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THESIS

MODELING OF PHYSICALLY-BASED PREDICTIVE FIRE EVENTS IN A VIRTUAL ENVIRONMENT FROM GEOSPECIFIC DATA

by

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September 2023

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Using a fast-running fire modeling software, HFIRE, surface fire spreads are simulated on the fictional continent of Dystopia. A Monte Carlo simulation is conducted to analyze wildfire events, assess fire spread, and evaluate direct and indirect impacts to a designated military installation. Model excursions consider how potential climate change consequences affect these impacts.

The findings underscore that drier conditions invariably result in increased fire severity and more frequent impacts to the military installation. Furthermore, it enables the identification of high-risk areas subject to wildfires. These results can facilitate enhanced preventive measures and more effective emergency responses, thereby minimizing the vulnerability of military installations to wildfires in an era of climate change.

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Table of Contents

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List of Figures

List of Tables

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List of Acronyms and Abbreviations

BAAF Bradshaw Army Airfield

CONUS continental United States

DCAP DOD Climate Adaptation Plan

DCRA DOD Climate Risk Analysis

DLA Defense Logistics Agency

DOD Department of Defense

EO Executive Order

EVC existing vegetation cover

FBFM Fire Behavior Fuel Models

FDS Fire Dynamics Simulator

GIS Geographic Information System

HFIRE High-resolution Fire Spread Simulator

KNN k-nearest neighbors

LACoFD Los Angeles County Fire Department

LOE Lines of Effort

MPI Message Passing Interface

NLCD National Land Cover Database

NIST National Institute of Standards and Technology

NPS Naval Postgraduate School

RAWS	Remote Automated Weather System
PSPS	Public Safety Power Shutoff
SAV	surface-area-to-volume-ratio
SERDP	Strategic Environmental Research and Development Program

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CHAPTER 1:
Introduction

1.1 Motivation

On January 27, 2021, President Biden issued Executive Order (EO) 14008, "Tackling the Climate Crisis at Home and Abroad," underscoring the United States' commitment to combating climate change (Biden 2021). This directive served to underscore the importance of integrating climate change considerations into policy-making at all levels. The DOD Climate Risk Analysis (DCRA) was subsequently published to confront the national security implications arising from climate change impacts.

The world is witnessing a dramatic surge in natural disasters such as wildfires, floods, droughts, typhoons, and other extreme weather events (Department of Defense, Office of the Undersecretary for Policy [Strategy, Plans, and Capabilities] 2021). These events will result in cascading effects on the Department of Defense (DOD)'s capacity to fulfill its missions both at home and while deployed. Not only do they have the potential to strain our own resources due to damage and loss, they also result in increased demand for humanitarian services. The heightened competition for resources underlines the potential risk to security and stability and the need to prepare for such events.

In adherence to EO 14008, the Department of Defense, Office of the Undersecretary of Defense [Acquisition and Sustainment] (2021) issued the DOD Climate Adaptation Plan (DCAP). This document underscores the imperative of integrating climate considerations into operations and policy-making processes. It delineates five primary Lines of Efforts (LOEs):

1. Climate-Informed Decision Making (LOE 1);
2. Train and Equip a Climate-Ready Force (LOE 2);
3. Resilient Built and Natural Installation Infrastructure (LOE 3);
4. Supply Chain Resilience and Innovation (LOE 4); and
5. Enhance Adaptation and Resilience Through Collaboration (LOE 5).

Further emphasizing this ongoing commitment, the 2022 DCAP Progress Report sheds light on advancements made in these endeavors while also highlighting existing constraints (Department of Defense, Office of the Undersecretary of Defense [Acquisition and Sustainment] 2022). In the progress report, all five are listed as "in progress," identifying the persistent need for action.

Natural disasters resulting from climate change pose an escalating threat to environments and the potential to cause serious disruption to our way of life. Wildfire risk is of particular concern as recent years have seen increased activity and trends suggest that the situation is unlikely to reverse (McWethy et al. 2019). Living with wildfires has been a part of several areas in the United States, notably Western states such as California, and it is likely that this will become more prevalent in other parts of the country and world. Wildfires can cause significant damage and impact to landscapes, populations, and can cause unexpected evacuations for personnel. Many efforts have been made to mitigate this threat and increase resilience to be better prepared for wildfire occurrence. The fact remains that an unexpected wildfire has the potential for catastrophic consequences, and even with considerable preparation there may be undiscovered impacts that result from such an occurrence.

1.2 Objective

In order to prepare forces for operation in changing environmental conditions, a necessary precursor is understanding how environments might change in response to natural disasters. Simulation and exercise provide a landscape to run no-risk, what-if scenarios that allow for the exploration of impacts, vulnerabilities, and response capabilities. Understanding the possible consequences of wildfire is of vital concern for military and civilian leaders. The ability to adapt to a dynamic environment is necessary in a world where change is inevitable. However, there are many possibilities in which the environment might change, thus the need for simulation and exercise. A virtual environment has many benefits for study and can be used as a model for experimentation. This thesis aims to support LOE 1: Climate-Informed Decision Making and LOE 2: Train and equip a Climate-Ready Force from the DOD Climate Adaptation Plan by delving into the dynamics of wildfire risk within a simulated virtual environment. By doing so, we seek to illustrate potential shifts in the intensity of these events as they respond to alterations in environmental conditions.

CHAPTER 2:
Background and Related Work

2.1 Importance of Wildfire to DOD

In 2019, DOD presented a report to Congress (Office of the Under Secretary of Defense for Acquisition and Sustainment 2019) highlighting the effects of climate change on different military installations. The report analyzed the current and potential vulnerabilities to climate related events including recurrent flooding, drought, desertification, wildfires, and thawing permafrost. The report states that the effects of climate change pose a national security threat, potentially affecting the missions, plans, and installations of the Department of Defense. Furthermore, the report studied 79 mission essential military installations and concluded that wildfire was a primary concern for nearly half (Office of the Under Secretary of Defense for Acquisition and Sustainment 2019).

Wildfires present significant hazards to the Department of Defense (DOD) in various ways. One concern is the direct impact to installations that are located in wildfire-prone areas, such as those in Western states. These installations risk loss of critical infrastructure, which can significantly impact operations. Critical infrastructure can include energy infrastructure, communications networks, and military assets themselves. This can have a profound impact on military operations, as well as lead to a significant financial burden. In addition to the loss of critical infrastructure, a wildfire in close proximity to a military installation can pose a direct danger to personnel and may require evacuation, further complicating the situation.

The indirect impact of wildfires on the readiness of the military is a major concern. The smoke and ash produced by wildfires can have a significant impact on air quality, making it difficult for military personnel to complete essential training and testing activities. This can have a significant impact on the readiness and ability of those personnel to carry out their mission. The lingering effects of wildfires, such as decreased air quality, can persist for an extended period of time, exacerbating the impact on military operations.

Wildfires are among the most unpredictable and uncontrollable natural disasters, posing unique challenges for the DOD. The uncertainty surrounding these fires is driven by the considerable variability in their intensity, size, and duration, which makes it difficult to predict their impacts accurately. This inherent unpredictability not only challenges effective preparation and response but also underscores the urgent need for continued research and strategic planning to better comprehend and mitigate the effects of wildfires.

These fires may start or evolve in a myriad of ways, demanding diverse responses that are often influenced by factors such as the proximity of fire ignition to a military installation. For instance, if a fire ignites close to a military base, it could pose a direct threat to the personnel, equipment, and infrastructure. Under such circumstances, the military's top priority becomes the safety of its personnel and assets, which may necessitate initiating evacuation procedures. However, the military's role is not confined to defensive actions. It may also be called upon to actively contribute to firefighting efforts, leveraging its resources and personnel to help control the spread of the fire. These complex dynamics illustrate the multifaceted relationship between wildfires and military preparedness, emphasizing the need for adaptive strategies and resilience.

DOD has been involved providing military support for fire suppression since the 1880s (U.S. Department of Agriculture 2017). Federal and state agencies can request the military's assistance during high wildfire activity for various support, including both aviation assets and ground forces. Most commonly, C-130s outfitted with fire suppression systems are requested and deployed. However, military personnel can also serve as firefighters after undergoing expedited field training (U.S. Department of Agriculture 2017). Furthermore, Defense Logistics Agency (DLA) provides logistical support to provide equipment and ready-to-eat meals for personnel in the field during firefighting efforts. In 2021, DLA supported 282 items and provided 263,000 meals, 1,945 miles of hose, and 5.1 million batteries (Beneki 2022).

2.1.1 Related Work at NPS

De Abreu (2020) identified increasing frequency of ignitions by utility companies' equipment, some of which led to substantial wildfires particularly in the Western United States. As a result, these companies have initiated large scale power outages, termed Public Safety Power Shutoff (PSPS), to reduce their risk. As De Abreu noted, these PSPS events can vary in size and duration, and cause significant social cost to customers. The problem as it pertains to DOD installations is twofold. First, many receive power from these utility companies and are susceptible to PSPS events; second, many installations are located in wildfire prone areas.

Firefighting departments responding to wildfire events must decide where to position their resources, such as different types of trucks and personnel with various qualifications. Scholz (2019) developed a mathematical model to determine the optimal placement of firefighting resources for the Los Angeles County Fire Department (LACoFD), which was subsequently improved upon by Seeberger (2020). This tool was effectively utilized by LACoFD and assessed that it outperformed previous models.

2.2 Current Fire Models and Simulation Tools

Rothermel Equations

Rothermel (1972) produced a set of equations that provide a quantitative means of predicting fire spread and intensity that are specifically suitable to surface fire spread. These equations have been around for decades, yet are still powerful enough to be used by today's modern software. The Rothermel equations together form a basic fire spread model that predicts rate of spread based on input parameters that can be calculated before a fire occurs. The input variables can be categorized as:

- Fuel particle properties – heat content, mineral content, and particle density;
- Fuel array arrangements – fuel load, surface-area-to-volume-ratio (SAV), mean depth of fuel bed, and dead fuel moisture of extinction; and
- Environmental variables – fuel moisture content, wind velocity, slope steepness (Rothermel 1972).

To facilitate the use of these inputs in equations, models, and systems, Rothermel introduced the concept of a fuel model that categorizes parameters of common wildfire fuels. A fuel model defines parameters for a particular vegetation type that influence burn characteristics. This eliminates the need to measure individual values such as SAV, heat content, and moisture content, as these values are typically inherent to the fuel type. Rothermel listed parameters for 11 different fuel models that have seen improvements over time. In 1976, Albini (1976) redefined the initial 11 and added two more, which were later described by

Anderson (1982) along with criteria for selecting a model. These 13 fuel models comprise four groups: grass, shrub, timber, and slash. Later, Scott and Burgan (2005) expanded to provide an additional 40 fuel models to account for dynamic conditions. Together, the 13 Anderson Fire Behavior Fuel Models (FBFM) along with the 40 Scott and Burgan FBFM are utilized by modern fire modeling software.

The earliest forms of predicting fire spread took the form of programmable field calculators using the Rothermel equations (Peterson et al. 2009). However, limitations of the Rothermel's model include the assumption of a homogeneous fuel bed, the alignment of wind directly with slope, and a wind speed limit above which the predicted rate of spread is constant. As computers became popular, the earliest forms of modeling fire spread took form. Albini (1976) wrote the first programs based on the Rothermel equations in FORTRAN IV named FIREMODS. He provided several changes to the equations such as updating coefficients and weighting parameters that have since over time been incorporated into the original model.

BEHAVE and BehavePlus

BEHAVE was first used in the field in 1984 as an early computer-based software that was also based on the Rothermel fire spread equations (Andrews 2014). In 2002, BEHAVE was updated to BehavePlus. It serves as a point fire modelling system, which means that conditions are held constant for each calculation. It uses all 53 standard FBFM and can be used to model fire behavior, fire effects, and the fire environment.

The benefit of this software is that the mathematical models are broken down into modules that can be used independently or linked together by the user. The BehavePlus software includes the following modules: probability of ignition, surface fire behavior, crown fire behavior, safety zone size, point source fire size and shape, fire containment due to suppression, max spotting distance, crown scorch height, and probability of tree mortality. Outputs of these modules take the form of tables and graphs allowing users to experiment with various parameters to evaluate cause and effect relationships and gain an understanding of fire behavior.

The primary limitation of BehavePlus is the visualization of outputs. It does not have the ability to display the results in a user-friendly format such as maps. However, this system works for uses cases that can be understood by simple tables and graphs.

FARSITE and FlamMap

Developers recognized a need for spatial modeling of fire behavior to easily visualize wildfire spread. FARSITE was introduced in the 1990's and incorporated existing models found in BEHAVE for surface fire, crown fire, spotting, post-frontal combustion, and fire acceleration into a 2D fire growth model (Finney 1998). FARSITE can simulate past fires, active fires, and potential fires and can generate maps representing this information. This allows for analysis of fire behavior on Geographic Information Systems (GISs) but also requires that the inputs to the model also be in GIS format. Specifically, FARSITE uses a vector-based algorithm to model the Rothermel equations, which is computationally intensive.

FlamMap built upon FARSITE and was developed for extending the usability of these models where input parameters have been mapped using GIS systems (Finney 2006). It requires that the inputs be in GIS raster theme with the following layers: elevation, slope, aspect, fuel model, canopy cover, canopy height, crown base height, and crown bulk density. The major benefit of this software is that the outputs can also be formatted in raster GIS layers, which provides 3D representation of fire behavior. FARSITE is no longer a standalone product; the current version of FlamMap now includes these modules and is the fire modeling software of choice for the U.S. Forest Service and National Park Service.

