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OPTIMIZING RESOURCE AUGMENTATION FOR WILDLAND FIRES

by

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June 2019

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During December 2017, the Los Angeles County Fire Department (LACoFD) responded to an unprecedented number of wildland fires spanning thousands of square miles within the county. While most of the fires were successfully contained, several caused widespread catastrophic damage. During red flag (high-risk) days, LACoFD currently uses augmented staffing, either by moving on-duty equipment and personnel, or mobilizing those who are off duty to reduce response time. Operational duty chiefs make these augmentation decisions based on current weather conditions and experience. This thesis develops regression models to estimate the probability and potential burned acreage of wildland fires in each of 21 sub-areas in the county. Then, a budget-constrained optimization model reassigns resources between sub-areas in order to minimize expected population displacement due to wildland fire. A comparison of these automated techniques with those manual decisions made during December 2017 reveals significant improvements to augmented staffing that can be made at a lower cost.

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OPTIMIZING RESOURCE AUGMENTATION FOR WILDLAND FIRES

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ABSTRACT

During December 2017, the Los Angeles County Fire Department (LACoFD) responded to an unprecedented number of wildland fires spanning thousands of square miles within the county. While most of the fires were successfully contained, several caused widespread catastrophic damage. During red flag (high-risk) days, LACoFD currently uses augmented staffing, either by moving on-duty equipment and personnel, or mobilizing those who are off duty to reduce response time. Operational duty chiefs make these augmentation decisions based on current weather conditions and experience. This thesis develops regression models to estimate the probability and potential burned acreage of wildland fires in each of 21 sub-areas in the county. Then, a budget-constrained optimization model reassigns resources between sub-areas in order to minimize expected population displacement due to wildland fire. A comparison of these automated techniques with those manual decisions made during December 2017 reveals significant improvements to augmented staffing that can be made at a lower cost.

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LIST OF ACRONYMS AND ABBREVIATIONS

10-Hr DFM	Ten Hour Dead Fuel Moisture
AIC	Akaike Information Criterion
AOM	Augmentation Optimization Model
AUC	Area under the Curve
BI	Burning Index
BIR	Burning Index Ratio
BIT	Burning Index Threshold
CA	Captain
CART	Classification and Regression Tree
CCC	Cubic Clustering Criterion
CI	Confidence Interval
C+NVC	Cost plus Net Value Change
DFM	Dead Fuel Moisture
ERC	Energy Release Component
FF	Fire Fighter
FFS	Fire Fighter Specialist
ILP	Integer Linear Program
KBDI	Keetch-Byram Drought Index
LA	Los Angeles
LAC	Los Angeles County
LACoFD	Los Angeles County Fire Department
LFM	Live Fuel Moisture
mpg	Miles per Gallon
NFDRS	National Fire Danger Rating System
NPS	Naval Postgraduate School
p-value	Probability Value
R^2	Coefficient of Determination
RADAR	Radio Detection and Ranging
RAWS	Remote Automated Weather Station
RH	Relative Humidity

ROC	Receiver Operator Characteristic
ROI	Return on Investment
SC	Spread Component
SE	Standard Error
WIMS	Weather Information Management System

EXECUTIVE SUMMARY

During the month of December 2017, the Los Angeles County Fire Department (LACoFD) reported to 22 wildland fires located throughout the nearly 5,000 square mile county. The fire department successfully contained 19 of the fires to within 10 burned acres. The three remaining fires, however, resulted in a combined burn area of over 21,000 acres, with close to 200 structures either destroyed or damaged (Alkonis and Pena 2018). During the month of November 2018, the Woolsey fire destroyed both recreational and residential property across LA and Ventura County, burning over 90,000 acres (Stiles and Schleuss 2018).

The United States Forest Service currently reports that 85% of wildland fires within the U.S. are caused by human factors. Leading causes include discarded cigarettes, equipment malfunction on highways, illegal campfires, and burning debris (Short 2017). Given that these fires are likely to occur due to the negligence of humans, how can we prevent them from escalating into widespread fires? Current statistics show that 90% of wildland fires can be contained or controlled by a strategy known as initial attack (National Interagency Fire Center 2000). Initial attack is a quick and heightened response by directing firefighting resources to a wildland fire. This strategy benefits from augmented staffing, where additional resources are pre-positioned alongside on-duty resources in preparation for a high-risk fire day. LACoFD practices augmented staffing in order to heighten its dispatch capability for responding to a possible wildland fire.

In Los Angeles County (LAC), augmented staffing decisions are made most often when there are periods of high winds and low relative humidity, both of which contribute to a high-risk fire classification known as red flag weather. Weather data is currently collected daily across the five climatic zones of LAC from an assembly of Remote Automated Weather Stations (RAWS); daily weather measurements are used to forecast fire danger indices using a series of equations generated by the National Fire Danger Rating System. The decision to augment staffing is based on one of these fire danger indices, the forecasted burning index (BI). When the daily forecasted BI exceeds the BI threshold (BIT) for its respective climatic zone, it is also classified as a high-risk fire day.

Ultimately, the decision to augment firefighting resources to fire stations within the climatic zone resides with Operational Duty Chiefs within LACoFD. The main concern that arises from LACoFD's current practice of augmented staffing regards the return-on-investment of fire-fighting resources. Cost is calculated using an Assistance-by-Hire rate, which is multiplied by the number of overtime hours worked by off-duty personnel. For the case of December 2017, LACoFD reported that augmented staffing cost in excess of $2.5 million for personnel alone (Alkonis and Pena 2018), a significant amount considering that this is only one month. In an effort to supplement decision making by Operational Duty Chiefs for augmented staffing, this thesis has developed a decision support tool to recommend augmented staffing plans. The goals for this thesis follow those set by LACoFD: protection of life, wildland fire stabilization, and property and environment protection and conservation.

The decision support tool produced by this research has been developed in two separate steps: statistical analysis and optimization. The former leads to two regression models. Each of these models contains between 10 and 25 predictor variables including interactions. The first regression uses historic forecasted weather and fire danger indices and wildland fire occurrence to estimate the probability of a wildland fire. With weather data from January 2000 to December 2018, over 100,000 observations have been collected, detailing forecasted weather and fire danger indices within each sub-area on every day during that time period, and if a wildland fire occurred or not. With these data, five separate logistic regression models are developed, each corresponding to a climatic zone of LAC. The second regression uses the past four years (January 2015–December 2018) of forecasted weather and fire danger indices, actual augmentation by LACoFD, and burned acreage outcome when a wildland fire did occur, in order to estimate the expected burned acreage should a wildland fire occur. The result of this analysis is a multiple linear regression model, in which the capability of pre-positioned resources is a major predictor of the burned acreage, along with the potential hose lay rate that can be achieved by firefighters.

Both of these regression models are used as input to the Augmentation Optimization Model to determine the optimal placement of firefighting resources across

LAC during a given day of red-flag weather for a 24-hour augmentation period. The augmented staffing plan recommended by the Augmentation Optimization Model considers the budget for augmented staffing during that day. The mixed-integer, linear optimization model incorporates wildland fire probability and expected burned acreage estimates as inputs from both regression models and aims to minimize the proportional estimated expected population displacement across LAC. The Augmentation Optimization Model optimizes across four types of decision variables, three of which correspond to the transport and employment of resources: on-duty staffed equipment, off duty equipment staffed by off-duty personnel, and additional staffing by off-duty personnel. The fourth decision variable represents a candidate resource package (a combination of the six firefighting resources considered in this research) that should be chosen. The set of candidate resources packages is bounded by the minimum and maximum allowed resources within a sub-area. In total, this model typically features over 700,000 variables and over 25,000 constraints.

This decision support tool has been tested against actual augmented staffing performed by LACoFD for the month of December 2017. The major differences between the actual and recommended staffing plans regards the movement and sources of firefighting resources. The Augmentation Optimization Model prioritizes re-organizing on-duty resources from sub-areas in which they will not likely be needed, whereas LACoFD has historically relied on augmenting off-duty equipment and personnel. Given the actual cost for augmentation, the Augmentation Optimization Model has successfully augmented daily staffing with significantly less money, the largest difference in augmentation cost being over $200,000.

This research currently splits LAC into 21 separate sub-areas each corresponding to a RAWS. These sub-areas do not correspond directly with the organizational administrative divisions of LACoFD. We recommend that these sub-areas be re-mapped by LACoFD personnel, so that the weather forecasts made for each RAWS are a better reflection of the weather within the sub-area. This remapping should also consider aspects such as terrain, slope, and brush type. This thesis also recommends that LACoFD continue to collect and catalogue the daily forecasted weather and fire danger indices data. The amount of firefighting resources pre-positioned the day before a wildland fire should also be recorded, regardless if augmented staffing has taken place. By detailing the number of firefighting resources that are available to respond to a wildland fire, LACoFD can better link a wildland fires burned acreage to the firefighting capability pre-positioned beforehand. This data collection would allow for future refinement of the estimated probability of wildland fire model and the expected burnt acreage model.

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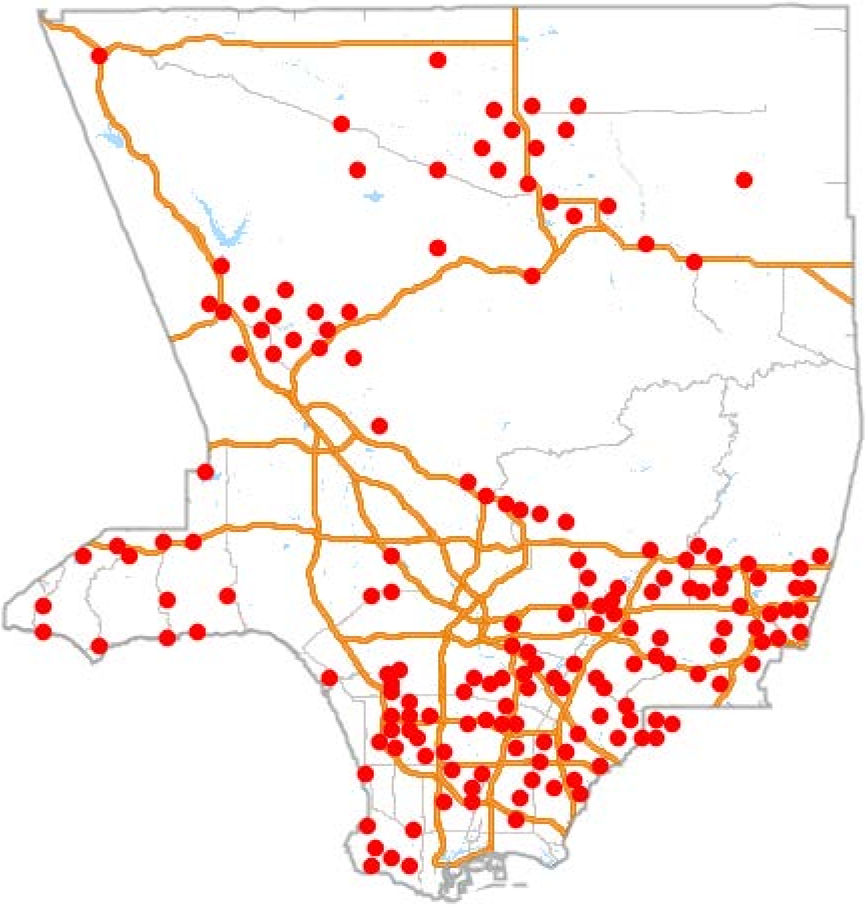
I. INTRODUCTION

A. BACKGROUND

“The mission of the Los Angeles County Fire Department (LACoFD) is to protect lives, the environment, and property by providing prompt, skillful and cost-effective fire protection and life safety services” (LACoFD 2017). With over 10 million residents living in Los Angeles County (LAC) and just over one million of those living outside of incorporated areas (County of Los Angeles 2010), LACoFD has the responsibility to provide fire protection across all areas, ranging from the urban districts of Los Angeles (LA) Basin to the rough terrain of the Santa Monica Mountains to the high desert flats of Antelope Valley. LACoFD’s inventory includes a vast assortment of firefighting equipment and staff, together known as firefighting resources, to accomplish this task, with one third of its personnel on duty at all times. Across the county LACoFD maintains 173 fire stations, as shown in Figure 1, allowing them to provide extensive coverage of high-risk wildland fire areas.



LACoFD fire stations are signified by a red dot. Santa Catalina Island (to the South) is not pictured.

Figure 1. LACoFD Fire Stations. Adapted from LACoFD (2018).

With such a vast, heterogeneous area to cover, LACoFD needs to maintain a wide array of firefighting resources in order to protect the lives of county residents. Four types of these resources are shown in Figure 2. The majority of LACoFD equipment consists of a fire engine, coming in three variants: Type I, Type III, and Type VI. The engine types largely differ in capability, with differences in pump capacity, water tank size, length of hose, and ladders. The Type I engine is the standard among the three and is best suited for structure fires in urban areas. The Type I engine can be staffed with either a three- or four-person crew, with personnel consisting of a Captain (CA), Fire Fighter Specialist (FFS), and a Fire Fighter (FF). The additional fourth member on the engine would be another FF. The Type III variant is made for use on wildland fires and is best suited when there is a need to travel off road. This engine will only be staffed by four personnel, similar to a fully staffed Type I engine. The Type VI engine is known as the patrol engine and is most often staffed by a FF and a CA if needed. The patrol engine is the smallest variant of the three and is the most maneuverable. Supporting these fire engines are Water Tenders which are equipped to haul water to the frontline of a fire.

From left to right and top to bottom are the Type I, III, and VI engine variants, and the water tender. In respective order, images are sourced from: Johanson (2010a), Deyo (2011), Johanson, (2010b), and Johanson (2010c).

Figure 2. LACoFD Firefighting Resources

Several other resources are used by LACoFD, but are not considered within the scope of this research. For example, LACoFD is among many firefighting agencies that also maintain helicopters for use in aerial firefighting. All helicopters are equipped with water drop tanks and are an invaluable asset to quickly minimize the spread of wildland fires. LACoFD maintains fueling points throughout the county and can send out Fuel Trucks for refueling. Other firefighting resources for use in urban areas include Quints and

Trucks. Quint stands for quintuple combination pumper; quintuple refers to its five main assets: pump, water tank, fire hose, aerial device, and ground ladders. A truck refers to the more traditional ladder truck without a pump and is the most commonly pictured firefighting apparatus. Much like Quints, there is no distinct advantage to using a Truck in a wildland fire. Both of these resources are most often left at the station for emergency responses required outside of the wildlands.

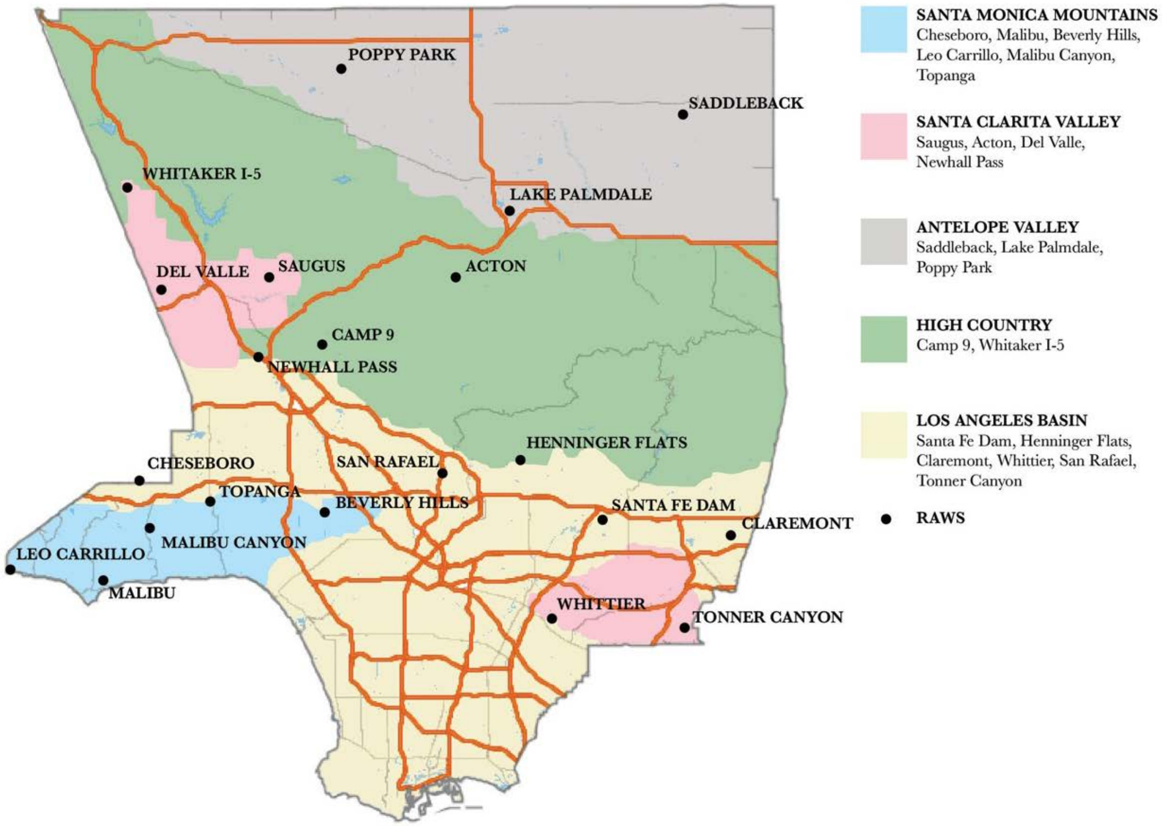
The most dangerous threat to LAC is wildland fire. Recently, the Woolsey fire burned over 90,000 acres across both recreational and residential land. The Woolsey Fire started on November 8, 2018, and lasted for 13 days, destroying just over 1,500 buildings. It is estimated to have cost $1.6 billion in damages to single-family homes alone (Stiles and Schleuss 2018). While the fire was eventually contained, the initial firefighting response failed to keep it controlled. The fire eventually spread over the steep, chaparral-covered canyons of Malibu. Extremely dry Santa Ana winds, with strong gusts that affect coastal southern California in the fall, were also a leading factor for the devastation.

B. CURRENT METHODS

In cases such as the Woolsey Fire, it is LACoFD's responsibility to recognize dangerous weather patterns and to augment their daily staffing of resources as necessary. This requires maximizing and advantageously pre-positioning the firefighting staffing prior to a possible wildland fire. The heightened response is commonly referred to as "initial attack," a strategy that relies on quick action on wildland fires in order to prevent further growth. The initial attack is then the combined response of both baseline and augmented resources, along with any other available firefighting resources able to answer the first alarm. Through guidance by LACoFD, augmented staffing typically occurs during periods of high winds and low relative humidity (RH). This combination is commonly referred to as "red-flag weather" and signifies when wildland fires would likely be most damaging.

Insight regarding when to augment staffing derives directly from LACoFD's fire weather forecast report. This report is one of many included in the daily message across all fire station sites and is used to determine staffing levels and the likelihood of wildland fires.

Weather data included in this daily report is collected autonomously from a large network of Remote Automated Weather Stations (RAWS) located across the five major climatic zones inside LAC. These areas are known as LA Basin, Santa Monica Mountains, Santa Clarita Valley, High Country, and Antelope Valley. Each area contains between two to six weather stations. The classification of RAWS by climatic zone is shown in Figure 3.



RAWS associated with each climatic zone are written below each respective zone within the legend. Santa Clarita and San Clemente Island are not pictured. Adapted from LACoFD (2018).

Figure 3. Los Angeles County Climatic Zones

Daily weather observations from RAWS are electronically reported to the Weather Information Management System (WIMS) and are processed by National Fire Danger Rating System (NFDRS) (Deeming et al. 1978) (Bradshaw et al. 1983). WIMS is then queried by LACoFD personnel to retrieve forecasted weather data and a fire danger analysis. All fire danger analysis calculations by the NFDRS algorithms are based on the once-daily, mid-afternoon weather observations and are forecasted for the following day. The NFDRS returns multiple parameters, each giving a measure of the relative significance of burning conditions and threat of fire in regards to certain components related to wildland fires.

Two parameters reported by NFDRS provide a measure regarding the difficulty of containing a wildland fire. The first of these parameters, the Spread Component (SC), is a measure of the theoretical ideal rate of wildland fire spread in units of feet per minute. The SC is based on a mathematical fire spread model developed at the Northern Forest Fire Laboratory (Rothermel 1972). The model combines the effects of wind, slope, fuel bed, and fuel particle size to predict the forward rate of fire spread. The SC often changes with fluctuations in wind and moisture contents of live and dead fuels. The second parameter, the Energy Release Component (ERC), is a measure “related to the available energy per unit area within the flaming front at the head of a fire” (Schlobohm and Brain 2002). To provide the ERC, the NFDRS equations combine the prediction of the rate of heat release per unit area during flaming combustion and the duration of flaming. For the ERC, daily changes often occur due to fluctuation in the moisture contents of the various fuel classes, which are reported as the Live Fuel Moisture (LFM) and Dead Fuel Moisture (DFM).

Fuels are dispersed across the five climatic zones and cause vast differences in the LFM and DFM measurements. One of the most common fuels found within LAC, chaparral, is known for its high flammability with low moisture content. LACoFD has a vegetation management unit that carries out foliage sampling. Foliage samples are taken bi-monthly in areas prone to wildland fire in order to determine the moisture content of the fuel. LFM readings are then entered weekly into WIMS to provide accurate measurements on fuel moisture within the five climatic zones.

The third parameter returned by the NFDRS equations is the Burning Index (BI) which is derived from both the SC and ERC using relationships originally developed by Byram for calculating flame length (Byram 1959). The BI measures the relative difficulty of containing a fire through the interrelationship of flame length and fire line intensity (Schlobohm and Brain 2002). The general rule of thumb, as reported by Scholobom and Brain, is to divide the BI by 10 to get the estimated flame length of a wildland fire.

LACoFD has established a Burning Index Threshold (BIT) across the five climatic zones of LAC. The BIT for each climatic zone is set at the 97th percentile of recorded BIs within that area, per historical records. LACoFD currently considers augmented staffing, response, and/or deployment of engines and crews when the average BI across all RAWS for a climatic zone is calculated to be above the BIT for that area. These threshold breakpoints in the BI are used to help guide staffing decisions. In our models, we maintain the BIT for consistency in the comparison with LACoFD decisions. However, our models are flexible to provide staffing recommendations for any BIT or no BIT at all.

