An Enhanced Model for Wildfire Propagation Prediction Using GIS

By

A. V. Dantanarayana

14020106

K. K. C. Perera

14020602

B. S. Wickramathilaka

14020912

This dissertation is submitted to the University of Colombo School of Computing

In partial fulfillment of the requirements for the

Degree of Bachelor of Science Honours in Information Systems

University of Colombo School of Computing

35, Reid Avenue, Colombo 07,

Sri Lanka

January, 2019

Declaration

I, A. V. Dantanarayana & 14020106 hereby certify that this dissertation entitled 'An Enhanced Model for Wildfire Propagation Prediction Using GIS' is entirely my own work and it has never been submitted nor is currently been submitted for any other degree.

....

Date Student's Signature

I, K. K. C. Perera & 14020602 hereby certify that this dissertation entitled 'An Enhanced Model for Wildfire Propagation Prediction Using GIS' is entirely my own work and it has never been submitted nor is currently been submitted for any other degree.

....

Date Student's Signature

I, B. S. Wickramathilaka & 14020912 hereby certify that this dissertation entitled 'An Enhanced Model for Wildfire Propagation Prediction Using GIS' is entirely my own work and it has never been submitted nor is currently been submitted for any other degree.

....

Date Student's Signature

I, Dr. G. D. S. P Wimalaratne, certify that I supervised this dissertation entitled ‘An Enhanced Model for Wildfire Propagation Prediction Using GIS’ conducted by A. V. Dantanarayana, K. K. C. Perera, and B. S. Wickramathilaka in partial fulfillment of the requirements for the degree of Bachelor of Science Honours in Information Systems.

....

Date Signature of Supervisor

Acknowledgement

First and foremost, we would like to express our sincere gratitude to our supervisor, Dr. G. D. S. P. Wimalaratne for his valuable support maximize the potential of our research. He provided dedicated guidance, motivation and knowledge in order to maximize the potential of our research. Furthermore we would like to give our thanks to the GRASS GIS user community for their support as well. And last but not the least, we would like to thank our dear families and fellow colleagues for their precious support given throughout this period to help us successfully complete this study.

Abstract

Wildfire modeling and simulation has been one of the major subjects under intense experimental research and theoretical work to address the ever-growing crisis of wildfire. Many researchers have benefitted from these work and have developed multiple wildfire propagation prediction systems for decision support. Despite the large-scale effort undertaken by the scientific community, it can be also observed that these advancements have become limited to the developed countries of the world. This can be attributed to the fact that a reliably accurate wildfire behavior model requires many input variables and acquiring these variables requires a great deal of infrastructure already in place. These infrastructures can be quite costly, making it infeasible for the developing countries to develop a wildfire propagation prediction system. The purpose of this research is to enhance an existing wildfire model in a manner that it requires less infrastructure at an acceptable accuracy level.

The study was begun by analyzing the existing models for extensibility and enhanceability. It was discovered that the Rothermel's Surface Fire behavior model can be enhanced by eliminating some of its many variables. Therefore a set of variables were selected through some rationale and were experimented upon using GIS platforms to observe the effect they have on the Rothermel's model. The study was conducted using historical wildfire data and the primary measure used was the Jaccard Similarity Coefficient. To assess the practicality of the model, a novel framework named 'MOD (Most Occurring Data) Sign' analysis was proposed.

The results of the study show that 'fuel particle moisture' and 'live fuel load' variables have significantly less effect on the Rothermel's model. It was also discovered through the MOD Sign Analysis that 'fuel particle moisture' was the more practical variable to eliminate rather than 'live fuel load'. Finally, it was concluded that a simplified model can be derived from the Rothermel's model by eliminating 'fuel particle moisture' variable and while 'live fuel load' may also be eliminated, the resulting model will not be suitable for decision making.

Table of Content

List of Figures

List of Tables

List of Acronyms

GIS	*Geographic Information System*
NWCG	*National Wildfire Coordination Group*
SQL	*Structured Query Language*
TXT	*Text format*
CSV	*Comma Separated Value*
MOD	*Most Occurring Data*
ROS	*Rate of Spread*
MRLC	*Multi-Resolution Land Characteristics Consortium*

Chapter 01

Introduction

Wildfire is a phenomenon that has occurred for millions of years since the appearance of terrestrial plants. While as a natural occurrence, wildfires were integral for the equilibrium of Earth's ecology, various human activities and recent climate changes are causing the increase of the frequency and severity of extreme weather conditions, which will in return increase the probability of a wildfire occurrences around the world. The severity of the crisis is steadily increasing that wildfires will be longer, produce more smoke and burn larger areas by the year 2050. [1] In another note, it is important to emphasize that wildfires contribute significantly to the world's greenhouse gas emission that drives global warming [1].

One of the major solutions that were applied to address this crisis was wildfire propagation modeling. Initially, this was to understand the phenomenon of wildfire. A few notable researchers such as Rothermel [2], Wagner [3], [4], Albini [5] Anderson [6], [7] have contributed tremendously to the understanding of the wildfire phenomenon and these models are now integrated into many applications such as FARSITE [8], BEHAVE [9], Firemap [10] etc. that are utilized for disaster management purposes in some regions of the world.

In this particular research, the possibility of optimizing one such model is investigated. Particularly in the context of reducing the number of variables in the mathematical model proposed by Rothermel [2]. Therefore some variables were identified and reduced from the mathematical equation to observe its effect on the overall behavior of the model. Insights gained from the observations were then incorporated into the research to create an enhanced model from the Rothermel's model [2].

1.1 Motivation

As noted before, many research has been conducted to understand the phenomenon of wildfires. And the mathematical models that resulted from these have been utilized in many solutions deployed across many regions of the world. But if one were to investigate where these disaster management solutions have been deployed in, it would be obvious that most of them are located in developed regions. One of the initial motivations this study had was to discover why such solutions were not deployed in developing regions even if they are heavily threatened by the wildfire crisis. From the investigations done, it was found that the most probable culprits for this particular dilemma were the lack of resources, infrastructure, and complexity of models.

Therefore the main motivation of the research was to discover a way to reduce the above-said barriers. To optimize a wildfire behavior model by reducing its complexity so that it would require fewer resources and infrastructure effectively reducing the effect of the previously mentioned barriers. Furthermore, the proposed derivative model should perform at an acceptable level of accuracy when compared to its base model.

1.2 Research Question

- How to enhance an existing wildfire spread prediction model so that it requires less resources and infrastructure?

The primary problem that is to be addressed is to investigate the possibility of an enhanced wildfire model. As a secondary focus, the effects of the individual variables to the overall model is investigated as well.

1.3 Aims & Objectives

Aim

To investigate the possibility of simplifying or optimizing an existing wildfire behavior model in order to remove economical and/or practical constraints when developing a real-time wildfire propagation prediction system in developing countries.

Objectives

- To study existing wildfire propagation models and related literature.
- To select a suitable wildfire propagation model that can be simplified/optimized.

- To identify a suitable benchmark dataset that contains necessary attributes that are required as input parameters for the selected model.
- To investigate the possibility of optimization/simplification of the selected model by altering the model.
- To validate enhanced models using benchmark data by comparing the base model results with altered model results.
- To draw conclusions and implement the optimized model.
- Compile a thesis detailing the background, research methodology & design, results, and evaluation process.

1.4 Research Approach

The research approach shall be a mixed research approach since design science is used to investigate, how to enhance an available wildfire spread prediction model and quantitative data to evaluate the said enhanced model.

The wildfire spread models were identified in the initial phase of the research in order to investigate the possibility of enhancing one of them by reducing one or more input variables from the original model. To ensure that the altered model provides an acceptable accuracy rate, the model shall be evaluated using a benchmark dataset on wildfires.

1.5 Scope

The scope of this study is to, a) evaluate the existing wildfire behavior models to identify the gaps and opportunities to improve and optimization b) find out the variables used in each wildfire behavior model and explore the gravity of each variable c) analyze and investigate how to manipulate or eliminate the use of these variables maintaining the accuracy of the model as much as possible, and d) evaluate the results of altered model with real spread of a wildfire to determine the accuracy.

One problem identified with existing fire behavior models is as mentioned in the objectives section is the use of a larger number of parameters. In the Rothermel's fire behavior model [2] it uses more than 20 parameters to calculate the rate of spread. So the main approach of the research is to reduce these number of parameters used and investigate to what extent the predictions can make accurately.

For the modeling purpose, the fire behavior module of GRASS GIS will be used. Wildfire and weather data are obtained from the United States' National Wildfire Coordination Group (NWCG). The completed research is expected to simplify the wildfire behavior modeling so the enhanced model can be used in situations where complex infrastructure is not available.

1.6 Delimitations

The following are the delimitation of this study,

- A fire behavioral model will not be developed from scratch. Only alterations would be made to an existing model.
- The possibility of predicting the spread of wildfire using a fewer number of variables shall be investigated. But the prediction may not be 100% accurate when compared with the benchmark.
- The fire behavioral model shall not be adapted to the Sri Lankan context due to the unavailability of detailed historical data making it impossible to evaluate the model as of now.

1.7 Structure of the Thesis

The related literature surrounding the problem domain is studied and analyzed in the Chapter 2. The design of research architecture and assumptions are included in the Chapter 3. The Chapter 4 describes the implementation process undertaken in the study and the Chapter 5 describes the experimental protocol, experimentation process, and the results gained in the study. Finally the Chapter 6 concludes the research by providing the conclusion and future works.

Chapter 02
Background

In this chapter, the background of the research context is explored. An introductory background to the context is given initially and then a comprehensive study is done on the related literature. Various mathematical models and related systems are investigated and in the end, they are analyzed and compared in an objective manner in order to provide hard facts on them.

2.1 Introduction

Wildfire occurs in an area of combustible vegetation mostly in the countryside. For a wildfire to ignite, the three basic elements of the fire triangle should be fulfilled. To name them, an Oxidizing agent (oxygen), Heat and Fuel [11]. Furthermore, depending on the conditions that caused the ignition, environmental variables, and the vegetation, a wildfire can be categorized into three main classifications. Ground fire, Surface fire, and Crown fire [11]. A ground fire generally occurs below the surface of the soil. It consumes subterranean roots and organic matter in the soil to sustain itself. An occurrence of ground fire can be observed via the smoke that is visible above the surface. While its spread is very slow compared to other classifications, ground fires have the capability to burn for days to months. In contrast, surface fires occur above ground consuming fallen tree leaves, bushes and other undergrowth obtaining some moderate height. The fire burns at relatively low temperature when compared to surface fires and the rate of spread is comparatively low as well. Crown fire as its name suggests, burns and spreads at the canopy level of trees [11]. Such fires have the potential to consume whole swathes of forests and property depending on the environmental and other conditions. The fires burn at a much higher temperature than other wildfire classifications and the rate of spread is much higher as well [11].

There may be several causes of wildfire ignition. But primarily there are two categories [11], 1) Wildfire caused by natural phenomenon. 2) Wildfire caused by human activities. Wildfires may occur due to a natural phenomenon such as lightning strikes or ignitions caused by trees rubbing with each other. However as humanity's footprint continues to encroach the ecology of the world, more often than not most wildfires occurring around the globe are caused directly or indirectly by human activities [11]. To name a few negligence, plantations, hunting, arson etc. But even with these natural or unnatural causes, a wildfire requires a set of conditions to ignite and spread. These conditions are high temperature, strong winds, low humidity etc. There are specific weather seasons that support such conditions and they are commonly known as fire seasons. These fire seasons may vary from one geographical location to another. [11]

2.2 Wildfire Propagation Modeling

Modeling of wildfire behavior has been an active scientific field since as early as the 1920s [37]. The first known work was by Hawley [39] and Gisborne [40], [41] who introduced the concept that measurements, observations, and theoretical considerations may affect the behavior of wildfires. These studies were done even when the consistent funding was not readily available [37]. The situation somewhat changed in the 1930s onwards due to studies conducted by Curry and Fons [42], [43] and Fons [15] who brought a more rigorous and methodical physical approach to the modeling and measuring of the behavior of wildfires. In the 1950s and 1960s, a considerable effort and resources were put into the field due to the insurgence of research initiatives conducted by State and Federal forestry agencies around the world. Most of these initiatives were State defense oriented initially. Therefore by 1970s, the interest in the field pummeled relatively low. But then again in the 1980s, more studies were conducted by those who had direct interests in studying the behavior of wildfires and by 1990s and onwards, the applied research in the field considerably increased due to technologies such as Geographical Information Systems and remote sensing [37].

Initially, when it came to the domain of disaster management, wildfire detection and prevention could be considered as the main pillars. Yet with the time, it has become obvious that the wildfire propagation prediction is also similarly an important aspect since the spread is the aspect that increases the intensity of the disaster [14]. As noted above, these wildfire models can be further enhanced with new technologies that enable predictions that would drastically improve the reaction times of responsible stakeholders.

Mathematical models themselves can be used to calculate wildfire spread. In order to create a mathematical model for wildfire spread, the variables which can affect the spread of wildfire such as wind velocity, wind direction, Slope or elevation of the area, the temperature of the wildfire and fuel bed moisture etc. are required [12]. Then to construct the equations, two types of approaches have taken by the researchers. The first approach is using available historical wildfire data or artificially creating the wildfire conditions on experiment labs and then try to find the variable combinations. This approach is considered as the Empirical approach [5], [6]. The second approach is to create the wildfire spread equations using physics principles, the main physics laws were used like heat flux, conductivity, thermodynamics etc. This approach is known as the physical approach [13]. Finally, those equations were combined to create a final mathematical model for the wildfire spread prediction. The reliability and accuracy are high in the wildfire spread models which were created using artificial tests and historic fire data [1], [2]. The main reason for that is the data which are taken in the field will not be accurate as the data taken from advanced sensors in the lab. Those data infields are mostly the data which is taken from nearest stations so the distance between that station and place where the wildfire occur matters. The artificial wildfires which are created in labs do not have such limitations. Therefore, most of the available wildfire models are created using artificial wildfires and finalized using checking them with actual data.

2.3 Literature Review

As noted in section 2.2, the history of wildfire propagation models started as early as the 1920s [37]. Therefore, almost a century worth of scientific advancement is available in the context. Thus only a few key models are discussed in the below section. Figure 2.1 illustrates the taxonomy of selected wildfire propagation models according to a classifications provided by Sullivan [36], [37], [38] and Perry [33]. Figure 2.2 represents how a fire is represented in a simulation [33].

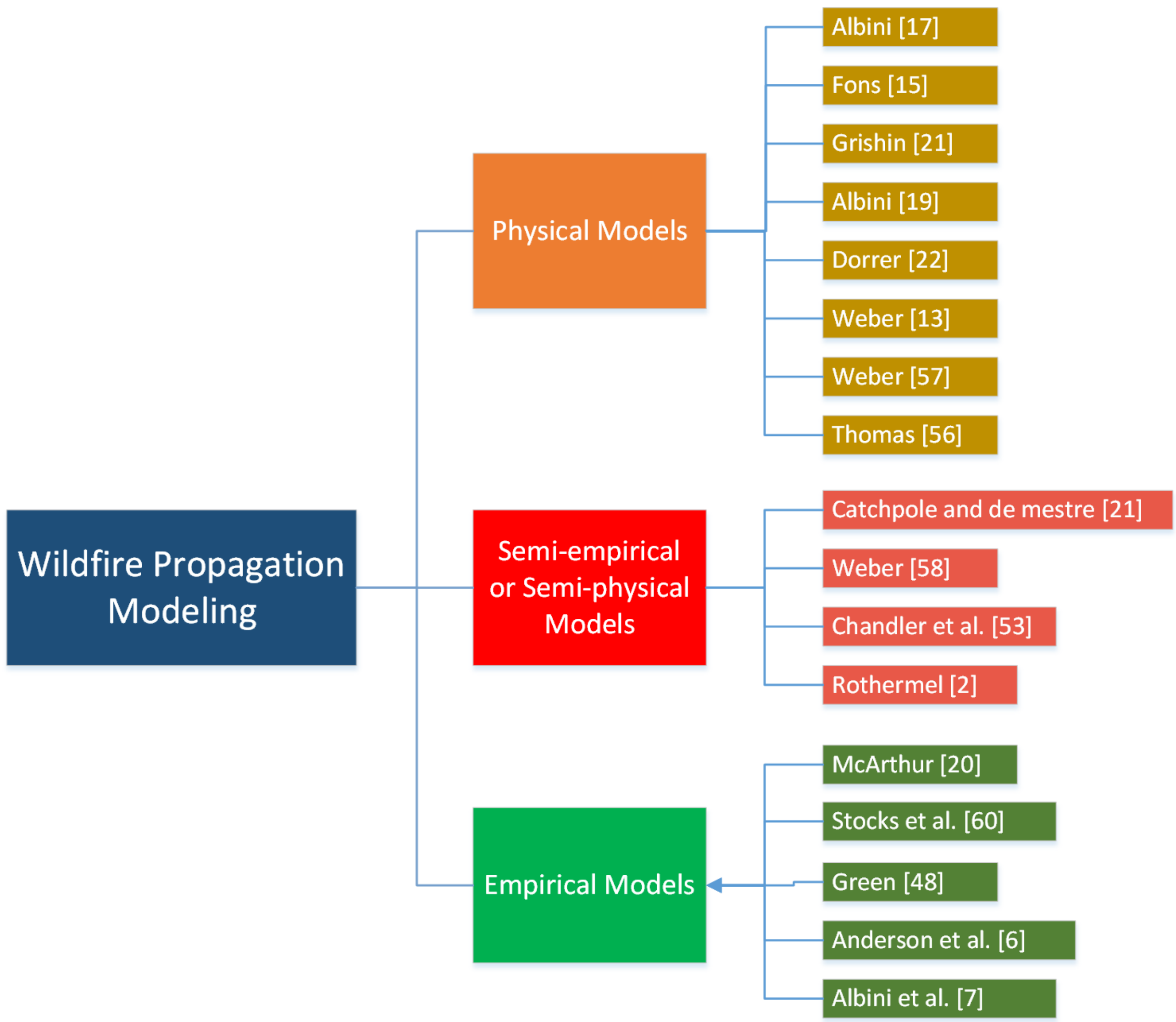

Figure 2.1: Wildfire propagation model classification

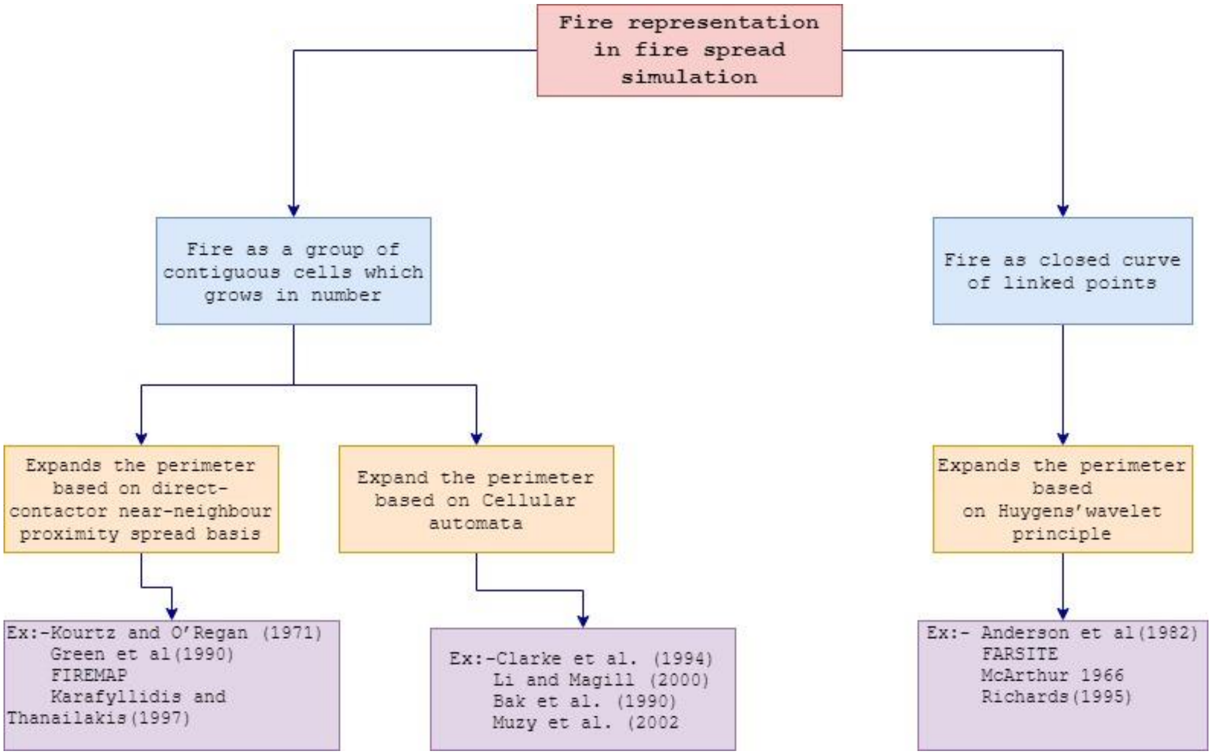

Figure 2.2: Fire representation in fire spread modeling

One of the first attempts to describe the behavior of wildfire spread via a mathematical model was done by W. Fons [15]. The focus of this study was the fire front or the head of the fire. It is in the fire front that affects an adjacent non-consumed fuel in the fuel bed by bringing them to ignition temperature. Thus Fons suggested that visualization of the wildfire spread can be taken as a series of fuel ignitions, in which the rate is controlled by the distance between particles and the ignition time. Fons' findings have been confirmed by the works of Tarrifa and Torraldo [16] later and were the basis for many influential studies in the context in the future.

Van Wagner [3] proposed a model for simply calculating the spread of the wildfire using basic physics. The model gives that the wildfire will spread in a semi-elliptical shape. The narrow end of the ellipse will be at the side of the direction of the wind. The model is simple and can be easily used for instances, where it is needed to act quickly by taking a rough idea of how the fire will spread.

Wagner [4] again proposed some criteria for the initiation of crown fire combustion and for minimum rates of spread and heat transfer to the crown fire combustion zone. His arguments depended upon three attributes of forest crowns: height above ground, foliar moisture content, foliar bulk density. Wagner proposed a simple but yet somewhat incomplete model where the initial surface fire intensity, crown fire spread rate, and the rate of forward heat transfer to the unburned crown fuel are considered and it was one of the earlier forays into the crown fire modeling context that was vital to later studies on crown fire.

One of the initial attempts at modeling wildfire spotting was conducted by Frank Albini [17]. Fire spotting is considered somewhat a chance event. The unpredictability of the event limits the capability to present it in the form of a mathematical model. Thus Albini proposed a set of sub models based on assumptions, inadequately supported empirical relationships, and approximations. These models would be refined throughout the next set of studies conducted by Albini. Some of them are noted below as well.

Albini et al. [20] proposed a model, an improvement to the models proposed in [17], to predict the maximum potential fire spotting distance from an active crown fire. In the study, the authors have presented several sub-models; a model for the height and tilt angle of the wind-blown line-fire flame front, a model for the burning rate of a wooden cylinder in cross flow, a 2-D model for wind-blown buoyant plume from the fire. The proposed model has shown some promise when compared with the existing information on crown fire spotting.

Albini [5] also presented a speculative model for forest fire spotting phenomenon. The author based his model on the assumptions that particles are lofted by the thermals generated by the fire and that thermals are generated due to the fluctuations in the fire intensity with time due to the variations in wind speed or the “gustiness” of the wind. Due to these speculative assumptions, the model can be considered as a theoretical construct and the author presumes that it will remain so even if the field test has shown it to be reasonably accurate.

Anderson et al. [21] have proposed the concept of Huygens’ Principle for fire propagation. The fire front is propagated as a continuous expanding fire polygon at specific timesteps. Each vertex of the fire polygon is considered to be independent. The spread rate and wind direction are taken into computation at each vertex and it will determine how the fire polygon is propagated. Anderson [22] also proposed based on his previous study that the wildfires spread in an elliptical manner and the length to width of the ellipse is based on wind velocity. These ratios also have been identified by using past studies on different vegetation. While Huygens’ wavelet principle for fire propagation simulation was formally introduced by Anderson et al. [21], the concept itself could be found in previous studies by Sanderlin and Van Gelder [44] and Sanderlin and Sunderson [45] for their wildfire propagation modeling system called FIREFIGHTER and also in researches done by Curry and Fons [43] and Van Wagner [3].

Richards [46] proposed a framework considering the modeling of fire spread in two dimensions for heterogeneous fuel and meteorological conditions. In the study, several shapes to describe the two-dimensional fire spread are examined. It was proposed that there may be other shapes than the elliptical model proposed the studies noted above. These complex shapes are double ellipse, teardrop, and lemniscate.

Rothermel [2] proposed a semi-empirical model for identifying the propagation of surface wildfire in different environments. It is a complex model which need lots of environmental data such as fuel behavior, slope, wind, temperature etc. It's used by the United States national forest department and tested in many wildfires and said to be the most accurate available surface fire propagation prediction model. Many computerized propagation tools/systems such as FARSITE [23], FLAMmap [24] etc. use the Rothermel model as the surface fire propagation spread model.

Another of Rothermel's major contributions to the domain was his proposed model for crown fire behavior [25]. In his study, the proposed model was intended to aid well-trained fire behavior analysts to use the model without computed assisted aid to determine the characteristics of a live crown fire. The outcomes in the model are the spread rate, intensity and the size of the crown fire. The model was proposed as a method of first approximation of a live crown fire in the Northern Rocky Mountains in the USA. But however, it has been integrated to predict the crown fire propagation in both FARSITE [23] and FLAMmap [24].

Weber [13] created a mathematical model to model wildfire propagation due to radiation. Thus it can be considered a physical model. The spread is calculated based on the heat energy, which is transferred to the fuel in the front of the fire using the radiation. This model is based, mainly on the thermodynamics laws and assumptions and therefore using this model in the practical scenario should be validated prior hand.

