A SPATIAL OPTIMIZATION APPROACH TO FINDING LOCATIONS FOR WILDFIRE FUEL TREATMENTS

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Wildfires are a major concern in many parts of the world. In order to minimize the threat posed by wildfires, prior to the ignition of a wildfire forest managers use fuel management activities to modify the volume and structure of fuel in the landscape with the goal of lessening the intensity and rate of spread of any wildfires that do ignite. This implies that one of the tasks of forest managers is to identify the spatial locations where forest fuels will be treated. Quantitative spatial optimization techniques have been proposed as a means of finding optimal or near-optimal locations for forest fuel management activities. The aim of this research is to develop a new heuristic algorithm that builds upon the earlier work of Valdez-Lazalde (2001) in this area. This earlier study proposed a method of quantifying the benefit obtained from a proposed fuel treatment activity, and used that metric in a steepest-decent type heuristic approach to develop proposed fuel treatment plans. This study replaces the steepest decent approach with a genetic algorithm. It is found that the genetic approach consistently produces better-performing fuel treatment plans than does either the steepest decent model or a series of fire management experts

who were asked to develop fuel management plans for the same hypothetical scenarios as were presented to the genetic and steepest decent models.

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CHAPTER 1

INTRODUCTION

1.1 Background

Forest fire is a major concern in many parts of the world. As described by Brown and Davis (1973), any wildfire not prescribed by an authorized plan constitutes a forest fire. In the United States, there are typically between 60,000 and 80,000 wildfires each year, burning 3 million to 10 million acres (National Interagency Fire Center, 2013). On average, fire seasons in 2016 are 78 days longer than they were in 1970 and the number of acres burned each year has doubled since 1980 (USDA, 2016).

Wildfires can cause extensive damage, both to property and life. According to the US Forest Service, wildfires in the United States destroy lives and livelihoods by devastating homes, damaging natural resources, and polluting water and air (USFS, 2015). In 2015, over half of the forest service's budget was allocated for fighting wildfires compared to 16 percent in 1995. Having to use such a high percentage of its budget to combat fire has never happened to the agency in its 111-year history. In 2015, fire costs totaled $2.6 billion, making that year the most expensive in the agency's history (USDA, 2016).

Saving lives and property from wildfires poses a challenge for natural resource managers. Forest fire management encompasses far more than attempting to extinguish fires once they have ignited; proactive management involves taking steps to minimize the risk of fire long before a wildfire actually occurs. Risk mitigation efforts include fire occurrence prediction, fuel management, fire prevention, and fire detection (Martell, 2007). Since fuel accumulation (i.e., the buildup within a forest of dead woody material that can readily burn) is a hazard which can

turn into a disaster, management actions to reduce fuel accumulation prior to the ignition of a wildfire can be an effective way of decreasing the intensity and/or slowing the spread of any wildfire that may ignite in the future. Fuel management refers to efforts to modify the volume and structure of fuel in the landscape such that the intensity of future wildfires are reduced (Pyne, 1984; Finney, 2001). The focus of fuel management is to reduce the effects of wildfire, not necessarily stopping such a fire (Finney and Cohen, 2003). Since the inception of the National Fire Plan in 2000, millions of dollars have been spent on fuel treatments, especially in the wildland/urban interface (WUI) zones (i.e., regions typically located on the periphery of urban areas where homes and other structures are constructed within or amid natural forests) where people and property are likely to be threatened by wildfire (United States Department of Agriculture/Forest Service, 2011).

In planning fuel treatment activities, one of the challenges faced by forest managers is the identification of the spatial locations where forest fuel will be treated. These decisions are always made within the constraints imposed by limited budgets. Until recent times, delineating the spatial location for forest fuel management was performed manually, based on the knowledge and experience of experts. This method is obviously very subjective and the results, including the effectiveness (the ability of the plan to reduce the hazards posed by wildfire) and efficiency (the ability of the plan to achieve its level of effectiveness at minimum cost) of the fuel treatment plans produced differ from individual to individual. A more objective and reproducible procedure that reliably produces efficient and effective plans is desirable.

In 2001, Valdez-Lazalde, produced a dissertation entitled; “Optimal Spatial Locations of Forest Fuel Management Activities” that presented a spatial optimization approach for locating

forest fuel management activities under budgetary constraints. While this technique was successful in some respects, it suffered from a number of serious limitations and weaknesses. The aim of the present research is to develop an improved heuristic algorithm based on global search optimization techniques and GIS principles which rectifies some of the acknowledged limitations mentioned in Valdez-Lazalde's study.

1.2 Purpose

The purpose of this proposed research is to develop and test the potential of an evolutionary algorithm approach to find near-optimal locations for forest fuel treatment. This research focuses on extending and improving the methods of the study conducted by Valdez-Lazalde (2001).

It is worth emphasizing that the research presented here is **NOT** intended to be applicable for use *during* wildfire suppression activities; in some sense, such tools already exist in the forms of fire behavior models such as BEHAVEPLUS (https://www.firelab.org/project/behaveplus) while in another sense such tools remain to be built (e.g., no system designed to optimize the deployment of wildfire suppression resources exists). Tools for use in a suppression setting require unique abilities that are not part of this study (i.e., the ability to incorporate data describing current weather and fire conditions, the ability to produce results in near real time, and so forth). The purpose of this study is to develop techniques that could be used as a tool fire managers could use *prior to* the ignition of a wildfire to optimize their fuel management activities.

Spatial optimization has been widely applied to various problems pertaining to natural resource management, land use modeling, transportation, retail location planning, resource allocation, ecosystem management and many other areas. According to Tong and Murray (2012), academic reference to spatial optimization within geography is first mentioned by Haggett (1975). Spatial optimization has gained wide attention from researchers. For example, numerous spatial optimization techniques have been applied to the p-median problem (Densham and Rushton, 1992; Church and Sorensen, 1996), problems pertaining to the contiguity of zones (Openshaw and Rao, 1995), continuous space coverage problems (Murray et al., 2008), and the maximal covering location problem (Tong et al., 2009).

Despite these efforts in other areas, not much attention has been given to developing quantitative approaches to the fuel management problem. The purpose of this study is to develop and evaluate a new spatial optimization approach for identifying locations to conduct fuel treatment operations. This new approach is based on a modification of the techniques presented by Valdez-Lazalde, and is evaluated against the same data used in that study. This new approach is more computationally efficient and produces more nearly optimal solutions than those produced in the earlier study.

1.3 Rationale

The methodology used in Valdez-Lazalde's (2001) study suffered from a number of flaws acknowledged by that author. First, one of the most fundamental drawbacks in Valdez-Lazalde's (2001) methodology was that it used a steepest descent optimization approach. This is a local search heuristic which is usually able to locate a local optima but not necessarily the

global optima. Secondly, the areas identified by Valdez-Lazalde's model to receive fuel treatment were highly fragmented, which is impractical in the real world. Thirdly, computational efficiency was another major weakness of Valdez Lazalde's model. The highly iterative nature of the model and the need to conduct multiple anisotropic cost spreading operations took a considerable amount of time and computational resources.

Heuristic global search methods (including evolutionary algorithms) have been widely applied to various spatial optimization problems, but to the best of the author's knowledge, no other study has applied an evolutionary approach to the forest fuel treatment problem. The first drawback with the previous study can be addressed by the very nature of the evolutionary approach, which obtains globally optimal or near-optimal solutions as opposed to the local solutions produced by Valdez-Lazalde's approach. Secondly, by applying contiguity checks to the initial solution formation process as well as to all genetic operations performed during the evolutionary process, this study focuses on non-fragmented solutions, thereby avoiding the fragmentation problem that plagued Valdez-Lazalde's study. Thirdly, the present research uses the A-star (A*) algorithm to replace the anisotropic cost spreading used by Valdez-Lazalde; this modification should allow this study's model to produce results in much less time than did Valdez-Lazalde's model.

1.4 Research Questions

Based on the preceding discussion, the three main research questions of this study are:

1. Can plausible and intuitively reasonable spatial locations for forest fuel management activities be identified using a combined GIS and genetic approach?

2. Can the ‘genetic and GIS’ approach yield better solutions to the problem of identifying spatial locations for forest fuel management activities, as compared to the ‘steepest descent’ approach?
3. Can the genetic and GIS approach produce solutions in a reasonable amount of time?

CHAPTER 2

LITERATURE REVIEW

In this section, literature regarding forest fire and fuel management, fire behavior and fuel models, optimization methods, spatial optimization techniques for forest fuel management and genetic algorithms are reviewed.

2.1 Forest Fire Management

Forest fire management is a multi-faceted task involving forest land management, fire prediction, fire modeling, fire prevention, fire detection, fire suppression and forest fuel management. Discussing each of these facets is beyond the scope of this study. Hence, in this section, only topics relevant to the aim of the current study will be discussed.

2.2 Fire Behavior Models

Effective fuel management strategies can be developed only after understanding how fire moves, spreads, intensifies and diminishes across a landscape—this is what is termed fire behavior. Hence, immense amounts of research have concentrated on developing fire behavior models. Surface fire rate of spread is an important measure of fire behavior and can be defined as the speed at which a fire's flame front moves forward (Valdez-Lazalde, 2001; Scott, 2012).

Fire behavior and rate of spread depends on a combination of factors such as fuel loading, moisture content, weather (primarily wind velocity and direction) and topography (Rothermel and Anderson, 1966; Brown and Davis, 1973). Simulation models varying in scale from local/stand level to landscape level are commonly used in order to understand fire behavior under

various fuel and weather conditions and to test the potential of fuel treatment programs (Ager et al., 2011). Different fire behavior models based on the spread of surface fires (i.e., a fire burning through fuels on the ground's surface) and crown fires (a fire burning through the treetops) have been developed. For example, Rothermel (1972) presents a surface model, and Van Wagner (1977), Rothermel (1991), and Cruz (1999) all present crown spread models. Scott (2012) provides an overview of fuel and fire behavior models.

In addition to fire behavior models, related tools have been developed. For example, FFE-FVS—The Fire and Fuel Extension to the Forest Vegetation Simulator—simulates tree growth and the accumulation of fuel over time (Reinhardt and Crookston, 2003). FuelCalc determines changes in surface and crown fuel loading after thinning, pruning, piling and/or prescribed fire (Lutes, 2016).

Rothermel's wildland fire spread model is widely used because of its robustness and the fact that it was derived from basic thermodynamic principles (Albini, 1976). Rothermel's model is used in this study in order to forecast the surface fire rate of spread which is later used within the fuel treatment optimization model. It is worth noting that nothing in this study's optimization model is dependent upon Rothermel's model; any other fire behavior model could be substituted for Rothermel's without altering the basic functionality of optimization system.

Details of fire behavior and Rothermel's fire spread equation are given by Scott (2012), Rothermel and Anderson (1966), and Rothermel (1972). Rothermel's model is based upon an equation that calculates fire rate of spread in the steady state and needs as input parameters relevant to wind speed and direction, terrain, fuel moisture, and a detailed description of the fuel

bed or *fuel model* (explained in section 2.3) through which the fire is burning (Valdez-Lazalde, 2001). Equation 2.1 summarizes Rothermel's equation.

$$\mathbf{R} = \frac{\mathbf{I_R} \times \boldsymbol{\chi} \times (\mathbf{1} + \mathbf{F_w} + \mathbf{F_s})}{(\mathbf{r_b} \times \mathbf{e} \times \mathbf{Q_{ig}})} \qquad \textit{Equation 2.1}$$

Where:

R = Fire rate of spread (ft $min^{-1)}$

I_R = Reaction intensity (Btu ft^{-2} min^{-1})

χ = Propagation flux ratio

F_w= Wind coefficient

F_S = Slope coefficient

r_b = Oven-dry bulk density (lb ft^{-3})

e = Effective heating number

Q_{ig} = Heat of pre-ignition (Btu lb^{-1})

2.3 Fire Fuel Models

Fuel models basically refer to the grouping of fuels with similar properties into categories of fuels that produce similar fire intensities and spread rates (Anderson, 1982). Fuel models are often used as inputs into fire behavior/spread models. Examples of fuel models used for fire behavior applications are the 11 fuel model (Rothermel, 1972), the 13 fuel model (Albini, 1976, Anderson, 1982), and the 40 fire behavior fuels model (Scott and Burgan, 2005). In this study the 13 fuel model (Albini, 1976, p 92) is used as input to the Rothermel's (1972) fire spread model.

The 13 fuel model distinguishes between two general types of fuel: foliage and wood. Each of these general types are subdivided based on size class. For example, wood is subdivided as 1 hour, 10, hour, 100 hour and 1000 hour. This refers to the time needed for the fuel size class to achieve 63% of its expected equilibrium moisture content; it is a measure of how quickly a fuel either dries out (and hence becomes more combustible) in dry weather or becomes damp (and hence less combustible) in wet weather (Valdez-Lazalde, 2001).

2.4 Optimization

An optimization problem is defined by three main components: (i) the objective function, (ii) the constraints, and (iii) the decision variables. The objective function refers to the goal or goals that are to be achieved. By their very nature, optimization problems involve minimizing or maximizing their objective function. Typical examples include minimizing cost or maximizing profit. Constraints correspond to the conditions that need to be satisfied in order to produce a feasible solution. For example, constraints can represent the limited budget available, or the minimum number of acres of land that must be allotted to a certain land use type, and so on. The decision variables represent the quantities whose values will be determined by solving the optimization problem. For example, in this study the values assigned to the decision variables identify which raster cells will receive fuel treatments and which will not. Each of these elements will be described in more detail in the following sections.

The objective function, constraints and decision variables are combined together to form an optimization problem that can be solved using either exact or heuristic methods (Tong and Murray, 2012). A simple example of optimization model involving decision variables x (where x

is a vector of *n* decision variables $x_1, x_2, \ldots, x_n$) might have an objective function *Y* (equation 2.2) and *m* constraints $Z_1, Z_2, \ldots, Z_m$ (equation 2.3). Note that in equation 2.3, the a_i values represent the right hand sides of the constraint equations.

$$\text{Maximize: } Y(x) \qquad \textit{Equation 2.2}$$

$$\text{Subject To: } Z_i(x) \leq a_i \quad \forall_i \quad (\forall_i = 1,2,.., m) \qquad \textit{Equation 2.3}$$

2.4.1 Objective Function

It is useful to distinguish between objective functions which can be expressed in terms of linear relationships between model variables (decision variables and any other internal variables used by the model) and nonlinear objective functions that involves at least one nonlinear relationship between model variables (Church at el., 2009). Figures 2.1 and 2.2 illustrates linear and non-linear objective functions. The optimization problems depicted in the figures involve only a single decision variable, whose value is shown along the x-axis. The allowed values of the decision variable (as determined by the constraints) are delimited by the two vertical lines shown in the figures. The values of the objective function is shown on the y-axis. In the case of a linear objective, the optimum value for the objective function is always obtained at a constraint boundary. With a nonlinear objective function, optima can be anywhere along the function's length.

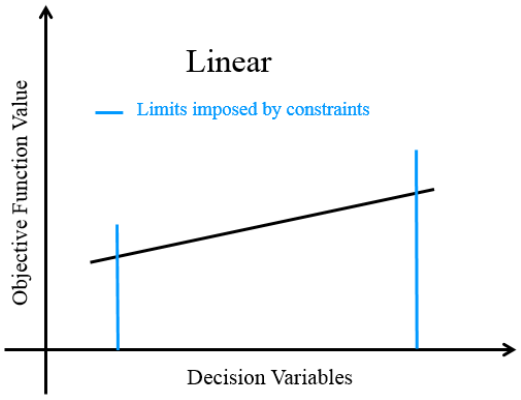


Figure 2.1. Linear objective function

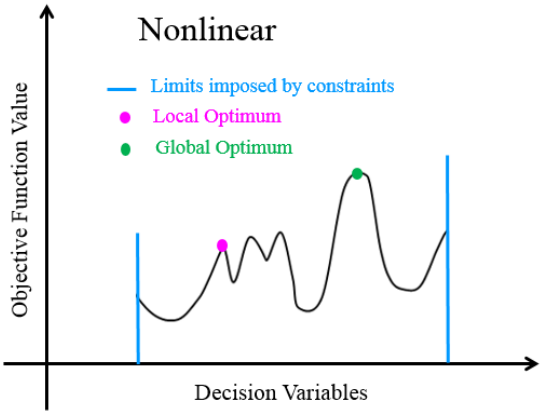


Figure 2.2. Nonlinear objective function

2.4.2 Constraints

Equation 2.3 refers to the set of constraints. As with the objective function, it is useful to distinguish between linear and nonlinear constraints. Nonlinear constraints add significantly to the complexity of an optimization problem; most problems with nonlinear constraints lack exact solutions and must be solved heuristically. The problem at the heart of this study falls into the nonlinear constraint category; as shall be seen, it will be solved using heuristics.

2.4.3 Decision Variables

The optimal value of decision variables are unknown at the start of an optimization problem and the goal of the problem is to find values for these variables that both (1) satisfy the constraints and (2) optimize the value of the objective function. Decision variables which can take on real values are termed continuous while decision variables which can take on only discrete, integer values are termed integer decision variables. Binary variables are a special case of integers where the variable can only assume values either 0 or 1.

2.4.4 Feasible Space

In optimization, the feasible space (also known as the feasible region, search space or solution space) refers to the set of values of the decision variables which satisfy all of the constraints. Thus an optimization problem's constraints delimit the feasible space. Any solution inside the feasible space is known as a feasible solution. If no point exists which can satisfy all the constraints, the feasible region is null and the problem is referred to as infeasible and has no solution. Optimization problems may be thought of as search problems, where the goal is to search through the feasible space to find a solution that optimizes the objective function.

Feasible spaces can be differentiated into convex and concave feasible sets. If all lines connecting all possible pairs of feasible solutions fall entirely within the feasible region, the region is referred to as a convex. Convex solution spaces lend themselves to easier solution strategies than the alternative, which are referred to as concave solution spaces. The reasons for this distinction in solution difficulty will become clear in the following sections.

2.4.5 Cases of Optimization Problems

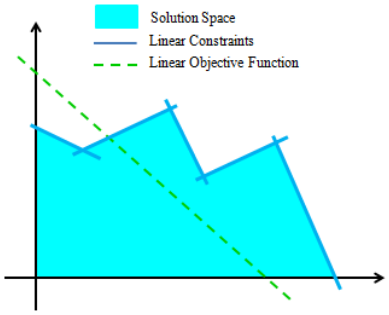
Different optimization models are created depending on the type of objective function, decision variables and constraints used in the model. Five different cases of optimization problem are illustrated in Figure 2.3. Linear Programming (LP) (Figure 2.3 A) refers to a model where both the constraints and objective function are linear and the decision variables are continuous. LP models are among the simplest of optimization problems to solve; the simplex method addresses LP models. Integer Linear Programming (ILP) (Figure 2.3 B) is a model where the objective function and constraints are still linear but the variables are limited to integer (or binary) values. ILP problems are noticeably more difficult to solve than LP problems, but can

often be addressed using various branch-and-bound approaches. Mixed models are optimization problems where some of the decision variables are continuous and other are integer. Nonlinear models are those with nonlinear constraints, objective functions, or both. Thus, mixed integer nonlinear programming (MINLP) refers to a model where decision variables are a combination of continuous and discrete, and the objective function and/or at least some of the constraints are nonlinear. MINLP models are among the most difficult of optimization problems to solve.

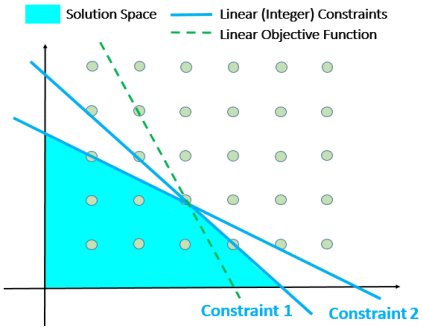
Another way to categorize optimization problems involves the number of objectives they consider. Single objective optimization problems consider only one objective function and the best possible solution for that single function is the optimal solution for the overall problem. Multiobjective optimization problems consider two or more objective functions and thus the solution that optimizes any one objective may or may not be the optimal solution to the overall problem. Without a clear-cut weighting system that allows the values of the various objective functions to be unambiguously combined, multiobjective functions are usually not solvable in that they have no unambiguously optimal solution.