High-resolution Fire Spread Simulator (HFIRE)

HFIRE was first introduced in 2001 as a spatial fire simulation model that utilizes a more efficient algorithm than FARSITE. HFIRE utilizes the same surface fire spread model as FARSITE, but it employs a raster-based approach as opposed to a vector-based approach, which significantly reduces computation time (Peterson et al. 2009).

Advantages of the HFIRE model are that it can be used in a variety of applications that require faster and more efficient simulations. For example, the model's reduced computation time allows it to be used in real-time simulations, which can be useful for fire management and emergency response. Additionally, the model's efficiency also allows it to run simulations over a longer period of time which is useful for understanding the long-term effects of fire on ecosystems and communities. Lastly, HFIRE's performance facilitates a large number of simulations to be run consecutively, enabling for a deeper analysis and more comprehensive insights.

HFIRE's primary limitation is that it does not include modules for spotting or crown fire behavior. In forested landscapes where trees are dominant, the model's depiction of fire propagation is limited to surface spread.

Fire Dynamics Simulator (FDS)

FDS is a computational fluid dynamics model of fire-driven fluid flow produced by the National Institute of Standards and Technology (NIST) (McGrattan et al. 2022). It works alongside Smokeview (Forney 2023), which is a separate program that allows visualization of the results of an FDS simulation. It has been widely used for designing smoke handling systems and fire reconstructions. FDS focuses on practical fire problems while also providing a tool to study fundamental fire dynamics and combustion. The model consists of hydrodynamic, combustion, and radiative heat transfer components. FDS uses a rectilinear mesh for geometry approximation and supports multiple meshes for complex computational domains. Parallel processing is achieved using OpenMP for single computers and Message Passing Interface (MPI) for computer clusters. The model also allows for the assignment of thermal boundary conditions and burning behavior for solid surfaces.

QUIC-Fire

QUIC-Fire was first introduced as a tool for planning prescribed fires by Linn et al. (2020). It is a fast running, 3D model, designed to assist in understanding the interaction between the atmosphere and fire behavior. QUIC-Fire uses a 3D wind solver and a cellular automata fire spread model to represent fire spread. Furthermore, it incorporates 3D vegetation structure alongside its fire spread model, wind solver, and fire-atmosphere feedback, making it useful for predicting complex fire behavior.

Benefits of the software are that it allows for 3D visualization of complex fire effects, however, the primary limitation of the software is that it is designed for simulation on flat terrain. Further developments are currently needed in order to enable its use in undulating terrain.

FIRETEC

FIRETEC is a physics-based, 3D computer code developed at Los Alamos National Laboratory to predict wildland fire behavior (Furman and Linn 2018). It combines models of combustion, heat transfer, aerodynamics, turbulence, and air flow to accurately represent the constantly changing interaction between fire and its environment. The applications of FIRETEC range from local tree configurations to weather conditions and can be used to investigate fire management practices, historical fires, and the impact of factors such as insect attacks on fire behavior. The primary downside of FIRETEC is the fact that it requires large amounts of data and a supercomputer for use.

Summary and Comparison

Table 2.1 details the advantages and disadvantages of the researched fire modeling software are summarized.

Table 2.1. Summary of Fire Modeling Software. The name of the software is listed in the leftmost column along with whether it supports fire modeling in 2D or 3D.

	Advantages	Disadvantages
BehavePlus (2D)	• Modules can be used independently to develop an understanding of fire behavior • Can run specific use case scenarios	• Limited ability to visualize outputs
FARSITE & FlamMap (2D)	• Feature rich • Easily visualized outputs	• High overhead required for input parameters • Long computational runtime to complete a simulation
HFIRE (2D)	• Computationally efficient, performs runs quickly • Ability to run single fire events or multiyear fire regimes	• No spotting or crown fire modules
FDS (2D or 3D)	• Utilizes OpenMP to exploit multiple processing units on a single computer • Can utilize MPI for computer clusters	• Software is CPU and memory intensive • Users can start simulations that are too large, requiring months to compute
QUIC-Fire (3D)	• Models interaction between fire and atmosphere • Can cover a range of fuel or weather conditions	• Limited to flat terrain • Requires 3D vegetation structure
FIRETEC (3D)	• Highly configurable, down to tree configurations and weather • Can investigate fire management practices, such as insect attacks on fire behavior	• Research tool only • Requires a supercomputer for use

2.3 Simulating Wildfire in a Virtual Environment

Dystopia is a fictional virtual environment originally developed for the Center for Homeland Defense and Security at Naval Postgraduate School (NPS) (Alderson and Darken 2019). Dystopia is a series of data layers that together form a rich environment, which in turn can be used for simulation and exercise. Over time, Dystopia has evolved into a rich world with properties representative of a real location.

Several fictitious military installations have been placed on Dystopia. Located inland, about halfway between Diablo Valley and Grim City is a Marine Corps Training Center encompassing an area of approximately 12 square miles. Secondly, El Dorado Air Force base is located in the western portion of El Dorado and encompasses an area of about 25 square miles. Its southern tip is just three miles from the southern coastline of Dystopia. Figure 2.1 showcases the Island of Dystopia, and highlights areas of interest for our study.

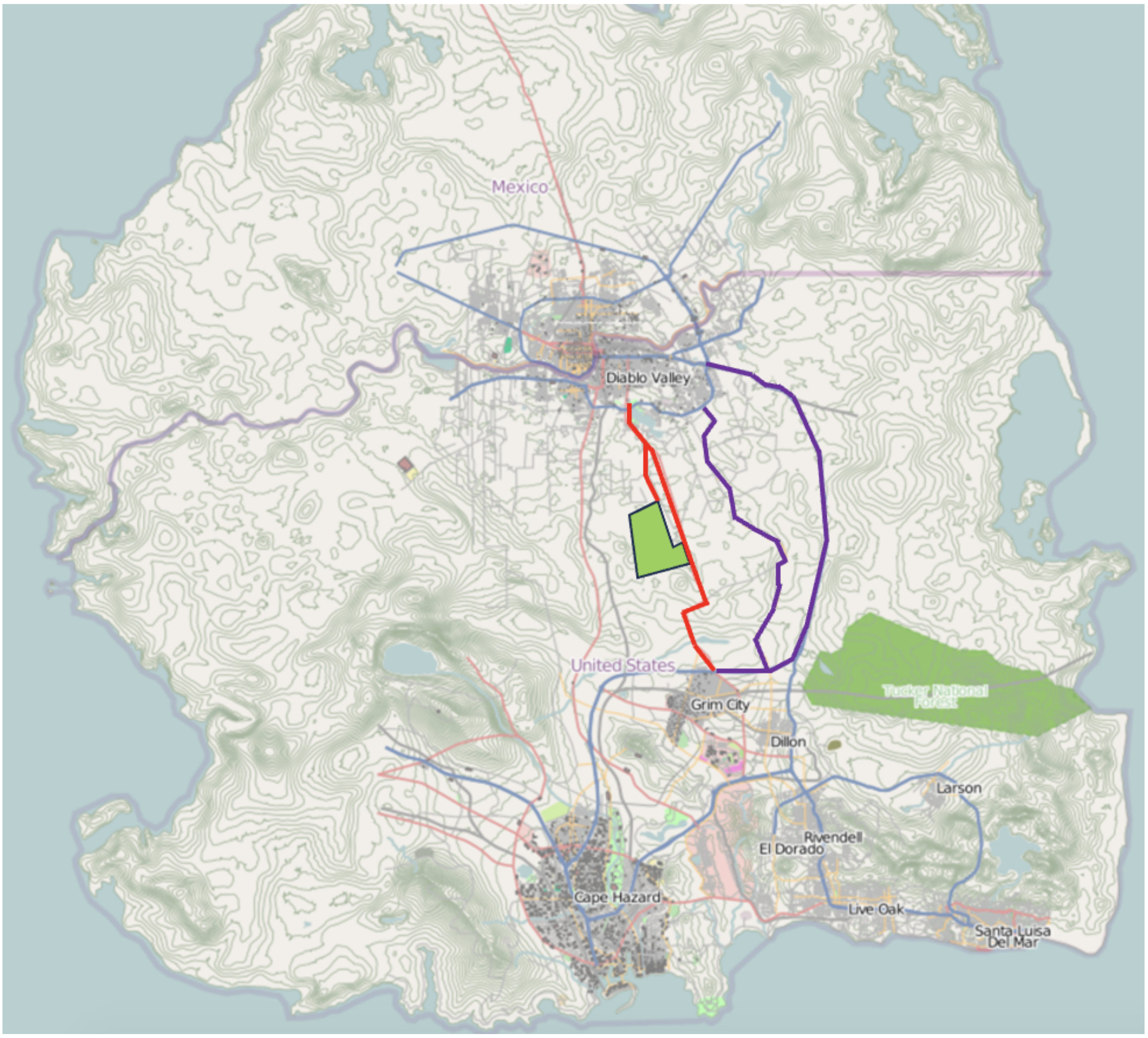

Figure 2.1. The Island of Dystopia with Highlighted Areas of Interest. Key strategic areas, including the Marine Corps Training Center installation boundary (green), access roads to the installation (red), as well as primary highways facilitating commercial transit between northern and southern municipalities (purple) are highlighted. Adapted from: Alderson and Darken (2019)

Furthermore, Dystopia is characterized by rugged, undulating terrain. The island is dominated by high mountains that extend inward from its coastline. The greatest elevation peaks are located in the southwestern portion of the island and extend up to approximately 9,000 feet. In contrast to its high mountainous regions, Dystopia's coastline is characterized by low-lying areas. This diverse topography provides a unique and varied landscape depicted in Figure 2.2.

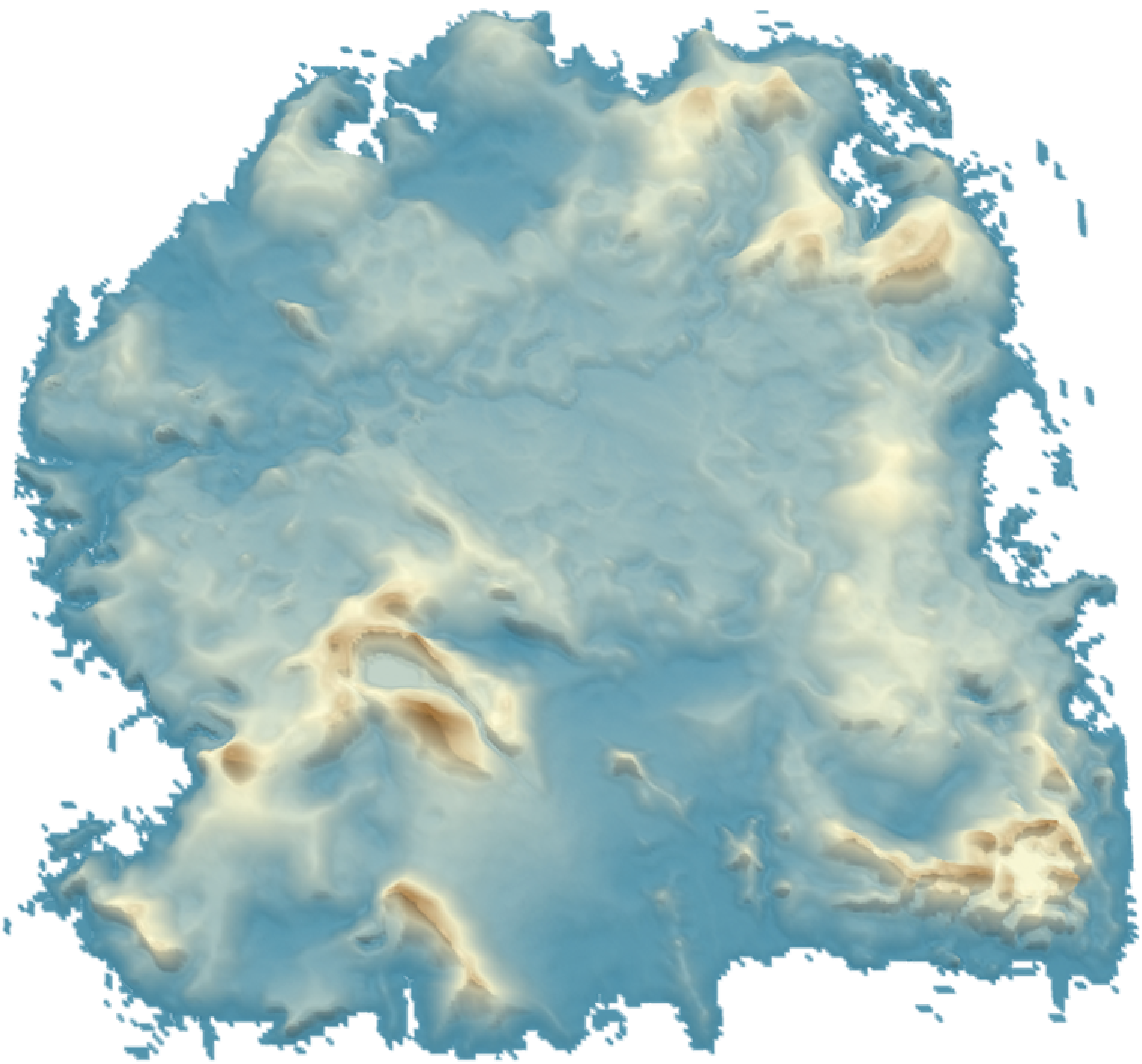

Figure 2.2. Dystopia's Elevation. Source: Center for Infrastructure Defense (2020)

Dystopia's geospatial data layers are projected in EPSG:4326 - WGS 84 (World Geodetic System 1984 2020) and its default location is centered at (0°N 0°E). Wigal (2021) developed a tool that enabled relocation of Dystopia's environment. Considering Dystopia's island setting and mountainous terrain, a logical choice for a real-world placement was to extend the Hawaiian islands to include the island of Dystopia. Figure 2.3 illustrates where the island would appear.

