STOCHASTIC PROGRAMMING MODEL FOR FUEL TREATMENT MANAGEMENT

A Thesis

by

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Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

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May 2014

Major Subject: Industrial and Systems Engineering

ABSTRACT

Due to the increased number and intensity of wildfires, the need for solutions that minimize the impact of fire are needed. Fuel treatment is one of the methods used to mitigate the effects of fire at a certain area. In this thesis, a two-stage stochastic programming model for fuel treatment management is constructed. The model optimizes the selection of areas for fuel treatment under budget and man-hour constraints. The process makes use of simulation tools like PHYGROW, which mimics the growth of vegetation after treatment, and FARSITE, which simulates the behavior of fire. The model minimizes the costs of fuel treatment as well as the potential losses when fire occurs. Texas Wildfire Risk Assessment Model (TWRA) used by Texas Forest Service (TFS) is used to quantify risk at each area. The model is applied at TX 12, which is a fire planning unit under the administration of TFS. Results show that the total of the expenditures on fuel treatment and the expected impact justify the efforts of fuel treatment.

DEDICATION

For my wife, Bayan, for her support, patience, and love. This work could not have seen the light without her presence beside me. May God bless her, protect her, and grant her a long, fruitful life.

ACKNOWLEDGEMENTS

I would like to express my very great appreciation to Dr. Lewis Ntaimo for his valuable and constructive suggestions during the development of this thesis work. His willingness to give his time so generously has been very much appreciated. May God bless him, grant him his wishes, and give him a long and happy life.

NOMENCLATURE

SP	Stochastic Programming
SIP	Stochastic Integer Programming
PHYGROW	Phytomas Growth Model
FARSITE	Fire Area Simulator
TWRA	Texas Wildfire Risk Assessment Model
WUI	Wildland/Urban Interface
FVS	Forest Vegetation Simulator
FFE	Fire and Fuels Extension
WFDSS	Wildland Fire Decision Support System
FPU	Fire Planning Units
FPA	Fire Program Analysis
WT	Wildfire Threat
VRI	Value Response Index

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1. INTRODUCTION

In recent years the number and intensity of wildfires has increased [6], leading to a dire need for solutions to alleviate the disastrous consequences of wildfires. A lot of research has been done on many aspects of the wildfire management problem, including prevention, preparedness, and response planning. However, fuel treatment, which is a preparedness strategy, has received mixed results in the literature as a tool for preventing large wildfires. Fuel treatment is a periodic process that aims to eliminate certain types of biomass to limit the spread or/and severity of fire when they happen. It largely depends on some important factors like the type of vegetation at the treatment area, proximity from living communities, the existence of species facing extinction, and trees of high economic value.

1.1 Research Objectives

This thesis focuses on the fuel treatment optimization problem to manage the fuel levels with a goal of preventing high intensity fires. In particular, a stochastic programming (SP) model for selecting the areas for fuel treatment, the type of fuel treatment option and level of treatment to use is introduced to minimize the costs and impact of wildfires when they occur. It provides decision makers with a fuel treatment plan that accounts for the different uncertain scenarios of vegetation growth and weather. The simulation tools PHYGROW and FARSITE are used to get required data for the parameters of the stochastic model. PHYGROW is an acronym that stands for Phytomas Growth Model. It is a simulation tool used primely in agricultural applications to simulate the growth of plants and estimate forage consumed by grazers [14]. FARSITE simulates fire behavior and growth to estimate some parameters that reflect the intensity of fire, like fireline intensity, which is the amount of energy released per unit length (kW/m) and final fire perimeter.

1.2 Problem Statement

The evidence on the importance of fuel treatment is mixed. Some literature point out that fuel treatment effectiveness is limited because of the unrealistic investments and its relative ineffectiveness when treated areas are hit with fire under severe weather conditions [3]. Other research support fuel treatment and demonstrate the importance of it [18] [17]. In general if fuel treatment is not implemented, wildfires can be more intense and severe when they occur. Therefore, there is a need for a model that optimizes the selection of areas to be treated while minimizing the undesirable consequences of wildfires.

1.3 Method of Approach

The effectiveness of fuel treatment is mainly dependent on weather, a probabilistic factor that is hard to be certain about. As the severity of weather increases, the chances of fire escaping control increases, even if fuel at that area is treated. For this reason, an optimization model that account for the different scenarios of weather conditions is needed. This work presents a stochastic integer programming model (SIP) for fuel treatment that optimizes the selection of fuel treatment type and level, while accounting for the uncertainty of weather. Stochastic programming is usually difficult to construct and needs powerful computing resources to solve.

Fuel treatment is carried out several months before fire season. So, a simulation software is used to determine the growth of treated fuels under different scenarios of temperature and precipitation levels to determine the level of vegetation at the beginning of fire season at a each area. The burn of vegetation is then simulated under different scenarios of weather conditions (low, moderate, high, and extreme) and some parameters are observed. These parameters are used to quantify the wildfire risk and the potential impact measured in dollars. The ratings for the wildfire risk are then fed to the stochastic programming model, and based on that the model determines the appropriate fuel treatment type and level for each area.

1.4 Organization of the Thesis

This work provides a brief description and literature review for fuel treatment. It includes the definition, description of the different types of fuel treatment along with the pros and cons of each, and a look over some of the optimization models in literature for fuel treatment. Next, an overview on the simulation models used to mimic vegetation growth are discussed. These models help in quantifying fuel loads during fire season. In order to quantify potential risk, a wildfire risk model needs to be used. Some of the methods used for wildfire risk assessment are discussed. Then the mathematical description of the model and its formulation are given along with testing and validation. A description of the study area is given and the design of the experiment is illustrated. Finally, the results for the experiment are discussed along with a conclusion and some suggestions for future work and development.