2.4.6 Solution Strategies—Exact vs. Heuristics

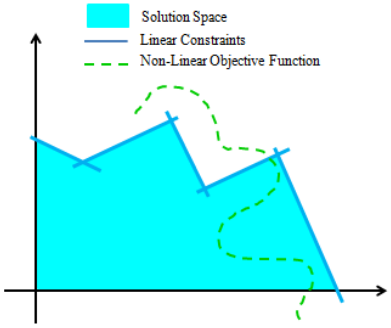
Two different solution strategies, known as exact and heuristics methods, can be used to solve optimization problems. Exact methods ensure optimal solutions, but typically can only be applied to problems that have extremely well defined characteristics. Exact solutions can be proved to be optimal. Examples of exact methods include the simplex method to solve LP



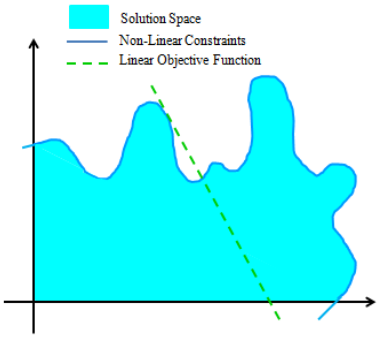
A. Linear objective function with linear constraints.



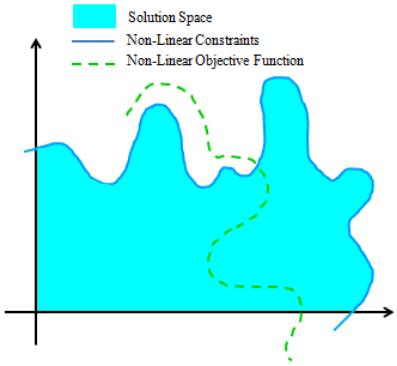
B. Linear objective function with linear (integer) constraints.



C. Non-linear objective function with linear constraints.



D. Linear objective function with non- linear constraints.



E. Non-linear objective function with non- linear constraints.

Figure 2.3. Five different cases of optimization

problems, and Dijkstra's algorithm for finding shortest paths through networks.

Heuristics methods are used when the problem does not conform to the requirement of an exact method, or when implementation of exact methods is expensive in terms of computation time, money (e.g., expensive commercial software), or effort required to develop the model. The solutions produced by heuristic methods cannot be proven to be optimal. However, heuristic methods are generally faster and more computationally efficient than exact methods, so they produce solutions much more quickly and efficiently than do exact methods. Furthermore, they can be applied to problems that have no exact solutions. A few examples of common heuristics are simulated annealing and genetic algorithms (Church and Murray, 2009). In general, practical exact methods exist to address most linear problems, while heuristic methods are commonly employed for nonlinear problems (Church and Cova, 2000).

2.4.7 Continuous vs. Discrete Optimization

In continuous optimization problems the decision variables can assume continuous values, so the number of possible solutions is infinite. Some discrete optimization problems also have infinite solution spaces; for example, an IP problem where the decision variables can assume any integer value. However, other discrete optimization problems have finite search spaces (e.g., a problem with a finite number of decision variables, each of which can only assume finite number of integer values), so at least in theory these problems could be solved by enumerating all possible solutions (i.e., complete enumeration). This sort of problem is termed a combinatorial optimization problem.

Unfortunately, while combinatorial optimization problems have finite solutions spaces, their solution spaces are often so huge that complete enumeration is impractical. For example,

consider the situation inherent in this study, where the goal is to identify raster cells where wildfire fuel treatment activities are to take place. Assume the study region is represented by a 100 by 100 matrix of raster cells. In this case there is one decision variable for each raster cell, and each decision variable is binary (either a fuel treatment is conducted on a cell or it is not). In this scenario, there are 2^{10000} possible combination of decision variable values—in decimal terms, that is approximately 2×10^{3010}. Even computers capable of constructing and evaluating trillions of variable combinations per second would take millennia to evaluate that number permeations of variable values. Given this, the only practical way to solve combinatorial problems involves some alternative to complete enumeration, and these alternatives are almost always heuristic in nature.

2.5 Spatial Optimization

Spatial optimization problems share the same three components as nonspatial problems: an objective to be optimized, decision variables to be assigned values, and constraining conditions (Tong and Murray, 2012). What differentiates spatial optimization from non-spatial optimization is spatial optimization's implementation of topological relationships and spatial interdependence in defining its objective function, decision variables and constraints (Tong and Murray, 2012). Spatial interdependence and topological relationships refer to properties such as distance, adjacency, connectivity, containment, intersection, shape, pattern and districts (Tong and Murray, 2012; Longley et al., 2011).

Even though the term spatial optimization has only recently been coined (Haggett, 1975), various geographic theories have relied on the concept for years. For example, consider ideas

such as the location rent-allocation of resources presented by Von Thünen (1826, 1966), transport cost minimization (Weber, 1909, 1929), and central place theory for arrangement of cities/towns (Christaller, 1933, 1966; Losch, 1940, 1954). All could be considered forms of (or consequences of) spatial optimization.

Spatial optimization is a combination of fields such as geographical information science, location science and operations research (Church and Murray, 2009). Most spatial optimization problems are computationally challenging (Armstrong, 2000; Tong and Murray, 2012). A few spatial optimization problems have exact solutions, but most must be addressed using heuristics. An example of a spatial optimization problem with an exact solution is the shortest problem which can be solved exactly using Dijkstra's algorithm (Collischonn and Pilar, 2000). A wide variety of heuristic methods applied to spatial optimization problems can be found in literature. Malczewski and Rinner (2015) differentiate these heuristics as basic heuristics and metaheuristics. Metaheuristics are flexible problem solving approaches that combine two or more basic heuristics (or multiple instances of a single heuristic) into an overall solution strategy. Examples of basic heuristic methods for spatial applications include greedy algorithms, Lagrangian relaxation techniques, and HERO optimization (Beasley, 1990; Li et al., 2014, Kim et al., 2015). Examples of meta heuristics for spatial applications are Monte Carlo integer programming (MCIP) (Nelson and Brodie, 1990), simulated annealing (Lockwood and Moore, 1993), tabu search (Murray and Church, 1995a), and genetic algorithms (Mullen and Butler, 1997; Li and Parrott , 2016).

2.6 Genetic Algorithms

The genetic approach is a machine learning technique based on genetics and natural selection. It is a meta-heuristic method which can be thought of as a guided random, multipoint search technique which belongs to the class of evolutionary algorithms. Genetic algorithms were developed by Holland (1975) and his student Goldberg (1989), who applied this method to solve a problem relating to gas-pipeline transmission. Some advantages of genetic algorithms (GAs) as mentioned by Haupt and Haupt (2004) are:

- They can function with both continuous and discrete variables,
- Derivative information is not required,
- They are capable of performing simultaneous search on different points within the solution space,
- They work efficiently with large numbers of variables,
- They support parallel computing,
- They are capable of dealing with complex solution spaces and escaping from local optimum,
- They produce numerous solutions,
- They can work with experimental data and analytical functions.

While GAs are well suited for complex problems with mixed variables, nonlinear functions, and/or large numbers of constraints and variables, traditional methods perform comparatively better for more classically defined problems with fewer variables, linear functions, etc. Unfortunately, real word problems are often not so simple as to be solved by traditional methods.

A typical GA starts by randomly constructing a group of feasible solutions known as a "population". Each solution in this population is known as an "individual," and this population represents the initial generation (generation 1) of the analysis. The GA approach operates by applying Darwin's theory of the survival of the fittest to the individuals in this population. Each individual is ranked based on its ability to optimize the objective function (i.e., its 'fitness'), and the probability that a solution will be propagated (in any form) into the next generation is a function of its fitness. Solutions can be propagated verbatim (this is termed replication), in randomly mutated form, or by randomly combining portions of two or more solutions into a hybrid (this is termed a crossover operation). The aim is to create a new generation of solutions (children) that share traits from the fittest previous solutions (parents). This process of generational reproduction continues until some stopping criterion is met. Haupt and Allen (2004) provide a description of a genetic algorithm.

The GA approach has been applied to a number of spatial problems. Zhou and Civco (1996) used GA to solve a spatial multi objective suitability analysis problem. Brookes (1997, 2001) integrated GA with a region-growing approach for identifying optimal patch configurations subject to multiple objective criteria. Li et al., (2005) integrated GIS and GA for optimal location search. Malczewski and Rinner (2015) provide a comprehensive discussion on conceptual and technical details of GA, as well as implementation of GA for spatial applications.

2.7 Spatial Optimization for Forest Fuel Management

Forest fuel management refers to modifying the amount, spatial distribution and/or structure of fuels found in the forest. Fuels include dead leaves and pine needles found on the

forest floor, dead woody material such as fallen branches or standing dead trees, or any other material that could serve as a source of fuel to a wildfire. Fuel can be treated through means such as the construction of fuel breaks, controlled burns, or mechanical removal of fuels (Minas et al., 2014, Bevers et al., 2004). Determining where to conduct these fuel treatment operations is a nontrivial problem.

Various techniques including optimization methods have been applied to many aspects of forest management in general and fire management in particular. Applications of operations research methods to forest fire studies date back to at least 1961 (Martell, 1982). Parks and Jewell (1962) used differential equations and calculus to identify the optimal levels of suppression for forest fires. Martell (1982) gives a good review of operations research studies in forest fire management from the 1960's through the 1980's. Bettinger (2010) provides a review of various models that are developed for incorporating wildfires into forest planning. Very little of this research has concentrated on locating areas for fuel treatment using spatial optimization (Kim et al., 2009).

Forest management and fuel treatments are conducted at either landscape or stand levels. Forest managers typically divide large forested areas into smaller management units (often called stands) that are treated as homogeneous units that are considered indivisible. Palma et al. (2007) developed a methodology to study the effects of harvesting a single forest stand on landscape flammability and expected losses. Shortest paths connecting the ignition points with values at risk were identified and stands were ranked based on their potential to disrupt the shortest paths in order to slow down the fire spread. Fire risk was obtained using the probability of fire ignition combined with probabilistic predictions of fire burn time and spread. Fire risk was then used to

rank the forest stands. A disadvantage of this study is that a single stand is treated at a time and the possibility of treating multiple stands simultaneously is ignored. Multiple stand treatments could produce different results. Stand-level models used for accessing fire risk in forests are often nonspatial since they assume that actions in any given stand do not affect fire risk in adjacent stands (Konoshima et al., 2008). Konoshima et al., (2008) combined a spatial fire behavior model and a stochastic dynamic optimization model to determine the optimal spatial pattern of fuel management and timber harvest. Effects of stand level management actions were examined to understand how it affects the fire risk in current and adjacent stands. Although fuel treatment planning at stand level is a choice due to its practical feasibility, the fact that the treatment at one stand affects the fire behavior in neighboring stands the spatial interactions between stands cannot be ignored. Various studies acknowledge this problem and landscape level fuel treatment optimization models were developed which are discussed in the following section.

As stated by Hof et al. (2000), slowing fire spread across the landscape to protect valuable resources is an option that falls on a spectrum ranging from letting a fire burn without disturbance and complete fire suppression. This concept was used by Hof et al. (2000) in a study which used a timing optimization model for fire and fuel management. The aim was to locate spatially optimal locations for fuel treatment, such that treatments maximize the delay in time of fire spread from ignition points to valuable areas. Various strategies such as treating cells/area around the fire's point of origin, cells around the area to be protected, a combination of both (termed the hourglass layout), or treating cells in the center of the grid were tested. Additionally, the impacts of increasing or decreasing the total number of cells to be treated (to reflect differing

budgets) were tested, as were the effects of changing the number of valuable areas to be protected. Treating cells/area along the path of fire spread was not tested in Hof's (2000) approach. Hof et al.'s study clearly mentions the need for research in the field of dynamic and spatial optimization. Hof and Omi (2003) investigated pre-defined sets of forest conditions for forest fuel management at a landscape scale and captured the spatial relationships between fuel loads as it affects fire behavior. The study points to the need for developing heuristics to obtain near-optimal solutions for fuel management activities. Although Finney (2002b) mentioned that genetic algorithms have been implemented for locating fuel treatment locations, no literature explaining the procedures, results and conclusions for the implementation and performance of genetic algorithm was found. In a latter publication, Finney (2007) developed a computational method to identify fuel treatment units and patterns for heterogeneous landscapes under different fire weather scenarios. Wei et al. (2008) developed a mixed integer programming model for locating fuel treatment areas across a landscape, using spatial information describing fire ignition risk, conditional probabilities of fire spread between raster cells, fire intensity levels and values at risk. Kim et al. (2009) used the Great Deluge Algorithm (GDA), a heuristic approach, for scheduling fuel treatment activities at landscape scale with different spatial patterns (e.g. dispersed, clustered and random). The effect of these patterns on simulated wildfire behavior was analyzed. It was observed that the spatial pattern of treatments did not affect the overall severity of wildfires burning across a larger landscape. The speed and quality of results for GDA was mentioned to be comparable with simulated annealing. Rytwinski et al. (2010) developed a combinatorial simulation-optimization problem with integer decision variables for allocating spatial-fuel treatment areas to reduce probability of fire damage at the landscape scale. It was

observed that the spatial relationships between selected fuel-breaks is an important factor in reducing a forest's total fire-risk. The study identifies the need for discovering methods to increase the efficiency of search procedure for finding high quality solutions in acceptable computing time. Wei (2012) used mixed integer programming to develop a fuel treatment optimization model by extending a fire suppression model to simultaneously consider many future fires across a landscape. Although, the model allocated fuel treatments in contiguous areas following regular and intuitive spatial patterns, it was observed that heterogeneous landscape conditions made fuel treatment decisions difficult and allocating fuel treatment in regular pattern was not an efficient strategy. The study concluded that smaller the raster cell size, higher is the computation time. Dantzig-Wolfe decomposition or Benders decomposition methods are suggested for modeling larger landscapes with thousands of cells. Arca et al. (2013) identified the high computation time issue and developed an approach for optimizing the layout of fuel treatments on a landscape using general-purpose computing on graphics processing units (GPGPU). A tabu tearch (TS) procedure was coupled with a wildfire simulator based on a cellular automata (CA) model to obtain fuel treatment layouts in a fraction of the time. Chung et al. (2013) developed simulated annealing algorithm to optimize locations and timing of fuel treatments at landscape scale. Changes in forest dynamics over time, fire behavior and spread, values at risk, and operational feasibility were considered. Belval et al. (2016) explored the multistage stochastic mixed integer program with full recourse to model spatially explicit fire behavior and to select suppression locations for a wildland fire. The model aimed at addressing stochastic weather related uncertainties in predicting future fire growth and behavior for making decisions relating to fire suppression.

Recent studies have also added the temporal component for fuel treatments placements at landscape level. Minas et al. (2014) developed a mixed integer programming model for selecting fuel treatment locations in a multi-period setting at landscape level. The model is capable of tracking fuel treatment decisions and fuel age over time thus capturing the effect of treatment due to vegetation regrowth. The grid representation restricts the representation to single vegetation type per treatment unit which is an unrealistic representation of the real world landscape where each grid can consists of different vegetation types of differing ages. Rachmawati et al. (2016) build upon Minas et al. (2014) model and developed a multi period, polygon-based mixed integer programming (MIP) model that breaks the connectivity of high risk regions in order to minimize fuel hazards in the landscape by tracking the age of different vegetation types to determine the optimal time and locations for conducting fuel treatments. Multiple vegetation types were represented within single treatment unit. Matsypura et al. (2017) developed a multi-period optimization framework based on mixed integer programming (MIP) to identify spatial locations for prescribed burning activities. The fuel accumulation was modeled using Olson's equation while graph-theory approach was used to model the fire spread and to consider irregular landscape connectivity.

Chung (2015) reviews various models and discusses the complexity of implementing operations research approach such as optimization for forest fuel treatment planning. The problem complexity is discussed in terms of where, when and how to perform fuel treatments. Various models implemented by previous studies are discussed with focus on their unique contributions, assumptions, and simplifications.

2.8 Origins of the Current Study

Valdez-Lazalde (2001) presented a spatial optimization model designed to find optimal locations for forest fuel management activities. Geographic Information System (GIS)—based spread cost analysis operations (to simulate the spread of a fire across the landscape) and a heuristic optimization algorithm were combined to locate areas for fuel treatment under budget constraints. In terms of effectiveness, i.e., the ability of a fuel management plan to increase fire burn times, the results produced by Valdez-Lazalde's model frequently outperformed the fuel management plans developed by fuel management experts. The major drawbacks of this model were:

(1) The use of steepest descent heuristic search algorithm, which gets struck in local optima and mostly locates the local optimal solution rather than the desired global optima.

(2) Due to the highly iterative nature of the model and limited computation power, the model required considerable amounts of time to perform cost spread operations and generate near-optimal solutions.

(3) The model did not consider spatial continuity as it generated treatment areas, and thus the results produced were highly fragmented and unrealistic.

The present study is an extension of Valdez-Lazalde (2001) research and addresses the major drawbacks mentioned above by implementing a combination of GIS and GA.

CHAPTER 3

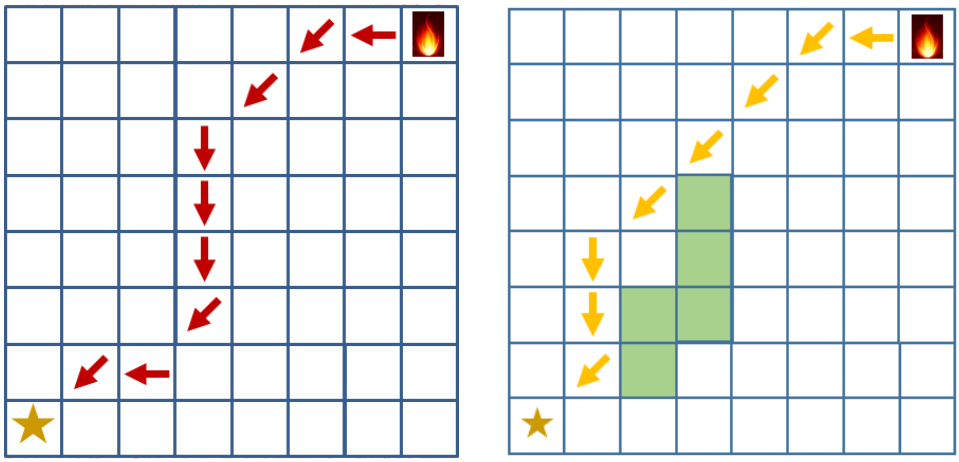
METHODOLOGY

The purpose of this research is to develop and test a spatial genetic algorithm (SGA) designed to identify optimal or near-optimal locations for forest fuel management subject to a set of constraints (budget and non-fragmentation). The results obtained using the SGA model are compared to expert prescriptions as well as to results obtained by Valdez-Lazalde's (2001) approach.

The basic idea behind this study is to delay fire spread from some predefined Ignition Point(s) (IPs) to predefined Point(s) of Value (POVs) through fuel treatments conducted prior to the ignition of any wildfire. Delaying spread time provides additional time, once a wildfire actually does ignite, to either suppress that fire before it reaches the POVs and/or take measures to lessen the impact of the fire once it reaches the POV (e.g., evacuations, removal of valuable items, etc).