The last parameter used in determining wildland fire potential is the Keetch-Byram Drought Index (KBDI), named after research by Keetch and Byram (1968). The KBDI indicates the relative amount of precipitation that would return the soil to its full moisture capacity. For these calculations, upper soil is assumed to have a maximum storage capacity of eight inches. As reported by Keetch and Byram, the index rating is numerical, ranging from 0 to 800, where 0 represents saturated soil, and 800 dry soil. The KBDI calculation is based on several assumptions, one of which is that drought reduction only occurs when daily rainfall exceeds 0.20 inches. Daily RADAR (Radio Detection and Ranging) rainfall data, rain gauge data, and daily maximum temperature are contributors to this calculation.

The information returned by the daily weather report is invaluable to forecasting wildland fires. Ultimately, the decision to augment staffing is dependent on the forecasted weather for the next day. Operational Duty Chiefs make specific decisions regarding the amount and type of resources to augment, and where to augment them. After hours, decisions are made by the Duty Deputy Chief and Duty Assistant Chief. The staffing and resource decisions are either county-wide or zone-specific. In cases where “red-flag weather” is forecasted out to 96 hours, the fire weather conditions are reassessed daily and decisions are made regarding the need to maintain, increase, or rescind the augmented staffing plan.

C. MISSION OBJECTIVES

LACoFD reached out to the Naval Postgraduate School (NPS) in May of 2018 with the goal of improving their resource augmentation decisions. Through their own personal review of resource augmentation, they seek:

- **Protection of Life:** LACoFD wants to minimize both population and firefighter loss should a wildland fire occur.

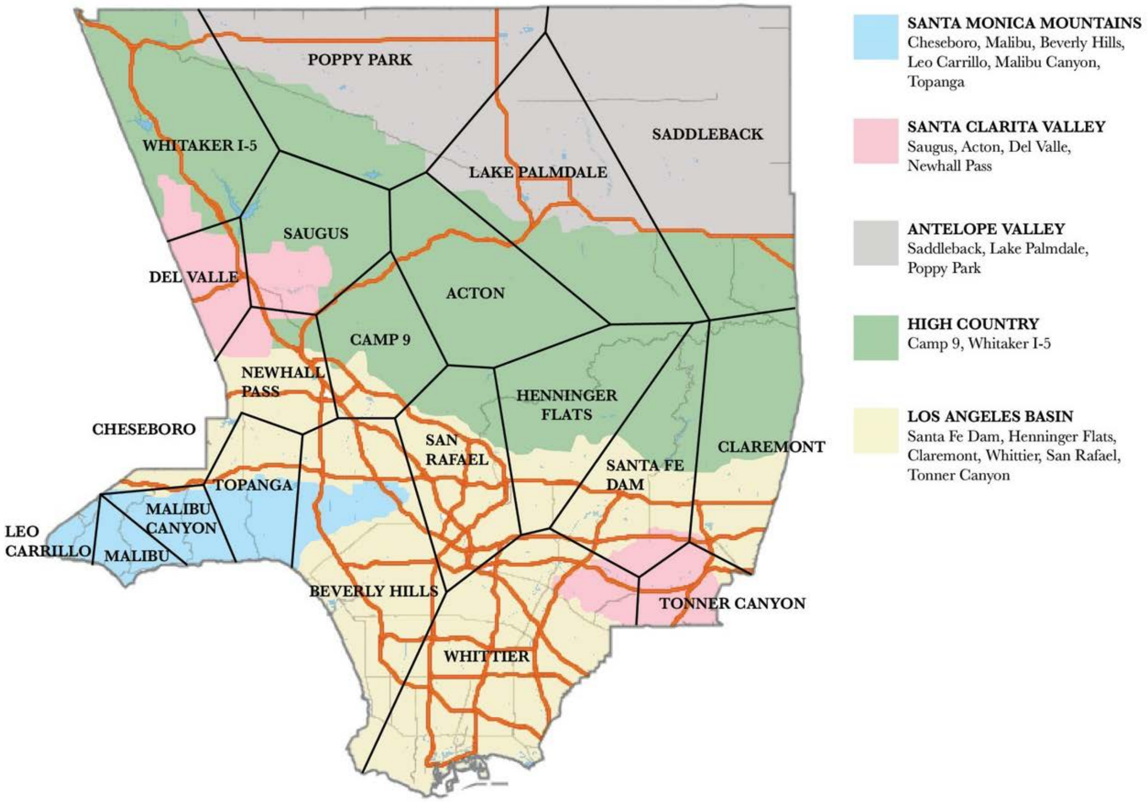
- **Incident Stabilization:** LACoFD wants to keep 95% of all wildland fires to an area of 10 burned acres or less.

- **Property and environment protection and conservation:** LACoFD wants to minimize the total wildland acreage burned.

Extending research by Cox and Hemme (2018), we seek computational tools that can help guide LACoFD’s augmentation decisions. The goal is to maintain the human influence on decision making and to supplement decisions with formal mathematical analysis. Given the recent events of Camp Fire, the deadliest and most destructive wildfire in California history (Gonzales and Chappell 2018), and the Woolsey Fire, this research is greatly needed. History has shown that destructive events like these will continue to happen unless there is human intervention and preparation. The optimal placement of firefighting resources is just one of many steps that can be taken to minimize the damage caused by these types of fires.

D. SCOPE OF RESEARCH

The optimization is limited to allocating resources across sub-areas within LAC rather than individual fire stations. Each sub-area corresponds to one of the 21 RAWS located within the county. Refer to Figure 4 for the chosen sub-areas alongside the five climatic zones. Fire stations are assigned to RAWS sub-areas by LACoFD personnel using past augmented staffing events as a reference. Fire stations not assigned to a RAWS sub-area after this review are assigned by drive-time distance, with each remaining station being assigned to the closest corresponding RAWS. This keeps our model reasonable in size and provides suggested movement of resources across sub-areas, giving Operational Duty Chiefs a base recommendation which can be interpreted down to the fire station level.



RAWS associated with each climatic zone are indicated below each respective zone within the legend. Santa Clarita and San Clemente Island are not depicted.

Figure 4. RAWS Sub-areas. Adapted from LACoFD (2018).

We are grateful that LACoFD has been willing to spend time and effort to provide historic data. One of the analyst’s hallmarks is that you never know what is important until you discover it. LACoFD obliged by providing weather and fire danger analysis records covering three years from 2015 to 2018. Prior to this research, LACoFD’s data collection was limited in that only paper copies of each weather report were catalogued. More daily fire weather data was eventually sourced through WIMS, with reports dating back to January 1, 2000. Furthermore, detailed reports were provided by LACoFD regarding any augmented staffing that occurred dating back to 2015. LACoFD has already begun to maintain more detailed records regarding the daily weather and initial response to wildland fires in response to our demonstrated need for and the usefulness of data. Further analysis of augmented staffing alongside differing weather conditions will benefit from this renewed effort.

E. THESIS OUTLINE

The remainder of this thesis is organized as follows. Chapter II discusses previous research on optimizing resource allocation for wildland fires. In Chapter III we explore statistical analysis to advise the augmentation problem. A collection of regression models is presented for their use within an optimization model; an Augmentation Optimization Model (AOM) is then presented. In Chapter IV we provide analysis on results from the AOM for the month of December 2017. In Chapter V we present our conclusions and potential extensions that require future research. A series of appendices provide more detailed information and results of this research.

II. LITERATURE REVIEW

Operations research has been used previously to recommend an initial attack in response to a wildland fire. Wiitala (1999) uses deterministic, dynamic programming to select the optimal initial attack within an efficient amount of time. Wiitala appropriately acknowledges the growing need for initial attack, a strategy that remains contingent on the knowledge of various subject matter experts. For a problem that requires both strong and quick initial attack responses, dispatchers need to evaluate a wide variety of factors when assessing which response of resources would be optimal. These factors, which include response times and fire-line building rates are not easily combined with fiscal constraints. With up to 30 different firefighting resources considered, the need for modeling these constraints also stems from the vast number of combinations that could possibly be dispatched. Wiitala addresses this problem through the implementation of a non-linear, mixed-integer programming problem seeking to minimize cost, with non-linearity deriving from the area-related costs and resource loss.

The initial attack problem is a time sensitive one. While Wiitala's model takes only two seconds to run on a 200 MHz micro-computer, decisions are committed after a wildland fire starts. Decisions such as this can be improved when historical data can provide valuable information in predicting the likelihood of a wildland fire occurring.

Donovan and Rideout (2003) also explore optimizing resource allocation for wildfire containment by developing an integer linear program (ILP) which minimizes a Cost plus Net Value Change (C+NVC) function, that accounts for all costs associated with fire suppression and the net fire-related damages. They recognize that a mathematical model could be used to model budget, time, and distance constraints commonly dealt with by firefighting managers. The C+NVC function has historically been used to identify the most economically efficient expenditure of firefighting resources. The function extends a previous one developed by Sparhawk (1925), which is the Least Cost plus Loss model. With the C+NVC function, the cost of pre-fire management, direct fire management, and net wildfire damages can all be minimized when determining which resources should be utilized. This function, however, does not identify the optimal resource package to be used for fire suppression, a problem commonly faced by firefighting managers. Fire suppression in this case refers to the various firefighting tactics used to contain and control wildland fires. Their research thus developed a model to determine the optimal firefighting resource package to respond to a single historic fire, thus demonstrating the possibility of utilizing optimization methods for wildland fire planning and budgeting.

Donovan and Rideout's model selects the optimal firefighting resource package that minimizes the C+NVC function subject to a collection of constraints related to the costs and damages of the fire and resources being used. By implementing an ILP they are able to perform sensitivity analysis on the constraints, demonstrating the ability of this model to respond to varying fires characterized by different parameters and behaviors. The ability to perform this analysis derives directly from the flexibility of the optimization problem. We note their problem is a knapsack problem, where a range of possible firefighting resource packages are pre-processed with a pre-defined benefit for fire suppression. Firefighting resource packages are specific, indivisible units that can be chosen and dispatched.

Through the implementation of their model, Donovan and Rideout perform sensitivity analysis by analyzing the effect of responding to a fire that is less damaging and to one that requires twice the response time. Donovan and Rideout impose a finite fire management budget; this constraint effectively limits total costs attributed to both pre-suppression and direct suppression.

Their testing of the sensitivity analysis and the addition of cost constraints intuitively shows that the reduction of budget is achieved at the expense of the total burned acreage and associated damage. Testing also shows that while doubling the arrival time to a given historical fire has a significant impact on the objective value of the C+NVC function, it has no significant impact on the firefighting resource package employed. This shows that adding a temporal and spatial element to a model will not affect which resources should respond for initial attack. The model ultimately relies on the use of historic fire data, which can create a large amount of variability. Performing this sensitivity analysis is thus beneficial in determining which parameters and constraints affect the optimal solution more, providing the ability for the user to outline where to seek improvement.

This thesis builds upon the optimization model provided by Cox and Hemme (2018) by incorporating their research together with elements mentioned previously. Hemme and Cox developed an Excel-based ILP to aid decisions in resource augmentation for LACoFD. This augmentation is centered on optimally deploying additional resources, from which eight are considered. The goal of their research is development of an optimization model and ultimately highlights further analysis that should be continued to refine the model.

Cox and Hemme utilize resource capability scores, a number that is a weighted sum of hose lay rate and production rate for the corresponding resource. Hose lay rate refers to the length of hose in feet that firefighters can lay in one minute; production rate refers to the length in feet of break line per minute firefighting personnel can clear. A break line refers to a gap in vegetation or brush that can slow or stop the progress of a wildland fire. Break lines are used predominantly in wildland fires in order to cut further spread. Cox and Hemme take these measurements from Rahn (2010). Rahn reports that the greatest increase in personnel efficiency occurs when the number of firefighters laying out a line of hose increases from a two- to a three-person crew. This increased efficiency can be linked to lower physical stress on firefighters and a more effective and quick initial attack. While these numbers can accurately assess the effectiveness of a resource, they are largely influenced by a variety of factors, including the type of terrain such as brush or slope, and equipment capability, such as water capacity and off-road ability. Cox and Hemme use the weighted capability score calculated for each resource alongside daily forecasted Burning Index (BI) data to determine which fire stations within LAC should receive augmented resources. Our research improves the capability score concept by including the implementation of a Return-on-Investment (ROI) function with respect to augmentation. The ROI function incorporates data forecasting for the estimated probability of wildland fire occurrence and expected burned acreage. An adaptation of the capability score developed by Cox and Hemme is utilized by this research to estimate the expected burned acreage of a wildland fire.

The original intention for the BI metric was to predict the potential for a fire to escape, as well as to provide insight on its possible destructiveness, all based on the fact that ignition had already occurred (Pyne et al. 1996). BI was developed through a need to establish a fire danger rating that could prominently be used in fire management planning. A few of the factors that need to be accounted for include the ease of ignition, rate of spread, difficulty of control, and fire impact, all of which describe the fire potential. These factors are commonly associated with a variety of weather elements and fuels, as well as human behavior and land use. Several fire danger ratings are in use today: Australia uses the McArthur Forest Fire Danger Index (1966, 1967), Canada uses the Fire Weather Index (Wagner and Edward 1974), and the U.S. uses the NFDRS. The range of these fire danger ratings can be associated to the broad generalizations used about fuel and landscape characteristics. The NFDRS fire danger rating produces four main indices to describe wildland fire potential: Spread Component (SC), Energy Release Component (ERC), Burning Index (BI), and Keetch-Byram Drought Index (KBDI). As mentioned above, both SC and ERC contribute to the value of the BI. This calculation is made through a series of physics-based nonlinear dynamic equations involving heat transfer and moisture exchange, which can then be related to the fire line intensity or flame length.

LAC exhibits singular fire potential due to the varied nature of its landscape and weather patterns. The county has a mixed climate, topography, and vegetation, all of which relate to a wide variation in land use. LAC is covered in dense contiguous chaparral shrub lands, providing the major fuel for wildland fires during the summer and fall drought. The summer and fall dry season are followed by the Santa Ana winds which have been reported as exceeding 60 mph and lasting from several days to several weeks (Keeley et al. 2004). The landscape of LAC, combined with its unique weather patterns, creates a distinct problem when using only BI to predict fire occurrences using a fixed threshold.

Previous studies have explored the effectiveness of using BI as a metric for predicting wildland fire activity, such as the daily number of wildfires, total area burned, and area burned per fire using burned acreage data ranging from January 1976 to December 2000 within LAC (Schoenberg et al. 2007). Schoenberg et al. find that the BI over-predicts wildfire activity during the winter and under-predicts wildfire activity in the fall. Fuel moisture has been cited as one of the possible explanations for the discrepancy between fall and winter for LAC. Furthermore, Schoenburg et al. state that while the BI accounts for a drought index and weather on a certain day, it does not take into account the cumulative effect of precipitation, or dry weather, on previous days. In their research, they conclude that because most weather variables are highly correlated in their original form, it may be easier to take into account that most wildfires occur during relatively dry seasons. They conclude that weather factors such as high temperatures and low relative humidity could thus be used to account for cumulative dryness.

Schoenberg et al. base their BI analysis on 592 wildfires catalogued between 1976 and 2000 that burned at least 10 acres. Of these cases, there are 362 days with exactly one wildland fire recorded, and 66 days with two or more wildfires. They find that the daily average BI score has low correlation with the number of wildfires, daily burn area, and the area burned per fire. In comparison, the correlation between the daily average wind speed and daily burn area is higher than that of BI, though still relatively low. The BI parameter does not fully account for otherwise relevant weather conditions related with the possibility of wildland fire activity. Influential factors such as drought severity and precipitation readings are largely unaccounted for when solely using the BI. It would be more advantageous to combine a multitude of factors, such as BI, wind speed, relative humidity, temperature, fuel moisture and precipitation over the previous 24 hours, as our research does.

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III. METHODOLOGY

This chapter describes the models used in this thesis. Estimating the probability of wildland fire occurrence is the first of two statistical models presented and is described alongside the various weather inputs used. The second statistical model, estimating the expected burned acreage of the wildland fire, is outlined via its input parameters and justification. The augmentation optimization model, AOM, is then explained in detail with its parameters, data inputs, decision variables, formulation, and constraints. Further justification and analysis is provided in Appendix A for the two statistical models.

A. ESTIMATED PROBABILITY OF WILDLAND FIRE

In the words of Box and Draper, “essentially, all models are wrong, but some are useful” (1987). Discussions with LACoFD personnel and staff during a site visit in February 2019, focused on the inputs that should be considered for estimating the probability of wildland fire. The objective is to develop an accurate model for this prediction while noting inputs that are found to be significant. The results of this effort are five separate logistic regression sub-models, one for each of the five climatic zones in LAC.

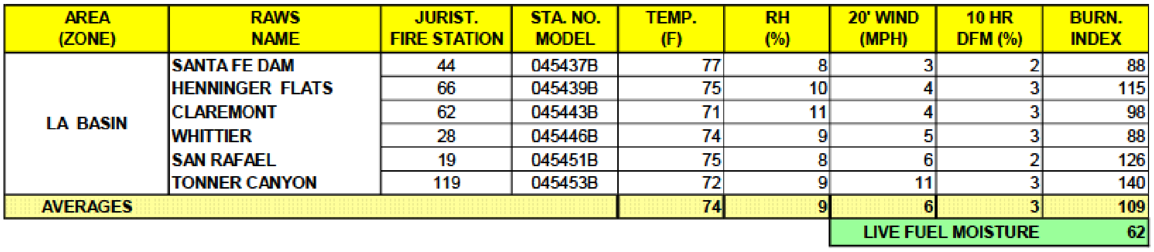
1. Human Negligence

With nearly 85% of wildland fires in the U.S. caused by humans, it would be wise to consider human negligence as a factor in a model used to predict wildland fires. These human-caused fires are largely a result of campfires left unattended, discarded cigarettes, burning debris, equipment malfunctions, and intentional acts of arson (Short 2017). Accounting for human negligence in the models discussed here, however, is nearly impossible. A surrogate factor discussed with LACoFD personnel to explain this phenomenon is population density. If an area has a higher population density, then the likelihood of human negligence resulting in fire is increased. Other possible factors mentioned are the number of hiking trails, or total length of trails, within the area. Similarly, one could count the number of campsites, including homeless campsites in particular. Both of these metrics could be used to account for negligent hikers and campers who might spark a fire. Another surrogate metric considered is a binary indicator for a weekend day. This factor is proposed as a way to account for a possible shift in the number of people outdoors. Ultimately, most of these factors were left out due to a lack of data, leaving these potentially useful predictors out of our models. The binary weekend indicator, however, is included in one of the five sub-models developed. Future research should be conducted to examine ways in which measures of human negligence could be collected and included in statistical models similar to those proposed here.

2. Initial Data Requirements

Data requirements were addressed prior to the start of this thesis and initially involved the procurement of the daily weather and fire danger analysis report produced by LACoFD. A portion of this report is shown in Table 1 for LA Basin on a particular day; a complete version of this report is shown in Appendix B: Appendix Figure 6. The report provides weather data for each of the five major climatic zones and then again by each RAWS within a zone. Data regarding temperature, Relative Humidity (RH), 20-foot wind speed, 10-hour Dead Fuel Moisture (DFM) and the Burning Index (BI) are listed. For each climatic zone, an additional metric for the LFM is included. Descriptions of these reported weather metrics follow in the remainder of this section.

Table 1. Daily Weather and Fire Danger Analysis Report for the LA Basin Climatic Zone



AREA (ZONE)	RAWS NAME	JURIST. FIRE STATION	STA. NO. MODEL	TEMP. (F)	RH (%)	20' WIND (MPH)	10 HR DFM (%)	BURN. INDEX
LA BASIN	SANTA FE DAM	44	045437B	77	8	3	2	88
	HENNINGER FLATS	66	045439B	75	10	4	3	115
	CLAREMONT	62	045443B	71	11	4	3	98
	WHITTIER	28	045446B	74	9	5	3	88
	SAN RAFAEL	19	045451B	75	8	6	2	126
	TONNER CANYON	119	045453B	72	9	11	3	140
AVERAGES				74	9	6	3	109
						LIVE FUEL MOISTURE		62

a. Temperature and Relative Humidity

The temperature reported in the weather report is recorded in degrees Fahrenheit. The RH is reported as a percentage, describing the proportion of water vapor in the air compared to the maximum amount of water vapor it could hold at that temperature. A reading of zero would signify that the air contains no water vapor and conditions are extremely dry.

b. 20-Foot Wind Speed

The 20-foot wind speed is in miles per hour and is defined as “sustained winds averaged over a 10-minute period and measured 20 feet above the average height of nearby vegetation” (Hinnant 2014). Wind direction can be recorded by RAWS; however, it is not reported.

c. 10-Hour Dead Fuel Moisture

Vegetation is commonly referred to as fuel when used in discussing wildland fires. The Dead Fuel Moisture (DFM) threshold (reported for a 10-hour period and termed 10-Hr DFM) is based on how long it would take for two-thirds of the dead fuel to equalize with the local moisture (National Oceanic and Atmospheric Administration 2019). Small vegetation such as grass, leaves, and mulch respond more quickly to atmospheric moisture content, and usually take 10 hours to adjust to moist or dry conditions. Larger vegetation, such as downed trees, may take up to 1,000 hours to adjust to the same moist conditions. This metric is widely used to describe wildland fire potential and is expressed as a percentage ratio of the amount of water in vegetation to the dry weight of the vegetation.

The brush type varies substantially across sub-areas of LAC. Several brush types are sampled for their fuel moisture, including: chaparral, chamise, hoary leaf ceanothus, bigpod ceanothus, black sage, purple sage, and sagebrush. The landscape and corresponding brush of an area are also strongly affected by recent wildland fires. If a RAWS sub-area has land that was recently scorched, referred to as a burn scar, then the likelihood of a wildland fire occurring is near zero due to the absence of burnable fuel. Data regarding availability of fuels was not available for inclusion in our wildland fire probability models, but we note that this would be an important enhancement to our models.

d. Burning Index

The range of a BI varies substantially between the five major climatic areas of LAC. And, BITs vary across climatic zones, as shown in Table 2. This suggests that a forecasted BI to BIT ratio, or Burning Index Ratio (BIR), could be used as an input factor. This would work well should the model be aimed at predicting fires across all zones. Because five separate models were made for each of the five climatic zones, the individual BI is used as the input instead.

Table 2. Burning Index Threshold for Los Angeles County Climatic Zones

Climatic Zone	Burning Index Threshold (BIT)
LA Basin	105
Santa Monica Mountains	94
Santa Clarita Valley	140
High Country	222
Antelope Valley	116

LACoFD has established a BIT across the five climatic zones of LAC. The BIT for each climatic zone is set at the 97th percentile of recorded BIs within that area, per historical records. The LA Basin BIT of 105 is exceeded by three of six RAWS sub-areas in Table 1, and by the average of the entire climatic zone.

e. Live Fuel Moisture (LFM)

LFM is included as a predictor in the wildland fire probability model where possible. Currently, only RAWS in four of the five major climatic zones in LAC report a LFM. Antelope Valley, being high desert, does not record LFM as it is predominantly dry grass. This qualitative difference in recorded metrics gives rise to the idea of dividing the wildland fire probability model into separate models for each of the five major zones.