2. LITERATURE REVIEW

In order to construct the stochastic programming model, a literature review for fuel treatment, vegetation growth simulation tools, wildfire risk models, and stochastic programming is needed to help in narrowing the focus of this thesis. The types of fuel treatment are presented. A glance over the optimization methods in literature for fuel treatment management is given. Different simulation tools for vegetation growth modeling are introduced. Some of the wildfire risk models are highlighted. Finally a short introduction for stochastic programming is given.

2.1 Fuel Treatment Optimization

Fuel treatment is a periodic process that aims to eliminate or reduce certain types of biomass to limit the spread or/and severity of fire when they occur. The importance of fuel treatment emerges from the fact that forests are always susceptible to ignition, because of either nature (lightning for example) or human carelessness. In order to protect plants of high economic value and people living on lands near forests (called wildland-urban interface (WUI), fuel treatment can be used to mitigate the impact of wildfires when they take place and minimize the economic and life losses. The different types of fuel can be characterized using several measures. According to the Northern Forest Fire Laboratory (NFFL), fuels are divided into 13 types or models that differs according to the following measures:(a) fuel loading: the total amount of biomass to the area it is covering (lb/ft^2); (b) surface area to volume of biomass ratio (ft^2/ft^3); (c) fuel depth: the height of the accumulation of dead biomass (litter, shrubs, limbs) (ft); (d) fuel particle density (lb/ft^3); (e) heat content of fuel: the amount of British thermal units (1Btu) in one unit of mass (Btu/lb); and (f) moisture of extinction: the maximum amount of moisture contained within a plant after which fire will not ignite it.

A suitable fuel model that represent the type of plantation at the site to be treated can be used to simulate the behavior of fires at this location. There are many methods that are used for fuel treatment table. Prescribed fire is the deliberate use of fire to burn vegetation at a piece of land under certain weather conditions. It is best to be carried out when humidity is high and wind speed is low to prevent fire from spreading rapidly and going out of control. The benefit of using this method is to get rid of surface fuels, which are considered the main reason for fire spread because wind carry the small, lit branches to ignite other areas. prescribed fire is costly due to the excessive precaution measures. A larger than usual team of firefighters have to be at the site and should be ready with enough equipment to contain the fire if it escapes control when sudden changes in weather happens. Prescribed fire, although is intended to burn surface fuel, can catch up to tree crowns and cause more debris and litter. It is advisable that the area to be treated is an open area with no canopy cover. Another fuel treatment method is wildland fire use. Naturally occurring wildfires are left deliberately to burn without direct intervention to suppress it. The advantages and disadvantages are the same as prescribed fire except that it is not costly, and that the source of ignition is nature.

A third fuel treatment type is thinning. Thinning is the mechanical cutting and removing of some of the trees, limbs or crowns in a piece of land. There are three main types of thinning [10]:

1. Low thinning: removes small trees on the surface level
2. Crown thinning: removes large trees and trim the crowns.
3. Selection thinning: removes the least desirable trees.

Unlike the previously mentioned methods, thinning is a controlled process. Operations to be done are carried out by specialists who use heavy equipment to remove debris and shrubs. Low thinning specifically emphasizes on the removal of ladder fuels that connect surface fuels with tree crowns. This helps in containing fire faster and stopping its spread. Crown thinning, on the other hand, emphasizes the trimming of tree crowns to reduce its density, lessen the fire severity and make the canopy hard to reach by burnt surface fuels. Since thinning does not involve the use of fire, implementing it under severe weather conditions (low moisture and high wind) is safe. Nevertheless, thinning has its own share of disadvantages. It is a very costly process because it is labor-intensive and involves the use of expensive equipment. In addition, the process leaves small branches and limbs that will increase surface level biomass in the short run.

Another fuel treatment method is grazing, where a group of grass-eating animals are brought together to consume vegetation and bring the overall level of green down. This method is typically used at grasslands with small trees and shrubs. It is relatively inexpensive, but takes a lot of time to apply. The combination of thinning and prescribed fire is often used. The area is treated first with thinning and then prescribed fire is used to burn slash and small branches. Since both of them are costly when done separately, their cost combined is obviously higher. Chemical herbicides are also used to inhibit the growth of plants. It is typically used after thinning or prescribed fire. This method is costly and could have adverse affects on environment and water when used for prolonged period of time, which further limit their frequent and widespread use as a treatment.

Choosing the most effective treatment depends on many factors like the type of vegetation to be treated, the weather on that day and the available budget. It is crucial to choose the most suitable fuel treatment to be implemented to insure maximum protection because fuel treatment when done wrongly may lead to increased risk of fire spread and severity. If a fire hit an area, it will continue to spread wildly if weather conditions are severe (hot, dry and windy) even if fuel was treated.

Trunfio, Arca, Ghisu, and Spataro [1] developed an optimization methods for fuel treatment using a heuristic optimization method called tabu search. The methodology makes use of a heuristic optimization method to estimate a good solution for the problem. The area to be treated is divided into several parts where each part have a probability of burn depending on historical data. The parts that have a probability of burn higher than a threshold is considered a candidate for fuel treatment. After implementation, burn probability is reduced. The objective is to make as much parts of land as possible to be within a probability less than the specified threshold. Some of the factors that affect the treatment are the arrangement of the treated area, the interaction between them, and the fact that only a limited area can be covered for treatment because of the high investment involved. The specific heuristic used is the tabu search method, where an initial arrangement of fuel treatment is given first, then a set of iterative improvements are done on the initial decision to optimize it.

Finney [7] presented a computational method to optimize fuel treatment locations. The method uses a minimum travel time algorithm developed by the same author that maximizes the minimum distance traveled by fire across a landscape. The aim is to hinder the travel of fire by choosing particular patterns of fuel treatment that will collectively interact to slow down the spread of fire.