The *F*astest *F*ire *S*pread *R*oute from the IP to the POV will be referred to as the FFSR. Figure 3.1(A) shows a hypothetical FFSR in red. Assume that before any fuel treatment operations are conducted, a fire spreading along this route will require 30 minutes to reach the POV. By definition, any other path will take longer than 30 minutes to reach the POV. Conducting a fuel treatment along the FFSR will force the fire to spread along another, slower route (or alternatively follow the same route but at a reduced rate of spread), thereby increasing the time needed to reach the POV and lessening the risk the fire poses to the POV. Figure 3.1(B) shows an illustration of a new FFSR (in orange) after conducting a fuel treatment on selected cells (in green) along and around the previous route. This new FFSR might take 40 minutes to

reach the POV causing a delay of 10 minutes (40 minutes post treatment-30 minutes pretreatment = 10 minutes increased burn time due to fuel treatment). The goal of the model developed in this study is to identify sets of raster cells where fuel treatments can be conducted that will maximize this increase in fire spread time. These raster cell sets are identified using a heuristic optimization approach based on genetic programming and a cost spreading technique implemented via the A* shortest path algorithm (Zeng and Church, 2009).



A. Fastest fire spread route from IP to POV before fuel treatment (30 minutes).

B. Fastest fire spread route from IP to POV after fuel treatment (40 minutes).

Figure 3.1. Fire spread route before and after conducting fuel treatment

3.1 Fuel Treatment Optimization Model

The following section describes the genetic approach used in this study and its implementation in a spatial environment for developing optimal fuel treatment plans.

3.1.1 General Approach

Genetic algorithms (GAs) are iterative heuristic optimization systems that try to find near optimal solutions by mimicking the process of natural selection. Figure 3.2 illustrates the general idea of a genetic algorithm. The algorithm starts with a first generation of randomly generated solutions. This set of solutions is known as a population. In the next step, each of these solutions is rated for its *fitness*; i.e., a measure of the quality of the solution. Higher quality (i.e., more optimal) solutions have higher fitness measures. The role of these fitness ratings is to give each solution a probability that it will be reproduced into the next generation. Each solution's chance of reproducing is proportional to its fitness. As shown in Figure 3.2, solutions reproduce into the next generation using three different processes. In *replication*, solutions are selected to be copied verbatim into the next generation based on a simple biased sampling process: any solution's chance of being selected for reproduction is directly proportional to its fitness. Replication simulates the biological process of cloning. *Mutation* is the process of randomly modifying a solution. Once again, solutions are selected for mutation via the same biased sampling process used in replication, and the modifications to selected solutions are created via some truly random process. Mutations simulate the biological process of asexual reproduction. In *crossover*, random parts of two existing solutions are combined to generate a new evolved solution. Once again, candidate solutions are chosen via the biased sampling process, and the portions of each existing solution to be combined are selected via a truly random process. Crossovers simulate the biological process of sexual reproduction.

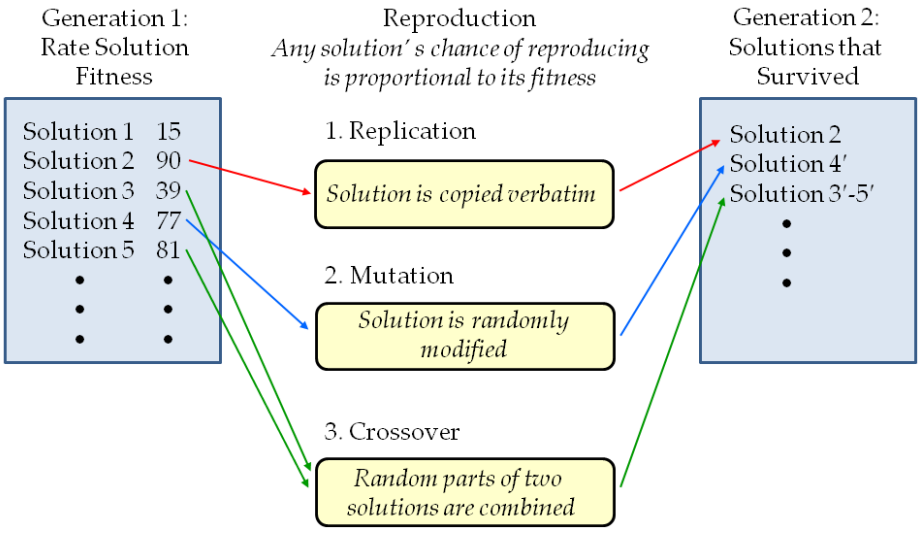


Figure 3.2. General idea of genetic algorithm

The biased nature of the processes used to reproduce solutions from the current population into subsequent generation ensures that on average, the overall fitness of solutions in later generations will be higher than that of earlier generations. It is this increase in fitness values that allows the genetic approach to identify improved solutions over the course of multiple generations.

Note that as implemented, most genetic systems add a fourth type of reproduction, typically referred to as copying, that simply applies the replication process to some predefined number of the best existing solutions, i.e., the solutions with the highest fitness ratings. This insures that the best solutions from previous generations are preserved in subsequent generations.

3.1.2 A Spatial Genetic Algorithm (SGA) for Identifying Wildfire Fuel Treatment Locations

Developing and testing a spatial fuel treatment optimization model is the heart of this research. For the fuel treatment location problem, the landscape is represented as a grid of raster cells. The first step involves locating the POV(s) the optimization model is intended to protect and the likely IPs of the wildfire. With these starting and ending points, and assuming terrain and fire fuels data is available in raster format, a graph suitable for fire spread analyses (as described in section 3.3.3) can be constructed. A shortest path analysis is then used to predict the path and time of spread of a wildfire igniting at the IPs and spreading to the quickest-to-reach POV. This spread path and time represent the risk to the POV under current fuel conditions—POVs that a wildfire can reach in a short amount of time are under greater risk than POVs that a wildfire will take a longer to reach.

Once this baseline risk level is established, a genetic approach is applied to the problem of determining which raster cells should receive fuel reductions. A set of cells to be treated is termed a solution, and the genetic approach begins by generating multiple solutions using pseudo-random processes described in sections 3.1.6 and 3.1.7. The fitness of each solution is then determined by (i) simulating a reduction in the fuel loading on the cells the solution calls for treating (section 3.1.5), (ii) recomputing fuel burn times through these cells under their reduced fuel loads (section 3.1.3), (iii) adjusting the impedance values in the graph to reflect these new burn times (section 3.1.5), and (4) using the fire spread analysis model to compute the new burn time and burn path from the IPs to the POVs under this new fuel regime. The increase in burn

time under this new scenario versus the burn time under the baseline situation is the measure of the risk reduction, and hence the fitness, of the solution.

Figure 3.3 shows a flowchart for the overall methodology. Steps 1 through 9 are associated with input dataset generation (details described in section 3.3) and steps 10 through 21 involve the implementation of the SGA fuel optimization model. The following sub sections discuss each of these processes in detail.

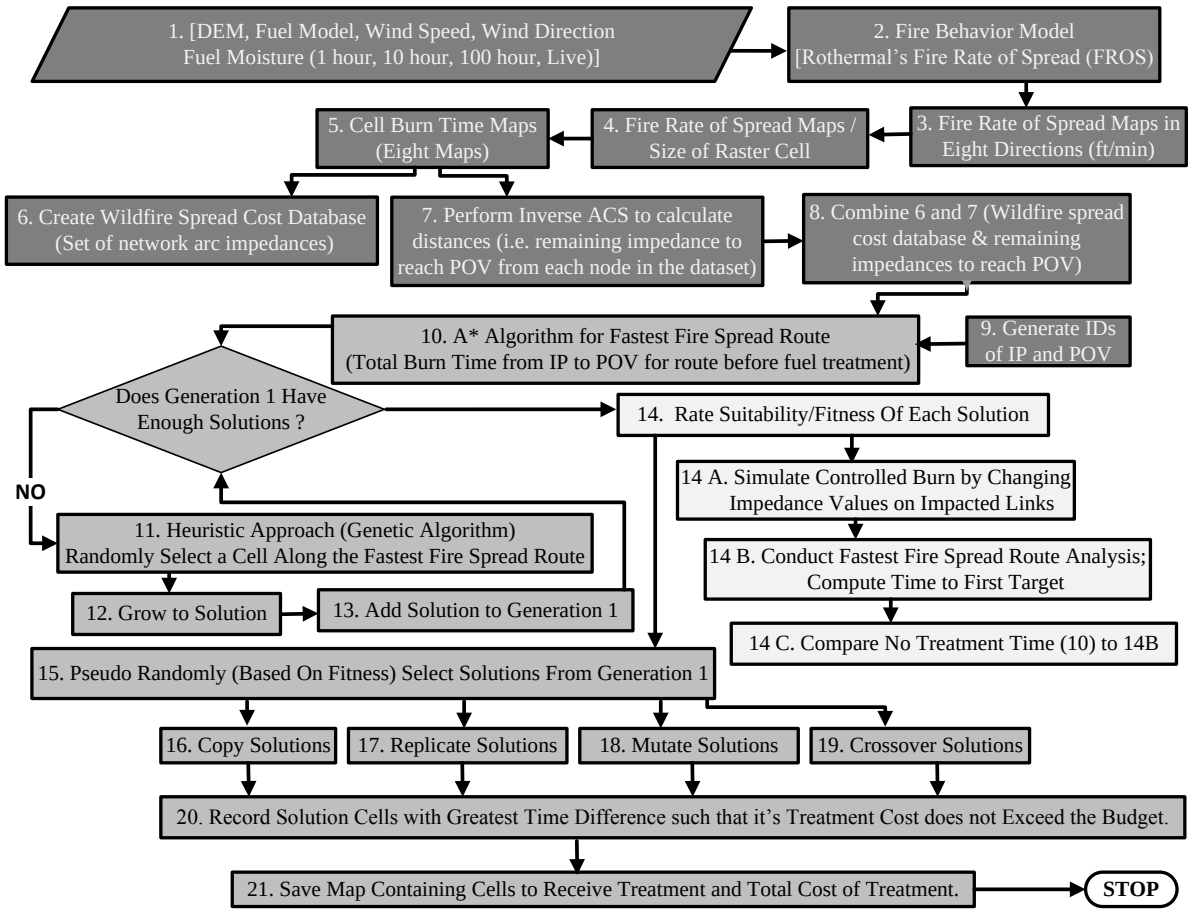


Figure 3.3. Methodology

3.1.3 A* Algorithm for Identifying Fastest Fire Spread Route (FFSR)

The A* shortest path algorithm is implemented for obtaining the FFSR. In order to evaluate the fitness of any solution, FFSR routes must be computed twice: once before conducting the fuel treatment and again after conducting the fuel treatment. The only difference between these two A* analyses is that after the treatment, impedance values (wildfire spread times) in the network are modified to reflect the impacts of the fuel treatment. An assumption about fuel treatment effectiveness used in Valdez-Lazalde's (2001) study is also used for the present research: fuel treatment double burn times. Thus, burn time impedance values for locations where fuel treatments take place have their burn times (impedance values) doubled.

It is worth noting that there are alternatives to the A* approach used here to find the FFSR. For example, an anisotropic cost spreading (ACS) technique could be used. Valdez and Dean (2000) employed ACS for obtaining the initial FFSR and implemented an improved ACS for finding the FFSR after conducting fuel treatments (Valdez and Dean, 2000). But, even after incorporating these improvements, the computation time was unmanageably slow. When the ACS approach was tested for the current research, it took at least an hour or more to find the FFSR for a single scenario. While this would not be unreasonable if the FFSR only had to be computed once or twice, in this model FFSRs has to be re-computed hundreds or thousands of times. Thus, the ACS approach is unworkable for this study, and is replaced by the network approach.

The most widely known way of solving shortest path problems through a network is by using Dijkstra's algorithm (Dijkstra's, 1959). In addition to being widely employed, Dijkstra's algorithm has the advantage of producing truly optimal solutions, so it was tested in an early

version of this study's model. It was observed that the time needed for Dijkstra's algorithm to find its solutions increased exponentially as the number of nodes/raster cells in the dataset increased. Figure 3.4 shows the graph for number of raster cells/nodes on x-axis and Dijkstra's algorithm run time on y-axis. For this study, the wildfire spread cost database used to obtain the FFSR consists 58250 raster cells/nodes (250 rows and 233 columns). With this number of nodes, it would have taken days to compute a single FFSR using Dijkstra's algorithm. This is clearly infeasible for the current research since routes need to be computed repeatedly. Thus, the idea of using Dijkstra's algorithm had to be dropped and the A* algorithm (Zeng and Church, 2009) is used as an alternative.

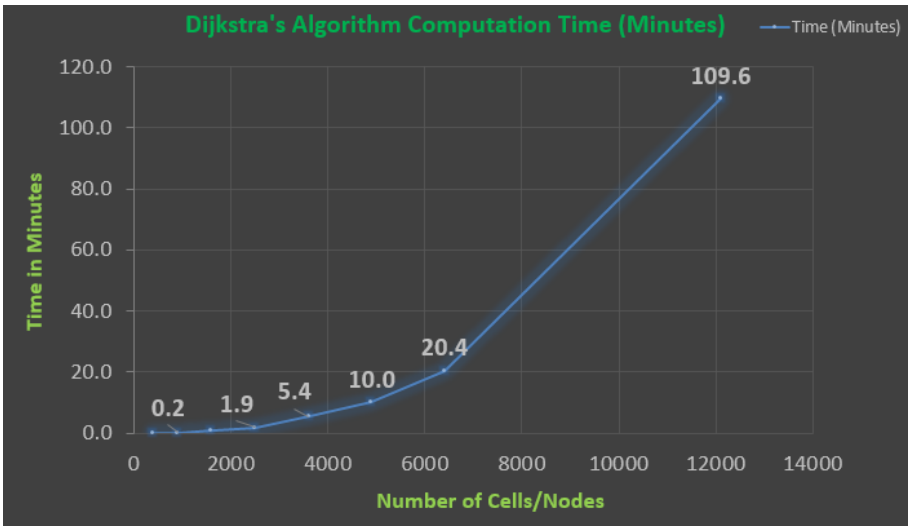


Figure 3.4. Run time for Dijkstra's algorithm; number of raster cells/nodes (x-axis) Vs computation time (y-axis)

The A* algorithm relies upon weights assigned *a priori* to each node. These weights are intended to reflect the total impedance from each node to the target of the shortest path. Initially, straight-line or Euclidean distances from each node to the target were used as weights. It was

observed that the straight-line distances did not correlate well with the impedances in the database, leading to significantly suboptimal fire spread routes (FSR).

In order to avoid the problem of suboptimal A* solutions, accurate network impedances are constructed and utilized within the A* algorithm. Network impedances are calculated using a single ACS analysis conducted prior to execution of the SGA model. Implementation of the A* algorithm using accurate network distances gives exact solutions. Thus, the initial, pre-treatment FFSR used in this study are unequivocally optimal routes. However, post-treatment routes are computed using A* weights that do not reflect fuel treatments, and hence may not be optimal. The fact that only a very small percentage of the weights within the network are changed in any given A* analysis implies that the impacts on the results should not be that sever, but only experimentation will reveal the precise impacts of these out-of-date weights.

3.1.4 Solution Formation Model

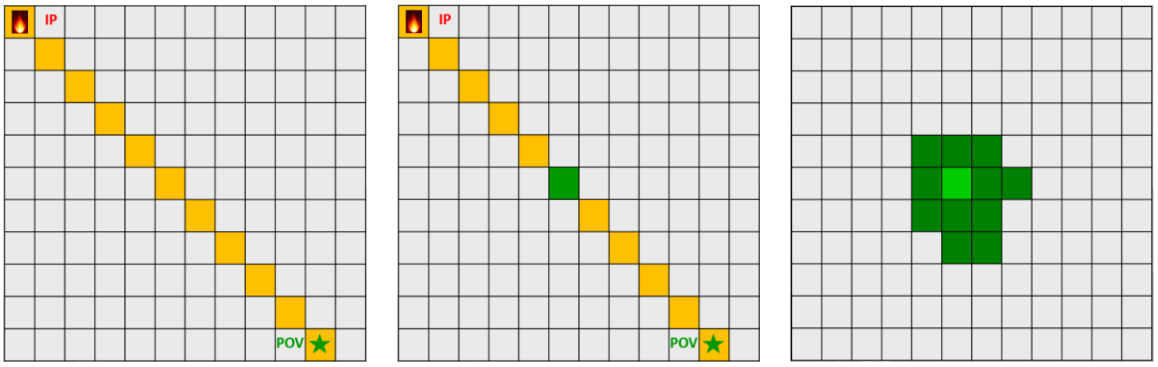
The first iteration (i.e., generation 1) of the genetic model must be seeded with hundreds of solutions, each of which identifies locations (i.e., sets of raster cells) where wildfire fuel treatments operations will be conducted. In order to generate these initial solutions for generation 1, a stochastic spatial region growing approach is used (Figure 3.5).

A solution is a group of contiguous raster cells whose total area does not exceed some predefined limit. In the real world, the total area that can be treated is governed by budget, which acts as a constraint for fuel treatment activities. Fuel treatment costs are a function of the type of treatment being conducted; for example, the cost of mechanical treatment (where heavy equipment is used to mulch fuels into tiny particles that quickly decompose) is directly proportional to the area being treated, while the cost of controlled burning (where under carefully

selected conditions, small fires are deliberately set to burn off fuels) is largely a function of the length of the perimeter of the area being treated (because firebreaks must be constructed along the perimeter of an area before a controlled burn can be conducted). For the purposes of this study, a maximum area constraint is used as a surrogate for budget, which is reflective of a mechanical treatment. Slight modifications to the model would allow it to place limits on perimeter, which would reflect controlled burning. However, these modifications are not implemented in this study.

Regardless of the method being used, fuel treatment operations are only practical on contiguous areas. Any fuel treatment operation has a fairly substantial fixed cost (associated with the expenses incurred in moving the material and manpower needed to conduct the fuel treatment operation into the remote areas where fuel treatment operations typically take place), so it is impractical to conduct noncontiguous fuel treatment operations. Valdez-Lazalde's model was not successful in ensuring the solutions it generated were contiguous; this study attempts to improve upon this aspect of Valdez-Lazalde's results.