Figure 2.3. Geospatial Representation of Dystopia's Location. The geospatial data layers are projected southeast of The Island of Hawaii.

The world of Dystopia is a compelling candidate for a simulation aimed at comprehending the potential consequences of wildfire events. The advantage of conducting a simulation in a fictitious setting lies in its inherent flexibility and control. In a created world like Dystopia, variables can be adjusted to encompass a broad range of scenarios that may be impractical or challenging to experiment with in real locations. Moreover, this circumvents potential bias associated with pre-existing knowledge or connections to real-world locales, leading to more objective insights. As a result, simulations within Dystopia can yield valuable, unbiased data in studying the implications of wildfire events.

Realistic modeling of these types of events requires the generation of realistic data layers. The spread of wildfires is a complex phenomenon that is influenced by a number of interrelated factors. These factors include weather conditions, vegetation and fuel type, topographical features such as slope steepness, and human activities (Sherwin et al. 2018). The detail of Dystopia's physical environment provides a framework for simulation that can aid in realizing some of these effects. Importantly, a wildfire can occur in any number of locations. With the use of tools identified in Section 2.3, it is possible to explore the relationship between fire spread perimeters, ignition points, and fire duration in various locations within the world of Dystopia. This thesis aims to delve deeper into this relationship and its implications for military installations within the world of Dystopia. By understanding the impact of these factors on fire spread, it is possible to develop more effective strategies for preventing and controlling wildfires in the future.

2.4 Research Questions

This thesis explores several research questions, including the following.

1. How might we generate vegetation data utilizing geographic features and heuristics?
2. To what degree can the effects of a wildfire be predicted and modeled in a virtual environment from geospatial data?
3. How frequently does a distribution of wildfires impact a military installation and its services?
4. How do potential consequences of climate change affect the frequency in which a military installation is affected by wildfires?

CHAPTER 3:
Model Development

This thesis explores the impact of wildfire on a fictional virtual environment by algorithmically generating the required data input layers for a chosen fire modeling software, HFIRE. We use HFIRE for its performance considerations and the ability to run wildfire simulation events quickly, which enables a large number of simulations to be performed. This chapter outlines the implementation of a baseline fire case developed for Dystopia. Figure 3.1 illustrates the necessary input files and corresponding output files.

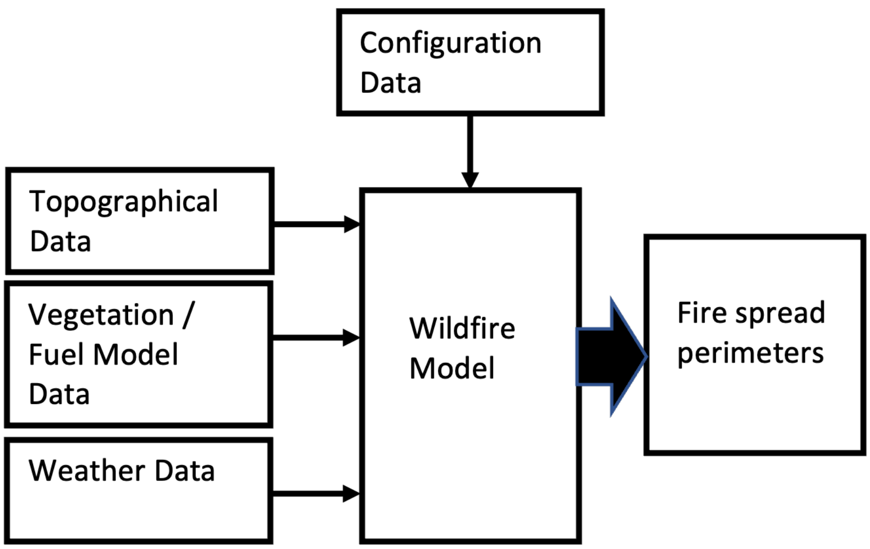

Figure 3.1. Schematic Diagram of the Wildfire Computational Framework. Inputs to the algorithm are annotated by skinny black arrows. Outputs are denoted by the thick black arrow.

3.1 Input Data

Because there are both physical and climate differences across all areas of the country, this thesis proposes an approach to generate environmental data that is realistic and based on micro-climates. This thesis explores the relationship of topographical properties of an environment with the resulting vegetation cover for a corresponding location. Specifically, it seeks to answer the question of whether the physical properties of elevation, slope, and aspect can be used to predict existing vegetation cover (EVC). Potential applications for use include realistic historical modeling of landscapes before imagery and land-surveying means became popular, hypothetical modeling of future terrain, as well as generation of synthetic data for virtual environments. There are several benefits of understanding this relationship and thus the desire to create a model that can predict vegetation cover from these three physical properties is the approach proposed here.

3.1.1 Topography

Physical terrain features are a critical factor in fire spread and therefore, an essential component of various fire models. To facilitate these models, HFIRE requires topographical data in three distinct raster files: elevation in meters, slope in degrees, and aspect in degrees. However, Dystopia's original data only included elevation data, which meant that the corresponding slope and aspect data layers had to be generated algorithmically. This process involved iterating over individual pixel values and computing the corresponding slope and aspect values before writing them to a file. The original elevation data layer and synthetically generated slope and aspect data layers are shown in Figure 3.2.

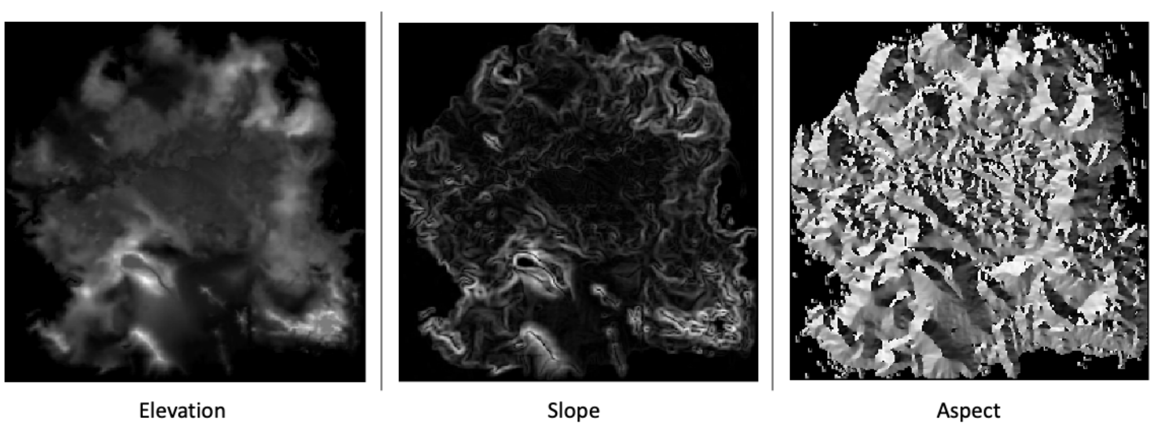

Figure 3.2. Topographical Analysis of Dystopia: elevation gradients, slope characteristics, and aspect orientation.

3.1.2 Generating Vegetation Layers Via Machine Learning

Fire modeling software relies heavily on the fuel models presented by Anderson (1982) or Scott and Burgan (2005), which are predominantly defined by the vegetation type for a particular location. Previously, Hammes (2001) presented a methodology for terrain modeling that was based on predicting the probability of certain ecotypes based on the parameters of elevation, relative elevation, slope, slope direction, and multi fractal noise. Utilizing this methodology, Hammes defined five ecosystems (dense bush, marshland, small bushes and grass, grass on steep slopes, and exposed rock) with minimum and maximum parameters. A series of formulas are introduced that calculate the probability of each of these ecosystems occurring, and then assigning that with the highest probability to that location. A benefit of this procedure is simple yet realistic predictions, enabling efficient performance for run-time calculations. His work also provides a framework for generating geotypical distributions of similar ecotypes for virtual environments.

Much of the literature found in conducting this research regarded the procedural generation of synthetic landscapes for use in video games. The problem is real-time rendering of detailed scenery computed on high performance video game consoles and computers, which is then displayed on high resolution monitors and virtual reality devices. The modeling of vegetation has become increasingly difficulty as processing power for gaming consoles and quality of display resolutions improve over time. The complexities in depicting a forest, the nuances of tree placement, and the detail of individual leaves must be incorporated into software for these landscapes to be deemed realistic. SpeedTree (Xiong and Huang 2010) is an example of a simulation system that offers high quality forestry visualization and is used by major game development companies.

This thesis includes the development of a GIS vegetation layer and corresponding fuel model for Dystopia. Specifically, we introduce a novel approach by generating vegetation data with machine learning algorithms based solely on the input parameters of elevation, aspect and slope.

Selection of Data

Geospatial data encompassing the continental United States (CONUS), Hawaii, and Alaska is widely available for download on the web. This thesis used data from the LANDFIRE website (U.S. Department of the Interior, Geological Survey, and U.S. Department of Agriculture 2016), an open source database for vegetation products. The data found on this site is required geospatial data for the widely used fire modeling software in the U.S. known as FlamMap discussed in Section 2.2. Data is provided in raster format for a variety of products that include vegetation cover, topographical features of elevation, aspect, and slope, as well as defined fire behavior fuel models. The large volume and variety of data accessible on this website lends itself to the possibility of creating a model for nearly any environment of choice. Given Dystopia's relocation southeast of the island of Hawaii described in Section 2.3, the island of Hawaii itself serves as the training data set for the following machine learning models.

Data Munging

The first step in this process is the reading and consolidation of data. The data munging process begins with translating the downloaded .tif raster files into a usable format for data analysis. We use a Python translator library, GDAL, to provide a single raster abstract data model for consolidation into text readable formats, which are then read into pandas data frames (The pandas development team 2020). In this data, elevation is represented in meters, slope in degrees, aspect in degrees from 0-359, and EVC as a number corresponding to a particular type.

The EVC for the data set comprises over 400 potential values, which created problems for the machine learning models during the early stages of testing. We observed that we could remove some of these categories from the data set and consolidate others. Wanting to explore potential vegetation growth, we omitted the instances of "open water" and "developed" categories as part of the data cleaning process. We also found a high number of different "tree cover", "shrub cover", and "herb cover" categories with varying percentages, such as 10% cover, 20% cover, etc. We decided to consolidate these varying percentages into a single category, leading to a successful machine learning algorithm. Table 3.1 depicts the final categories for EVC.

Table 3.1. Existing Vegetation Cover Categories

Class	Description
0	Barren
1	Cultivated
2	Herbaceous
3	Shrubland
4	Forest

These categories are specifically chosen as they match the National Land Cover Database (NLCD) Class Legend and Description (Multi-Resolution Land Characteristics 2021). Other examples of data cleaning involves the removal of extraneous "NoFill" values that were identifiable in the data set as the value -9999.

The resulting frequency distribution of vegetation data is illustrated in Figure 3.3.

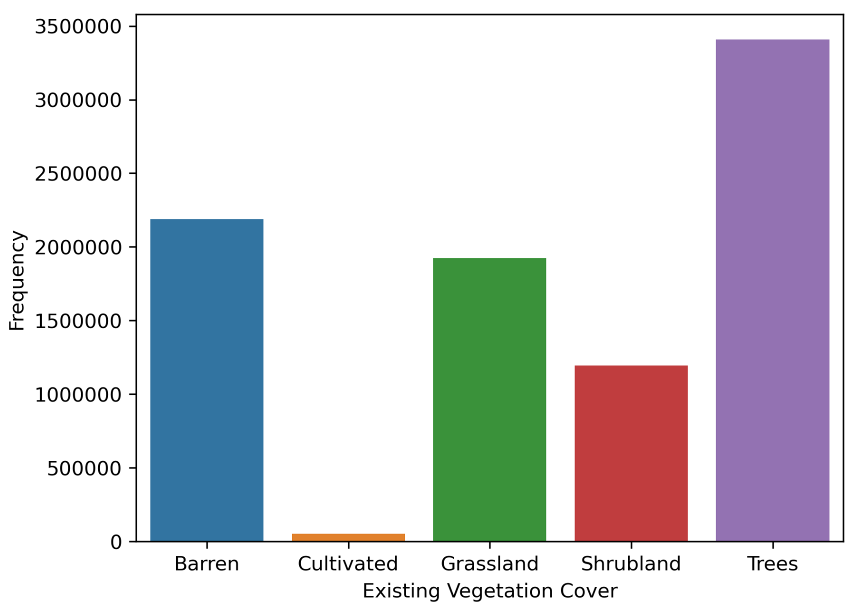

Figure 3.3. Vegetation Distribution for the Island of Hawaii.

Models

We collected data that resulted in labeled information, shaping it into a supervised machine learning problem. The model aimed to make predictions using similarity metrics of stored data points. We measured the features of elevation, slope, and aspect, and used them as the feature vector for the model. These metrics, being numeric, are applicable to distance-based algorithms once we scale the features. We employed Python's sci-kit learn libraries (Pedregosa et al. 2011; Géron 2017) to create machine learning models. The classifiers we trained on the data set to evaluate performance included k-nearest neighbors (KNN), logistic regression, decision tree, random forest, and voting ensemble.

Model Results

The initial KNN model, trained on unbinned data, yielded a model with an accuracy of 0.05, a clear sign of suboptimal performance. We assessed this is the result of the classifier predicting one of 400 categories based solely on three features. The data was subsequently cleaned, consolidating all instances of varying percentage classes into a single category, thereby reducing the complexity of the problem to only five distinct vegetation categories. This refinement in the data preparation stage enabled the creation of more precise and reliable models during testing. Subsequently, a second KNN model was trained using the updated dataset, and the updated results are detailed in Table 3.2.