Karafyllidis [26] tried to use the approach of genetic algorithm in order to optimize wildfire models or the algorithms. A pool of algorithms is mutated and tested for the outcome with a set of test data. If the derived or the mutated algorithm show a greater accuracy or greater fitness as they are measured, it can be taken as the next generation of an algorithm that can predict the wildfire spread.

A study was conducted by Yongzhong et al. [27] to expand the Rothermel's [2] model by considering the spatial and temporal dynamics within Cellular Automation framework. For this purpose, the authors have devised a one-neighbor ignition algorithm in order to describe the fire propagation by employing a hexagon-based cellular automata model. The advantages in the use of cellular automata method are that it is a rather powerful modeling technique and it is a preferred choice when modeling spatial and temporal variability. While it expands on an already tested fire propagation model, the drawbacks the base model had were such as multiple parameters required for calculation etc. may still affect a system implemented in this approach.

Karouni et al. [28] proposed a semi-empirical model that may better suit a developing country such as Lebanon, where they intended to implement a fire behavior prediction system. They used the experimental results that were used in Anderson's study [22] and relied on the Surface fire behavior model of Rothermel [2]. Parameters used in the model were weather, topography, wind direction, wind speed, slope coefficient, and fuel moisture content.

Kreye et al [50] suggested that there is not much effect from the fuel load to the rate of spread according to their experiments on the wildfire propagations using test wildfires. They have used the surface fuels from forests and use them in controlled environments in order to find the effect from each variable, fuel load and fuel moisture. Though the compactness increase with the increasing of fuel load which eventually increase the fuel bed bulk density, as per their experiment it didn't inhibit any sign of affecting of the rate of spread of wildfire. Thus the fuel load, which is a variables that is present in the Rothermel's surface fire behavior model have the potential to be removed with the experiments.

In 1998 Lopes, et al. came up with FireStation [29] a system that uses a raster-based GIS platform and Rothermel's surface fire spread model [2] to predict the spread. It uses both single and double ellipse template depending on the wind speed and is also capable of identifying the spread of the fire from cell to cell in a GIS platform.

Another GIS-based research was conducted by Guariso & Baracani [47]. In the study, they used two layered raster based cellular automata, one layer representing the forest canopy and its combustion and the other representing surface fuel and its combustion. They used this concept to present a simulation software that is intended for small-scale fires in the Mediterranean region. Variables other than the two represented in raster layers are introduced through the Rothermel's surface fire behavior model [2]. The modeling software is capable of real-time fire behavior prediction.

Vaclav [51] has conducted wildfire modeling using the r.ros and r.spread modules in Grass GIS. The model which was implemented is not changed but the basic of resources that are needed for running a wildfire simulation is presented there. A new module is tested and implemented as r.fire.spread which helps to get the intermediate output of the wildfire based on the time given as a parameter. Furthermore the simulations can be done based on changing moisture and wind conditions using that module in Grass GIS which cannot be done using normal r.ros and r.spread modules.

In 2004 Finney [23] came up with FARSITE, a fire growth simulation modeling system. It uses spatial information and uses many existing models for calculating the fire spread. Because of its complexity, only the users with proper fire behavior training should use FARSITE for making decisions. FARSITE can be used to compute wildfire growth and behavior for a long time under heterogeneous conditions which will be an added advantage if the fire couldn't be stopped at the first stage. It incorporates the existing models to a 2-dimensional fire growth model which makes this fire model an accurate but simple model. A specialty about FARSITE is that it is one of the first attempts at incorporating many aspects of fire behavior that have already been studied and verified individually. To be exact, FARSITE incorporates existing surface fire, crown fire, point-source fire acceleration, spotting, and fuel moistures models and studies. Thus it is rather useful in exploring the connections between the above-stated fire behavior models and understand them.

Coen et al. [30] proposed a wild land fire behavior model called WRF-Fire, which was integrated into the Weather Research and Forecasting (WRF) public domain numerical weather prediction model. What makes this approach unique is that it incorporates both surface fire behavioral models and atmospheric model. In an abstract manner, the model takes near-surface winds from the atmospheric model. These winds are passed to the fire propagation model and along with the local fuel characteristics and topography gradients, they are used to calculate the fire spread rate and direction. When the fires are ignited and the fuel is consumed, it would release sensible and latent heat fluxes into the atmospheric model’s lower layers, driving boundary-layer circulations. Thus the combined model continues to explore the sensitivity of the simulated fire characteristics such as perimeter shape, spread rate, fire intensity, terrain, fuel, wind etc. The dynamic nature of the WRF-Fire provides more in-depth insight into the fire propagation in a realistic manner.

G. Perry, A. Sparrow, and I. Owens [34] proposed PYROCART, proposed a raster-based wildfire propagation prediction system that incorporates Rothermel's [2] model and GIS. The study was intended as a test to investigate whether models such as Rothermel's [2] can be applied in New Zealand's ecosystem. And the tool was shown to have an accuracy rate of 80% in its predictive results.

BEHAVE [9] is a fire modeling and behavior prediction system that is better suited for real-time wildfire propagation predictions or unplanned ignition prescribed wildfires. Such a system would be particularly useful in supporting decisions when it comes to managing assets and resources in an active fire damage mitigation scenario (ex:- firefighters, aerial drones etc..). The system itself incorporates many wildfire behavior models such as Rothermel [2], [25], Albini [17], Albini et al. [18], Wagner [4] etc. It also incorporates ArcGIS as well.

IGNITE [48] is another fire behavior modeling system, which was developed by D. Green and A. Tridgell. It is yet another GIS-based cellular automata and it was intended not as a real-time disaster management decision support system, but as an educational tool. By using IGNITE, users can simulate major historical fires where it would allow the users to simulate specific conditions or actions that could affect the wildfire scenario. Therefore the users can observe the effect of the action on the wildfire and learn whether the action was a mistake or not. Such training would be invaluable since actions leading to disasters in a real-world wildfire scenario may result in loss of life and property, whereas IGNITE allows them to experiment without risk.

Coleman and Sullivan [49] presented a wildfire behavior prediction application called SiroFire, which was to be used by fire control officers to support decision making in wildfire scenarios. It incorporates several fire behavior models such as Rothermel's surface fire model [2], McArthur's model [20] etc. The application can run under Microsoft Windows operating system in a PC in DOS protected mode. The application was intended for Australian region by configuring the propagation models to better suit Australian Grasslands and forest litter fuel. The application was never used operationally and currently exists as a prototype due to ceased developments. Though it was continued to be used as a training tool for volunteer bush fighters.

2.4 Comparison

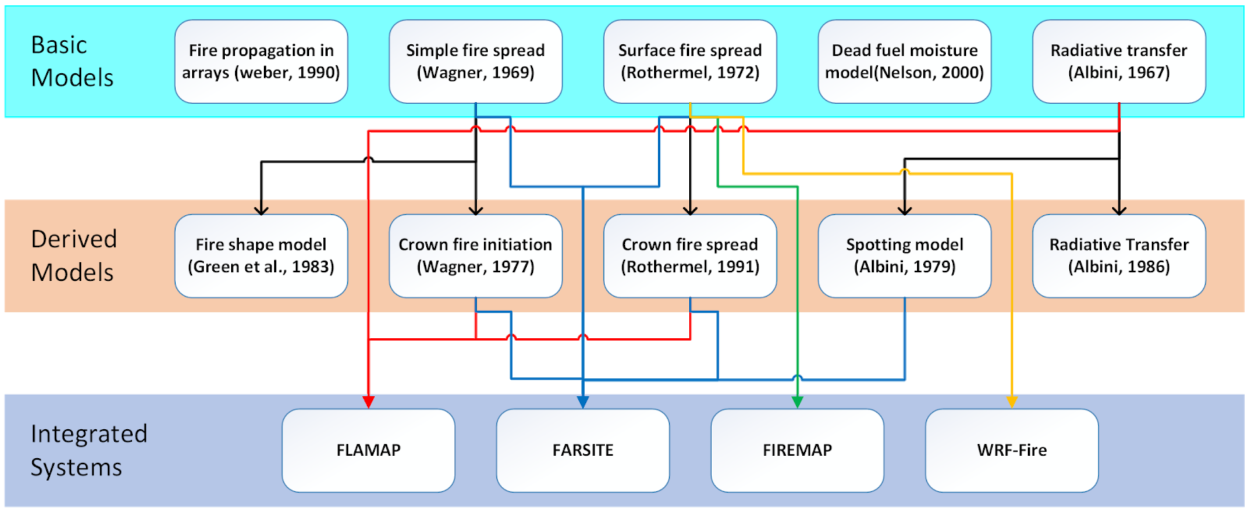

Figure 2.3: Evolution of wildfire propagation modeling

As noted in figure 2.3, there are several wildfire propagation models. Earlier models have contributed to the later models and the principles of those models have become more fine-tuned as of today, with continuous findings. Even though there are multiple fire behavior models available, they do not address the same context. As noted in the section 2.1, there are different aspects to a wildfire. More often than not, these aspects are related (ex:- crown fire is initiated after a surface fire fulfils a certain criteria, spot fires are chance occurrences and can occur with both surface and crown fires etc..). Thus to provide a more comprehensive wildfire behavior predictive solution, several models such as Wagner's crown fire model [4], Rothermel's surface fire model [2], Anderson's elliptical fire spread model [22] etc. need to be combined. A good example for such tool would be FARSITE [23]. However there are some tools that integrate traditional mathematical models and some external but vital aspects such a WRF-Fire [30] system. Its use of an atmospheric model along with the surface fire behavior model and adds some dynamic nature that represents the real-world fire behavior than a static model.

Van Wagner's [3] simple fire growth model which can be considered as one of the most preliminary approaches to all surface fire spread models. Wagner's model is based on Anderson's elliptical fire spread model [22] which was created by using results from test fire. Rothermel [2] uses the same variables used in the Wagner but also it also uses the fuels, moisture and many other variables, which are not included in the Wagner [3] or Anderson [22]. Therefore, Rothermel's model can be taken as an improvement of above-mentioned surface fire models.

Rothermel's model [2] in particular seems to have a larger impact since it is integrated into most of the wildfire spread prediction system such as Firemap [31], FARSITE [23], SiroFire [49], IGNITE [48] etc. According to Karouni et al. [28], Rothermel's model has been proven and tested in both theory and practice. But one of its drawbacks lies in the high number of input parameters required, which is about 24 [28]. Karouni et al. also notes that there is a possibility of optimizing the Rothermel's model [2] by eliminating parameters that have less effect on the overall output. But in doing so, it might reduce the accuracy of the overall model. But achieving an acceptable amount of prediction accuracy while reducing one or more variables could be considered as an achievement.

Nelson [32] suggested a dead fuel moisture model to divide the fuel in the fuel bed of the vegetation. Fuel plays an important part in wildfire propagation. Rothermel [2] uses the dead fuel moisture in calculating the fire spread. Nelson's [32] dead fuel moisture model alone cannot be used to model the wildfire spread accurately, but by integrating it with another model, it may enhance the accuracy of the spread prediction of that model as in the Rothermel [2] by giving an enhanced view of the fuel bed of the vegetation. Therefore in this aspect as well, Rothermel's model can be considered as the superior.

While surface fire models seem to be at the forefront when it comes to applicability, other aspects of wildfire such as crown fire and spot fire is present as well. But they seem to be less prominent since both of them are considered to be less understood phenomenon than surface fires and inaccurate, particularly spot fires. Frank Albini was one of the pioneers in studying the spot fire phenomenon. Due to the unpredictable nature of the phenomenon, he has often stated that the models are rather speculative [5], [17].

Though the above situation is not exactly applicable for crown fires, Perry [33] noted that crown fire too is a poorly understood phenomenon. This statement is further established by the fact that there seems to be comparatively rather low number of studies on crown fire rather than surface fire. Furthermore, crown fires do not usually occur spontaneously. Furthermore, for a crown fire to initiate, a certain minimum temperature at the base of the crown layer or a surface intensity is necessary [4]. In the wildfire behavior modeling context, this criterion is represented usually by a surface fire reaching a certain intensity leading to a fire initiation at the crown layer. Thus to model a crown fire, one may also require a surface fire model to simulate the initiation conditions. But the fact is that all surface fires do not convert to crown fires, and probability of such occurrence is low as well [33].

There also seem to be several researches that attempts to localize overseas models such as Rothermel's [2] to suit a local ecosystem. Coleman and Sullivan's SiroFire [49] and Karouni et al.'s [28] study are some examples in this context. Such research are certainly viable since, almost all of the mathematical models are implemented while keeping a certain set of geographical attributes in mind. But these geographical attributes changes from one geographical area to another. One may not find the same fuel bed content in USA and in Sri Lanka, the climates may differ, while one region considers crown fires a highly destructive force of nature, some regions may consider them a minor annoyance due to certain climate conditions. Thus these overseas models need to be configured for them to be really applicable to the local context.

Therefore, it can be concluded that of mathematical models representing aspects of a wildfire, surface fire is the most studied and understood phenomenon. Thus optimization attempts or new developments are somewhat difficult in the sub context. But crown fire and spot fire shows some good opportunities for improvements or from-scratch models, provided that there are necessary historical data for validation and most importantly, laboratory based test environments [36], [2] to conduct experimentation in order to gain more accurate results in an ethical manner. These conditions are also applicable to wildfire behavior model localizations as well.

But it is to be noted that in this particular research, historical wildfire data in the Sri Lankan region or a laboratory environment is not available. Thus a viable and accurate method to conduct experimentation on crown fires, spot fire phenomenon are seemingly unavailable. Although, since surface fire models such as Rothermel's [2] is already tested and accurate, any new models or existing model optimizations can be easily compared against for validation purposes.

Furthermore, there are many wildfire behavior prediction systems available. While some of them are prototypes such as SiroFire [49], there are several systems that are used for decision supporting even today. Feature comparison between some of the leading systems are given below in table 2.1.

Table 2.1: Comparison of leading systems for wildfire propagation prediction

	BEHAVE [9]	***FIREMAP [31]***	***FARSITE [23]***	***I-REACT [1]***
Available online	NO	YES	NO	YES
Use real-time sensor data	NO	Some Extent	NO	YES
Has alerting real time	NO	NO	NO	YES
Rothermel model used	YES	YES	YES	YES

The table 2.1 is a comparison of features in a selected few propagation systems currently in usage. While all the systems are seen to be using the Rothermel's model [2], I-REACT [1] is the only system that provides real time alerting of wildfire situations. I-REACT also employs real-time sensor data where as other systems do not except for FIREMAP [31] where sensor data are used to some extent but not in real-time. I-REACT and FIREMAP are the only system among the compared systems to be available online.

2.5 Summary

In this chapter, the related background and literature were studied. The focus was given to wildfire behavior prediction systems and to a few leading wildfire propagation prediction systems available. The models were then compared and analyzed in order to determine a model that can be enhanced. Several taxonomies on wildfire propagation models were illustrated as well.

Chapter 03

Design

In this chapter, the methodology and the design of the proposed wildfire propagation model are presented. A special focus is given on how the Rothermel's surface fire behavior model [2] was analyzed and how the variables in the model were investigated to determine their effect on the overall model. The chapter also discusses how the necessary data was collected as well. The research is to follow a mixed approach that combines design science [52] and quantitative analysis [53].

3.1 High Level Overview of Approach

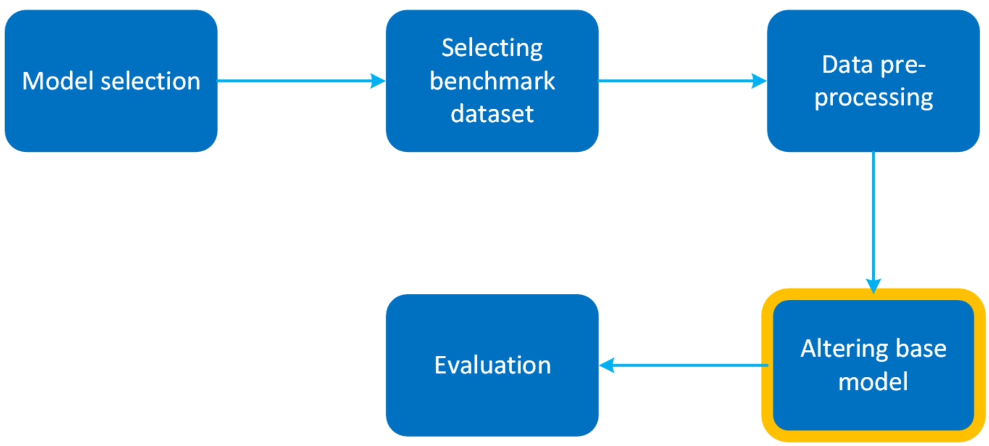

Figure 3:1: High-level architecture of the research

I. Model Selection

As the purpose of this research was to enhance a wildfire propagation model, literature relating to the context were studied and multiple models that address various aspects of wildfire phenomenon was analyzed. The selection of the final model-to-be-enhanced occurred in two steps. 1) Studying the general domain and identifying key propagation models. 2) Analyzing the key models for optimization possibilities. 3) Weighing the potential advantages and significance of exploiting the identified possibilities. 4) Weighing the feasibility of exploiting the identified possibilities. 5) Weighing the testability or the evaluability of the said possibility. While the 1) and 2) activities were sequential, other activities were conducted in a parallel manner.

As described in section 2.3, related literature was studied and key propagation models were identified. There were several types of propagation models addressing several aspects of wildfires such as surface fire, crown fire, spot fire, radiative fire transfer etc. While there were numerous models, throughout the almost a century-long scientific history of the domain, few models stood out. Rothermel's surface fire model [2], Wagner's crown fire initiation model [4], Rothermel's crown fire model [25], Albini's spot fire model [17], [20] etc.

The identified key models were then analyzed for potential enhancements. Due to the comparatively low number of studies done on crown fires and spot fires and the general lack of proper understanding about the said phenomenon, it was determined that one of the models in the said categories may very well be worth studying and enhancing. Then again, while the Rothermel's surface fire behavior model [2] was discovered to be used in almost all of the wildfire propagation systems and has been tested and proven in the practicality of the model, there seems to be a drawback in it. Karouni et al. [28] note that The Rothermel's model [2] requires 24 input variables in order to execute the simulation. To measure these input variables, a number of infrastructure and resources needs to be allocated. And for a country that lacks such resources, an undertaking of such project may very well be unfeasible. Thus Karouni et al. [28] also note that it may be possible to optimize the model by eliminating one or more of the input variables in Rothermel's model. Another potential and applicable enhancement are to localize an overseas model to suit a local ecosystem. Since most of the available propagation models are initially developed for North American region or European region, applying such models to a local context requires a considerable amount of effort.

In the next phase, the enhancement possibilities are examined for their potential advantages, significance, feasibility, and evaluability. As noted in the analysis in section 2.4, due to the low number of studies in both crown fires and spot fires [33] when compared to surface fires, the significance of enhancing a model from one of these categories are rather high. It is the same with a model localization as well. But the speculative nature of spot fires [5], [17] and its chance nature limits the historical fire data availability. In such a scenario, the best possible manner to evaluate an enhanced spot fire model would be to use laboratory environments. Unfortunately for this particular study, such facilities were unavailable. The same arguments can be made for crown fire models as well but to a lesser extent. While the significance of such research may be rather high, the feasibility and evaluability aspects suffer.

Localization attempt to configure a model such as Rothermel's model [2] would have been an ideal research avenue for this particular study. But the lack of local historical wildfire data and support from the local authorities have led to abandoning such study. It is also a high significance but low feasibility and evaluability study, similar to the above-noted enhancement possibilities.

As a research gap exists in reducing the number of input variables in the Rothermel's model [2] as noted by Karouni et al. [28], as also noted in the section 2.4, it is a viable study. There is a considerable significance in the study and historical data can be easily collected from regions where such data were meticulously collected and the Rothermel's model was implemented with the ecosystem of USA in mind. Thus such study is highly feasible and evaluable.

Therefore, according to the analysis in section 2.4 and the model selection rationale, the Rothermel's [2] surface fire behavior model was selected as the model-to-be-enhanced.

II. Benchmark Dataset

An accurate dataset is critical for a successful evaluation of the findings. Thus a credible data source that contains historical wildfire data is necessary. Furthermore, the dataset needs to contain certain variables that are needed as input variables for the Rothermel's surface fire behavior model [2]. As examples, the location of wildfire origin, elevation, aspect and environment parameters such as temperature, humidity, wind speed, wind direction etc. are just some of the necessary data that should be included in the dataset. Another criterion for the benchmark dataset collection was the size of the dataset. The candidate dataset should be of a substantial size so that after preprocessing the data, an adequate amount of data can be used for the evaluation purposes.

The above rationale was used to identify an appropriate dataset. The National Wildfire Coordination Group (NWCG) from the United States has been collecting the weather data for each wildfire that has occurred in the USA since the 1970s. Another positive aspect was that the data were freely available from their website. Furthermore, it was the only credible data source that appears to have the necessary data required for this research that could be found.

II. Data Preparation

Even though the required data can obtain from the National Wildfire Coordination Group (NWCG), these data cannot be directly used in this research. The necessary inputs for the research are included in two different data files. One file includes the weather parameter data and the other contains the data such as the date of wildfire, location of origin etc. Therefore these two files should be merged by using the weather station numbers referenced in both files.

Table 3.1: Attributes of weather data file in W Weather Observation Data Transfer Format, 2013. Attributes that will be used for the analysis are shaded in gray.

1. Record type	2. Station Number	3. Observation date	4. Observation time	5. Observation type	6. State of weather code
7. Dry bulb temperature	8. Atmospheric moisture	9. Wind direction	10. Average wind speed over a 10-minute	11. Measured 10-hour time lag fuel moisture	12. Maximum Temperature
13. Minimum Temperature	14. Maximum relative humidity	15. Minimum relative humidity	16. Precipitation duration	17. Precipitation amount based on Measurement Type code	18. Wet flag
19. Herbaceous greenness factor	20. Shrub greenness factor	21. Moisture Type code	22. Measurement Type code	23. Season code	24. Solar radiation
25. Wind direction of peak gust during the hour	26. Speed of peak gust during the hour	27. Snow Flag (Y/N)			

Table 3.2: Attributes of wildfire occurrence file in PCHA Fire Output Format. Attributes that will be used for the analysis are shaded in gray.

1. REPORTING FS REGION	2. REPORTING FS UNIT	3. FIRE NUMBER	4. DISTRICT NUMBER	5. STATISTICAL CAUSE	6. GENERAL CAUSE
7. SPECIFIC CAUSE	8. CLASS OF PEOPLE	9. FIRE SIZE CLASS	10. TOTAL AREA BURNED	11. FS AREA BURNED	12. NON-FS, UNDER FS PROTECTION AREA BURNED
13. NON-FS AREA BURNED	14. VEGETATION COVER TYPE	15. NFMAS ASPECT	16. TOPOGRAPHY CODE	17. FMZ_CODE	18. BLANK
19. REPRESENTATIVE WEATHER STATION NUMBER	20. NFDRS FUEL MODEL	21. FIRE INTENSITY LEVEL	22. FIRE INTENSITY SOURCE	23. LATITUDE	24. LONGITUDE
25. TOWNSHIP	26. RANGE	27. SECTION	28. SUB-SECTION	29. PRINCIPAL MERIDIAN	30. SLOPE PERCENT
31. ASPECT CLASS	32. ELEVATION (FEET)	33. STATE CODE	34. COUNTY CODE	35. PROTECTION AGENCY	36. OWNERSHIP AT ORIGIN
37. PRESCRIBED FIRE (Y/N)	38. ESCAPED FIRE (Y/N)	39. INITIAL SUPPRESSION STRATEGY	40. FFF COST, IN DOLLARS	41. FIRE IGNITION DATE (YYYYMMDD)	42. FIRE IGNITION TIME (HH24MI)
43. FIRE DISCOVERY DATE	44. FIRE DISCOVERY TIME	45. FIRST ACTION DATE	46. FIRST ACTION TIME	47. SECOND ACTION DATE	48. SECOND ACTION TIME
49. DECLARED WILDFIRE DATE	50. DECLARED WILDFIRE TIME	51. FIRE CONTAINED DATE	52. FIRE CONTAINED TIME	53. FIRE CONTROLLED DATE	54. FIRE CONTROLLED TIME
55. FIRE OUT DATE	56. FIRE OUT TIME	57. FIRE NAME	58. FIRE ID	59. PCODE	60. WILDERNESS

Since the data comes in a simple text file, some preprocessing has to be performed to separate the data into relevant attributes and the incomplete records are ignored. Then these data are loaded into a SQL database as two different tables. As stated above, all relevant data about a wildfire, including weather data, can be accessed from a simple select operation. Weather data table and wildfire data table respectively have 27 (Table 3.1) columns and 60 columns (Table 3.2). But for the research, only 18 attributes will be used. One reason being, some of the wildfire records lacks some important information related to fire such as the area burnt or the temperature. These types of data cannot be used for benchmarking purposes and these data rows are removed from the data set. Furthermore, a reduction was done to remove the unwanted attributes from the end table. As an example, the dataset contains data fields such as fire_id, Fire_name, Organization identified etc. Those fields are useless for benchmarking the model and therefore, they can be eliminated from the data set. The sample of the data which can be used for the comparison with the model is selected based on the quality of the final aggregated dataset taken from the preprocessing.

In GRASS GIS, the data cannot be directly fed in txt or CSV formats. GRASS GIS employs the reusability. Therefore each input variable should be fed into the system as a separate file. The implemented model uses 11 data fields for running the model and there are 11 separate data files for each wildfire. Thus the selected sample benchmark data set should be converted to that format. One dominant function of the research is to create these files from the available data.