The initial solution formation process starts by randomly selecting a node along the FFSR (Figure 3.5 B). Recall that nodes in the graph correspond to raster cells; thus, the randomly selected node along the FFSR can also be thought of as a raster cell along that route. This initial node/cell is used as the starting point for the solution formation process. Once the initial cell is selected, all eight of its neighbors are identified and one of these eight cells is randomly selected. Two validity checks are performed on this neighboring cell: i) ensure that the cell is within bounds of the study area, ii) ensure that the cell is not part of the solution already. If both of these conditions are satisfied, the cell in consideration is added as part of the solution, and the



A. FFSR

B. Randomly selected node along FFSR.

C. Solution formation around the node.

Figure 3.5. Solution formation process using the spatial region growing approach

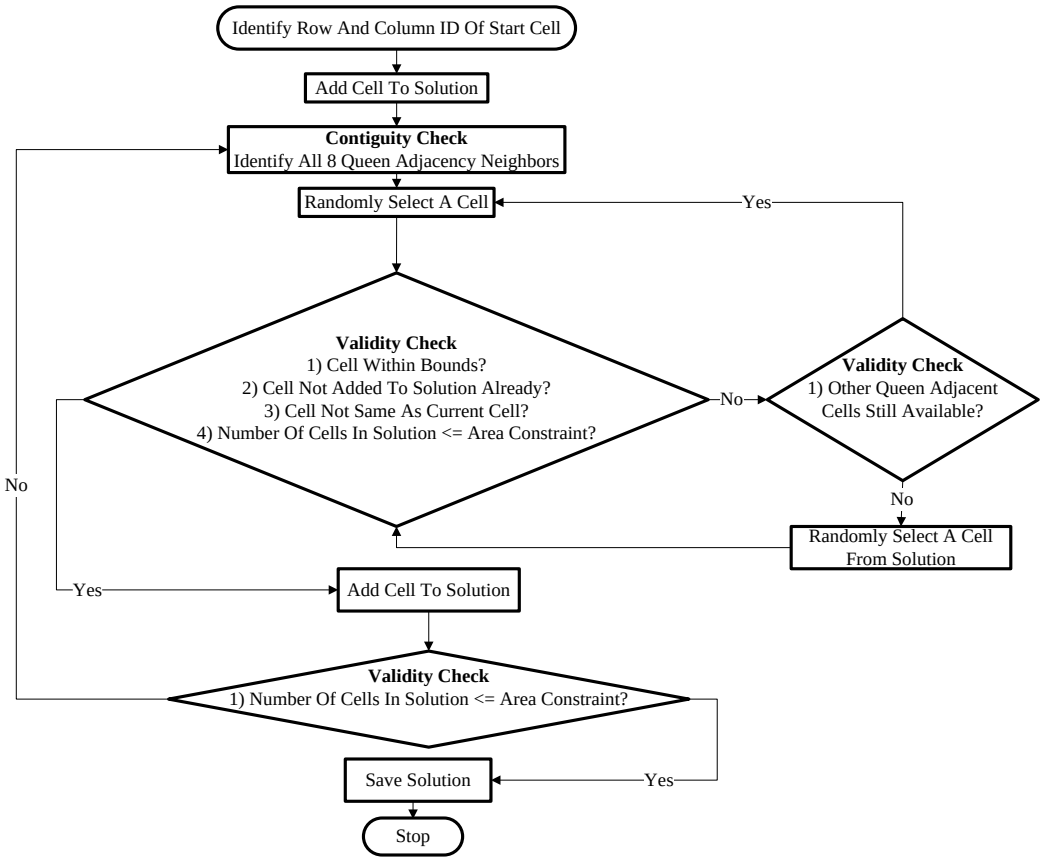


Figure 3.6. Flowchart for solution formation process

algorithm loops on to investigate another of the neighbors of the original cell. This process guarantees contiguity of cells in the solution without creating any donut-shaped area or holes in the solution. If one or both of the constraints are violated, the algorithm loops on to another neighboring cell without adding the current neighbor to the solution. If all neighbors of the current cell have been evaluated, another cell currently in the solution is randomly selected, and the process of evaluating neighbors is repeated for this new cell. It is worth noting that when a cell is randomly selected from the solution, doughnut shaped holes in the solution are possible. In order to test the impact of this possibility, 500 solutions were generated and inspected by hand. It is found that while 213 (42.6%) of the solutions contain holes, all of the holes are very minor (only one of a few cells in extent), and hence could be ignored when the model's solution is implemented in the field.

3.1.5 Fuel Treatment Effectiveness

The effectiveness of a fuel treatment is evaluated by the increase in burn time after the treatment is conducted versus the original, pre-treatment burn time. Both burn times are calculated using the A* fire spread analyses discussed in section 3.1.3. The pre-treatment fire spread analysis is conducted using a network whose impedances represent current fuel conditions (section 3.3.1). Impedances in the network used for the post-treatment fire spread analysis are modified to reflect an assumed doubling of burn times through all treated cells. Thus, impedance values for network links connecting two treated cells are doubled and impedance values of network links connecting one treated and one untreated cell are increased to 150% of their original value.

3.1.6 Rating Solution Fitness

Each individual solution within the genetic approach must have its fitness rated. Solution fitnesses are computed using the increase in burn time information, as described in previous sections. These fitnesses allow us to compute the probability of any solution being selected for inclusion in the subsequent generation using equation 3.1. In practice, the probabilities produced by equation 3.1 are normalized to one.

$$p_i = f_i \Big/ \sum_{i=1}^{N} f_i \qquad \textit{Equation 3.1}$$

where,

p_i = *Probability of a solution being selected*

f_i = *Fitness of solution i*

N = *Number of solutions*

3.1.7 Roulette Wheel/ Fitness Proportionate Selection of Solutions

The probabilities computed by equation 3.1 are used in the roulette wheel/fitness proportionate selection method (Haupt and Haupt, 2004) to pseudo-randomly select solutions from previous generations for propagation into the current generation. This process ensures that solutions are selected in a manner that reflects their just described probability of being propagated.

3.1.8 Spatial Genetic Operations

Three unique spatial genetic operations are implemented in this study, and one of these operations is utilized in two different manors. These processes are described below.

A. Replication/Copy

Replication and copying involve exactly what their names imply: duplication of an unaltered version of a solution from one generation to the next. This duplication process is used in two different context (hence the two terms): *replication* refers to the process whereby some predefined number of pseudo randomly selected solutions from the current generation are duplicated in the next generation, where selection probabilities are biased to favor solutions with higher fitness values (see sections 3.1.6 and 3.1.7). As mentioned previously, this replicates the natural process of cloning. *Copying* refers to the process whereby the *X* solutions with highest fitness values (where *X* is a value defined *a priori* by the analyst) are duplicated into the subsequent generation. This process has no direct counterpart in natural evolution, but has been found in past studies employing genetic approaches to improve efficiency by ensuring that the most fit solutions are preserved in subsequent generations **(**Haupt and Haupt, 2004**).**

B. Mutation

In mutation a predefined percentage of the solutions from the previous generation are pseudo-randomly selected (based on their fitness, as described in sections 3.1.6 and 3.1.7), pseudo randomly altered (as described below), and placed in the current generation. In this study, mutations are conducted using the procedure described in the flowchart shown in Figure 3.7. This process starts by randomly determining what percentage of the cells in a solution are to be impacted by the mutation (call this percentage *y*). Next, the mutation is randomly assigned to one of the four cases depicted in Figure 3.8. These cases involve mutating the cells on the right, left, top or bottom of the solution. Once the case is chose, *y*% of the solutions cells are removed from the selected side of the solution, and the same number of cells are then randomly added back to

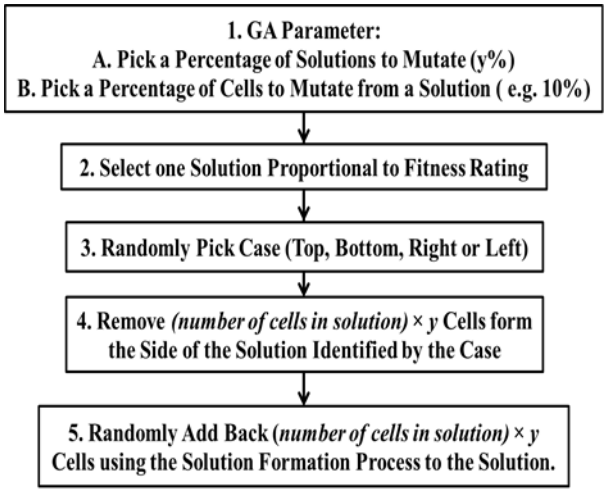


Figure 3.7. Flow chart for mutating a solution

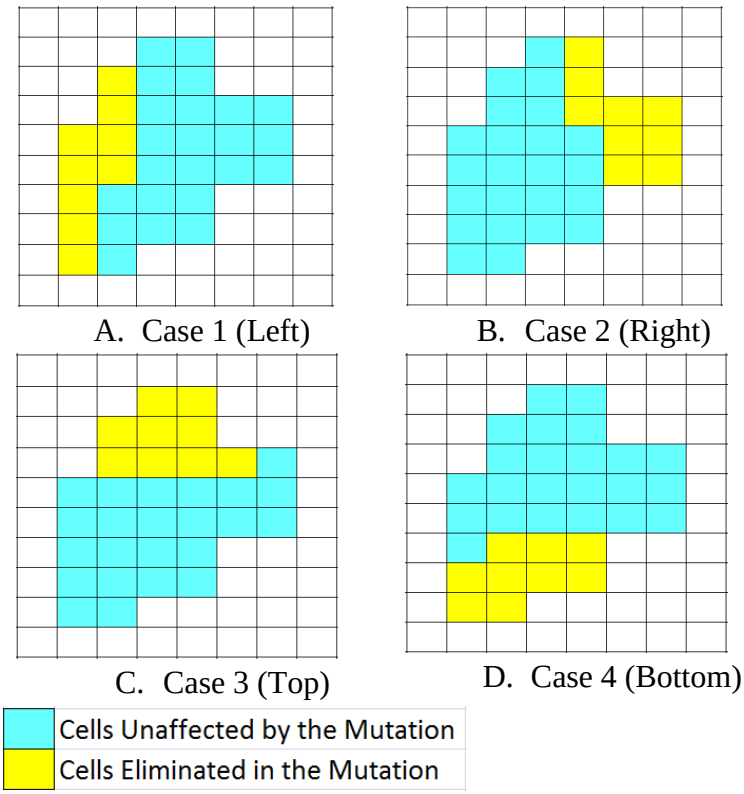
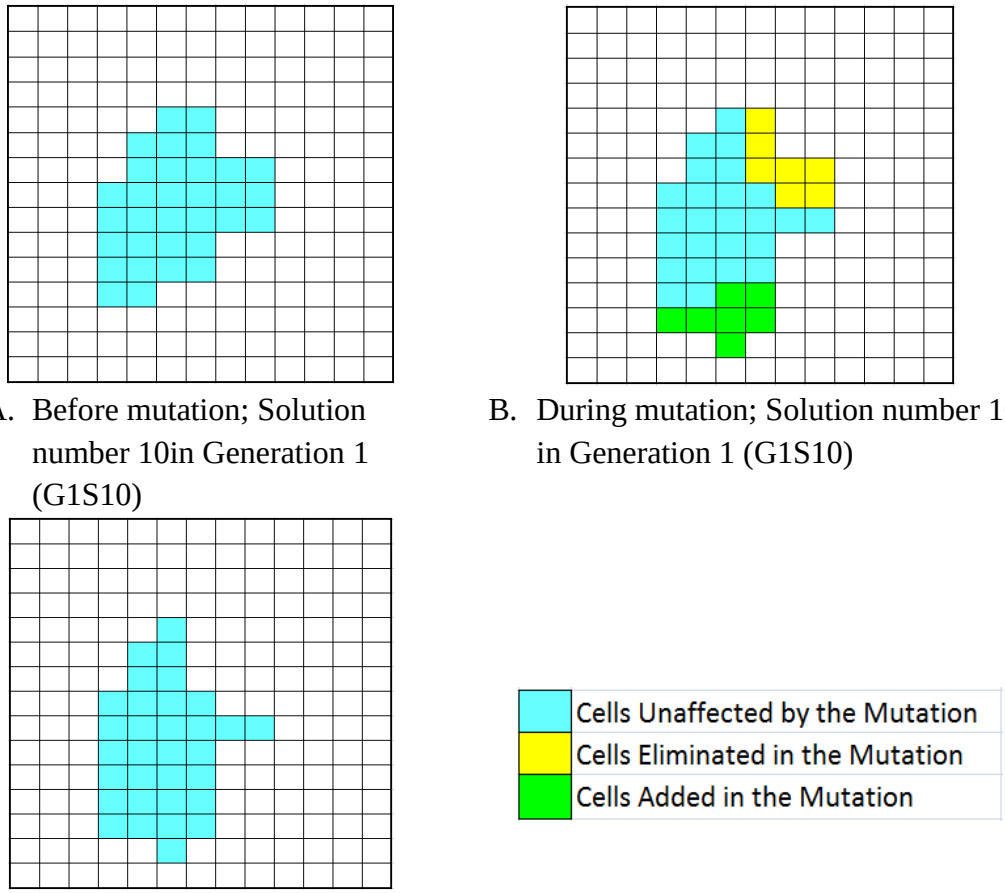


Figure 3.8. Mutation case selection for removing y% cells (yellow) from the solution

the solution using the solution formation process described in section 3.1.4. Figure 3.9 shows a graphic of a solution before and after mutation.



A. Before mutation; Solution number 10in Generation 1 (G1S10)

B. During mutation; Solution number 10 in Generation 1 (G1S10)

C. After mutation; Solution number 200 in Generation 2 (G2S200)

Figure 3.9. Solution mutation

E. Crossover

In a crossover, portions of two solutions from the previous generation are combined to create a new solution that is placed in the current generation. Two solutions from the previous generation are pseudo randomly selected based on their fitness values using the techniques

described in sections 3.1.6 and 3.1.7. For both of these two selected solutions, one of the four selection cases shown in Figure 3.10 is randomly selected. Depending on the selected case, a center line is created which divides the solution into two halves. Cells on one side of this line are then eliminated. For example, if case left is selected (Figure 3.10 A), a vertical center line (red) is created and all cells (yellow) on the left side of the center line are removed from the solution.

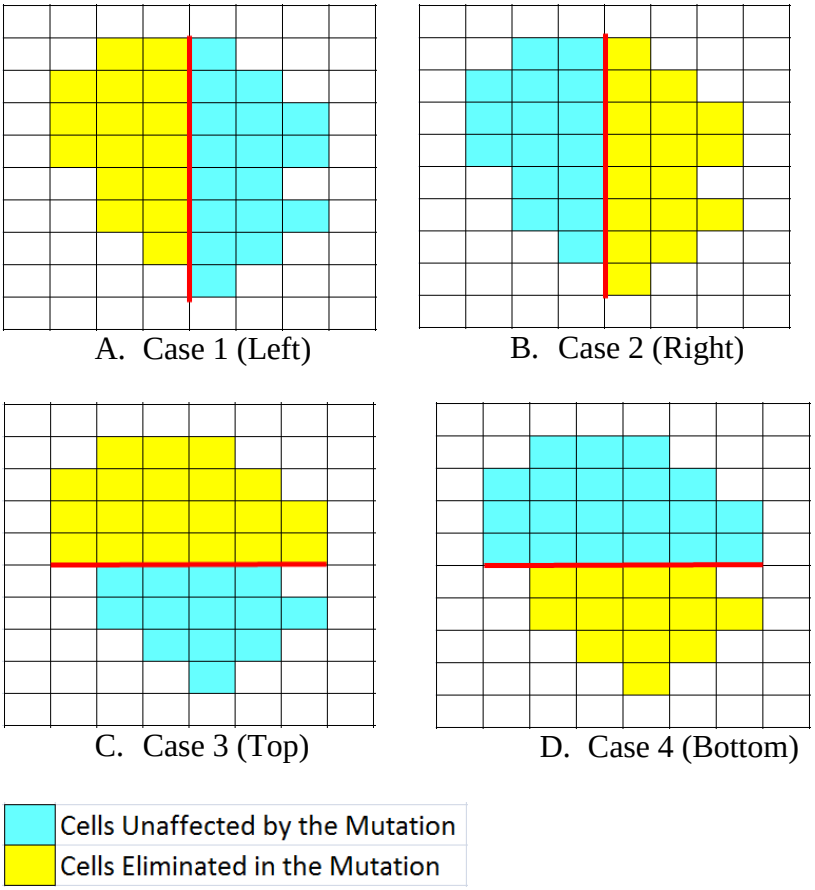
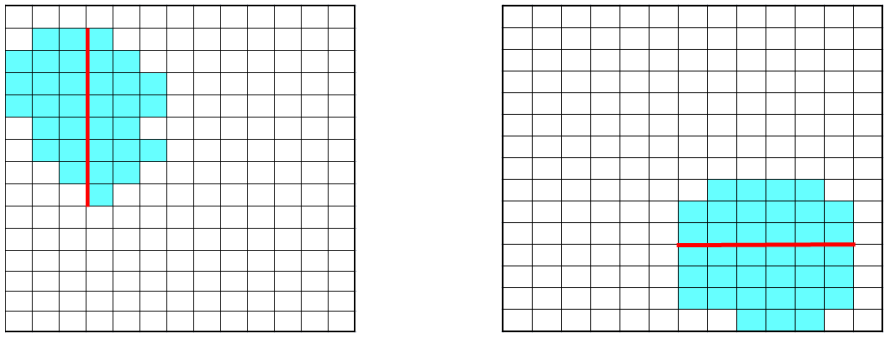
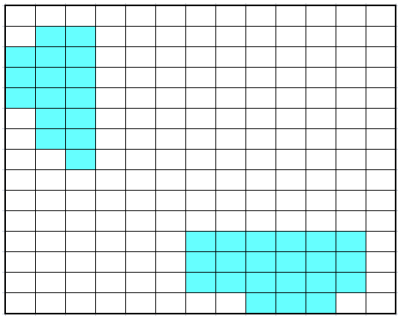


Figure 3.10. Crossover case selection for removing cells from the solution

Once half of the cells in each selected solution have been eliminated, the remaining cells from both solutions are combined together to form a new solution (Figure 3.11). A validity check is performed to ensure that the new combined solution does not exceed the area constraint.



A. Solution Map 1 before crossover B. Solution Map 2 before crossover



C. Result of crossover of solution 1 and 2.

Figure 3.11. Solution crossover

3.1.9 Data Management

This section describes the details of how the custom software developed to implement the spatial genetic model operated (a screenshot of the software's interface is shown in Figure 3.12). At the beginning of every generation, two digital folders are created at a user defined location. The two folders are named G*X*_Ascii and G*X*_Binary, where 'G' stands for generation and *X* is

the generation number. In every generation, once a new solution is formed, a copy of the solution is saved in Grid ASCII format in the G*X*_Ascii folder. Addition information such as the solution's folder location on disk, fitness, bounding rectangle and number of cells are saved to disk in binary format.

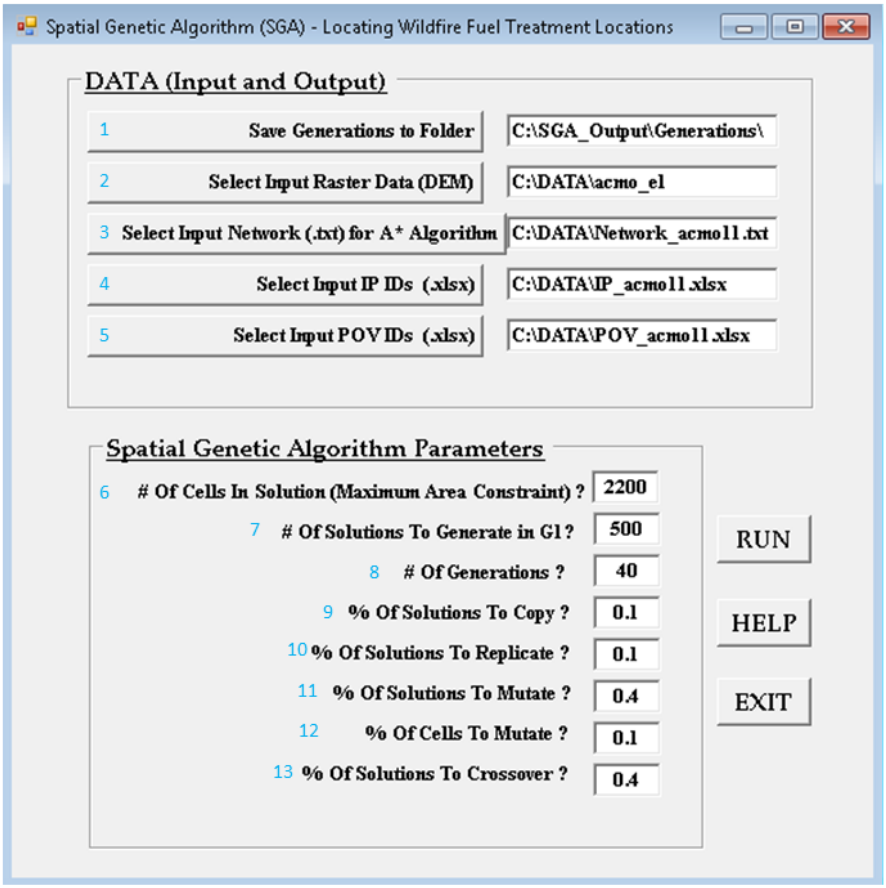


Figure 3.12. SGA model user interface developed in VB.NET

At the end of every generation, a list of all solutions in the generation is saved to disk in .txt format. This list is sorted in descending order of fitness and contains i) the ID number of each solution, ii) the solution's fitness, and iii) the solution's propagation probability.

