will differ among fires represented by a given RFL. Some fires will be more, and

[12] Determining optimal levels of fuel treatment would require a non-linear formulation and heuristic rather than exact optimization model because the effect of fuel treatment by level (intensity) varies (Mercer *et al.* 2008).

others less, accessible to suppression resources than assumed by the RFL point, which may affect the accuracy of fire simulations. While it is conceptually possible to increase the number of RFLs without limit, it can be challenging to assign historical fires to a very large number of locations based on similarity across multiple attributes such as geographic location, fuel, slope, resource arrival times, and complicating factors such as homes, fences, or unique terrain features, and historical fire locations that are distant from the road network and lightning-prone ridges may not be useful predictors of future fire location. Furthermore, simulation time increases at least linearly with RFL count.

Second, I assumed that stations at the edge of the three-unit study area only serve fires within the study area and not outside, whereas, in practice, stations may serve fires in any adjacent fire planning unit and the results do not account for these edge effects. As a result, the optimization may deploy suppression resources to the interior of the study area where they have access to more fires. In practice, stations may serve fires in any adjacent fire planning unit and my results do not account for these edge effects.

Lastly, my optimization model is static in the sense that it determines optimal deployment given an approximation of the probability distribution of fire locations and intensities during a single day during the high fire season. I solved for optimal deployment given uncertainty about the number and location of fires during a severe fire day because this is the type of day when initial attack resources will be challenged to meet demands for fire suppression and because escaped fires may cause catastrophic damage and be very expensive to extinguish. My model is not dynamic and does not account for a sequence of days during the fire season where what happens during one day influences what happens on the next. It may be possible to model fire day as a Markov process and use stochastic dynamic programming to determine optimal resource deployment.

6.7. Policy Implications

Some of my conclusions provide insights into current IA firefighting policy with regards to improving the effectiveness of allocating firefighting resources for initial attack. Furthermore, the information about the relative importance of components of the setting in California and the ROK help to identify "rules of thumb" about IA firefighting resource allocation and fire prevention activities in particular ecological or policy settings.

1) Budget and Capacity Constraints

Budget and station capacity constraints not only limit the number of IA resources but also influence the appropriate mix of deployed resources due to the differences in cost and productivity across resource types. The change in mix of resources across management units and at particular stations as the budget and station capacity change depends on attributes like unit cost, productivity, response times and abundance of each resource type. A reduction in budget or station capacity may decrease the use of some resources while increasing the use of others due to interplay among these attributes among resources types. For example, a budget cut that eliminates part of the funding for a helicopter may result in the rest of the helicopter funding being redirected into an increase in the number of dozers due to their lower unit cost. Considering the deployment of all IA resources simultaneously reveals complexities in the mix of resources because of differences in the usefulness and unit cost of each resource.

2) Landscape Accessibility

Infrastructure, such as forest roads and highways, is critical for allowing IA resources to arrive at potential fire locations within a required time limit. Fire managers tend to allocate IA firefighting resources to a central location so that firefighting resources can cover a wide area. However, travel times for ground resources are dependent on the road systems, so centralization of resources may not result in the best outcome. For example, if a fire location is far from a station, but is next to a highway, resources from the station can reach the fire location rapidly because the highway may provide the direct path to get the fire location.

3) Protection Priority

The priority of a fire manager to protect resources drives changes in the spatial allocation of firefighting resources across a landscape. Fires located near large populations or particularly valuable resources may receive a higher priority for initial attack than identical fires in other locations. The binary-covering variable is defined for each fire, together with the resource and response-time requirements that are related to the expected fire intensity and priority of each fire depending on its location. These variables provide a ranking for each fire that helps the fire manager allocate IA firefighting resources effectively on a fire day with multiple fire events.

4) Initial Attack vs. Ignition Prevention

The tradeoff relationship between IA resources and fire ignition prevention is determined by comparing the marginal benefit of additional IA firefighting resources with the marginal benefit of additional fire ignition prevention. The marginal benefit of each is measured in terms of reducing the expected number of fires not receiving a standard response. If the marginal benefit of fire ignition prevention is bigger than the marginal benefit of IA firefighting resources, the policy should be to first increase spending on ignition prevention until the marginal benefit of each is equal. Furthermore, when a fire manager implements a fire ignition prevention policy by assigning a policy to a specific area, the optimal spatial allocation of IA resources deployed is also determined by the marginal benefit of the fire ignition prevention across fire locations.

However, in practice, a fire manager must also consider external factors that affect the optimal fire prevention policy. The social cost of fire ignition prevention efforts influences the optimal level of fire ignition prevention effort. The social cost reduces the optimal fire ignition prevention effort, and may instigate a conflict between the government and society that precludes successful implementation of a fire ignition prevention policy. Moreover, intensive fire prevention efforts ultimately facilitate greater accumulation of vegetation fuels, leading to increased fire hazard. When fires do occur, they are more likely to grow large and incur losses. Thus, fuel reduction treatments, which affect wildfire behavior and enhance fire suppression capability merit greater consideration as a fire prevention strategy.

5) Contrasting fire issues in California and the ROK (Table 6-1)

Optimal IA fire suppression planning in California and South Korea is influenced by fire characteristics, terrain, budget and capacity constraints, and policy goals. The information about the relative importance of each of these components for a given setting will help to identify rules of thumb to be followed when allocating IA resources in particular ecological and policy settings.

Fire characteristics and the common causes of fires both affect the optimal fire management policy. The optimal deployment of IA resources allocates more firefighting resources around potential fire locations that have the greatest fire loads. In the ROK, for example, wildfires occur near populated areas because fires are mainly human-caused. Thus, fire managers will realize a greater benefit from allocating firefighting resources in populated areas. By restricting human activities in the mountains, a fire manager can control the total number of fires effectively. However, natural fire ignitions, like lightning, are of concern to fire managers in California (Figure 6-1) because multiple, nearly-simultaneous lightning ignitions, which sometimes occur during the dry season (e.g., summer), are more likely to result in escaped fires that may threaten human communities. Fire managers in the ROK don't worry much about lightning fire ignitions because lightning there is almost always accompanied by significant precipitation.