A mixed integer programming model was introduced by Wei, Rideout, and Kirsch [24]. The goal of the model is to minimize the total expected impact of potential fire. This objective is achieved by choosing the optimal type of fuel treatment to be applied at each area. Risk is represented using three different measures: a) probability of burn for each area obtained using simulation; b) probability that fire spread to adjacent area; and c) conditional probability of fire spreading into area B given that the adjacent area A is under fire.

Similarly, Minas, Hearne, and Martell [11] devised a mixed integer programming model for multi-period fuel treatment decisions. The model takes into account the different patterns of fuel treatment that can collectively slow down the growth of fire.

2.2 Vegetation Growth Models

The importance of vegetation growth simulation models in fuel treatment management is to estimate the amounts of biomass in treated and untreated areas. This estimation of amounts helps in analyzing the potential wildfire risks and impact on WUI and high value resources. Two simulation models are highlighted here. The first one is forest vegetation simulator (FVS) [21]. It gives information that describe the change in vegetation following management decisions like fuel treatment. There are many extensions for the model. fire and fuels extension (FFE) helps in linking fuel loadings obtained from FVS with fire behavior to make predictions on how severe fires will be when they occur. Consequently, FVS along with FFE can be used for fuel treatment decisions.

The second vegetation growth simulation model is PHYGROW [4]. It is a simulation tool that models on a day-by-day basis the growth of grass and small trees in a resource-limited area. It is also used to model forage consumption by grazers.

2.3 Wildfire Behavior and Risk Models

Risk within wildfire context is usually defined as the probability that the impact, loss, and negative consequences of fire at a certain piece of land that is “highly” susceptible to fire is “high”. The threshold levels indicated by the words “highly” and “high” are to be set by management. They are subject to the opinion of the experts in the field of fire management. There are many risk assessment models made for decision support. Wildland Fire Decision Support System (WFDSS) is utilized in quantifying the risk of a fire reaching a highly valued resource like WUI and natural resources using probability of burn.

Finney, McHugh, Grenfell, Riley, and Short [8] devised a simulation system that estimates some of the stochastic parameters of wildfire risk for fire planning units FPU in order to quantify the probability of burn. FPU is a specific geographic area that is under the administration of one or more fire management units.

Fire Program Analysis (FPA) is another decision support system for wildfire planning. “In FPA effectiveness is assessed in terms of multiple performance measures that are consistent with land management goals and objectives. The performance measures broadly address reducing the probability of occurrence of costly fires, reducing the probability of occurrence of fire in the Wildland/Urban Interface (WUI), increasing lands meeting or trending towards the attainment of land management objectives including protecting highly valued resources, and maintaining a high initial attack success rate” [9].

Another wildfire risk assessment model was made by Preisler, Brillinger, Burgan, and Benoit [13]. Risk is defined with a) probability of burn, b) probability that a fire escapes control given that an ignition happened, and c) the probability of large fire. Texas Forest Service (TFS) has devised the Texas Wildfire Risk Assessment Model, a tool that helps in quantifying the risk at a certain piece of land. Wildfire risk is defined through many different parameters. This model is used in this thesis to quantify the wildfire risk at a given piece of land. The model uses two main risk measures, Wildfire Threat (WT) and Value Response Index (VRI). WT is the probability that a fire will occur. VRI is a rating of the impact of wildfire.Each of these measures depend on the values of various other parameters, like the wildland-urban interface, slope and topography, and weather.

2.4 Stochastic Integer Programming

Stochastic programming is a field of optimization that deals with decision-making problems involving data uncertainties. A set of scenarios with associated probability of occurrences are given. These data are usually collected based on historical observances. There are several approaches to deal with the uncertainty. Expected Value Solution takes the expectation of all scenarios into a single value and do calculations based on it. This transforms the problem into a deterministic formulation that is easy to solve. A serious disadvantage of this solution is that it does not accommodate all scenarios.

"Fat" solution is another approach where constraints with the tighter bounds only are considered into the solution, while the less tight are regarded as redundant. It yields a deterministic formulation but is overly conservative and usually infeasible. Scenario Analysis formulates a deterministic version of the problem for each individual scenario separately. This approach is very popular but a disadvantage of it is that it does not give an overall solution that reflect all the scenarios together since no one can guarantee a scenario to take place over the others. Chance (Probabilistic) Constraints change the constraints that involve uncertainty into a probabilistic constraint, where the probability that the constraint will hold is bound by a risk factor determined by specialists. This take care of risk explicitly but it is difficult to compute and may lead to non-convex models, where optimization is difficult.

An increasingly popular approach is the Two-Stage Recourse Model. It introduces explicitly what is called corrective actions. The decision variables are divided into two types: first stage variables, which are determined here and now, and second stage variables, which depends on the realization of the uncertain data. It penalizes corrective actions, called recourse actions in Stochastic Programming. The advantage of this approach is that risk is taken care of explicitly. The problem of this approach is that the size of the problem increase fast even with small number of scenarios and variables. This problem can be alleviated by using decomposition techniques. Also with time, the advances of computer technology may make this problem history. For more on stochastic programming, refer to the textbook [2] or [15].

3. SIP MODEL FOR FUEL TREATMENT OPTIMIZATION

In this chapter, the mathematical model is presented along with a detailed description of the process. The model uses two simulation tools, PHYGROW and FARSITE to quantify fuel loadings and assess fire parameters necessary for the run of the model. The TWRA model transforms fire parameters to ratings that reflect the risk level of each area under study. The validity of the model and test results are discussed at the end.