Table 3.2. KNN Results

	Without Hyperparameter Tuning	With Hyperparameter Tuning
Accuracy	0.60	0.62
Precision	0.59	0.61
Recall	0.60	0.62
F1	0.59	0.61

We used a grid search algorithm to identify optimal hyperparameter choice for n-neighbor, weighting for distance, and metric for distance. The following parameters that resulted were: n-neighbor=9, weights=uniform, distance=minkowski.

Furthermore, we train KNN models on values from k=1 to k=30, simultaneously recording model accuracy. Figure 3.4 shows the results, which indicate plateauing accuracy around k=9. This pattern is indicative of potential overfitting for models trained on values where k>9, and thus, the value yielded from the grid search algorithm seems appropriate.

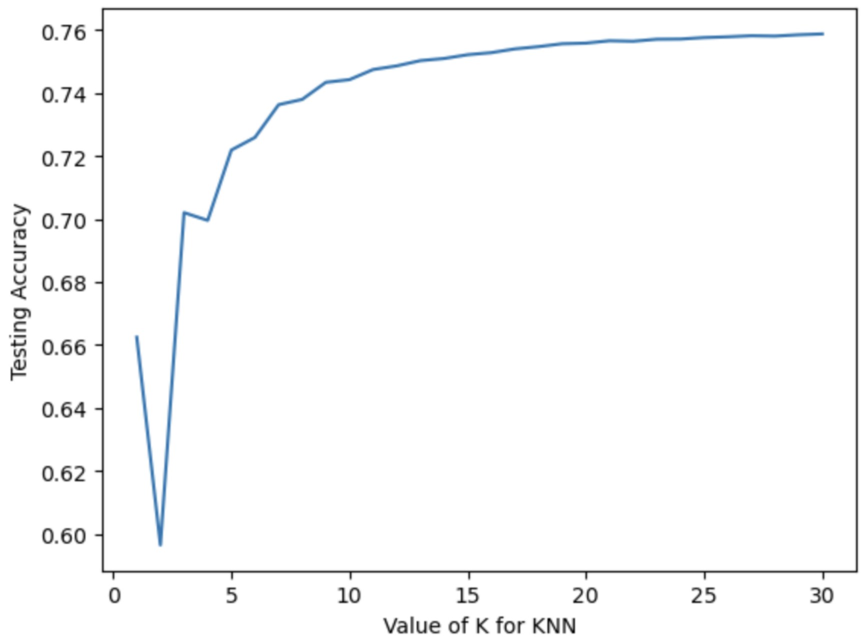

Figure 3.4. Accuracy vs. K. Plateauing accuracy is an indicator of potential overfitting.

Table 3.3 is the classification report for the best performing KNN model. The findings from this report underscore that the category posing the greatest challenge for model classification is ‘Category 1: Cultivated’. Our assessment suggests that this likely stems from the relatively low-frequency distribution, as depicted in Figure 3.3.

Table 3.3. KNN Classification Report

Category	Precision	Recall	F1-score	Support
0	0.70	0.74	0.72	436719
1	0.12	0.02	0.03	10623
2	0.49	0.49	0.49	384607
3	0.44	0.30	0.36	239317
4	0.68	0.74	0.71	682007
Accuracy			0.62	1753273
Macro Avg	0.49	0.46	0.46	1753273
Weighted Avg	0.61	0.62	0.61	1753273

Subsequent models were trained on the data set to observe any potential improvements in these statistics. Table 3.4 represents the best performing models of each machine learning algorithm, and summarizes weighted averages for accuracy, precision, recall and F1 for each.

Table 3.4. Summarized Model Results

	KNN	Logistic Regression	Decision Tree	Random Forest	Voting Ensemble
Accuracy	0.62	0.57	0.64	0.64	0.61
Precision	0.61	0.53	0.63	0.63	0.59
Recall	0.62	0.57	0.64	0.64	0.61
F1	0.61	0.50	0.63	0.62	0.60

A grid search is employed to determine the optimal hyperparameter selection for each algorithm. The best performing logistic regression model consists of an LBGFS solver with ridge regression, and decision tree with a maximum depth of 10. Bagging is utilized in the form of a random forest model comprised of 100 decision trees with the same maximum depth found in a single decision tree model. The voting ensemble incorporates the resulting

KNN, logistic regression, decision tree, and random forest models as voting members, and allowing soft voting between members outperformed hard voting.

Overall, the models performed similarly with only minor improvements in metrics. The classification reports for each model show similar issues with category 1 classification as well.

Each of the models trained provided insight into the data set. A unique component of the random forest module in sklearn is the ability to quantify feature importance for the trained model. Figure 3.5 illustrates these findings.

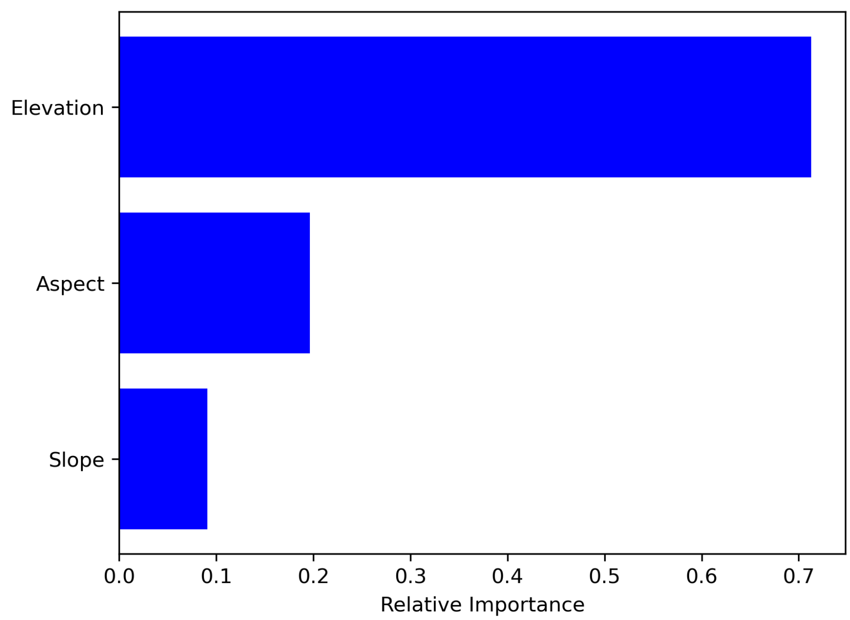

Figure 3.5. Relative Feature Importance within the Random Forest Algorithm. An analysis of the influencing variables and their respective significance in the model's classification process.

While all three features impact the target variable, elevation serves as the most influential feature.

Importance of Data Selection

Further experimentation was done with several different data sets to determine effects on the algorithm performance. The models were trained on data that included 1. the entirety of Hawaii, 2. the island of Oahu, 3. the Island of Hawaii also known as "The Big Island", and 4. the islands of Maui, Molokai, and Lanai (comprising Maui County). The models performed with similar accuracy, precision, and recall between data sets, and when utilized to make predictions, produced decisions that reflected the data set they were trained on. For instance, on Oahu, the overwhelming majority of vegetation cover is labeled as forest, so models trained on that data set produced vegetation predictions with a high percentage of forest. When the model was trained on "Big Island" data, more predictions were herbaceous and barren to due to the higher percentages of these categories found on that island.

Machine Learning Output

Due to the similarity in performance of the various machine learning algorithms, the KNN model described in Section 3.1.2 was trained on the Island of Hawaii dataset to perform classification predictions on Dystopia. The resulting frequency distributions are depicted in Figure 3.6

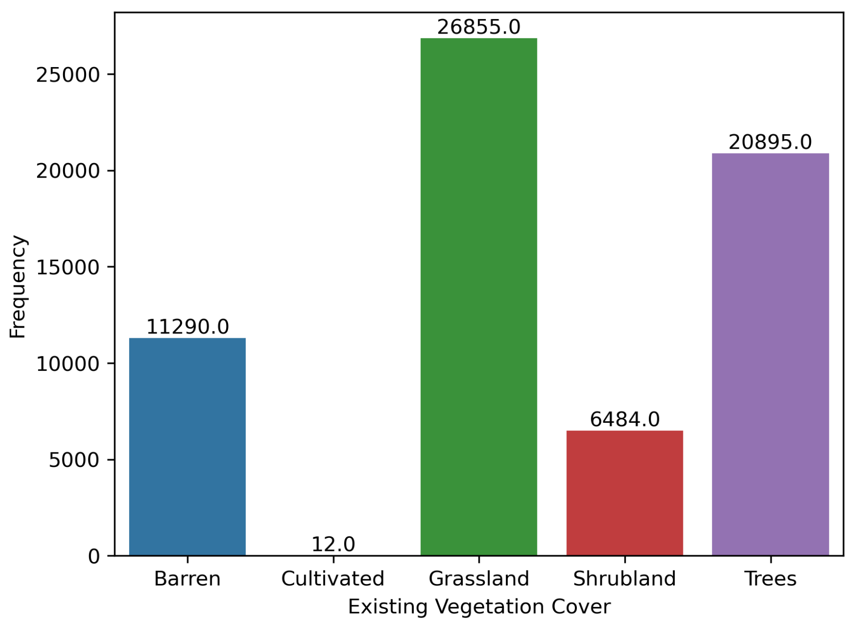

Figure 3.6. Vegetation Distribution for Dystopia.

Fuel Model Development

The machine learning algorithm outputs a mapping of EVC values, as delineated in Table 3.1, to corresponding geographical locations. From this information, a GIS data layer is constructed, laying a critical foundation for the development of fuels data, which is an essential input to the fire model. The computational workflow that encompasses this processing is illustrated in Figure 3.7.

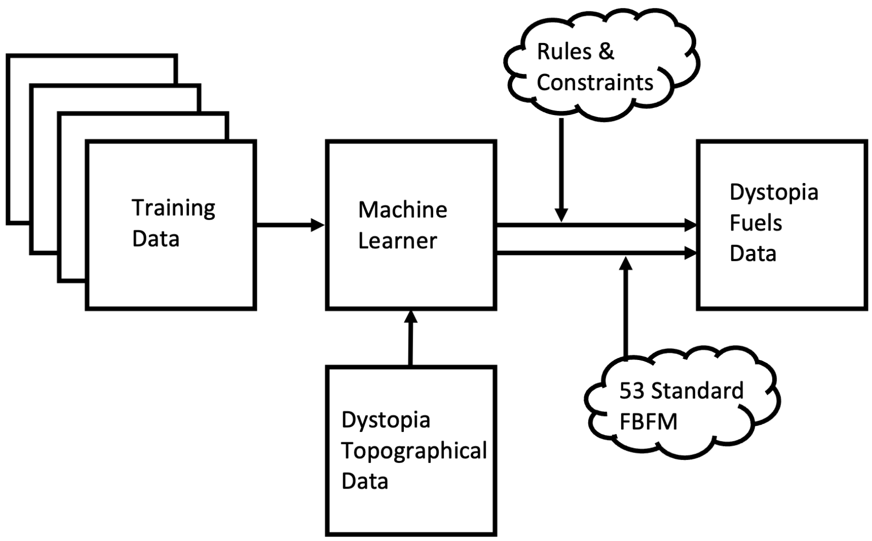

Figure 3.7. Schematic Diagram of the Fuel Data Computational Framework. The KNN machine learning model generates an EVC classification. Subsequently, Dystopia's predefined regions are taken into consideration prior to the assignment of an appropriate FBFM.

Training data consisted of the elevation, aspect, slope, and EVC files for a particular region of interest. The machine learning algorithm was trained and tested on this data, at which point the topographical data files of Dystopia's elevation, aspect, and slope were fed in. This produced an output of potential EVC categories for each of Dystopia's data points. However, certain regions of Dystopia are defined, such as major population centers, buildings, parks, rivers, etc., which were then accounted for. Finally, the 53 standard FBFM discussed in Section 2.2 are applied to the output, producing a final data layer consisting of fuels data for Dystopia.

Figure 3.8 provides a color mapped visual depiction of the resulting fuel layer generation.