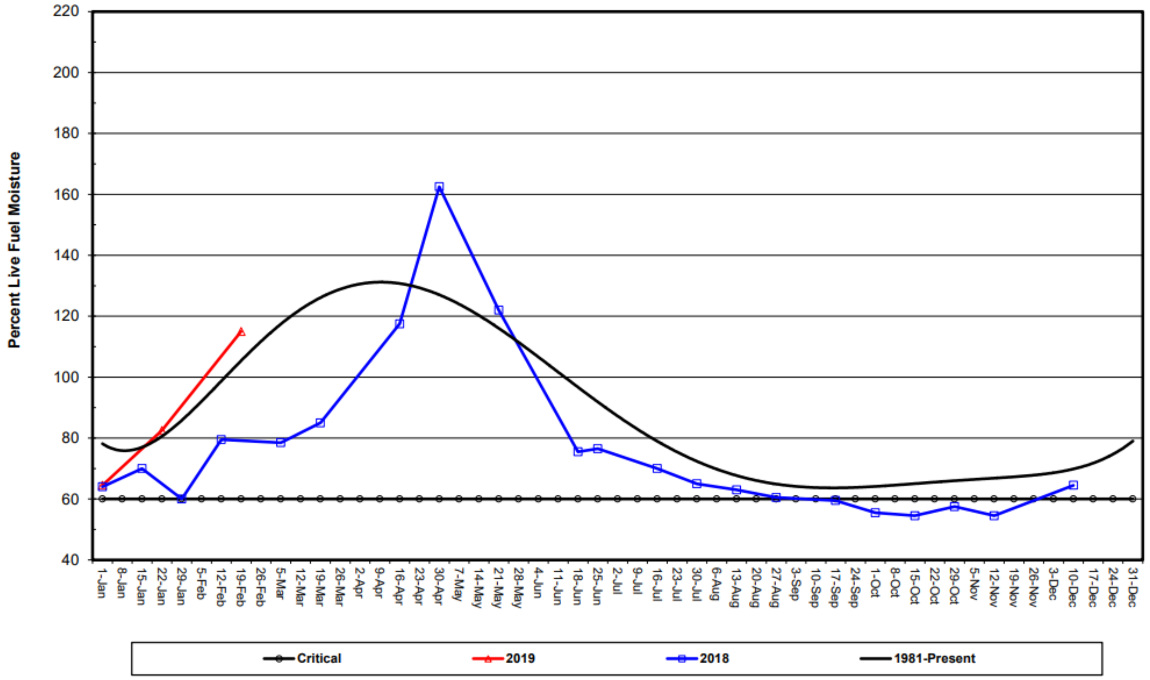
LFM is the percentage ratio of the water weight of a living vegetative fuel to its dry weight. It is one of the major contributors to determining the amount of fuel available to a potential wildland fire. Fuels with higher moisture content will generally reduce the rate of energy released during a fire due to the moisture’s large heat capacity. Of note, moisture content can be greater than 100 percent. The National Wildfire Coordinating Group (2006) states the range of LFM alongside a physical descriptor of the fuel as follows:

- LFM = 300: Fresh foliage, annuals developing early in the growing cycle;
- LFM = 200: Maturing foliage, still developing, with full turgor;
- LFM = 100: Mature foliage, new growth complete and comparable to older foliage;
- LFM = 50: Entering dormancy, discoloration starting, some leaves may have dropped from stem; also indicative of drought conditions;
- LFM < 30: Completely cured (to be treated as dead fuel).

3. Follow-on Data

The weather and fire danger analysis data provided by LACoFD is a small subset of the data that is sourced daily from WIMS by the Forestry Division. Data detailing the three other fire danger indices also were sourced due to their likely importance in the models. The indices mentioned here refer to the SC, ERC, and KBDI, as described in Section I.B and Section II.

Discussions with LACoFD personnel revealed other seasonal data that may be useful to the models. With each data point indicated by a date and RAWS sub-area, information regarding month, year day, week of the year, and weekday were sourced for each observation. These data, excluding weekday, are also possibly correlated to other factors already collected such as LFM. Figure 5 shows the percent LFM across Santa Clarita Valley chamise from 1981 to 2019, with two lines showing 2018 (blue) and 2019 (red) data, up to February, 2019. Low points in this plot indicate the fire seasons, with 60% LFM indicated as the critical point for fire danger. An indicator for weekend was also included as a predictor due to its possible link to the human negligence factor, with a zero indicating a weekday, and one indicating weekend days (Friday, Saturday, and Sunday).



We note that for 2018, the Live Fuel Moisture fell below the critical threshold from September to November. For 19-Feb, the line for 2019 is at roughly 118, the line for the average LFM from 1981-Present is at roughly 105, and the line for 2018 is at roughly 79. This indicates that fuel in 2018 was comparatively drier than the average at this time period; the figure also indicates that the LFM in 2019 is already above average at this time.

Figure 5. Live Fuel Moisture from 1981 to February 2019 for Chamise in the Santa Clarita Valley Climatic Zone. Adapted from LACoFD (2018).

These data, alongside the initial fire danger analysis and weather data collected, have been combined with data provided by LACoFD outlining all brush and wildland fires recorded since January 2000. Combining these two data sets indicates which RAWS sub-areas had a fire event and the corresponding day it occurred.

4. Model Format and Justification

We develop a logistic regression model (McCullagh 2018) to estimate the probability of a wildland fire. In a logistic regression model, the logarithm of the odds, or log-odds, of an event (e.g. occurrence of a wildland fire) is expressed as a linear combination of one or more independent variables, also known as predictors. For a probability of p, the odds is defined in Equation (1).

$$odds = \frac{p}{1-p} \tag{1}$$

Predictors can be either be continuous or binary, with the latter used to represent categorical independent variables. The linear combination of terms is shown in Equation (2) (Faraway 2016). In this equation, $\hat{\eta}$ is an estimate of the log-odds, $\hat{\beta}_0$ represents the estimate for the log-odds with follow-on $\hat{\beta}$ terms signifying the estimators for the corresponding independent variables. In this case, there are q predictor terms.

$$\hat{\eta} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \ldots + \hat{\beta}_q x_q \tag{2}$$

The linear combination of terms is then passed through the inverse logit function, which is used to transpose the logarithm of the odds into a corresponding probability for an outcome value of one (in our case representing the occurrence of a wildland fire). Assuming the odds are an exponential function of η, the inverse logit function shown in Equation (3) gives the transformation of the log-odds to the corresponding estimated probability. The estimated probability is then used as the likelihood for a wildland fire, versus no fire.

$$\hat{p} = \frac{e^{\hat{\eta}}}{1+e^{\hat{\eta}}} \tag{3}$$

a. Estimated Parameter Coefficient, $\hat{\beta}$

The estimated parameter coefficient describes the size of the contribution of its corresponding predictor. Furthermore, a positive sign on the coefficient indicates that an increase in the variable increases the probability of an outcome. In the case of our model, where the fire danger indices are calculated using weather measurements, parameters are inherently correlated. This high correlation results in some cases where the sign on an estimated parameter does not intuitively make sense with regards to the increased, or decreased, probability of a wildland fire. These correlations are often incorporated through other parameters or interactions, thus balancing or flipping the effect of a parameter that gives an uncommon indication of fire outcome. Parameter estimates give the log-odds ratio associated with a unit change of one to the corresponding variable, with all other parameters held constant. Descriptor variables in a model can include interactions, when the effect of one variable depends on the value of another variable, and transformations to account for non-linear relationships between an outcome and the predictor variable. Furthermore, variables can either be numerical or categorical, with the latter of the two represented by a set of reference cells or binary values. In this reference cell coding, the parameter coefficients indicate the average log-odds difference in the outcome when the baseline variable is zero and the comparison variable is one.

b. Model Selection

The selected logistic regression sub-models are developed using stepwise regression to minimize the Akaike Information Criterion (AIC) (Akaike 1973) (Faraway 2016). The AIC provides a measure of the predictive accuracy of an estimated statistical model. With sub-models developed using this stepwise regression, a Receiver Operator Characteristic (ROC) curve (Fawcett 2006), defined in forthcoming Section III.A.4.f, is plotted for each sub-model on a separate validation set for that climatic zone. Validation sets for these sub-models comprise a random 20% of the respective climatic zone's original data set, to be used as a separate test set in order evaluate a developed model. The area under the curve (AUC) for each ROC is then used to evaluate the model's performance on the data set (Fawcett 2006). This method is used to evaluate the ability of a regression model for two-state (binary) classification problems.

The chosen sub-models by climatic zone for estimating the probability of a wildland fire occurring are displayed in tables in Appendix A alongside their respective predictor's statistics. The table for each logistic regression lists attributes of the estimated parameters $\hat{\beta}_1, \cdots, \hat{\beta}_q$ of the logistic regression, $\hat{\beta}$ standard error (SE), Wald Chi-Squared ($\chi 2$) Test statistic, probability value (*p*-value) for the Wald Test, odds-ratio, and the 95% confidence interval (CI) on the odds-ratio.

c. Estimated Parameter Standard Error

The estimated parameter standard error gives the variability of the parameter coefficient and is used for testing whether the respective parameter coefficient is significantly different from zero. The ratio of the coefficient to its standard error is used in the Wald Test to test its significance as a predictor within the model.

d. Wald Chi-Squared Test Statistic and p-value

The Wald Test assesses the significance of particular predictor variables within a statistical model (Agresti 1990). With a binary outcome variable and an associated set of explanatory variables, the Wald Test provides a way to test whether or not the estimated parameters associated with each predictor variable are zero or not. We can conclude that a parameter associated to a predictor variable is not zero and is otherwise significant at the 95% confidence level when a Wald Test returns a significant probability value (*p*-value) below 0.05. A significant *p*-value suggests that the tested variable should be included in the model. This test is an approximation of the likelihood ratio test; however, it is acceptable here for use due to our large sample size and small number of predictors.

e. Odds Ratio and 95% Confidence Interval

The odds ratio provides a measurement of likelihood from individual predictor variables. The odds ratio for a predictor variable is interpreted as the effect of a unit change in the predictor variable with the other variables held constant. The odds ratio then provides relative information regarding the variable's influence on the model outcome; each odds ratio is reported alongside its 95% CI. Odds ratios generally do not provide valuable information if a predictor variable is found to carry an interaction with other predictor variables.

f. Receiver Operator Characteristic

When the output is a two-state classification problem, regression models return an estimated probability that there will be a success (in this case a wildland fire) as opposed to a failure (no wildland fire), given a set of predictor variables. Turning the (continuous) estimated probability into a (discrete) specific classification can then be arbitrary, with the common method typically assigning a threshold of probability 0.5. If the model predicts higher than this threshold, then the result is positive, and if not the result is negative. This threshold, however, is neither ideal nor realistic to many situations analyzed.

Through the use of the ROC, the assigned threshold probability is varied in order to calculate metrics for the sensitivity and specificity of a model. Sensitivity, in this case, refers to the probability of predicting a wildland fire when it actually does occur, better known as a true positive. Conversely, specificity pertains to the probability of predicting that a wildland fire will occur when it actually does not, also known as a false positive. Intuitively, these two probabilities are functionally related, where an increase in the sensitivity of a model usually corresponds to lower specificity. Setting a threshold probability to signal a situation such as a wildland fire occurring or not can thus be problematic. A threshold is often set low to avoid "missing" any odd situations that would result in a positive classification. This method however can trigger many false positives. If the threshold is set too high, errors then come in the form of missing true positives. Both of these errors come with their own cost, with often one being more serious than the other.

The common metric used to evaluate the accuracy of a model is the area under the ROC curve (Fawcett 2006), referred to as the AUC. For this metric, an AUC value of one indicates a perfect model while a value of 0.5 represents a worthless one. The common example here would state that flipping a coin, or random guessing, would perform just as well as a model with an AUC of 0.5. Each sub-model chosen for this thesis is thus aimed at maximizing the AUC for the ROC curve.

5. Los Angeles Basin

LA Basin is the most concentrated part of LAC in population and in regards to geography. The basin is separated from the rest of LAC by the Santa Monica and San Gabriel Mountains to the north, the Santa Ana Mountains to the east, and the Pacific Ocean to the west and south. This area is also highly susceptible to Santa Ana winds in the fall. Altogether, the basin is classified as a coastal lowland area, otherwise known as low desert.

This sub-model was developed using 32,084 observations and is shown in Appendix Table 1. The following paragraphs discuss the chosen parameters as well as model justification.

Relative Humidity (RH) is featured predominantly in the logistic regression model; the variable has a positive interaction with temperature and a negative interaction with Energy Release Component (ERC). The main estimated predictor for RH is itself negative, where an increase in RH relates to a smaller probability of wildland fire, as expected. An increase in temperature, wind, and Burning Index (BI) also relates to a higher estimated probability with all main effects shown to be positive. The categorical variable RAWS was found to have a significant coefficient, with the parameters for these showing the estimated trends of fire probability in each respective sub-area. Three of the four NFDRS fire danger indices are featured in this sub-model as well, excluding the Keetch-Byram Drought Index (KBDI).

The ROC curve for this sub-model is shown in Appendix Figure 1. The AUC for the sub-model is calculated to be 0.802, indicating that the model performs well in classifying wildland fires.

6. Santa Monica Mountains

The Santa Monica Mountains are a coastal mountain range within LAC. Due to their proximity to LA and other large cities within the densely populated county, this mountain range is regarded as one of the most visited natural areas within California. These mountains feature a large number of trailheads and campsites despite featuring rough terrain covered in chaparral and sagebrush. Furthermore, increasing numbers of homes, roads, and businesses are locating in this area.

The sub-model for this climatic zone features several positive parameter coefficients that are found significant in estimating the probability for wildland fire. The sub-model has been developed using 29,512 observations and is shown in Appendix Table 2. The following paragraphs outline the chosen parameters and provide justification for choosing this sub-model.

The major weather measurements included in this sub-model include temperature and wind, with wind shown to be the more significant coefficient of the two. Temperature is found to have a negative interaction with the BI within the zone for predicting wildland fire. Another interaction within the sub-model is with LFM and Week, indicating that wildland fires within this zone occur more often later in the year. The RAWS sub-areas in the zone were each found to have significant parameter coefficients, with Malibu having the largest positive coefficient and Beverly Hills the largest negative coefficient.

The sub-model performs well, as shown by the ROC curve in Appendix Figure 2. The AUC is calculated to be 0.769 for the ROC when the sub-model is used on a validation set, as detailed in Section III.A.5.

7. Santa Clarita Valley

Santa Clarita Valley lies within the center of LAC, nestled between the Sierra Pelona Mountains to the north, the San Gabriel Mountains to the east, and the Santa Susana Mountains to the south. The valley is also bordered by Lake Piru and is part of the upper watershed of the Santa Clarita River. The climate within this zone is moderate, with temperatures ranging from 70 to 100 ^{o}F in the summer and 30 to 50 ^{o}F in the winter. The wildland fire danger within this zone arises from dry hills covered in chaparral.

The sub-model for this climatic zone features all weather measurements and fire danger indices. A variety of interactions between these two data types are also included within the chosen sub-model. This sub-model has been developed using 22,286 observations and is shown in Appendix Table 3. Details regarding the sub-model are further explained in the following paragraphs.

Most forecast weather measurements trend as expected, with temperature and wind both indicated as positive. RH has a negative coefficient, indicating that higher amounts of water vapor present in the air are less associated with wildland fire. RH is also found to interact with the RAWS sub-areas variables, where the coefficient for RH within Del Valle is indicated as positive. The week of the year is also found to have a significant negative coefficient, indicating that later weeks in the year have a decreased chance for wildland fire to occur. The KBDI estimator is positive as well, with larger values for this variable indicating the amount of water needed to return dry soil to saturated. As expected, larger values are thus associated with wildland fire.

The sub-model produced for Santa Clarita Valley does not perform as well when using the ROC curve to evaluate its performance on a validation set of data. The sub-model has an AUC of 0.691 for the ROC curve, and is shown in Appendix Figure 3. While the sub-model does not perform as well as the others, the model does outperform random guessing and can be justified for use.

8. High Country

High Country refers to the mountainous region within the center of LAC. These mountains are part of the Transverse Ranges, a group of mountain ranges within southern California. The majority of these mountains are within California's chaparral and woodlands ecoregion, with lower elevations covered by chaparral and higher elevations by conifer forests. The tallest feature in LAC, Mount San Antonio, rests at 10,068 feet above sea-level, and is part of the San Gabriel Mountains.

The sub-model for High Country is estimated using 12,070 observations and features all but two of the weather measurements and fire danger indices, LFM and KBDI. The sub-model does include multiple interactions, two of which are by RAWS sub-areas. The chosen sub-model and statistics are shown in Appendix Table 4; a description of the sub-model parameters and a justification for this sub-model are provided in the following paragraphs.

All main effects of the chosen parameters trend positively except for three, where an increase in ERC, SC, and the 10-Hr DFM is indicated as decreasing the likelihood of wildland fire. Due to the high correlation of parameters, this is likely offset by another term. Of the positive main effects, the KBDI coefficient is not significant per the Wald Test. The parameter does however have a significant coefficient through its interaction with the LFM. This BI coefficient is significant in its interaction with wind; wind is also found to have significant coefficients regarding interactions with temperature, ERC, and the 10-Hr DFM. The Weekend parameter coefficient is significant in this climatic zone, indicating that fires occur more often on the weekend as opposed to weekdays (Monday through Thursday).

With the sub-model tested on a validation set, the ROC curve produced gives an AUC of 0.682 and is shown in Appendix Figure 4. While it cannot be classified as a “good” model, it does provide valuable insight in regards to weather trends within the region. This knowledge, tied with subject matter experts, will enhance the current practice of prediction.

9. Antelope Valley

Antelope Valley is the last major climatic zone within LAC and can be classified as high desert. The valley is part of the western tip of the Mojave Desert, which is the driest desert in North America. Moisture within this zone thus is primarily water runoff from the paralleling San Gabriel Mountains. Wildland fires within this zone are relatively easy to control due to a square-grid road system allowing for easy cut-offs of fires. These fires thus do not provide much danger to the county, however can be a threat due to the low humidity and high temperatures in the summer and early fall.

The sub-model for this climatic zone is estimated using 16,534 observations and incorporates nearly all available inputs. LFM is not included within this regression model as it is currently not collected within this climatic zone. The chosen sub-model and associated statistics are shown in Appendix Table 5. The following paragraphs provide an explanation in regards to the sub-model estimators and its justification.

The temperature coefficient was found to be significant within the sub-model, both in regards to its main effect and interactions with KBDI and week of the year. The week of the year also interacts negatively with KBDI and wind. BI and RH are found to have a significant coefficient in their interaction with the 10-Hr DFM, both of which are negative. The RAWS categorical parameter coefficients are both significant yet differ in sign, with Lake Palmdale indicated as the more likely sub-area of three to have a fire within this zone.

Testing the sub-model against a validation set proved successful, with an ROC curve calculated to have an AUC of 0.803; this curve is shown in Appendix Figure 5.

B. EXPECTED BURNED ACREAGE OF WILDLAND FIRE

Should a wildland fire occur, it is fortuitous to be prepared with the appropriate level of firefighting resources for initial attack. This response is largely dependent on the number of resources that are currently staffed and those that have been augmented in preparation. The number of individual resources currently augmented is based on the forecasted weather and BI. This section identifies which weather and fire danger indices are best matched with certain types of resources when responding to a wildland fire. Given any resource configuration and forecasted weather and fire danger indices, the regression model estimates an expected burned acreage in the event that a wildland fire should occur. This section ultimately produces an ROI function through multiple linear regression (Myers 1990).

1. Data Requirements

This model is built using data collected solely from 2015 to 2018, due to limitations regarding LACoFD's access to augmented staffing plans before 2015. The burned acreage of all wildland and brush-type fires during this time period was sourced from LACoFD and tied into the data collected previously. These data were meshed through linking dates and sub-areas of both data sets together. Any cases where a sub-area did not experience a wildland fire event on a certain date were removed from the collective data set. From this, augmented staffing plans supplied by LACoFD were parsed to determine if augmentation occurred on a date for a listed sub-area. The total amount of resources within a sub-area is then the sum of the total baseline resources and the augmented resources pre-positioned. Firefighting resources considered in this collection are the Type I, III, VI engines, Water Tenders, an additional Firefighter (FF) on a Type I engine, and an additional Captain (CA) on a Type VI engine.

a. Predictors

The majority of predictors used in the estimated probability of wildland fire model are included within this model as well. These predictors include the 10-hour DFM, wind speed, week number of the year, temperature, RH, ERC, KBDI, SC, and BI. Additional predictor variables included in the model that have not been used previously include a binary indicator for climatic zone, the combined capability of pre-positioned firefighting resources, and the cluster to which a weather pattern belongs.

b. Pre-positioned Resource Capability

In keeping with research done by Cox and Hemme (2018), this regression model utilizes a combined capability score regarding the amount of fire-fighting resources pre-positioned. Cox and Hemme establish this capability score to quantify the combined capability that resources bring to a wildland fire, thus establishing an ability to assess the value of firefighting resources against each other. As described in their research, the capability score for a resource is a combination of its hose lay rate and production rate, both in units of feet per minute. Differences between these two aspects of firefighting stem from the weather conditions during a wildland fire. With high winds, wildland fire is likely to jump across any fire break lines; LACoFD thus relies on resources that are more capable in spreading out water to stop fire spread. In cases where a wildland fire is within an urban area, production rates are not as valuable with no brush to clear. While there is no single measure to evaluate the effectiveness of all fire-fighting resources, we develop a capability score for a total pre-positioned amount of resources.

LACoFD currently practices a specific firefighting strategy to contain and control a wildland fire. Ideally, initial deployment to a wildland fire will consist of seven engines and four hand crews. The resources are strategically spread out around the wildland fire to minimize potential damage. The common practice is to assign two engines to the left flank (upwind or downslope), two engines to the right flank, and two engines to the front of the fire in cases when structure defense is required. If structure defense is not needed, the two engines are assigned to the most active flank. The final engine is staffed for water supply for a helicopter, should one be responding. The four hand crews are spread out similarly, with two crews assigned to each flank. These hand crews break the brush line, ensuring there is a gap between burned fuel and green brush. From discussions with LACoFD, we determined that LACoFD equipment and personnel are focused on water for firefighting rather than breaking line, thus placing an emphasis on their ability to lay out hose alongside a wildland fire.