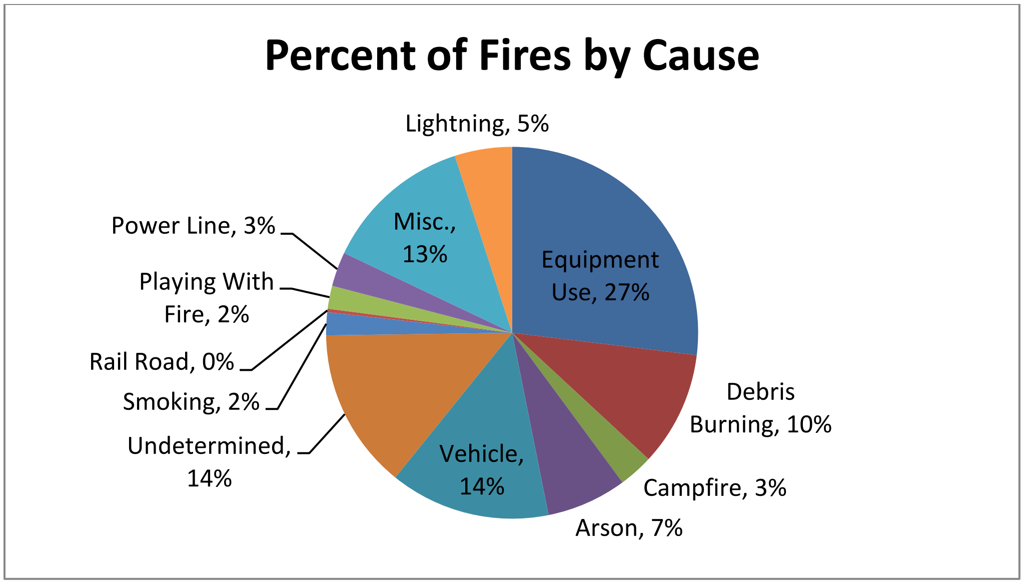


Figure 6-1 Percent of Wildland Fires by Cause in California during 2000 - 2005 (Source: http://cdfdata.fire.ca.gov/incidents/incidents_statsevents)

Terrain is an important driver of optimal fire policy. Areas that are difficult to access due to topographical challenges preclude the use of ground based resources because such resources cannot reach a fire location within a reasonable amount of time. While ground resources are actively used in California, the use of ground resources is limited by difficult terrain, especially in mountainous areas with limited road access.

Resource deployment that results from relaxing constraints on station capacity achieves greater containment success by encouraging consolidation of resources into stations with high dispatch frequency, thus increasing the likelihood of resource availability during a high fire season. Even though there may be little cost savings (economy of scale) by increasing the capacity of a station, enhancing the capacity of core stations produces gains in the performance of IA resources without an increase in the budget (i.e., providing emergency services to more fire locations within a short time).

Because the landscapes are not homogeneous by fire location, both in terms of the probability of a fire escaping IA and the values of each location to be protected, the protection priorities of each fire manager affect the optimal allocation of IA firefighting resources that have to arrive at fire locations within the given response time. In California and the ROK, the top priority of fire agencies is to protect the lives and property of human communities from wildland fires, so their policies bear some resemblance. For example, both countries concentrate IA firefighting resources in stations near populated areas. In fire prevention policy, the ROK makes a huge effort to control human access to susceptible forests, while California encourages home owners to build a vegetation-free zone of defensible space in order to increase the likelihood of surviving a fire.

Fire prevention policy is limited by socio-economic factors. For instance, the people of the ROK accept fire ignition prevention policy to protect their forests from human-made fires. However, Californians may find the policy unacceptable because they think the opportunity costs to society from limiting their access to recreational areas during a fire season are intolerable, since the high fire season coincides with the prime vacation season. Low tolerance for smoke (or fire) near residential areas limits the attractiveness of prescribed fire to many land managers. In particular, the people of the ROK have very low tolerance for wildfires and smoke, so a fuel treatment policy founded on prescribed fire is generally considered a non-starter.

Table 6-1 Descriptive comparison between California and ROK fire regimes by their goals, environments, socio-economic factors, and fire policies.

	California	Republic of Korea
Goal	To protect people from fires, respond to emergencies, and protect and enhance forest, range, wildlife habitat, and watershed values while providing social, economic, and environmental benefits to urban and rural residents.	
Environment	Area: 163,696 sq mi Population: 37 Million Forest type: Conifer and Mixed forest (young & old forests); Grass and Shrubs Annual fires (#): 3,440 (5-year average) Causes: lightning (5-10%), human caused fires (>90%) Fire season: summer	Area: 38,691 sq mi Population: 50 Million Forest type: Conifer and Mixed forest (mostly young forests) Annual fires (#): 460 (5-year average) Causes: Lightning (<1%), human-caused fires (>95%) Fire season: spring

Socio-economic	High Population Density Good forest roads (infrastructure) Low tolerance of wildfires (e.g., smoke) Expensive houses (built of wood) Many recreation activities in forests	High Population Density Limited forest roads Low tolerance of wildfires (e.g., smoke) Many temples (built by wood) cf. houses (built of concrete) Increasing recreation activities in forests
Fire Policy	Effective fire suppression policy Various types of firefighting resources (Engines, Dozers, Hand-crews, Helicopters, Air-tankers) Increasing fuel management activities	Effective fire suppression policy Limited type of firefighting resources (Hand-crews, Helicopters) Maintaining effective ignition prevention
Fire Prevention Policy	Fuel treatment (Thinning + Prescribed burning) Prevention enforcement Education (Smokey Bear)	Fire ignition prevention (laws, enforcements, regulations) Education

6.8. Concluding Remarks

In this dissertation, I combined a scenario-based, standard-response optimization model with a stochastic fire simulation model to improve the efficiency of the deployment of suppression resources for initial attack on wildland fires in California and the ROK. Using the model framework, I explored opportunities for improved overall efficiency in fire management in wildland forest landscapes of California and the ROK. I found important policy implications by conducting sensitivity analyses on key parameters such as budget, capacity, weight of each fire location, and seasonal rate of fire ignition.

1) The performance of the IA system can be improved with changes to budget and station capacity, both of which affect the optimal spatial allocation of IA resources among bases. While fire suppression effectiveness will be negatively impacted by declining budgets, resource deployments that result from relaxing constraints on station capacity can achieve greater containment success by encouraging consolidation of resources into stations with high dispatch frequency, thus increasing the probability of resource availability on high fire count days.