3.1 System Description

In the fuel treatment problem, a set of representative areas, that is areas with similar vegetation cover, and the level of treatment, which represents the reduction of vegetation cover in percent, are chosen for treatment within budget and time constraints. The goal of this stage is to minimize costs of the fuel treatment. Then, using the simulation tool PHYGROW, the growth of vegetation over a specific period of time before the fire season is simulated. the final vegetation levels at each selected area gets ignited with simulated fire using FARSITE and is left to burn. Some parameters that reflect the level of wildfire risk of the treated piece of land is observed, and changes in the decision for the locations to be treated are made until the optimum areas are chosen (see Figure 3.1).

To represent this problem in mathematical terms, a two-stage model is constructed. In the first stage a "here-and-now" decision regarding the type of treatment to be used at each area to minimize cost is made. Since fuel treatment is costly and time consuming, constraints for maximum budget and working days are taken into account. In the second stage, the decision is to designate each treated area as safe or dangerous. The classification is based on a wildfire risk model developed

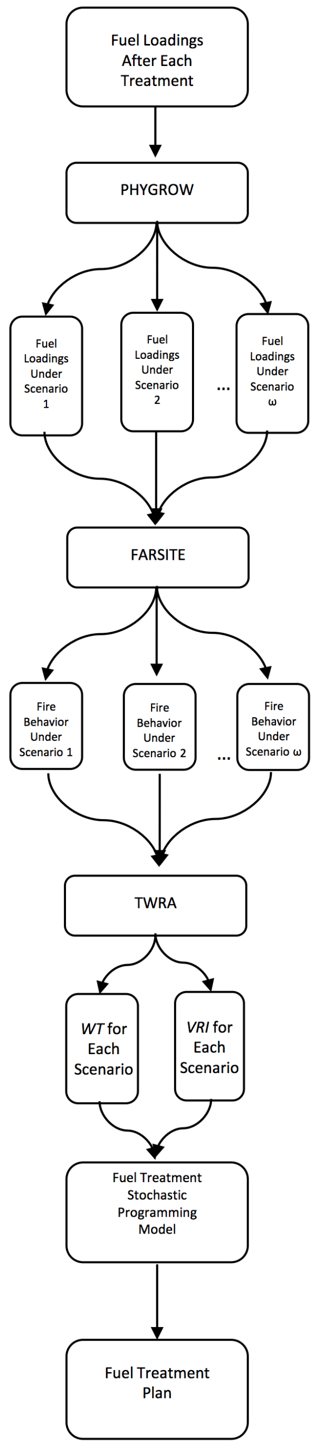

Figure 3.1: The Process for Stochastic Programming Model

by Texas Forest Service, named Texas Wildfire Risk Assessment Model (TWRA). The model uses two main risk measures, Wildfire Threat (WT) and Value Response Index (VRI). WT is the probability that a fire will occur. VRI is a rating of the impact of wildfire. WT values range from 1-7, where the range 1-2 represents low threat, 3-6 represents moderate risk, and 7 corresponds to high risk. Likewise, VRI ranges between -9 and +9, where -9 means a heavy impact and +9 means low impact. Each of these measures depend on the values of various other parameters. Some of these parameters are deterministic, like the wildland-urban interface (WUI), slope and topography, and some are stochastic, like weather, historic fire locations, and fireline intensity (see figure 3.2 for all parameters).

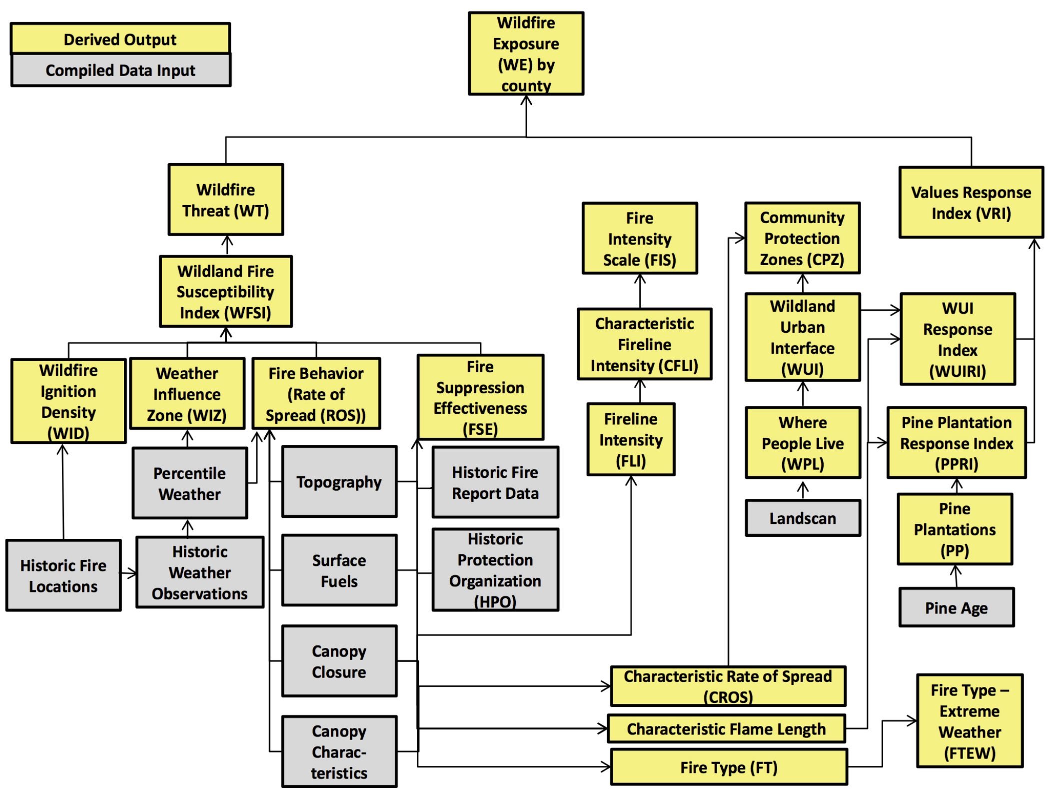

Figure 3.2: The Texas Wildfire Risk Assessment Model [6]

Risk level is a 0-1 decision variable that designates an area to be of low or high risk. A certain area is considered low in risk if the values for the WT and VRI are less than a predefined threshold. For example, a decision maker may consider a rating of 4 for WT as the maximum acceptable level, and a rating of -4 for VRI to be the highest acceptable rating. Depending on the output of the second stage, a recourse action takes place to revise the decisions made in the first stage.