The equation developed to calculate the capability of a pre-positioned amount of resources is thus centered on the potential average hose lay rate that can be achieved on scene. Research by Rahn (2010) shown in Table 3 displays the average time to lay out a 100-foot hose at a slope grade of 0%. This table provides a metric that allows for an evaluation of the potential advantage of adding more personnel to the pre-positioned resources. Research performed by Rahn also measured the production rate of personnel in conducting clearing actions. While production rate is largely influenced on slope and brush type, Cox and Hemme (2018) take the three major types of brush within LAC and calculate a weighted average production rate for a crew ranging from one to four people. These measurements are shown in Table 4.

Table 3. Average Hose Lay Rate. Adapted from Rahn (2010) and Hemme and Cox (2018).

Personnel (Including FFS on Engine)	**Average Hose Lay Rate, δ [feet/min][a]**
3	35.97
4	45.25
5	88.50
6	94.34

[a] Measurements calculated for 0% slope grade on a 100 foot hose.

Table 4. Los Angeles County Average Production Rates. Adapted from Hemme and Cox (2018).

Brush Type	**Number of RAWS Sub-areas**	**Number of Personnel**			
		1	**2**	**3**	**4**
Brush-5	14	3.3	6.6	13.2	17.6
Chap-4A	4	2.2	3.3	8.8	16.5
Grass-1A	3	6.6	13.2	26.4	38.5
Weighted Average		**3.6**	**6.9**	**14.2**	**20.4**

All production rates, ρ, are given in units of feet per minute.

For any given candidate resource package for a RAWS sub-area, the capability score is calculated using the forthcoming Equations (5) and (6) depending on the ratio of personnel to hoses in a pre-positioned set of resources. The first equation is used when this ratio is at least three and the second equation when this condition is not true. Variables considered within these equations are described as they appear. P is the total number of personnel in the pre-positioned resources, excluding water tenders. H is the total amount of hoses available to be used in the pre-positioned resources. The average hose lay rate is labelled as $\bar{\delta}$; this value is linearly interpolated, as indicated by the function $L(x)$ within both equations, from Table 3 using the previously defined ratio. For example, given a personnel to hose ratio of 3.2, the interpolated hose lay rate is 37.83 feet per minute, as shown in Equation (4).

$$L(3.2) = 35.97 + (3.2 - 3)(45.45 - 35.97) = 37.83 \tag{4}$$

The water capacity of each equipment is labeled as ω and the number of each resource within those pre-positioned is N. Both of these variables have a subscript label noting their designation, found in Table 5. The weighted average production rate of the Type VI resource and additional CA are labeled as ρ with a subscript labeling their designation.

For both conditions, the average hose lay rate is multiplied by the number of hoses within the pre-positioned resources. This is then multiplied by a Water Tender multiplier, a calculation used to assess the potential benefit of adding more water tenders to the pre-positioned resources. The calculation uses the specific water capacities of each equipment, listed in Table 5 for reference. The ratio of the additional water capacity that can be supplied by water tenders is divided by the water capacity already within the pre-positioned resources. This multiplier places a larger influence on water tenders when there are limited resources and conversely a smaller influence when there already is a large supply of water pre-positioned. This matches realistic conditions, where a water tender is more useful when it can supply water to a resource and thus allow that resource to stay on scene for longer periods of time, rather than leave for resupply. Finally, when Type VI engines are re-organized to focus on breaking line versus laying hose, as in Equation (6), the weighted average production rate of the potential Firefighter (FF) and Captain (CA) that staff those equipment are added to the capability score.

$$Capability = \bar{\delta} H\left(1+\frac{\omega_{WT}N_{WT}}{\omega_{T1}N_{T1}+\omega_{T3}N_{T3}+\omega_{T6}N_{T6}}\right) \text{ if } \frac{P}{H}\geq 3, \text{ where}$$
$$\bar{\delta} = L\left(\frac{P}{H}\right) \tag{5}$$

$$Capability = \bar{\delta} H\left(1+\frac{\omega_{WT}N_{WT}}{\omega_{T1}N_{T1}+\omega_{T3}N_{T3}+\omega_{T6}N_{T6}}\right)+\rho_{T6}N_{T6}+\rho_{CA}N_{CA} \text{ if } \frac{P}{H}< 3, \text{ where}$$
$$\bar{\delta} = L\left(\frac{P-N_{T6}-N_{CA}}{H-N_{T6}}\right) \tag{6}$$

Table 5. LACoFD Firefighting Resources. Adapted from Hemme and Cox (2018).

Firefighting Resource	**Type I Engine (3-person)**	**Type III Engine (4-person)**	**4th FF on Type I Engine**	**Type VI Engine (Patrol) (1-Person)**	**CA on Type VI Engine**	**Water Tender**
Designation	T1	T3	T6	4FF	CA	WT
Resource Composition	Type I Engine staffed with 1 CA, 1 FFS, and 1 FF	Type III Engine staffed with 1 CA, 1 FFS, and 1 FF	1 FF added to 3-person Type I Engine	Type VI Engine with 1 FF	1 CA added to Type VI Engine	Water Tender staffed with 1 FFS
Water Capacity (ω) [Gallons]	500	750	-	250	-	3,000
Production Rate (ρ) [feet/min]	-	-	-	3.6	3.3	-

c. Weather Clustering

We use *k*-means clustering (Lloyd 1982) to group similar weather conditions and fire danger indices within LAC, to determine if certain weather clusters resulted in a certain burned acreage response, whether it be large or small. Given the number of clusters (*k*), the *k*-means clustering method finds the cluster to which each observation belongs using Euclidian distance from the observation to the cluster center. This method continues until convergence, where initial cluster centers are chosen at random and are recomputed after observation assignment, thus creating new cluster means. Although the cluster centers are guaranteed to converge to a mean, they are not guaranteed to be optimal. For the clustering of weather patterns, there is no true classification known with which to compare, thus requiring the need for a clustering criterion for evaluation. For this research the cubic clustering criterion (CCC) was used, which is calculated by comparing the observed coefficient of determination (R^2) of the clustering method to the approximate R^2 from the null hypothesis that the data are sampled from a uniform distribution. A positive value for the CCC implies that the R^2 value obtained from clustering is greater than that expected if the data derived from a uniform distribution, thus indicating an increased likelihood for the presence of clusters (SAS Institute Inc. 1983).

Using this method, 30 clusters were recognized based on the four weather forecast variables: temperature, wind, RH, and DFM, and the four fire danger indices: BI, ERC, SC, and KBDI. The cluster means and counts from the data set are shown in Table 6. Of note, cluster 29 is the only cluster with one observation. This observation derives from the Camp-9 sub-area, which resides in the High Country climatic zone. The RAWS for this sub-area sits at 4,000 ft. elevation, which explains why there is a relatively large BI of 256 with such a low temperature of 37 ^{o}F on this specific day. Furthermore, this observation occurred during peak fire season in the month of November during the Santa Ana winds with the wind speed recorded at 48 miles per hour. In total, this fire event is recorded as burning 0.21 acres of wildland. Observations such as this one bring into question the source from which a wildland fire sparked. With no data to support this question, there is as likely a chance that this wildland fire occurred due to lightning strike as that it occurred due to human negligence.

Table 6. Clustering for Forecast Weather Variables and Fire Danger Indices

Cluster	**Observations**	**Temperature**	**RH**	**Wind**	**10-Hr DFM**	**BI**	**ERC**	**SC**	**KBDI**
1	147	74.8	16.8	6.5	4.3	53.4	34.9	18.9	679.7
2	68	91.8	13.8	21.3	2.7	125.2	22.5	151.5	438.8
3	85	70.8	11.4	18.1	3.2	114.5	30.0	101.5	684.1
4	44	86.9	13.5	13.3	2.7	217.8	104.3	108.9	588.2
5	30	71.9	30.5	35.0	5.2	140.5	15.8	275.1	567.5
6	159	96.3	15.9	7.3	3.3	123.3	75.8	43.5	606.5
7	210	91.4	30.4	8.2	5.9	44.2	33.9	11.1	614.0
8	137	72.9	54.2	8.5	9.5	29.9	17.7	9.1	588.8
9	97	69.1	56.0	8.6	10.0	27.9	16.7	7.9	175.6
10	142	99.4	15.0	7.7	3.8	57.3	38.7	18.4	639.3
11	39	61.0	72.3	9.3	12.3	16.4	7.1	7.6	456.8
12	81	87.1	14.0	8.3	3.2	112.8	71.2	39.1	241.7
13	29	68.3	27.9	26.7	4.9	120.4	16.7	185.6	667.0
14	143	95.2	14.3	14.1	3.3	91.3	22.9	77.1	639.2
15	86	77.2	22.4	7.7	5.2	47.0	38.4	12.5	165.5
16	159	93.8	13.2	21.9	2.7	130.3	22.5	163.0	703.0
17	84	89.6	14.2	28.6	2.7	155.5	22.0	242.5	687.3
18	77	58.3	31.6	10.1	6.5	47.0	21.3	24.7	607.2
19	126	86.3	15.6	8.3	4.0	58.5	43.7	17.1	421.7
20	217	83.3	42.4	8.6	7.7	37.3	26.1	9.8	577.4
21	91	90.1	13.5	13.3	3.1	152.9	62.9	83.6	687.0
22	156	75.2	10.7	6.1	3.0	130.7	89.4	42.0	653.6
23	27	62.7	10.8	24.1	3.0	210.6	73.5	143.6	643.4
24	62	77.0	28.7	16.2	5.6	80.4	27.4	56.8	462.4
25	26	92.4	13.5	13.1	2.7	200.1	95.3	98.9	298.6
26	145	87.7	31.8	8.3	6.1	41.5	33.1	9.7	398.5
27	33	66.3	42.4	25.6	7.4	90.5	12.3	146.9	461.7
28	172	77.2	42.2	9.0	7.8	36.1	24.1	10.0	300.7
29	1	37.0	22.0	48.0	6.0	256.0	55.0	287.0	692.0
30	20	64.7	14.1	14.6	3.6	176.1	76.2	94.6	290.4

The average forecast weather variable and fire dangers indices are listed for each cluster.

2. Data Limitations

Due to the amount of data collected, regression modelling of the expected burned acreage was limited in scope. Dividing data into the five climatic zones as done with the previous model resulted in too few data points for modeling purposes. Therefore, a multiple linear regression was performed on the logarithmically transformed burned acreages pronounced. This transformation of the output variable was required due to the skewness of the data. Out of 2,919 data points, 84 observations contained burned acreages greater than 10 acres. The largest burned acreage is recorded at burning roughly 41,000 acres. The majority of the data set, however, is comparatively smaller, with the smallest fire recorded burning 100 sq. ft. of wildland, roughly 0.002 acres. A logarithmic transformation is found to better reflect the assumptions of a linear regression model.

Evaluating data prior to model fitting identified several key problems that can be addressed with future data collection. The first regards topography and vegetation. In speaking with LACoFD officials, factors such as terrain, specifically slope, as well as brush and elevation, play a significant role in their ability to contain a wildland fire upon arrival. Factors such as these were not collected, with the assumption that these elements would be picked up by the RAWS sub-area categorical variables. For example, the topography and vegetation of the Camp-9 sub-area is inherently different from that of the Whittier sub-area. Another problem stems from designating where a wildland fire sparked. This research separated fires by the Euclidian distance of the latitude and longitude of a wildland fire spark to the latitude and longitude of each RAWS. The smallest distance thus denoted to which sub-area the wildland fire belonged. This Euclidian distancing and sub-area assignment does not account for features regarding terrain and elevation, and should be re-evaluated moving forward. More importantly, this research would benefit from a more holistic examination of the specific areas for which a RAWS accurately forecasts the weather.

Other issues that arose when developing this model regard the total amount of resources pre-positioned for the wildland fires that resulted in burning over 10 acres. When LACoFD fortunately augmented more resources to a sub-area on days prior to a large wildland fire, the regression modeling saw certain resources as having a positive effect on burned acreage; augmenting certain resources, such as Firefighters, thus meant a larger wildland fire was likely to occur. The “Capability” score was thus introduced to assess the combined ability of all resources pre-positioned. This metric was found to have a constructive relationship with the expected burned acreage, where an increase in resource capability led to a decrease in burned acreage.

3. Model Format

A multiple linear regression model (Myers 1990) on the logarithmic transform of burned acreage is developed for all of LAC using least squares estimation (Charnes et al. 1976). The burned acreage response variable is transformed using the natural logarithm to get the response as close to a normal distribution as possible. Least squares estimation is then used to minimize the sum of squared errors when predicting values of the response variable with the chosen model. The multiple linear regression model developed thus carries the form shown in Equations (7) and (8) (Faraway 2016). In these equations, $\hat{\beta}_0$ represents the estimate of the intercept of the linear combination. The intercept gives the expected value of the response given that all parameters have values of zero. Other $\hat{\beta}$ terms correspond to the predictor variables. In this case, there are q predictor terms.

$$\log(\hat{y}) = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \cdots + \hat{\beta}_q x_q \tag{7}$$

$$\hat{y} = e^{\hat{\beta}_0} e^{\hat{\beta}_1 x_1} \cdots e^{\hat{\beta}_q x_q} \tag{8}$$

Interpreting the effect of an estimated parameter coefficient on the transformed response is not as intuitive as it is with a more general linear model. One method mentioned by Faraway (2016) for approximating the influence of an estimated parameter is useful for those with a coefficient less than 0.25 where $\log(1+x) \approx x$. Thus for an increase in x by one unit, there would be a percent increase in $\hat{y}$ by its corresponding $\hat{\beta}$.

Similar concerns that arise with the estimated probability of wildland fire model regarding correlated parameters also come into play with this model. Given that the fire danger indices are constructed using forecasted weather measurements from each RAWS, the estimated parameter coefficients within the regression model may not intuitively make sense regarding their influence of the response. These trends, however, are expected to be met by other variables or interactions within the model.

4. Model Justification

In developing a model for estimating the expected burned acreage of a wildland fire, it was first determined that the response would need to be transformed. This stemmed from the large sample of wildland fires resulting in burned acreages of 0-10 acres and significantly fewer observations ranging from 10 – 40,000 burned acres. Given that the response is strictly positive and continuous, the Box-Cox transformation method (Box and Cox 1964) was used to determine the appropriate power transformation to modify the distributional shape of the original data set. With the transformed data set, assumptions regarding the normality of the response can be better justified. The Box-Cox transformation method is provided in Equation (9), with *y* denoting the response and λ the power transformation which is chosen using maximum likelihood (Cox and Snell 1968).

$$y_i^{(\lambda)} = \begin{cases} \dfrac{y_i^{\lambda} - 1}{\lambda} \text{ if } \lambda \neq 0, \\ \ln(y_i) \text{ if } \lambda = 0 \end{cases} \tag{9}$$

The value of λ selected using the Box-Cox transformation for this data set is -0.15. Because λ is close to zero, a natural logarithmic transformation on the response variable is justified.

The chosen multiple linear regression model on the transformed response was then developed using stepwise regression in minimizing the AICc, a version of the Akaike Information Criterion (AIC) used when the sample size is small (Akaike 1973) (Hurvich and Tsai 1993). The small-sample version of this criterion ensures that the AIC does not select too many parameters thus leading to an over-fit model. With a model developed using this stepwise regression, a 10-fold cross-validation was then used to evaluate the model's performance on the data set. Cross-validation (Kohavi 1995) provides another step in model selection towards evaluating the performance of the selected model on the data set. Using this process, the data set is split into 10 mutually exclusive subsets; the model is then trained using nine subsets and tested with the remaining subset left out. This process is repeated 10 times, each time leaving out a new subset. The results from the test steps are then averaged to produce a single estimated coefficient of determination (R^2) value. In estimating the R^2 value of the fitted model, the selected model was evaluated and tested against a classification and regression tree (CART). CART provides a regression method relying on *if-then* binary splits on predictors in order to create an accurate prediction of a response. We decided not to adopt CART due to its tendency to produce cases where similar sets of predictor values lead to the same response, which complicates an optimization model. Because of this, while both regression models performed similarly with regards to their prediction capability, the multiple linear regression model was chosen.

5. Model

The selected model is shown in Appendix C, with each term listed alongside its estimated parameter, estimated parameter standard error, *t*-test statistic, and *p-value*. The model has a cross-validated coefficient of determination (R^2) value of 0.1096 when using 10-fold cross-validation, as detailed in Section III.B.4.

Of the predictor terms kept in the model by stepwise regression, there are several that are noteworthy. The combined capability of resources pre-positioned within a sub-area before a wildland fire has been found to be the most significant explanatory component. The capability variable is also found to have significant coefficients in its positive interactions with the Energy Release Component (ERC) and 10-Hr Dead Fuel Moisture (DFM), and a negative interaction with Relative Humidity (RH). The climatic zone binary indicator has a significant coefficient for Santa Clarita Valley and High Country, where both zones are likely to have larger burned acreages should a wildland fire occur. The week number of the year is also included, where later weeks in the year are associated with larger wildland fires. This makes sense, as most fires in the January and February occur near Lake Palmdale and Poppy Park where they are much easier to contain and control. Wind, Burning Index (BI), and temperature all trend as expected, where increases in all three are associated with an increase in expected burned acreage. The ERC, Spread Component (SC), Keetch-Byram Drought Index (KBDI), and 10-Hr DFM are shown to be negatively related to the expected burned acreage; each of these variables are included in interactions as well. These variables are likely highly correlated with other predictors and expected trends in the data are likely met elsewhere. The cluster to which a weather condition belongs is also influential, with three cluster coefficients shown to be significant; these are highlighted in bright yellow in Appendix Table 6.

C. OPTIMIZATION MODEL

For any given period of interest (e.g., a week), the Augmentation Optimization Model (AOM) seeks to optimally determine: (a) which sub-areas within LAC will need firefighting resource augmentation; (b) the supply of the resources, either externally or by transfer between sub-areas; and (c) the amount of each firefighting resource required to minimize expected population displacement due to a wildland fire.

1. Specifications

The AOM is developed to provide realistic augmented staffing decisions to Operational Duty Chiefs within LACoFD alongside estimated predictions from the estimated probability of wildland fire model and expected burned acreage model. The optimized placement of firefighting resources by the AOM is intended as a recommendation and does not guarantee the reported outcome regarding burned acreage. The following sub-sections provide information regarding the model structure.

a. Firefighting Resources

For this model, augmentation is currently limited to the resources and personnel listed in Table 7 and Table 8, alongside their recorded availability and associated cost for either movement or employment.

Table 7. Firefighting Resources Considered for Augmentation

Resource Index	**1**	**2**	**3**	**4**	**5**	**6**
Resource Name	**Type I Engine (3-person)**	**Type III Engine (4-person)**	**4th Firefighter on Type I Engine**	**Type VI Engine (Patrol) (1-Person)**	**CA on Type VI Engine**	**Water Tender**
Resource Explanation	Staffed with 1 CA, 1 FFS, and 1 FF	Staffed with 1 CA, 1 FFS, and 2 FF	1 FF added to 3-person Type I Engine	Staffed with 1 FF	1 CA added to Type VI Engine	Staffed with 1 FFS
Number of Equipment in LACoFD	218 (158 Active, 60 Reserve)	8 (5 Active, 3 Reserve)	N/A See 0	37 (34 Active, 3 Reserve)	N/A See 0	12 (9 Active, 3 Reserve)
Personnel within Resource	3	4	1	1	1	1
Equipment Type Resource (binary)	1	1	0	1	0	1
Personnel Type Resource (binary)	0	0	1	0	1	0
Gas mileage (mpg)	4.5	7	-	9	-	4.5

Gas mileage is reported in miles per gallon (mpg).

The number of off-duty personnel available for augmentation in LACoFD is based on regulations set forth by the Los Angeles County Firefighters Association. These regulations specify the availability of personnel depending on the number of hours worked during that week. On average, it is expected that a third of all off-duty personnel will be available for augmentation on any day. The numbers reported in Table 8 thus specify this constraint while denoting the individual overtime hourly rates for each respective person.

Table 8. Personnel Considered for Augmentation

Personnel Index	**1**	**2**	**3**
Personnel Name	**Captain (CA)**	**Fire Fighter Specialist (FFS)**	**Fire Fighter (FF)**
Number of Off-Duty Personnel in LACoFD	152	141	166
Overtime Hourly Rate (x1.5)	77	65	55

The overtime hourly rate is also referenced as an “Assistance-by-hire” rate.

b. Transfer of Firefighting Resources

The augmented staffing of resources is currently achieved via three separate transfer options. The flow of internal resources (those that are staffed daily, termed frontline) are allowed to transfer between individual sub-areas. The flow of external equipment-type resources (those that are marked on reserve for the day) are allowed to transfer from specific LACoFD fire stations to sub-areas. A daily report indicates the location of this reserve equipment by fire station. This report changes daily, with some equipment requiring maintenance and repair. Because it is provided by station, it is thus easier to report and augment this equipment by fire station. The third type of transfer regards external personnel (the off-duty personnel who are allotted as available for augmentation). These resources do not require a “transfer,” such as between sub-areas, as these resources are typically picked up by equipment on route for an augmentation assignment. Furthermore, off-duty personnel can be pulled from sub-areas requiring the augmentation, thus not requiring any physical form of transport.

c. Firefighting Resource Costs

The model accounts for the costs associated with the augmentation of resources. This includes the cost of movement over miles travelled as well as the cost of employment for the personnel staffed on the equipment. The average gas mileage in miles per gallon (mpg) for each respective equipment-type resource is sourced through LACoFD personnel. The distance between sub-areas and stations is calculated through Maptitude, mapping software produced by the Caliper Corporation (2019). The employment cost is calculated only for incremental external resources brought in from off-duty status. These employment costs are calculated using the overtime hourly rate for each respective person and a 24-hour augmentation schedule. This decision falls in line with current practice by LACoFD, where augmentation typically only occurs during daylight hours when the temperature is highest.

d. Candidate Resource Packages

The AOM optimizes placement of six resources, together called a “resource package.” The set from which the AOM choses the optimal package for each sub-area is thus called the “candidate resource packages.” For any given sub-area, the allotted set of resource packages from which the AOM can chose depends on the minimum and maximum allowed number of resources within a sub-area.

For the minimum limit, data were collected by station regarding the amount of equipment that must remain on station. LACoFD is currently on contract with multiple cities in LAC, all of which require them to keep a certain set of equipment available in case a structure fire occurs. Typically, Trucks and Quints are left behind as they are better equipped for the urban environment. However, a few stations are required to keep a Type I or Type VI engine behind. Stations which are allowed to go “dark,” where no resources remain at a station, are respectively noted as well. With each station tied to a specific sub-area, the minimum resources by sub-area could thus be summed.