2) The priority of a fire manager to protect resources changes the spatial allocation of firefighting resources across a landscape. By ranking each fire based on the importance of resources at risk, fire managers can better allocate IA firefighting resources effectively on days with multiple fire events.

3) I derived the tradeoff relationship between the number of IA firefighting helicopters and the level of fire ignition prevention efforts, using the standard response optimization model. Fire ignition prevention is cost-effective in reducing the number of fires that do not receive a standard response, as well as IA firefighting helicopters given the current budget. However, social cost can limit the implementation of the fire prevention policy.

4) California and the ROK have important policy goals in common regarding the early containment and successful suppression of unwanted fires but there are also important differences in weather (and thus fire timing), fuels, terrain, and policy context, which produce distinct IA configuration and allocation decisions between the California case and the ROK case.

Taken together, the results of this research emphasize the economic tradeoffs among resources and across locations. The results also suggest that combining optimization and simulation models of initial attack can inform and supplement planners' intuition regarding the efficient deployment of suppression resources. Furthermore, this study constructs a foundation for future work by establishing the application of the simulation-optimization framework to other settings, creating a platform to explore other policy goals, and building the capacity for sophisticated forest land risk management at a landscape scale.

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APPENDICES

APPENDIX A. Spatial Allocation of Initial Attack Resources

Table A-1 The spatial deployment of initial attack resources by type and by case in the study area (AEU: [A], NEU: [N], and TCU: [T]).

[Unit] Station	Engine							Dozer							Hand-crew							Helicopter						
	A	B	C	D	E	F	G	A	B	C	D	E	F	G	A	B	C	D	E	F	G	A	B	C	D	E	F	G
[N] AUBURN	2	1	7	1	9	1	6	1	2	2	2	3	1	2	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[A*] BIG HILL	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	0	0	0	0	0	0
[T*] COLUMBIA AAB	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	2	2	3	2	1	1
[A] DEW DROP FFS	1	0	0	2	0	0	0	0	0	0	1	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[A] EL DORADO FFS	1	2	5	2	3	2	5	1	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[A] GARDEN VALLEY FFS	2	2	0	2	0	2	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[A] GEORGETOWN ENF	0	1	0	1	2	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N*] GRASS VALLEY	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2	3	7	3	6	3	4
[A] GROWLERSBURG CC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	5	3	2	4	4	2	2	-	-	-	-	-	-	-
[A] MT DANAHER FFS	2	2	0	2	0	2	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[A] PACIFIC ENF	0	0	0	1	0	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[A] PILOT HILL FFS	2	2	4	2	4	2	4	0	1	1	0	0	1	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[A] PINE GROVE CC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	4	3	3	5	4	2	3	-	-	-	-	-	-	-
[A] PINE LODGE FFS	1	2	0	2	4	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T] SAN ANDREAS	2	2	3	2	3	2	2	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[A] SUTTER HILL FFS	2	2	3	2	5	2	3	1	1	1	2	2	1	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[A] ZION FFS	2	2	2	2	0	2	2	0	1	0	1	0	1	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N] ALTA	2	1	0	1	0	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-

[N] CHALLENGE	0	1	0	1	0	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N*] CHICO	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	0	0	0	0	0	0
[N] COLFAX	2	2	0	2	0	2	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N] COLUMBIA HILL	2	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N] DOBBINS	2	1	0	1	3	1	0	1	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N] DUTCH FLAT	0	1	0	1	0	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N] FOOTHILL	0	1	2	1	0	1	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N] FOREST HILL	2	0	0	2	0	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N] FOWLER	0	1	0	1	0	1	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N] HIGGINS CORNER	2	0	0	0	2	0	0	0	0	1	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N] LINCOLN	0	1	0	1	0	1	0	0	0	0	1	1	0	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N] LOMA RICA	1	0	0	2	0	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N*] MINDEN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	0	0	0	0	0	0
[N] NEVADA CITY	2	2	5	2	3	2	3	1	0	0	1	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N] NORTHSTAR	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N] ROUGH AND READY	0	1	0	1	0	1	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N] SMARTVILLE	2	1	7	1	7	1	3	0	1	1	1	1	1	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N] TRUCKEE CALFIRE	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[N*] VINA	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2	3	0	3	2	1	1
[T] ALTAVILLE	0	2	0	1	0	0	0	1	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T] ARNOLD FFS	2	2	3	2	0	2	0	0	1	1	1	0	1	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T] BASELINE CC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	2	5	3	5	5	3	3	-	-	-	-	-	-	-
[T] BUCK MEADOW	0	1	0	1	0	1	0	0	1	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T*] COLUMBIA CREW	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	0	0	0	0	0	0
[T*] COLUMBIA DROP	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	3	2	3	3	3	2
[T] COPPEROPOLIS FFS	1	2	3	2	4	2	2	0	2	3	1	3	2	2	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T] COUNTERVILLE	0	0	1	0	1	0	1	0	0	0	0	0	1	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T] DORRINGTON	0	1	0	1	0	1	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T] ESPERANZA	1	2	0	2	2	0	0	0	0	0	1	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-

[T] GROVELAND	2	0	0	1	0	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T] HERMIT SPRINGS FFS	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T*] HOLLISTER	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	0	0	0	0	0	0
[T] LONG BARN	0	1	0	1	0	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T] MURPHYS FFS	1	2	0	2	3	2	3	0	2	0	2	1	2	2	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T] SKULL CREEK FFS	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T] SONORA	2	0	1	2	3	0	0	0	0	1	2	2	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T] TWAIN HARTE	2	0	0	1	0	0	0	0	0	0	0	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T] VALLECITO CREW	-	-	-	-	-	-	-	-	-	-	-	-	-	-	4	5	5	5	5	5	3	-	-	-	-	-	-	-
[T] VALLEY SPRINGS FFS	1	1	0	2	0	0	0	0	0	0	1	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
[T] WEST POINT	1	0	0	2	0	0	0	0	0	0	1	0	0	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Total	51	45	46	58	58	33	34	7	12	11	18	13	11	9	15	14	13	19	18	12	11	8	11	11	12	13	8	8

* Available bases for deploying air resources.