II. Altering the Base Model

As stated before, one of the objectives in the research is to simplify a fire behavior model by reducing the number of input parameters required and investigate to what extent the predictions are similar to the actual spread of a wildfire. One requirement in this process was to select a modeling platform to run the fire behavior models. The open source platform GRASS GIS catered all the modeling specification from its fire behavior module. The wildfire spread simulation in GRASS GIS is done using three modules, namely r.ros, r.spread and r.spreadpath. Since the source codes of these modules are available for the public and the modified or newly created modules can be locally installed using the GRASS g.extension, the alterations of fire behavior models and visualization became possible. Primarily the fire behavior model in GRASS GIS use Rothermel's surface fire model. The model alteration process is illustrated in the figure 3.2 and a simulation of a wildfire in GRASS GIS in two separate lag times is depicted in the figure 3.3.

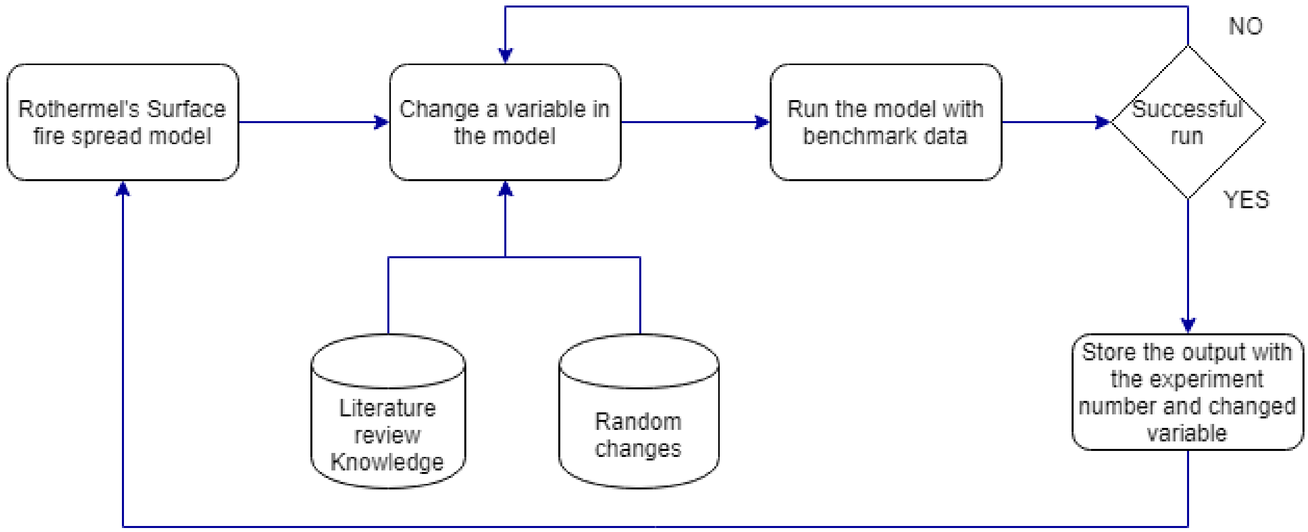

Figure 3.2: Base model alteration process

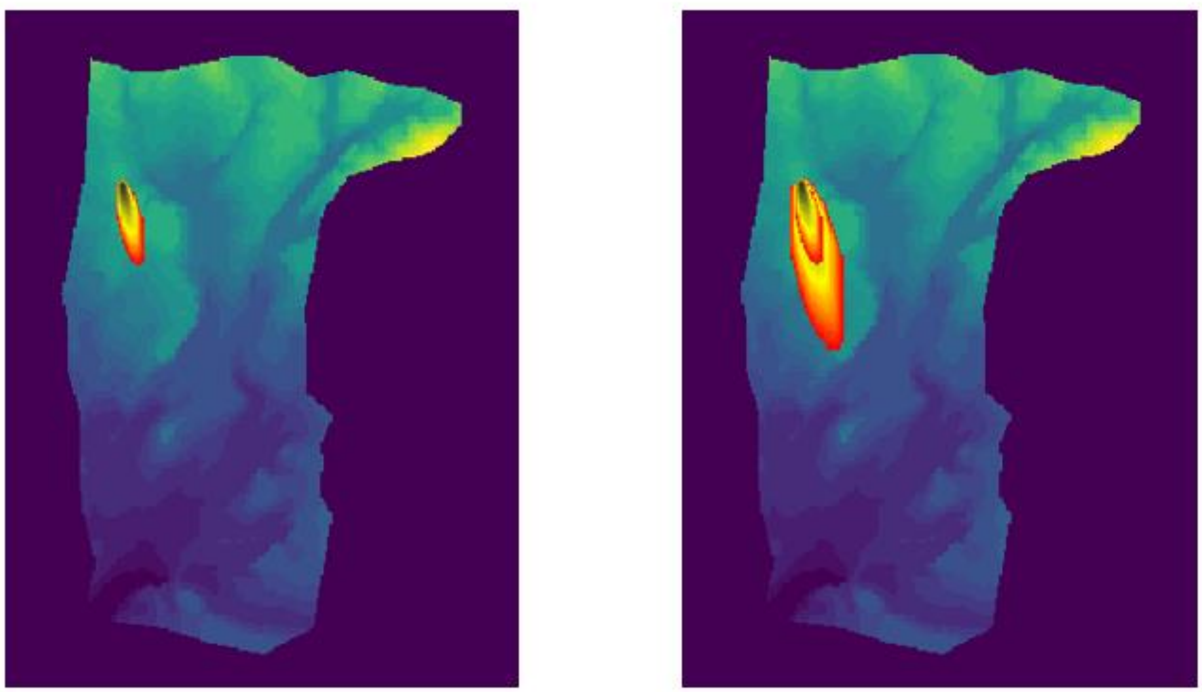

Figure 3.3: A fire simulation of a wildfire using GRASS GIS; A spread of a wildfire in different time intervals. Left: 10 min after ignition, Right: 20 min after ignition

II. Evaluation

Initially a pilot study was conducted by altering the default data available in GRASS GIS. The shapefile of the base model prediction is compared against each of the predictions in the five altered models. Statistical measures used in this analysis is the 1) Jaccard similarity coefficient and 2) Euclidean distance between mean coordinates of the base model and altered model spreads. Thus the results are evaluated in 2 statistical methods to ensure its validity.

After the pilot study, random sampling is applied to the dataset and an unbiased sample of 10 wildfires were selected. These wildfires are then configured into the GRASS GIS and then the base Rothermel's propagation prediction spreads are computed for each of the wildfires.

Jaccard Similarity Coefficient

Jaccard Similarity Coefficient is a statistical index by P. Jaccard [54] in 1901. It is a rather straightforward comparison method particularly suited for geometric shape comparisons such as wildfire spread shapes [55]. The value is defined by dividing the intersection burned area of two different wildfire spreads by the union of the two spreads. Thus initially base model spreads and altered model spreads for each of the sample objects are computed and then all the 7 spreads (1 base model + 5 altered models) are input into the QGIS. Then the intersections and unions are computed for each of the base - altered spread combinations. This process is continued to other sample objects as well. Intersection and union operations are somewhat computationally intensive due to the large attribute tables for each spread. The Jaccard Similarity Score is often involved in evaluating wildfire propagation simulations according to J. Filippi, V. Mallet and B. Nader [55]. Thus it is considered to be the primary evaluation method in this study.

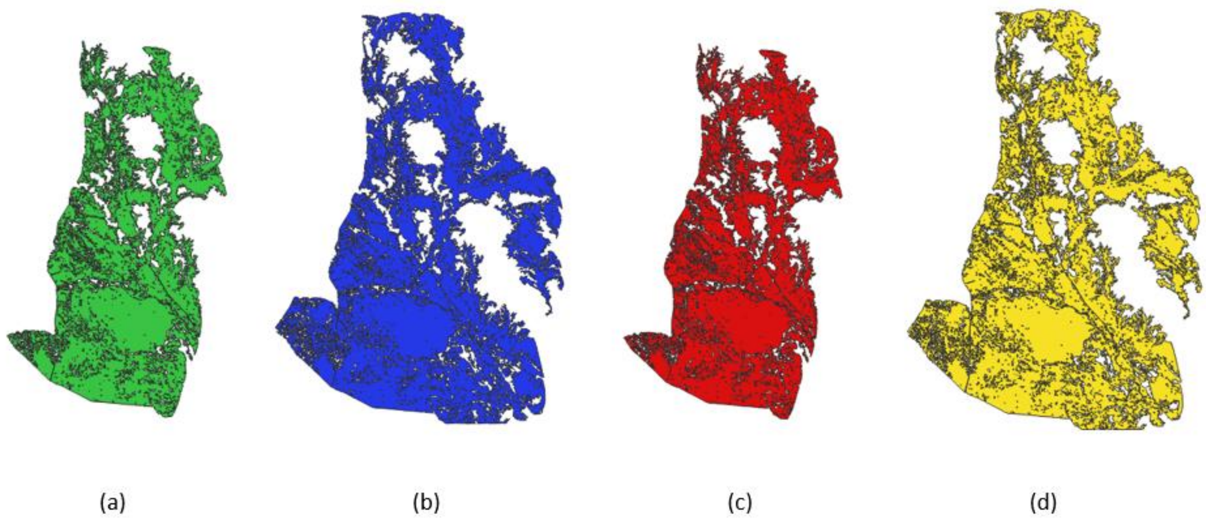

Figure 3.4: a) Base model spread, b) altered model spread, c) intersection between a & b, d) union between a & b.

Consider,

Spread of base model = $S^0(t)$

Spread of altered model = $S(t)$

$$J = \left| \frac{S^0(t) \cap S(t)}{S^0(t) \cup S(t)} \right| \qquad (1)$$

Score range - [0, 1]

Best score - 1

Euclidean distance between mean coordinates

The second statistical measure employed in the study is the Euclidean distance MOD (Most Occurring Data) Sign analysis between mean coordinates of the base model spread and the altered model spreads. While the Jaccard Similarity Coefficient can be used to measure the similarity between shapes, to provide a more sound statistical evaluation, mean coordinates for all spreads are calculated. Then the scatter plots are drawn for each alteration. If the distance between the mean coordinates of an altered model and the base model is 0, it can be considered as an exact match.

Only the sign of the distance measure is used for the analysis using this method. The sign is measured using a relativity measure. If the size of the altered model wildfire spread is larger than the base model, the distance is calculated from the center coordinate/mass of the altered model to the base and relative to that the sign is given as positive(+). If the altered model spread is smaller than the base the distance is measured from the base model center to altered model center and the sign is given as negative(-). The sign of the 0's also taken as positive (+). For all the wildfires used for study, these signs were tabulated and get the MOD(Most Occurring Data) sign as the sign of that altered model respective to the base model. The positive (+) and the negative (-) signs assigned to the measured Euclidean distances are to identify the practicality of the altered models. The models which have a MOD sign positive are taken as practical models than models which show negative (-) MOD sign.

The complete design overview is depicted in the figure 3.5.

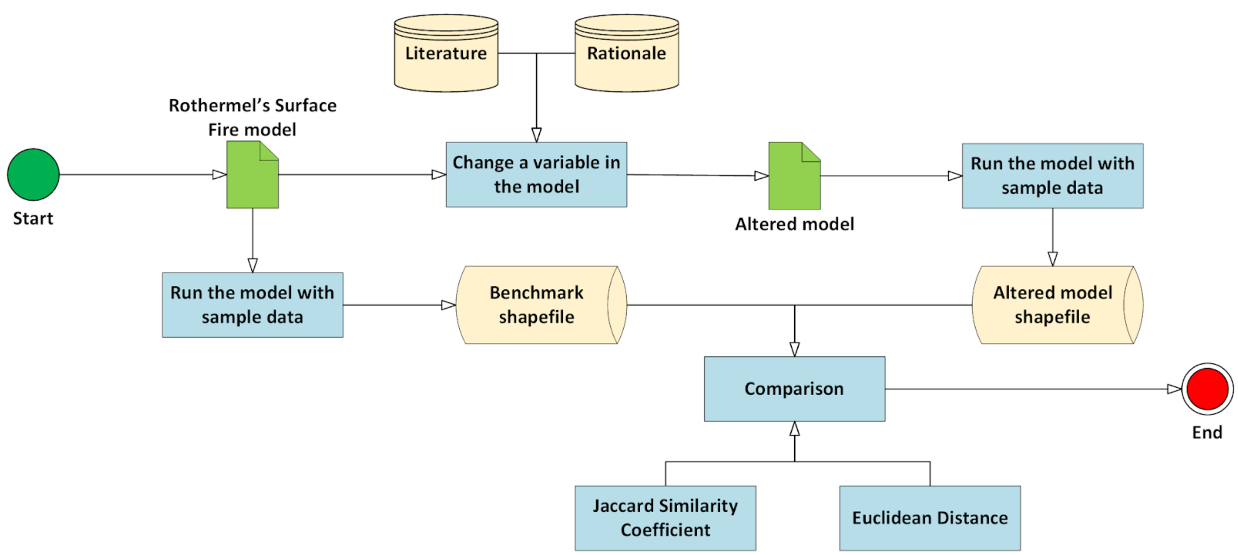

Figure 3.5: Design overview

3.2 Design Assumptions

The following are considered as the design assumptions taken for this particular study.

- The output spread by the Rothermel's [2] base model is considered as the actual spread of the historical wildfire in the primary analysis. The spread is then considered as a benchmark to evaluate altered models.

- Some parameters are taken from the closest weather station to the fire origin coordinates. These parameters are assumed to be the actual coordinates affecting the wildfire.
- It is assumed that benchmark data are accurate.
- When altering the base model by eliminating a variable, it is assumed that the effect of the eliminated variable to the overall model is isolated and not correlated with other variables.

3.3 Rothermel's Surface Fire Behavioral Model

$$R = \frac{I_R \xi \left(1 + \phi_w + \phi_s\right)}{\rho_b \varepsilon Q_{ig}}$$ Rate of spread (ft/min) (2)

$$I_R = \Gamma' w_n h n_M \eta_s$$ Reaction intensity (Btu/ft 2-min) (3)

$$\Gamma' = \Gamma'_{max} \left(\beta / \beta_{op}\right) exp \left[A\left(1 - \beta / \beta_{op}\right)\right]$$ Optimum reaction velocity (min-1) (4)

$$A = 133\sigma^{-0.7913}$$

$$\Gamma' = \sigma^{1.5}\left(495 + 0.0594\sigma^{1.5}\right)^{-1}$$ Maximum reaction velocity (min-1) (5)

$$\beta_{op} = 3.348\sigma^{-0.8189}$$ Optimum packing ratio (6)

$$\beta = \rho_b / \rho_p$$ Packing ratio (7)

$$\eta_M = 1 - 2.59 r_M + 5.11\left(r_M\right)^2 - 3.52\left(r_M\right)^3$$ Moisture damping coefficient (8)

$$r_M = M_f / M_x \ \ (max = 1.0)$$

$$\eta_s = 0.174 S_e^{-0.19} \ \ (max = 1.0)$$ Mineral damping coefficient (9)

$$\xi = (192 + 0.2595\sigma)^{-1} exp\left[\left(0.792 + 0.681\sigma^{0.5}\right)(\beta + 0.1)\right]$$ Propagating flux ratio (10)

$$\phi_w = C U^B \left(\beta / \beta_{op}\right)^{-E}$$ Wind factor (11)

$$C = 7.47 exp\left(-0.133\sigma^{0.55}\right)$$

$$B = 0.02526\sigma^{0.54}$$
$$E = 0.715exp\left(- 3.59\ X\ 10^{-4}\sigma\right)$$

$$\phi_s = 5.275\beta^{-0.3}(\tan\phi)^2$$ Slope factor (12)

$$\varepsilon = exp\left(- 138/_{\sigma}\right)$$ Effective heating number (13)

$$Q_{ig} = 250 + 1116M_f$$ Heat of pre-ignition (Btu/lb) (14)

3.1.1 Rate of Spread (2)

In a wildfire propagation simulation, the final equation that the simulation needs to calculate is the Rate of spread equation (ROS). But to determine the variables necessary for such calculation, there are numerous mathematical equations that are necessary for calculating other variables that matter. It would affect the accuracy of the model to an unacceptable level if one were to eliminate a variable from the final equation itself. A more reasonable approach would be to simply eliminate variables in secondary equations to gauge their effect on the final outcome.

$$R = \frac{I_R\xi\left(1 + \phi_w + \phi_s\right)}{\rho_b\varepsilon Q_{ig}}$$

R Rate of spread (ft./min)

I_R Reaction intensity (B.t.u./ft.^{2} min.)

ϕ_w Wind coefficient

ϕ_w Slope coefficient

ϕ_s Ovendry bulk density (lb./ft.^{3})

ε Effective heating number

Q_{ig} Heat of pre-ignition (B.t.u/lb.)

3.1.2 Reaction Intensity (3)

The heat release rate per unit area of the fire front is called the reaction intensity [2]. The heat release rate is determined by the burning gases produced by burning organic matter in the fuels. Reaction velocity is another major equation that highly affects the final outcome of the model and similarly to ROS, it is appropriate to affect the variables of the equation indirectly.

$$I_R = \Gamma' w_n h n_M \eta_s$$

I_R Reaction intensity (Btu/ft 2-min)

Γ' Potential reaction velocity (min.-l)

w_n Net initial fuel loading (lb./ft.2)

h Heat content of fuel (B.t.u./lb.)

n_M Moisture damping coefficient having values ranging from 1 to 0, dimensionless.

η_s Mineral damping coefficient having values ranging from 1 to 0, dimensionless.

3.1.3 Optimum reaction velocity (4)

Reaction velocity is the ratio of the reaction zone efficiency to the reaction time [2]. It is another major equation relevant to the fire propagation. From it, the completeness and the rate of fuel consumption can be determined.

$$\Gamma' = \Gamma'_{max}\left(\beta/\beta_{op}\right) exp\left[A\left(1 - \beta/\beta_{op}\right)\right] \quad (4)$$

$$A = 133\sigma^{-0.7913} \quad (4)$$

$$\Gamma' = \sigma^{1.5}\left(495 + 0.0594\sigma^{1.5}\right)^{-1} \quad (5)$$

$$\beta_{op} = 3.348\sigma^{-0.8189} \quad (6)$$

$$\beta = \rho_b/\rho_p \quad (7)$$

Γ' Potential reaction velocity (min.-l)

β Packing ratio (dimensionless)

β_{op} Optimum packing ratio (dimensionless)

σ Fuel particle surface area to volume ratio (ft.-2)

σ_{op} Optimum fuel particle surface area to volume ratio (ft.-2)

ρ_b fuel array bulk density (lb ./ft.3)

ρ_p fuel particle density (lb./ft.3)

3.4 Summary

In this chapter, a detailed description on the architecture of the research was given. Model selection criteria, selection benchmark data, data pre-processing, model alteration and evaluation were elaborated in a detailed manner and design assumptions were given as well. Furthermore, the Rothermel's [2] model was analyzed noting its equations and variables as well.

Chapter 04

Implementation

Implementation was done through the Grass GIS open source software. Grass GIS is used because it has an integrated wildfire spread simulation module. This chapter describes the implementation methods and decisions taken in the process of implementation. Implementation of the design could be done in 3 steps. Importing the data as layers to the Grass GIS, Run the ROS model and then run the r.spread module to get the spread. As prerequisite Grass GIS software should be installed and it should be in an Ubuntu or Linux based computer. The Grass GIS in Microsoft Windows doesn't allow to install extensions from different paths. After the alteration r.ros module with the altered main file should be installed separately in order to gain the final outcome. Therefore, an operating system with a Linux kernel base should be used.

4.1 GRASS GIS

GRASS GIS is a free and open source Geographic Information System software platform, which is used in geospatial data management and analysis, image processing, graphics and maps production, spatial modeling, and visualization. When compared with other solutions, GRASS GIS is used mostly for scientific purposes. Currently, GRASS GIS is used by researchers, universities, and government agencies.

With the approach of the research, there were two possibilities, either to develop the modeling and visualization from the scratch or use existing tools. The requirements of the study were to run the fire behavior model, visualize the results and comparison. The r.ros module of the GRASS GIS implements the Rothermel's surface fire behavior model and since the software is open source, the changes to the model can be done conveniently.

4.2 Fragmentation of the benchmark dataset

The benchmark data set consist of data from 1964 to 2017. The dataset is very large and using all the data of wildfires for the benchmarking purposes is not practical. Thus that before creating the database from the set of files which downloaded from the National Wildfire Coordination Group (NWCG) a sample should be selected. The wildfire data set consist of wildfire data from 35 regions and the weather data set consist of data from 52 regions.

Hence the wildfire dataset has a comparatively smaller number of regions and also it's the main focus of the research based on that the sample is selected. For selecting the sample a simple random sampling was done. The threshold was set to 10 regions thus that the data set is manageable within the time frame for the research.

After selecting the random 10 regions and related weather data as a sample, the main sample is again divided into 4 main samples based on the area(high and low) that it covers and the year of occurrence(before 2000 and after). The main rationale behind these 2 sample fragmentation was,

1. Area: - The changed wildfire model should be compatible in using in any fire like the base model. If the changed model shows a high error rate when the area is small/ large but good with only one aspect (small/large), that alteration cannot be taken as stable. Thus to take the alteration as stable wildfires in both aspects should show low errors which means low area changes from the real area. From the selected sample 2 sets of data were created as wildfires with high area burnt and wildfires with low areas burnt.

2. Year of occurrence: - The wildfire data which were taken in past days like 1964 can be error-prone. The details given could be stated as approximately due to difficulties like reaching the place as well as the errors of the equipment used at that time. But the data from the years before 2000 cannot be neglected because many wildfire models were created based on the data from that era. Thus that the altered model should be tested with wildfires of both aspects. For that this sampling was done.

The end of this process, a sample of 10 wildfires was selected and was consequently experimented upon.

4.3 Generating Custom Dataset for Fire Simulation

Generating a custom data set other than the demo set provided, is one of the biggest challenges that was faced during the implementation. The documentation provided by Grass GIS didn't mention any detail on how to create a custom data set. After researching through available documentation, articles, from the user email list of Grass GIS, some leads were found regarding the preparation of a custom dataset. As custom data, many files should be created and those should be created using the modules in the Grass GIS. The benchmark dataset contains all the necessary data and using that data, custom data sets for many wildfires can be created. Main files that should be created per one wildfire in order to simulate a wildfire are slope, wind direction, wind speed, slope, aspect, fuel model, fire origin, live moisture.

4.3.1 Generating aspect and slope files

To generate the slope and aspect files the elevation map of the respective area should be inserted to the Grass GIS. Those elevations files can from the United States Geological Survey (USGS) Earth Explorer database and then it can be imported to the Grass GIS. Thus that using the r.slope.aspect this can be

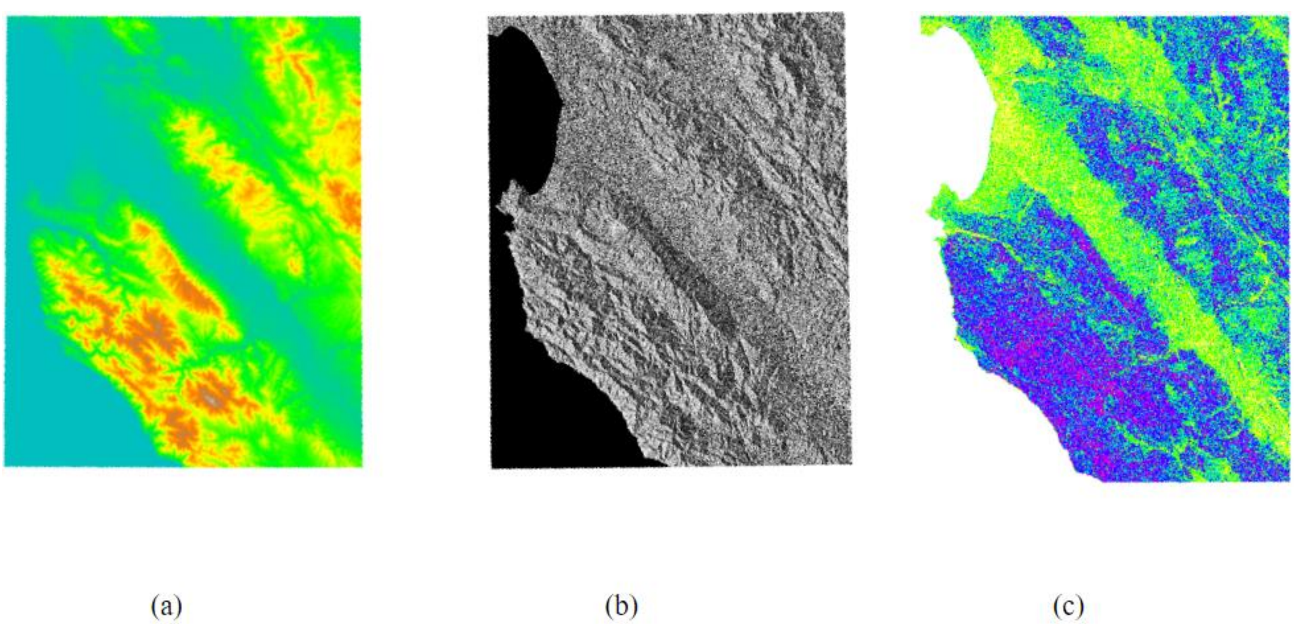

Figure 4.1: (a) Elevation map obtained from United States Geological Survey (USGS); (b) Aspect map generated from (a); Slope map generated from (a)

4.3.2 Generating the fire origin

The ignition point of a specified wildfire can be obtained from the data gathered from the National Wildfire Coordination Group (Table 3.2). To mark this point in a raster map GRASS GIS raster digitizer can be used. It provides facility to mark a point in a map and this will be used as the ignition point.