The maximum allowed resources in each sub-area required more effort to produce. From conversations with LACoFD, it is clear that they are only limited by the number of parking spaces surrounding a fire station and the number of restroom utilities within the station. While it would be unlikely for LACoFD to send nearly all resources to one sub-area for augmentation, LACoFD can technically provide for that scenario. With this predicament, it was decided to limit the allotment of resources to a sub-area with respect to current procedures. LACoFD currently deploys strike teams, a combination of the same type of resources with a central leader and communications. An Alpha Engine strike team configuration has five Type I Engines, each staffed with four personnel; these teams are frequently added to initial attack. Strike teams are similarly formed with Type VI Engines, known as Foxtrot Engine strike teams, and follow the same procedure. With this information, each sub-area is allotted the ability to contain at most two Alpha and one Foxtrot strike team. The maximum allotment of Type III Engines and Water Tenders within the sub-areas is based on the limited supply of these equipment-type resources. Because LACoFD only maintains five Type III Engines, it was determined that any sub-area could receive these. For Water Tenders, LACoFD notes that any sub-area cannot hold more than one based on past augmented staffing. Certain sub-areas were restricted to holding two Water Tenders due to their baseline level already staffing those two.

The next section describes the notation and mathematical formulation for the AOM that adheres to the above specifications.

2. Indices and Sets

$r \in R$	set of firefighting resource types (r = 1, 2, … , 6);
$w \in W$	set of RAWS, or sub-areas (w = 1, 2, …, 21);
$s \in S$	set of fire stations (s = 1, 2, …, 194);
$p \in P$	set of firefighting types of personnel (p = CA, FFS, FF);
$k \in K$	set of all possible candidate resource packages;
$(k, w) \in KW$	subset of $K \times W$ where resource package k is a candidate for RAWS sub-area w;
$(w, w') \in WW$	subset of $W \times W$ where a resource transfer from RAWS sub-area w to w' is possible; note that $w \neq w'$.

3. Parameters [Units]

$\hat{p}_w$	estimated probability of wildland fire in RAWS sub-area w, given by the probability of wildland fire logistic regression sub-models;
$\hat{f}_{kw}$	estimated expected fire damage if fire occurs and candidate resource package k is chosen for RAWS sub-area w, given by the estimated expected burned acreage regression model [acres];
ρ_w	population density in RAWS sub-area w [population/acre];
b_{rw}	baseline of the staffed resource type r in RAWS sub-area w [resource unit, e.g., Type 1 Engine (3-person)];
$\overline{b}_{rs}$	available amount of external resource type r for augmentation at station s [resource unit];
M_{rw}	maximum allowed number of resource type r in RAWS sub-area w, including baseline and augmented [resource unit];
m_{rw}	minimum allowed number of resource type r in RAWS sub-area w, including baseline and augmented [resource unit];
$t_{rw'w}$	transport cost to send resource type r from RAWS sub-area w' to w [\$/unit of resource];
h_{rsw}	transport and 24-hour employment cost for external resource type r being sent to RAWS sub-area w from station s [\$/unit of resource];

α_p	available amount of off-duty personnel *p* that can be called in for augmentation [personnel unit];
n_{rp}	number of personnel *p* needed to staffed resource type *r* [personnel unit];
e_r	binary indicator denoting if resource type *r* is tied to a piece of firefighting equipment;
d_r	binary indicator denoting if resource type *r* is personnel only;
μ_r	total number of equipment LACoFD maintains by resource type *r* [resource unit];
ω_r	available amount of off-duty personnel that can be called in for augmentation by resource type *r* [personnel unit];
π_r	24-hour employment cost for external personnel only type resource *r* [$/unit of personnel].
C	user-defined augmentation budget [$].

4. Derived Data

$K_w \subset K$	set of candidate resource packages for RAWS sub-area *w:*

$$K_w = \left\{ k = \left(u_{rw}^k \right)_{\substack{r \in R, \\ w \in W}} \mid m_{rw} \le u_{rw}^k \le M_{rw} \qquad \forall r \in R, w \in W \right\}; \qquad (10)$$

u_{rw}^k	total number of resources of type *r* in candidate resource package *k* in RAWS sub-area *w*.

5. Decision Variables [Units]

$X_{rw'w}$	amount of resource type *r* transferred from RAWS sub-area *w'* to *w*, for all resources [resource unit];
E_{rsw}	amount of external resource type *r* sent to RAWS sub-area *w* from fire station *s*, for equipment-type resources [resource unit];
Z_{rw}	amount of external resource type *r* sent to RAWS sub-area *w*, for personnel-type resources [personnel unit];

Y_{kw}	1 if candidate resource package k is used in RAWS sub-area w, and 0 otherwise [binary].

6. Formulation

$$\min_{X,E,Z,Y} \sum_{(k,w)\in KW} \rho_w \hat{p}_w \hat{f}_{kw} Y_{kw} \tag{11}$$

subject to:

$$\sum_{\substack{r\in R,\\ w\in W}} d_r \pi_r Z_{rw} + \sum_{\substack{r\in R,\\ (w',w)\in WW}} t_{rw'w} X_{rw'w} + \sum_{\substack{r\in R,\\ w\in W,\\ s\in S}} e_r h_{rsw} E_{rsw} \le C \tag{12}$$

$$\sum_{k\in K_w} Y_{kw} = 1 \qquad \forall w \in W \tag{13}$$

$$b_{rw} + d_r Z_{rw} + \sum_{s\in S} e_r E_{rsw} + \sum_{w'|(w',w)\in WW} X_{rw'w} - \sum_{w'|(w,w')\in WW} X_{rww'} = \sum_{k\in K_w} u^k_{rw} Y_{kw} \qquad \forall r \in R,\ w \in W \tag{14}$$

$$\sum_{w'\in W|w'\neq w} X_{rww'} \le b_{rw} \qquad \forall r \in R,\ w \in W \tag{15}$$

$$\sum_{w\in W} E_{rsw} \le \overline{b}_{rs} \qquad \forall r \in R, s \in S \mid e_r = 1 \tag{16}$$

$$\sum_{w\in W} Z_{rw} \le \omega_r \qquad \forall r \in R \mid d_r = 1 \tag{17}$$

$$X_{rw'w} = 0 \qquad \forall r \in R, (w', w) \in WW \mid BIR_{w'} \ge 1 \tag{18}$$

$$X_{rww'} = 0 \qquad \forall r \in R, (w, w') \in WW \mid BIR_{w'} < 1 \tag{19}$$

$$\mathrm{E}_{rsw} = 0 \qquad \forall r \in R, s \in S, w \in W \mid BIR_w < 1 \wedge e_r = 1 \tag{20}$$

$$Z_{rw} = 0 \qquad \forall r \in R, w \in W \mid BIR_w < 1 \wedge d_r = 1 \tag{21}$$

$$\sum_{\substack{r\in R,\\ s\in S,\\ w\in W}} e_r n_{rp} E_{rsw} + \sum_{\substack{r\in R,\\ w\in W}} d_r Z_{rw} \le \alpha_p \qquad \forall p \in P \qquad (22)$$

$$\sum_{(k,w)\in KW} u_{rw}^{k} Y_{kw} \le \mu_r \qquad \forall r \in R \mid e_r = 1 \qquad (23)$$

$$X_{rw'w} \ge 0 \qquad \forall r \in R, (w', w) \in WW \quad (24)$$

$$E_{rsw} \ge 0 \qquad \forall r \in R,\ \mathrm{s} \in \mathrm{S}, w \in W \qquad (25)$$

$$Z_{rw} \ge 0 \qquad \forall r \in R, w \in W \qquad (26)$$

$$Y_{kw} \in \{0,1\} \qquad \forall k \in K_w, w \in W \qquad (27)$$

7. Constraint Descriptions

A brief explanation of the mathematical formulation follows:

- Equation (10) expresses the feasible candidate resource packages that can be used within RAWS sub-area *w*. A package specifies a combination of resource types, all of which must be within the minimum and maximum allowed number for the sub-area *w*.

- Equation (11) is the objective function of the optimization model: the objective is to minimize the expected total amount of population displaced by wildfires. For a given sub-area, this is estimated to be proportional to the sub-area’s population density, the estimated fire damage given the augmentation package chosen, and the probability that such fire actually occurs.

- Each constraint (12) ensures that the cost of augmentation is kept to within an input budget. Cost is calculated as the transport cost for each resource, both on-duty (frontline) and off-duty (reserve) and the employment cost for off-duty personnel.

- Each constraint (13) ensures that each sub-area *w* receives exactly one candidate resource package.

- Each constraint (14) ensures the conservation of flow of resources. For each resource type *r* and sub-area *w*, the baseline number of resources in the sub-area plus the number of personnel-only type resources from reserve plus the number of resources being received from other RAWS sub-areas plus the number of resources being received from reserve status minus the number of resources the sub-area is transferring to other sub-areas, needs to be equal to the total number of resources required for the candidate resource package for each resource *r* and RAWS sub-area *w*.

- Each constraint (15) ensures that for each resource type *r* and sub-area *w*, the number of resources being transferred out of sub-area *w* cannot be greater than the number of baseline resources within sub-area *w*.

- Each constraint (16) ensures that for each resource type *r*, the number of reserve resources being sent out from each station *s* to all other sub-areas is not greater than the number of reserve resources available at each fire station *s*.

- Each constraint (17) ensures that for each resource type *r*, the number of off-duty personnel that can be augmented does not exceed the number of personnel available for augmentation. This constraint further bounds those resources that require equipment augmentation as requiring zero extra personnel, as this is already accounted for with E_{rsw}.

- Each constraint (18)–(21) provides bounds on the respective decision variable regarding transport. Constraint (18) ensures that resources cannot be sent out of an area with a BIR greater than or equal to one. Similarly, constraint (19) ensures that resources cannot be sent to areas with a BIR less than one. Constraint (20) and (21) state that reserve resources cannot be sent to a RAWS sub-area *w* with a BIR less than one.

- Each constraint (22) ensures that for each personnel type *p*, there are enough off-duty personnel to staff the reserve equipment called in from reserve status.
- Each constraint (23) ensures that for each resource unit *r*, the number of equipment being utilized cannot be greater than the number of equipment that LACoFD maintains.
- Each constraint (24)–(27) establish the decision variable domains.

The AOM is currently implemented using the Python computer language (Rossum and Drake 2009) and Pyomo optimization software (Hart et al. 2011, 2017); the entire decision support tool comprises of over 1,000 lines of Python code. The AOM constitutes 150 lines and is currently solved using the CPLEX Optimizer for Pyomo (International Business Machines 2019). The AOM typically contains over 700,000 variables and 25,000 constraints when run. The AOM is, on average, solved within eight minutes when using CPLEX to an optimality gap of 2%.

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IV. ANALYSIS

This chapter presents an analysis of the Augmentation Optimization Model (AOM) performance and predictive capability as compared to actual augmentation performed by LACoFD during the month of December 2017. The AOM is provided forecasted weather and fire danger indices as input from each day there was at least one RAWS forecasting a Burning Index (BI) above its Burning Index Threshold (BIT). The AOM's output is then matched with actual augmentation with varying limits made on budget allowance. This analysis is performed to confirm the AOM's assignment of resources across the RAWS sub-areas, ensuring that resource movement is reasonable and efficient.

The average daily augmentation cost for personnel as reported by LACoFD for December 2017 is $134,000 (Alkonis and Pena 2018). This cost is averaged across the 14 days where augmentation occurred and is calculated using the assistance-by-hire billing rates for the fiscal year 2017–2018, as shown previously in Table 8.

Two budgets were used to test the AOM: the average daily augmentation cost for December 2017 and the specific cost for augmentation on each day modeled. Larger budgets are not considered for this analysis due to multiple optimal solutions occurring within a 2% threshold of the true optimal solution; in other terms, larger budgets produce diminishing returns. The budgets reported by the AOM thus solely account for the augmentation of the six resources considered within the AOM to include transportation and employment.

During the month of December 2017, there were 321 cases in which a RAWS forecasted a BI above its respective BIT. This is almost half of the 651 forecasts made during this time period (one forecast per sub-area, per day). Of these 321 cases, a wildland fire resulted in the RAWS sub-area on the following day only 45 times. Of these 45 wildland fires, the largest fire occurred in the Saugus RAWS sub-area, burning over 6,000 acres of land. As reported by LACoFD, this fire is estimated to have threatened 1,300 structures, requiring 5,000 people to evacuate the area. The majority of the remaining wildland fires, however, span between 0.1 and 5 acres. The vast difference between these outcomes are likely explained by a variety of reasons, to include weather and available resources advantageously, and as it turns out fortunately, pre-positioned.

Table 9 provides information regarding the 18 days which will be tested and compared using the AOM. This table only shows the 45 sub-areas where a wildland fire occurred on a day where the BI was forecasted above the BIT. LACoFD also augmented resources to other sub-areas with a forecasted BI above BIT. Furthermore, 19 wildland fires occurred during this time period in sub-areas which did not have a BI forecasted above their BIT. The total cost of augmenting resources for any given day is not solely limited to the RAWS sub-areas listed in the table for the respective day, but rather for the entire day (typically a 24-hour staffing). Also, this cost reported by LACoFD does not include the associated costs regarding the transport of resources. LACoFD currently augments resources to various stations aligned within a Battalion organizational structure; these stations do not explicitly align with stations associated to each RAWS sub-area we have developed with this research. It is assumed that Operational Duty Chiefs will follow similar practice with station assignment for augmented resources when using the AOM. Finally, the amount of resources listed include both the baseline and augmented resources pre-positioned for the date and sub-area indicated.

Table 9. December, 2017: LACoFD Augmentation to RAWS Sub-Areas with Forecasted BI above BIT. Adapted from Alkonis and Pena (2018).

Date Dec. 2017	RAWS	Forecasted Weather and Fire Danger Indices						Total Number of Pre-positioned Resources						Burned Acreage	Cost of Aug. (Pers. Only)
		Temp.	RH	Wind	BI	SC	10-Hr DFM	Type I	Type III	Type VI	4th FF	CA	Water Tender		
5	Saugus	55	7	21	170	128	3	10	1	2	8	2	3	6049	$288,000
	Santa Fe	72	10	8	106	34	4	18	1	5	6	3	1	0.25	
	Newhall Pass	52	9	22	141	103	3	5	0	4	1	2	2	0.12	
6	Saugus	61	9	29	203	182	3	10	1	2	8	2	3	0.12	$267,000
	Santa Fe	78	5	6	106	29	3	18	1	5	6	3	1	1	
	Tonner Canyon	69	7	19	159	77	3	7	0	2	3	1	2	1.42	
	Beverly Hills	71	8	10	149	58	3	14	0	1	3	0	0	422	
7	Santa Fe	77	3	6	113	31	2	18	1	5	6	3	1	0.21	$198,000
	Claremont	72	5	8	137	45	2	11	0	0	3	0	0	0.11	
	Leo Carrillo	78	5	13	137	54	2	1	0	1	1	1	0	1	
8	Beverly Hills	74	5	10	167	65	2	14	0	1	3	0	0	0.11	$73,000
	Whittier	76	7	8	107	32	3	53	0	2	24	0	0	0.11	
	Tonner Canyon	70	6	15	165	72	2	7	0	1	0	0	1	0.11	
9	Santa Fe	82	5	7	129	39	2	18	1	3	5	1	0	5	$54,000
	Beverly Hills	85	8	5	136	41	2	14	0	1	3	0	0	0.11	
	Claremont	77	8	8	145	48	3	11	0	0	0	0	0	0.11	
10	Whittier	85	5	15	168	72	2	53	0	2	24	0	0	0.21	$54,000
	San Rafael	78	5	7	152	47	2	4	0	1	1	0	0	0.11	
11	Whittier	78	10	7	126	39	3	53	0	3	27	1	0	0.12	$90,000
	Tonner Canyon	77	8	10	163	60	2	7	0	1	0	0	2	0.11	
12	Saugus	75	2	12	151	82	2	5	1	0	2	0	4	2.5	$156,000
	Claremont	77	6	6	144	42	2	11	0	0	3	0	0	0.11	
	Whittier	82	5	7	134	41	2	53	0	5	29	3	0	0.5	

Date Dec. 2017	RAWS	Forecasted Weather and Fire Danger Indices						Total Number of Pre-positioned Resources						Burned Acreage	Cost of Aug. (Pers. Only)
		Temp.	RH	Wind	BI	SC	10-Hr DFM	Type I	Type III	Type VI	4th FF	CA	Water Tender		
14	Whitaker	68	10	19	262	152	2	1	0	1	1	1	0	1	$192,000
15	Beverly Hills	80	14	4	133	39	3	14	0	1	3	0	0	0.11	$96,000
	Whittier	75	15	6	120	36	3	53	0	5	29	3	0	0.1	
16	Whittier	74	27	8	108	39	5	53	0	5	29	3	0	0.11	$90,000
17	Acton	56	15	25	177	146	3	2	0	3	2	2	2	0.12	$192,000
	Whittier	73	15	15	177	86	4	53	0	5	29	3	0	1	
18	Malibu	65	16	9	161	66	4	3	0	2	3	1	2	0.21	$96,000
22	Beverly Hills	64	17	7	143	54	4	14	0	1	3	0	0	0.11	$35,000
	Whittier	60	12	9	134	49	4	53	0	3	24	1	0	0.11	
	San Rafael	61	15	5	121	35	4	4	0	1	1	0	0	1	
	Malibu Canyon	64	8	12	165	72	3	5	0	4	5	4	0	0.12	
23	Beverly Hills	69	14	5	132	43	4	14	0	1	3	0	0	0.2	None
28	Beverly Hills	87	10	1	110	25	3	14	0	1	3	0	0	0.1	None
	Claremont	82	11	5	134	37	3	11	0	0	0	0	0	0.3	
	San Rafael	79	10	9	169	61	3	4	0	1	1	0	0	0.11	
29	Claremont	79	13	4	121	31	3	11	0	0	0	0	0	0.5	None
	Whittier	83	16	5	115	33	4	53	0	2	24	0	0	0.2	
30	Beverly Hills	77	17	3	116	33	4	14	0	1	3	0	0	0.2	None
	San Rafael	79	13	4	119	31	3	4	0	1	1	0	0	0.11	

The table outlines the forecasted weather and NFDRS fire danger indices (orange) for the indicated date and RAWS sub-area (purple). The total resources (blue) pre-positioned for the date within the sub-area include the baseline resources and those which were augmented. The burned acreage (red) of the actual wildland fire that occurred on the indicated date within the RAWS sub-area is listed alongside the total cost of augmented resources (green).

In comparing AOM output to the actual LACoFD augmentation, the budget is varied to show its effect on the allowed amount of augmentation and the expected burned acreage. We explore two excursions with the AOM objective function: first, modifying expected burned acreage, $\hat{f}_{kw}$, to zero for sub-areas w with a forecasted BI less than its respective BIT; second, without this modification. For brevity, we only show results of the first excursion. We note that (as would be expected) with the second excursion, fewer internal transfers of resources occur from sub-areas below the BIT.

Table 10 shows the AOM decision regarding the candidate resource package chosen for the respective RAWS sub-area for the same budget used by LACoFD. The AOM results for augmenting with a budget of $134,450.55, the average daily budget, are shown in Appendix Table 7 in Appendix D. The AOM output regarding the transfer of resources for December, 14, 2017, with a budget of $134,450.55 is shown in Appendix E.

On days such as December 7, 2017, where 19 out of 21 RAWS forecasted a BI above their respective BIT, augmentation relied on staffing of the external equipment that was available as well as off-duty personnel. This is due to the fact that on-duty resources could only be sourced from two RAWS sub-areas, Poppy Park and Saddleback, both of which are already limited in the number of resources available. On days such as these, it is typical for LACoFD to bring in extra personnel to staff the frontline equipment, typically increasing the number of FFs, FFSs, and CAs within each station. The AOM does follow this practice, with the expected burned acreage model indicating that these personnel contribute significantly to a firefighting effort. This is significant with regards to cost, as these two personnel account for a large portion of the cost of augmentation. With the model largely considering transferring and activating off-duty personnel to staff equipment, augmented staffing costs largely consist of overtime pay for those personnel. There is a limit regarding available on-duty personnel to be moved; this limit mainly depends on the number of sub-areas which do not have a forecasted BI above their BIT. This is significant as the cost of augmenting one off-duty CA is $1,848 for 24-hours and $1,220 for one off-duty FF. Costs associated with overtime hours are also a factor when utilizing off-duty equipment for augmented staffing. This equipment is solely staffed by off-duty personnel, with their cost of a 24-hr. augmentation period.

Table 10. December 2017: AOM Augmentation with Same Budget

Date Dec. 2017	RAWS	Type I	Type III	Type VI	4th FF	CA	WT	Estimated Probability of Fire[b]	Expected Burned Acreage[c]	Cost of Aug.
5	Saugus	12	2	3	12	3	3	0.19	6.24	$84,000
	Santa Fe	19	1	2	19	2	0	0.12	1.24	
	Newhall Pass	12	1	2	12	2	2	0.15	1.57	
6	Saugus	12	1	0	12	0	3	0.25	11.52	$87,000
	Santa Fe	19	1	2	19	2	0	0.15	1.28	
	Tonner Canyon	12	0	1	12	1	2	0.08	5.57	
	Beverly Hills	18	0	1	18	1	0	0.14	1.27	
7	Santa Fe	19	1	2	19	2	0	0.16	1.28	$151,000
	Claremont	11	0	0	11	0	0	0.13	1.32	
	Leo Carrillo	1	0	0	1	0	0	0.03	1.75	
8	Beverly Hills	14	0	1	14	1	0	0.15	1.34	$72,000
	Whittier	61	1	3	61	3	2	0.47	1.21	
	Tonner Canyon	7	0	1	2	0	1	0.08	1.51	
9	Santa Fe	19	1	2	19	2	0	0.18	1.34	$54,000
	Beverly Hills	19	0	1	19	1	2	0.18	1.29	
	Claremont	11	0	0	0	0	0	0.14	1.31	
10	Whittier	54	0	3	52	1	0	0.59	1.43	$54,000
	San Rafael	2	0	1	0	0	0	0.08	1.36	
11	Whittier	63	1	4	63	4	2	0.46	1.23	$88,000
	Tonner Canyon	7	1	1	7	1	1	0.09	1.38	
12	Saugus	7	2	0	7	0	2	0.13	1.57	$107,000
	Claremont	11	0	0	11	0	0	0.14	1.31	
	Whittier	58	0	3	58	3	1	0.53	1.28	
14	Whitaker	2	0	0	2	0	0	0.06	9.28	$191,000
15	Beverly Hills	16	0	1	4	0	0	0.16	1.27	$93,000
	Whittier	62	0	3	63	3	2	0.40	1.15	
16	Whittier	63	0	3	63	3	2	0.35	1.16	$87,000
17	Acton	2	0	1	2	0	1	0.13	38.11	$135,000
	Whittier	54	0	3	54	3	0	0.39	1.27	
18	Malibu	8	0	1	8	0	2	0.03	1.20	$87,000
22	Beverly Hills	18	1	6	4	0	2	0.13	1.17	$31,000
	Whittier	54	0	3	53	1	2	0.32	1.21	
	San Rafael	2	0	1	0	0	0	0.03	1.18	
	Malibu Canyon	5	0	0	1	0	2	0.03	1.28	
23	Beverly Hills	14	0	1	4	0	0	0.14	1.20	$49,000[a]
28	Beverly Hills	14	0	1	4	0	0	0.18	1.32	$46,000[a]
	Claremont	11	0	0	0	0	0	0.13	1.32	
	San Rafael	2	0	1	0	0	0	0.07	1.32	
29	Claremont	11	2	2	0	0	2	0.11	1.27	$49,000[a]
	Whittier	63	2	7	63	7	2	0.46	1.27	
30	Beverly Hills	19	0	6	12	0	2	0.15	1.22	$48,000[a]

[a] Days on which LACoFD did not augment staffing were given a budget of $50,000.