APPENDIX B. Sample Average Approximation (SAA) Method

(1) California case

To investigate how the number of scenarios used affects the optimal solution and objective function value, I estimated lower and upper bounds for the objective function value using the sample average approximation method suggested by Linderoth *et al.* (2006). I solved four sets of twenty replicates of the optimization problem with low station capacity and current budget (case B, Table 5-1). The twenty replicates in each set are constructed with N independent scenarios, with N equal to 30, 50, 100, and 200 scenarios to form the four sets. The lower bound estimate ($\bar{L}$) for each set is the mean of the objective function values over the twenty replicates. To compute an upper bound estimate for each set ($\bar{U}$), I took the deployment obtained from the optimization model in each of the replicates and computed the expected number of fires not receiving a standard response using all 5,814 scenarios. The lowest expected value provides an upper bound for the objective function value (Table A-2). Once I had lower and upper bounds, I computed the confidence interval for the gap ($\bar{G}$) by using the SAA method suggested by Mak, Morton, and Wood (1999). The optimal gap is reduced by 6% of the upper bound estimate when the sample size is increased from 30 to 100, while the optimal gap is reduced only by 1% of the upper bound estimate when the sample size is increased from 100 to 200. The narrowness of the gap implies that not much will be gained by expanding from 100 to 200 scenarios. Further, resource deployments are also stable across replicates with 100 or 200 scenarios. From these results, I concluded that 100 randomly selected scenarios adequately represent the distribution of severe fire days obtained with my fire ignition and intensity models. This result is consistent with previous studies that conclude that a relatively small sample of scenarios is sufficient to represent the distribution of scenarios in optimization problems (Snyder *et al.* 2004, Linderoth *et al.* 2006).

(1) Korean case

To verify whether the number of scenarios used is adequate to solve my optimization problem, I also estimated lower and upper bounds for the objective values in the ROK case using the SAA method. I solved three sets of ten replicates of the optimization problem with low station capacity and the current budget (OPT, Table 5-2). The ten replicates in each set are constructed with N independent scenarios, with N equal to 30, 50, and 100 scenarios to form the four sets. The lower bound estimate ($\bar{L}$) for each set is the mean of the objective function values over the twenty replicates. To compute the upper bound for each set ($\bar{U}$), I took the deployment obtained from the optimization model (in each of the replicates) and computed the expected number of fires not receiving a predefined standard response using 1,000 scenarios that are randomly drawn from the fire simulation model (Table A-3). I computed the confidence interval for the gap ($\bar{G}$) by using the SAA method. The optimal gap is reduced by 16% of the upper bound estimate when the sample size is increased from 30 to 100, while the optimal gap is reduced only by 1% of the upper bound estimate when the sample size is increased from 50 to 100. The size of the gap implies that not much will be improved by expending from 100 to more scenarios. In addition, resource deployments are stable across replicates with 50 or 100 scenarios. In conclusion, 100 randomly selected scenarios adequately represent the distribution of severe fire days obtained with my fire ignition and intensity models as well as California case.

Table A-2 Means of the objective function value (expected number of fires not receiving a standard response) for Case B (low station capacity and current budget) in the California study, computed with sets of 20 replicates with increasing numbers of scenarios (N).

N	Lower Bound ($\bar{L}$) 95% conf. int.[1]	Upper Bound ($\bar{U}$) 95% conf. int.[2]	Optimal Gap ($\bar{G}$)[3]	95% conf. int.[3]
30	1.72 ± 0.18	1.99±0.04	0.27	[0, 0.49]
50	1.77 ± 0.10	2.01±0.04	0.24	[0, 0.38]
100	1.82 ± 0.05	1.97±0.04	0.15	[0, 0.24]
200	1.84 ± 0.03	1.97±0.04	0.13	[0, 0.20]

[1] This average is obtained from the objective functions by solving equation (4-1) – equation (4-6) for 20 replicates with N scenarios.
[2] For each of the 20 optimal deployments obtained with N scenarios, I determined the optimal dispatch using 5814 scenarios and computed the associated expected number of fires not receiving a standard response. From these 20 replicates, I chose the smallest objective function value as the lower bound.
[3] The optimal gap is calculated as: $\bar{L} - \bar{U}$, and the confidence interval is calculated by using the method suggested by Mak *et al.* (1999).

Table A-3 Means of the objective function value (expected number of fires not receiving a standard response) for OPT Case (with station capacity and current budget) computed with sets of 10 replicates with increasing numbers of scenarios (N).

N	Lower Bound ($\bar{L}$) 95% conf. int.[1]	Upper Bound ($\bar{U}$) 95% conf. int.[2]	Optimal Gap ($\bar{G}$)[3]	95% conf. int.[3]
30	0.399 ± 0.107	0.508±0.075	0.109	[0, 0.291]
50	0.472 ± 0.098	0.505±0.074	0.033	[0, 0.205]
100	0.478 ± 0.080	0.505±0.074	0.027	[0, 0.181]

[1] This average is obtained from the objective functions by solving equation (4-1) – equation (4-6) for 10 replicates with N scenarios.
[2] For each of the 10 optimal deployments obtained with N scenarios, I determined the optimal dispatch using 1000 scenarios and computed the associated expected number of fires not receiving a standard response. From these 10 replicates, I chose the smallest objective function value as the lower bound.
[3] The optimal gap is calculated as: $\bar{L} - \bar{U}$, and the confidence interval is calculated by using the method suggested by Mak *et al.* (1999).

APPENDIX C. Spatial Pattern of Korean forest fires by Forest Fire Cluster.