4.2.3 Generating the fuel model

To create fuel model raster file we collect land cover maps from the Multi-Resolution Land Characteristics Consortium (MRLC).

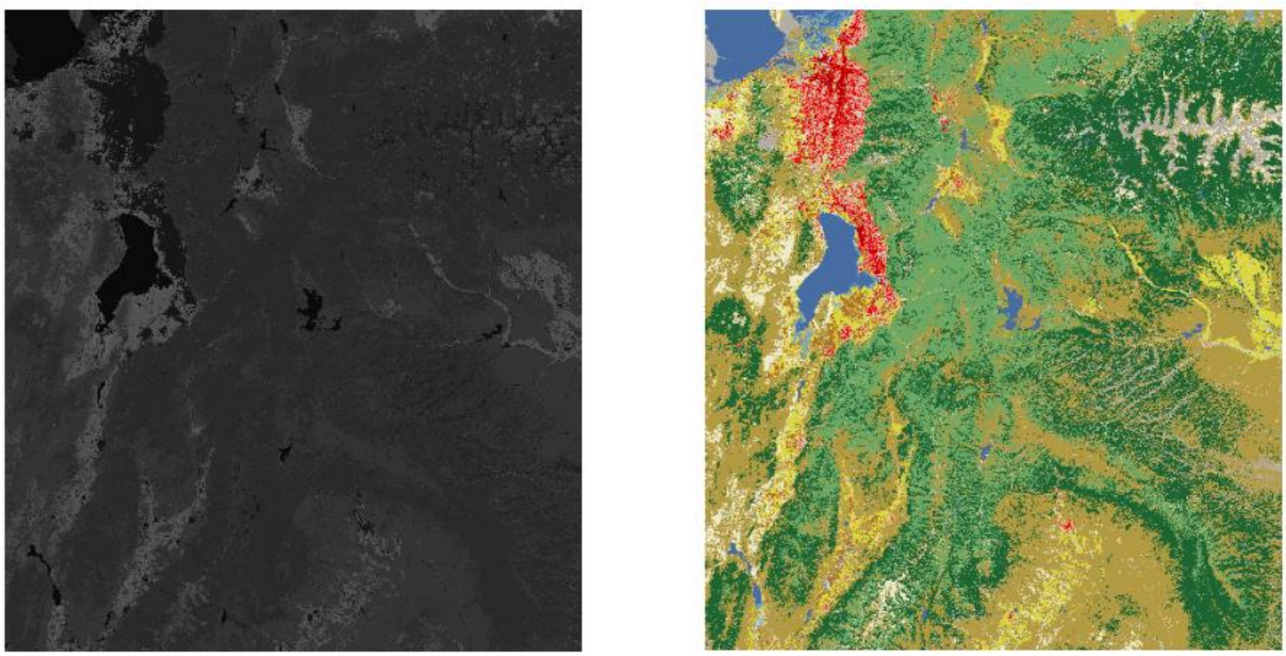

Figure 4.2: A land cover map obtained from Multi-Resolution Land Characteristics Consortium; Left: Unprocessed map, Right: Processed map by changing colors interactively according to categories.

Table 4.1: Multi-Resolution Land Characteristics Consortium (MRLC) National Land Cover Database 2011 (NLCD) Legend.

	11 Open Water		51 Dwarf Scrub
	12 Perennial Ice/ Snow		52 Shrub/Scrub
	21 Developed, Open Space		71 Grassland/Herbaceous
	22 Developed, Low Intensity		72 Sedge/Herbaceous
	23 Developed, Medium Intensity		73 Lichens
	24 Developed, High Intensity		74 Moss
	31 Barren Land (Rock, Sand, Clay)		81 Pasture/Hay
	41 Deciduous Forest		82 Cultivated Crops
	42 Evergreen Forest		90 Woody Wetlands
	43 Mixed Forest		95 Emergent Herbaceous Wetlands

4.3.4 Generating the wind speed and wind direction

Wind speed and wind direction raster files can be manually created from the r.mapcalc module using the data collected from National Wildfire Coordination Group (Table 3.1). Example commands to create these raster files are as below.

r.mapcalc --overwrite expression=wind_speed = 120

r.mapcalc --overwrite expression=wind_direction = 156

4.3.5 Generating the live moisture

The land cover map obtained from the MRLC contained 20 categories. The next step is to create raster file assigning live moisture values for each of the 20 categories.

4.4 Importing Dataset to GRASS GIS

At the start of the GRASS session (figure 4.3), the demo data or the custom data that are going to be used for wildfire simulation has to be selected. The process can be done in 2 methods,

1. Use demo data which is available in the Grass GIS documentation can be downloaded, extracted and make use of it.

2. Generate custom data set using the benchmark dataset

The demo data provided by the Grass GIS are relevant to one specific fire and the exact location of the fire origin is also not included in the data, thus it could be only used for demo purposes or pilot studies. As explained in section 4.1, custom data sets can be generated from the benchmark dataset. This is the methodology used in the implementation.

The path to the data should be selected from the starting screen depicted in figure 4.3 and then the session can be started.

Figure 4.3: The First screen of Grass GIS

The Grass will start with two screens and one screen is for layer management, which is named layer manager as shown in figure 4.4. The layers which need to be seen on the visualization or the layers which can be used for any type of computation can be seen in this window. The other screen, Map display screen is the main display, which shows visualizations of the map layers. Several map layers can be imported to the layer manager at once and specific layers, which need to be seen from the map display window can be selected.

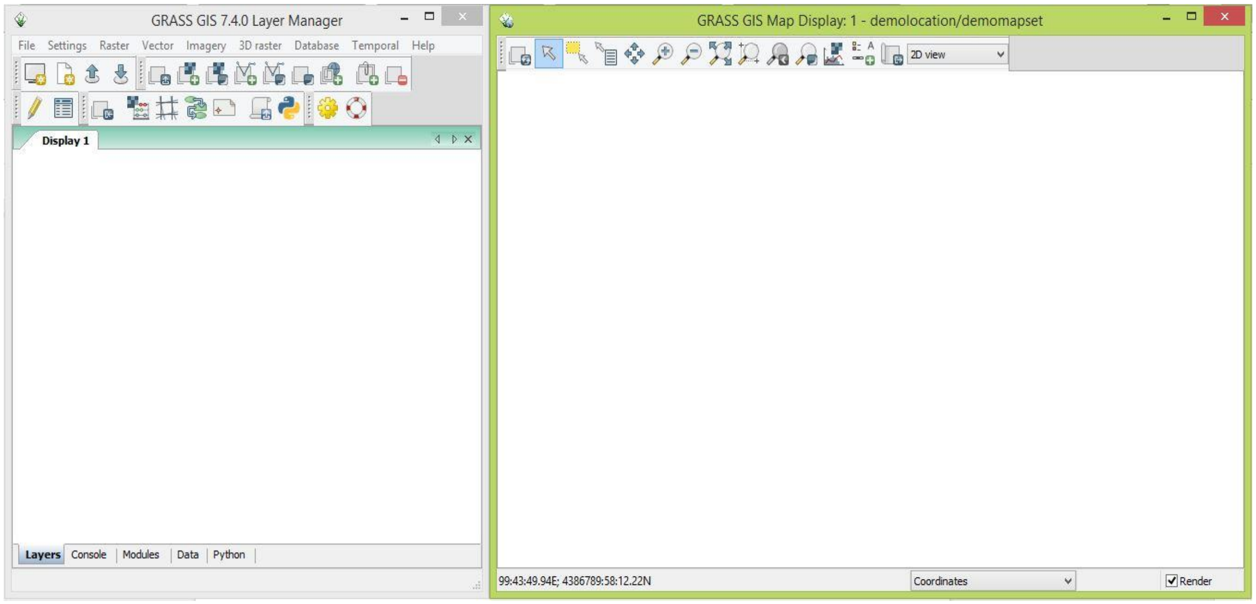

Figure 4.4: Layer Manager and Map display screens of Grass GIS

To run the wildfire spread calculation, all raster layers that provide the necessary data should be imported. The files are 1hour_moisture, aspect, elevation, fie origin, fuel_model, live_moisture, slope, wind_direction, wind_speed. All these files should be generated and imported per one wildfire to simulate the wildfire.

4.5 Altering the Implemented Rothermel's Model

The base model (Rothermel's surface fire spread model) is implemented in the Grass GIS in C language. The file named as main is positioned inside the r.ros module. After installing the Grass GIS the file cannot be accessed directly. For that, the source code of the Grass GIS should be downloaded separately. Inside the Source code in the extensions section, the r.ros module can be seen as a folder. The main file resides inside that folder and the changes can be done by opening file with an editor. The C file consists of the basic variables and equations of the Rothermel's model. The alterations can be done by removing or altering the variables and equations from the file and installing using the following command.

g.extension extension=<name> url=<url>

After running the command, the altered main file will be installed as the basic model for running the wildfire simulation.

4.6 Executing the r.ros module

Module r.ros is the wildfire modeling module of the Grass GIS. Rothermel [2] is the implemented basic wildfire spread model here. After importing the layers those layers can be separately inserted into the module. There are 2 ways for inserting the imported layers into the module and run.

1. Selecting the files from the GUI and run
2. Selecting the files from a command in the console and run.

4.6.1 Select the files from GUI

Go to raster→ wildfire modeling → Rate of spread (r.ros) in the layer manager window. Then from the next window that appears in the required tab, the files from the folder that was selected at the start of the session have to be selected. All files in the tab are required and if one file is missing, the module will not run. The main files that need to be selected here are fuel model, live moisture, and output raster maps for base ROS, Maximum ROS and direction of the maximum ROS.

In the next tab which is mentioned as optional, it also contains another set of files that need to be selected in order to run the wildfire modeling. The files that should select in the optional tab are 1-hour moisture, midflame wind velocity, wind direction, slope, elevation, aspect and output raster map for maximum spotting distance. Spotting here is an optional behavior so that files related to that are optional for running the module.

After selecting all relevant files, in the top of the optional tab, there is an option "Allow output files to overwrite files" this option should be enabled since if the existing files have data and if those files do not support overwriting, the data which generated from running the simulation cannot be stored there. It will lead to a loss of information. Thus this particular option should be enabled in order to preserve the data when running the simulation. After selecting the aforementioned the run button has to pressed and it will show in a console window the status of the simulation as completed or not and if any error happened the error as well.

4.6.2 Select the files from the command line

The most convenient and nimble way to execute r.ros module is using the command line. Here r.ros command will be used to initiate the execution by using input and output raster files as parameters. Following is a sample command to execute r.ros module.

r.ros --overwrite --quiet model=fuel_model@demomapset moisture_1h=1hour_moisture@demomapset moisture live=live_moisture@demomapset velocity=wind_speed@demomapset direction=wind_direction@demomapset slope=slope@demomapset aspect=aspect@demomapset elevation=elevation@demomapset base_ros=my_ros.base max_ros=my_ros.max direction_ros=my_ros.maxdir spotting_distance=my_ros.spotdist

In this command, we use fuel model, moisture_1h, moisture_live, velocity, direction, slope, aspect, elevation raster files and create three output files as the base rate of spread, max rate of spread and direction of the max rate of spread. These output files later used in r.spread module as the input

4.7 Execution the r.spread

r.spread module is used for simulating elliptical spreads along with time. Following the r.ros module, this r.spread module should be run using the ROS calculated in the r.ros module. The visualization of the wildfire with the time is done in this module.

Similar to the way that r.ros module ran stated in the 4.5 section, the r.spread module too can be run in two methods,

1. Run using GUI
2. Run using the command line

4.7.1 Execution using GUI

Go to raster → wildfire modeling → anisotropic spread simulation (r.spread) from the layer manager window. Afterward, when the next window appears, the input files should be selected. From the input tab, the files to be selected are files for base ROS, Maximum ROS, the direction of the maximum ROS (Which were considered as the output files when running the r.ros module), starting source (fire_origin), wind speed and maximum spotting distance. In the output tab, the file for output spread time observed has to be selected. Afterward, from the optional tab, select the 'allow output files to overwrite existing files' option is to be selected to save the outputs from the simulation as well as to enable reuse. At last, press the 'run' button and it will take some time for running and in the map display window, it will display the simulated wildfire spread.

4.7.2 Execution using the command line

The r.spread module also can run in the console with r.spread module. Again the input and output raster files are used as parameters. Here the rate of spread files generated from r.ros module the ignition point of the fire, wind speed and direction will be used as input files and it generates. Following is a sample command to execute r.ros module.

r.spread --overwrite base_ros=my_ros.base@demomapset max_ros=my_ros.max@demomapset direction_ros=my_ros.maxdir@demomapset start=fire_origin@demomapset spotting_distance=my_ros.spotdist@demomapset wind_speed=wind_speed@demomapset output=spread_time_observed

The output of this module is the visualization of wildfire spread in the map display window as the illustrated in figure 4.5.

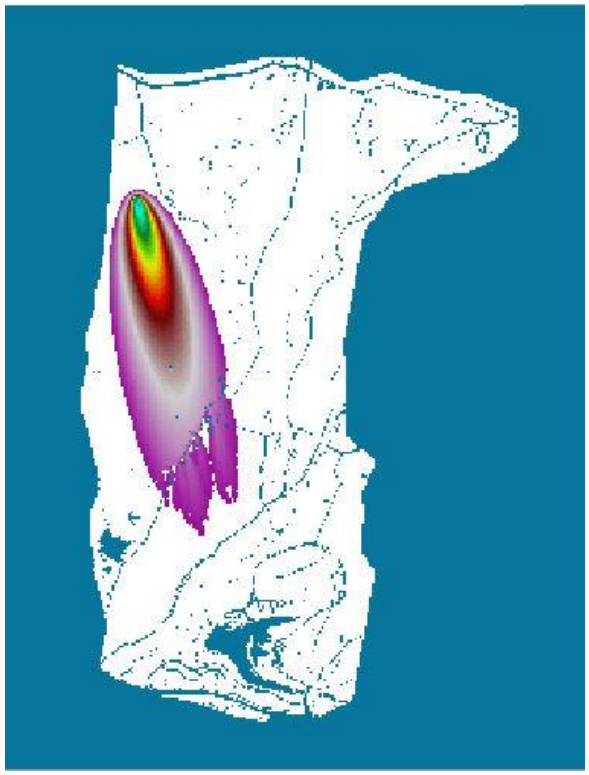

Figure 4.5: The output from running the base Rothermel model for demo data

4.8 Summary

This chapter elaborates on the configuration of GRASS GIS and implantation of altered models in a highly technical detail. The main topics discussed in the chapter are the data sample selection process, custom dataset generation, importing data to GRASS GIS, alteration of GRASS GIS and execution of r.spread and r.ros modules in GRASS GIS.

Chapter 05

Evaluation & Results

Evaluating the precision of a wildfire spread simulation is a critically important task. In general, the spread of a wildfire is measured using the area burned. However, the measuring of the performance of a wildfire model does not have a specific evaluation technique. The performance of the existing wildfire model can be measured using the area which given as output. In this chapter, the pilot data and sample data are experimented and analyzed upon to determine the similarities between the base model propagations and altered model propagations. The primary statistical measure used in this venture is the Jaccard Similarity Coefficient. Secondarily the Euclidean distances between the mean coordinates of propagations are measured.

5.1 Evaluation Experiment

5.1.1 The Aim of the Experiment

The aim of this evaluation experiment is to consider the similarity between the outputs of Rothermel's [2] model and the altered models that were derived from the Rothermel's model by eliminating variables. Each of the five models defined has a single variable of the base Rothermel model eliminated and the effects of the each eliminated variable on the base model is assessed.

5.1.2 Experiment Design

The main Apparatus used for the evaluation experiment is GRASS GIS, r.ros & r.spread modules. The diagrammatical representation of the evaluation experiment and experimental protocol are given below.

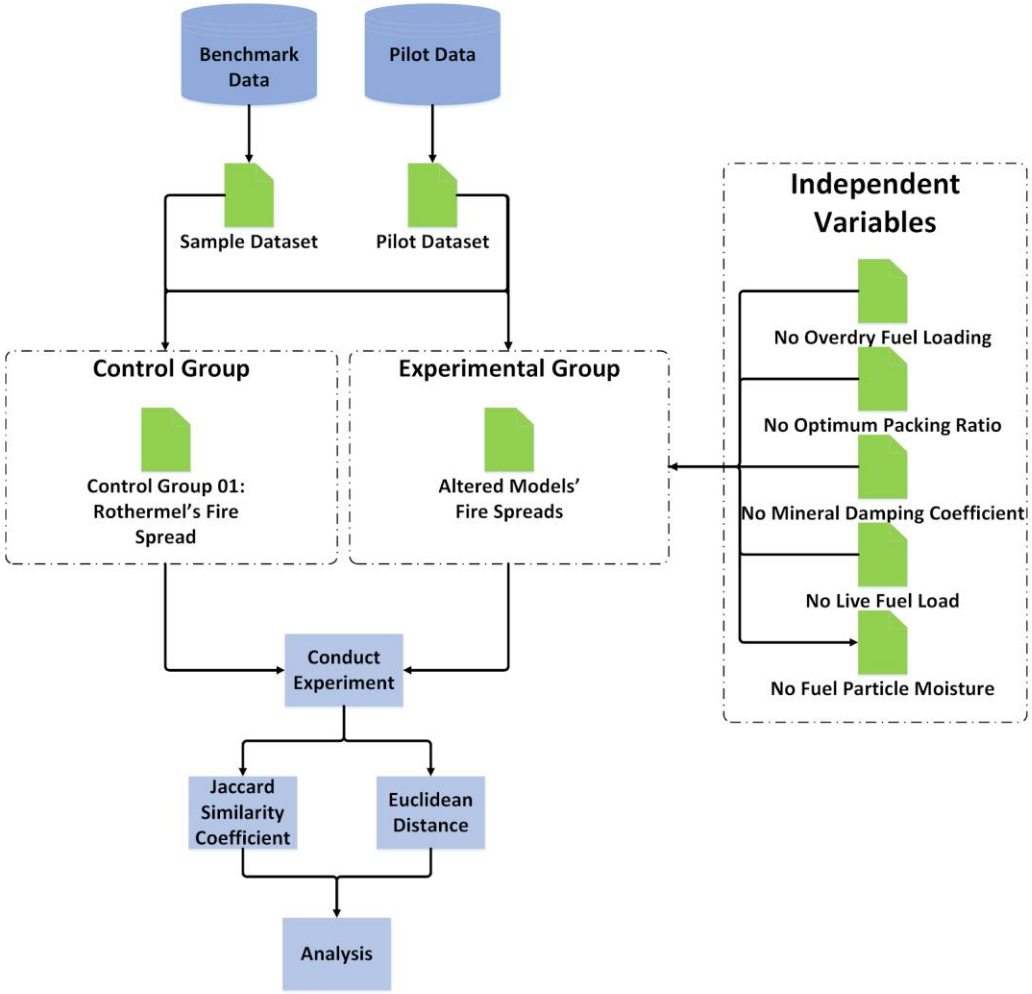

Figure 5.1: Design of the evaluation Experiment

Experimental Protocol

Table 5.1: Experimental protocol

Purpose	A possibility exists in optimizing Rothermel's [2] model by reducing its variables [28]. Thus five variables have been identified from the related literature and it should be investigated to determine whether these variables can be eliminated.
Materials	Rothermel's Surface Fire Behavior Model [2], Dataset: National Wildfire Coordination Group (NWCG), GRASS GIS sample dataset.
Method	1. Create an altered instance of Rothermel's model for each of the identified variables (eliminate the variable from the base model). 2. Run each of the altered models for sample objects. 3. Acquire shapefiles for each instance in step 2. 4. Calculate the Jaccard Similarity Coefficient and Euclidean distance of mean coordinates. (refer to section 3.1)
Controls	Fire spread shapefiles for each sample object by executing Rothermel's model [2].

5.1.3 Variables

- Independent Variables
    - Ovendry fuel loading
    - Optimum packing ratio
    - Mineral damping coefficient
    - No live fuel load
    - No fuel particle moisture
- Dependent variable
    - Area of spread
    - Mean coordinate of the spread

- Fixed variables
    - Other input variables of Rothermel's model except for independent variables.

5.1.4 Experiment

The experiment was done using the base model and the altered models. Initially, a sample of wildfires was selected from a historical wildfire dataset with the necessary weather data. Afterward, the base model was run with the data and the spreads are exported as a shapefile. The other altered models were executed after the base model and their shapefiles were exported respectively as well. The shapefiles were then imported to the QGIS software and afterward, each of these altered model shapefiles was compared with the base model shapefile. The union and the intersection of the two selected spreads were calculated, for calculation of the Jaccard Similarity Coefficient [55]. Thereafter, the Euclidean distance between the centers of masses of two spreads should be calculated. The mean coordinate module in QGIS executes an algorithm for calculating the center of mass of each spread and output a point for each spread. Then the measure line tool in QGIS can be used to measure the distance between those two points to get the Euclidean distance.

The positive and negative signs were given based on the direction of mean coordinate when compared to the base model. The distance is measured from the center of mass (mean coordinate) in the base model spread to the center of mass in the altered model spread. If the direction of measuring was towards the fire origin from the base model simulation, the Euclidean Distance is taken as negative (-). If the direction is away from the fire origin the Euclidean distance is taken as positive (+). The rationale behind the giving signs is if these models were used for wildfire disaster management system the simulated spreads should be larger than or equal to the real spread. The negative(-) spreads shows a smaller area than the actual spreads hence if that happens the wildfire will spread more than the predicted area destroying people, infrastructure, and resources. Therefore, such risks have to be taken under consideration in wildfire disaster management. The models were evaluated based on the positive (+) and negative (-) aspects of its spread. The positive (+) sign models were chosen from the study to reduce the risks in false alert due to the model.

5.2 Pilot Study

As an initial study on how a wildfire simulation would behave based on the changes that were done to the Rothermel's model, the demo data of the wildfire, which were provided in the GRASS GIS were used. It contains the data of a single wildfire. The results of this pilot study are included in this chapter.

5.2.1 Variable Elimination

I. Eliminating the "Optimum Packing Ratio"

Kreye et al. [35] states that 'surface fuel loading' is weakly correlated with the ROS (Rate of Spread) while wind and fuel attribute hold high correlation. Thus the variables that are related to the surface fuel loading such as 'optimum packing ratio', which calculates the optimum ratio for packing the fuel for efficient spread of a fire can be eliminated. After the said elimination, the spread is altered as follows.

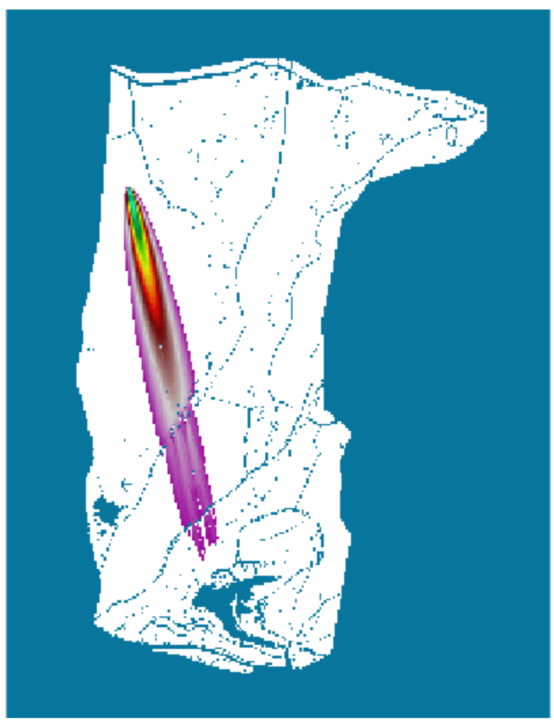

Figure 5.2: The output of the Rothermel model without optimum packing ratio

II. *Eliminating the Ovendry Fuel Loading*

As stated in the Sullivan [36], the fuel load is the weakest identified correlation with the ROS. Oven-dry fuel loading is the dried load of the fuel in that area. Thus with that information, a rationale can be created that if that variable removed it will not affect the simulation. After the elimination, the spread is altered as follows.

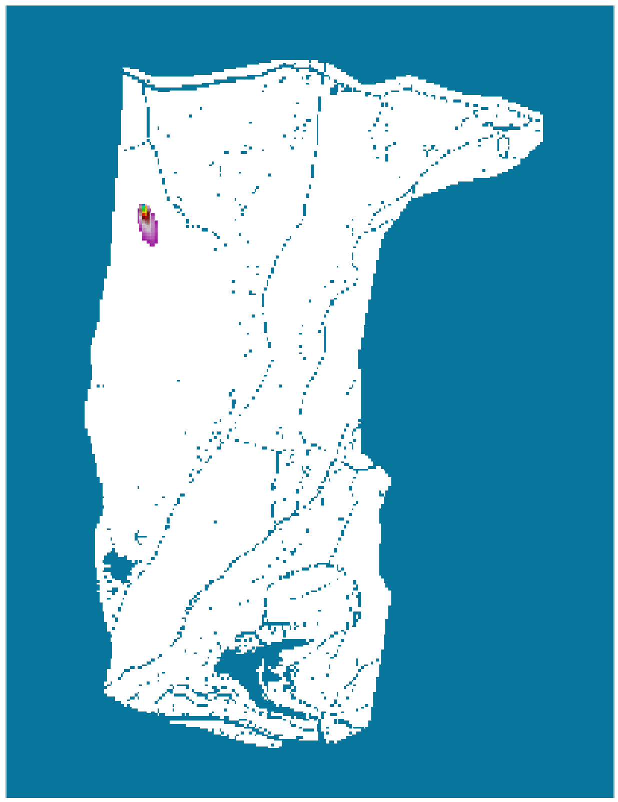

Figure 5.3: Output of the Rothermel model without oven-dry fuel loading

III. Eliminating the Mineral Damping Coefficient

The mineral content in fuels can be effective for a spread of fire. The mineral content in most wild fuels is at a very much low level. The reason for that is most fuels are consist of biodegradable material like plants in a forest. The base Rothermel model [2] gives a small number for the mineral content in wildfires in all fuel models used. Based on that rationale the mineral damping coefficient is removed and checked the effect.