Fuel treatment decisions take place several months before the fire season starts. Consequently, the vegetation level steadily increase as the fire season approach. Therefore, the model accounts for the different possible rates of growth. There are many factors that can affect the growth of vegetation after fuel treatment is done. These factors include temperature, precipitation levels, forage consumption, water storage levels, land slope and many others. Out of these factors, temperature and precipitation levels are accounted for specifically in this study. The growth of plants is simulated under different scenarios of temperature and precipitation levels. Since fuel treatment effectiveness is not the same under different weather conditions, the simulation of fire behavior is also done under four different scenarios of weather (low, moderate, high, and severe). Some assumptions inherent in this model are listed below.

Assumptions:

1. Interactions between areas are assumed to be neglected. Although significant [16], it is out of the scope of this study. We are only concerned about the reduction of risk measures values at areas that received fuel treatment.

2. The planning horizon for the fuel treatment is assumed to be one fire season.

3. Fuel treatment costs, wildfire risk measures WT and VRI for fire happening

under each of the four weather scenarios (low, moderate, high, and extreme) are given.

4. Probabilities for each scenario are assumed to be estimated.

3.2 Mathematical Formulation

Before stating the mathematical model, notations and decision variables for the first and second stage are given.

Notation

Sets:

Ω: Set of scenarios.

p_ω: Probability of scenario $\omega \in \Omega$.

I: Index set for areas.

J: Index set for fuel treatment types.

Decision Variables

First Stage:

$$x_{ij} : x_{ij} = \begin{cases} 1 & \text{if area } i \in I \text{ is treated with fuel treatment } j \in J \\ 0 & \text{otherwise} \end{cases}$$

Second Stage:

y_{1i}^{ω}: Risk level of area $i \in I$ in relation to wildfire threat under scenario $\omega \in \Omega$,

$$y_{1i}^{\omega} = \begin{cases} 1 & \text{if area } i \in I \text{ is of low risk in relation to wildfire threat} \\ 0 & \text{otherwise} \end{cases}$$

y_{2i}^{ω}: Risk level of area $i \in I$ in relation to value response index under scenario $\omega \in \Omega$, $y_{2i}^{\omega} = \begin{cases} 1 & \text{if area } i \in I \text{ is of low risk in relation to value response index} \\ 0 & \text{otherwise} \end{cases}$

Parameters

First Stage:

d_{ij}: Number of days to do fuel treatment j at area i.

d_{total}: Total number of working days available before fire season.

c_{ij}: Cost of fuel treatment j at area i.

B: Maximum budget available.

Second Stage:

$g_{1i^{\omega}}$: Potential impact of fire in relation to WT at location i under scenario ω.

$g_{1i^{\omega}}$: Potential impact of fire in relation to VRI at location i under scenario ω.

T_1: Threshold for wildland threat.

T_2: Threshold for value response index.

WT_{ij}^{ω}: wildland threat rating at area $i \in I$ that was treated with fuel treatment $j \in J$ under scenario $\omega \in \Omega$.

VRI_{ij}^{ω}: value response index rating at area $i \in I$ that was treated with fuel treatment $j \in J$ under scenario $\omega \in \Omega$.

Objectives & Constraints

First Stage:

$$Min \sum_{i=1}^{|I|} \sum_{j=1}^{|J|} c_{ij} x_{ij} + E[f(x, \widetilde{\omega})] \tag{3.1}$$

c_{ij} is the cost of fuel treatment type j (grazing, prescribed fire, mechanical removal or do nothing)at location i. $E[f(x, \widetilde{\omega})]$ is the expected outcome of the second stage which represents the potential impact of areas high in wildfire risk, and is measured in dollars. The expectation is computed by multiplying the probability of each scenario p_ω by the decision variables of the second stage for that scenario.

$$\sum_{j=1}^{|J|} x_{ij} = 1, \; \forall i \in I \tag{3.2}$$

This constraint restricts only one type and level of treatment to be implemented at each area.

$$\sum_{i=1}^{|I|} \sum_{j=1}^{|J|} d_{ij} x_{ij} \leq d_{total} \tag{3.3}$$

d_{ij} is the number of days allocated to implement fuel treatment j at location i, and d_{max} is the maximum number of days available.

$$\sum_{i=1}^{|I|} \sum_{j=1}^{|J|} c_{ij} x_{ij} \leq B \tag{3.4}$$

The total cost for fuel treatment must not surpass the maximum budget available B. This constraint can be ignored if costs do not pose a restriction.

$$x_{ij} \in \{0, 1\} \tag{3.5}$$

Binary requirement for decision variable x_{ij}

Second Stage:

For each outcome $\omega \in \Omega$ of $\widetilde{\omega}$, we have:

$$f(x, \omega) = Min \sum_{i=1}^{|I|} g_{1i^\omega}(1 - y_{1i}^\omega) + g_{2i^\omega}(1 - y_{2i}^\omega) \tag{3.6}$$

The objective in this stage is to maximize the number of areas that have a risk level of 1, which indicates a low impact from fire.

$$y_{1i}^{\omega} \leq \sum_{j=1}^{|J|} x_{ij}\left(\frac{T_1}{WT_{ij}^{\omega}}\right),\ \forall i \in I \tag{3.7}$$