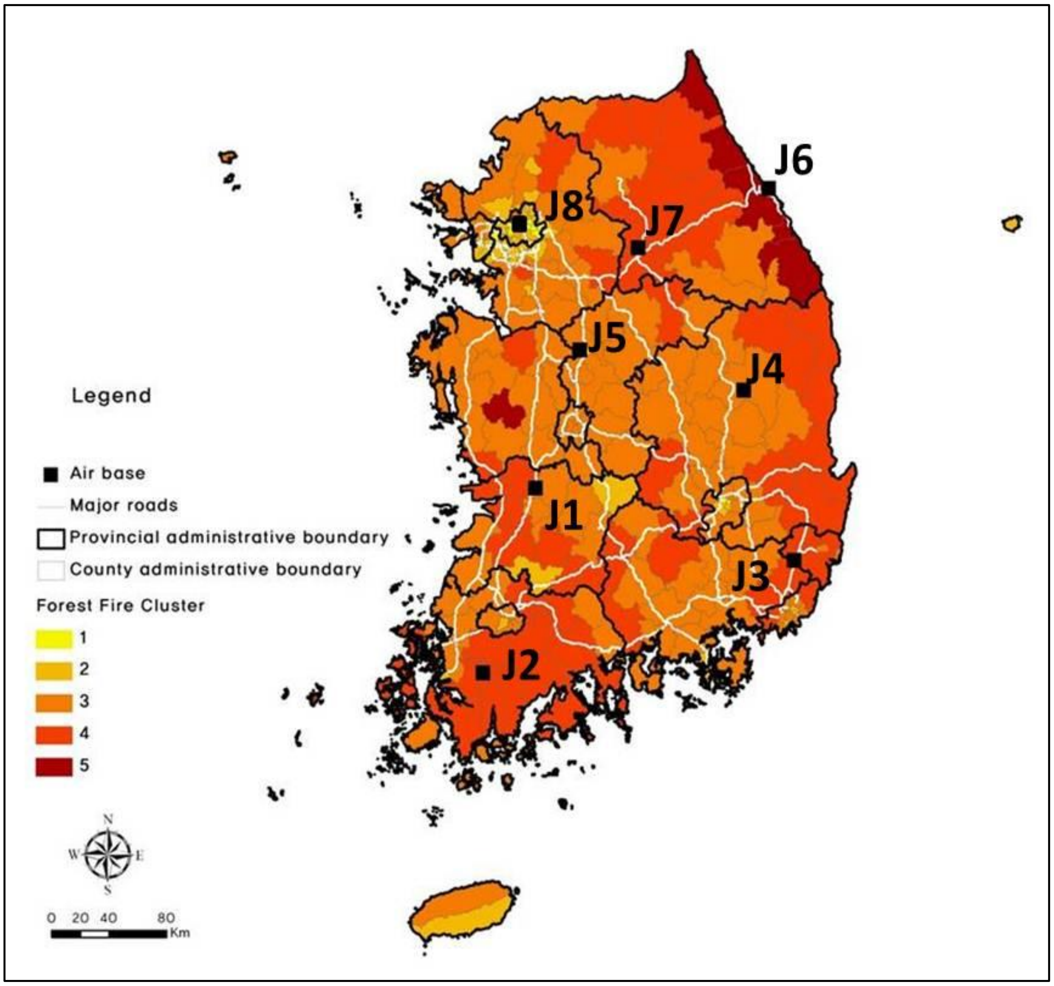

Figure A-1 Forest Fire Clusters[13] Based on Forest Fire Statistics between 1991 to 2007 (Lee and Lee 2009, *p*. 19).

[13] The forest fire clusters represent regional forest fire patters. Forest fire ignition and spread characteristics were analyzed based on forest fire statistics. For the cluster analysis, fire occurrences, burned area, rate of spread, and burned area per fire were parameterized. The minimum administrative districts (228 in total) were classified into 5 clusters by fire susceptibility.

APPENDIX D. Stochastic Korean Fire Occurrence Model

Overview

To develop the fire occurrence model for the ROK, I use four evaluation criteria: distribution of number of fires per year, distribution of fires by time of day, frequency and severity of multiple fire days, and distribution of fire by season. The objective of this study is to examine close correspondence between generated sequences of fires and historical fire records with respect to the four evaluation criteria. In order to capture the scale of the fire management problem, correspondence between the historical and generated distribution of number of fires per year is critical. To simulate initial attack on fire days, agreement between historical and generated distributions for time of day is important; as is reflecting the fact that the usage of some suppression resources can be limited by the time of day. For example, some air resources are operated only during daylight hours. With respect to the frequency and severity of multiple fire days, correspondence between historical and generated sequences of fires is required for evaluating the ability of the Korean Forest Aviation Headquarters (KFAH) to deal with severe fire seasons. Given seasonal differences in fire agency's staffing and response capabilities, a match between the historical and generated fire sequences with respect to the distribution of fires by season is also important.

Methods

To construct the Korean stochastic simulation model of fire occurrence, I follow the method of Fried and Gilless (1988), which was employed in building the fire occurrence module of CFES2. Next event, clock-driven simulators are often based on a single distribution describing the time between events. From an estimated distribution for the time between fire events, I can generate the initial structure for the fire occurrence model, assuming that sequential fire ignitions occur over the course of a year or season. From a first ignition, I can then determine the time of each subsequent ignition by incrementing the simulation clock using a randomly drawn value from this distribution. The sequences of fires thus generated include both periods of intense, possibly overlapping, fire activity, as well as periods with relatively few fires.

For the ROK, an exponential from well represent the fire event distribution needed for a fire occurrence model based on fire frequency, as most simulation models use inter-arrival time distributions (Ross 2007; Law and Kelton 1982). For the ROK, the estimated distributions are used to generate a sequence of fire events that corresponds with historical patterns. However, the resulting distribution of fire occurrence by time of day does not show the diurnal pattern attribute of real fires. Basically, fires have an equal probability of occurring at night or during the day. Consequently, if the simulation of initial attack aims to reflect the influence of time of day on dispatch policies, firefighting tactics, and effectiveness, simulation results based on a fire event occurrence model might have serious bias. Although this approach is inappropriate in this study, the concept of a fire event distribution proves useful in validating the structure selected for the fire occurrence model.

Fried and Gilless (1988) suggested an alternative structure, in which fire ignitions for a day are generated independently of those for preceding or subsequent days. This structure requires the estimation of several distributions, which together could be used to generate a sequence of fire ignitions over the course of a day. This structure is capable of producing a pattern of fires with a more acceptable distribution by time of day, even though it is more complex.

The alternative structure uses three distributions to generate a sequence of fire ignitions. For each day in a year or season, a randomly drawn value from a Bernoulli (0, 1) distribution determines whether any fires occur on that day. Given that one or more fires occur, a randomly drawn multiplicity value from a second, discrete distribution would determine their number. The ignition time for each of these fires would then be determined by randomly and independently drawn values from a third distribution.

The analysis of the Korean annual pattern of fire occurrence identifies dates that divides the year into three seasonal classes of relatively homogeneous fire frequencies. These classes are denoted as the Low, Transition, and High fire seasons. The distributional forms that best describe the probability of occurrence (FIREDAY), the number of fires per day (MULTIPLICITY), and the time of day (FIRETIME) of the fires for the ROK, by season, is then identified.