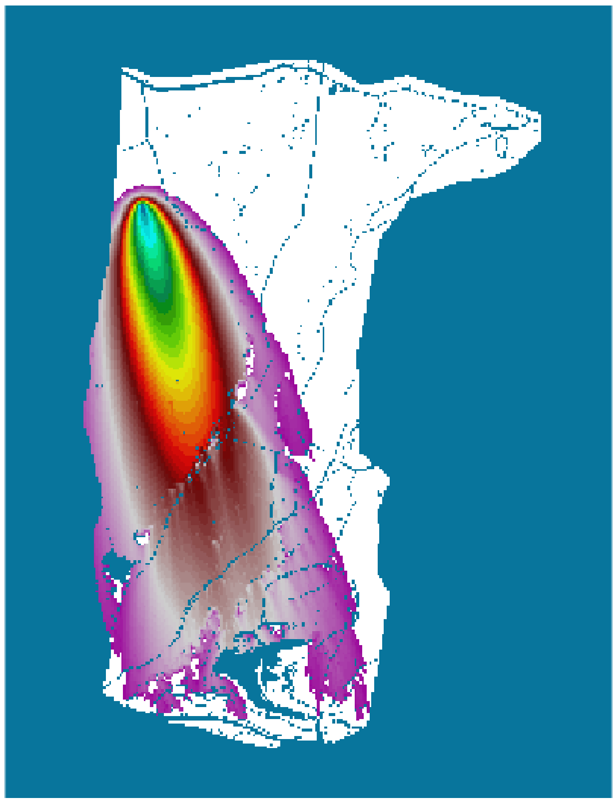

Figure 5.4: Output from the Rothermel model without mineral damping coefficient

IV. *Eliminating the Live Moisture/ Live fuel load*

The live moisture is the moisture which is at the top of the fuel bed. Mainly the moisture from the air the precipitation is measured as the live moisture. After a wildfire is initiated, the radiation [13] effect from the fire front can evaporate the moisture in the fuel instantly. Thus that the effect from the live moisture can be removed based on that rationale.

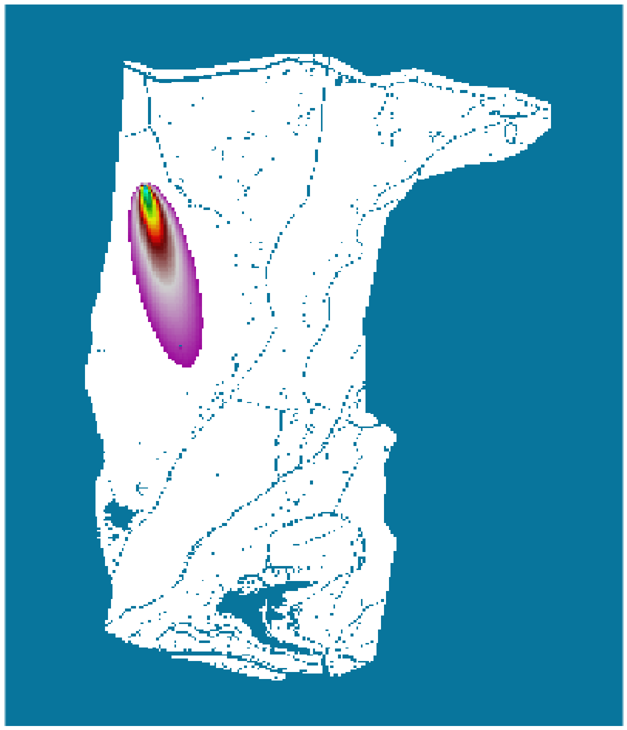

Figure 5.5: Output from the Rothermel model without live moisture

V. *Eliminating Fuel Particle Moisture*

The fuel particle moisture is calculated based on moisture (lb) and Ovendry wood (lb). The amount of moisture which is absorbed by the wood is the final outcome. Thus the absorbed moisture can be evaporated by increasing the temperature of wildfire. The effect from the absorbed moisture can be in a low state to the spread of the wildfire due to the high temperature on most fire fronts. Based on that rationale the alteration was done.

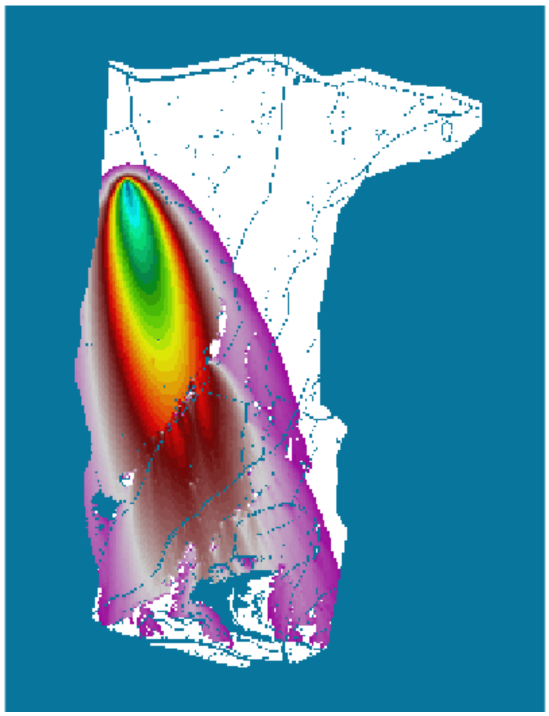

Figure 5.6: Output from the Rothermel model without Fuel particle moisture

Results from these alterations were used for evaluation of the altered models with the output from the base model and the past wildfires. The visualized output maps were exported as shapefiles separately. The output shapefiles are then imported into QGIS platform and the symmetrical difference between altered models and the base model is taken. The results of the pilot run showed the level of deviation of altered models from the base model.

5.2.2 Results of the Pilot Study

I. Jaccard Similarity Coefficient

Table 5.2: Jaccard Similarity Coefficient - Pilot study

Model	**Area of Spread**	**Jaccard Similarity Coefficient**
No Ovendry fuel Loading	39,059	0.01998
No Optimum packing ratio	1,107,598	0.56668
No mineral damping coefficient	5,949,304	0.32853
No Live fuel load	630,522	0.32259
No fuel particle moisture	6,496,926	0.30084

The Jaccard Similarity Coefficient was calculated according to the (1) equation. It was discovered that the best score of 0.56668 was found in the altered models with 'optimum packing ratio' variable eliminated. Both models with 'mineral damping coefficient' and 'fuel particle moisture' reduced had Jaccard scores of 0.32853 and 0.30084 respectively. The models with 'live fuel load' and 'Ovendry fuel loading' reduced, produced scores of 0.32259 and 0.01998 respectively in the pilot study.

II. Euclidean Distance between mean coordinates

Results from the alterations and the base model were converted to point layers using the mean coordinate module in QGIS. The Euclidean distances between the points were measured for the comparison. The benchmark set for the distance is 0. An exact match of the 2 spreads is considered as a Euclidean distance 0. The Euclidean distances generally depend on the size of the area of spread in the wildfire. Thus the acceptable deviation from the base model may vary from fire to fire.

Table 5.3: Euclidean distances - Pilot study

Model	**Euclidean Distance from base model Center (in Meters)**
No Live fuel load	563.270(-)
No fuel particle moisture	852.393(+)
No mineral damping coefficient	800.514(+)
No Optimum packing ratio	249.442(+)
No Ovendry fuel Loading	1208.348(-)

It was discovered that the lowest Euclidean distance of 249.442 meters was found between the centroid of the altered model with 'optimum packing ratio' variable eliminated and the centroid of the base model. Both models with 'mineral damping coefficient' and 'fuel particle moisture' reduced had distances of 800.514 meters and 852.393 meters respectively. The models with 'live fuel load' and 'Ovendry fuel loading' reduced, produced distances of 563.270(-) meters and 1208.348(-) meters respectively in the pilot study.

5.2.2 Analysis

I. Jaccard Similarity Coefficient

The similarity scores observed in the pilot study depicts average to low scores. Therefore these results alone seem to convey that the eliminated variables have a much larger impact on the Rothermel's [2] model than anticipated. But it should be also noted that the terrain used in the demo data of GRASS GIS depicts a mostly flat surface without many obstacles that obstruct the fire spread in an elliptical shape. Thus the demo data is much more sensitive to any changes when compared with terrain that has variable elevations that can be found in most wildfires.

II. Euclidean Distance between mean coordinates

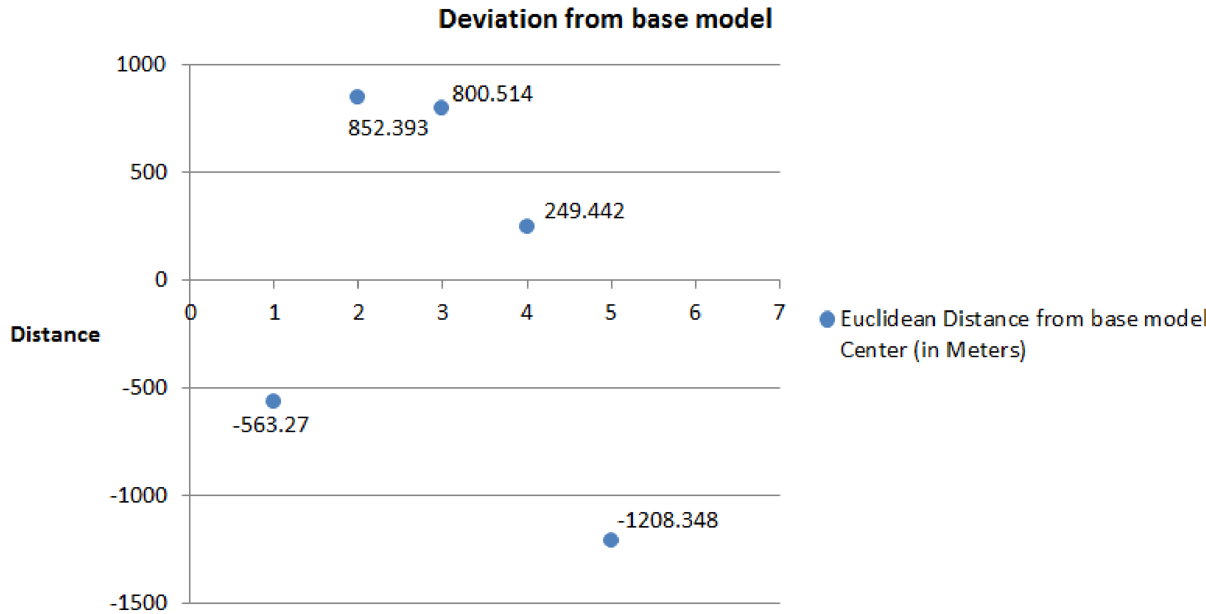

Figure 5.7: Mean coordinate deviation - Pilot study

As compared with the evaluation technique 1 results, the results from the evaluation technique 2 also showed nearly the same results. 'No Live fuel load', 'No fuel particle moisture', and 'No mineral damping coefficient' models had similar similarity coefficients in the Jaccard analysis. Similarly, the Euclidean distances between base spread and altered models are closer to each other compared to other distances according to table 5.3. 'No Optimum packing ratio' model could be observed to have the highest similarity score and the lowest Euclidean distance measured while the 'No Ovendry fuel Loading' model can be observed to have the lowest similarity score and the highest Euclidean distance.

As noted in section 5.1.2, the positive (+) and the negative (-) signs assigned to the measured Euclidean distances are to identify the practicality of the altered models. But since it is not possible to derive a viable model from the pilot study itself, the measure will not be that much of a use in this scenario. But it is possible to reject (-) models as possible contenders for the viable altered models.

5.3 Sample Data

The sample of the historical wildfires used for the study is given in the table 5.4.

Table 5.4: Sample data

Wildfire Name	**State**	**Fire Ignition**		**Fire Containment**		**Lag Time (mins)**	**Area Affected (ha)**
		Date	**Time (hr)**	**Date**	**Time (hr)**		
McKenna	New Mexico	2016/05/06	1300	2016/09/07	0800	178260	10210.0
Barrel	South Dakota	2011/07/19	1500	2011/09/02	1500	64800	3213.0
Seven Mile	Arkansas	2015/10/16	1604	2015/11/06	1315	30071	20.8
Blue Gravel	North Carolina	2015/04/11	1300	2015/04/24	0930	18510	521.0
Old Timer	Idaho	2011/10/01	1500	2011/10/21	1006	28506	117.0
Rush	California	2014/01/19	0800	2014/01/20	1607	1927	0.1
Tom Basin	Nevada	2011/09/30	2200	2011/10/19	2000	27240	5125.0
West Fork Road	Montana	2015/03/28	1330	2015/04/06	1300	12930	398.0
Chipmunk Spring	Arizona	2014/07/08	1735	2014/07/21	1606	18631	14.0
Devenport	Utah	2016/08/26	1623	2016/09/26	1145	44362	320.0

5.4 Results Analysis

5.4.1 Jaccard Similarity Coefficient Analysis

I. *Analysis: Eliminating the 'Optimum Packing Ratio'*

The figure 5.8 illustrates the variability of the Jaccard Similarity Coefficients for the model, in which the 'optimum packing ratio' variable is eliminated from the base model. Scores are calculated for each of the 10 wildfires in the sample.

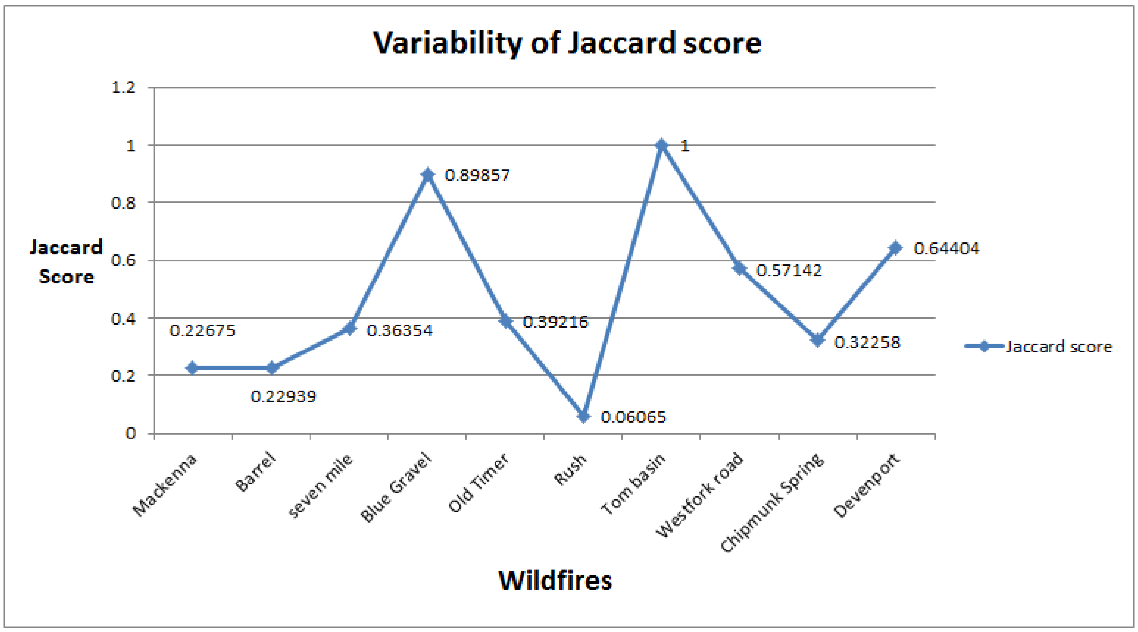

Figure 5.8: Variability of Jaccard score - 'Optimum Packing Ratio'

The mean of the Jaccard Similarity Coefficient for eliminating the optimum packing ratio from the base model is 0.47091 which is calculated based on 10 wildfires from the benchmark dataset.

Mean Jaccard Similarity Coefficient = 0.47091

The score variability can be affected due to the environment as well. So the score can be affected by noise or outlier variables in the environment. However, as seen from the mean of the score this model is near to the half of the perfect Jaccard Similarity Coefficient of 1. Thus this model can be taken as a weak model when compared to the base model, though it shows a perfect alignment in a few instances. As an example, a perfect match can be observed in Tom basin wildfire. But as an average, it greatly underperforms the benchmark level to be selected as a good alteration derived from the base model.

II. *Analysis: Eliminating the 'Ovendry Fuel Loading'*

The figure 5.9 illustrates the variability of the Jaccard Similarity Coefficients for the model, in which the 'Ovendry fuel loading' variable is eliminated from the base model. Scores are calculated for each of the 10 wildfires in the sample.

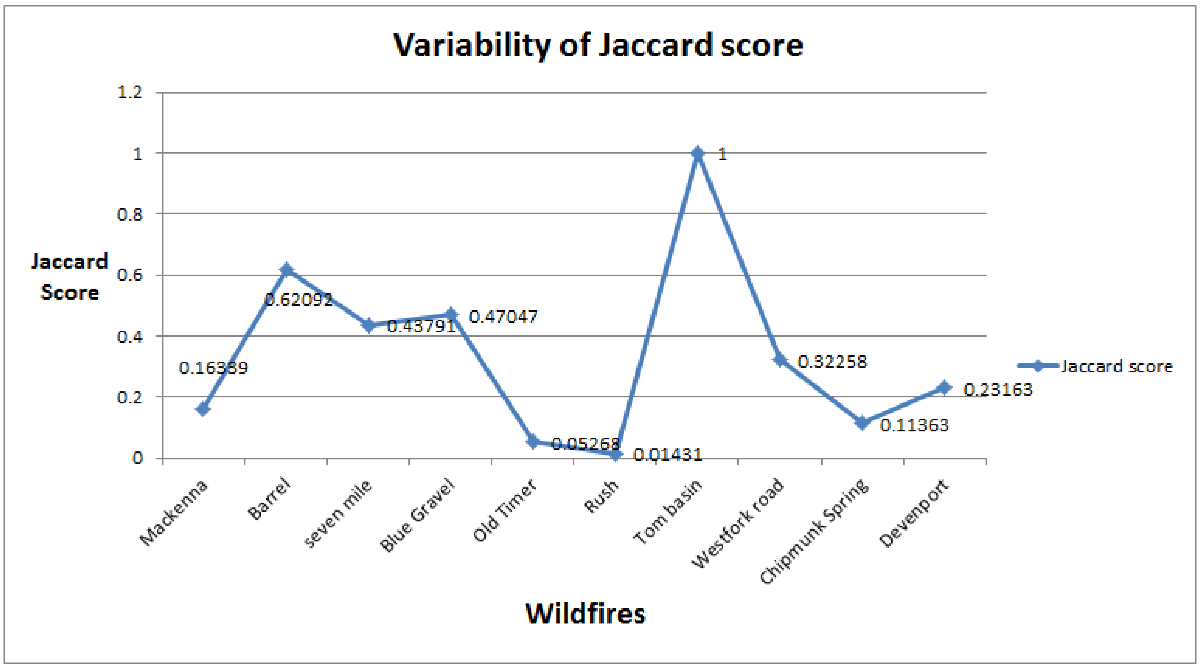

Figure 5.9: Variability of Jaccard score - 'Ovendry Fuel Loading'

The mean of the Jaccard Similarity Coefficient for eliminating the Ovendry Fuel Loading from the base model is 0.34275 which is calculated based on 10 wildfires from the benchmark dataset.

Mean Jaccard Similarity Coefficient =0.34275

As seen from the mean this model also shows a weak correlation to the base model. While the model scored perfectly in one instance, to all other sample objects below average correlation is given.

III. Analysis: Eliminating the 'Mineral Damping Coefficient'

The figure 5.10 illustrates the variability of the Jaccard Similarity Coefficients for the model, in which the 'Mineral Damping Coefficient' variable is eliminated from the base model. Scores are calculated for each of the 10 wildfires in the sample.

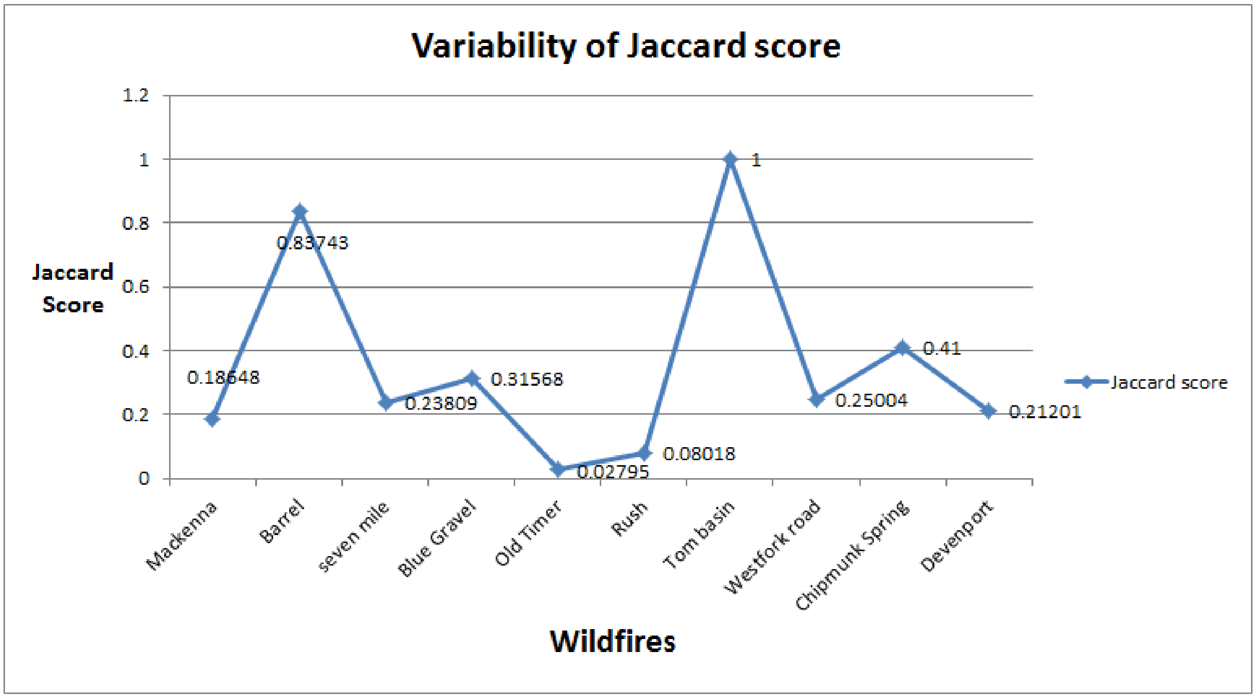

Figure 5.10: Variability of Jaccard score - 'Mineral damping coefficient'

The mean of the Jaccard Similarity Coefficient for eliminating the mineral damping coefficient from the base model is 0.35578 which is calculated based on 10 wildfires from the benchmark dataset.

Mean Jaccard Similarity Coefficient = 0.35578

As seen from the Jaccard Similarity Coefficient mean, this model too, is not significantly matched with the base model. The figure 5.10 shows a high reduction of the intersection of final areas of the wildfires. Thus this model may be used to identify the influence of the mineral damping coefficient.

*IV.	Analysis: Eliminating the Live Moisture*

The figure 5.11 illustrates the variability of the Jaccard Similarity Coefficients for the model, in which the ‘Live moisture’ variable is eliminated from the base model. Scores are calculated for each of the 10 wildfires in the sample.

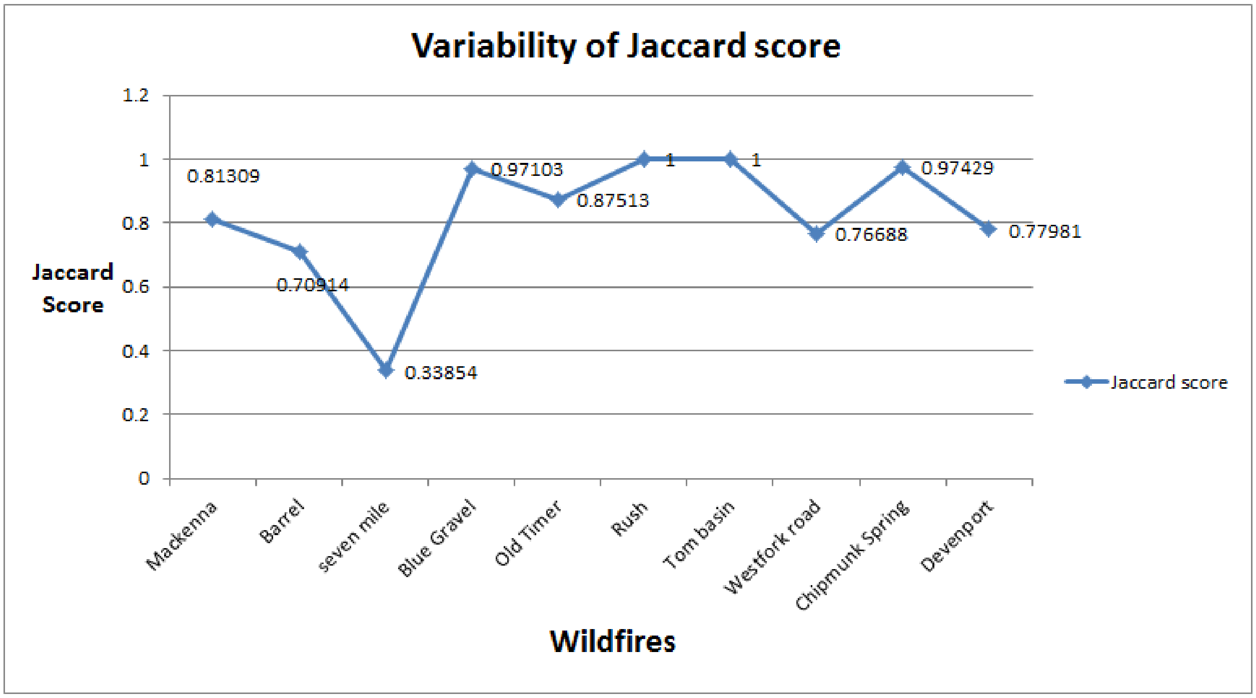

Figure 5.11: Variability of Jaccard score - ‘live fuel load’

The mean of the Jaccard Similarity Coefficient for eliminating the ‘live fuel load’ from the base model is 0.82279 which is calculated based on 10 wildfires from the benchmark dataset.