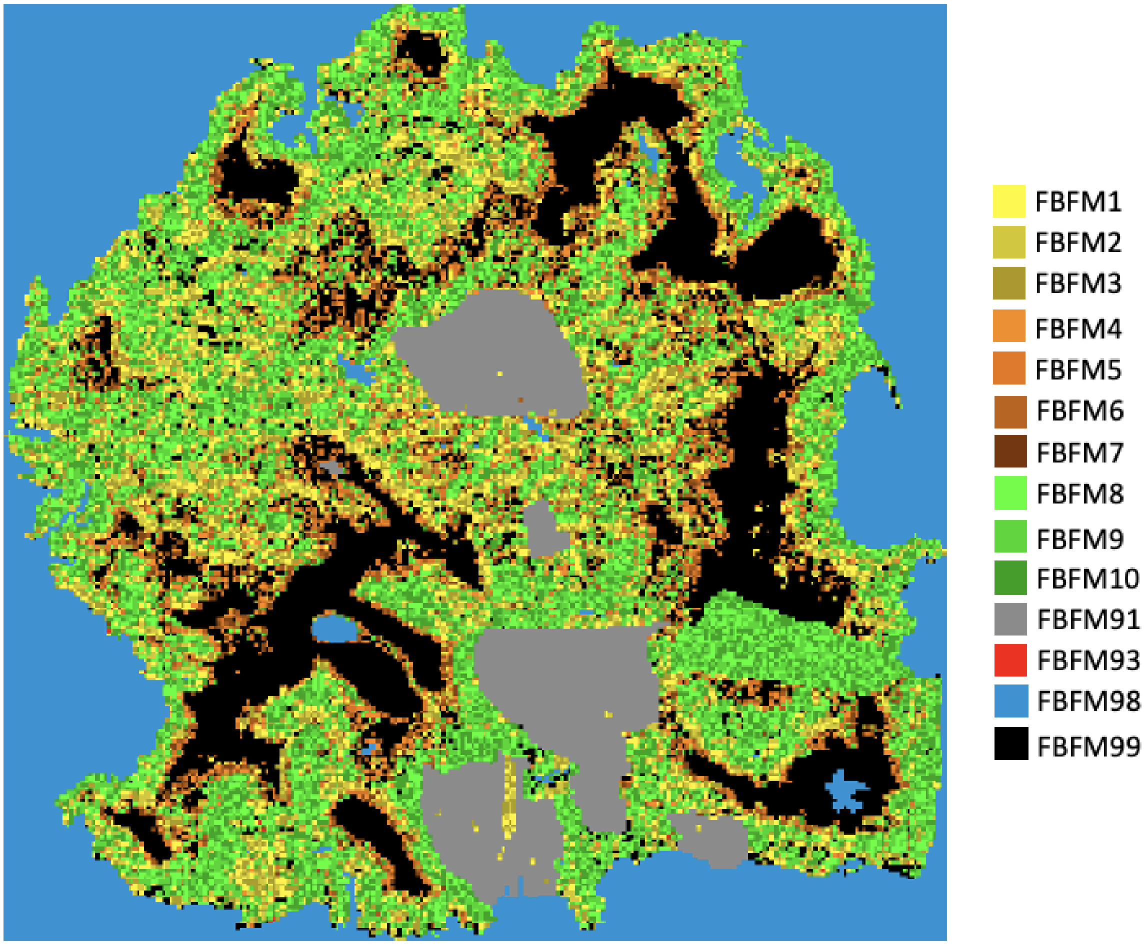

Figure 3.8. FBFM data layer for Dystopia. FBFM 1-3 denote grassland. FBFM 4-7 denote shrubland. FBFM 8-10 denote forest. FBFM 91 denotes urban areas. FBFM 93 denotes cultivated areas. FBFM 98 denotes water. FBFM 99 denotes barren.

3.1.3 Weather Data

Weather data for the simulation was selected to be representative of the island of Hawaii to coincide with Dystopia's chosen geographic location. Specifically, we chose to analyze Remote Automated Weather System (RAWS) data over a four day period at Bradshaw Army Airfield (BAAF) (Camp Pohakuloa, HI, USA), serving as realistic inputs to the fire model. The weather inputs for HFIRE are broken down into wind and fuel moisture data.

Wind

Two key components of wind are inputs to the fire model: speed and azimuth. Wind speed is delineated as sustained in miles per hour. Wind azimuth is represented in degrees from the direction in which the wind originates. Both elements are broken down on an hourly basis and are input into the model as separate text files.

The representative wind data captured over the designated time period can be effectively visualized using a wind rose diagram, as illustrated in Figure 3.9.

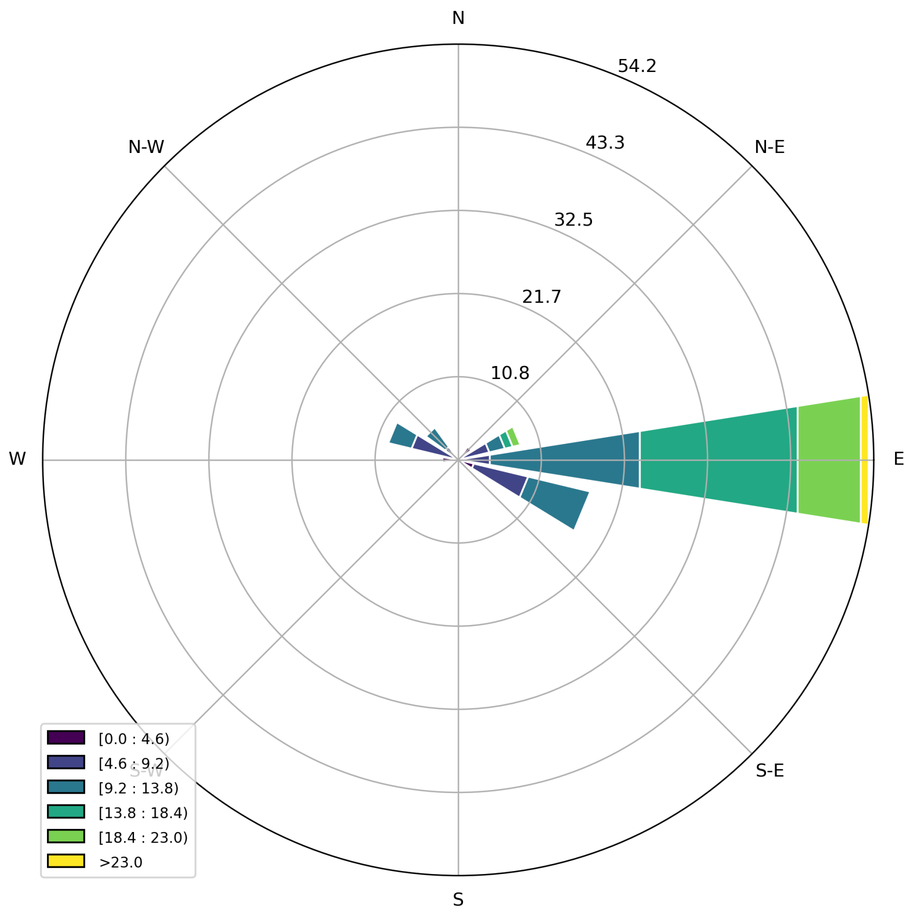

Figure 3.9. Wind Rose Visualization of Representative Wind Data. Each spoke represents a compass direction, the length of each spoke is proportional to the amount of time the wind blows from that particular direction, and color signifies the intensity of the wind speed.

Fuel Moisture

Fuel moisture levels are classified into three distinct categories: 10-hour dead fuel moisture, herbaceous live fuel moisture, and woody live fuel moisture. These categories each represent the corresponding water content in their respective types of fuels. The 10-hour dead fuel moisture value is highly variable, often changing on an hourly basis. This fluctuation is largely governed by environmental factors, particularly temperature and relative humidity. On the other hand, the herbaceous and woody live fuel moisture values are primarily influenced by the type of plant they originate from. Unlike the 10-hour dead fuel moisture, these values remain consistent throughout the day. However, they can exhibit alterations based on the changing seasons and the plants' corresponding growth cycles.

Figure 3.10 illustrates a distribution of dead 10-hour fuel values present in the simulation.

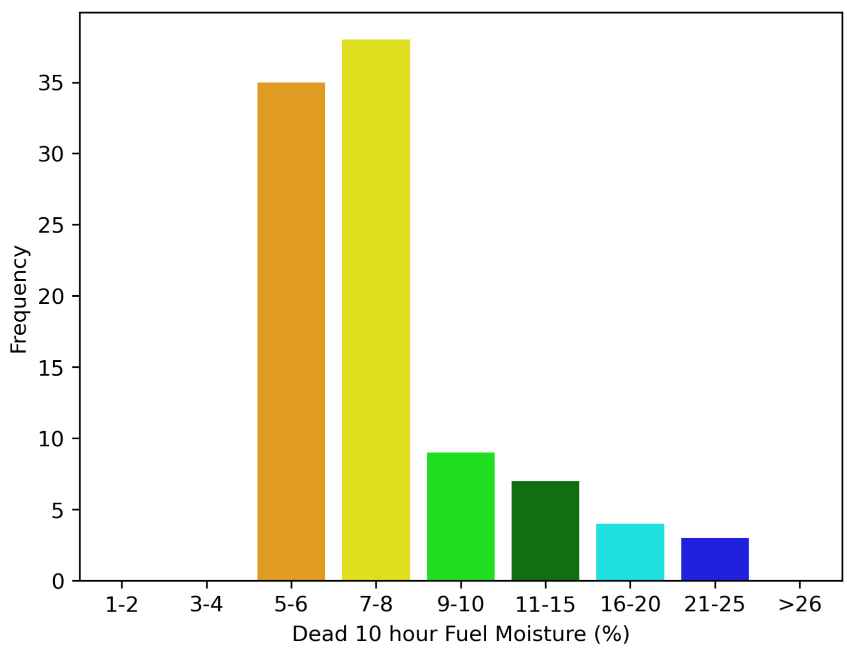

Figure 3.10. Distribution of 10-Hour Dead Fuel Moisture Levels.

3.1.4 Configuration Data

The configuration data for the model consists of an ignition point, the start date and time, the end date and time, and the interval between each time step. We choose ignition points uniformly at random among ignitable locations. Additionally, we control for duplicate ignition points to ensure that there are no repeat fire events. We conduct the simulation over a seventy-two hour period, using an hourly time step interval. Figure 3.11 shows a visual illustration of the ignition points chosen by the algorithm.

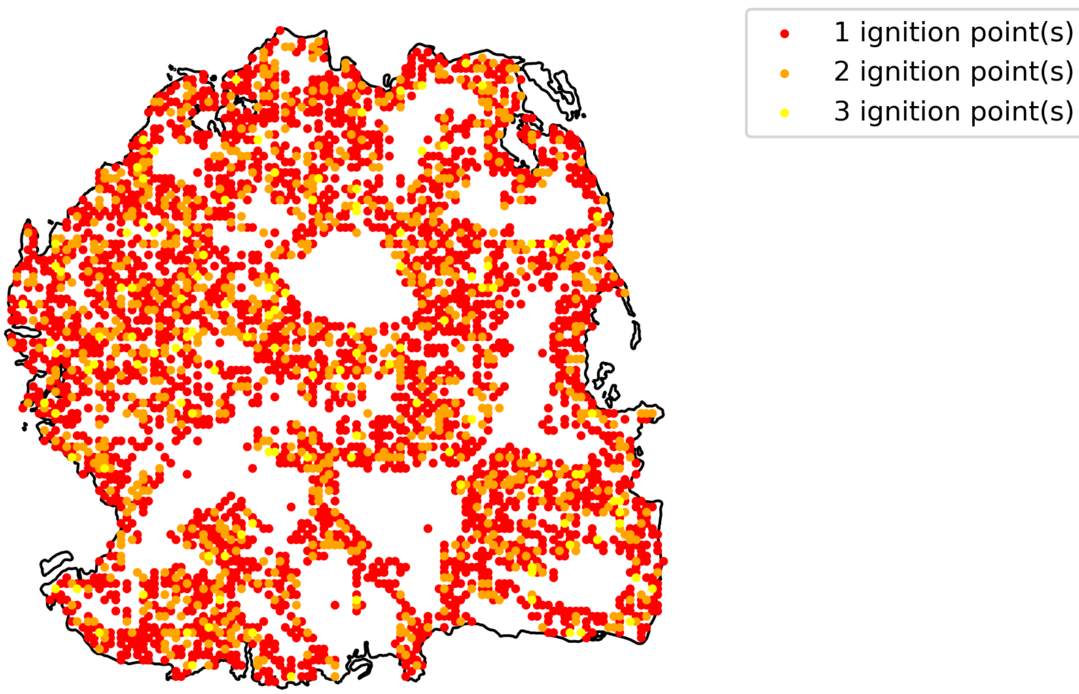

Figure 3.11. Ignition Point Distribution Map. The number of ignition points contained within a 1 kilometer grid square is depicted.

3.2 Implementation of HFIRE

We run HFIRE by invoking a Windows batch file that processes the corresponding input files for each data type as delineated in Section 3.1. A script starts the batch file, adjusting the ignition point to a new location for each simulation run. Through this process, we perform a wildfire simulation, accounting for defined environmental parameters and conditions based on the provided inputs.

3.3 Output Data

The output data generated from the wildfire simulation consists of raster files depicting the cells combusted at each designated time step interval. The spatial extent of these cells represents the progression of the fire perimeter at the corresponding time, effectively illustrating the dynamic nature of wildfire spread.

We then convert the raster data into vector data, and subsequently encode them into geojson files. This transformation enhances visualization and also enables effective overlay capabilities onto Dystopia's pre-existing data layers. Consequently, this conversion allows for a more comprehensive and insightful evaluation of the wildfire's progression in relation to key geographical features and structures within Dystopia. Figure 3.12 illustrates how the result of a single simulation can be visualized.