[b] The estimated probability of fire is the output given by the regression model $\hat{p}$.

[c] The estimated expected burned acreage is the output given by the regression model $\hat{f}$.

The AOM currently sources internal resources from those sub-areas that are closest and do not likely require them. Factors included within the AOM for this transfer of internal resources currently only incorporate the distancing between RAWS sub-area centers. The second aspect of this reassignment, regarding the consequences of removing resources, is currently not incorporated in the model. Rather than haphazardly depleting sub-areas to only their minimum required forces, as bounded by the minimum allowed staffing level in the model, the estimated probability could be used as a contributor to the decision regarding where internal resources might be sourced from. A weighted decision can then be made between the cost of transportation and the likelihood that a wildland fire might actually occur within the sub-area sourced for resources.

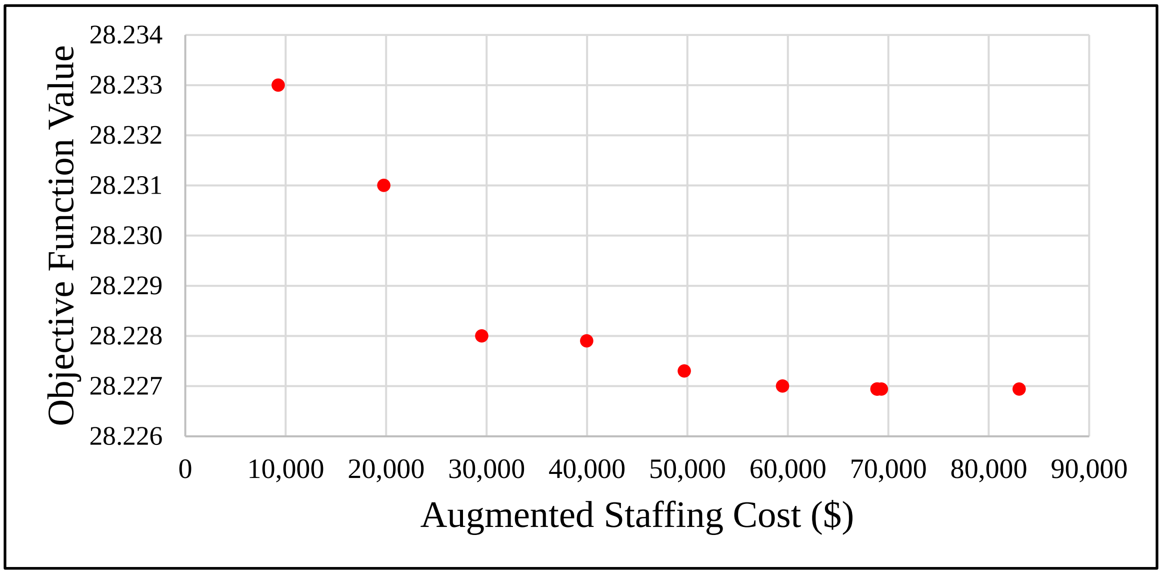
The AOM correctly accounts for the population density of each RAWS sub-area when considering an augmented staffing plan. Output from the AOM on December 14th, 2017, with a budget of $134,000, shown in Appendix E, shows this logic. From this output, the Camp-9 and Whitaker I-5 sub-areas are indicated as having expected burned acreages of 10.15 and 9.30 acres, respectively. The Acton sub-area is similarly recorded as expected to have a large burned acreage at 12.12 acres should a wildland fire occur. These three areas are noteworthy in that they all are recorded as having the lowest population densities within LAC. Conversely, the Whittier and Beverly Hills sub-areas have the highest population densities and are according staffed to ensure the lowest expected burned acreage occurs within these sub-areas, with 1.30 and 1.40 acres expected, respectively. This logic shows that the objective function correctly minimizes the expected proportional population displacement across LAC, assigning resources to those sub-areas which require more protection for the public. People within those sub-areas where the population density is lowest will not always be excluded. The estimated probability of wildland fire is used as a multiplier within the objective function to ensure that in cases where a wildland fire is extremely likely and widespread, there is a larger influence associated with that sub-area's potential population displacement.

On an average day, the augmented staffing plan recommended by the AOM is over $40,000 less expensive than the augmented staffing chosen by LACoFD. The largest difference in cost between augmented staffing plans is from December 5th, 2017, where the

AOM found an optimal augmented staffing plan costing over $200,000 less than what LACoFD required. The sub-areas indicated as having wildland fires on this day appropriately received more resources than what LACoFD assigned. This indicates that the AOM correctly recognizes the sub-areas which require resources the most, and repositions them accordingly.

The calculated estimated probabilities for a wildland fire during December 2017 show a wide variance with respect to their predictability, or classification. For the entire month of December 2017, the average estimated probability for a wildland fire is 0.194 on days and sub-areas in which a wildland fire did occur. The lowest estimated probability, 0.03, is given four separate times for differing sub-areas. The highest estimated probabilities, 0.59 and 0.53, both occur in the Whittier sub-area. Differences in estimated probabilities likely stem from differences in sub-area size and data collection for those areas. For Whittier, the sub-area spans nearly an eighth of the county across a largely urban region. Despite this, Whittier accounted for a large proportion of the wildland fires that occurred within LAC. All of these wildland fires, however, only spanned between 0 and 10 acres. The climatic zone which contains the Whittier sub-area, Los Angeles Basin, is also the best in terms of resulting in the fewest false positives as indicated by the sub-model's ROC curve.

The AOM also allows for analysis regarding the return-on-investment with regards to higher budgets for augmentation. Figure 6 shows the trend for increased budgets from $10,000 to $90,000 with respect to the optimal objective function value returned by the AOM. The optimal objective function value represents the proportional total expected population displacement across the entire county, given in units of people. The trend shown in Figure 6 is expected, with increased budgets allowing for more augmentation and thus lower expected burned acreages across the county. The increments at which the optimal objective function value decreases with regards to an increased budget describes the return-on-investment for that augmented staffing plan. For December 6th, 2017, we observe diminishing return on investment after $30,000. The augmented staffing plan recommended by the AOM for this budget is compared to actual augmentation by LACoFD in Table 11. With nearly a tenth of the cost, the AOM efficiently reassigns more resources to the four sub-areas which actually had a wildland fire on that day. Furthermore, the AOM does not prioritize augmenting Type VI Engines but does recognize the added benefit of staffing Type I Engines with a 4th FF.



The objective function value [expected population displacement] is plotted with increased budgets for augmented staffing. The objective function value with no budget for augmentation is 65.606. The return-on-investment between increasing the budget from $20,000 to $30,000 is the slope between these two points: we can estimate that $3.33 million are required to have one less person displaced.

Figure 6. December 6, 2017, Return on Investment

Table 11. December 6th, 2017, LACoFD and AOM Augmented Staffing Plans

	RAWS Sub-Area	Type I	Type III	Type VI	4th FF	CA	WT	BIR > 1	Fire (Acres)
LACoFD Augmented Staffing Plan **Cost: $267,000**	Santa Fe Dam	18	1	5	6	3	1	1	1
	Henninger Flats	5	2	1	3	1	0	1	-
	Claremont	11	0	0	3	0	0	0	-
	Whittier	53	0	4	29	2	0	0	-
	San Rafael	4	0	2	1	1	0	1	-
	Tonner Canyon	7	0	2	3	1	2	1	1.42
	Cheseboro	5	1	3	5	2	2	1	-
	Malibu	3	0	2	3	1	2	1	-
	Beverly Hills	14	0	1	3	0	0	1	422
	Leo Carrillo	1	0	1	1	1	0	1	-
	Malibu Canyon	5	0	4	5	4	0	1	-
	Topanga	7	0	0	7	0	0	1	-
	Saugus	10	1	2	8	2	3	1	0.12
	Acton	2	0	3	2	2	2	0	-
	Del Valle	1	0	0	1	0	0	1	-
	Newhall Pass	5	0	4	1	2	2	1	-
	Camp-9	2	0	2	2	2	0	0	-
	Whitaker	1	0	1	2	1	0	1	-
	Poppy Park	2	0	1	1	1	0	0	-
	Saddleback Butte	1	0	1	1	1	0	0	-
	Lake Palmdale	11	0	0	6	0	0	0	-
AOM Augmented Staffing Plan **Cost: $30,000**	Santa Fe Dam	19	1	2	5	0	0	1	
	Henninger Flats	5	2	0	2	0	0	1	
	Claremont	8	0	0	0	0	0	0	
	Whittier	41	0	1	1	0	0	0	
	San Rafael	2	0	1	0	0	0	1	
	Tonner Canyon	12	0	1	12	1	2	1	
	Cheseboro	2	1	1	1	0	1	1	
	Malibu	3	0	1	2	0	1	1	
	Beverly Hills	18	0	1	18	1	0	1	
	Leo Carrillo	1	0	0	0	0	0	1	
	Malibu Canyon	5	0	0	1	0	0	1	
	Topanga	1	0	0	0	0	0	1	
	Saugus	12	1	0	12	0	3	1	
	Acton	2	0	0	0	0	0	0	
	Del Valle	1	0	0	0	0	0	1	
	Newhall Pass	12	0	5	10	0	2	1	
	Camp-9	1	0	0	0	0	0	0	
	Whitaker	2	0	0	1	0	0	1	
	Poppy Park	2	0	0	0	0	0	0	
	Saddleback Butte	3	0	0	0	0	0	0	
	Lake Palmdale	9	0	0	0	0	0	0	

Each resource column indicates the total amount pre-positioned within the RAWS sub-area. The BIR > 1 column uses a one to indicate if the RAWS sub-area had a forecasted BI above its corresponding BIT within that sub-area.

The results shown in Table 11 indicate that the AOM is capable of outperforming the augmentation by LACoFD with regards to cost in most cases. Furthermore, with nearly a tenth of the cost of augmentation, the AOM appropriately reallocates resources to sub-areas where a wildland fire occurred on that specific day. For each of the four sub-areas where a wildland fire occurred, the AOM sends at least one more Type I engine there as compared to LACoFD's augmentation. For three of these sub-areas, the AOM also ensures that each of the Type I Engines in the sub-area contain a 4th FF. This is to be expected, with the hose lay rate increasing by 10 feet per minute when a fourth person is added to a 3-man crew. Of note, rather than sourcing resources from off-duty status, the AOM prioritizes taking resources from those sub-areas which do not have a BI forecasted above their BIT. Indications of this can be seen for those sub-areas which are indicated as "0" in the "BIR > 1" column. The most significant example regarding this is Whittier, where nearly all staffed 4th FFs in the sub-area have been sent elsewhere in the county. This is expected, as Whittier is predominantly an urban sub-area and does not experience large wildland fires as frequently as other sub-areas.

Currently, the AOM is configured to report a solution to the decision-maker when the optimization reaches an integer solution within a 2% integer gap tolerance of the optimal solution (the solution method used develops a bound on the best possible solution that is compared to the best solution found, and declares success when these to values are sufficiently close. Setting this "integer gap tolerance" lower can lead to endless computation). As mentioned previously, analysis such as that shown in Figure 6 indicates that there are likely multiple optimal solutions with varying costs within the 2% threshold of the optimal solution. As such, the AOM should be updated to include cost penalty terms within the objective function. These penalty terms can then be associated with using more of the budget when it is not necessarily required. Another method that can be used is a hierarchical optimization. In this method, the AOM can be run as it is currently and the corresponding objective function value can be stored. An aspiration constraint can then be constructed on the stored objective function value with a new objective function minimizing the cost of augmentation. The solution from this problem would thus minimize the cost of augmentation while maintaining the previously achieved objective function value regarding the estimated population displacement.

The AOM uses the BIT explicitly for determining augmentation assignment. This becomes problematic, with cases such as the one that follows showing where this model might fail. For the month of December 2017, LAC responded to a wildland fire at the Kagel Canyon inside the Angeles National Forest. This location currently falls into the RAWS sub-area of Camp-9, where the forecasted BI for the sub-area on the day of the fire was 143, merely two thirds of the threshold set for that climatic zone (222). This fire is now referred to as the “Creek Fire,” burning over 15,000 acres and leading the evacuation of roughly 150,000 people. While LACoFD was correct in augmenting staffing on this day, the AOM would not consider this area as requiring augmentation. Conversations with LACoFD have indicated that this is likely due to current zoning for RAWS sub-areas. Although this fire is registered as occurring in the High Country climatic zone, it is more likely that it occurred in the Santa Clarita Valley climatic zone. The threshold in this zone is comparatively lower at 140 and thus would have indicated a need for augmentation. Future research is highly recommended into amending geographically precise RAWS sub-areas which better match the terrain, brush, slope, and weather in each respective area.

V. CONCLUSIONS

This thesis develops a decision support tool using statistical analysis and a mathematical optimization model to recommend an augmented daily staffing plan for locating six types of firefighting resource given a budget for augmentation. This recommendation is to be utilized by an Operational Duty Chief within LACoFD as needed. With respect to the three original mission objectives presented by LACoFD, where it is desired to minimize population loss, minimize wildland burned acreage, and stabilize wildland fire incidents, this research has successfully achieved the first two and provides recommendations with regard to the third.

We develop two regression models used to estimate the probability of a wildland fire occurring within each of the five climatic zones of LAC and to estimate the expected burned acreage should a wildland fire occur. These regression models are built on data sourced from WIMS and LACoFD, with each containing roughly 20 explanatory parameters. The selected regression models are justified using a series of stepwise regressions for minimizing a commonly used measure of prediction error. Each regression model is further tested against separate validation subsets to evaluate their effectiveness with regards to predictability.

We develop an Augmentation Optimization Model (AOM) that utilizes the regression model input. The optimization model exhibits both network and knapsack structures, where the transfer of on-duty and off-duty resources must be optimized across the county in order to minimize the expected population displacement within LAC.

When should augmentation take place? Augmentation needs be balanced so that LACoFD can provide effective protection for both life and property while still meeting yearly budget limits. Augmentation, while effective, comes with its own shortcomings as well. Personnel are often removed from their families on short notice, typically receiving an assignment only the night before. The costs for augmentation are also problematic, as shown by the $2.5 million spent for December 2017. The problems with augmentation thus raise questions regarding the decisions that which form augmented staffing plans. Current methods used by LACoFD are subjective, often relying on Operational Duty Chief's previous experience and knowledge of the area; relying on such personal judgement is reasonable, but methods such as these suggested here can sharpen thumbrules.

We recommend future research to thus explore when augmentation should take place. While the AOM provides optimal augmentation regarding the estimated probability of wildland fire and expected burned acreage, it does not provide new methods for deciding when augmentation should occur. The estimated probability of wildland fire provides a potential platform for this new method, however the sub-models presented within this thesis require further research. As mentioned previously, wildland fire is highly susceptible to the human interaction with nature. By creating a logistic regression centered solely on weather and fire danger factors, a highly explanatory parameter of human negligence is left out of this equation. Thus, we recommend that human factors associated with wildland factors be researched in order to refine the sub-models. If these sub-models become more capable in their forecasting, or classification, we recommend that these be used to aid in the decision regarding when to augment resources.

We recommend that this research be further expanded to incorporate other resources such as helicopters, dozers, and hand crews, among many other resources. Regression models provide the ability to reveal underlying interrelationships between these resources and can provide valuable information regarding any possible interactions as explored in this research. The AOM can thus be adapted to incorporate camp locations for hand crews and fueling locations for helicopters. Optimizing placement for all of these resources thus provides a holistic approach regarding decisions on pre-positioning.

Configurations within the AOM regarding the penalty for using more budget than necessary should also be incorporated. While pre-positioning more capability into a sub-area will inherently reduce the estimated expected burned acreage of a wildland fire, there is only so much return that can be received from that investment. Penalty terms can thus account for this, ensuring the AOM does not exceed needed resources to a sub-area merely because there is still budget to spend. We recommend that these penalties be discussed with LACoFD.

The regression models and AOM built with this research combine to form an efficient and capable decision support tool to recommend augmented staffing plans to

Operational Duty Chiefs within LACoFD. The recommended staffing plan takes current methods practiced by LACoFD and determines an efficient placement of firefighting resources throughout LAC given the capability they provide to a firefighting effort and their associated costs. The augmented staffing plan determined to be optimal by the AOM is thus a recommendation, where decisions can then be made by experienced professionals.

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APPENDIX A. ESTIMATED PROBABILITY OF WILDLAND FIRE

The following section provides a logistic regression for each climatic zone to estimate a probability of wildland fire. Each table outlines the parameters that were chosen to be included within the regression and their respective statistics. These statistics include each estimated parameter coefficient, standard error, Wald-test statistic, and p-value. For the main-effects, the odds ratio and its respective 95% confidence interval are also provided. We also include the ROC curve for each climatic zone's sub-model.

A. LOS ANGELES BASIN

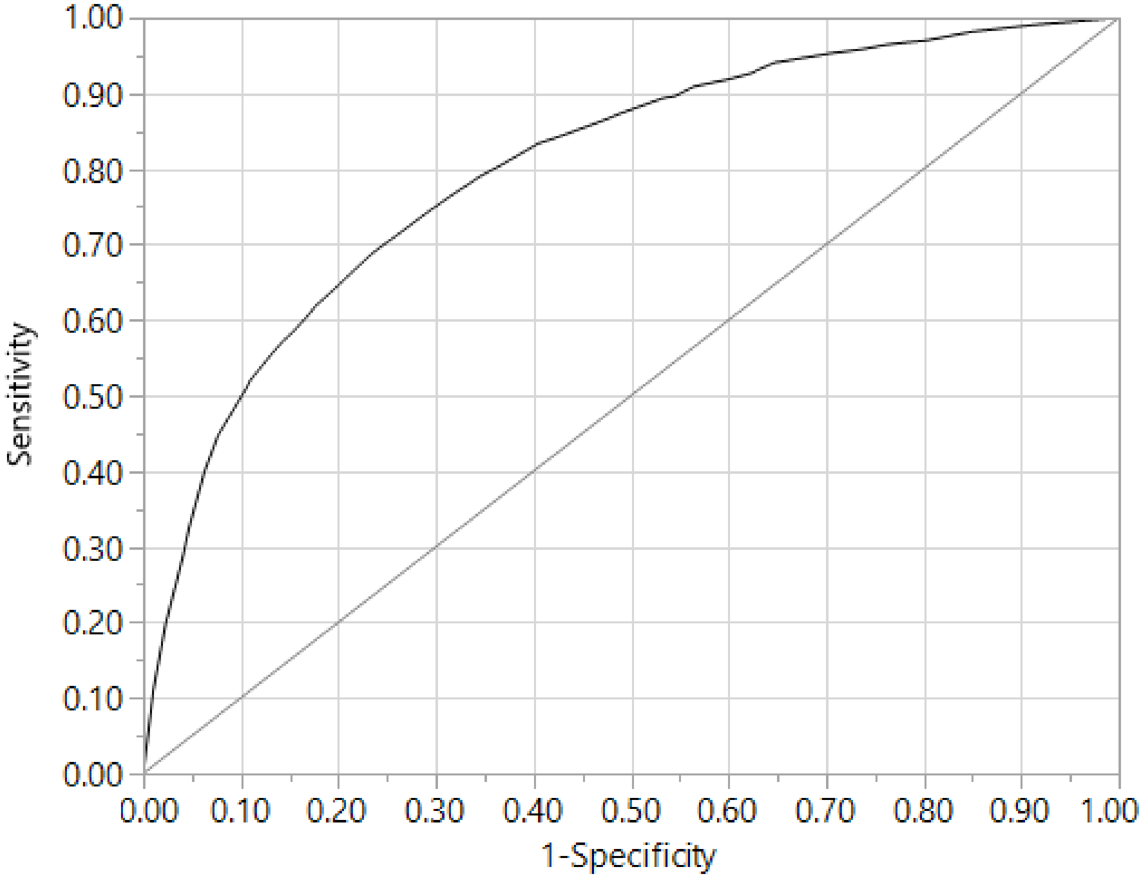
LA Basin includes six RAWS sub-areas: Santa Fe Dam, Henninger Flats, Claremont, Whittier, San Rafael, and Tonner Canyon.

Appendix Table 1. Logistic Regression Analysis for LA Basin

Term	$\hat{\beta}$	$\hat{\beta}$ **SE**	**Wald** $\chi 2$	***p-value***	**Odds Ratio**	**95% CI Odds Ratio**
Intercept	-6.66	3.68E-01	327.54	<.0001		
BI	1.70E-02	6.90E-03	6.07	0.014	1.017	[1.003, 1.031]
Temperature	5.44E-02	3.24E-03	281.75	<.0001	1.056[a]	[1.049, 1.063]
RH	-1.05E-02	4.08E-03	6.65	0.010	0.990[a]	[0.982, 0.997]
Wind	1.92E-02	9.79E-03	3.84	0.050	1.019	[1, 1.039]
ERC	-2.21E-02	7.92E-03	7.78	0.005	0.978[a]	[0.963, 0.993]
LFM	7.93E-03	9.20E-04	74.45	<.0001	1.008	[1.006, 1.01]
SC	-2.21E-02	9.44E-03	5.48	0.019	0.978	[0.96, 0.996]
Temperature x RH	7.60E-04	1.63E-04	21.75	<.0001		
RH x ERC	-3.43E-04	1.10E-04	9.71	0.002		
RAWS - CLAREMONT	8.46E-02	5.59E-02	2.29	0.130		
RAWS - HENNINGER FLATS	-1.12E+00	9.44E-02	140.58	<.0001		
RAWS - SAN RAFAEL	-6.76E-01	6.58E-02	105.74	<.0001		
RAWS - SANTA FE DAM	2.18E-01	5.35E-02	16.62	<.0001		
RAWS - TONNER CANYON	-3.79E-01	7.04E-02	28.97	<.0001		

[a] Odds ratios not meaningful due to involvement with compound effects.