Data

The Korea Forest Service has built fire databases for the landscape of the ROK that includes eight distinct provinces. These databases include the date and time of occurrence, location, size at arrival and upon control, and rate of spread for each wildland fire since 1991. The data used for the research include fire information during 1991-2007, which contain 7,448 wildland fires (438 fires/year on average).

Results

Figure A-2 shows histograms of the number of fires per week for each ranger unit during the periods covered by the data. Inspection of these histograms and Tukey multiple range tests of fire event frequency by week indicated that the weeks could be classified into fire seasons (Table A-4). For the ROK, mean fire event frequency is significantly different for each season as shown by the mean and 95% confidence interval plots of fire event frequency for each week in Figure A-3.

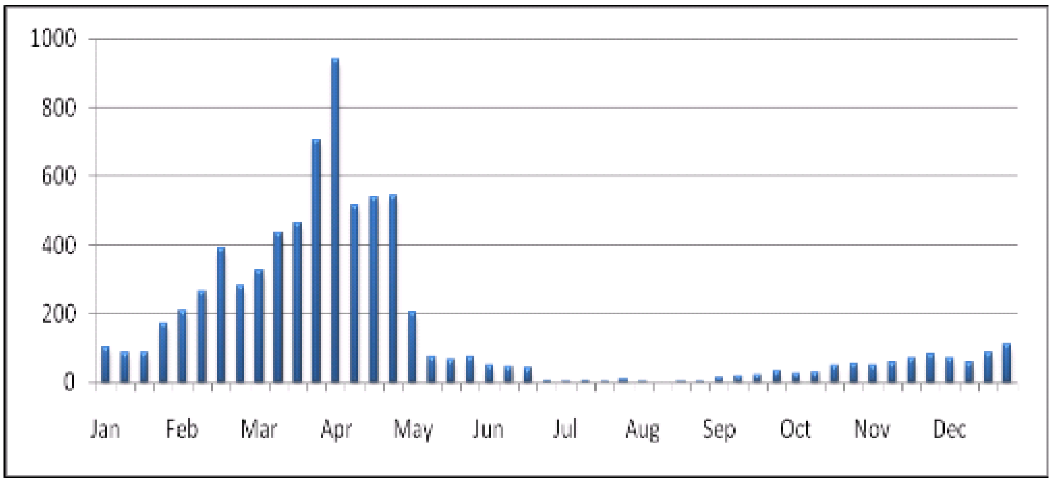

Figure A-2 Number of fires per week over 17 years, 1991 - 2007.

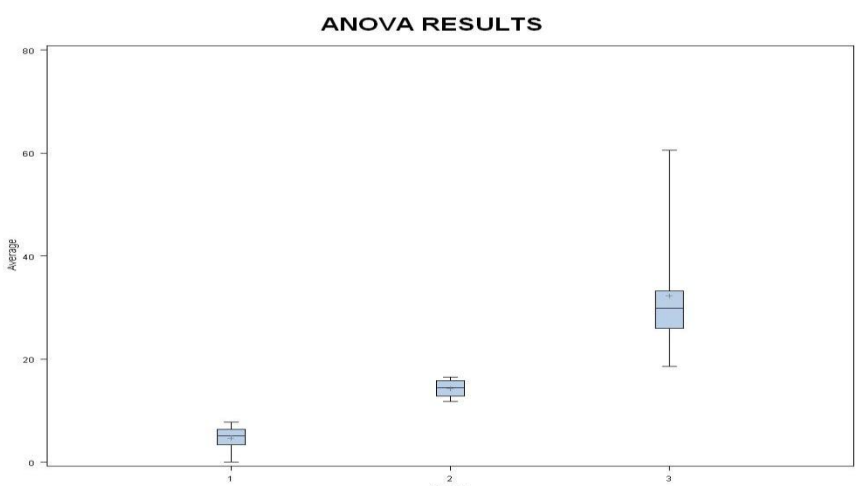

Figure A-3 Average and 95% confidence interval plots of fire frequency per week for the *Low*(1), *Transition*(2), and *High*(3) fire seasons.

Table A-4 The results of Tukey's Studentized Range Test for Average

Comparisons significant at the 0.05 level are indicated by ***				
Season Comparison	Difference Between Means	Simultaneous 95% Confidence Limits		
3-2	17.946	9.775	26.117	***
3-1	27.578	22.609	32.546	***
2-3	-17.946	-26.117	-9.775	***
2-1	9.631	2.331	16.932	***
1-3	-27.578	-32.546	-22.609	***
1-2	-9.631	-16.932	-2.331	***

For each day during the period 1991 – 2007 for the ROK, FIREDAY is defined as a Bernoulli variable equal to 1 if any fires occurred on that day and 0 otherwise. A Bernoulli distribution of the form is as follows:

$$p(x) = \begin{cases} 1-\pi & if\ x=0 \\ \pi & if\ x=1 \\ 0 & otherwise \end{cases}$$

Where:

x = FIREDAY is fit for each fire season.

The parameter π can be interpreted as the probability of one or more fires occurring on any one day. Estimated values for π are shown in Table A-5.

Table A-5 Probabilities of one or more fires occurring on a day by region and season.

Season	All	KW	SKI	CB	CN	KB	KN	JB	JN
High	0.68	0.31	0.39	0.26	0.28	0.30	0.27	0.32	0.30
Trans	0.60	0.22	0.18	0.10	0.21	0.18	0.16	0.18	0.18
Low	0.25	0.06	0.04	0.02	0.03	0.05	0.04	0.02	0.03

*Each represents a province as follows: KW: Kangwon; SKI: Seoul, Kyunggi, and Inchun; CB: Chungbuk; CN: Chungnam; KB: Kyungbuk; KN: Kyungnam; JB: Junbuk; JN: Junnam.

For the ROK, histograms showing the relative frequency of Multiplicity (number of fires per day) for days in the High season on which fires occurred are shown in Figure A-4. For each season, the transform (MULTIPLICITY -1) is best described by a geometric distribution with probability mass function as follows:

$$p(x) \quad = \quad \emptyset(1-\emptyset)x \qquad if\ x \in \{0,1,\dots\}$$

$$0 \qquad otherwise$$

Where:

x = the number of fires on one day -1.