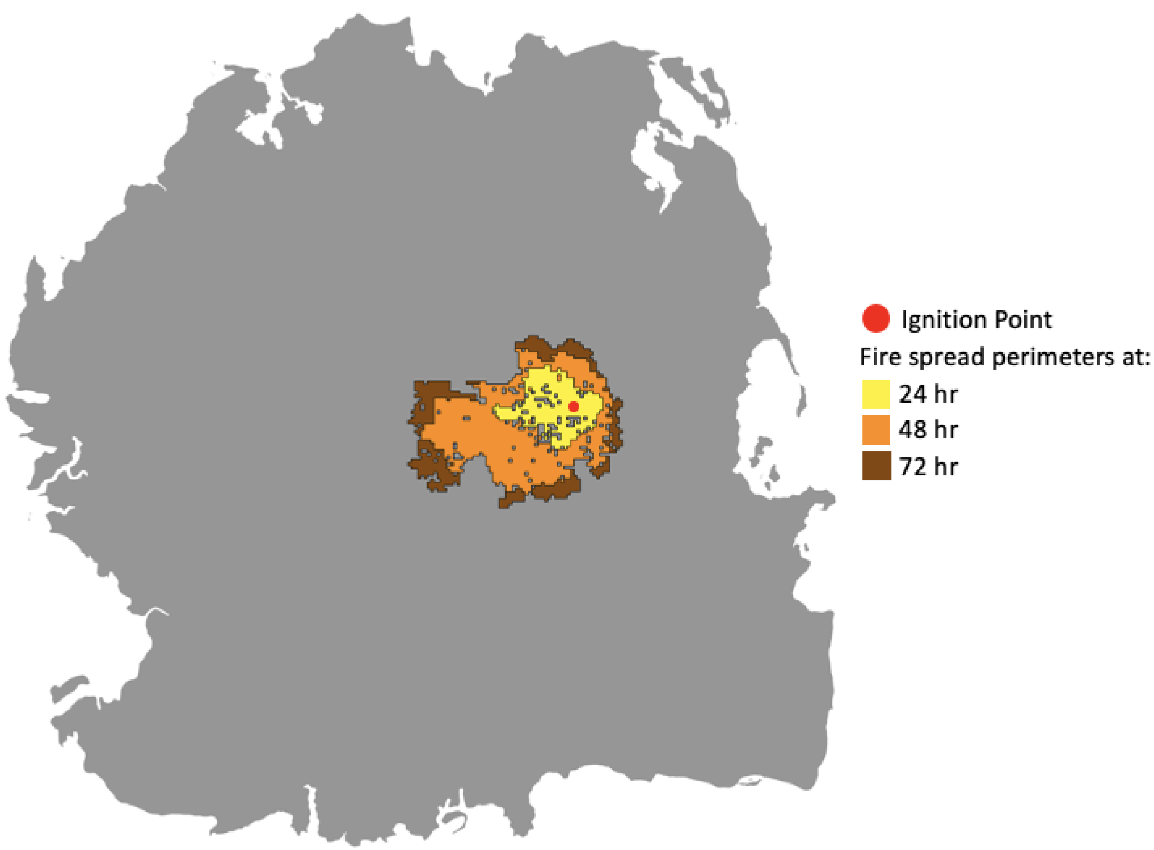

Figure 3.12. Visualization of an Example Wildfire Simulation.

CHAPTER 4:
Results

In this chapter, we conduct a Monte Carlo simulation of wildfire events to address the research questions identified in Section 2.4. The experiment encompasses a series of individual wildfire simulations, enabling a detailed analysis of the dispersion of wildfire sizes, the time frame required for fires to attain particular sizes, the initiation points of the most severe fires, and the frequency at which varying wildfire sizes affect a specified military installation. We begin these simulations with a prescribed set of inputs, collectively referred to as the *baseline case*. We then repeat the simulation under different environmental conditions to represent potential consequences of climate change and the effects on wildfire behavior.

4.1 Baseline Case

The input data for the baseline case consists of 14 files.

Topography Data

1. `elevation.asc` - Contains the raster data associated with elevation in meters.
2. `aspect.asc` - Contains the raster data associated with aspect in degrees.
3. `slope.asc` - Contains the raster data associated with slope in degrees.

Files #1-3 are plain text format, but they can be viewed in GIS software such as QGIS (QGIS Development Team 2023). Each has 256 rows, 256 columns, and a cell size of 470 pixels. The simulation requires that the dimensions for all three are identical.

Fuel Data

4. `fuel.asc` - Contains the raster data associated with the fuel model, using the procedure delineated in Section 3.1.2. The dimensions for this file must match that of files #1-3.
5. `all_models.fmd` - Is a plain text file that defines the parameters for all fuel models present in the raster file. The simulation requires that all ignitable fuel models be

defined.

Environmental Data

This data was taken from RAWS data over the period 1 Jun 2022 through 4 Jun 2022 at BAAF.

6. `dys_fixed.wsp` - Is a plain text file containing the wind speed in sustained knots.
7. `dys_fixed.waz` - Is a plain text file containing the wind azimuth in degrees.
8. `dys_fixed.10h` - Is a plain text file containing the hourly values for 10-hour dead fuel moisture.
9. `dys_fixed.lfh` - Is a plain text file containing the data for herbaceous live fuel moisture.
10. `dys_fixed.lfw` - Is a plain text file containing the data for woody live fuel moisture.

For files #6-8, the simulation requires that the data be formatted `YEAR MONTH DAY`, followed by hourly values. Files #9-10 define a single value held constant for the entire simulation.

Configuration Data

11. `HFire12d.exe` - Is the Windows Application File. This is the main executable for HFIRE and runs the software's main functionalities.
12. `dys_0batch_hf.bat` - Is the Windows Batch File which executes the simulation via the command-line interpreter.
13. `dys_frap.cfg` - Is a plain text file containing the configuration data. It also defines the simulation start date and time, and end date and time.
14. `dys_pt.igs` - Is a plain text file containing the ignition point data. This file defines a single gridded location utilizing the projection from files #1-4.

For each trial we consider fire propagation over a total of 72 simulated hours.

4.1.1 Sample Size Selection

The procedure delineated in Section 3.2 is implemented to conduct 5000 trials of the wildfire simulation. Figure 4.1 shows the resulting distribution of fire sizes at 24, 48, and 72-hour intervals.

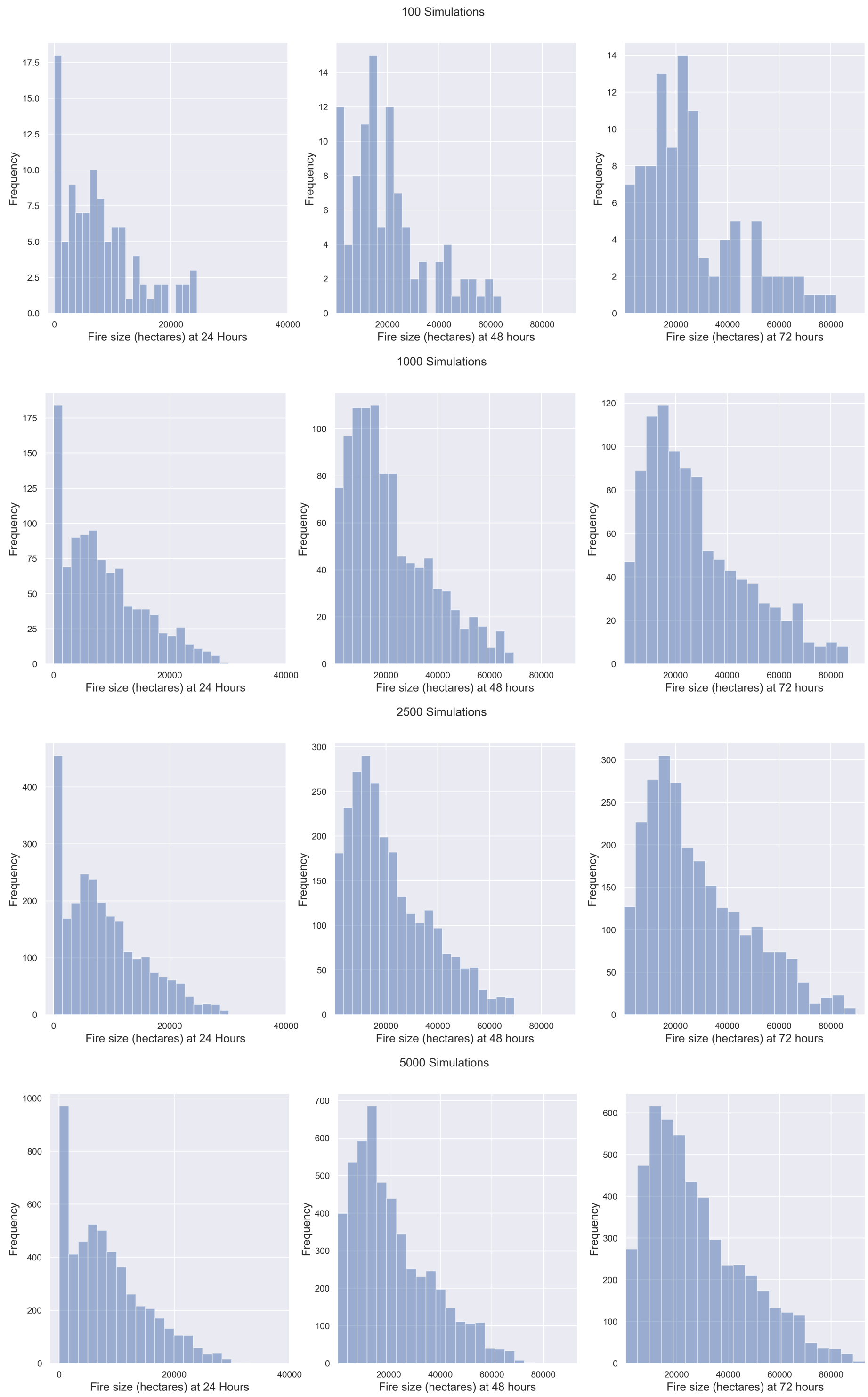

Figure 4.1. Distribution of Fire Sizes after 24, 48, and 72 Hours. With more trials, the distribution becomes more smooth. For subsequent analysis, we conduct 5,000 trials per experiment.

The initial series of 100 trials demonstrates fire size distributions with irregular patterns. As the trial count increases to 1000, the distribution becomes more regular. This normalization process continues with an increasing number of trials, and at 5000 trials the distributions appear fairly smooth.

On a MacBook Air personal laptop computer with an M1 processor and 8 GB RAM, conducting 100 trials requires approximately 15 minutes. The time required increases proportional to the number of trials, with 1000 trials requiring around 2.5 hours, 2500 trials requiring approximately 6 hours, and 5000 trials taking roughly 12 hours. Balancing computational performance, runtime considerations, and the regularity of distributions, we choose 5000 trials for all subsequent experiments.

4.1.2 Analysis of Baseline Case

Figure 4.2 illustrates the progression of fire size over time. The minimum fire size represents a significantly small value that is greater than zero. This occurs when a randomly selected ignitable location is surrounded by unburnable areas, such as a baseball field surrounded by a parking lot. The median fire size after 72 hours was approximately 25,000 hectares, while the largest fire size recorded approached approximately 90,000 hectares. Although the distance between various percentiles is generally consistent, a greater gap exists between the 95th percentile of fires and the maximum fire size, suggesting a long tail in this distribution. This indicates that the worst fires have the potential to cause damage at a magnitude that far exceeds the majority of other wildfires.

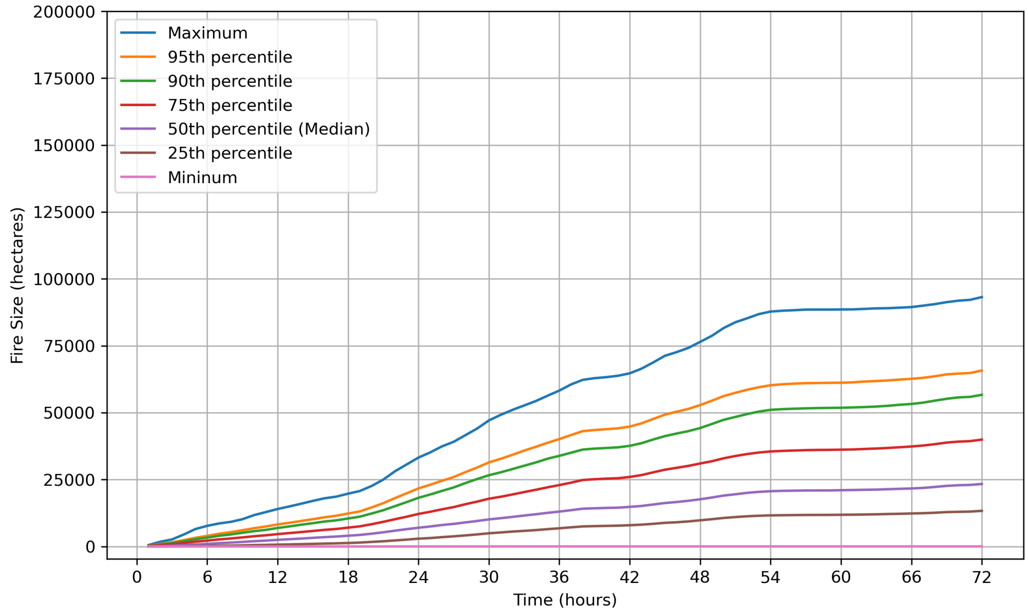

Figure 4.2. Fire Size Progression, Baseline Case. The gap is largest between the 95th percentile and maximum, indicating that outliers can have the most catastrophic effects.

For the same simulation trials in the baseline case, Figure 4.3 shows the time required to reach specific fire sizes. For the baseline scenario, no fires reached a size of 100,000 hectares after 72 hours.

At 48 hours, approximately 75% of fires reached 10,000 hectares, 35% reached 25,000 hectares, 5% reached 50,000 hectares, and a very small percentage reached 75,000 hectares. During the first six hours of the simulation, no fires reached a size of 10,000 hectares.