3.2 Study Area

The following section describes the study area and data that are used for this study. The SGA model is tested using three different "scenarios." Each scenario is defined by a unique combination of terrain, fuel loadings and type, wind direction and speed, and location of IPs and POVs. These test scenarios are selected to reflect diverse values of each of these factors. The terrains used in the testing scenarios come from subsections of USGS 7.5 minute quadrangle maps in Yosemite National Park (Figure 3.13). Each of these areas covers approximately 5240 ha (12950 acres) and is represented in the dataset using 30-by-30 meter raster cells. Table 3.1 summarizes the other factors that make up each scenario. All three scenarios were also employed in Valdez-Lazalde's (2001) study and are used in the present study in order to compare results.

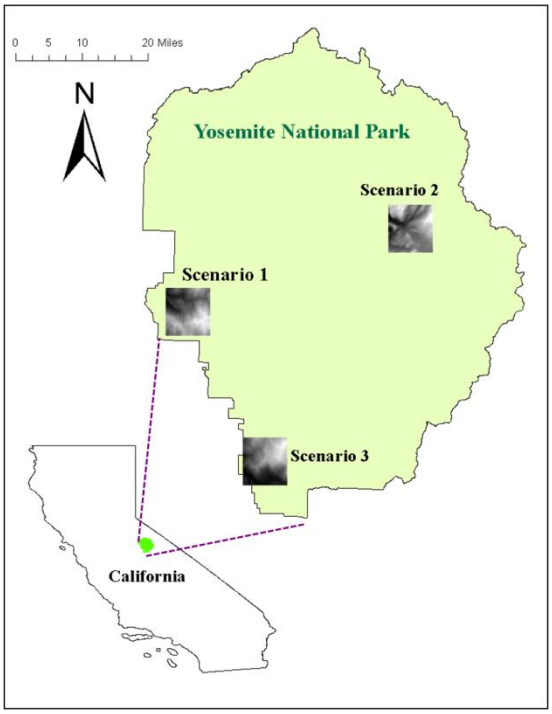


Figure 3.13. Study Area—Yosemite National Park, California

Table 3.1. Description of three test scenarios used in the study

Scenario	Data	Fuel Type (# cells)																Terrain (DEM)	Wind Direction	Wind Speed
		Grass			Shrubs				Timber			Slash			Custom					
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	99			
1	Acmo11	183	62	0	0	629	0	0	1418	1128	1172	0	0	0	1011	1655	22	1352 - 2174	5	360
2	Fari33	323	1819	0	0	2612	0	0	1092	1964	202	0	0	0	13	163	709	2255 - 3020	5	90
3	Wawo11	358	342	0	0	1251	0	0	1852	1653	962	0	0	0	1195	1502	132	1158 - 2417	3	45

3.3 Data Preparations

The datasets used in Valdez-Lazalde's (2001) investigation are used for this study. Sections 3.3.1 through 3.3.3 include descriptions of this data.

3.3.1 Creating Inputs for Calculating Burn Time Map

Rothermel's fire spread model, described in section 2.2, is used to calculate the burn time, i.e., the time (in minutes) it takes a wildfire to burn from the center of one raster cell to the center of an adjacent raster cell. Burn time is used as the network impedance when computing fire spread routes. Note that the total time of the FFSR should not be confused with the burn time for an individual cell. The FFSR is basically the summation of burn time for each raster cell that falls along the fire spread route.

Twelve different fuel parameters are derived for each raster cell using the guidelines mentioned in Albini (1976). These parameters are used in the Rothermal's fire spread model to obtain burn time maps in eight different directions. The following is a brief description of each of these twelve parameters.

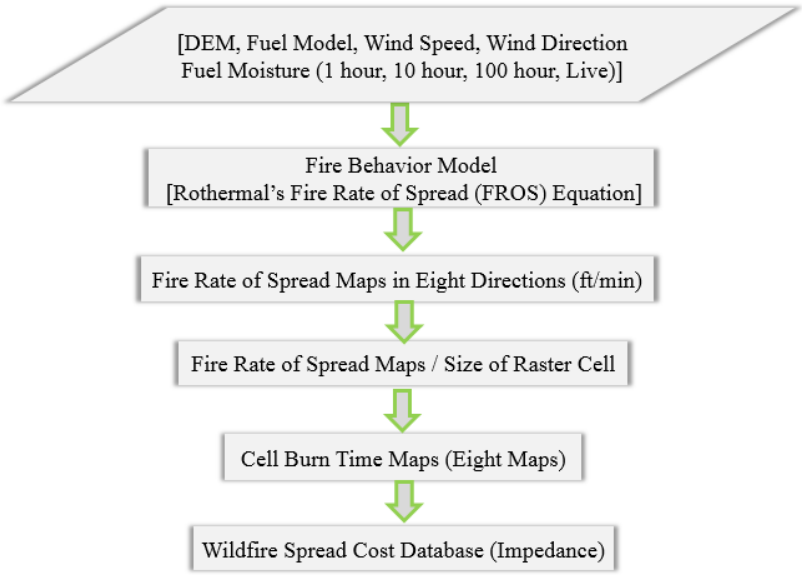


Figure 3.14. Flowchart for obtaining wildfire spread cost database

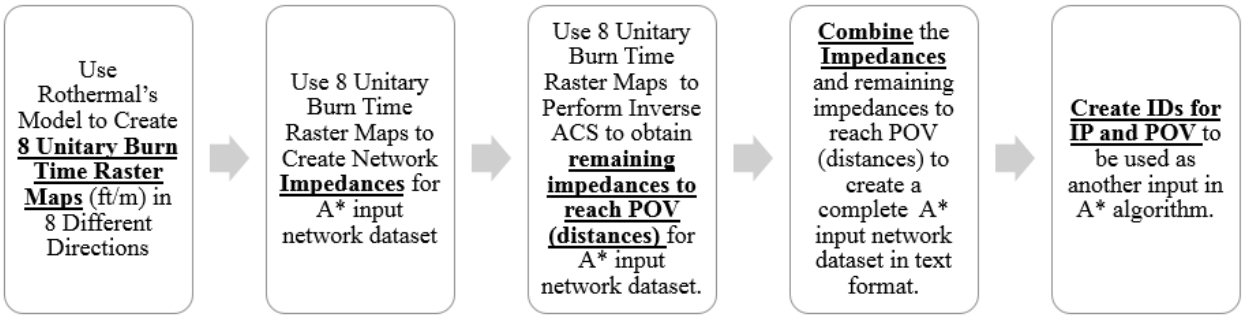


Figure 3.15. Flow chart of data creation process

1. Fuel Load

Fuel load is the amount of fuel available for combustion and has nonlinear effects on fire spread and intensity, in that, rate of spread may actually decrease as fuel load increases (Van Wagtendonk, 2006).

2. **Fuel Depth**

   Fuel depth is the average distance from the bottom of the litter layer to the top of the layer of fuel; i.e., the vertical thickness of the surface fuel (National Wildfire Coordinating Group, 2017).

3. **Fuel Surface to Volume Ratio**

   This is the surface area of an average fuel particle divided by its volume. Large surface area-to-volume ratios increase the rates of energy and mass exchange with the gaseous phase, leading to lower ignition delays and higher rates of fire spread (Chandler et al. 1983).

4. **Dead Fuel Moisture**

   Moisture of dead fuel is a measure of the amount of water in dead fuel. Moisture content determines the amount of fuel available to burn. The fuel moisture content for a totally dry dead fuel is zero. Fires ignite readily and spread rapidly when fuel moisture content is low. Conversely, fires do not ignite easily when fuel moisture content is high since heat energy is utilized to evaporate the water from the dead fuel before it can burn (Burgan and Rothermel, 1984).

5. **Live Fuel Moisture**

   Live Fuel moisture describes the moisture content within living vegetation.

6. **Moisture of Extinction**

   Moisture of extinction is the dead fuel moisture content at which fire will not spread with a uniform front (Burgan and Rothermel, 1984). This represents a maximum moisture content beyond which a wildfire cannot be sustained.

7. **Net Fuel Loading for Live Fuel**

   Net fuel loading for live fuel type is calculated by dividing the live fuel load by 1.0555. This reduction to the live fuel load is intended to correct for the portion of live fuels that are incombustible; e.g., the portion of plant matter composed of minerals.

8. **Net Fuel Loading for Dead Fuel**

   The net fuel loading for dead fuel type is summation of weight factors for surface area values of individual fuel types. Once again, this correction is intended to eliminate the incombustible portion of dead fuels.

9. **Effective Heating Number Times Heat of Preignition**

   The effective heating number reflects the efficiency of heating as a function of particle size. It is a measure of the fraction of the potential fuel whose temperature must be raised to the ignition point before the fuel will actually ignite. Heat of preignition is the change in specific heat from ambient to ignition temperature and the latent heat of vaporization of the moisture (Rothermel, 1972).

10. **Moisture Damping Coefficient for Live Material**

    The moisture damping coefficient accounts for the decrease in intensity caused by the combustion of fuels that initially contained moisture (Rothermel, 1972).

11. **Wind Speed**

    Wind speed is the rate of the movement of wind in distance per unit of time.

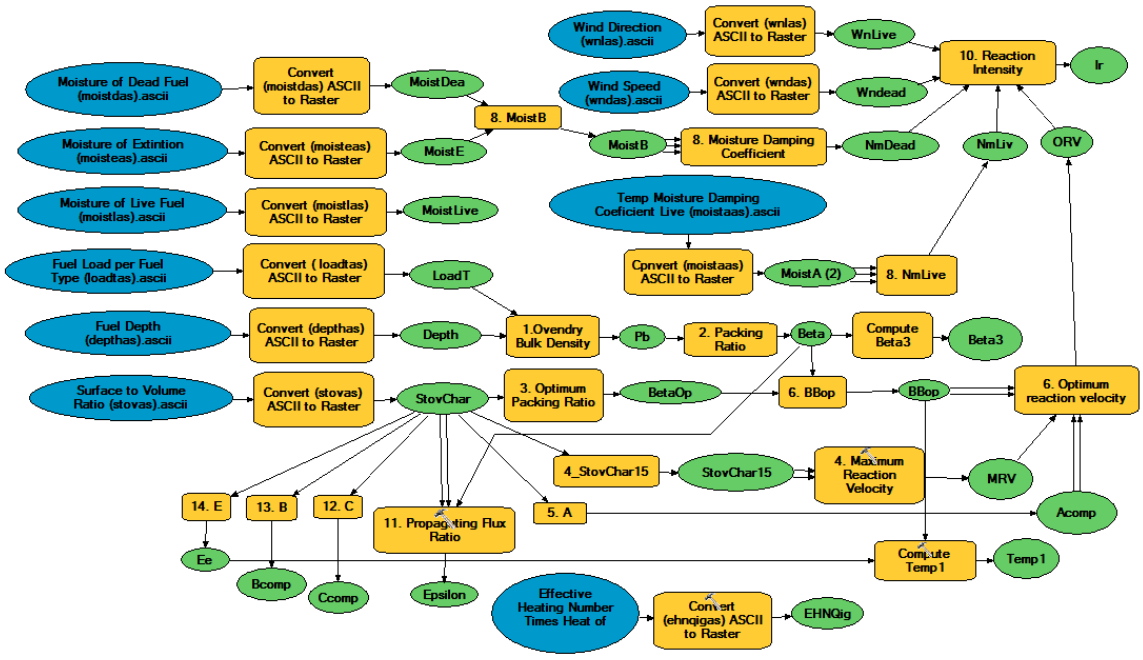
12. **Wind Direction**

    Wind direction is the direction from which the wind is blowing.

3.3.2 Computing Wildfire Unit Cost Datasets

Rothermel's model is implemented in ArcGIS model builder (Figure 3.16). The outputs of this ArcGIS model are eight directional burn time raster datasets. Inputs include the twelve datasets described in section 3.3.1, along with a DEM from which eight terrain gradient databases are created.

The wind coefficient used in the model represents the effect of wind speed on fire rate of spread and is a dimensionless factor in Rothermel's model (1972). The wind direction and wind speed datasets (obtained in section 3.3.1) are used to compute the wind coefficient for each scenario, using the logic outlined in Figure 3.16 (B).



A. Part 1 of Rothermel's model

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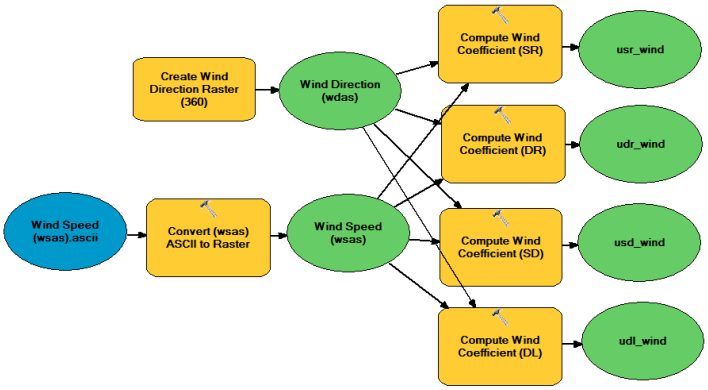
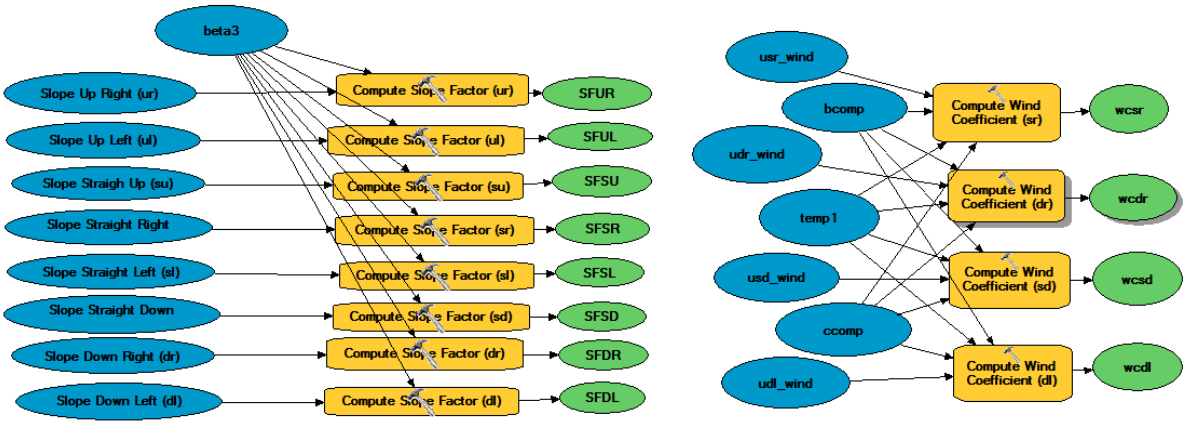


B. Part 2 of Rothermel's model

Figure 3.16. Rothermel's fire spread model implemented in ArcGIS model builder



C. Part 3 of Rothermel's model

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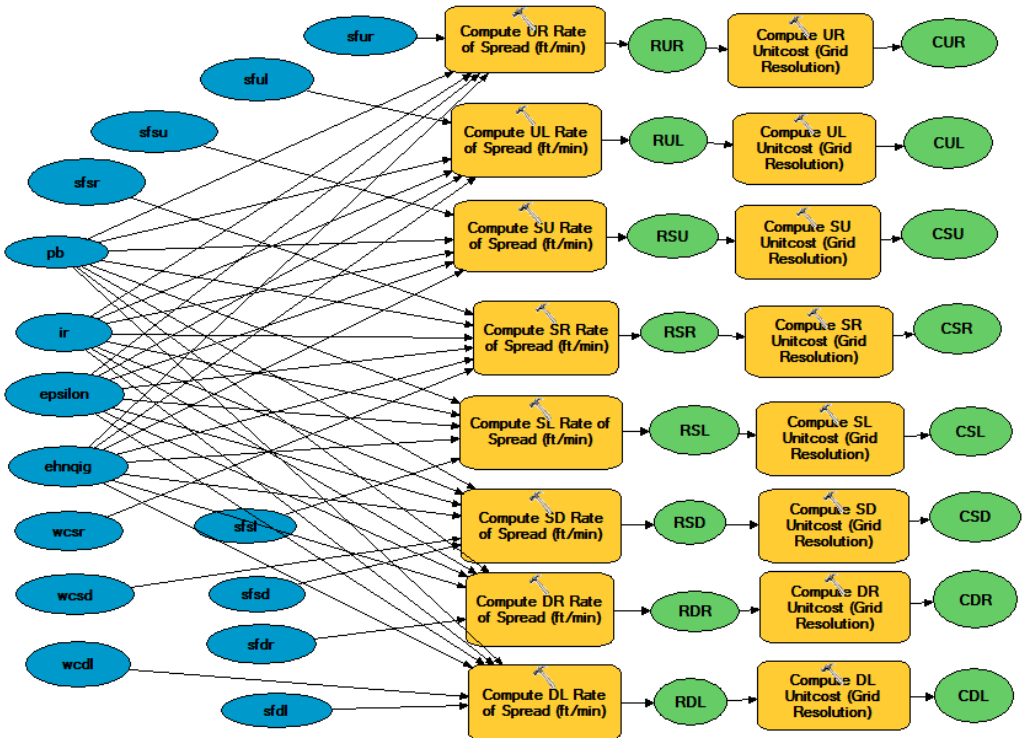


D. Part 4 of Rothermel's model

Figure 3.16. Rothermel's fire spread model implemented in ArcGIS model builder (Continued)

3.3.3 Creating Node ID and Network Dataset

A raster dataset for each scenario has 250 rows and 233 columns; i.e., 58,250 raster cells. The center point of each of these cells is considered to be a node in a graph that represents the raster matrix for the purposes of modeling fire spreading. Each node is numbered starting from 1 to 233 for row 1, 234 to 466 for row 2 and so on (Figure 3.17). The graph is connected by joining each pair of neighboring nodes to form an edge.

The eight unit cost (burn time) datasets derived in section 3.3.2 are used to create the network impedances assigned to each arc in the graph. Each edge is assigned an impedance value

from the wildfire unit cost databases described in section 3.3.2, using averages of cell values for rooks-case adjacent cells and averages times the square root of two for diagonally adjacent cells.

Node 1	Node 2	Node 3	. . . .
Node 234	Node 235	Node 236	. . . .
Node 467	Node 468	Node 469	. . . .
. . . .	. . . .	. . . .	. . . .

Figure 3.17. Network nodes for cells in a raster dataset

CHAPTER 4

RESULTS AND DISCUSSIONS

The Spatial Genetic Algorithm (SGA) model described in the methodology chapter is tested using three different scenarios, where each scenario is a unique combination of terrain, fuel loading, wind direction and speed, and configurations of ignition points (IPs) and points of value (POVs) (section 3.3). The SGA model uses the parameters listed in Table 4.1 for these scenario analyses. Results for scenario 1, 2 and 3 are obtained by repetitions of the same SGA model parameters (section 4.1 to 4.3).

Table 4.1. List of scenarios and associated parameters used in SGA model

Scenario	**1**	**2**	**3**
Geographic Area	Acmo11	Fari33	Wawo11
Area Constraint (Maximum Allowable Treatment Cells)	2200	2200	2200
Solutions in Generation 1	500	500	500
Number of Generations	40	40	40
% Copy	10	10	10
% Replicate	10	10	10
% Mutate	40	40	40
% Cells Mutate	10	10	10
% Crossover	40	40	40

4.1 Results for Scenario 1

4.1.1 Fuel Treatment Effectiveness and Area Analysis (Scenario 1)

Fuel treatment effectiveness is evaluated by the increase in burn time after conducting a fuel treatment. This is a measure of the degree of optimality of a solution; i.e., the greater the increase in burn time, the better the quality of the solution. Table 4.2 shows the results for

scenario 1, which compares the effectiveness of the fuel treatment plans produced by this study's SGA model, each of five human wildfire managers, and the Steepest Decent Algorithm (SDA) employed by Valdez-Lazalde (2001). Clearly, the solution produced by the SGA model substantially outperformed all of the alternatives. It is also interesting to note the wide variation in effectiveness among the solutions produced by the experts, and the relatively modest effectiveness of the SDA results.