Estimated geometric distributions are shown superimposed on the MULTIPLICITY histograms. Estimates of $\emptyset$ are given in Table A-6 along with χ^2

goodness-of-fit statistics for each fire season. The degree of MULTIPLICITY represented in the Low and Transition seasons is sufficient to calculate χ^2 statistics, and the fit of these geometric distributions over all seasons combined is reasonably good, far better than any logical alternatives such as the exponential distribution. Estimates of ∅, by region, are given in Table A-7.

Table A-6 Estimated μ parameters and chi-squared goodness-of-fit significance levels for geometric distributions fitted to (Multiplicity -1) by seasonal range.

Season	μ	Chi-Square	DF	Pr > ChiSq
High	0.2041	4730.0513	32	<.0001
Transition	0.2940	1962.9030	20	<.0001
Low	0.7148	71428.6311	17	<.0001

Table A-7 Estimated μ for geometric distributions fitted to (Multiplicity -1) by region and season.

Season	All	KW	SKI	CB	CN	KB	KN	JB	JN
High	0.20	0.79	0.66	0.85	0.78	0.73	0.82	0.78	0.77
Trans	0.29	0.91	0.93	0.96	0.92	0.94	0.91	0.90	0.92
Low	0.71	0.98	0.99	0.99	0.99	0.98	0.94	0.99	0.99

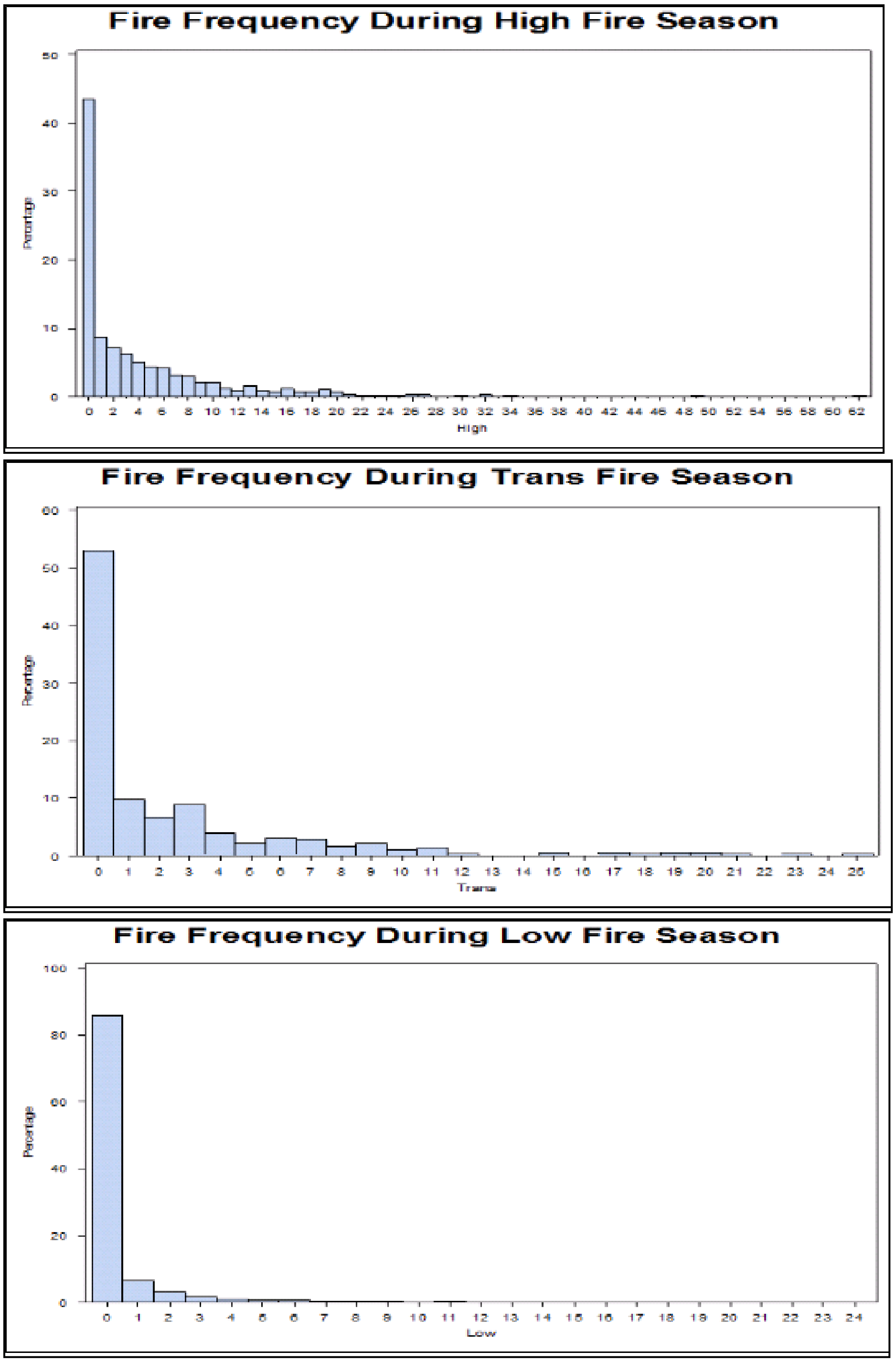

Figure A-4 Relative histogram of historical fires by fire season, 1991 - 2007.

Unlike FIREDAY and MULTIPLICITY, FIRETIME exhibits no seasonal differences. Thus, a single FIRETIME distribution was estimated for each ranger unit. Frequency distributions of FIRETIME varied in appearance, but all had central tendencies when left-shifted 3 hours (so that 0 corresponded to 3 A.M. and 23 to 2 A.M. the next day) (Figure A-5). For the ROK, the FIRETIME distribution has high, narrow frequency peaks from 1 P.M. to 4 P.M., and is best fit by the Poisson distribution as follows:

$$g(x) = \begin{cases} \frac{(e^{-\lambda}\lambda^{x})}{x!} & if \quad x \in \{0, 1, \ldots\} \\ 0 & \text{otherwise} \end{cases}$$

The fitted FIRETIME distribution is shown super-imposed on the corresponding FIRETIME histograms (Figure A-5). χ^2 Goodness-of-fit significance levels and estimated parameters for each FIRETIME distribution are reported in Table A-8 (Estimates of parameters are reported in Table A-9).