Mean Jaccard Similarity Coefficient = 0.82279

Due to the high mean Jaccard Similarity Coefficient observed from the sample of 10 fires exceeding that of the 3rd quartile of the optimum score, the model can be considered as a success. Even Though there is some error, due to the trade-off between the accuracy and eliminating input variables, the error may be considered as negligible depending on the context.

V. Analysis: Eliminating 'Fuel Particle Moisture'

The figure 5.12 illustrates the variability of the Jaccard Similarity Coefficients for the model, in which the 'Fuel Particle Moisture' variable is eliminated from the base model. Scores are calculated for each of the 10 wildfires in the sample.

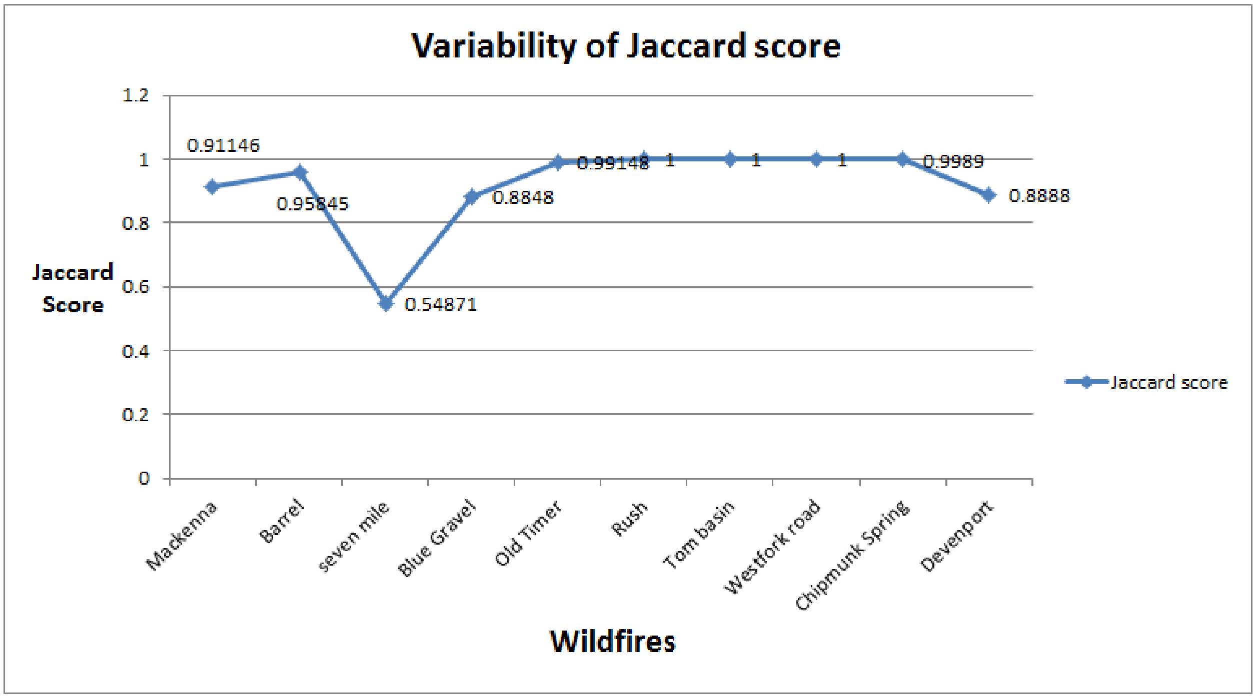

Figure 5.12: Variability of Jaccard score - 'fuel particle moisture'

The mean of the Jaccard Similarity Coefficient for eliminating the 'fuel particle moisture' from the base model is 0.91826, which is calculated based on 10 wildfires from the benchmark dataset.

Mean Jaccard Similarity Coefficient = 0.91826

This particular model shows even greater accuracy than the previous model with 0.82279. Thus the eliminated variable can be considered to have a lesser effect on the overall model. Thus eliminating the variable from the base model may be possible.

VI. *Analysis of a minor alteration: 'Modified moisture'*

The figure 5.13 illustrates the variability of the Jaccard Similarity Coefficients for the model where live moisture is replaced with 1-hour moisture related to vegetation. Scores are calculated for each of the 10 wildfires in the sample.

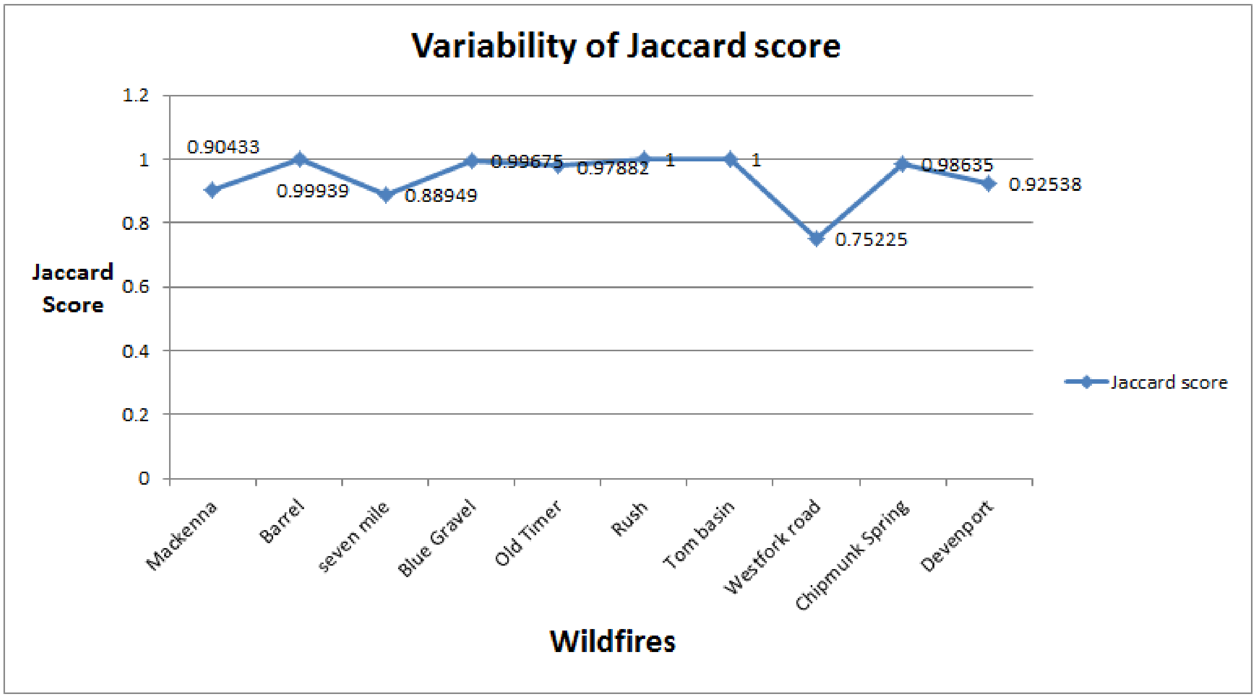

Figure 5.13: Variability of Jaccard score - 'modified moisture'

The mean of the Jaccard Similarity Coefficient for eliminating the fuel particle moisture from the base model is 0.94327, which is calculated based on 10 wildfires from the benchmark dataset.

Mean Jaccard Similarity Coefficient = 0.94327

The minor change to the model to have produced an acceptable accuracy rate. Even Though the modification to the input variables for the base Rothermel model is minor in this case, a minor change in input data has produced a valid output relevant to the base model. This also can be used in practical scenarios to improve the performance of a model.

5.4.2 Euclidean Distances Analysis / MOD Sign Analysis

The Euclidean distance measure was taken based on the center of mass of each spread. The distance measure was intended as a validation method for the results gained from the Jaccard Similarity Coefficient and present a strong and novel final argument.

The distances were changing based on the size of the wildfire. Thus only the sign of the distance was used. The sign is measured using a relativity measure. If the size of the altered model wildfire spread is larger than the base model, the distance is calculated from the center coordinate/mass of the altered model to the base and relative to that the sign is given as positive (+) while if the altered model spread is smaller than the base the distance is measured from the base model center to altered model center and the sign is given as negative (-).

Table 5.5: Euclidean distances MOD (Most Occurring Data) Sign analysis

Model	**No fuel particle moisture**	**No mineral damping coefficient**	**No Live fuel load**	**No Optimum packing ratio**	**No Ovendry fuel Loading**	**Modified moisture**
Mackenna	-	+	-	+	+	-
Barrel	+	+	-	-	-	-
seven mile	-	+	-	-	-	-
Blue Gravel	+	+	-	+	-	-
Old Timer	-	+	-	+	+	-
Rush	0	+	0	+	+	0
Tom basin	0	0	0	0	0	0
Westfork road	0	+	-	+	+	-
Chipmunk Spring	+	+	+	+	+	+
Devenport	-	+	-	+	+	-

If we consider the 0's also as positives a MOD (Most Occurring Data) sign can be calculated based on the signs. The final sign will be the sign which most occurs than the average number of cases. Based on that rationale a MOD (Most Occurring Data) sign analysis can be done as follows. Since the analysis was done based on 10 wildfires the number of signs in positive (+) or negative (-) should be more than 5 to be selected as the MOD sign.

- No fuel particle moisture :- (+)
- No mineral damping coefficient :-(+)
- No Live fuel load :-(-)
- No Optimum packing ratio :-(+)
- No Ovendry fuel loading :-(+)
- Modified moisture :-(+)

5.4.3 Consensus of Analysis

When considering the Jaccard Similarity Coefficient Analysis, models that had 'live fuel load' and 'fuel particle moisture' variables eliminated had the highest scores. Other models such as 'No mineral damping coefficient', 'No Optimum packing ratio', 'No Ovendry fuel loading' were observed to have less than moderate scores in the similarity analysis. Therefore when compared to the first two models mentioned, the latter three models can be considered less than optimal. But nevertheless, these results can be taken as a measure of effect of each variable on the Rothermel's [2] model. The model with a minor alteration of live fuel moisture, based on vegetation named the 'Modified moisture' was observed to have a high similarity score as well.

When the MOD Sign analysis is considered, most models can be observed to have positive signs. Eventhough the 'No live fuel load' model had a high similarity score, it is the only model that scored negatively. Therefore the 'No fuel particle moisture' model can be considered as the most optimal model from both analysis.

5.5 Individual Sample Wildfire Analysis

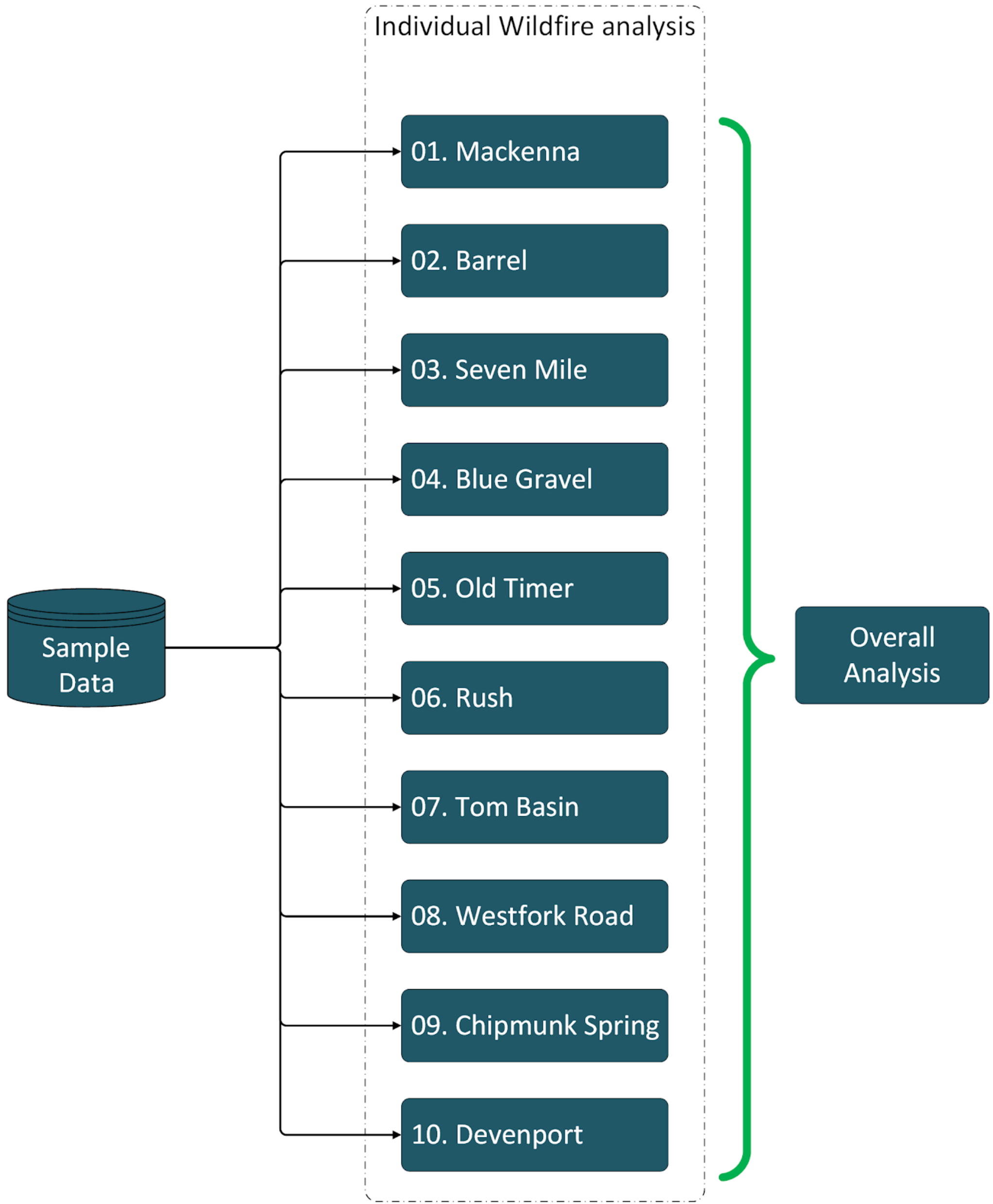

Figure 5.14: Flow of wildfire analysis

5.5.1 MacKenna Wildfire

I. *Jaccard Similarity Coefficient*

Table 5.6: Jaccard Similarity Coefficient - Mackenna wildfire

Model	**Area of spread(m^2)**	**Jaccard Similarity Coefficient**
Base(Rothermel model)	396,297,630	*
No fuel particle moisture	361,209,731	0.91146
No mineral damping coefficient	2,125,100,890	0.18648
No Live fuel load	322,226,955	0.81309
No Optimum packing ratio	1,747,672,548	0.22675
No Ovendry fuel Loading	2,425,341,496	0.16339
Modified moisture	358,384,321	0.90433

* The benchmark model

'No particle moisture', 'No live fuel load', and 'Modified moisture' models can be observed to have high similarity scores of 0.91146, 0.81309, and 0.90433 and other models such as, 'No mineral damping coefficient', 'No optimum packing ratio', and 'No overdry fuel loading' models can be observed to have rather low similarity scores of 0.18648, 0.22675, and 0.16339.

II. *Euclidean distance between mean coordinates*

Table 5.7: Euclidean distances - Mackenna wildfire

Model	Euclidean Distance from base model Center (in Meters)
No Live fuel load	3430.094(-)
No fuel particle moisture	1697.574(-)
No mineral damping coefficient	9215.572(+)
No Optimum packing ratio	42,254.861(+)
No Ovendry fuel Loading	41,273.322(+)
Modified moisture	1697.574(-)

In the Mackenna wildfire, it was discovered that the lowest Euclidean distance from the base model spread mean coordinate to altered model coordinates of 1697.574 meters was found in both 'No fuel particle moisture' model and 'Modified moisture' model. While 'No live fuel load' model also displayed somewhat lesser Euclidean distances, the other two models seemingly have a high deviation with very large Euclidean distances. The diagrammatic representation of the Euclidean distances is given below.

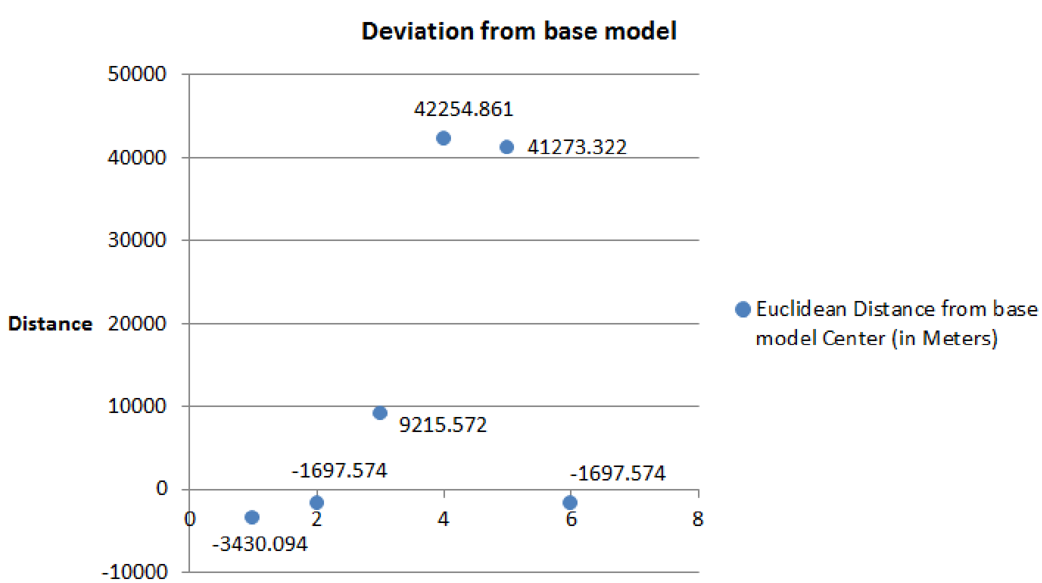

Figure 5.15: Mean coordinate deviation - Mackenna wildfire

Similarly to the Jaccard similarity analysis, the 'No Live fuel load', 'No fuel particle moisture', 'Modified moisture' have reasonably similar propagation. Especially the latter two models. But in other models, there seem to be very high deviations even having very large Euclidean distances more than 40km.

5.5.2 Barrel Wildfire

I. *Jaccard Similarity Coefficient*

Table 5.8: Jaccard Similarity Coefficient - Barrel wildfire

Model	**Area of spread(m^2)**	**Jaccard Similarity Coefficient**
Base(Rothermel model)	719,214,630	*
No fuel particle moisture	750,390,225	0.95845
No mineral damping coefficient	858,833,043	0.83743
No Live fuel load	510,030,084	0.70914
No Optimum packing ratio	164,986,094	0.22939
No Ovendry fuel Loading	446,574,980	0.62092
Modified moisture	718,781,354	0.99939

* The benchmark model

As noted in the above table, when compared with other models, 'No fuel particle moisture' model and 'No mineral damping coefficient' model shows high correlations of 0.95845 and 0.83743 respectively, to the base model. While both 'No Live fuel load' and 'No Ovendry fuel Loading' respectively shows average Jaccard Similarity Coefficient scores of 0.70914 and 0.62092, 'No Optimum packing ratio' model shows the least correlation of 0.22939.

II. *Euclidean distance between mean coordinates*

Table 5.9: Euclidean distances - Barrel wildfire

Model	**Euclidean Distance from base model Center (in Meters)**
No Live fuel load	2448.982(-)
No fuel particle moisture	332.229(+)
No mineral damping coefficient	2353.783(+)
No Optimum packing ratio	6570.379(-)
No Ovendry fuel Loading	3913.646(-)
Modified moisture	1.905(-)

It was discovered that the lowest Euclidean distance of 332.229 meters was found between the mean coordinate of the altered model with ‘fuel particle moisture’ variable eliminated and the mean coordinate of the base model. Both models with ‘mineral damping coefficient’ and ‘Live fuel load’ reduced had distances of 2353.783 meters and 2448.982(-) meters respectively. The models with ‘optimum packing ratio’ and ‘ovendry fuel loading’ reduced, produced distances of 6570.379(-) meters and 3913.646(-) meters respectively in the study. The diagrammatic representation of Euclidean distance between mean coordinate deviations from the base model mean coordinate is illustrated in the figure 5.16.

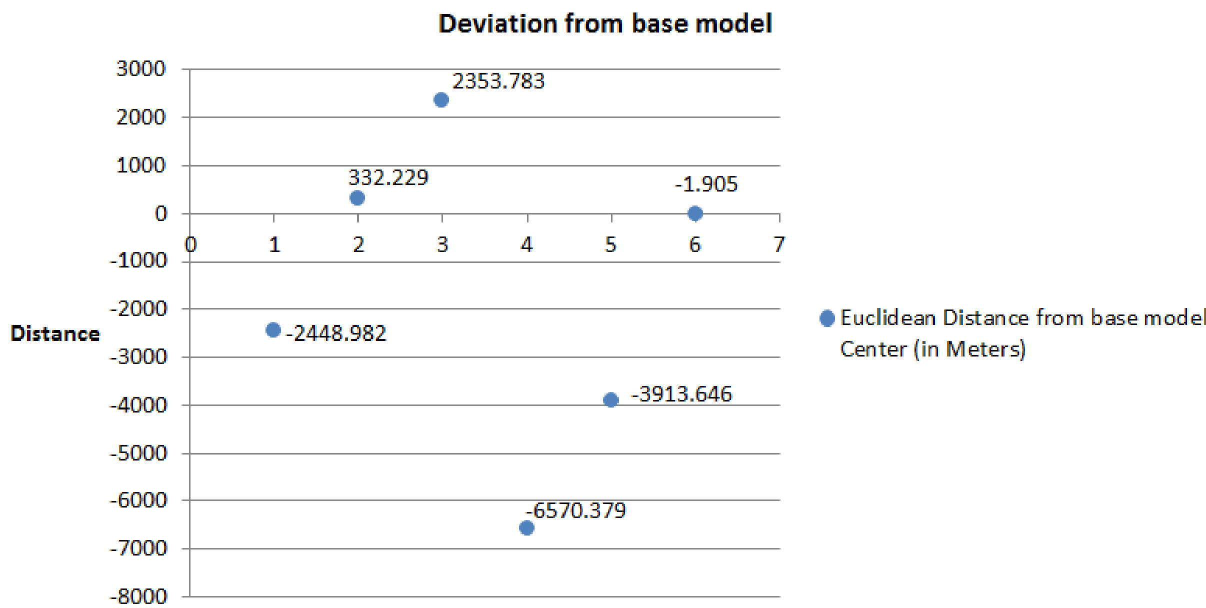

Figure 5.0:16: Mean coordinate deviation - Barrel wildfire

5.5.3 Seven Mile Wildfire

I. *Jaccard Similarity Coefficient*

Table 5.10: Jaccard Similarity Coefficient - Seven Mile wildfire

Model	**Area of spread(m^2)**	**Jaccard Similarity Coefficient**
Base(Rothermel model)	120,754	*
No fuel particle moisture	66,259	0.54871
No mineral damping coefficient	507,167	0.23809
No Live fuel load	40,880	0.33854
No Optimum packing ratio	43,900	0.36354
No Ovendry fuel Loading	52,880	0.43791
Modified moisture	107,411	0.88949

* The benchmark model

The ‘Seven Mile’ wildfire only produces average to low similarity coefficient scores when compared with the Rothermel model’s spread except for ‘Modified moisture’ model. While the ‘Modified moisture’ model can be observed to have a similarity value of 0.88949, the next highest similarity score is the 0.54871 score of ‘No fuel particle moisture’ model. ‘No Ovendry fuel loading’, ‘No Optimum packing ratio’, ‘No Live fuel load’, and ‘No mineral damping coefficient’ models display similarity scores of 0.43791, 0.36354, 0.33854, and 0.23809 respectively.

II. Euclidean distance between mean coordinates

Table 5.11: Euclidean distances - Seven Mile wildfire

Model	**Euclidean Distance from base model Center (in Meters)**
No Live fuel load	31,528.352(-)
No fuel particle moisture	21,072.510(-)
No mineral damping coefficient	32,856.01(+)
No Optimum packing ratio	10,258.53(-)
No Ovendry fuel Loading	38,672.240(-)
Modified moisture	9,528(-)

The Euclidean distances between the mean coordinate for the base model and mean coordinates for the altered models in ‘Seven Mile’ wildfire, also reflects its Jaccard Similarity analysis. ‘Modified moisture’ model holds the lowest Euclidean distance of 9528m and the Euclidean distances for ‘No Optimum packing ratio’, ‘No fuel particle moisture’, ‘No Live fuel load’, ‘No Ovendry fuel Loading’, and ‘No mineral damping coefficient’ are 10,258.53, 21,072.510, 31,528.352, 38,672.240, and 38,672.240. The deviations of altered models stated in the table 5.11 can be illustrated in the figure 5.17.