The common metric used to evaluate the accuracy of a model is the area under the Receiver Operator Characteristic (ROC) curve, referred to as the Area under the Curve (AUC). For this metric, an AUC value of one indicates a perfect model while a value of 0.5 represents a worthless one (i.e. random guessing).



The x-axis shows the "False Positive Rate" and the y-axis the "True Positive Rate."

Appendix Figure 1. ROC Curve for LA Basin Sub-model with an AUC of 0.802

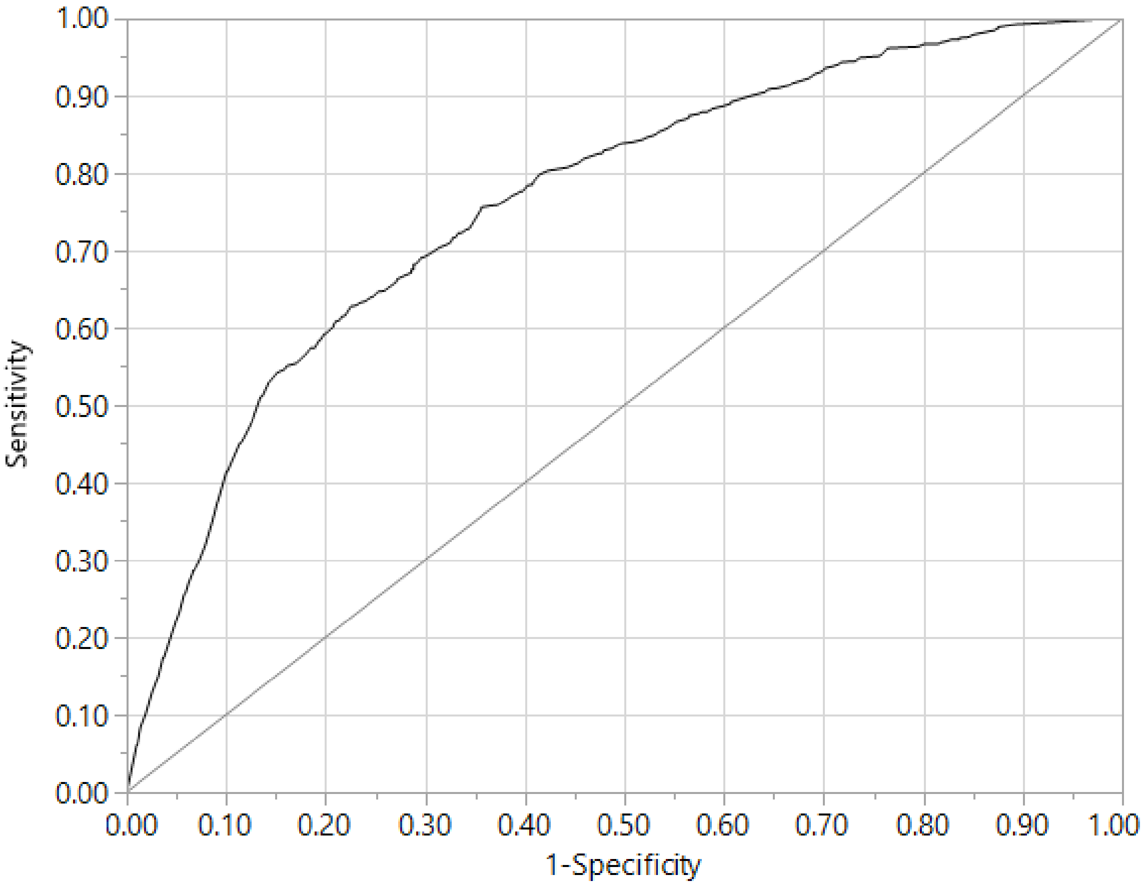
B. SANTA MONICA MOUNTAINS

Santa Monica Mountains includes six RAWS sub-areas: Cheseboro, Malibu, Beverly Hills, Leo Carrillo, Malibu Canyon, and Topanga.

Appendix Table 2. Logistic Regression Analysis for Wildland Fire in Santa Monica Mountains

Term	$\hat{\beta}$	$\hat{\beta}$ SE	Wald $\chi2$	*p-value*	Odds Ratio	95% CI Odds Ratio
Intercept	-6.67	5.18E-01	166.01	<.0001		
BI	3.12E-03	1.30E-03	5.78	0.016	1.003[a]	[1.001, 1.006]
Temperature	2.54E-02	4.18E-03	36.85	<.0001	1.026[a]	[1.017, 1.034]
Wind	3.07E-02	1.03E-02	8.87	0.003	1.031[a]	[1.011, 1.052]
LFM	9.72E-03	2.47E-03	15.51	<.0001	1.010[a]	[1.005, 1.015]
DFM	-3.08E-02	1.54E-02	3.99	0.046	0.970[a]	[0.941, 0.999]
Month	1.22E-01	1.16E-01	1.12	0.291	1.130	[0.901, 1.418]
Week	-2.33E-02	2.66E-02	0.77	0.381	0.977[a]	[0.927, 1.029]
BI x Temperature	-1.90E-04	7.17E-05	6.99	0.008		
LFM x DFM	8.13E-04	2.08E-04	15.34	<.0001		
LFM x Week	5.50E-04	1.83E-04	9.04	0.003		
RAWS – Beverly Hills	1.48E+00	7.90E-02	353.20	<.0001		
RAWS – Cheseboro	2.21E-02	9.71E-02	0.05	0.820		
RAWS – Leo Carrillo	-3.61E-01	1.35E-01	7.15	0.008		
RAWS – Malibu	3.57E-02	1.12E-01	0.10	0.750		
RAWS – Malibu Canyon	-1.61E-01	1.49E-01	1.17	0.280		
Wind x RAWS – Beverly Hills	-6.65E-02	1.51E-02	19.36	<.0001		
Wind x RAWS – Cheseboro	6.22E-03	1.71E-02	0.13	0.717		
Wind x RAWS – Leo Carrillo	4.75E-02	2.81E-02	2.85	0.091		
Wind x RAWS - Malibu	-3.46E-02	1.68E-02	4.22	0.040		
Wind x RAWS – Malibu Canyon	-1.54E-03	1.83E-02	0.01	0.933		

[a] Odds ratios not meaningful due to involvement with compound effects.



Appendix Figure 2. ROC Curve for Santa Monica Mountains Sub-model with an AUC of 0.769

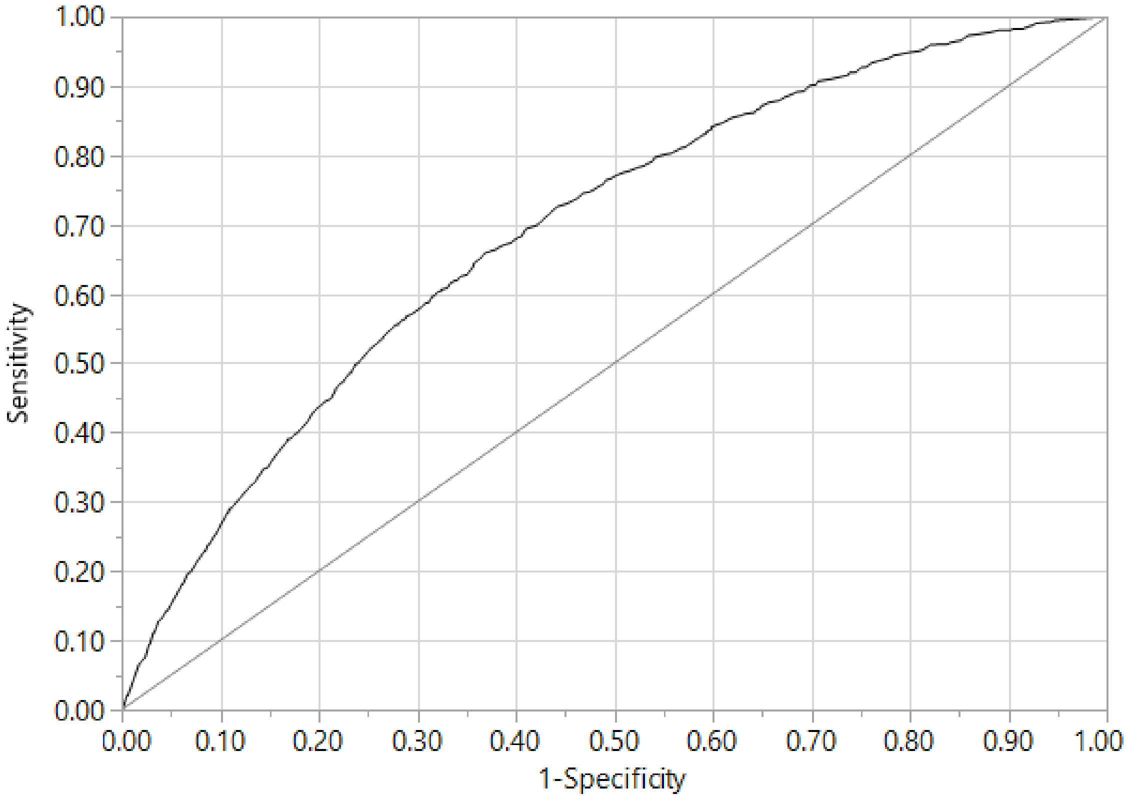
C. SANTA CLARITA VALLEY

Santa Clarita Valley includes four RAWS sub-areas: Saugus, Acton, Del Valle, and Newhall Pass.

Appendix Table 3. Logistic Regression Analysis for Wildland Fire in Santa Clarita Valley

Term	$\hat{\beta}$	$\hat{\beta}$ **SE**	**Wald $\chi 2$**	***p-value***	**Odds Ratio**	**95% CI Odds Ratio**
Intercept	-5.87956	0.48773	145.32	<.0001		
BI	-1.2E-05	0.001274	0	0.9926	0.999[a]	[0.997, 1.002]
Temperature	0.030192	0.003388	79.4	<.0001	1.031[a]	[1.023, 1.038]
RH	-0.00956	0.003926	5.93	0.0149	0.990[a]	[0.983, 0.998]
Wind	0.047763	0.008844	29.17	<.0001	1.049[a]	[1.031, 1.067]
LFM	0.00739	0.002014	13.46	0.0002	1.007	[1.003, 1.011]
KBDI	0.000178	0.000315	0.32	0.5725	1.000[a]	[1, 1.001]
Week	-0.0081	0.003559	5.18	0.0229	0.992[a]	[0.985, 0.999]
BI x Temperature	-0.00021	6.46E-05	10.97	0.0009		
Temperature x KBDI	-0.00011	2.21E-05	25.48	<.0001		
RH x KBDI	-8.18E-05	1.65E-05	24.64	<.0001		
Wind x KBDI	0.00014	4.52E-05	9.57	0.002		
KBDI x Week	-5.89E-05	0.000021	7.86	0.005		
RAWS - Acton	-0.39278	0.080098	24.05	<.0001		
RAWS – Del Valle	-0.05377	0.063492	0.72	0.397		
RAWS – Newhall Pass	0.032195	0.069522	0.21	0.6433		
RH x RAWS - Acton	-0.00182	0.005343	0.12	0.7334		
RH x RAWS – Del Valle	0.015547	0.004428	12.33	0.0004		
RH x RAWS – Newhall Pass	-0.00563	0.004813	1.37	0.2425		
Wind x RAWS - Acton	0.017652	0.012952	1.86	0.1729		
Wind x RAWS – Del Valle	0.024595	0.014231	2.99	0.0839		
Wind x RAWS – Newhall Pass	-0.01187	0.015548	0.58	0.4452		

[a] Odds ratios not meaningful due to involvement with compound effects.



Appendix Figure 3. ROC Curve for Santa Clarita Valley sub-Model with an AUC of 0.691

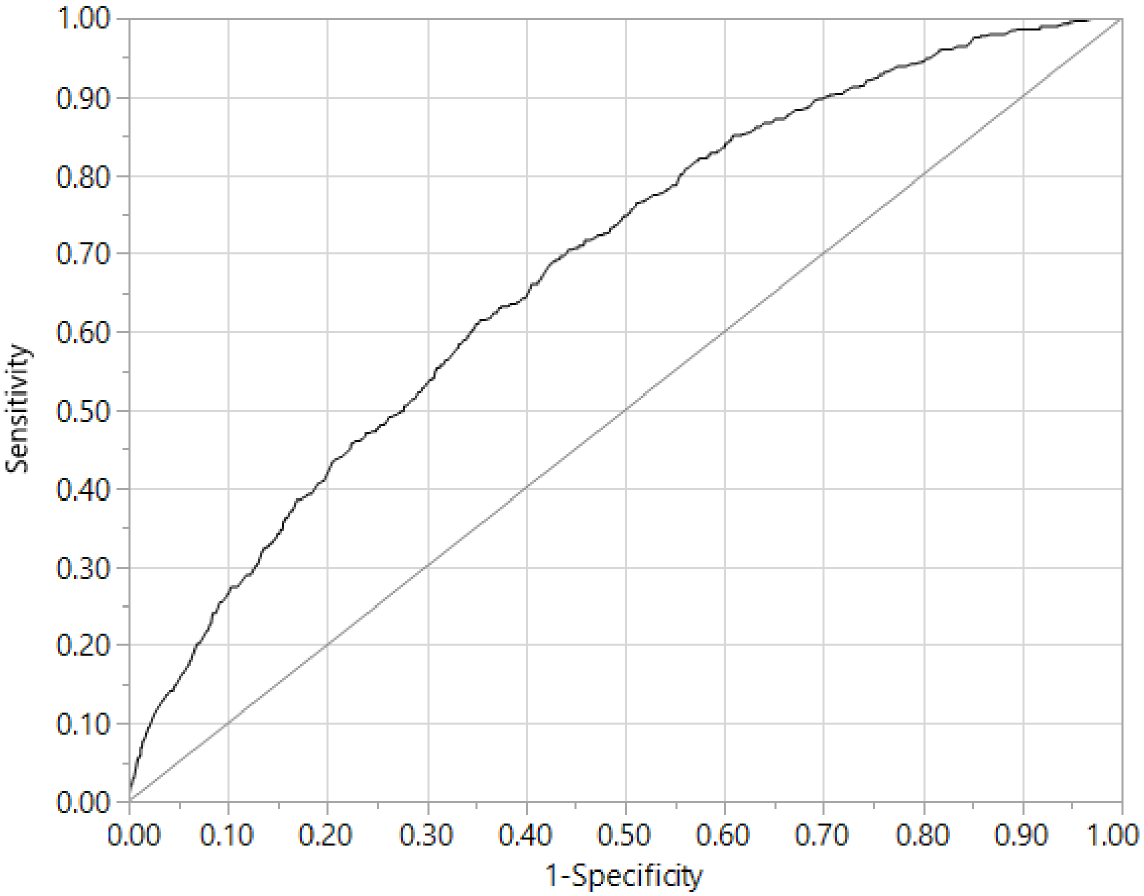
D. HIGH COUNTRY

High Country includes two RAWS sub-areas: Camp-9 and Whitaker I-5.

Appendix Table 4. Logistic Regression Analysis for Wildland Fire in High Country

Term	$\hat{\beta}$	$\hat{\beta}$ **SE**	**Wald $\chi2$**	***p-value***	**Odds Ratio**	**95% CI Odds Ratio**
Intercept	-6.25	1.18E+00	27.85	<.0001		
Weekend	1.88E-01	8.77E-02	4.61	0.032	1.207	[1.017, 1.434]
BI	6.59E-02	1.94E-02	11.50	0.001	1.068[a]	[1.028, 1.11]
Temperature	3.66E-02	5.07E-03	52.23	<.0001	1.037[a]	[1.027, 1.048]
RH	2.42E-02	9.88E-03	6.00	0.014	1.025[a]	[1.005, 1.045]
Wind	3.56E-02	1.84E-02	3.73	0.053	1.036[a]	[0.999, 1.074]
LFM	1.14E-02	3.17E-03	12.92	0.000	1.011[a]	[1.005, 1.018]
ERC	-7.70E-02	2.26E-02	11.65	0.001	0.926[a]	[0.886, 0.968]
SC	-6.43E-02	2.08E-02	9.57	0.002	0.938[a]	[0.9, 0.977]
KBDI	3.30E-04	3.69E-04	0.80	0.370	1.000[a]	[1, 1.001]
10-Hr DFM	-2.37E-01	7.25E-02	10.73	0.001	0.789[a]	[0.684, 0.909]
RAWS – Camp-9	-4.07E-02	5.21E-02	0.61	0.434		
BI x Wind	1.49E-03	3.79E-04	15.51	<.0001		
Temperature x Wind	3.03E-03	7.56E-04	16.03	<.0001		
Temperature x LFM	4.66E-04	1.93E-04	5.80	0.016		
Temperature x 10-Hr DFM	3.24E-03	1.06E-03	9.42	0.002		
RH x LFM	2.90E-04	1.16E-04	6.27	0.012		
RH x SC	3.61E-04	1.62E-04	4.94	0.026		
Wind x ERC	-2.12E-03	7.88E-04	7.23	0.007		
Wind x 10-Hr DFM	9.35E-03	2.79E-03	11.23	0.001		
LFM x KBDI	5.16E-05	1.20E-05	18.60	<.0001		
ERC x 10-Hr DFM	-4.78E-03	1.30E-03	13.64	0.000		
Temperature x RAWS – Camp-9	-1.19E-02	4.32E-03	7.54	0.006		
RH x RAWS – Camp-9	-1.17E-02	3.24E-03	13.14	0.000		

[a] Odds ratios not meaningful due to involvement with compound effects.



This is the least impressive performance out of the five climatic zone predictive models, but still preferable to lack of such guidance.

Appendix Figure 4. ROC Curve for High Country Sub-model with an AUC of 0.682

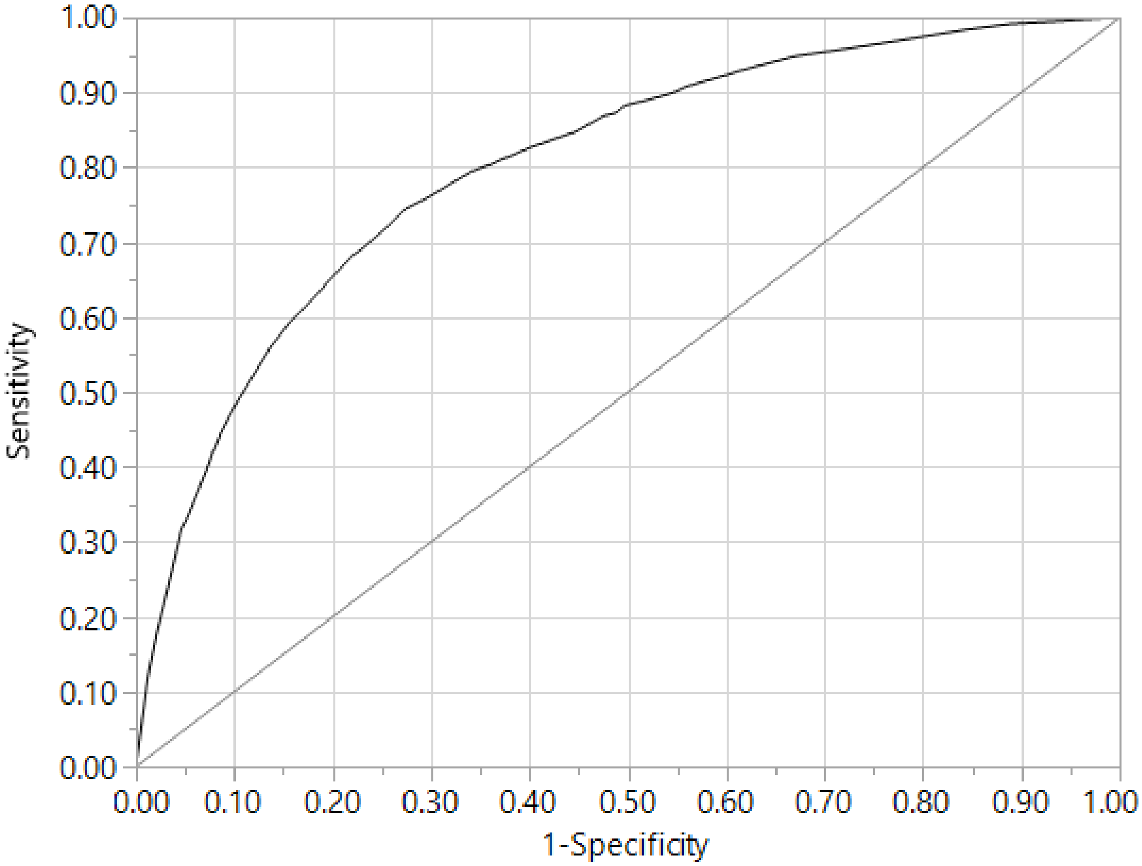
E. ANTELOPE VALLEY

Antelope Valley includes three RAWS sub-areas: Poppy Park, Saddleback, and Lake Palmdale.