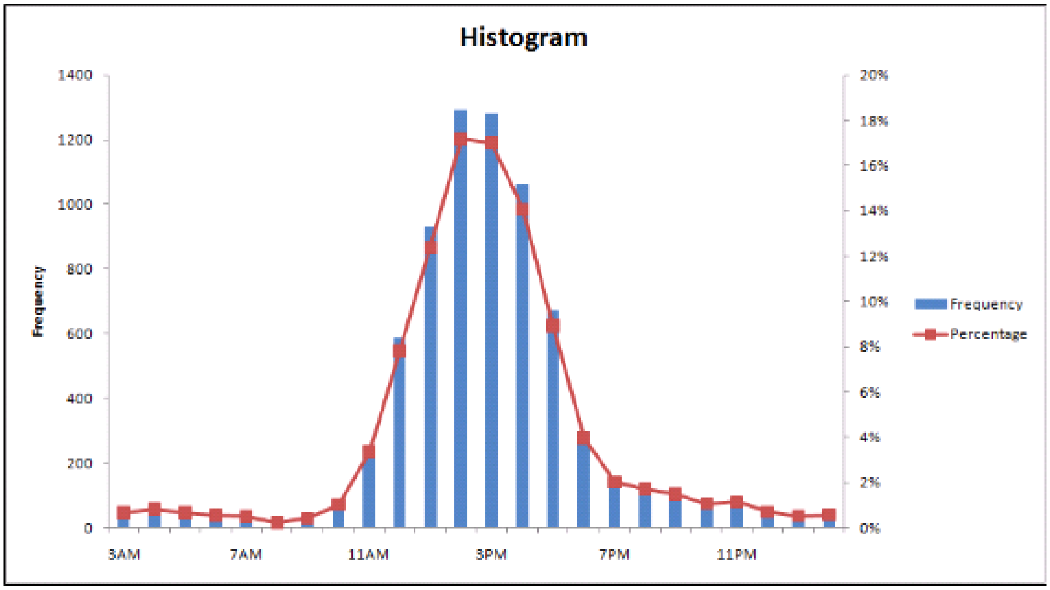

Figure A-5 Histogram of the relative frequency of historical fires by time of day and the corresponding fitted time distribution.

Table A-8 Distribution parameter and chi-squared goodness of fit significance levels for *Poisson* distribution fitted to time of day.

Best fitting distribution	Poisson
Transformation	1. subtract 2 2. if result is <0 then add 24
Estimated parameter	Lambda = 12.05
Chi-square Sig. level.	0.00

Table A-9 Parameters on time of day by region.

	All	KW	SKI	CB	CN	KB	KN	JB	JN
Time	12.05	11.42	12.17	11.58	11.54	12.07	12.23	12.32	12.21

Statistical Validation Results

A primitive version of the fire-occurrence module based on the distributions described above generated 20 years of fires for the ROK. To test the validity of the overall model structure, I compared subsets of the generated fires with their historical counterparts using the time between fires variable. I also compared the generated and historical distributions for the number of fires per year.

I found satisfactory correspondence between historical and generated fire event frequency distributions, as demonstrated by the descriptive statistics in Table A-10. In no case are the historical and generated distributions wildly disparate. The tabular results of a more formal statistical comparison are summarized in Table A-11. The paired box and whisker plots for each season clearly show similar central tendencies and degrees of variability for the historical and generated fires. Means, and to a lesser extent, medians, corresponded well. No consistent bias is observed for the differences in means, medians, or variances. The T-test indicates that the hypothesis that the historical and generated fire event frequency distributions are part of the same distribution could not be rejected at the 0.05 significance level (Table A-11).

Table A-10 Descriptive statistics for historical and generated distributions of the time between fires by season.

	Low		*Trans*		*High*	
	Historical	Simulated	Historical	Simulated	Historical	Simulated
Mean	0.33	0.36	1.63	1.77	4.30	4.12
Standard Error	0.0137	0.0188	0.10	0.15	0.18	0.20
Standard Deviation	0.91	0.95	2.30	2.61	5.95	5.43
Sample Variance	0.83	0.91	5.29	6.79	35.37	29.49
Kurtosis	24.9	16.1	4.14	14.62	14.07	13.17
Skewness	4.2	3.6	1.95	3.18	2.81	2.79
Range	11	8	14.00	20.00	63.00	51.00
Minimum	0	0	0.00	0.00	0.00	0.00
Maximum	11	8	14.00	20.00	63.00	51.00
Sum	1457	943	861.00	550.00	4901.00	3133.00
Count	4386	2580	527.00	310.00	1140.00	760.00

Table A-11 The results of t-Test: Paired Two Samples for Means.

	Low		*Trans*		*High*	
	History	*Simulated*	*History*	*Simulated*	*History*	*Simulated*
Mean	0.37	0.37	1.6903	1.7742	4.2882	4.1224
Variance	0.94	0.92	5.2630	6.7903	37.7970	29.4909
Observations	2580	2580	310.0000	310.0000	760.0000	760.0000
Pearson Correlation	0.0099		0.0332		-0.0123	
Hypothesized Mean Difference	0		0.0000		0.0000	
df	2579		309.0000		759.0000	
t Stat	0.1888		-0.4325		0.5538	
P(T<=t) one-tail	0.4251		0.3328		0.2899	
t Critical one-tail	1.6454		1.6498		1.6469	
P(T<=t) two-tail	0.8502		0.6657		0.5799	
t Critical two-tail	1.9609		1.9677		1.9631	

Summary and Conclusion

In this study, a stochastic Korean fire occurrence model is developed by season, based on the historical fire data. The model is utilized to generate sequences of fire events that are consistent with Korean fire history. For the fire occurrence simulation, a three-stage approach is employed. First, a random draw from a Bernoulli distribution is used to determine if any fire occurs for each day of a simulated fire season. Second, if a fire does occur, a random draw from a geometric multiplicity distribution determines their number. Last, ignition times for each fire are randomly drawn from a time of day distribution. These specific distributional forms are chosen after an analysis of Korean historical fire data. Maximum Likelihood Estimation (MLE) is used to estimate the primary parameters of the stochastic models. Fire sequences generated with the model appear to follow historical patterns with respect to diurnal distribution and total number of fires per year. I expect that the results of this study will assist a fire manager for planning fire suppression policies and suppression resource allocations.

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