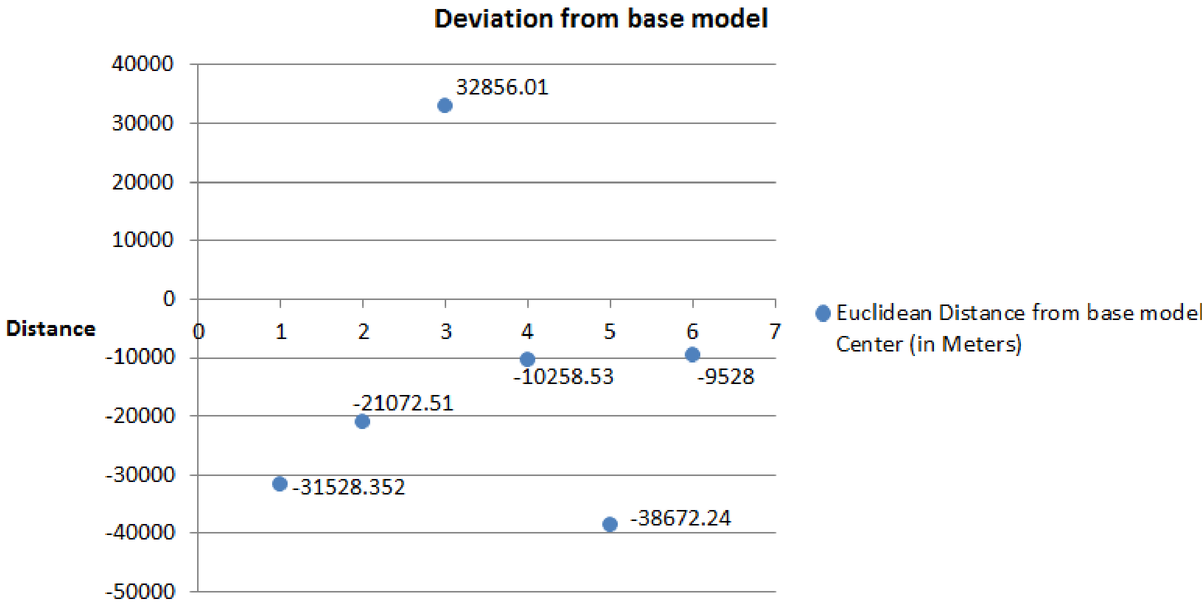

Figure 5.17: Mean coordinate deviation - Seven Mile wildfire

5.5.4 Blue Gravel Wildfire

I. *Jaccard Similarity Coefficient*

Table 5.12: Jaccard Similarity Coefficient - Blue Gravel

Model	**Area of spread(m^2)**	**Jaccard Similarity Coefficient**
Base(Rothermel model)	1,923,055	*
No fuel particle moisture	2,173,423	0.88480
No mineral damping coefficient	6,091,734	0.31568
No Live fuel load	1,867,353	0.97103
No Optimum packing ratio	1,728,010	0.89857
No Ovendry fuel Loading	904,747	0.47047
Modified moisture	1,916,817	0.99675

* The benchmark model

In the Blue Gravel wildfire, it can be observed that 'No fuel particle moisture', 'No Live fuel load', and 'No Optimum packing ratio' can be observed to show high coefficient scores when compared with other models. They are respectively 0.88480, 0.97103, and 0.89857. 'No mineral damping coefficient' and 'No Ovendry fuel loading' both show low coefficient scores of 0.31568 and 0.47047.

II. Euclidean distance between mean coordinates

Table 5.13: Euclidean distances - Blue Gravel wildfire

Model	**Euclidean Distance from base model Center (in Meters)**
No Live fuel load	15,900.000(-)
No fuel particle moisture	1907.864(+)
No mineral damping coefficient	17,991.055(+)
No Optimum packing ratio	3136.562(+)
No Ovendry fuel Loading	26,394.390(-)
Modified moisture	8.373(-)

It was discovered that the lowest Euclidean distance of 1907.864 meters was found between the mean coordinate of the altered model with 'fuel particle moisture' variable eliminated and the mean coordinate of the base model. Both models with 'mineral damping coefficient' and 'Live fuel load' reduced, had distances of 17,991.055 meters and 15,900 meters respectively. The models with 'optimum packing ratio' and 'ovendry fuel loading' reduced, produced Euclidean distances of 3136.562 meters and 26,394.390 meters respectively in the study. The diagrammatic representation of mean coordinate deviations from the table 5.13 is illustrated in the figure 5.18.

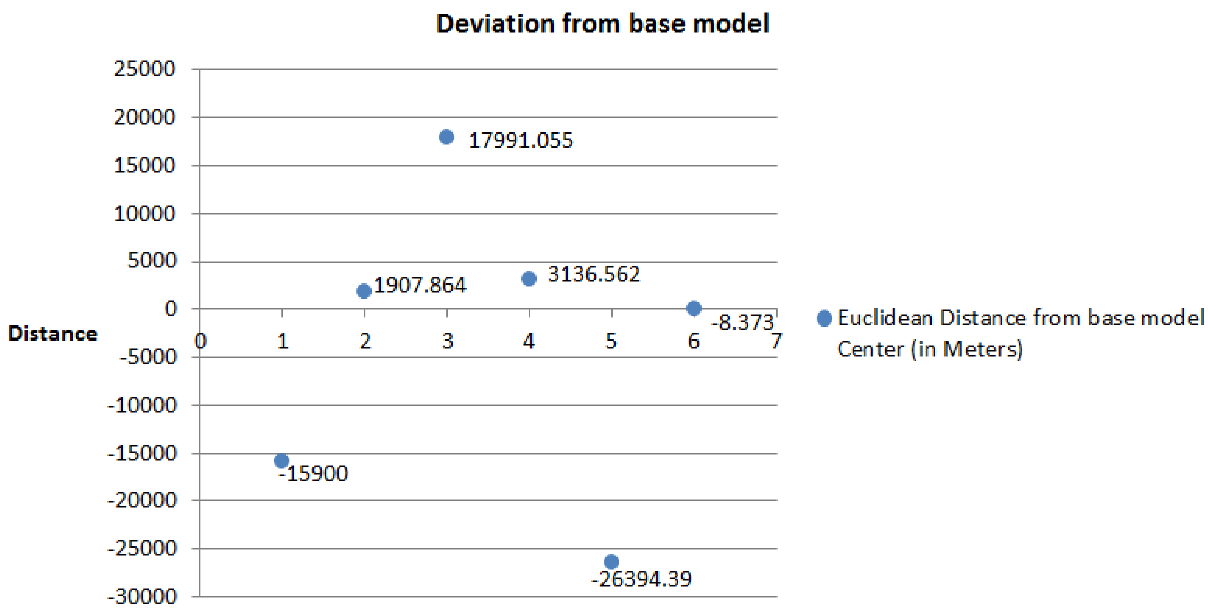

Figure 5.18: Mean coordinate deviation - Blue Gravel wildfire

5.5.5 Old Timer Wildfire

I. Jaccard Similarity Coefficient

Table 5.14: Jaccard Similarity Coefficient - Old Timer wildfire

Model	**Area of spread(m^2)**	**Jaccard Similarity Coefficient**
Base(Rothermel model)	25,847,578	*
No fuel particle moisture	26,069,581	0.99148
No mineral damping coefficient	924,580,885	0.02795
No Live fuel load	22,620,147	0.87513
No Optimum packing ratio	10,136,539	0.39216
No Ovendry fuel Loading	490,602,070	0.05268
Modified moisture	25,300,278	0.97882

* The benchmark model

For the ‘Old Timer’ wildfire, it was discovered that ‘No fuel particle moisture’, ‘No live fuel load’, and ‘Modified moisture’ models present a good level of correlation to the base model. Their Jaccard Similarity Coefficients are 0.99148, 0.87513, and 0.97882. But ‘No Optimum packing ratio’, ‘No mineral damping coefficient’, and ‘No ovendry fuel loading’ display low level of correlations of 0.39216, 0.02795, and 0.05268.

II. *Euclidean distance between mean coordinates*

Table 5.15: Euclidean distances - Old Timer wildfire

Model	**Euclidean Distance from base model Center (in Meters)**
No Live fuel load	630.836(-)
No fuel particle moisture	49.391(-)
No mineral damping coefficient	19,574.587(+)
No Optimum packing ratio	1725.655(+)
No Ovendry fuel Loading	16,986.660(+)
Modified moisture	94.519(-)

Similarly to the Jaccard Similarity Coefficient for the ‘Old Timer’ wildfire, ‘No fuel particle moisture’, ‘No Live fuel load’, and ‘Modified moisture’ models’ mean coordinates show closer Euclidean distances to the base model mean coordinates. Especially ‘No fuel particle moisture’ and ‘Modified moisture’ models. They show 49.391m and 94.519m Euclidean distances respectively. Except for ‘No Live fuel load’, which shows 630.836m Euclidean distance, other models show rather high Euclidean distances. The diagrammatic representation of mean coordinate deviations from the table 5.15 is illustrated in the figure 5.19.

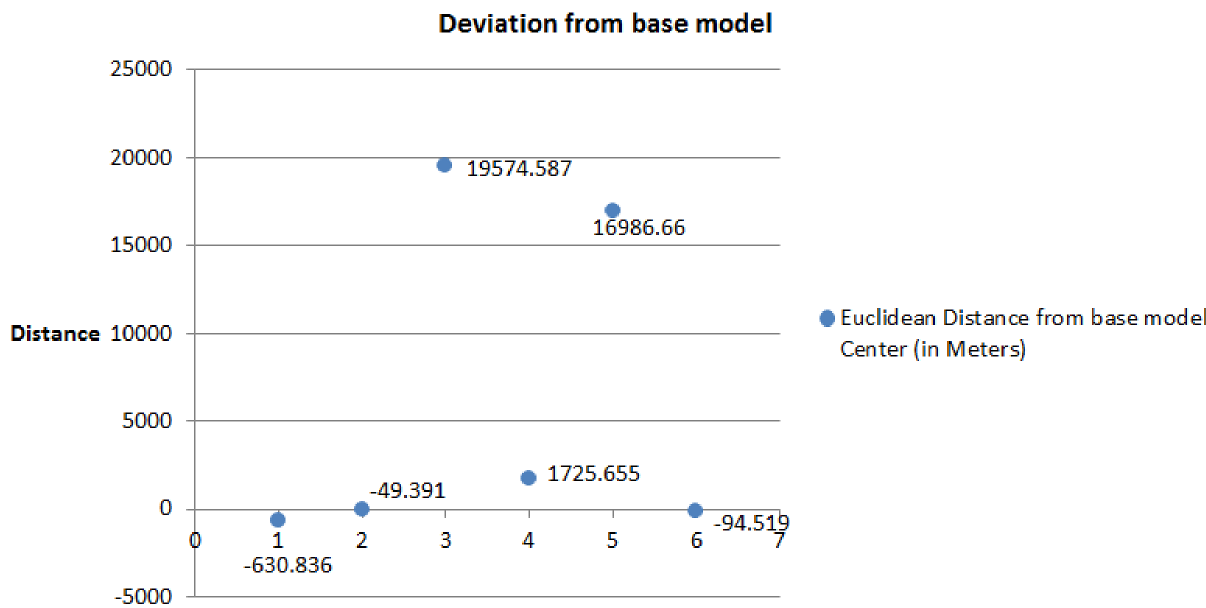

Figure 5.19: Euclidean distances - Old Timer wildfire

5.5.6 Rush Wildfire

I. *Jaccard Similarity Coefficient*

Table 5.16: Jaccard Similarity Coefficient - Rush wildfire

Model	**Area of spread(m^2)**	**Jaccard Similarity Coefficient**
Base(Rothermel model)	30,605	*
No fuel particle moisture	30,605	1.00000
No mineral damping coefficient	381,666	0.08018
No Live fuel load	30,605	1.00000
No Optimum packing ratio	504,537	0.06065
No Ovendry fuel Loading	2,137,870	0.01431
Modified moisture	30,605	1.00000

* The benchmark model

Similarly to the ‘Old Timer’ wildfire, ‘Rush’ wildfire displays a good Similarity score for ‘No fuel particle moisture’, ‘No live fuel load’, and ‘modified moisture’ models. But in this case, they seem to be at perfect accuracy. While the previously noted models show such accuracy, ‘No mineral damping coefficient’, ‘No optimum packing ratio’, and ‘No ovendry fuel loading’ display abysmal similarity rates of 0.08018, 0.06065, and 0.01431.

II. Euclidean distance between mean coordinates

Table 5.17: Euclidean distances - Rush wildfire

Model	**Euclidean Distance from base model Center (in Meters)**
No Live fuel load	0.000
No fuel particle moisture	0.000
No mineral damping coefficient	272.983(+)
No Optimum packing ratio	610.072(+)
No Ovendry fuel Loading	855.772(+)
Modified moisture	0.000

It was observed that in ‘Rush’ wildfire, since the spread output for the base model, ‘No fuel particle moisture’, ‘No live fuel load’, and ‘modified moisture’ were the same, there were no Euclidean distances between them. Though the other models too displayed lesser Euclidean distances between their spread mean coordinates and base model mean coordinates when compared to previous wildfires observed, this may be mainly due to the smaller size of this particular wildfire. The diagrammatic representation of Euclidean distances depicted in the table 5.17 is illustrated in the figure 5.20.

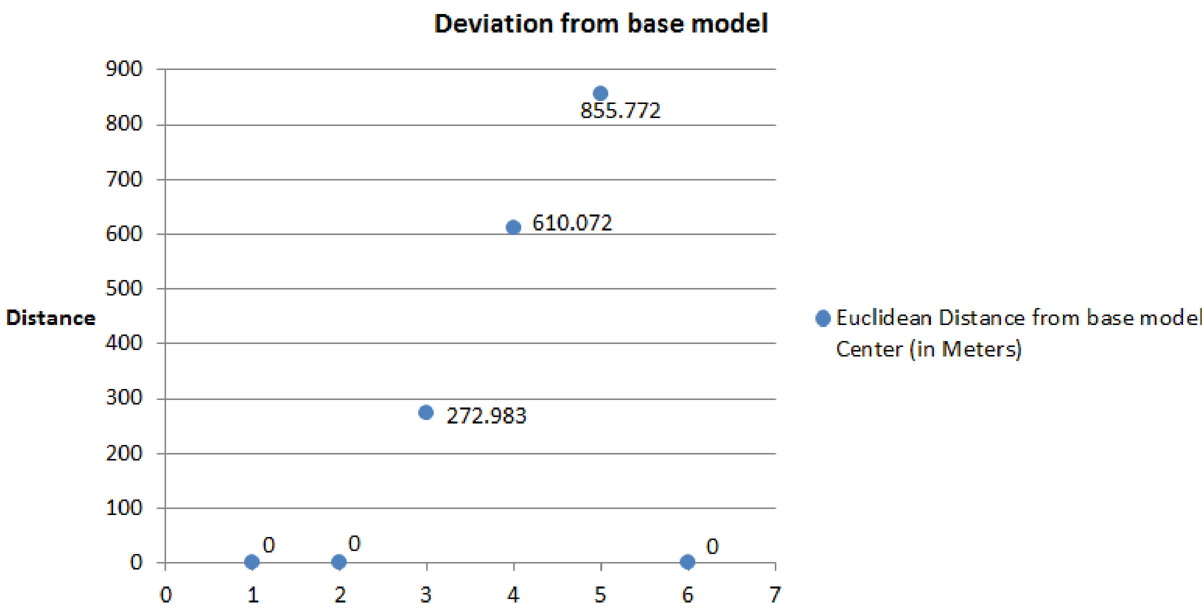

Figure 5.20: Mean coordinate deviation - Rush wildfire

5.5.7 Tom Basin Wildfire

I. Jaccard Similarity Coefficient

Table 5.18: Jaccard Similarity Coefficient - Tom Basin wildfire

Model	**Area of spread(m^2)**	**Jaccard Similarity Coefficient**
Base(Rothermel model)	548,424	*
No fuel particle moisture	548,424	1.00000
No mineral damping coefficient	548,424	1.00000
No Live fuel load	548,424	1.00000
No Optimum packing ratio	548,424	1.00000
No Ovendry fuel Loading	548,424	1.00000
Modified moisture	548424	1.00000

* The benchmark model

In the ‘Tom Basin’ wildfire, all altered models and the base model displayed the same spread output leading to perfect similarity scores for all models.

II. Euclidean distance between mean coordinates

Table 5.19: Euclidean distances - Tom Basin wildfire

Model	**Euclidean Distance from base model Center (in Meters)**
No Live fuel load	0.000
No fuel particle moisture	0.000
No mineral damping coefficient	0.000
No Optimum packing ratio	0.000
No Ovendry fuel Loading	0.000
Modified moisture	0.000

As noted in the similarity analysis above, since the spread output is the same for all models, the mean coordinates are the same for each model. Thus the Euclidean distances are 0. The diagrammatic representation of the table 5.19 is illustrated in the figure 5.21 s well.

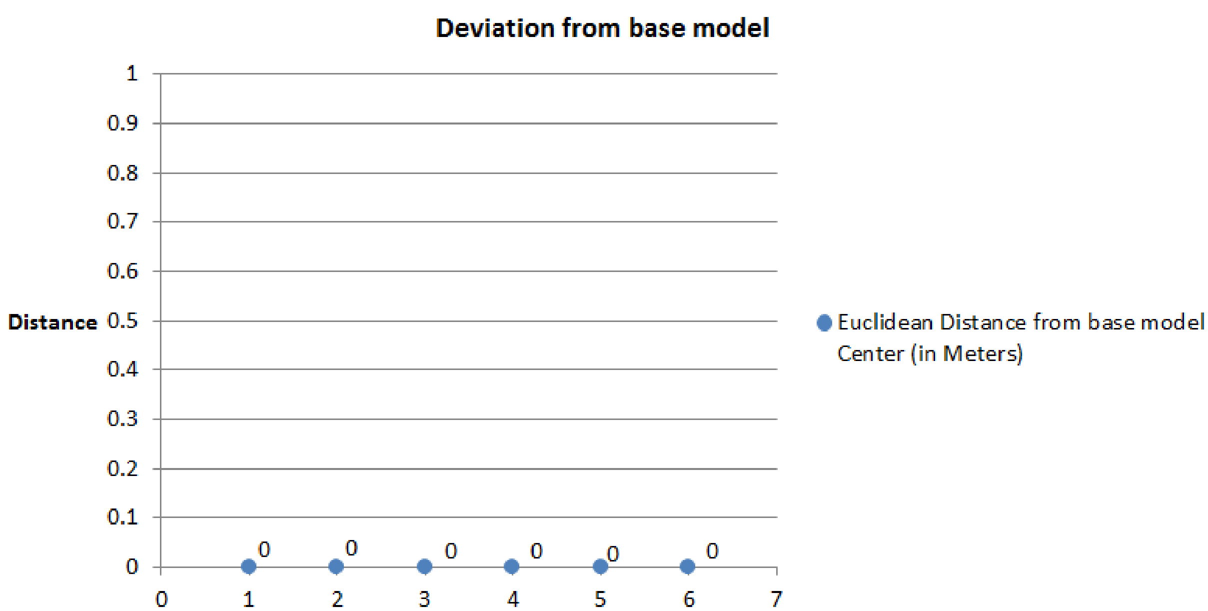

Figure 5.21: Mean coordinate deviation - Tom Basin wildfire

5.5.8 Westfork Wildfire

I. *Jaccard Similarity Coefficient*

Table 5.20: Jaccard Similarity Coefficient - Westfork Road wildfire

Model	**Area of spread(m^2)**	**Jaccard Similarity Coefficient**
Base(Rothermel model)	816,177,851	*
No fuel particle moisture	816,177,851	1.00000
No mineral damping coefficient	3,264,711,404	0.25004
No Live fuel load	627,549,115	0.76688
No Optimum packing ratio	1,428,311,239	0.57142
No Ovendry fuel Loading	2,530,151,338	0.32258
Modified moisture	613,972,798	0.75225

* The benchmark model

Again, ‘No fuel particle moisture’, ‘No live fuel load’, and ‘modified moisture’ models can be observed to have good similarity scores. Particularly ‘No fuel particle moisture’ have perfect similarity. The other two models display 0.76688 and 0.75225 similarity scores respectively. Though ‘No mineral damping coefficient’, ‘No Optimum packing ratio’, and ‘No Ovendry fuel loading’ models can be observed to have comparably low similarity scores of 0.25004, 0.57142, and 0.32258 respectively.

II. *Euclidean distance between mean coordinates*

Table 5.21: Euclidean distances - Westfork Road wildfire

Model	**Euclidean Distance from base model Center (in Meters)**
No Live fuel load	1312.680(-)
No fuel particle moisture	0.000
No mineral damping coefficient	23,054.204(+)
No Optimum packing ratio	36,833.638(+)
No Ovendry fuel Loading	40,811.292(+)
Modified moisture	1176.679(-)

While ‘No fuel particle moisture’ model shows no Euclidean distance to the base model mean coordinates due to being identical to the base model in the spread, both ‘No live fuel load’ and ‘Modified moisture model’ can be observed to have Euclidean distances of 1312.680 and 1176.679. While >1km can be considered a relatively high error, due to the size of the wildfire, it can be considered acceptable. The diagrammatical representation of the Euclidean distances in table 5.21 is illustrated in figure 5.22.

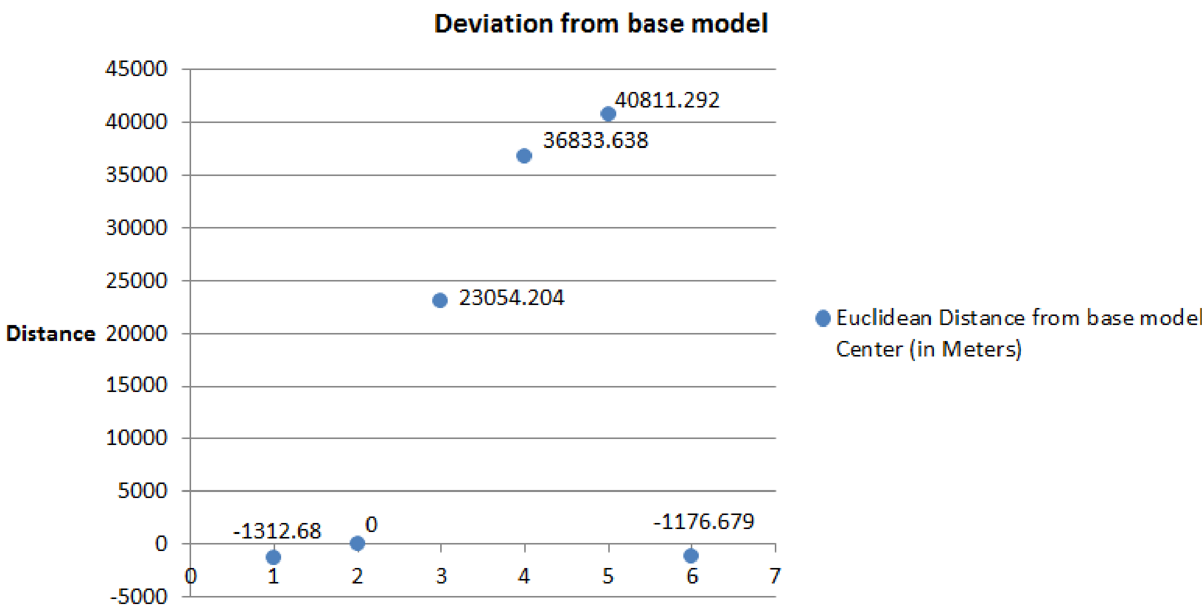

Figure 5.22: Mean coordinate deviation - Westfork Road wildfire

5.5.9 Chipmunk Spring Wildfire

I. Jaccard Similarity Coefficient

Table 5.22: Jaccard Similarity Coefficient - Chipmunk Spring wildfire

Model	**Area of spread(m^2)**	**Jaccard Similarity Coefficient**
Base(Rothermel model)	521,120,477	*
No fuel particle moisture	520,550,664	0.99890
No mineral damping coefficient	1,302,801,193	0.41000
No Live fuel load	507,726,563	0.97429
No Optimum packing ratio	1,615,473,478	0.32258
No Ovendry fuel Loading	4,585,860,197	0.11363
Modified moisture	514,010,588	0.98635

* The benchmark model

In the ‘Chipmunk Spring’ wildfire, ‘No fuel particle moisture’, ‘No live fuel load’, and ‘Modified moisture’ models have near perfect Jaccard Similarity Scores of 0.99890, 0.97429, and 0.98635. Although other 3 models display average to low similarity scores of 0.41000, 0.32258, and 0.11363 respectively in ‘No mineral damping coefficient’, ‘No optimum packing ratio’, and ‘No ovendry fuel loading’.

II. *Euclidean distance between mean coordinates*

Table 5.23: Euclidean distances - Chipmunk Spring

Model	**Euclidean Distance from base model Center (in Meters)**
No Live fuel load	176.431(+)
No fuel particle moisture	98.569(+)
No mineral damping coefficient	4285.572(+)
No Optimum packing ratio	30,346.306(+)
No Ovendry fuel Loading	29,146.993(+)
Modified moisture	110.561(+)

The near-perfect similarity scores displayed in the evaluation technique 01 for ‘Chipmunk Spring’ wildfire is also reflected in the Euclidean distance analysis. ‘No live fuel load’, ‘No fuel particle moisture’, and ‘Modified moisture’ model mean coordinates can be observed to have Euclidean distances to the base model mean coordinate of respectively, 176.431, 98.659, and 110.561 in meters. Though comparably, other models can be observed to have rather high Euclidean distances. The diagrammatic representation of the Euclidean distance given in the table 5.23 is illustrated in figure 5.23.