WT_{ij}^{ω} is the wildland threat rating for area i treated by treatment j under scenario ω. T_1 is the maximum wildland threat value allowed before an action has to be made. The decision variable y_{1i}^{ω} will get a value of 1 if $(\frac{T_1}{WT_{ij}^{\omega}})$ is equal to 1 or more.

$$y_{2i}^{\omega} \leq \sum_{j=1}^{|J|} x_{ij}\left(\frac{T_2}{VRI_{ij}^{\omega}}\right),\ \forall i \in I,\ \forall k \in K \tag{3.8}$$

VRI_{ij}^{ω} is the value response index rating for area i treated by treatment j under scenario ω. T_2 is the maximum value response index value allowed before an action has to be made. The decision variable y_{2i}^{ω} will get a value of 1 if $(\frac{T_2}{VRI_{ij}^{\omega}})$ is equal to 1 or more.

$$y_{1i}^{\omega} \in \{0, 1\} \tag{3.9}$$

$$y_{2i}^{\omega} \in \{0, 1\} \tag{3.10}$$

Binary requirements for decision variables y_{1i}^{ω} and y_{2i}^{ω}

3.3 Model Testing and Verification

The model was tested on an area under the jurisdiction of Texas Forest Service (TFS). This area is at the northeastern part of Texas and is called Texas Destrict 12 (TX12). This area has been divided into several parts to make fuel treatment decisions for. Some of the necessary parameters data was provided by TFS. The other parameters were estimated or obtained from other resources in literature and online.

The data was entered to the simulation models to calculate the necessary input for the stochastic programming model. Initial testing results showed that the model is working well, and some of the extreme outcomes were tested. For example, the likelihood of the model choosing no treatment as the best possible option was examined. This instance can happen under either of three conditions. The first one is that the treatment cost is as much as the expected impact or higher. This means that the costs of fuel treatment are not justified by the lower impact. The second condition is when all WT and VRI values are above the threshold. This indicate that treatment is not required since the wildfire risk is low. The last condition manifests itself when wildfire risk ratings are all below the threshold. Because of this, the impact will become inevitable. To minimize losses, the model will not assign any treatments because this will add to the total cost without any tangible benefit. Another examined scenario is if the cost and number of working days of one treatment type is less than all the others. This will cause the model to exclusively pick this treatment type.

4. COMPUTATIONAL EXPERIMENTS

The stochastic programming model is applied to Texas district 12 (TX12), a fire planning unit under the administration of TFS located in northeastern Texas. The model will be tested using CPLEX12, a linear programming solver. The description of the test area and the types of fuel is given first, the design of the experiments is outlined and then the results of the study are given.

4.1 Study Area

The stochastic programming model was tested using historical data for TX12. (see Figure 4.1). Historically, this area is known to be susceptible to wildfire, with a total of 13,163 fire occurrences in the period 1985-2006.

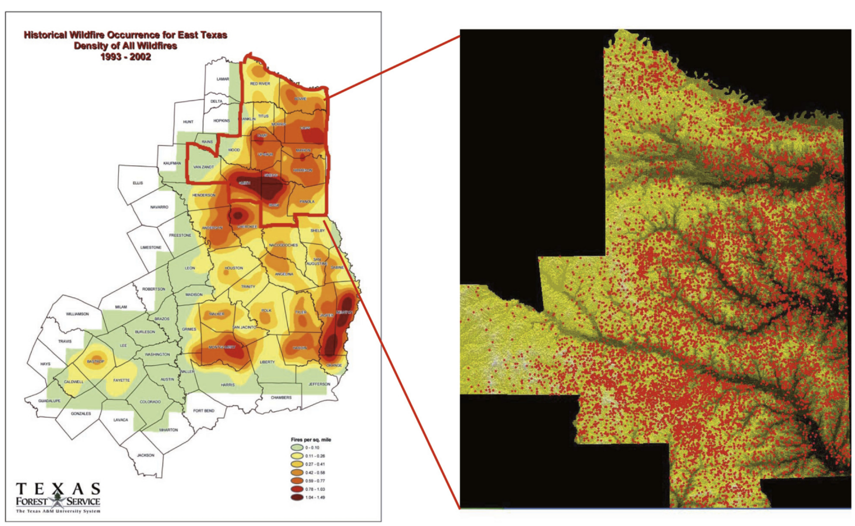

Figure 4.1: Location of TX12 [12]

The type of vegetation in that area is described using Northern Forest Fire Laboratory (NFFL)fuel models, which include fire models 5, 8, 9, custom models GR01, GR02, GR03, 9HWD, and 9PPL (Figure 4.2).