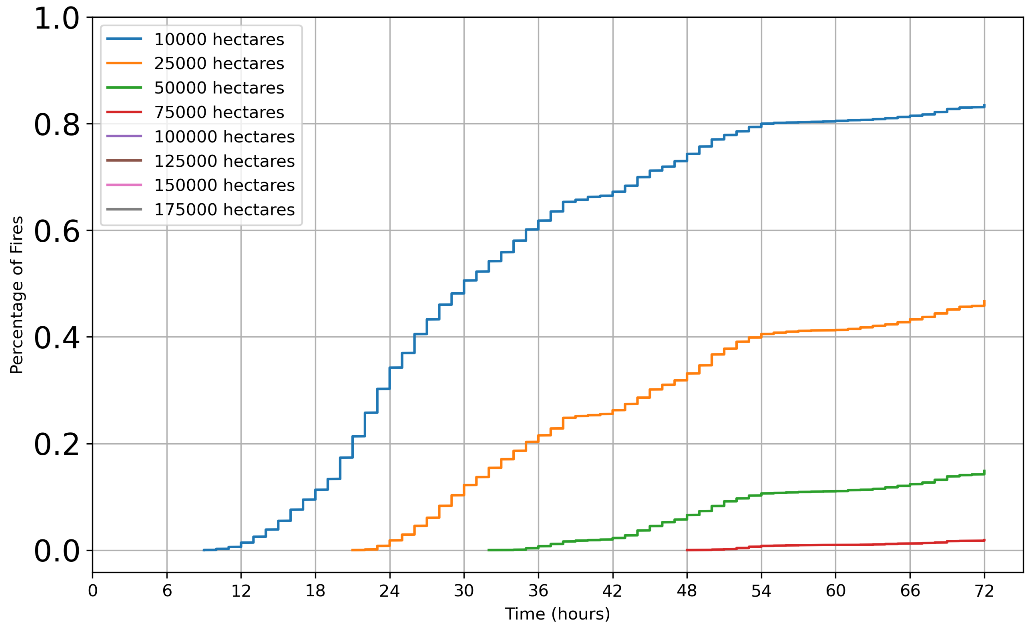

Figure 4.3. Cumulative Distribution of Wildfire Time-to-Size, Baseline Case. This illustrates wildfire growth rate in the baseline case.

For the baseline case, we also consider the impacts to our military installation by assessing the frequency in which the fire perimeters crossed any of the areas of interest represented in Figure 2.1. *Boundary intersections* indicate the percentage of times the fire reaches the installation boundary. *Access intersections* indicate the percentage of times the fire crosses a road leading to the installation. Finally, *commerce intersections* indicate the percentage of times the fire crosses a commerce road between northern and southern cities. The frequencies at 24, 48, and 72 hours are depicted in Table 4.1.

Table 4.1. Intersection Frequencies, Baseline Case

Hour Interval	Boundary Intersections	Access Intersections	Commerce Intersections
24	0.038	0.060	0.093
48	0.082	0.094	0.129
72	0.094	0.106	0.145

There is a steady increase in frequency for each column at 24, 48, and 72 hours. This highlights the increased impact on the installation itself, accessibility, and commerce routes as time progresses and the fire expands in the baseline case.

4.2 Changes In Wildfire Behavior Under Potential Climate Change Scenarios

To assess the possible consequences of climate change on wildfire behavior, we adjust the inputs to the fire simulation to represent progressively drier conditions. Specifically, the fuel moisture values, in `dys_fixed.10h`, `dys_fixed.lfh`, and `dys_fixed.lfw` are adjusted to simulate environments that are 10%, 20%, 30%, 40%, and 50% drier than the baseline case. Each of these conditions is reflective of a potential future scenario under the influence of climate change. By conducting these simulations, we aim to gain a deeper understanding of how changing environmental factors could affect wildfire patterns.

4.2.1 Impact on Wildfire Size

Figure 4.4 illustrates the fire size over time for all six cases. Our analysis shows that although the minimum fire size is consistent across various conditions, a consistent pattern of increased fire size across all other percentiles is observed. This indicates that not only the extreme fire events but also the more typical fire sizes are likely to grow larger as conditions become drier. However, the maximum fire size under each condition exhibits the most dramatic increase. This signifies that the largest fires, which often have the most devastating impacts, could become approximately twice as large under drier conditions.

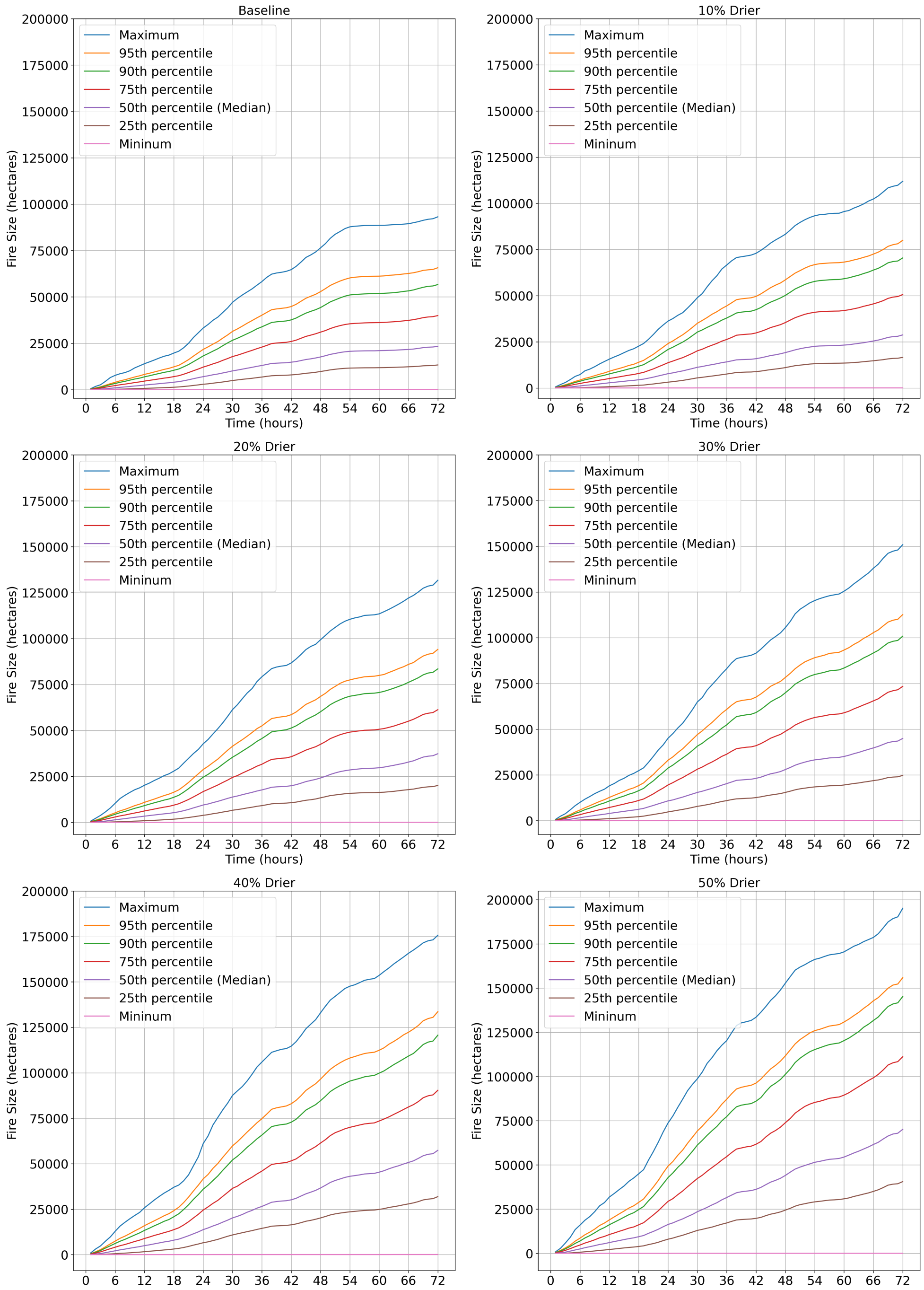

Figure 4.4. Fire Size Progression, Comparison. A substantial increase in wildfire size, particularly at later hours in the simulation, is evident under drier conditions. This has profound impacts for wildfires that are cannot be contained.

Figure 4.5 and Figure 4.6 depict heatmaps of the median and maximum fire sizes over time, respectively. The horizontal axis denotes time in hours, progressing from left to right. Looking from left to right across the heatmap, one observes the evolution of a fire's size over time under a specific dryness scenario.

Conversely, the vertical axis displays the range of conditions, from the baseline at the bottom to the most extreme dryness scenario at the top. Looking from bottom to top enables a comparison of the influence of varying degrees of dryness on fire size at a particular hour interval.

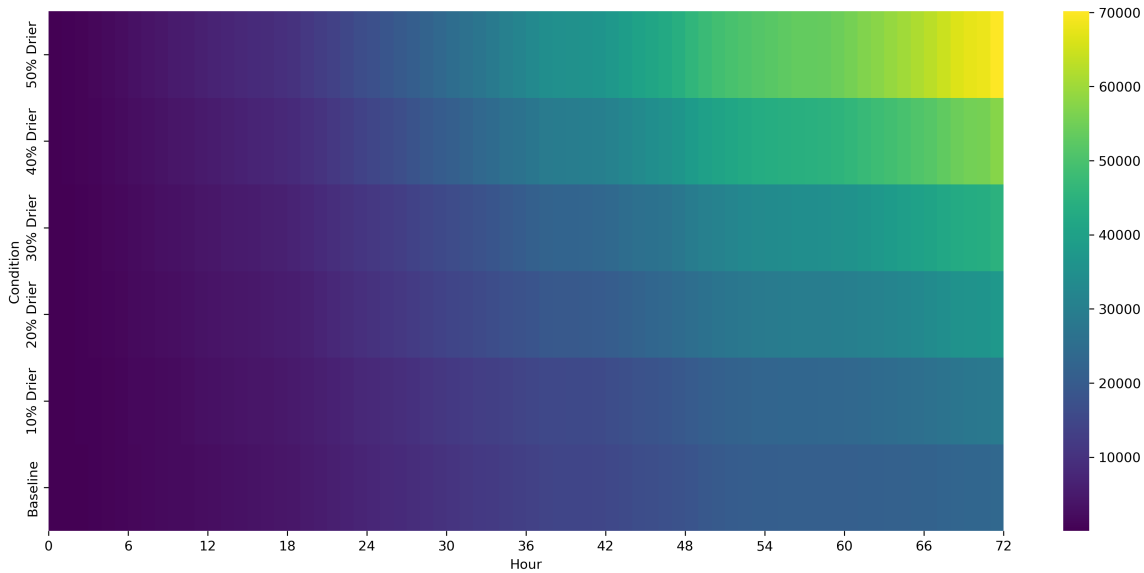

Figure 4.5. Median Fire Size (in hectares) for Varied Conditions. The contrast in gradients is most pronounced at later hours in the simulation

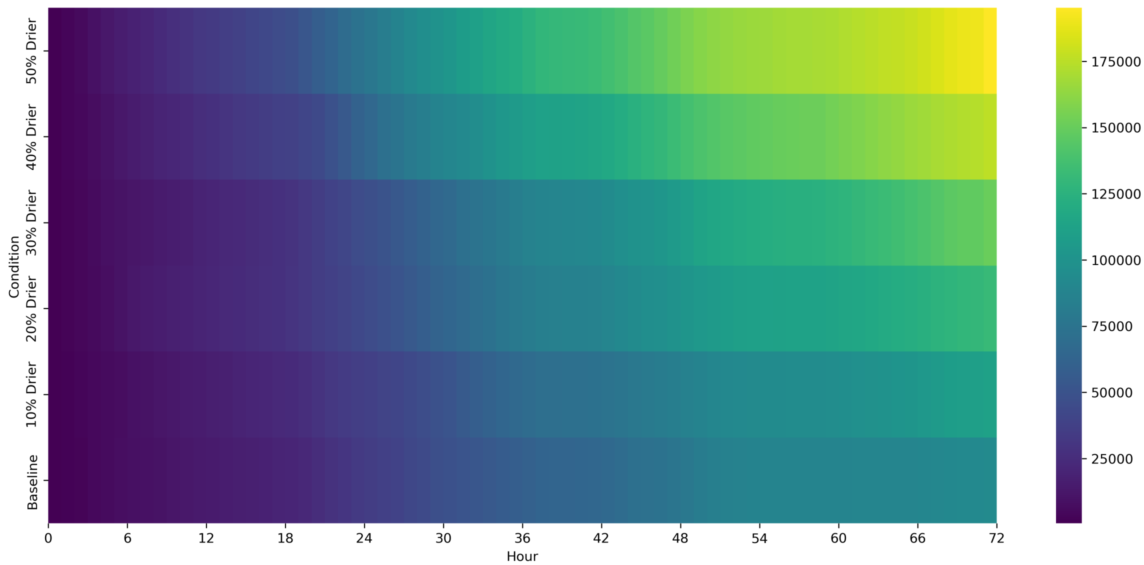

Figure 4.6. Maximum Fire Size (in hectares) for Varied Conditions. The maximum fire size at 72 hours approximately doubles under conditions that are 50% drier.

4.2.2 Impact on Wildfire Growth Rate

Figure 4.7 offers a visual representation of the time it takes for fires to reach specific sizes under conditions that are 10% to 50% drier. A key observation is that as conditions become increasingly arid, lines corresponding to larger fire sizes begin to appear on the graphs. This reaffirms our previous finding that drier conditions tend to foster larger wildfires.

Further, a pattern emerges across increasing levels of dryness. As conditions worsen, the time frame for wildfires to reach a particular size decreases. This pattern suggests an acceleration in the rates of fire spread corresponding to increasingly dry conditions.