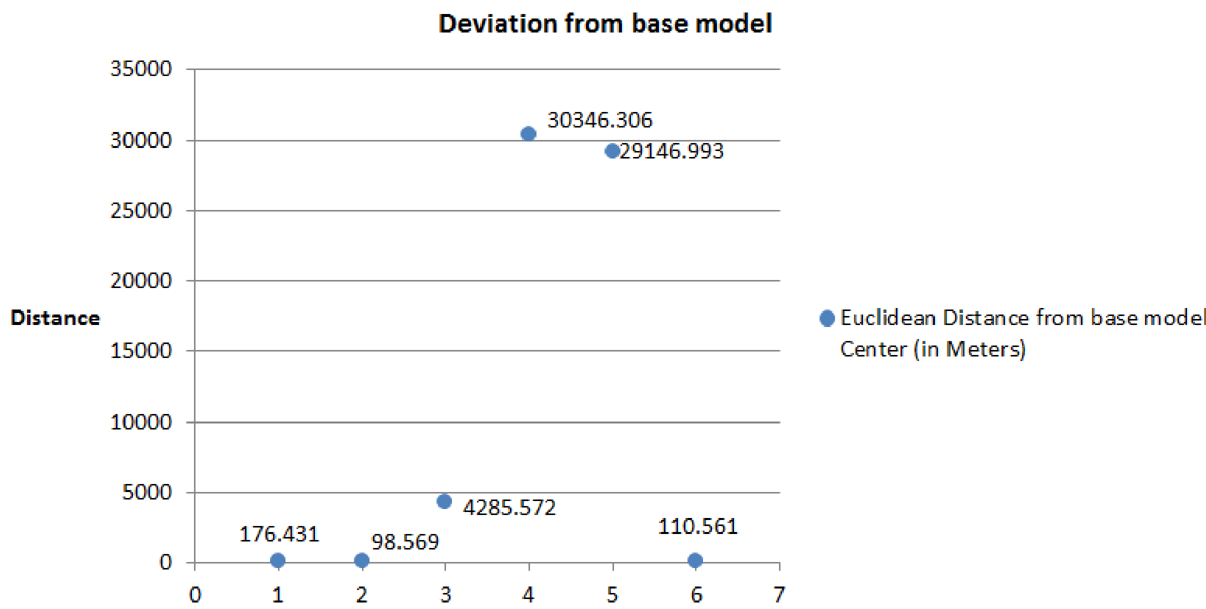

Figure 5.23: Mean coordinate deviation - Chipmunk Spring wildfire

5.5.10 Devenport Wildfire

I. *Jaccard Similarity Coefficient*

Table 5.24: Jaccard Similarity Coefficient - Devenport wildfire

Model	**Area of spread(m^2)**	**Jaccard Similarity Coefficient**
Base(Rothermel model)	122,360,860	*
No fuel particle moisture	137,669,788	0.88880
No mineral damping coefficient	577,157,759	0.21201
No Live fuel load	95,418,316	0.77981
No Optimum packing ratio	189,988,979	0.64404
No Ovendry fuel Loading	528,263,951	0.23163
Modified moisture	113,230,887	0.92538

* The benchmark model

Similarly to previous samples, 'No particle moisture', 'No fuel load', and 'Modified moisture' models display high similarity scores of 0.88880, 0.77981, and 0.92538. But 'No mineral damping coefficient' and 'No ovendry fuel loading' models display low similarity scores of 0.21201 and 0.23163 and 'No optimum packing ratio' only displays a moderate similarity score of 0.64404.

II. Euclidean distance between mean coordinates

Table 5.25: Euclidean distances **-** *Devenport wildfire*

Model	**Euclidean Distance from base model Center (in Meters)**
No Live fuel load	962.119(-)
No fuel particle moisture	599.823(-)
No mineral damping coefficient	6411.359(+)
No Optimum packing ratio	1173.777(+)
No Ovendry fuel Loading	7483.117(+)
Modified moisture	38.387(-)

'No live fuel load', 'No fuel particle moisture', and 'Modified moisture' model mean coordinates can be observed to have Euclidean distances to the base model mean coordinate of respectively, 962.119, 599.823, and 38.387 in meters. 'No optimum packing ratio' has a moderately lesser Euclidean distance, but 'No mineral damping coefficient' and 'No oven dry fuel loading' display large Euclidean distances of 6411.359 and 7483.117 respectively. The diagrammatical representation of the Euclidean distances in table 5.25 can be illustrated in the figure 5.24.

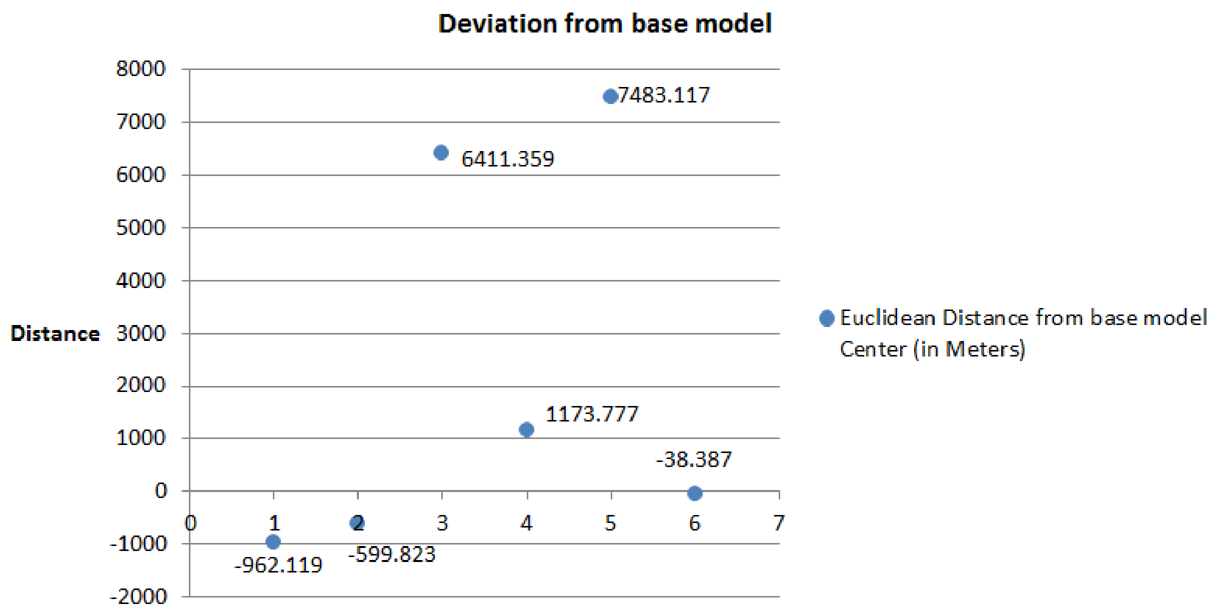

Figure 5.24: Mean coordinate deviation - Devenport wildfire

5.6 Discussion

Among the six altered models investigated in chapter 5, it was discovered that the models that had 'fuel particle moisture' and 'live fuel load' variables eliminated, had the best Jaccard Similarity scores of 0.91826 and 0.82279. Furthermore, the 'modified moisture' model too had a similarity coefficient of 0.94327. But since the purpose of the research was to enhance an existing wildfire propagation model by eliminating barriers that obstructed the implementation of the said model in a real-time wildfire propagation prediction system in developing countries, the former two findings can be considered as the major findings of the research. Furthermore, the Euclidean distance analysis between centers of masses of model spreads indicates that the better model between 'No fuel particle moisture' and 'No live fuel load' in a practical perspective, is the 'No fuel particle moisture' model, based on their MOD signs as well as the similarity coefficient.

As another finding of the research, the 'modified moisture' model can be presented. The accuracy of a model can be enhanced using the modified moisture input in wildfire simulation. Another secondary discovery was that some of the rationale taken for the selection of potential variables that could be eliminated, were conflicted when compared with the results of this study. The design of the study was to determine the correlation of the selected variables. Sullivan [36] noted that the fuel load is the weakest identified correlation with the rate of spread. But when

‘Ovendry fuel loading’ variable was eliminated, only a similarity score of 0.34275 was achieved. The variable, ‘Optimum packing ratio’ was selected from Kreye et al.’s [35] statement that ‘surface fuel loading’ is the weakest correlation with the rate of spread. But when ‘Optimum packing ratio’, a variable that is related to deriving the surface fuel loading was eliminated, the resulting correlation was as low as 0.47091. Similarly ‘Mineral damping coefficient’ variable can be observed to have a larger impact on the Rothermel’s model that it was presumed to be. The similarity coefficient acquired for the ‘No mineral damping coefficient’ was as low as 0.35578.

The novelty of the study lies in the fact that even though there have been many enhancement on existing fire behavior models as noted in the sections 2.3 and 2.4, there haven’t been any attempt at enhancing the Rothermel’s model [2] by eliminating its variables and achieving an acceptable accuracy rate to the extent of the knowledge of the research team. The closest study that was found by the authors of this research was by Karouni et al. [28], who proposed a semi-empirical model that may better suit a developing country such as Lebanon. While they proposed a semi-empirical model by simplifying Rothermel’s model [2] combining with Andersons’s [6] experimental study, even though it was intended for the ecosystem of Lebanon, it was not validated by using historical wildfires. Thus unlike Karouni et al.’s [28] study, the purpose of this particular research was to differentiate itself by investigating the Rothermel’s model for weaker input variables and enhancing the model by eliminating those variables. In order to ensure the realism of the findings, a set of historical wildfire data was used for evaluation as well, unlike Karouni et al.’s study. Furthermore, the authors proposed a novel wildfire propagation model analysis framework to assess the practicality of a wildfire propagation model in real world. It was named MOD (Most Occurring Data) Sign analysis and is a simple measure that is easy to understand and use.

There are several limitations to the study. One is that even though there are 24 variables in the Rothermel’s model, the research only investigates five variables, although they are based on some rationale. Some variables such as wind direction, wind speed, elevation, fire origin etc. have a very high impact on the model output, thus cannot be eliminated. But the effect of eliminating these variables could have been still investigated. Another limitation is that even if the effects of a single variable elimination was investigated in the research, there could still be combinations of the selected variables that could produce an even better result. Yet another weakness was the inability to produce real fire spreads for the sample wildfires in order to compare them against the Rothermel’s model and altered models. The benchmark considered in the study is the Rothermel’s model, not the real spread. Thus any attempt to prove the superiority of altered models over the Rothermel's model is not possible in this study.

5.7 Summary

This chapter elaborated on the evaluation experiment and result analysis of the research. A set of models were derived from the Rothermel's surface fire behavior model and the analysis was carried out in two phases. 1) Pilot wildfire analysis 2) Sample wildfire analysis. The primary measure taken was the Jaccard Similarity Coefficient. As a secondary measure, Euclidean distances from the center of mass of the benchmark model to each altered model center of mass and MOD Sign analysis was applied to measure the practicality of the altered models.

Chapter 06

Conclusion

In this chapter, a conclusion and a summary of the study in relation to its research aims & objectives, research problem, and limitations of the current work is given. Furthermore, at the end of the chapter, suggestions for future works are discussed as well.

6.1 Conclusion

In this thesis, a study was conducted to enhance an existing wildfire behavior model to use fewer resources in a practical implementation as the research problem. To achieve this, initially the background literature was studied to select a suitable model and the Rothermel's surface fire behavior model was selected based on a set of criteria. Afterward, a set of altered models were implemented by eliminating a few variables from the Rothermel's model and a sample of historical fires was acquired from a benchmark dataset. Then an implementation and configuration process was carried out via GRASS GIS. Finally, the output spread files for altered models were compared against benchmark Rothermel's model output using the Jaccard Similarity score and Euclidean distance between the centers of masses in spreads.

It was discovered in the analysis that among the altered models, acceptable high similarity scores were found in models where 'fuel particle moisture' and 'live fuel load' variables were eliminated. But from the MOD Sign analysis, it was conveyed that in practical perspective, 'No fuel particle moisture' model was better than 'No live fuel load'. A secondary finding was the 'Modified moisture' model that performed with high accuracy when compared with the benchmark spread.

The significance of the high similarity coefficients in the 'no fuel particle moisture' and 'no live fuel load' models is that these eliminated variables have very less effect on the overall Rothermel's model. Therefore it may be possible to eliminate the variable altogether from the model albeit at the cost of a small reduction in the overall accuracy. But eliminating these variables may lead to the reduction of resources, effort, and cost required to establish the infrastructure for acquiring the inputs for the model. Rothermel's model is one of the most essential propagation models in the current day and many propagation prediction systems make use of the model due to its accuracy and applicability. But the model itself has 24 variables. For a country or a region that has fewer resources in hand but a real need to implement a wildfire propagation prediction system, they can use an altered model with less variables instead of Rothermel's model with an acceptable loss of accuracy.

Furthermore, the study proposed a novel assessment framework to evaluate the practical feasibility of the altered models by calculating the MOD sign for each altered models. Since the altered models were supposed to simplify the Rothermel's model, errors in accuracy were expected. In a particular wildfire scenario, if the model output spread area is greater than that of the actual wildfire spread, the decisions taken considering the model output can be adjusted from the feedback from local firefighters and remote sensors. But if the predicted spread is lesser than the actual spread, then it may result in directing assets to areas already under threat. Thus decisions based on this information may lead assets into danger more than the alternative. MOD Sign analysis was intended as a simple mean to ensure that the altered models do not possess operational dangers when associated with real-time wildfire disaster management and decision making.

6.2 Future Work

The approach used in the study is novel and can be used for further researches as well as adding improvements for the methodology used. The Grass GIS doesn't provide a complete guide on conducting wildfire simulations using the software and therefore, a separate tool which helps for easy alteration of the base model and integration with a GIS can be explored. The Rothermel model is used as the base model for the study but there are some other models which are used for other aspects like crown fire, spotting etc. These models too can be explored for alteration and optimization opportunities. The Rothermel model is developed by adding other aspect models as well in the modern wildfire simulation systems. An approach to compare the performance of those improved wildfire simulation models with basic models can be explored in future researches using this type of GIS-based visualization methodology.

Another possible avenue would be to localize a fire behavior model so that it would better represent the behavior of a fire in a specific region. In this case, modifying a fire behavior model that is optimized to better suit a forest area in Sri Lanka that is heavily under wildfire threat is a great opportunity for a future study.

As this research only explored the wildfire propagation prediction, it is also possible to investigate the possibility of integrating wildfire detection as well. Such a thing can be achieved via IoT sensor kits, UAVs or even by continuing in the same avenue of GIS by utilizing satellites as wildfire detection and monitoring agents. Furthermore, a real-time web application can be developed that has both the wildfire detection and propagation prediction capabilities as well.

References

[1] C. Bielski et al., "Coupling early warning services, crowdsourcing, and modelling for improved decision support and wildfire emergency management", 2017 IEEE International Conference on Big Data (Big Data), 2017.

[2] R. Rothermel, “A mathematical model for predicting fire spread in wildland fuels”. Intermountain Forest And Range Experiment Station., 1972

[3] C. Wagner, "A Simple Fire Growth Model", Department of fisheries and forestry, Petawawa Forest Experiment Station, Chalk River, Ontario, 1969.

[4] C. Wagner. “Condition for the start and spread of a crown fire”. Ontario: Canadian Forest service petawawa forest experiment station, pp. 23-34, 1977

[5] F. Albini, M. Alexander, and M. Cruz, “A mathematical model for predicting the maximum potential spotting distance from a crown fire”. *International Journal of Wildland Fire*, 2012

[6] H. Anderson, “Predicting Wind- Driven Wild Land Fire Size and Shape”. Intermountain Forest and Range Experiment Station Ogden, UT 84401,1983

[7] D. Anderson, E. Catchpole, N. De Mestre and T. Parkes, "Modelling the spread of grass fires", 1982.

[8] M. Finney, “FARSITE”. Ogden, UT: U.S. Dept. of Agriculture, Forest Service, Rocky Mountain Research Station, 2004.

[9] P. Andrews, “BEHAVE: fire behaviour prediction and fuel modelling system – BURNsubsystem,Part1”, USDAForestService, Intermountain Forest and Range Experiment Station, General Technical Report INT194, 1986.

[10] D. Crawl, J. Block, K. Lin and I. Altintas, "Firemap: A Dynamic Data-Driven Predictive Wildfire Modeling and Visualization Environment", *Procedia Computer Science*, vol. 108, pp. 2230-2239, 2017.

[11] "Wildfire and People", *Ruk*, no. 33, pp. 1-36, 2017.

[12] "Mathematical Modeling", *Mat.univie.ac.at*, 2018. [Online]. Available: https://www.mat.univie.ac.at/~neum/model.html. [Accessed: 15- Nov- 2018].

[13] R.O. Weber, "Analytical models for fire spread due to radiation", *Combustion and Flame* vol. 78, pp. 398-408, 1989

[14] "Software can model how a wildfire will spread", *The Economist*, 2018. [Online]. Available: https://www.economist.com/science-and-technology/2018/08/02/software-can-model-how-a-wildfire-will-spread. [Accessed: 15- Nov- 2018].

[15] W. L. Fons, "Analysis of fire spread in light forest fuels". *Journal of Agricultural Research*, pp. 93-121, 1946.

[16] Tarifa, C. S., and A. M. Torralbo, "Flame propagation along the interface between a gas and a reacting medium". *Eleventh Symposium (International) on Combustion (Berkeley, California 1967).* Pittsburgh: The Combust. Inst, Pp. 533-544, 1967.

[17] F. Albini, "Spot fire distance from burning trees - a predictive model", USDA Forest Service, Intermountain Forest and Range Experimental Station, General Technical Report INT-56, 1979.

[18] Albini et al., "Calibration of a large fuel burnout model", *International Journal of Wildland Fire*, vol. 5, pp. 81-91, 1995.

[19] F. Albini, M. Alexander, "Potential Spotting Distance from Wind-Driven Surface Fires". Intermountain Forest And Range Experiment Station., 1983

[20] A. McArthur, "Weather and grassland fire behavior", *Leaflet 100*, Commonwealth Department of National Development, Forestry and Timber Bureau, 1966.

[21] A. Grishin, “Steady-state propagation of the front of a high-level forest fire”. *Soviet physics, Doklady*, vol. 28, no. 4, pp. 328-330, 1984.

[22] G. Dorrer, “A model of the spreading of a forest fire”, *Heat Transfer - Soviet Research*, vol. 16, pp. 39 -55, 1984.

[23] M. Finney, “FARSITE”. Ogden, UT: U.S. Dept. of Agriculture, Forest Service, Rocky Mountain Research Station, 2004.

[24] Finney, M. A. 2006. “An overview of FlamMap fire modeling capabilities”. In: Fuels management—how to measure success: conference proceedings. 2006 March 28-30; Portland, Oregon. Proceedings RMRS-P-41. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station: pp. 213-220.

[25] R. Rothermel, “Predicting Behavior and Size of Crown Fires in Northern Rocky Mountains”. Intermountain Forest And Range Experiment Station, 1991

[26] Karafyllidis I, “Acceleration of cellular automata algorithms using genetic algorithms” *Advances in Engineering Software,* vol. 30, no. 6, pp. 419–437, 1999.

[27] Zhang Yongzhong, E. Youhao, Han Tao, Zou Songbing and Wang Jihe, "A CA-based information system for surface fire spreading simulation", 2018.

[28] A. Karouni, B. Daya, S. Bahlak and P. Chauvet, "A Simplified Mathematical Model for Fire Spread Predictions in Wildland Fires Combining between the Models of Anderson and Rothermel", *International Journal of Modeling and Optimization*, vol. 4, no. 3, pp. 197-200, 2014.

[29] Lopes A, Cruz M, Viegas D, “Firestation – an integrated system for the simulation of wind flow and fire spread over complex topography”, in *III International Conference on Forest Fire Research and 14th Conference on Fire and Forest Meteorology*, Luso, Portugal, Nov. 1998, pp. 16–20.

[30] J. Coen, M. Cameron, J. Michalakes, E. Patton, P. Riggan and K. Yedinak, "WRF-Fire: Coupled Weather–Wildland Fire Modeling with the Weather Research and Forecasting Model", *Journal of Applied Meteorology and Climatology*, vol. 52, no. 1, pp. 16-38, 2013.

[31] D. Crawl, J. Block, K. Lin and I. Altintas, "Firemap: A Dynamic Data-Driven Predictive Wildfire Modeling and Visualization Environment", *Procedia Computer Science*, vol. 108, pp. 2230-2239, 2017.

[32] R.M. Nelson, "Prediction of diurnal change in 10-h fuel stick moisture content", *Canadian Journal of Forest Research*, 30:1071-1087 2000

[33] G. Perry, "Current approaches to modelling the spread of wildland fire: a review", *Progress in Physical Geography*, vol. 22, no. 2, pp. 222-245, 1998.

[34] G. Perry, A. Sparrow and I. Owens, "A GIS-supported model for the simulation of the spatial structure of wildland fire, Cass Basin, New Zealand", *Journal of Applied Ecology*, vol. 36, no. 4, pp. 502-518, 1999.

[35] J. Kreye, L. Kobziar and W. Zipperer, "Effects of fuel load and moisture content on fire behaviour and heating in masticated litter-dominated fuels", *International Journal of Wildland Fire*, vol. 22, pp. 440–445, 2013.

[36] A. Sullivan, "Wildland surface fire spread modelling, 1990–2007. 2: Empirical and quasi-empirical models", *CSIRO Sustainable Ecosystems and CSIRO Climate Adaptation Flagship*, 2009.

[37] A. Sullivan, "Wildland surface fire spread modelling, 1990–2007. 1: Physical and quasi-physical models", *CSIRO Sustainable Ecosystems and CSIRO Climate Adaptation Flagship*, 2009.

[38] A. Sullivan, "Wildland surface fire spread modelling, 1990–2007. 3: Simulation and mathematical analogue models", *CSIRO Sustainable Ecosystems and CSIRO Climate Adaptation Flagship*, 2009.

[39] L. Hawley, “Theoretical considerations regarding factors which influence forest fires”, *Journal of Forestry,* vol. 24, no. 7, pp. 756–763, 1926

[40] H. Gisborne, “The objectives of forest fire-weather research”, *Journal of Forestry,* vol. 24, no. 7, pp. 756–763, 1927.

[41] H. Gisborne, “The complicated controls of fire behavior”, *Journal of Forestry,* vol. 24, no. 7, pp. 756–763, 1929.

[42] J. Curry, W. Fons, “Rate of spread of surface fires in the Ponderosa pine type of California”, *Journal of Agriculture Research*, vol. 57, no. 4, pp. 239-267, 1938.

[43] J. Curry, W. Fons, “Forest-fire behavioral studies”, *Mechanical Engineering*, vol. 62, pp. 219-225, 1940.

[44] J. Sanderlin, J. Sunderson, “Simulation for wildland fire management and planning support (fireman): executive summary”, Mission Research Corp, spec. 200, 1975.

[45] J. Sanderlin, R. Van Gelder, “Simulation of fire behavior and suppression effectiveness for operational support”, in *Wildland Fire Management. Proceedings of the First International Conference on Mathematical Modeling,* Rolla, MO, Sept. 1977, vol. 2, pp. 619-630.

[46] G. Richards, “A general mathematical framework for modeling two-dimensional woodland fire spread”, *International Journal of wildland fire,* vol. 5, pp. 63-72, 1995.

[47] G. Guariso, and M. Baracani. “A simulation software of forest fires based on two-level cellular automata”, in *Proceedings of the IV International Conference on Forest Fire Research, 2002 Wildland Fire Safety Summit,* Luso, Portugal, Nov. 2002, pp. 100.

[48] D. Green, A. Tridgell and A. Gill, "Interactive simulation of bushfires in heterogeneous fuels", *Mathematical and Computer Modelling*, vol. 13, no. 12, pp. 57-66, 1990.

[49] J. Coleman and A. Sullivan, "A real-time computer application for the prediction of fire spread across the Australian landscape", *SIMULATION*, vol. 67, no. 4, pp. 230-240, 1996.

[50] J. Kreye, L. Kobziar and W. Zipperer, "Effects of fuel load and moisture content on fire behaviour and heating in masticated litter-dominated fuels", 2018.

[51] V. Petras, "Wildfire modeling in GRASS GIS", Geospatial Modeling and Analysis North Carolina State University, 2014.

[52] P. Offermann, O. Levina, M. Schönherr and U. Bub, "Outline of a design science research process", *Proceedings of the 4th International Conference on Design Science Research in Information Systems and Technology - DESRIST '09*, 2009.

[53] G. Morgan, J. Gliner and R. Harmon, "Quantitative Research Approaches", *Journal of the American Academy of Child & Adolescent Psychiatry*, vol. 38, no. 12, pp. 1595-1597, 1999.

[54] P. Jaccard, "E´tude comparative de la distribution florale dans une portion des Alpes et des Jura", *Bulletin de la Socie´te´ Vaudoise des Sciences Naturelles*, vol. 37, pp. 547–579, 1901.

[55] J. Filippi, V. Mallet and B. Nader, "Representation and evaluation of wildfire propagation simulations", 2018.

[56] P. Thomas, "Some aspects of the spread and growth of fire in the open", *Forestry*, vol. 20, pp. 139-164, 1967.

[57] R. Weber, "Thermal theory for determining the burning velocity of a laminar flame using the inflection point in the temperature profile", *Combustion and Flame*, vol. 78, pp. 398-408, 1989.

[58] R. Weber, "Modelling fire spread through fuel beds", *Progress in Energy and Combustion Science*, vol. 17, pp. 67-82, 1991.

[59] C. Chandler, P. Cheney, P. Thomas, L. Trabaud, and D. Williams, "Fire in forestry", *Forest fire behavior and effects*, vol. 1, pp. 39-52, 1983.

[60] B. Stocks, B. Lawson, M. Alexander, C. van Wagner, R. McAlphine, T. Lynham, and C. Dubé, "The Canadian Forest Fire Danger Rating System: an overview", *Forestry Chronicle*, vol. 65, pp. 450-457, 1989.