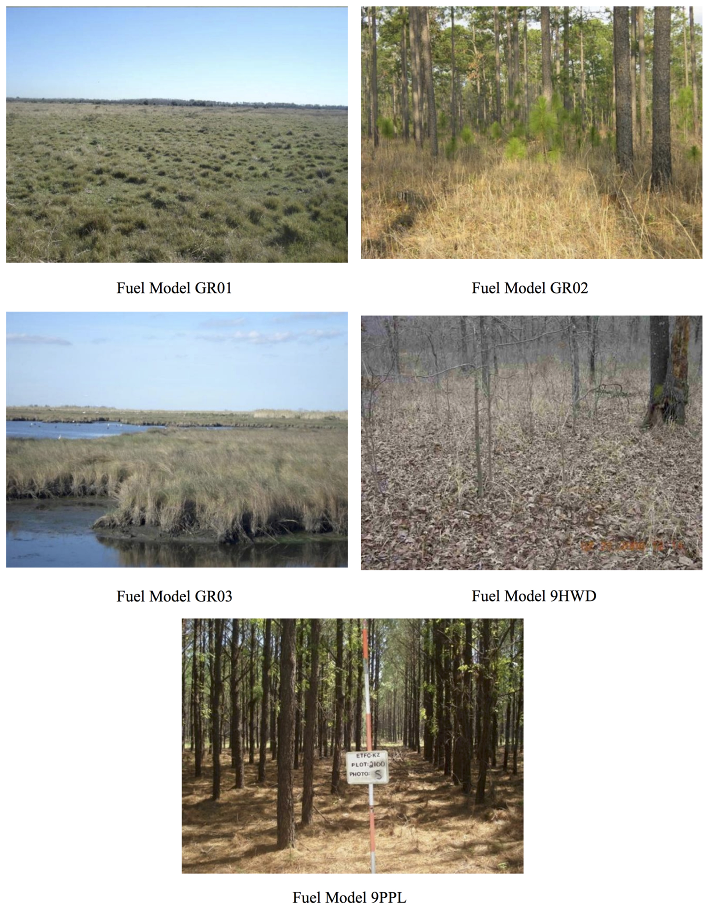

Figure 4.2: Fuel Types [20]

Due to limitations in PHYGROW, only grass and shrubs are considered for study. Consequently, a set of 15 areas with similar vegetation of grass and shrubs were selected for fuel treatment (Figure 4.3). Each area was assumed to be 200 ha. The areas were chosen with enough distance between them to make them isolated in order to prevent interactions between them.

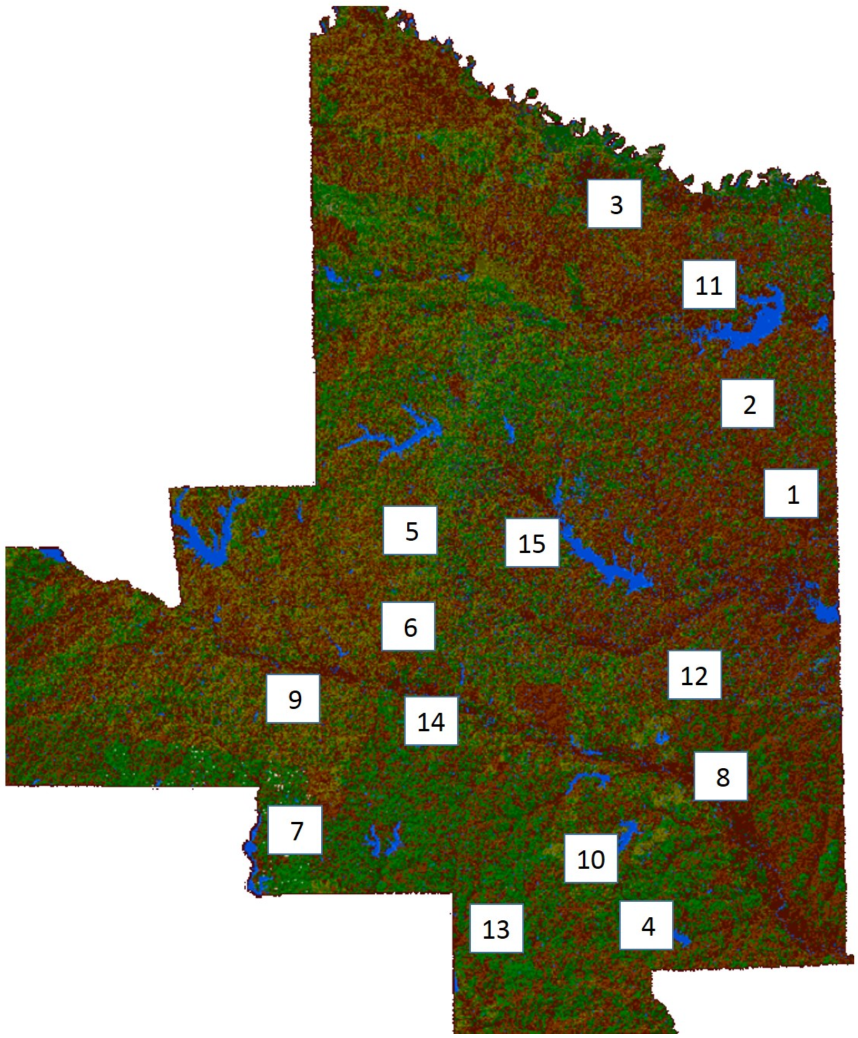

Figure 4.3: Potential Areas for Fuel Treatment

The simulation models required to estimate the parameters of the stochastic programming model requires several field data. Particularly, data for historical weather, soil, and plants are needed. In addition, a detailed description for the topography of the land is necessary for the simulation model. These data were supplied by the TFS.

4.2 Design of Experiments

Some of the data necessary to run the stochastic programming model was obtained from the simulation software FARSITE and others were estimated using online resources and literature. These data include the probabilities for all scenarios, the estimated impact in dollars for each scenario, the costs of applying each level of fuel treatment at each area under study, and the expected number of days necessary to do each type and level of fuel treatment.

Because data necessary for PHYGROW input could not be obtained at the time of this study, the experiments were executed using the default fuel loadings in FARSITE. These fuel loadings were considered as the vegetation levels at the beginning of the fire season. For this experiment, two levels of fuel treatment was considered for grazing and mechanical removal (20% and 35%). Since prescribed fire eliminates all fuels, it has only one level of fuel treatment (100%). These levels were accounted for in FARSITE by reducing the vegetation level by the percentage of each level of fuel treatment. Areas treated with prescribed fire were assumed to regain 40% of their fuel volume at the beginning of the fire season. As for the weather conditions, three levels were examined, moderate, high, and extreme. Also, probability of occurrence of each weather condition was assumed to be equally likely (Table 4.1).