Appendix Table 5. Logistic Regression Analysis for Wildland Fire in Antelope Valley

Term	$\hat{\beta}$	$\hat{\beta}$ **SE**	**Wald $\chi 2$**	***p-value***	**Odds Ratio**	**95% CI Odds Ratio**
Intercept	-3.02	6.12E-01	24.41	<.0001		
BI	-4.19E-03	5.12E-03	0.67	0.413	0.996[a]	[0.986, 1.006]
Temperature	1.88E-02	2.82E-03	44.34	<.0001	1.019[a]	[1.013, 1.025]
RH	3.21E-02	7.15E-03	20.21	<.0001	1.033[a]	[1.018, 1.047]
Wind	-2.17E-02	1.88E-02	1.33	0.248	0.979[a]	[0.943, 1.015]
ERC	8.22E-02	2.81E-02	8.56	0.003	1.086[a]	[1.027, 1.147]
SC	3.71E-03	1.96E-03	3.58	0.058	1.004[a]	[1, 1.008]
KBDI	-2.06E-03	2.47E-04	69.46	<.0001	0.998[a]	[0.997, 0.998]
10-Hr DFM	-1.44E-01	4.42E-02	10.63	0.001	0.866[a]	[0.794, 0.944]
Week	-8.49E-03	3.51E-03	5.87	0.015	0.992[a]	[0.985, 0.998]
BI x 10-Hr DFM	-3.62E-03	6.81E-04	28.22	<.0001		
Temperature x KBDI	-5.70E-05	1.50E-05	14.52	0.000		
Temperature x Week	-4.79E-04	1.88E-04	6.49	0.011		
RH x 10-Hr DFM	-3.76E-03	7.39E-04	25.91	<.0001		
Wind x Week	-7.29E-04	3.21E-04	5.18	0.023		
ERC x SC	-6.44E-04	1.69E-04	14.54	0.000		
KBDI x Week	-1.37E-04	2.03E-05	45.02	<.0001		
RAWS - Lake Palmdale	1.44E+00	4.41E-02	1068.40	<.0001		
RAWS - Poppy Park	-3.67E-01	4.99E-02	53.90	<.0001		
Temperature x RAWS - Lake Palmdale	4.38E-03	2.75E-03	2.53	0.112		
Temperature x RAWS - Poppy Park	-1.38E-02	3.15E-03	19.23	<.0001		

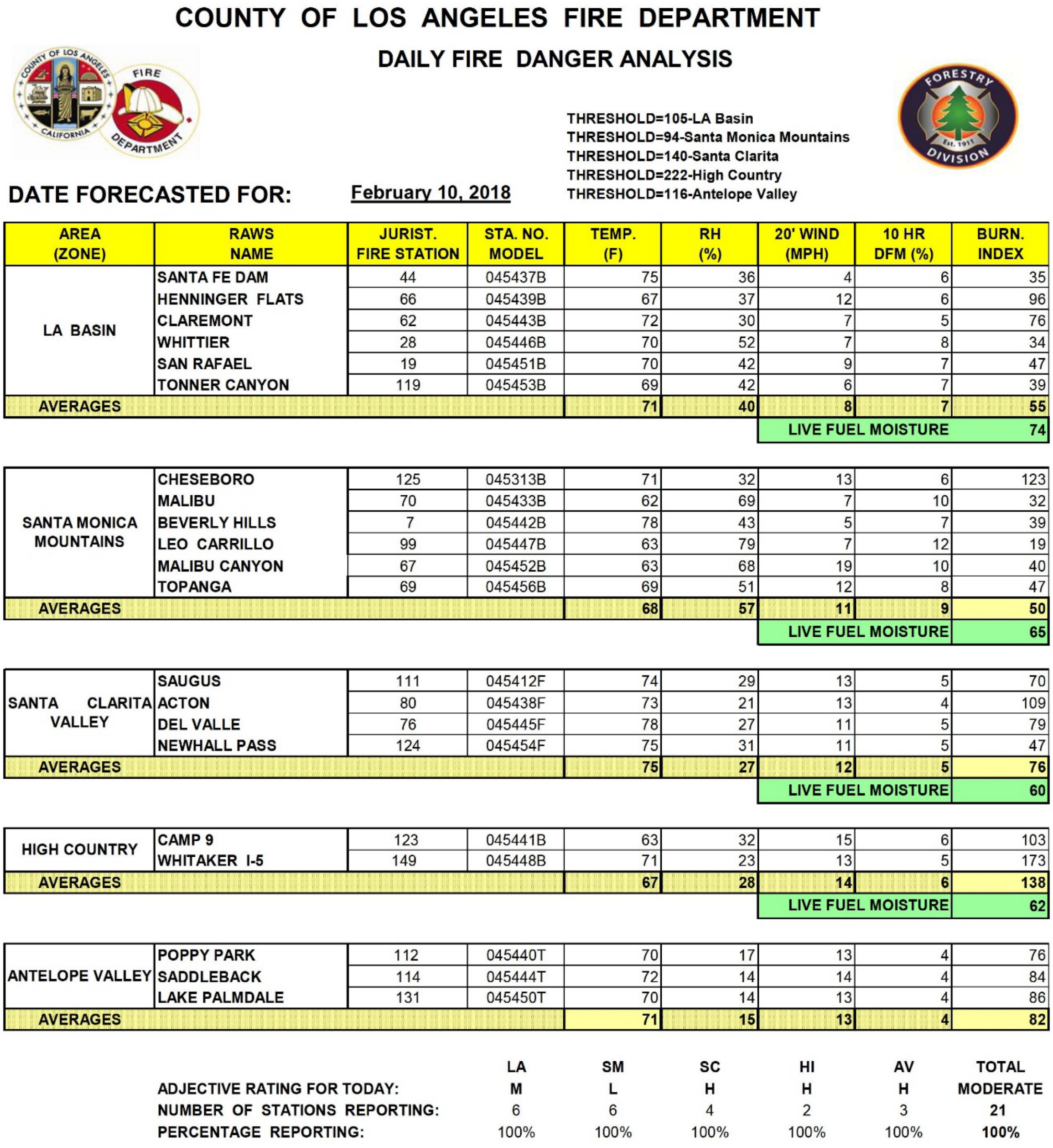
[a] Odds ratios not meaningful due to involvement with compound effects.



Appendix Figure 5. ROC Curve for Antelope Valley Sub-model with an AUC of 0.803

APPENDIX B. FIRE WEATHER DANGER REPORT

The following figure is a sample of a daily report, providing forecasted weather and fire danger data to LACoFD personnel. This report is one of many currently used by Operational Duty Chiefs in LAC for determining augmented staffing plans.



COUNTY OF LOS ANGELES FIRE DEPARTMENT

DAILY FIRE DANGER ANALYSIS

THRESHOLD=105-LA Basin
THRESHOLD=94-Santa Monica Mountains
THRESHOLD=140-Santa Clarita
THRESHOLD=222-High Country
THRESHOLD=116-Antelope Valley

DATE FORECASTED FOR: February 10, 2018

AREA (ZONE)	RAWS NAME	JURIST. FIRE STATION	STA. NO. MODEL	TEMP. (F)	RH (%)	20' WIND (MPH)	10 HR DFM (%)	BURN. INDEX
LA BASIN	SANTA FE DAM	44	045437B	75	36	4	6	35
	HENNINGER FLATS	66	045439B	67	37	12	6	96
	CLAREMONT	62	045443B	72	30	7	5	76
	WHITTIER	28	045446B	70	52	7	8	34
	SAN RAFAEL	19	045451B	70	42	9	7	47
	TONNER CANYON	119	045453B	69	42	6	7	39
AVERAGES				71	40	8	7	55
						LIVE FUEL MOISTURE		74
SANTA MONICA MOUNTAINS	CHESEBORO	125	045313B	71	32	13	6	123
	MALIBU	70	045433B	62	69	7	10	32
	BEVERLY HILLS	7	045442B	78	43	5	7	39
	LEO CARRILLO	99	045447B	63	79	7	12	19
	MALIBU CANYON	67	045452B	63	68	19	10	40
	TOPANGA	69	045456B	69	51	12	8	47
AVERAGES				68	57	11	9	50
						LIVE FUEL MOISTURE		65
SANTA CLARITA VALLEY	SAUGUS	111	045412F	74	29	13	5	70
	ACTON	80	045438F	73	21	13	4	109
	DEL VALLE	76	045445F	78	27	11	5	79
	NEWHALL PASS	124	045454F	75	31	11	5	47
AVERAGES				75	27	12	5	76
						LIVE FUEL MOISTURE		60
HIGH COUNTRY	CAMP 9	123	045441B	63	32	15	6	103
	WHITAKER I-5	149	045448B	71	23	13	5	173
AVERAGES				67	28	14	6	138
						LIVE FUEL MOISTURE		62
ANTELOPE VALLEY	POPPY PARK	112	045440T	70	17	13	4	76
	SADDLEBACK	114	045444T	72	14	14	4	84
	LAKE PALMDALE	131	045450T	70	14	13	4	86
AVERAGES				71	15	13	4	82

	LA	SM	SC	HI	AV	TOTAL
ADJECTIVE RATING FOR TODAY:	M	L	H	H	H	MODERATE
NUMBER OF STATIONS REPORTING:	6	6	4	2	3	21
PERCENTAGE REPORTING:	100%	100%	100%	100%	100%	100%

Appendix Figure 6. LACoFD Daily Fire Danger Analysis Report

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APPENDIX C. EXPECTED BURNED ACREAGE MODEL

This appendix provides the multiple linear regression for LAC in estimating expected burned acreage. Appendix Table 6 outlines the predictors included within the regression and their respective statistics. These statistics include the estimated parameter coefficient, standard error, Students *t*-test statistic, and p-value.

Appendix Table 6. Multiple Linear Regression Model for the Expected Burned Acreage of a Wildland Fire

Term	$\hat{\beta}$	$\hat{\beta}$ **SE**	***t*-statistic**	***p-value Pr(>|t|)***
Intercept	-0.805	0.616	-1.31	0.191
Wind	0.028	0.013	2.19	0.029
BI	0.010	5.24E-03	1.86	0.064
Temperature	0.013	4.38E-03	2.86	0.004
RH	5.91E-03	0.007	0.81	0.419
ERC	-0.020	0.010	-2.13	0.033
SC	-0.012	3.65E-03	-3.40	0.001
KBDI	-1.12E-03	3.43E-04	-3.26	0.001
TEN	-0.143	0.056	-2.57	0.010
Capability	-3.14E-04	5.10E-05	-6.15	<.0001
BI x RH	-3.29E-04	1.14E-04	-2.88	0.004
BI x KBDI	-2.80E-05	1.45E-05	-1.94	0.053
Wind x Temperature	-1.42E-03	4.89E-04	-2.91	0.004
RH x SC	3.06E-04	1.01E-04	3.03	0.002
RH x Capability	-1.73E-05	8.69E-06	-1.99	0.047
Wind x ERC	-9.31E-04	4.87E-04	-1.91	0.056
Wind x 10-Hr DFM	-0.018	4.41E-03	-4.06	<.0001
ERC x KBDI	6.15E-05	1.98E-05	3.11	0.002
ERC x Capability	6.77E-06	2.19E-06	3.10	0.002
SC x KBDI	2.43E-05	9.52E-06	2.56	0.011
KBDI x 10-Hr DFM	2.87E-04	1.30E-04	2.21	0.027
10-Hr DFM x Capability	1.70E-04	5.74E-05	2.97	0.003
Week Number	8.01E-03	2.83E-03	2.83	0.005
Los Angeles Basin	-0.108	0.103	-1.05	0.295
Santa Monica Mountains	-0.153	0.104	-1.47	0.142
Santa Clarita Valley	0.197	0.100	1.97	0.049
High Country	0.394	0.146	2.70	0.007

Term	$\hat{\beta}$	$\hat{\beta}$ **SE**	***t*-statistic**	***p-value Pr(>|t|)***
Weather Cluster - 1	0.238	0.205	1.16	0.246
Weather Cluster - 2	-0.024	0.277	-0.09	0.931
Weather Cluster - 3	-0.211	0.213	-0.99	0.321
Weather Cluster - 4	0.531	0.351	1.51	0.131
Weather Cluster - 5	-0.038	0.487	-0.08	0.939
Weather Cluster - 6	-0.137	0.213	-0.64	0.521
Weather Cluster - 7	-0.203	0.186	-1.10	0.274
Weather Cluster - 8	0.032	0.265	0.12	0.905
Weather Cluster - 9	-0.222	0.333	-0.67	0.505
Weather Cluster - 10	-0.088	0.213	-0.41	0.680
Weather Cluster - 11	0.062	0.435	0.14	0.887
Weather Cluster - 12	0.180	0.256	0.70	0.483
Weather Cluster - 13	-0.031	0.359	-0.09	0.932
Weather Cluster - 14	-0.203	0.196	-1.03	0.302
Weather Cluster - 15	-0.546	0.254	-2.15	0.032
Weather Cluster - 16	0.339	0.252	1.35	0.178
Weather Cluster - 17	0.249	0.368	0.68	0.498
Weather Cluster - 18	-0.158	0.237	-0.67	0.506
Weather Cluster - 19	-0.079	0.197	-0.40	0.689
Weather Cluster - 20	-0.146	0.200	-0.73	0.465
Weather Cluster - 21	0.074	0.232	0.32	0.750
Weather Cluster - 22	0.027	0.241	0.11	0.910
Weather Cluster - 23	1.490	0.395	3.78	0.000
Weather Cluster - 24	-0.485	0.214	-2.26	0.024
Weather Cluster - 25	0.314	0.419	0.75	0.454
Weather Cluster - 26	-0.227	0.195	-1.16	0.245
Weather Cluster - 27	0.195	0.352	0.56	0.579
Weather Cluster - 28	-0.325	0.219	-1.48	0.138
Weather Cluster - 29	-0.894	1.709	-0.52	0.601

The significant weather cluster coefficients have been highlighted in bright yellow, these include weather clusters 15, 23, and 24.

APPENDIX D. AUGMENTATION OPTIMIZATION MODEL RESULTS

This appendix provides the AOM output with a budget cap of $134,450.55, the average daily cost of augmentation by LACOFD during December 2017. The total amount of pre-positioned resources is listed alongside the estimated probability of wildland fire, expected burned acreage, and cost of augmentation.

Appendix Table 7. December, 2017: AOM Augmentation with $134,450.55 Budget

Date Dec. 2017	RAWS	Type I	Type III	Type VI	4th FF	CA	Water Tender	Estimated Probability of Fire	Expected Burned Acreage	Cost of Aug.
5	Saugus	12	2	0	12	0	3	0.19	6.50	$66,641.21
	Santa Fe	19	1	2	19	2	0	0.12	1.24	
	Newhall Pass	12	1	5	9	0	2	0.15	1.52	
6	Saugus	12	1	0	12	0	3	0.25	11.52	$86,685.75
	Santa Fe	19	1	2	19	2	0	0.15	1.28	
	Tonner Canyon	12	0	1	12	1	2	0.08	5.57	
7	Santa Fe	19	1	2	5	0	0	0.16	1.29	$9,240.00
	Claremont	11	0	0	0	0	0	0.13	1.32	
	Leo Carrillo	1	0	0	1	0	0	0.03	1.75	
8	Beverly Hills	14	0	1	14	1	0	0.15	1.34	$115,739.82
	Whittier	61	1	3	61	3	2	0.47	1.21	
	Tonner Canyon	7	0	1	7	1	1	0.08	1.50	
9	Santa Fe	19	1	2	19	2	0	0.18	1.34	$74,272.15
	Beverly Hills	19	0	1	19	1	2	0.18	1.29	
	Claremont	11	0	0	0	0	0	0.14	1.31	
10	Whittier	54	0	3	54	3	0	0.59	1.42	$124,555.91
	San Rafael	2	0	1	2	0	0	0.08	1.36	
11	Whittier	63	2	4	63	4	2	0.46	1.23	$99,005.80
	Tonner Canyon	7	0	1	7	1	1	0.09	1.38	
12	Saugus	7	1	0	7	0	2	0.13	1.57	$106,950.32
	Claremont	11	0	0	11	0	0	0.14	1.32	
	Whittier	58	0	3	58	3	1	0.53	1.28	
14	Whitaker	2	0	0	1	0	0	0.06	9.30	$124,643.18
15	Beverly Hills	18	0	1	16	1	0	0.16	1.26	$125,244.21
	Whittier	63	0	3	63	3	2	0.40	1.15	
16	Whittier	63	0	3	63	3	2	0.35	1.16	$124,714.80
17	Acton	2	0	1	2	0	1	0.13	8.74	$125,377.58
	Whittier	54	0	3	54	3	0	0.39	1.27	
18	Malibu	3	0	1	2	0	1	0.03	1.21	$122,118.13

Date Dec. 2017	RAWS	Type I	Type III	Type VI	4th FF	CA	Water Tender	Estimated Probability of Fire	Expected Burned Acreage	Cost of Aug.
22	Beverly Hills	19	0	6	12	0	2	0.13	1.17	$122,587.68
	Whittier	59	0	3	59	3	2	0.32	1.21	
	San Rafael	2	0	1	0	0	0	0.03	1.18	
	Malibu Canyon	10	0	0	8	0	1	0.03	1.28	
23	Beverly Hills	14	0	1	4	0	0	0.14	1.20	$110,727.32
28	Beverly Hills	14	0	1	4	0	0	0.18	1.32	$119,932.43
	Claremont	11	0	0	0	0	0	0.13	1.32	
	San Rafael	2	0	1	0	0	0	0.07	1.32	
29	Claremont	15	2	0	15	0	2	0.11	1.27	$99,345.05
	Whittier	63	2	7	63	7	2	0.46	1.27	
30	Beverly Hills	19	0	1	19	1	2	0.15	1.23	$123,688.74

The Whittier RAWS sub-area on December 10, 2017, has an estimated probability of wildland fire of 0.59 per day. This Poisson probability might also be interpolated as an exponential expected number of days between fires as 1/ 0.59 = 1.7. However, the expected burned acreage for that day is only 1.42 acres. On December 6, 2017, near Saugus, the estimated probability is 0.25 but the estimated burned acreage should a wildland fire occur is 11.52 acres.

APPENDIX E. AUGMENTATION OPTIMIZATION MODEL OUTPUT

This appendix provides a sample output from the AOM for augmented staffing on December 14, 2017, with a budget of $134,450.55. The output lists the three possible transport options: internal transfer of equipment, external transfer of equipment, and external transport and employment of external personnel. The output then shows the chosen candidate resource package for each sub-area, as well as the estimated probability of fire and expected burned acreage. Two sub-areas on this day, Malibu and Del Valle, did not have weather forecasts and were not thus not considered for augmentation.

```
Augmented Staffing for December 14, 2017 with $134,450.55:

Internal Transfer of Resources:
MALIBU           to WHITTIER          : 1 Water Tender
LAKE PALMDALE    to SAUGUS            : 3 Type I Engine (3-person)
LAKE PALMDALE    to SAUGUS            : 6 4th FF for Type I Engine
LAKE PALMDALE    to SAUGUS            : 1 Water Tender
MALIBU           to NEWHALL PASS      : 1 4th FF for Type I Engine
MALIBU           to NEWHALL PASS      : 1 Type VI Engine (1-person)
LAKE PALMDALE    to NEWHALL PASS      : 1 Water Tender

External Transfer of Equipment type Resources:
Station 20        to WHITTIER          : 1 Type I Engine (3-person)
Station 28        to WHITTIER          : 1 Type I Engine (3-person)
Station 191       to WHITTIER          : 1 Type I Engine (3-person)
Station 80        to SAUGUS            : 1 Type I Engine (3-person)
Station 108       to SAUGUS            : 1 Type I Engine (3-person)
Station 4         to NEWHALL PASS      : 1 Type I Engine (3-person)
Station 31        to NEWHALL PASS      : 1 Type I Engine (3-person)
Station 65        to NEWHALL PASS      : 1 Type I Engine (3-person)
Station 66        to NEWHALL PASS      : 1 Type I Engine (3-person)
Station 67        to NEWHALL PASS      : 1 Type I Engine (3-person)
Station 170       to NEWHALL PASS      : 1 Type I Engine (3-person)

Augmentation of Personnel type Resources:
33 Off-Duty 4th FF for Type I Engine to   WHITTIER
5 Off-Duty 4th FF for Type I Engine to    SAUGUS
11 Off-Duty 4th FF for Type I Engine to   NEWHALL PASS
1 Off-Duty CA for Type VI Engine to       WHITTIER
3 Off-Duty CA for Type VI Engine to       NEWHALL PASS

Candidate Resource Package Chosen:
(T-I, T-III, 4th FF on T-I, T-VI, CA on T-VI, WT)
SANTA FE DAM              (19, 1, 5, 2, 0, 0)
HENNINGER FLATS           (5, 2, 2, 0, 0, 0)
CLAREMONT                 (11, 0, 0, 0, 0, 0)
```

```
WHITTIER                  (57, 0, 57, 3, 2, 1)
SAN RAFAEL                (2, 0, 0, 1, 0, 0)
TONNER CANYON             (7, 0, 0, 1, 0, 1)
CHEESEBORO                (2, 1, 0, 1, 0, 1)
MALIBU                    (3, 0, 0, 0, 0, 0)
BEVERLY HILLS             (14, 0, 4, 1, 0, 0)
LEO CARILLO               (1, 0, 0, 0, 0, 0)
MALIBU CANYON             (5, 0, 1, 0, 0, 0)
TOPANGA                   (1, 0, 0, 0, 0, 0)
SAUGUS                    (12, 1, 12, 0, 0, 3)
ACTON                     (2, 0, 0, 1, 0, 1)
DEL VALLE                 (1, 0, 0, 0, 0, 0)
NEWHALL PASS              (12, 0, 12, 3, 3, 2)
CAMP-9                    (2, 0, 0, 0, 0, 0)
WHITAKER I-5              (2, 0, 1, 0, 0, 0)
POPPY PARK                (2, 0, 0, 0, 0, 0)
SADDLEBACK                (3, 0, 0, 0, 0, 0)
LAKE PALMDALE             (9, 0, 0, 0, 0, 0)
```

Estimated Probability of Wildland Fire and Expected Damage

```
SANTA FE DAM       Estimated Probability of Fire: 0.19
                        -Expected Fire Damage: 1.39 acres
HENNINGER FLATS    Estimated Probability of Fire: 0.04
                        -Expected Fire Damage: 1.50 acres
CLAREMONT          Estimated Probability of Fire: 0.15
                        -Expected Fire Damage: 1.37 acres
WHITTIER           Estimated Probability of Fire: 0.53
                        -Expected Fire Damage: 1.30 acres
SAN RAFAEL         Estimated Probability of Fire: 0.09
                        -Expected Fire Damage: 1.81 acres
TONNER CANYON      Estimated Probability of Fire: 0.10
                        -Expected Fire Damage: 1.74 acres
CHEESEBORO         Estimated Probability of Fire: 0.07
                        -Expected Fire Damage: 1.68 acres
MALIBU             **NO WEATHER FORECAST**
BEVERLY HILLS      Estimated Probability of Fire: 0.17
                        -Expected Fire Damage: 1.40 acres
LEO CARILLO        Estimated Probability of Fire: 0.02
                        -Expected Fire Damage: 1.32 acres
MALIBU CANYON      Estimated Probability of Fire: 0.05
                        -Expected Fire Damage: 1.65 acres
TOPANGA            Estimated Probability of Fire: 0.02
                        -Expected Fire Damage: 1.37 acres
SAUGUS             Estimated Probability of Fire: 0.17
                        -Expected Fire Damage: 9.06 acres
ACTON              Estimated Probability of Fire: 0.12
                        -Expected Fire Damage: 12.12 acres
DEL VALLE          **NO WEATHER FORECAST**
NEWHALL PASS       Estimated Probability of Fire: 0.14
                        -Expected Fire Damage: 8.82 acres
CAMP-9             Estimated Probability of Fire: 0.11
                        -Expected Fire Damage: 10.15 acres
WHITAKER I-5       Estimated Probability of Fire: 0.06
                        -Expected Fire Damage: 9.30 acres
POPPY PARK         Estimated Probability of Fire: 0.08
```

```
SADDLEBACK         Estimated Probability of Fire: 0.03
LAKE PALMDALE      Estimated Probability of Fire: 0.27
```

Cost of Augmentation

```
         Internal:              $ 332.96
         External:              $ 52238.22
         Extra Personnel:       $ 72072.00
         Total:                 $ 124643.18
```

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