Table 4.2. Results for increase in burn time and number of cells in solution for scenario 1

Evaluator	SGA Model	Expert 1	Expert 19	Expert 20	Expert 21	Expert 33	SDA Model
Burn Time After Treatment (minutes)	821.21	539.48	466.98	524.98	493.16	466.57	473.48
Burn Time Before Treatment (minutes)	463.04	463.04	463.04	463.04	463.04	463.04	463.04
Increase in Burn Time (minutes)	358.16	76.43	3.93	61.93	30.11	3.52	10.43
% Increase Over Untreated Burn Time	77.35	16.50	0.85	13.37	6.50	0.76	2.25
Number of Cells Treated	1622	866	1161	818	1341	973	2194
% Permissible Area Treated	73.73	39.36	52.77	37.18	60.95	44.23	99.73
Performance Ratio	1.05	0.42	0.02	0.36	0.11	0.02	0.02

Other interesting aspects of these results are shown in Figure 4.1, which shows simple schematic maps of the fuel treat plans that produced the results described in Table 4.2. These maps strongly imply that experts 1, 19, 20 and 21 all employed a strategy of treating fuels near the POVs, while expert 33 employed a strategy that treated fuels near the IPs. The SDA model treated a scattering of areas distributed along what appear to be various fire spread routes connecting different IP/POV pairs. None of these approaches was as effective as the SGA model's approach of treating both areas around a single ignition point and a single POV, and elongating its treatments around along the FFSR. Intuitively, this SGA strategy makes sense, because the quality of a solution is measured by the increase it produces in the *fastest* fire burn time. If the fastest fire burn time involves the IP(s) near the north and west edges of the study area and the northwestern POV, focusing on treating fuels in this area is the obvious way of producing high quality solutions. Further, the SGA models strategy of treating areas near BOTH the IPs and POVs seems intuitively more balanced than treating only areas near one or the other.

The area of treatment, i.e., the percentage of the total number of treated cells allowed under the budget constraint a solution actually treats, is used to measure the efficiency of solutions. If the effectiveness of two solutions is the same, the solution that treats a smaller percentage of the allowable area achieves its effectiveness at lower cost, and hence is more efficient. The maximum area allowed for fuel treatment is 2200 cells (200 hectares) for all scenarios.

This idea of effectiveness vs. efficiency is captured in the performance ratio (shown in the last row of Table 4.2), which is simply the percentage increase in burn time a solution produces divided by the percentage of the allowable number of cells the solution treats. Higher

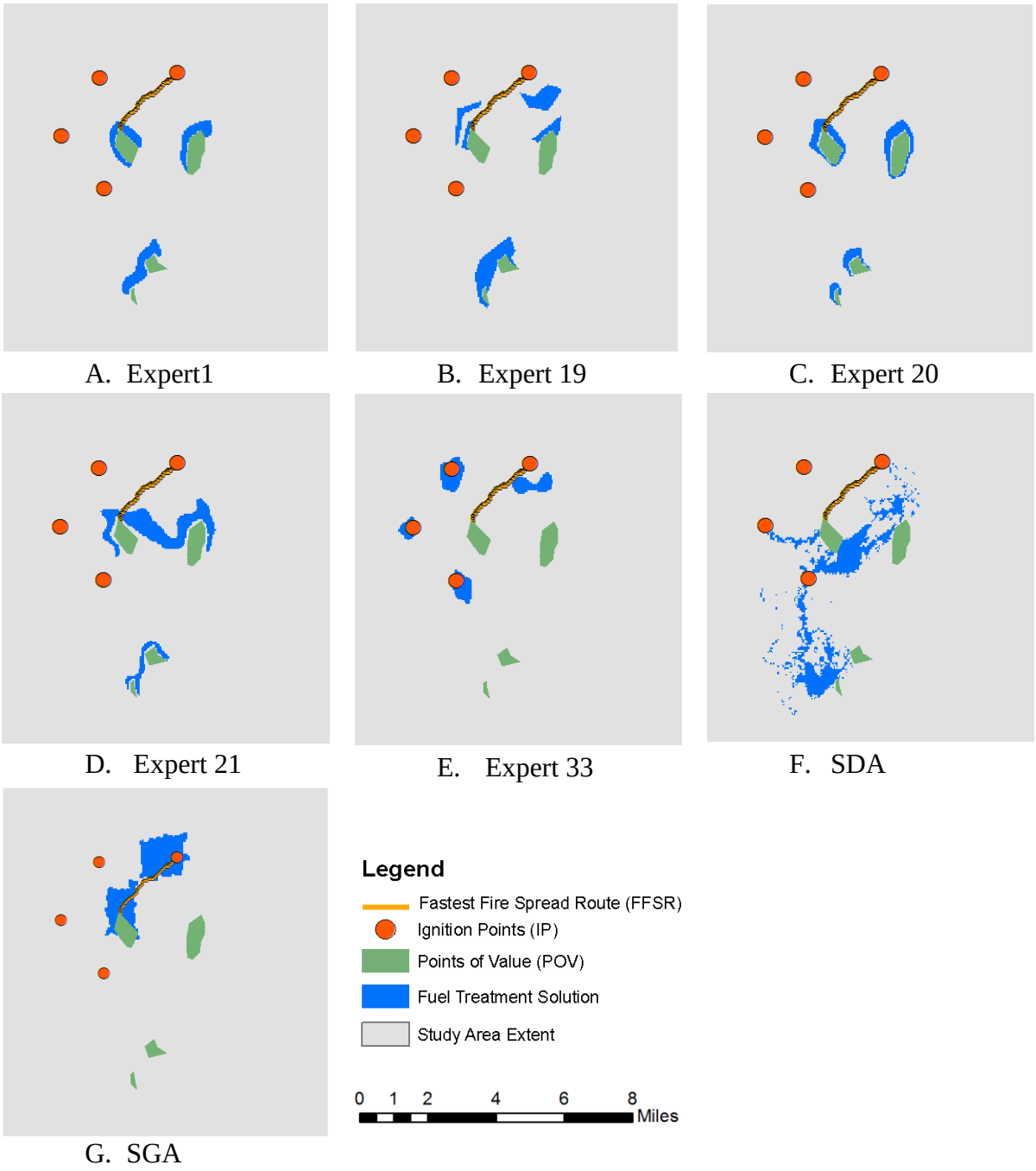


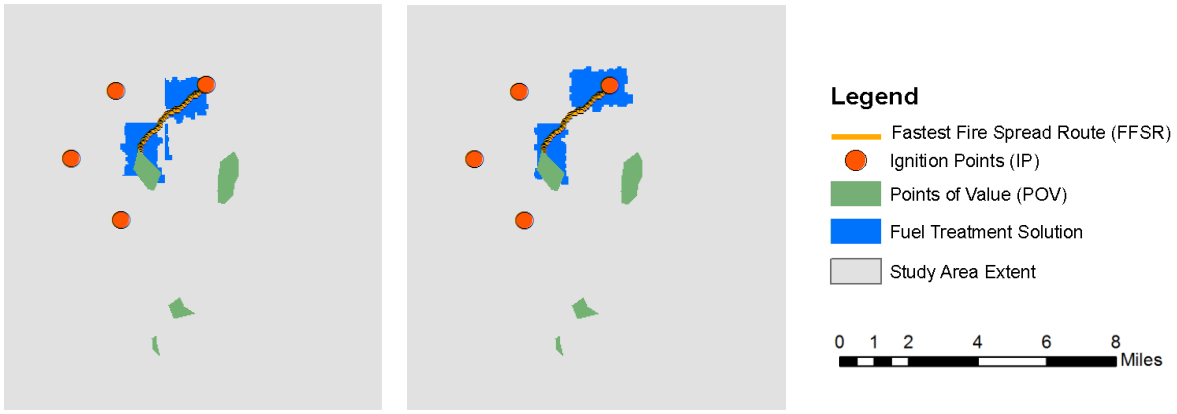
Figure 4.1. Fuel treatment locations for scenario 1 identified by experts (A to E), SDA model (F) and SGA model (G)

values of this ration reflect solutions that are highly effective, highly efficient, or both, while lower values characterize solutions that are not as effective, not as efficient, or both.

In scenario 1, the SGA model produced by far the highest performing fuel treatment plan, which increased the burn time more than 77% over the pre-treatment time while treating less than 74% of the allowable area. This gave the SGA results a performance ratio over one. None of the other solutions produced performance ratios over 0.42, with the SDA model and two of the experts producing results with performance ratios of 0.02.

It is interesting to note that each of the experts' plans treated even fewer cells than did the SGA model, with three of the five experts choosing to treat less than half the permissible number of cells. The reason for this is unknown, but one possible explanation is that the experts were overly conscious of the area limit and were hesitant to produce plans that even approached this limit.

Figure 4.2 shows two alternative solutions generated by the SGA model. Each of these solutions is suboptimal in that they did not increase burn times as much as did the SGA solution show in Figure 4.1 and described in Table 4.2. However, these solutions do illustrate the results of a differing fuel treatment strategy. The SGA optimal solution shown in Figure 4.1 clearly attempts to create treated buffers around both the IP and the POV, but it also stretches these buffers to encompass most of the FFSR. The alternatives shown in Figure 4.2 do less of this elongation, and have correspondingly lower efficacies. This illustrates the sensitivity of the solution to relatively minor changes in the spatial locations of the fuel treatments.



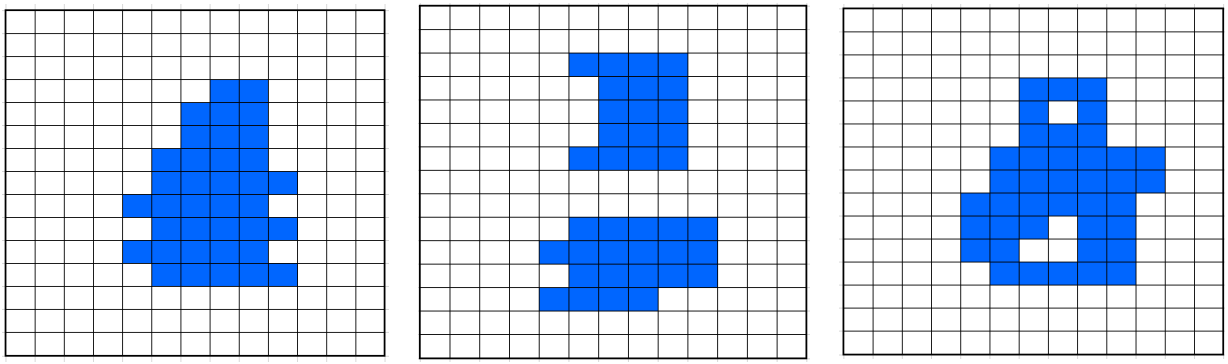
A. 259.73 (56.09%) B. 319.92 (69.09%)

Figure 4.2. Fuel treatments with increase in burn time values for scenario 1, identified by SGA model

4.1.2 Fragmentation of Fuel Treatments (Scenario 1)

The feasibility and plausibility of the solutions is evaluated by the degree of fragmentation in the solution. The number of patches/fragments is used as a quantative measure to evaluate the degree of fragmentation. Figure 4.3 shows an example of how the numbers of patches are computed for any given solution. A solution with no gaps/holes (Figure 4.3 A) is considered to have one patch, while a solution with gaps/holes (Figure 4.3 C) within the treatment is considered fragmented with three patches. Table 4.3 shows the number of fragments/patches in every solution for scenario 1, identified by the SGA model, experts and the SDA model.

In case of scenario 1, the expert fuel treatments included anywhere between two to five different patches (Table 4.3). The SDA fuel treatment is highly fragmented, where cells are treated between the IP and POV in 95 total patches. It is interesting to note that the SGA model fuel treatments are similar to that of the experts in terms of fragmentation.



A. One patch B. Two Patches C. Three Patches

Figure 4.3. Number of patches in a solution

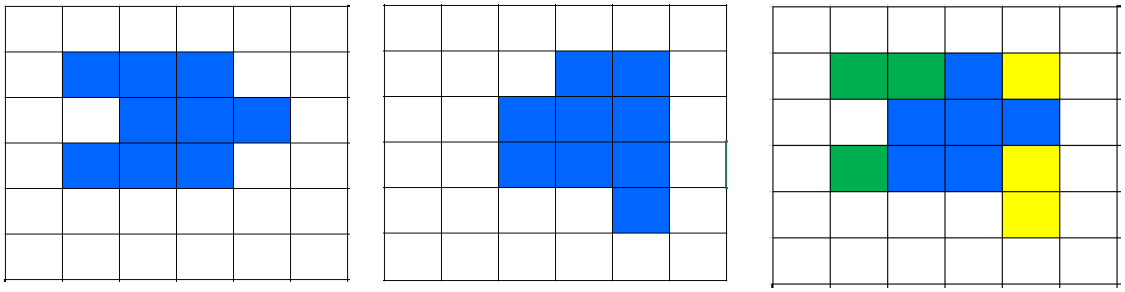
Table 4.3. Number of fragments/patches in a solution for scenario 1 identified by SGA model (1), experts (2 to 6) and, SDA model (7)

	Evaluator	# Fragments/Patches
1	SGA	2
2	Expert 1	3
3	Expert 19	5
4	Expert 20	4
5	Expert 21	2
6	Expert 33	4
7	SDA	95

4.1.3 Spatial Overlap (Scenario 1)

Spatial overlap between the fuel treatments is used as one of the criteria to evaluate the degree of similarity between the fuel treatment locations. While visualization is one way to understand spatial overlap, a physical overlay process can provide a more quantitative metric. Figure 4.4 shows an example of how when comparing two solutions, raster cells are categorized as either common (found in one solution but not the other), commission (found in one solution arbitrarily selected as the reference solution but not in the other solution, which is termed the

base) or omission (found in the base but not in the reference solution). For all subsequent evaluations, the SGA model's fuel treatment is used as the base map.



A. Reference Map (Solution 1)

B. Base Map (Solution 2)

C. Common = 6 (blue), commission = 3 (green), omission = 3 (yellow).

Figure 4.4. Spatial overlay of two different solutions and resulting number of common, commission and omission cells

Figure 4.5 shows the spatial location of fuel treatements for scenario 1 generated by the SGA and SDA models, along with those produced by the experts. Table 4.4 shows the measures of spatial overlap between the solutions obtained using the SGA model as the base of the comparison.

Figure 4.5 and Table 4.4 reveal that there is little spatial overlap between the SGA results and either the SDA or expert fuel treatment plans. The expert prescription with the most spatial overlap with the SGA results shares only 10% common cells, and the SDA results share only slightly more than 1% common cells. Clearly, the SGA model, the experts and the SDA model were developing fuel treatment plans that are quite dissimilar.

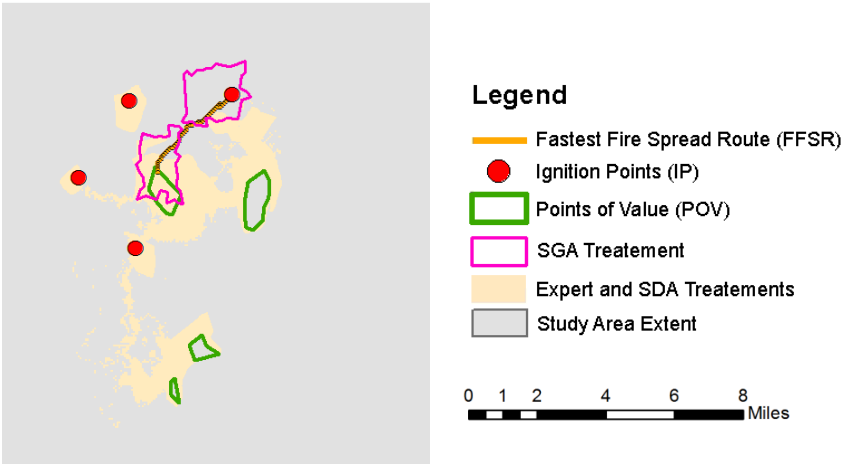


Figure 4.5. Spatial location of fuel treatments generated by SGA model, SDA model and experts for scenario 1

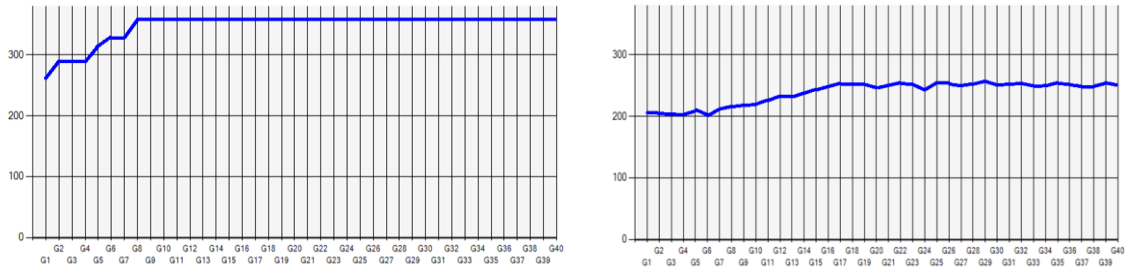
Table 4.4. Spatial overlap (using SGA results as the base for comparison) of fuel treatments for scenario 1

Reference Solution	# Common Cells	# Commission	# Omission
Expert 1	167 (7.20%)	699 (30.12%)	1455 (62.69%)
Expert 19	161 (6.14%)	1000 (38.14%)	1461 (55.72%)
Expert 20	222 (10.01%)	596 (26.88%)	1400 (63.12%)
Expert 21	206 (7.48%)	1135(41.17%)	1416 (51.37%)
Expert 33	45 (1.77%)	928 (36.40%)	1577 (61.84%)
SDA	45 (1.20%)	2149 (57%)	1577 (41.90%)

4.1.4 SGA Model Performance (Scenario 1)

Figure 4.6 depicts the performance of the SGA model in scenario 1. Part A shows that the fitness of the best solution found to date improves steadily from generate 1 to generation 9. The solution that ultimately proves to have the best fitness found across all generations is obtained in generation 9, so the graph flattens out and no further improvement is seen in subsequent generations. Figure 4.6 B shows that the average fitness of all the solutions in a generation keeps improving until generation seventeen 17. The graph then becomes somewhat steady, showing

only random perturbations around an average value. This is intuitively reasonable; even after the best possible solution is found in generation 9, the genetic process continues to improve average solution quality (by replacing significantly inferior solutions with better solutions) until all remaining solutions are within the range of variation inherent in the reproduction process.



A. Fitness of best solution. B. Average fitness of all solutions.

Figure 4.6. SGA model performance graph with generation (x-axis) and fitness values (y-axis) for scenario 1

Figure 4.7 shows the evolution of the fittest solution produced by the SGA model from generation 1 through generation 9 (recall that the best solution found remained unchanged after generation 9).