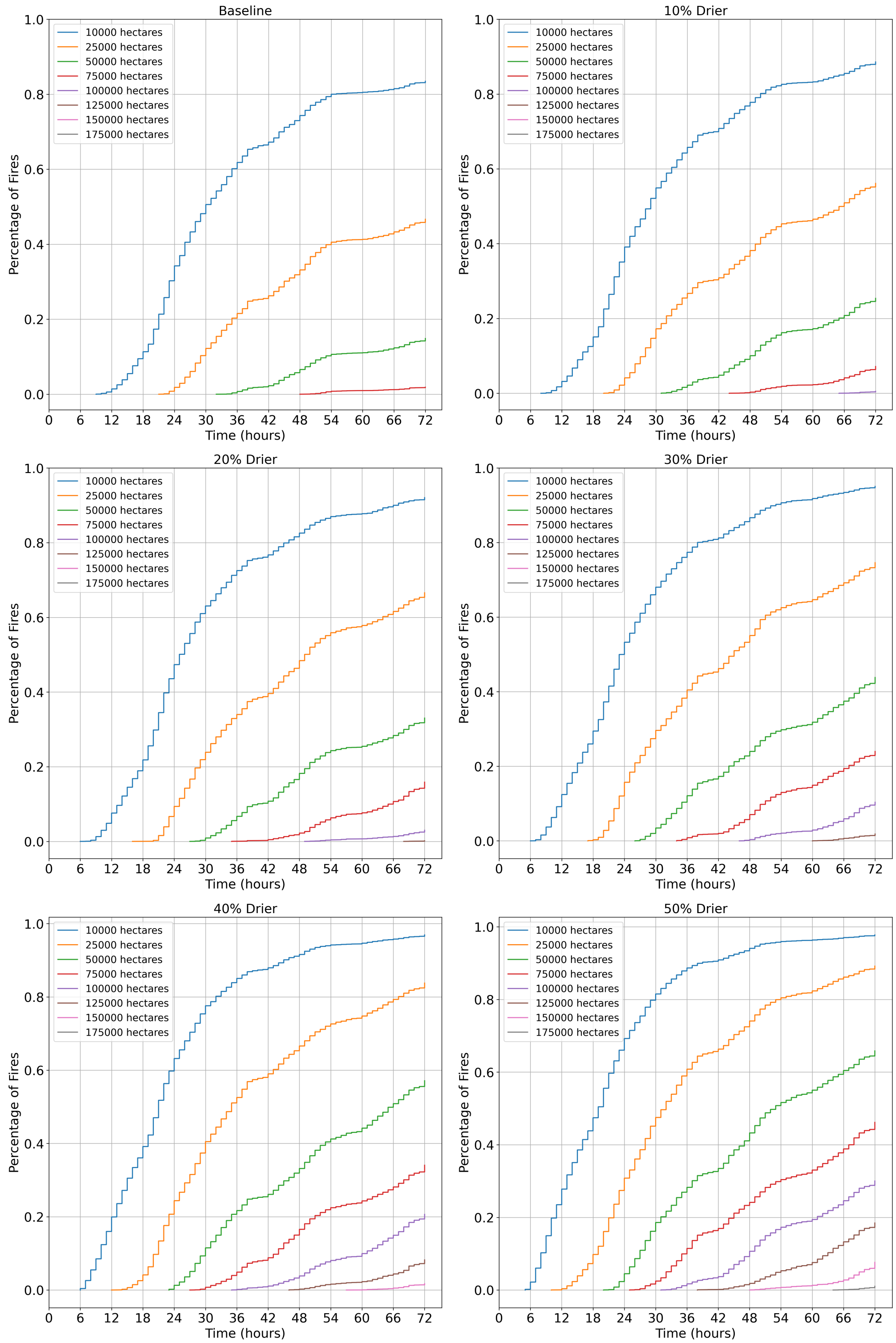

Figure 4.7. Cumulative Distribution of Wildfire Time-to-Size, Comparison. Drier conditions tend to foster larger wildfires, and there is an acceleration in the rates of fire spread corresponding to increasingly dry conditions.

4.2.3 Impact on Military Installation

Tables 4.2, 4.3, and 4.4 display the intersection frequencies for impact at our military installation at 24, 48, and 72 hours for the varying conditions, respectively.

Analyzing the intersection frequencies over time, there is a clear upward trend in all categories as the conditions become drier. This indicates that under drier conditions, fires are more likely to intersect these key areas, indicating an increased risk of damage, reduced access, or degraded services in such situations.

With one exception (i.e., commerce intersections at 24 hours under the 10% drier condition), increasing levels of dryness results in a strict increase for the frequency of intersections for each category. It is noteworthy that the increase in intersection frequencies is most significant at the 40% drier conditions. For example, under 40% drier conditions, the probability that a fire intersects with the boundary of our installation more than doubles. Collectively, these results suggest that beyond a certain level, the impact on intersection frequencies may escalate at a more rapid pace.

Table 4.2. Intersection Frequencies at Hour 24. Percent increase from the baseline case is delineated in parenthesis.

Condition	Boundary Intersections	Access Intersections	Commerce Intersections
Baseline	0.0380	0.0600	0.0926
10% Drier	0.0384 (1%)	0.0654 (9%)	0.0926 (0%)
20% Drier	0.0522 (37%)	0.0754 (26%)	0.0998 (8%)
30% Drier	0.0578 (52%)	0.0826 (38%)	0.1054 (14%)
40% Drier	**0.0772 (103%)**	**0.0946 (58%)**	**0.1172 (27%)**
50% Drier	0.084 (121%)	0.0976 (63%)	0.1222 (32%)

Table 4.3. Intersection Frequencies at Hour 48. Percent increase from the baseline case is delineated in parenthesis.

Condition	Boundary Intersections	Access Intersections	Commerce Intersections
Baseline	0.0822	0.0936	0.1288
10% Drier	0.0908 (10%)	0.103 (10%)	0.1314 (2%)
20% Drier	0.1066 (30%)	0.117 (25%)	0.1434 (11%)
30% Drier	0.1122 (37%)	0.1208 (29%)	0.1562 (21%)
40% Drier	**0.1286 (56%)**	**0.1352 (44%)**	**0.1816 (41%)**
50% Drier	0.1356 (65%)	0.1464 (56%)	0.2044 (59%)

Table 4.4. Intersection Frequencies at Hour 72. Percent increase from the baseline case is delineated in parenthesis.

Condition	Boundary Intersections	Access Intersections	Commerce Intersections
Baseline	0.0940	0.1062	0.1452
10% Drier	0.1132 (20%)	0.123 (16%)	0.1636 (13%)
20% Drier	0.1284 (37%)	0.1406 (32%)	0.1788 (23%)
30% Drier	0.1392 (48%)	0.1508 (42%)	0.2008 (38%)
40% Drier	**0.1584 (69%)**	**0.1736 (63%)**	**0.236 (63%)**
50% Drier	0.1684 (79%)	0.1992 (88%)	0.2594 (79%)

4.2.4 Worst Fire Ignition Point Locations

The next step in our analysis aims to determine the origin points of the most catastrophic fires. We identify the largest 10% of fires based on the extent of fire spread at the 72-hour mark. Figure 4.8 displays the corresponding ignition points of these fires for each condition from baseline to 50% drier.

Figure 4.8. Ignition Points of Largest 10% of Fires at Hour 72. The invariance of these points under increasing dryness conditions suggests some areas are always at higher risk of producing large fires.

A significant observation is the consistent spatial distribution of ignition points across all the simulated conditions. This persistence signals the existence of high-risk areas, regardless of the degree of dryness.

4.2.5 Worst Case Fire Spread

Finally, we take a closer look at the maximum fire size under the 50% drier condition; see Figure 4.9. This offers a detailed visualization of the fire spread's geographical extent, highlighting areas affected by the worst-case scenario fire. By overlaying the fire spread data layers on a geographical layout, we can identify areas of critical concern and identify potential intersections with critical infrastructure.

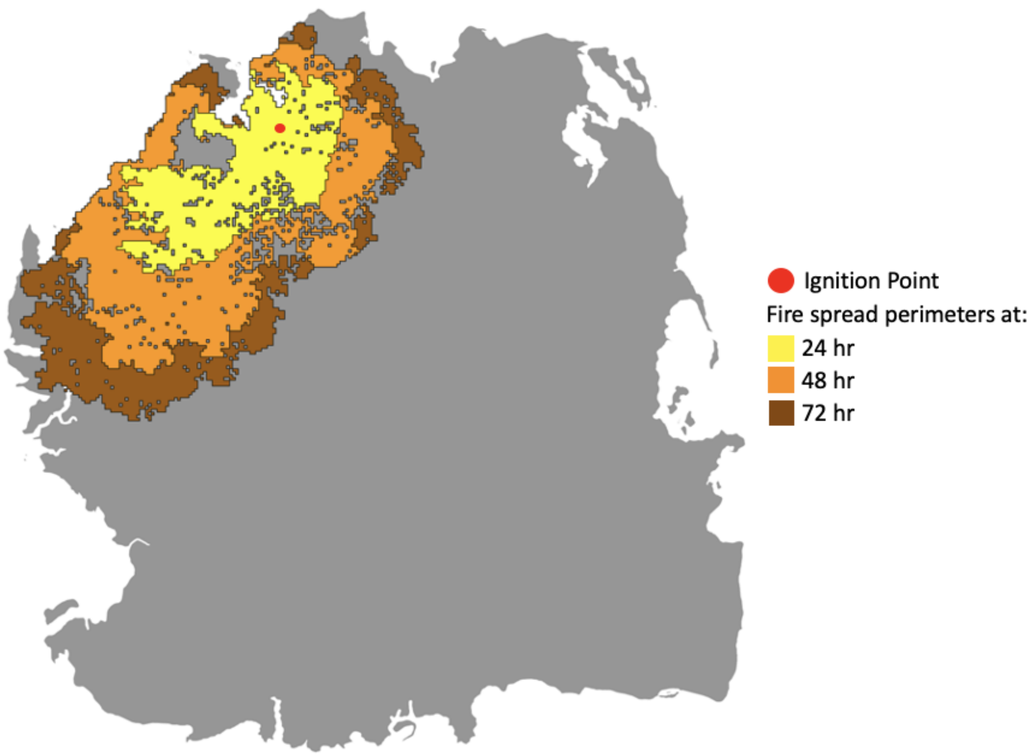

Figure 4.9. Worst Fire Spread as Observed Under 50% Drier Condition. Fire spread perimeters over time can inform potential emergency management and/or evacuation planning.

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CHAPTER 5: Conclusion

5.1 Summary

This thesis develops a computational framework for simulating realistic geospatial wildfire behavior, suitable for assessing potential impacts to military installations and the communities in which they reside. Using a fast-running fire modeling software, HFIRE, we simulate surface fire spreads on the geospatially realistic, but fictional island of Dystopia, which we geolocate as part of the Hawaiian Island chain. We augment existing terrain data with geographically relevant weather (temperature and wind) data. We generate synthetic vegetation data for Dystopia using machine learning techniques trained on the Hawaiian Islands.

We use Monte Carlo simulation to generate ensembles of wildfire events, assess fire spread, and evaluate direct and indirect impacts to a designated military installation. Model excursions consider how potential climate change consequences affect these impacts.

Our findings underscore that drier conditions invariably result in increased fire severity and more frequent impacts to the military installation. Furthermore, it enables the identification of high-risk areas subject to wildfires. These results can facilitate enhanced preventive measures and more effective emergency responses, thereby minimizing the vulnerability of military installations to wildfires in an era of climate change.

5.2 Assumptions and Limitations

Any interpretation of our work should bear the following assumptions and limitations in mind. First, the algorithmic generation of vegetation data in our study considered only specific topographical features of elevation, aspect, and slope. While these factors are influential, they may not fully capture the complexity and uniqueness of real-world vegetation landscapes.

Secondly, our choice of weather data for the simulated environment of Dystopia was driven by an analysis of RAWS data over a specific four-day period at BAAF. This data serves as a realistic input to the model, but different weather conditions will lead to alternative simulation outcomes.

In addition, the use of HFIRE in our study, has its own set of limitations. It represents surface fire spread in two-dimensions, thereby excluding complex fire behaviors such as spotting or crown modules. This simplification limits the accuracy of the complex dynamics of real-world wildfires.

Finally, we emphasize that the fire spread simulations studies here do not consider fire suppression efforts (i.e., firefighting). Simulating the ongoing interaction between active suppression and fire behavior remains an open area of research.

5.3 Future Work

The model we present in this thesis has inherent flexibility to run a myriad of scenarios. We demonstrate potential consequences of climate change with a drier, more arid scenario, but there are a number of environmental conditions that can be adjusted to gauge its effects on wildfire behavior. For instance, wind is a primary driver of wildfire spread, and the same process we outline can be repeated with wind conditions that represent a 10%-50% increase from the baseline case.

More broadly, each of the components in our computational framework (Figure 3.1) could be augmented or swapped with more sophisticated models. By design, several other existing wildfire models (such as those reviewed in Table 2.1) could be used in place of HFIRE. Collectively, these tools could come together to enable more realistic simulations, such as 3D fire modeling within the Dystopia. For example, the generation of 3D vegetation from the FastFuels model could be used in place of our machine learning model and combined with QUIC-Fire simulation to analyze the effect of more complex fire behavior (Parsons et al. 2023) on the military installations within Dystopia.

Alternatively, while the simulations we conduct utilize fictitious GIS data layers, the process could be repeated with real world topography, fuels data, and environmental data. This would enable a facilities manager to assess wildfire risks for a specific location and explore how frequency of impact might change under varying conditions. Also, the focus of this thesis is on wildfire risk, yet modeling of other extreme weather events would be beneficial. For example, impacts of hurricanes to DOD installations could be explored with the acquisition of appropriate models and data. It is crucial to consult with subject matter experts to ensure the accuracy of the models and data, as well verifying that relevant risk scenarios are being analyzed.

Ultimately, the techniques and analysis in this thesis have significant implications for DOD. There are a number of military installations in the U.S. that are prone to wildfire risk. The type of simulations conducted on the fictional island of Dystopia can be applied to assess vulnerabilities of a real world location. Moreover, this computational framework can serve as a platform for the development of new analytic techniques to assess and mitigate wildfire risk. Finally, these simulations can be applied to develop novel training and education to help commanders and personnel become better prepared to deal with unprecedented challenges from extreme weather and climate change (Alderson et al. 2022).

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