Weather	Moderate	High	Extreme
Wind speed (mph)	4-6	12-15	15-18
Humidity (%)	40-60	35-50	30-45
Temperature (f)	60-80	60-80	60-80
Probability	0.33	0.33	0.34

Table 4.1: Weather Conditions

The costs and required number of days for each type of fuel treatment was obtained from several sources [19][22][23] (Table 4.2). For this experiment, *fireline intensity* was used as the wildfire risk measure instead of WT and VRI. The threshold value used was 1,000 kW/m, based on the study by Duguy et al.[5]. These authors considered *fireline intensities* larger than this number to be of extreme intensity, which means to be high in wildfire risk. The total *budget* and number of *man-days* available were assumed to be $1,000,000 and 1,200 days successively. These values were chosen based on the maximum number of days and maximum budget needed to implement the most expensive and time consuming fuel treatment, which is prescribed fire. The numbers used in this model are 50% less than the numbers for prescribed fire.

Treatment Type	G	MT	PF
Cost ($/ha)	988	1,111	926
Area per day (ha/day)	1.07	0.404	0.81

Table 4.2: Fuel Treatment Costs

4.3 Simulation Results and Discussion

The model was implemented and solved using CPLEX 12.1. A total of 135 variables and 62 constraints were generated. The model run took less than a second to finish. The optimal objective function value obtained is $1,002,613. The values for the decision variable x_{ij} are shown in Table 4.3.

Area (x_{ij})	G 20%	G 35%	MT 20%	MT 35%	PF 100%	No Treatment
1					x	
2			x			
3					x	
4				x		
5					x	
6					x	
7			x			
8					x	
9					x	
10		x				
11					x	
12			x			
13				x		
14		x				
15			x			

Table 4.3: Optimal Values for x_{ij}

The total cost comprises the fuel treatment cost and the expected impact from fires that have a *fireline intensity* value higher than the threshold. Fuel treatment costs amount to $301,000 and total expected impact is $701,613. To see if the total cost incurred is worth the effort, a comparison between the optimal total cost and the total impact if no treatment is made. The total impact for no treatment option is $2,855,789.5, which is almost three times the optimal cost. The number of days utilized for the fuel treatment is 1,168 days. This number is very close to the total number of days available. Cost of fuel treatment is $301,000, $699,000 less than the budget available.

The sensitivity of the budget and total man-days available were both examined. $1,000,000 and 1,000 days were applied to the model until a budget of $10,000,000 and 10,000 days was reached. These changes did not affect the solution dramatically. The reason is that the best fuel treatment option is the cheapest one that renders an area safe, and it had already been achieved with the original budget and total number of days.

Another factor examined is the *fireline intensity* threshold. It was varied from 500 to 5000 in increments of 500 kW/m. It turns out that this value is a very sensitive one. Increasing this value rendered some areas safe, which allowed more fuel treatments to be done. Decreasing it, on the other hand, made the impact of some areas to be inevitable.

The huge reduction in total cost shows that fuel treatment, even if it does not eliminate the wildfire risk complectly, can reduce it by a significant margin. The total impact cost avoided by implementing fuel treatment is almost 1.5 times the impact cost if no treatment is carried out. This implies that for each $1 spent in fuel treatment, a saving of $6.15 is made. It should be noted that the treatment cost for each fuel treatment type was assumed to be the same for each area. Sometimes fuel treatment at some areas can be cheaper or more expensive depending on some factors regarding the topography of area.

The optimal level and type of fuel treatment for each area differs because of several reasons. One reason is that the wildfire risk at some areas can only be reduced below threshold by removing large volumes of fuel levels, so they are given the priority for fuel treatments with high levels of vegetation removal. Another reason is the cost of treatment. Cost increases as the level of removed vegetation increases. So the model will assign high-level fuel treatments to areas high in *fireline intensity*. Other areas with lower *fireline intensities* will be assigned the cheapest and the minimum level of fuel treatment that renders each area safe.

There are other options that can be investigated in this work. One of them is the study of the effect of each weather condition separately on the fuel treatment decisions. It is expected that as the severity of weather increases, the effectiveness of fuel treatment will be low. Another option is to assume that either an infinite budget is available or that there are enough staff to carry out any fuel treatment type at any area. The corresponding constraint of any one of them can be removed and changes in the other are made to study its sensitivity to the stochastic programming model. Also the areas chosen do not overlap with each other. Interacting areas can be studied by accounting for the interaction by adding additional constraints that capture it.

5. SUMMARY AND FUTURE RESEARCH

This chapter gives an overall summary of the thesis and points out possible future research extensions.

5.1 Summary

The state of fuel treatment optimization models in literature shows a lack of work that explicitly tackle some of the important probabilistic elements inherent in fuel treatment problems. Stochastic programming specifically is sometimes difficult to use due to the challenges in defining the problem and the first and second stage variables. Also the excessive time needed to solve it due to the rapid growth of the problem size and number of scenarios even with few stochastic parameters pose a challenge. In this work, however, the solution time was less than a second because there was only one stochastic parameter and only three scenarios.

This thesis presented a model that include at its core the different possible scenarios of weather as one of the critical parameters that affect the fuel treatment decisions. The test of the model shows that fuel treatment can have a positive effect on the wildfire risk. Fuel treatment practices reduced the total costs by about 3 times than if no fuel treatment was done. This gives an indication of how effective is fuel treatment.

5.2 Future Research

This model can be extended to account for post treatment decisions, like the problem of optimizing deployment of firefighting resources and their dispatch. Since this work considered only grass and shrubs because of their fast growth and simulation limitations, the study period was one fire season. Another possibility is to make a variant of the model that takes into account multiple study periods to simulate the growth of slow aging trees. Including the possibility of the interaction of fuel treatment areas, the different possible patterns of treatment and how the overall effect on wildfire risk will look like are some stochastic elements worth looking into.

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