The evolution process of this solution involves four mutations, four crossovers and one copy operation. Following the progression of this solution over generations highlights the impacts crossovers and mutations can have on fitness values. For example, in Figure 4.7, the general shape of what ultimately proves to be the best solution first appears in 4.7 F; this shape arose from a crossover operation. After this general shape is achieved, the fitness of solutions G through K remain constant (299.71) from generations 4 through 8 even though their spatial distributions are slightly different from one another. But there is a drastic improvement in the solution fitness value from 299.71 (K) to 358.16 (L) between generations 8 and 9. This

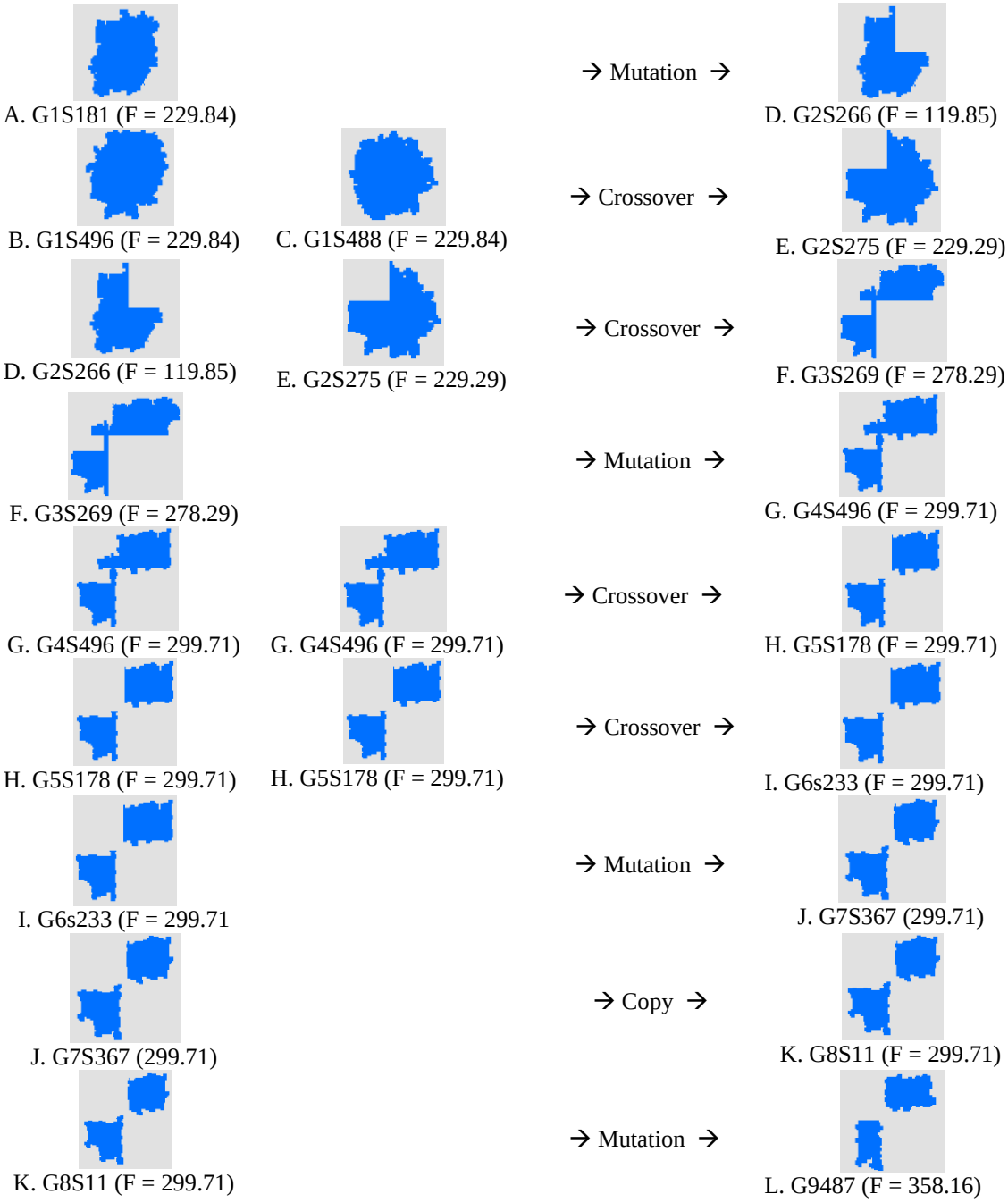


Figure 4.7. Evolution of solutions from generation 1 through 9 to obtain the best fitness solution for scenario 1

improvement is obtained by a mutation process.

It is worth noting that even though the spatial arrangement of many of the solutions shown in Figure 4.7 are not drastically different, slight variations can have dramatic impacts on fittness.

4.2 Results of Scenario 2

4.2.1 Fuel Treatment Effectiveness and Area Analysis (Scenario 2)

The results for scenario 2 are shown in Figure 4.8 and Table 4.5. The SGA model solution produces the best increase in burn time (100%), while the SDA produced a 56.9% increase and the expert prescriptions resulted in 26.9% to 35.47% increases. In this case, it seems the SGA model achieved its impressive results largely by treating far more cells than any of the other approaches: the SGA model treated over 90% of the permissible number of cells; the SDA 63%, and none of the experts choose to treat even half the permissible number. Treating this increased number of cells allowed the SGA two effectively block two POVs from two IPs; something that none of the other solutions was able to achieve.

The performance ratios achieved under scenario 2 were in general higher than those achieved under scenario 1, with one of the experts (number 32) achieving a very impressive ration of over 1.5. However, it is important to note that the performance ratio is unitless, and hence there are scaling issues to consider as well. While expert 32's fuel treatment plan was more efficient than the plan produced by the SGA model (producing roughly a 1.5% increase in burn time for every 1% increase in the allowable number of cells treated), it simply did not produce as large an increase in burn time as did the SGA plan.

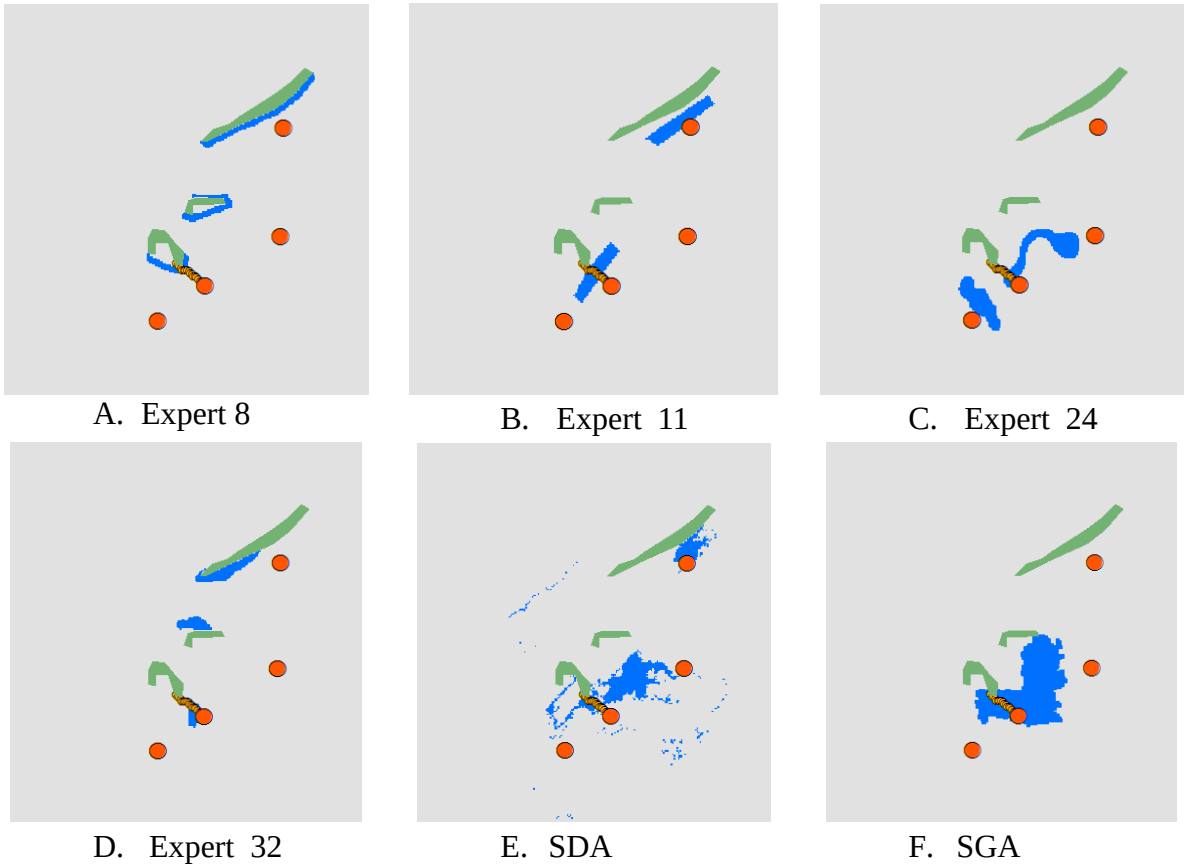


Figure 4.8. Fuel treatment locations for scenario 2 identified by experts (A to D), SDA model (E) and SGA model (F)

Table 4.5. Results for increase in burn time and number of cells in solutions for scenario 2

Evaluator	SGA Model	Expert 8	Expert 11	Expert 24	Expert 32	SDA Model
Burn Time After Treatment (minutes)	300.50	190.79	197.99	203.66	203.66	235.89
Burn Time Before Treatment (minutes)	150.25	150.25	150.25	150.25	150.25	150.25
Increase in Burn Time ((minutes)	150.25	40.53	47.73	53.41	53.41	85.63
% Increase Over Untreated Burn Time	100.00	26.97	31.77	35.54	35.54	56.99
Number of Cells Treated	1986	662	697	951	500	1394
% Permissible Area Treated	90.27	30.09	31.68	43.23	22.73	63.36
Performance Ratio	1.11	0.90	1.00	0.82	1.56	0.90

4.2.2 Fragmentation of Fuel Treatments (Scenario 2)

Fragmentation followed much the same pattern as seen in the results for scenario 1 (see Table 4.6). The SDA fuel treatment plan is fragmented (80 patches) to the point where the

Table 4.6 Number of fragments/patches in a solution for scenario 2 identified by SGA model (1), experts (2 to 5) and, SDA model (6)

	Evaluator	# Fragments/Patches
1	SGA	1
2	Expert 8	3
3	Expert 11	2
4	Expert 24	2
5	Expert 32	3
6	SDA	80

feasibility and plausibility of the solution is questionable. The expert fuel treatments included two to three patches while the SGA model produced a single patch.

4.2.3 Spatial Overlap (Scenario 2)

Figure 4.9 shows the spatial location of all fuel treatements generated for scenario 2. Table 4.7 shows the spatial overlap between the solutions. The percentage common cells

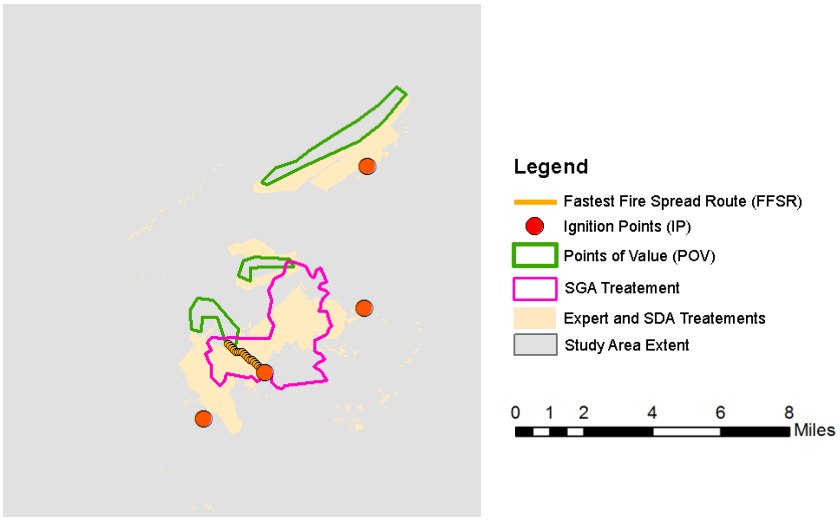


Figure 4.9. Spatial location of fuel treatments generated by SGA model, SDA model and, experts for scenario 2

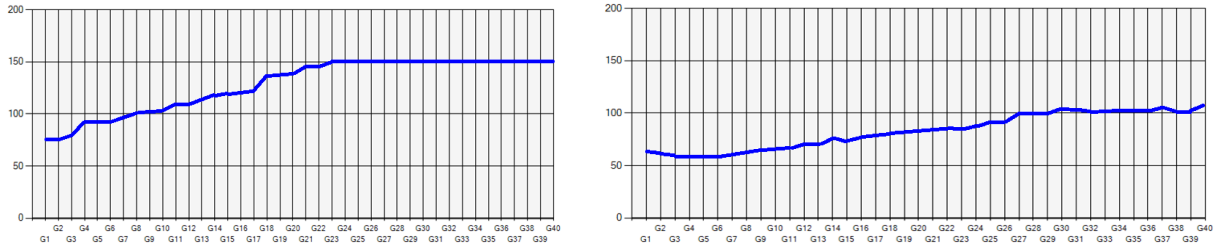
Table 4.7. Spatial overlap (using SGA results as the base for comparison) of fuel treatments for scenario 2

Reference Solution	# Common Cells	# Commission	# Omission
Expert 8	128 (5.08%)	534 (21.19%)	1858 (73.73%)
Expert 11	198 (7.97%)	499 (20.08%)	1788 (71.96%)
Expert 24	404 (15.95%)	547 (21.60%)	1582 (62.46%)
Expert 32	74 (3.07%)	426 (17.67%)	1912 (79.27%)
SDA	731 (27.60%)	663 (25.02%)	1255 (47.37%)

between the SGA model and expert fuel treatments varies between 3.04% and 15.95% cells while between the SGA model and SDA model fuel treatments, there are 27.60% common cells. While this degree of commonality is higher than that seen in scenario 1, Figure 4.9 shows that the SGA model treats cells at substantially different spatial locations compared to all experts and the SDA model.

4.2.4 SGA Model Performance (Scenario 2)

In case of scenario 2, the solution with best fitness (Figure 4.10 A) is obtained in generation 23 and the average fitness of all solutions (Figure 4.10 B) does not improve drastically after generation 27. Given this, it appears unlikely that the genetic model would have been able to find superior solutions even had it been allowed to continue its processing beyond the 40 generations actually used in this study.



A. Fitness of best solution B. Average fitness of all solutions

Figure 4.10. SGA model performance graph with generation (x-axis) and fitness values (y-axis) for scenario 2

4.3 Results for Scenario 3

4.3.1 Fuel Treatment Effectiveness and Area Analysis (Scenario 3)

Figure 4.11 and Table 4.8 show the results for scenario 3. The solution obtained by the SGA model produces best increase in burn time (60.46%), although the solution produced by the SDA model was not far behind (53.54%). The effectiveness of the experts' plans were

substantially less, even though five of the six the experts clearly placed their treatments in generally the same area as did the SGA and SDA models.

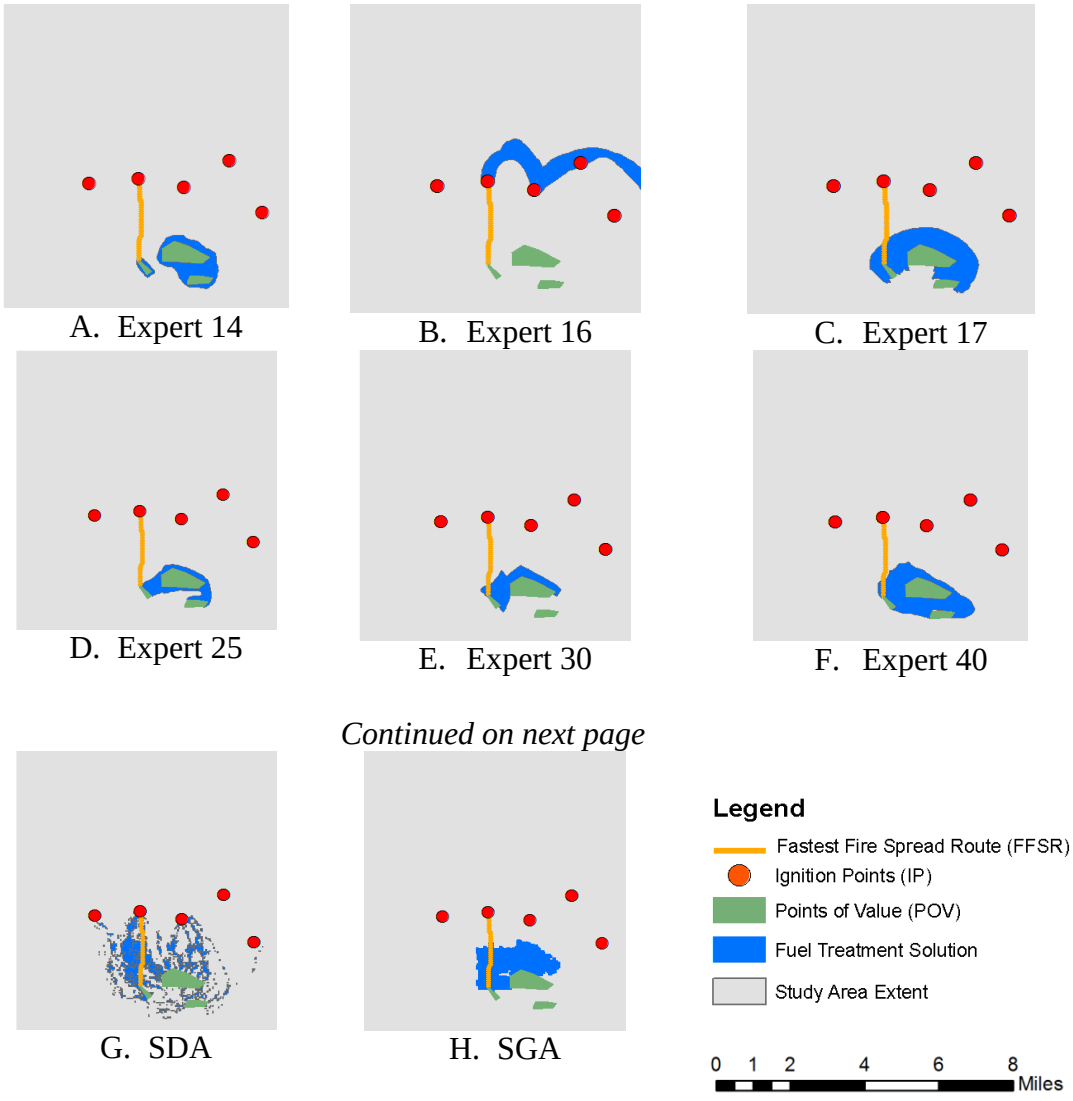


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Figure 4.11. Fuel treatment locations for scenario 3 identified by experts (A to F), SDA model (G) and, SGA model (E)

Table 4.8. Results for increase in burn time and number of cells in solutions for scenario 3

Evaluator	SGA Model	Expert 14	Expert 16	Expert 17	Expert 25	Expert 30	Expert 40	SDA Model
Burn Time After Treatment (minutes)	661.96	446.47	423.28	555.83	412.90	469.34	469.65	633.41
Burn Time Before Treatment (minutes)	412.52	412.52	412.52	412.52	412.52	412.52	412.52	412.52
Increase in Burn Time (minutes)	249.44	33.94	10.75	143.31	0.38	56.82	57.13	220.89
% Increase Over Untreated Burn Time	60.46	8.22	2.60	34.74	0.09	13.77	13.85	53.54
Number of Cells Treated	2200	1589	2045	2255	1191	783	2268	2481
% Permissible Area Treated	100.00	72.23	92.95	102.50	54.14	35.59	103.09	112.77
Performance Ratio	0.60	0.11	0.03	0.34	0.00	0.39	0.13	0.47

It is interesting to note that both models and three of the six experts came close to or even exceeded the maximum permissible area to treat. It seems clear that in this scenario, treating larger areas improves efficacy, right up through the maximum permissible treatment area. This pattern was not seen in the other scenarios.

4.3.2 Fragmentation of Fuel Treatments (Scenario 3)

The expert fuel treatments consisted of either 1 or 2 patches (Table 4.9). The SGA fuel treatment plan contained a number of unrealistic holes (discussed in the Methods chapter); this

accounts for the 4 patches shown in Table 4.9. The SDA fuel treatments are once again highly fragmented, which again reduces the feasibility and plausibility of the solution.

The experts generally treated cells either around the POVs, although expert 16's strategy was unclear. The SGA model clearly uses the same strategy of treating fuels near the POVs as did most of the experts, but the precise spatial locations of the various treatments are slightly different, and these slight differences are enough to account for the differing levels of effectiveness seen among the various fuel treatment plans.

Table 4.9. Number of fragments/patches in a solution for scenario 3 identified by SGA model (1), experts (2 to 7) and, SDA model (8)

	Evaluator	# Fragments/Patches
1	SGA	4
2	Expert 14	2
3	Expert 16	1
4	Expert 17	1
5	Expert 25	1
6	Expert 30	1
7	Expert 40	1
8	SDA	156

4.3.3 Spatial Overlap (Scenario 3)

The number of common cells between the SGA and the other treatment plans (Table 4.10 and Figure 4.12) was higher under this scenario than what was seen under the two previous scenarios. However, there were still significant differences between the fuel treatment plans (expert 17, whose plan had the greatest similarity with the SGA results of any of the experts or the SDA model, had less than 40% of its cells in common with the SGA results), and these differences allowed the SGA model to produce a more effective plan than any of the others. This

once again illustrates the sensitivity of the solution to changes in the spatial locations of the fuel treatments.

Table 4.10. Spatial overlap (using SGA results as the base for comparison) of fuel treatments for scenario 3

Reference Solution	# Common Cells	# Commission	# Omission
Expert 14	387 (11.30%)	1202 (35.10%)	1835 (53.60%)
Expert 16	0 (0.00%)	2045 (47.93%	2222 (52.07%)
Expert 17	1263 (39.30)	992 (30.87%)	959 (29.83%)
Expert 25	427 (14.30%)	764 (25.59%)	1795 (60.11%)
Expert 30	596 (24.74%)	187 (7.76%)	1626 (67.50%)
Expert 40	889 (24.69%)	1379 (38.30%)	1333 (37.01%)
SDA	1158 (32.67%)	1323 (37.32%)	1064 (30.01%)

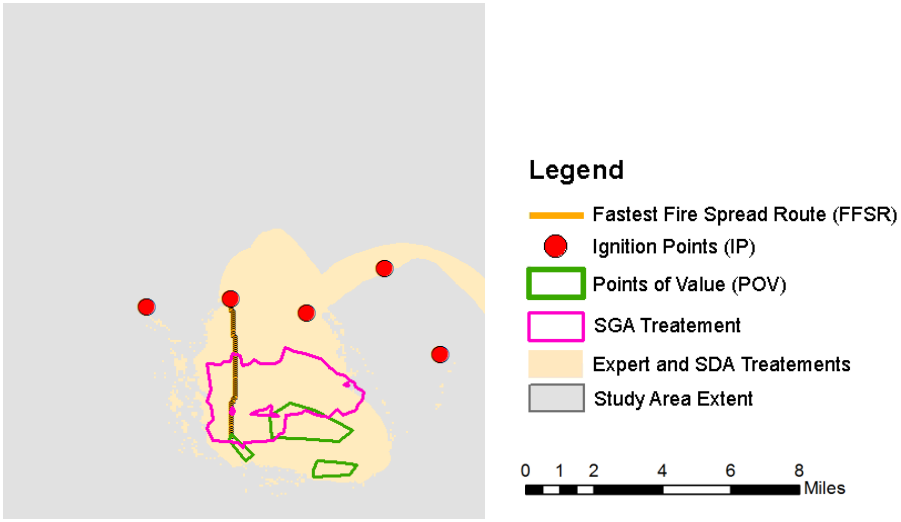
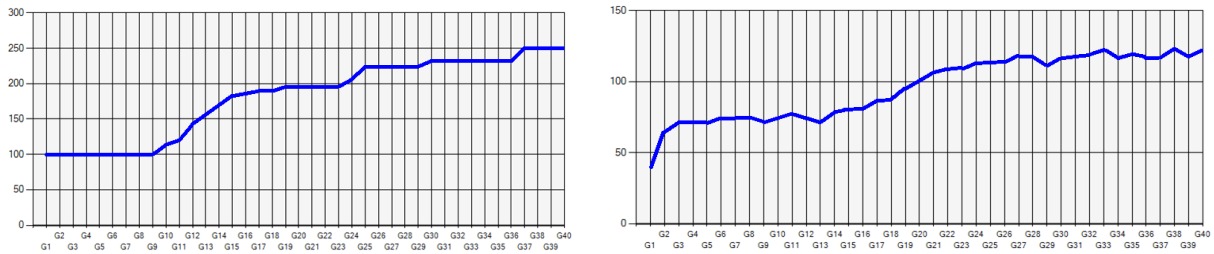


Figure 4.12. Spatial location of fuel treatments generated by SGA model, SDA model and, experts for scenario 3

4.3.4 SGA Model Performance (Scenario 3)

In scenario 3 (Figure 4.13 A), the best solution is found in generation thirty seven (G37). It is observed that the quality of the solutions remains steady from generation 1 to 9, and suddenly improves in generation 10. Further analysis shows that the best solution in generation 10 (Figure 4.14 B) is a result of a mutation of a solution from generation 9 (Figure 4.14 A). The solution quality then improves steadily from generation 10 to generation 15 (G15) and keeps improving (albeit more slowly) until generation 37. The average fitness of solutions (Figure 4.13B) reflects a similar pattern, and average solution quality keeps improving until generation 27.



A. Fitness of best solution. B. Average fitness of all solutions.

Figure 4.13. SGA model performance graph with generation (x-axis) and fitness values (y-axis) for scenario 3

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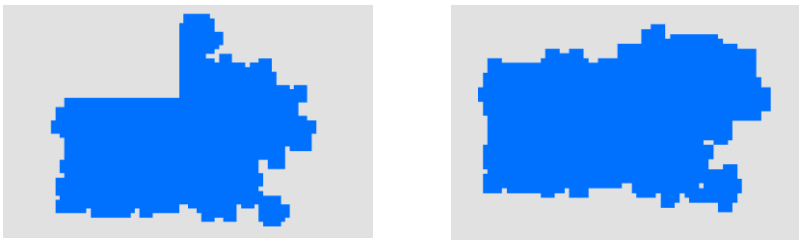

A. G9S184 (F = 100.24) B. G10S371 (F = 113.82)

Figure 4.14. Evolution of a solution through mutation (scenario 3)

4.4 Summary of Results (Scenario 1, 2 and 3)

The results for scenarios 1, 2 and 3, discussed in the sections above (4.1 to 4.3), can be viewed as three repetitions of the same experiment. All three scenarios feature identical model parameters (outlined in Table 4.1); the only thing that is changed between the scenarios are the test sites. In all three scenarios, the SGA model outperformed both the SDA and the experts. The spatial overlap analysis shows that for all three scenarios, the percentage of common cells between the SGA treatments and expert treatments as well as those between the SGA treatments and SDA treatments is always less than 40%. The SGA model adheres to the area constraint by never exceeding the maximum permissible treatment area. The degree of fragmentation in the treatments produced by the SGA model is always lower compared to both the experts and SDA treatments thereby increasing the plausibility of these treatments. For scenario 1 and 2, the SGA model performance graphs illustrate that that model iterates through generations in order to produce the best (near optimal) solution. In scenario 3, it is certainly plausible that more improvement would be seen in the best overall solution after generation 40.

4.5 SGA Model Computation Time and Performance

In this section the SGA model computation time is analyzed for scenario 1. Recall that the model parameters described in Table 4.1 were used in this analysis. The specifications and configuration of the computer system used are shown in Table 4.11.

Table 4.11. System specification for recording SDA model computation time

Operating System	Windows 7
Processor	Intel(R) Core(TM) i7-3770 CPU @ 3.40GHz 3.40 GHz
RAM	16 GB
System Type	64-bit Operating System

The time required to complete a single instance of each process involved in the implementation of the SGA model is recorded in Table 4.12, while the time required to complete all instances of each process required in a single generation of the modeling process is recorded in Table 4.13.

In total, the SGA model required eight days, twelve hours, forty five minutes and twenty six seconds to complete forty generations of analyses for scenario 1 (Table 4.13). Five hundred solutions were created in the first generation in eight hours, eleven minutes and two seconds. Each proceeding generation consisted of five hundred solutions generated by the genetic operations copying (10% i.e., 50 solutions), replication (10% i.e., 50 solutions), mutation (40% i.e., 200 solutions) and crossover (40% i.e., 200 solutions). The time required to generate a single solution in generation 1was trivial and was recorded as zero seconds. Similarly, the time required to copy and replicate a single solution was trivial and was recorded as zero seconds. The SDA model took three seconds to mutate a single solution and the total time required to mutate 40% of all solutions (i.e., 200 solutions) was three hours, twenty seven minutes and forty four seconds. Performing a single crossover required four seconds and performing crossovers on 40% of all solutions (i.e., generating 200 new solutions) consumed two hours, fifty four minutes and forty eight seconds. In general, each individual instance of a process took only seconds to complete

(Table 4.12), with the most time consuming process being modifying the impedance values of a network.

Table 4.12. SGA model computation time for single intermediate processes

	Process	Seconds
1.	Read input raster data (DEM)	05
2.	Read input A* network	05
3.	Read input sources (IP)	02
4.	Read input targets (POV)	02
5.	Find A* route before treatment	01
6.	Randomly select cell along FFSR	00
7.	Identify row ID and column ID of a node	00
8.	Generate a solution	00
9.	Identify bounding box of a solution	01
10.	Modify impedances of a network	40
11.	Find A* route after treatment	02
12.	Restore network impedances	15
13.	Save solution map to disk in GRIDASCII format	02
14.	Save solution information to disk in binary format	00
15.	Copy a solution	00
16.	Replicate a solution	00
17.	Crossover two solutions	04
18.	Mutate a solution	03

Table 4.13. SGA model computation time for major processes multiple times in one generation

	Process	Days	Hours	Minutes	Seconds
1.	SGA model run time for entire process	08	12	45	26
2.	Generating 500 solutions	0	08	11	02
3.	All genetic operations (generation 2 to 40)	08	04	34	10
4.	Copy 10% solution in a generation	0	0	0	0
5.	Replicate 10% solutions in a generation	0	0	0	0
6.	Mutate 40% solutions in a generation	0	03	27	44
7.	Crossover 40% solutions in a generation	0	02	54	48

It is interesting to compare these performance metrics to those reported for the SDA model. The SDA model required a minimum of three hours and up to more than forty eight hours to produce a single solution (Valdez-Lazalde, 2001). The SGA model dramatically reduces this amount of time. It is undoubtedly true that some of this improved performance is due to the much more modern and capable computer hardware used here to record SGA performance compared to the hardware used by Valdez-Lazalde to record SDA performance, but given the relative simplicity of the techniques used here to generate initial solutions and genetically propagate existing solutions compared to the very intensive calculations needed in the SDA approach (where a cost spreading or network analysis is required after identifying each cell to include in the solution) it stands to reason that some of this increased performance is due to the inherent advantages of the SGA approach.

CHAPTER 5

CONCLUSIONS

5.1 Summary and Conclusions

In this research, a *Spatial Genetic Algorithm* (SGA) is developed and its ability to identify optimal or near-optimal locations for forest fuel management subject to a set of constraints (budget and non-fragmentation) has been tested. This research improves on some of the limitations encountered in Valdez-Lazalde's (2001) approach.

The SGA model is tested using three different scenarios, each of which consists of a geographic location where fuel treatments occur and its terrain, the fuel conditions throughout the landscape, wind conditions, and locations of ignition points (IPs) and points of value (POVs). Each of the three scenarios employed in Valdez-Lazalde's (2001) study are used in the present study for comparison. The results from the SGA model are also compared with expert prescriptions. Quantative comparisons of results from all three techniques (SGA model, Valdez model, and experts) are performed on fuel treatment effectiveness (measured by the increase in burn time), area (which in this context is a proxy for the budget constraint), number of patches in the solutions (which is a measure of fragmentation), and spatial overlap (which measures one aspect of spatial commonality between results). Following are the conclusions of this research:

5.1.1 SGA Fuel Treatment Optimization Model Solution Quality and Comparison

1. The SGA successfully identifies plausible and intuitively reasonable spatial locations for fuel management activities. In contrast to Valdez-Lazalde (2001)'s results, the spatial locations (solutions) identified by SGA show little to no fragmentation.

2. The solutions identified by the SGA outperform both the expert prescriptions and the solutions obtained by Valdez-Lazalde (2001), by producing higher increases in burn time.
3. The spatial overlap of solutions obtained by all three approaches shows that fuel treatments identified by the SGA model are at different spatial locations than the treatments identified by either the experts or Valdez-Lazalde's (2001) model. The difference in the spatial locations of the SGA treatments is one of the reasons for obtaining solutions with greater increase in burn time.
4. The SGA model always adheres to the budget (i.e., area) constraint. Simultaneously, it is also able to obtain solutions with higher effectiveness than either of the other two approaches. Both the experts and Valdez's model occasionally violated the budget by treating more area than allowed, but still resulted in lesser increase in burn time compared to the SGA model. It can be inferred that treating a greater number of cells does not necessarily lead to higher increase in burn time. The placement of treatments by the SGA illustrates the sensitivity of the solution to changes in the spatial locations of the fuel treatments.
5. In its current form, the SGA is faster than the Steepest Decent Approach (SDA) employed by Valdez-Lazalde, but there is immense scope to improve the SGA model's computation time (see section 5.2).

5.2 Recommendations for Future Studies

1) Although the SGA model produces results faster than Valdez-Lazalde (2001) approach, it cannot be denied that in its current form the SGA model takes impractical amounts of

processing time. However, there is immense scope to decrease run time using tools and techniques such as graphics processing unit (GUP) computing and parallel processing. Each individual process within the SGA model takes anywhere between zero to forty seconds, but the SGA model iterates through millions of processes. The fact that each of these processes is being performed sequentially adds up to long computation times. However, parallel and GPU computing approaches will allow many of these operations to be performed simultaneously, which have the potential of dramatically decreasing overall computation times. Further research in this area would seem to be warranted.

2) The A* algorithm is exact when accurate network distances are used as weights. In the SGA model, initially network distances are used as weights but these distances change as fuel treatment operations are applied. However, weights are never updated to reflect these changes, so latter applications of the A* algorithm may produce non-optimal solutions. Future research should investigate the impacts of this phenomenon, and once the model is parallelized, the possibility of eliminating the problem by recomputing and updating the post treatment network weights may become practical.
3) The current solution formation algorithm is designed such that occasionally, doughnut shaped areas or holes are created. In order to avoid this problem, after every solution is formed, a final scan process can be performed to identify all the holes and fill them, while maintaining the area constraint. The impacts of such a modification (both in terms of final solution quality and execution time) could be investigated in further research.
4) The current research lacks enough repetitions to constitute a through sensitivity analysis of the impact of SGA model parameters on solution characteristics. The reason for this

lack of repetition was the long execution times required by the model. Once a faster, parallel system is in place, various model parameters such as number of solutions, generations, cells in solution, percentage of copying, mutation, crossover of solutions, percentages of cells to be mutated and number of solutions to be crossover can be experimented with to study the model sensitivity.

5) A faster version of the SGA model would allow fire management researchers to evaluate different fire management strategies. For example, by first limiting the ability of the model to find solutions to only the areas around IPs, and then limiting the model to the areas around POVs, the relative effectiveness of two different management strategies can be compared. This sort of research could be immensely beneficial to forest fire researchers.

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BIOGRAPHICAL SKETCH

Vaishnavi Thakar was born in Pune, India. She attended high school in Pune after which she enrolled at the University of Pune, India and graduated with a Bachelor of Science in Geography. She then pursued her Master of Science in Geoinformatics from the University of Pune, India. It was during this time she became interested in the application of Geoinformatics for disaster management. Pursing her interest in this topic, she moved to Dehradun, India to complete an internship and her Master's research at the Disaster Mitigation and Management Center, Government of Uttarakhand, India. After her graduation, Vaishnavi accepted a geospatial researcher position with the Geoinformatics Center, Asian Institute of Technology in Bangkok, Thailand. She worked on various projects involving application of Geospatial technology for disaster management in Asian countries. Her interest in Geospatial research motivated her to enter the doctoral program in Geospatial Information Sciences at The University of Texas at Dallas in Richardson, Texas. During the course of pursuing her PhD, she also earned a Master of Science degree in Geospatial Information Sciences from The University of Texas at Dallas. Vaishnavi was a Teaching Assistant from 2013 to 2017. She was an instructor for an introductory GIS course during Fall 2015 and Fall 2016 in the Geospatial Information Sciences Department at The University of Texas at Dallas.

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RESEARCH INTRESETS

- Spatial Optimization.
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PUBLICATIONS

Peer Reviewed Journal Articles

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- Dean, Denis; **Thakar, Vaishnavi**; Sirdeshmukh, Neeraj. (2015) *Optimal Routefinding Across Landscapes Featuring High-cost Linear Obstacles*. Transactions in GIS. DOI: 10.1111/tgis.12170

Book Chapters

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Conference Proceedings

- J.Fowze, **Vaishnavi Thakar**, S.Wahyu, R Shofiyati, M. Hazarika, L. Samarakoon. (2010).*Landslide susceptibility assessment in agricultural land using remote sensing and GIS: A Case Study in East Java, Indonesia*. 31st Asian Conference on Remote Sensing, pp 1446 – 1451.

Conference Presentations

- **Thakar, Vaishnavi**; Dean, Denis. . (2017). *Genetic Algorithm for Spatial Optimization of Wildfire Fuel Treatment Locations.* Abstracts of the 2017 Annual Meeting of the Association of American Geographers. Boston, Massachusetts.

- **Vaishanvi Thakar**. (2016). A *Spatial Region Growing Approach for Forest Fire Fuel Management.* Abstracts of the 19th Annual Washington GIS Conference, Tacoma, Washington.
- **Thakar, Vaishnavi**; Dean, Denis. . (2016). *Insights into Practical Implementation of Genetic Algorithm for Spatial Problems: Case Study in Forest Fire Fuel Treatment Location Identification.* Abstracts of the 2016 Annual Meeting of the Association of American Geographers. San Francisco, California.
- E Scott Morris; **Vaishnavi Thakar**; Daniel A. Griffith. (2015). *Respondent Driven Sampling and Spatial Autocorrelation*. Abstracts of the 13th International Conference on Geocomputation, Texas, USA.
- **Thakar, Vaishnavi**; Dean, Denis. (2015). *A Spatial Optimization Approach to Finding Locations for Wildfire Fuel Treatments.* Abstracts of the 2015 Annual Meeting of the Association of American Geographers. Chicago, Illinois.
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SCHOLARSHIPS/AWARDS

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PROFESSIONAL SERVICE

Journal Article Reviews:

- Geographical Analysis : 2013 (1)
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PROFESSIONAL MEMBERSHIP

Member, Association of American Geographers (AAG).

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PROFESSIONAL EXPERIENCE

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Graduate Teaching Assistant, University of Texas at Dallas 2013 – 2017

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GIS Intern, Office of Emergency Management, City of Dallas, TX Fall 2012

- Developed a ‘Common Operating Picture’ in the emergency operations center.
- Assisted the city staff in efforts to enhance incorporation of GIS in the Emergency Operations Center.

Geospatial Researcher, Asian Institute of Technology, Thailand 2009 – 2010

- Managed two major projects on implementation of geospatial technology for

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- Developed research methodologies and geospatial models for disaster management.
- Conducted training activities and capacity building for local government officials of Asian countries on utilization of GIS technology and satellite images for disaster management.
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